Managing Propagation of Site-Wide Disturbances using Model Predictive Control with Forecasting

Thesis by
Francesco Borghesan

In Partial Fulfillment of the Requirements for the
PhD in
Chemical Engineering

Supervisor: Nina F. Thornhill, Imperial College London
Cosupervisor: Moncef Chioua, ABB Corporate Research Center Germany



IMPERIAL COLLEGE LONDON
London, United Kingdom

May 2021

DECLARATION OF ORIGINALITY AND COPYRIGHT

I confirm that the material presented in this thesis is fully the result of my own work unless otherwise mentioned.

The copyright of this thesis rests with the author. Unless otherwise indicated, its contents are licensed under a Creative Commons Attribution-Non Commercial 4.0 International Licence (CC BY-NC).

Under this licence, you may copy and redistribute the material in any medium or format. You may also create and distribute modified versions of the work. This is on the condition that: you credit the author and do not use it, or any derivative works, for a commercial purpose.

When reusing or sharing this work, ensure you make the licence terms clear to others by naming the licence and linking to the licence text. Where a work has been adapted, you should indicate that the work has been changed and describe those changes. Please seek permission from the copyright holder for uses of this work that are not included in this licence or permitted under UK Copyright Law.

ACKNOWLEDGEMENTS

I would like to thank Nina Thornhill, my *Doktormutter*. She is one of the most emotionally intelligent person I have ever met. She was always positive in these four years and half, and generous in compliments, even if these compliments were not always deserved. It has been though to follow all her remarks about the structure and writing of the thesis. Nonetheless, it is her merit if the content of this thesis is, hopefully, a bit understandable.

I would like to thank the people in ABB Germany who bore me for two years, in particular my co-supervisor Moncef Chioua, who has a large technical but also humanistic knowledge. Also my office neighbour Iiro Harjunkoski, who tolerated me even though he could hear the jokes and laughs coming from my office. With Reinhard Bauer and Dennis Janka I spent a wonderful time playing kickers in ABB, a highlight of the PhD, to be honest!

In ABB Norway, a special thanks goes to Trond Haugen and Charlotte Skorup who welcomed me and organized the series of interviews with ABB experts that contributed to Chapter 3 of this thesis.

Unforgettable are the other PhD colleagues in Germany, Frederik Schulze Spüntrup, Matthieu Lucke, Giancarlo Dalle Ave, Jesus Hernandez, and Egidio Leo. I enjoyed the funny stories we shared and the support you gave me, organising regular calls even after the end of the project.

Thank you also to Marta Zagorowska and Ruomu Tan for the long talks and dinners in London before the pandemic hit us. Hopefully, we can meet soon together.

An acknowledgement is needed for my former colleagues Harald Hoffmann and Peter Venhoff. Harald taught me how a chemical plant works and how to operate one during disturbances. Peter, with his knowledge, also helped me understanding the topics of Chapter 3.

I cannot forget Szymon Bartus and Felipe Huerta Perez. Being closed for one year at home because of a pandemic might not be easy but you helped so much in this period.

Finally, thank you to my family and especially to my mother, my first teacher of mathematics, who has had always a lot of patience with me. I dedicate this thesis to her.

ABSTRACT

Disturbances are undesired deviations of process variables from their set-points. Many disturbances are characterised by the repetitions of fast and complex patterns, and by the fact that such disturbances can propagate. If they propagate within a plant they are called plant-wide disturbances. If they propagate also to utilities of a process site, they are called site-wide disturbances.

Control systems play a role in the propagation of disturbances. A common requirement of a control system is to maintain a controlled variable at its set point by rejecting a disturbance. However, rejecting a disturbance can lead to further propagation of the disturbance elsewhere in the system. Hence there is a need for a trade-off. Plant operators can prefer to manually control a section of a production site to manage this trade-off, when a disturbance occurs.

To automatically manage the response to plant-wide and site-wide disturbances, this thesis proposes Model Predictive Control (MPC) with disturbance forecasting. Since there have been very few publications focusing on the causes and mechanisms of propagation of site-wide disturbances, this thesis contains a review of the possible disturbances occurring between process plants, steam utility and electrical utility. This analysis identifies the important scenarios where the proposed MPC framework might be useful, and also provides the research community a structured discussion about the topic of site-wide disturbances.

The thesis presents a k-nearest neighbours method for the prediction of disturbances. The algorithm uses a novel weighting method that makes the prediction more robust. The method is compared with other k-nearest neighbours methods and autoregressive models on industrial datasets.

The proposed MPC framework with disturbance forecasting is compared with other industrial frameworks on three simulated case studies. The case studies are a laboratory CSTH tank, an industrial steam boiler and an industrial distillation column. Incorporation of a prediction of the future evolution of a disturbance in model predictive control reduces the propagation of disturbances in most cases by a value between 65% and 95%, and improves the tracking of set-points up to 10%. This allows management of the trade-off between disturbance propagation and rejection of the disturbance from the controlled variables.

The approaches and novel results of the research are examined critically, with suggestions for future work.

PUBLISHED CONTENT AND CONTRIBUTIONS

The work of the thesis has been published in the following articles:

- F. Borghesan, M. Chioua, and N. F. Thornhill. Forecasting of process disturbances using k-nearest neighbours, with an application in process control. *Computers and Chemical Engineering*, 128:188 – 200, 2019a. ISSN 00981354
- F. Borghesan, M. Chioua, and N. F. Thornhill. Forecast of persistent disturbances using *k* -nearest neighbour methods. In *Computer Aided Chemical Engineering, Volume 44*, pages 631–636, 2018a
- F. Borghesan, M. Chioua, and N. F. Thornhill. An MPC with disturbance forecasting for the control of the level of a tank with limited buffer capacity. In *2018 26th Mediterranean Conference on Control and Automation (MED)*, pages 1–9, 2018b

CONTENTS

Declaration of originality and copyright . . . 2
Acknowledgements . . . 3
Abstract . . . 4
Published Content and Contributions . . . 5
Contents . . . 6
List of Figures . . . 11
List of Tables . . . 17
Chapter 1: Introduction . . . 20
1.1 Background and motivation . . . 20
1.1.1 Disturbances in process control . . . 20
1.1.2 Economic impact of disturbances . . . 21
1.1.3 The role of control systems in disturbance propagation . . . 22
1.1.4 Propagation of disturbances within a production site . . . 23
1.1.5 The aim of the PhD . . . 24
1.2 Disturbances in site utilities . . . 25
1.2.1 Site utilities . . . 25
1.2.2 Disturbances . . . 26
1.3 Propagation of disturbances . . . 29
1.3.1 Possible disturbance propagation paths in a production site . . . 29
1.3.2 The role of controllers in disturbance propagation . . . 31
1.3.3 Example: disturbance propagation through a plant . . . 32
1.3.4 Example: disturbance propagation between a plant and a steam utility . . . 33
1.3.5 Example: disturbance propagation between plant and electric utility . . . 34
1.4 Operating a process in case of plant-wide disturbances . . . 34
1.5 Model predictive control . . . 36
1.5.1 Use of MPC in process industry . . . 36
1.5.2 Features of MPC for disturbance handling . . . 37
1.5.3 Current limitations of industrial MPCs for disturbance handling . . . 37
1.6 Research statement and technical objectives of the thesis . . . 39
1.6.1 Publications . . . 41
1.7 Summary . . . 41
Chapter 2: Literature review . . . 43
2.1 Introduction . . . 43
2.2 Model predictive control . . . 44
2.2.1 Introduction . . . 44
2.2.2 Handling of external disturbances . . . 45
2.2.3 Frozen Time MPC (FTMPC) . . . 51

2.2.4 Preview MPC . . . 53
2.2.5 Stochastic MPC . . . 55
2.2.6 Deterministic MPC . . . 57
2.2.7 Conclusions on model predictive control . . . 59
2.3 Time series forecasting . . . 60
2.3.1 Introduction . . . 60
2.3.2 Statistical methods . . . 63
2.3.3 Machine learning methods . . . 68
2.3.4 Conclusions on time series forecasting . . . 74
2.4 Summary . . . 75
Chapter 3: Disturbance propagation in a production site . . . 77
3.1 Introduction . . . 77
3.2 Description of the systems considered . . . 79
3.2.1 Process plant . . . 79
3.2.2 Steam system . . . 80
3.2.3 Electrical utility and electromechanical loads . . . 83
3.3 Propagation of disturbances within a plant . . . 86
3.3.1 Overview of propagation mechanisms . . . 86
3.3.2 The three cases considered and possible causes . . . 87
3.3.3 Energy balance . . . 89
3.3.4 Variation of temperatures and composition profile of a distillation column . 89
3.3.5 Incorrect separation of components . . . 89
3.3.6 Variation of internal mass flows in the column . . . 90
3.3.7 Effects on the levels of the units . . . 90
3.3.8 Reaction of the level controllers . . . 90
3.3.9 Variations of flow through a valve . . . 91
3.3.10 Further propagation of disturbance downstream . . . 91
3.3.11 Conclusions on disturbance propagation within a plant . . . 91
3.4 Propagation of disturbances between electrical utility and process plant . . . 92
3.4.1 Overview of the propagation mechanisms . . . 92
3.4.2 Variation of the frequency . . . 93
3.4.3 Voltage variations and voltage dips . . . 96
3.4.4 Disturbances propagating from the process to the electric grid . . . 100
3.4.5 Conclusions on disturbance propagation between electrical utility and plant 101
3.5 Propagation of disturbances between steam utility and process plant . . . 102
3.5.1 Overview of the propagation mechanisms . . . 102
3.5.2 Low steam quality . . . 104
3.5.3 Variation of the energy in the boiler . . . 111
3.5.4 Variations of level of water in the drum of a boiler . . . 115
3.5.5 Conclusions on disturbance propagation between steam utility and production plant . . . 117
3.6 Propagation of disturbances between steam utility and electrical utility . . . 118
3.6.1 Overview of the propagation mechanisms . . . 118
3.6.2 Disturbances in island mode caused by an imbalance between power generated and consumed . . . 118

3.6.3 Limits of pressure variation for a boiler and a steam turbine . . . 119
3.6.4 Conclusion on the disturbance propagation between steam utility and electrical utility . . . 119
3.7 Summary . . . 120
Chapter 4: Disturbance prediction . . . 122
4.1 Introduction . . . 122
4.2 $k-$Nearest neighbours . . . 123
4.2.1 Basic concepts of nearest neighbour prediction . . . 123
4.2.2 Two versions of the algorithm . . . 125
4.2.3 A fixed number of neighbours versus a maximal neighbours distance . . . 126
4.3 Measuring accuracy . . . 127
4.3.1 Measuring the accuracy of the prediction for varying values of k and m at an instant of time t . . . 127
4.3.2 Measuring the accuracy of the prediction for varying values of k and m over an interval of time . . . 127
4.4 Training of the optimal parameters . . . 128
4.4.1 Finding the tuning parameters through an optimization problem . . . 128
4.4.2 Evaluating the accuracy of the training process for the choice of the tuning parameters . . . 128
4.5 Assessing the predictability of a time series . . . 129
4.5.1 Qualitative method to assess the predictability . . . 129
4.5.2 Quantitative method to assess the predictability . . . 129
4.6 The autoregressive model as reference of comparison . . . 130
4.7 Real industrial disturbances . . . 131
4.7.1 Qualitative assessment the predictability . . . 133
4.7.2 Quantitative assessment the predictability . . . 133
4.8 Results: effect of k and m on $E_{av\,\mathrm{int}}$ . . . 135
4.8.1 Choice of settings of parameters . . . 135
4.8.2 The effect of m on $E_{av\,\mathrm{int}}$ . . . 135
4.8.3 The effect of k on $E_{av\,\mathrm{int}}$ . . . 137
4.8.4 Effects of weighted and unweighted method on E_{av} . . . 138
4.9 Results: comparison of the techniques considered for disturbance forecasting . . . 138
4.9.1 Overview . . . 138
4.9.2 The searching grid, training and testing interval . . . 139
4.9.3 Performance of various strategies . . . 139
4.9.4 Comparison of the performance between the Base strategy, and the Opt k and Opt $D_{\max}$ strategies . . . 141
4.9.5 Comparison of the performance between the Opt k and Opt $D_{\max}$ strategies 142
4.9.6 Analysis of the metrics γ about the quality of prediction in the test interval . 142
4.9.7 Comparison between the weighted and unweighted method . . . 143
4.9.8 Comparing the behaviour of the $k-$nearest neighbour method with the linear AR model . . . 143
4.9.9 Variation of the values of E_{av} over time . . . 143
4.10 Results: examples of prediction at one instant of time . . . 146
4.11 Summary . . . 148

Chapter 5: MPC with disturbance forecasting with applications . . . 149
5.1 Introduction . . . 149
5.2 Background and motivation . . . 151
5.2.1 MPC formulation . . . 151
5.2.2 Tuning the disturbance horizon . . . 157
5.2.3 The metrics for performance monitoring . . . 159
5.3 Implementation of the MPC with disturbance forecasting . . . 160
5.3.1 Implementing the disturbance forecast in the MPC framework . . . 160
5.3.2 The difference between sampling of the MPC controller and sampling of the disturbance time series for time-series forecast . . . 161
5.3.3 The tuning of the controlled variables acting as buffer . . . 162
5.4 Evaluating the MPC performance . . . 163
5.5 Introduction to the case studies . . . 164
5.6 Case studies: the Continuous Stirred Tank Heater (CSTH) . . . 166
5.6.1 Objective of the case study of the CSTH . . . 166
5.6.2 Physical model of the CSTH . . . 166
5.6.3 Strategies of the MPC for the CSTH . . . 167
5.6.4 Tuning of the MPC . . . 168
5.7 Case study: the steam boiler . . . 169
5.7.1 Objective of the case study of the steam boiler . . . 169
5.7.2 Physical model . . . 169
5.7.3 Disturbances and configurations considered . . . 170
5.7.4 Strategies for MPC controller . . . 173
5.7.5 The tuning and the constraints on the controlled variable . . . 176
5.8 Case study: the VAC column . . . 179
5.8.1 Physical model of the azeotropic column . . . 179
5.8.2 Control configuration considered . . . 183
5.8.3 Disturbances considered . . . 184
5.8.4 The strategy of the MPC controller . . . 184
5.8.5 Tuning of the MPC controller . . . 186
5.9 Summary . . . 190
Chapter 6: MPC with disturbance forecasting: results . . . 191
6.1 Introduction . . . 191
6.2 The real industrial disturbances . . . 195
6.3 Results: the CSTH . . . 196
6.3.1 Introduction . . . 196
6.3.2 Simulated sinusoidal disturbances . . . 196
6.3.3 Real disturbances . . . 199
6.3.4 Conclusions for the CSTH . . . 202
6.4 Results: the steam boiler . . . 203
6.4.1 Introduction . . . 203
6.4.2 The parameters of the disturbances . . . 204
6.4.3 Disturbance from the load . . . 205
6.4.4 Disturbance from the heat provided to the boiler . . . 217
6.4.5 Conclusions for the steam boiler . . . 237

6.5 Results: the VAc column . . . 239
6.5.1 Introduction . . . 239
6.5.2 Analysis of the metrics . . . 241
6.5.3 Examples of control responses . . . 249
6.5.4 Comments on the impact of tuning weights on the controller response in presence of abrupt disturbances . . . 253
6.5.5 Analysis of the metrics when the sampling rate of the measurement of the disturbance is faster than the controller sampling . . . 254
6.5.6 Conclusions for the VAc . . . 259
6.6 Summary . . . 260
Chapter 7: Critical evaluation of the thesis and future work . . . 264
7.1 Summary and discussion of contribution of the thesis . . . 264
7.2 Review of persistent and abrupt disturbances in a process site . . . 265
7.2.1 Merits of the method proposed . . . 265
7.2.2 Limits of the method proposed . . . 265
7.2.3 Future work . . . 266
7.3 Prediction of persistent and abrupt industrial disturbances, and assessment of their forecastability . . . 267
7.3.1 Merits of the methods proposed . . . 267
7.3.2 Limits of the methods proposed . . . 268
7.3.3 Future work . . . 269
7.4 MPC with a data driven multi-step prediction, tested on industrial case studies . . . 270
7.4.1 Merits of the method . . . 270
7.4.2 Limits of the method . . . 270
7.4.3 Future work . . . 271
7.5 Analysis with new metrics to assess a controller when handling propagating disturbance 272
7.5.1 Merits of the method . . . 272
7.5.2 Limits of the method . . . 272
7.5.3 Future work . . . 272
7.6 Summary . . . 273
Chapter 8: Summary and conclusions . . . 274
Bibliography . . . 277

LIST OF FIGURES

Number *Page*

1.1 Examples of persistent and abrupt disturbances. Tag 25 is the controlled temperature. Tag 29 is column feed. Tag 30 is the trend of the steam flow (picture from Thornhill et al. (2003)). 21
1.2 Flow sheet of Eastman Chemical Company case study (from Thornhill et al. (2003)). 22
1.3 Examples of persistent disturbance. 27
1.4 Possible paths of disturbance propagation. 30
1.5 Example of propagation of a disturbance. A change of the feed can have effects on other variables such as the bottom level and thebottom outflow. 31
1.6 Schematics of the process and mechanical components considered by Cecilio et al. (2011) (picture from Cecilio et al. (2011)) 35
1.7 Time trends of process, control, electrical and mechanical measurements (from Cecilio et al. (2011)). 35
1.8 Example of a feed disturbance 38
2.1 MPC frameworks to handle external disturbances 46
2.2 Depiction of available time series forecasting methods 61
2.3 List of considered time series forecasting methods 67
2.4 Depiction of available time series forecasting methods (from Thornhill (2005b)). . . 71
3.1 Possible path of disturbance propagation 77
3.2 The principle of recycling in chemical plants 79
3.3 Distribution in a steam utility. 81
3.4 Example of an industrial distribution grid (from Mohd Noor (2018)). 84
3.5 Depiction of a distillation column. 87
3.6 Considered paths of disturbance propagation in a distillation column 88

3.7 Evolution of the system over the plane representing mass flow and pressure ratio of the compressor after a decrease of 0.5 Hz of the frequency of the grid from 50 Hz. . 95
3.8 Motor torque response after a decrease of 0.5 Hz of the frequency of the grid from 50 Hz 95
3.9 Distance to surge response after a decrease of 0.5 Hz of the frequency of the grid from 50 Hz 96
3.10 Voltage variation of -3% of the nominal value for 10 s 99
3.11 Voltage variation of -50% of the nominal value for 350 ms 100
3.12 Considered paths of disturbance propagation in a steam utility connected to a plant . 103
3.13 Considered paths of low steam quality 105
3.14 Two examples of experimental water hammers 107
3.15 Oscillatory and abrupt flow instabilities. 108
3.16 Effect of abrupt disturbances, maybe caused by water hammer or geysering, or temperature of the process fluid. Trend over time of Tag 27 (bottom temperature of a column), Tag 28 (steam pressure in the reboiler of the column) and Tag 30 (steam flow) of the dataset used in Thornhill et al. (2003) 110
3.17 Considered paths for a variation of energy in a boiler. 112
3.18 Considered paths for variations of the level. 116
4.1 An example of a persistent disturbance and representation of terminology (from Borghesan et al. (2019a)) 124
4.2 The time series considered for the section regarding the results of the prediction methods. 132
4.3 Phase space plots of sections of the considered time series 134
4.4 Effect of parameters k and m on prediction of Tags 33 and 34 with $t_1 = 400, t_2 = 1425$ and $h = 15$. Effect of parameters k and m on prediction of Tag 30 with $t_1 = 6000, t_2 = 7000$ and $h = 15$. 136
4.5 Optimal distances achievable over time for various strategies 144
4.6 Examples of predictions obtained with the weighted and unweighted k-nearest neighbours methods using the parameters obtained from the training and with the AR model 147
5.1 Representation of the prediction, disturbance and control horizons 152

5.2 Case study of the CSTH. 167
5.3 Case study of the steam boiler. 169
5.4 Step test response of the nonlinear model of the steam boiler and of the linearised model used by the corresponding MPC controller 171
5.5 Case study of the VAc distillation column. 180
5.6 The temperature profile found for the VAc distillation column 182
5.7 The structure of the VAc distillation column 182
5.8 The step responses of the model of VAc distillation column linearised at the operating point defined in Table 5.11. The model has been scaled over the span of its manipulated and controller variables, where the span is the difference between maximum and minimum value of the variable considered. The step responses show the variations in spans of the controlled variables for a variation of one span of the manipulated variable. Therefore, the step responses provide only a qualitative information given the high non-linearity of the distillation column. 185
6.1 Case study of CSTH. Duplicated from Fig. 5.2. 196
6.2 Results of the responses of the level (CV), of the set-point of the valve position (MV), and of the outflow for a sinusoidal disturbance of the inflow (dashed in blue in the pictures). 197
6.2 *(continued)* Results of the responses of the level (CV), of the set-point of the valve position (MV), and of the outflow for a sinusoidal disturbance of the inflow (dashed in blue in the pictures). 198
6.3 Results of the response of the level (CV) and of the outflow using real disturbances from a SE Asian refinery and from Eastman Chemical company plant. The inflow of the tank is dashed in blue. The value of the metrics $E_{av\,\mathrm{int}}$ is in yellow. 200
6.3 *(continued)*Results of the response of the level (CV) and of the outflow using real disturbances from a SE Asian refinery and from Eastman Chemical company plant. The inflow of the tank is dashed in blue. The value of the metrics $E_{av\,\mathrm{int}}$ is in yellow. 201
6.4 Case study of the steam boiler. Duplicated from Fig. 5.3. 203

6.5 Performance matrices with Tag 34 as disturbance acting on the steam outflow
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC . . . 207
6.6 Performance matrices with Tag 33 as disturbance acting on the steam outflow.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC . . . 212
6.7 Performance matrices with Tag 30 as disturbance acting on the steam outflow.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC . . . 213
6.8 Disturbances from the steam outflow. The trend of the disturbance is dashed in blue. Tag 34 CS 60 - CH 3 - DH 3 and DH 15 for case of long disturbance horizon.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples. 215
6.9 Case study of the boiler. Duplicated from Fig. 5.3. 218
6.10 Performance metrics with Tag 34 as disturbance acting on the heat provided to the steam boiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC . . . 219
6.11 Performance metrics with Tag 33 as disturbance acting on the heat provided to the steam boiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC . . . 222
6.12 Performance metrics with Tag 30 as disturbance acting on the heat provided to the steam boiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC . . . 224
6.13 Disturbances from the heat provided to the boiler. The trend of the disturbance is dashed in blue.
Tag 34 CS 60 - CH 7 - DH 7/15. CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples. 225

6.14 Disturbances from the heat provided to the boiler. The trend of the disturbance is dashed in blue.
Tag 30, CS 60 - CH 7 - DH 3. CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples. 227
6.15 Case study of the VAc distillation column. Copied from Fig. 5.5. 239
6.16 Performance metrics with Tag 34 as disturbance acting on the heat provided to the column through the steam in reboiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN, 2 - Strategy with Prediction ON with perfect knowledge, 3 - Strategy with prediction OFF, 4 - Strategy with FTMPC 242
6.17 Performance metrics with Tag 33 as disturbance acting on the heat provided to the column through the steam in reboiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN, 2 - Strategy with Prediction ON with perfect knowledge, 3 - Strategy with prediction OFF, 4 - Strategy with FTMPC 244
6.18 Performance metrics with Tag 30 as disturbance acting on the heat provided to the column through the steam in reboiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN, 2 - Strategy with Prediction ON with perfect knowledge, 3 - Strategy with prediction OFF, 4 - Strategy with FTMPC 248
6.19 Trends over time of variables related to the VAc column with a disturbance acting on the heat provided to the boiler - Tag 34 - CS 60 - CH 90 - DH 15 250
6.20 Trends over time of variables related to the VAc column with a disturbance acting on the heat provided to the boiler - Tag 33 - CS 60 - CH 90 - DH 15 251
6.21 Trends over time of variables related to the VAc column with a disturbance acting on the heat provided to the boiler - Tag 30 - CS 60 - CH 90 - DH 5 252
6.22 Values of the metrics E_{av} using three sampling rates for the measurement of the disturbance in case of Tag 30. 255

6.23 Performance metrics with Tag 30 as disturbance acting on the heat provided to the column through the steam in reboiler. Controller sampling equal to 60s.

LEGEND: CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN with sampling of the disturbance measurement equal to 60s, 2 - Strategy with Prediction ON with k-NN with sampling of the disturbance measurement equal to 5s, 3 - Strategy with Prediction ON with perfect knowledge, 4 - Strategy with prediction OFF, 5 - Strategy with FTMPC 257

6.24 Performance metrics with Tag 30 as disturbance acting on the heat provided to the column through the steam in reboiler. Controller sampling equal to 20s.

LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN, 2 - Strategy with Prediction ON with perfect knowledge, 3 - Strategy with prediction OFF, 4 - Strategy with FTMPC 258

LIST OF TABLES

Number *Page*

2.1 Cost functions and constraints for various MPC formulations 47
2.1 Commonly used statistical models for time series forecasting 64
2.2 Machine learning methods for time series forecasting 69
3.1 Manufacturer standard settings for the Siemens steam turbine SST-400 connected to the generator in Lerch (2016). 94
3.2 Average duration and depth of voltage dips in two surveys 97
4.1 Predictability index for the three main time series considered with $h = 15$ and $m = 30$ 133
4.2 Range of the parameters for the search grid optimization algorithms 140
4.3 Values of $E_{av\,\mathrm{int}}$ obtained with the considered strategies, values of the metric γ to measure the accuracy of the training and values of the metric Ξ to evaluate the performance of weighted method in comparison to the unweighted one 141
5.1 Variables and parameters in the optimization problem of the MPC. 155
5.2 How the disturbance horizon is set in academic literature. 156
5.3 The relationships between the three case studies 165
5.4 Tuning parameters of the MPC for the CSTH case study 168
5.5 Constraints of the MPC for the CSTH case study 168
5.6 Tuning parameters of the MPC for the steam boiler 177
5.7 Constraints of the MPC for the steam boiler 178
5.8 The steady state values of the flows, reboiler heat and condenser duty of the original model and the one developed 181
5.9 Controlled and manipulated variable of the case study of the VAC distillation column. 183
5.10 Tuning parameters of the MPC for the VAc distillation column 187
5.11 Nominal values of the MPC for the VAc distillation column 188
5.12 Constraints of the MPC for the VAc distillation column 189
6.1 The three MPC strategies compared for dealing with the disturbance values. 192
6.2 Metrics for the evaluation of a controller 193

6.3 List of questions solved in this chapter and where they are treated. 194
6.4 Values of the metrics for the evaluation of the MPC performance 199
6.5 Questions for the case study of the CSTH and answers. 202
6.6 Parameters of the tested disturbances for the case study of the steam boiler 204
6.7 Indication of ideal values of metrics for the case study of boiler where disturbances come from the steam outflow. 205
6.8 Description of the metrics in Fig. 6.5, when the disturbance comes from the steam outflow requested by the loads using the Tag 34 208
6.9 Comparison of the values of the metric Γ_{Pressure} and Γ_{Level} for the best tunings of the strategies Prediction ON and FTMPC when the disturbance comes from the loads. . 209
6.10 Comparison of the values of the metric Γ_{Pressure} and Γ_{Level} for the best tunings of the strategies Prediction ON and FTMPC when the disturbance comes from the loads. . 210
6.11 Comparison of the values of the metric Γ_{Pressure} and Γ_{Level} for the best tunings of the strategies Prediction ON and FTMPC when the disturbance comes from the loads. . 211
6.12 Values Γ_{Pressure} and $\sigma_{\text{Power Delivered}}$ for the tuning parameters CS 60 - CH 3 - DH 3. . 216
6.13 Indication of ideal values of metrics for the case study of boiler where disturbances come from the heat provided. 218
6.14 Description of the metrics in Fig. 6.10, when the disturbance comes from the heat provided to the boiler using Tag 34 220
6.15 Comparison of the values of the metric $\sigma_{\text{Power Delivered}}$ for the best tunings of the strategies Prediction ON and FTMPC when the disturbance comes from the heat provided. 229
6.16 Values of the the metrics for the steam boiler when the disturbance acts on the heat provided - Tag 34.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples. 231
6.17 Values of the the metrics for the steam boiler when the disturbance acts on the heat provided - Tag 33.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples. 233

6.18 Values of the the metrics for the steam boiler when the disturbance acts on the heat provided - Tag 30.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon 235
6.19 Questions for the two case studies of the steam boiler and answers. 238
6.20 Parameters of the tested disturbances for the case study of the VAc Column 240
6.21 Indication of ideal values of metrics for the case study of the VAc column. 240
6.22 Questions and answers solved by the case study of the VAc distillation column. . . . 259
6.23 List of questions for this chapter and answers. 262

Chapter 1

INTRODUCTION

This chapter states the research aim of this thesis and its technical objectives, while providing first an introduction to the problems that are to be faced. The chapter starts with an overview that describes the background and the motivation, using case studies taken from the literature. Specifically, the overview introduces the concepts of disturbance (an undesired deviation of a process variable for its set-point), disturbance propagation, site utility, and how the problems of a disturbance propagating are solved. At the end of brief overview, the research aim of the thesis is presented.

After the brief overview, the chapter analyses the problem in detail. Section 1.2 describes the concepts of site utilities and of disturbances. Section 1.3 focuses specifically on disturbance propagation while Section 1.4 highlights the impact of such propagating disturbances. Once the characteristics of disturbances and the problems they cause have been described, Section 1.5 proposes a controller framework that might mitigate these issues, which is based on a time series forecasting of disturbances integrated in an MPC controller. Section 1.6 reaffirms the research aim and defines the technical objectives of the the thesis, indicating the chapters that focus on each technical objective. This chapter finishes with the summary in Section 1.7.

1.1 BACKGROUND AND MOTIVATION

1.1.1 Disturbances in process control

In process plants, a disturbance is an undesired, transitory deviation of a variable from its desired set point or desired value. Generally, the trends over time of disturbances can be different because of their different causes. However, the focus of this thesis is specifically on fast and complex disturbances.

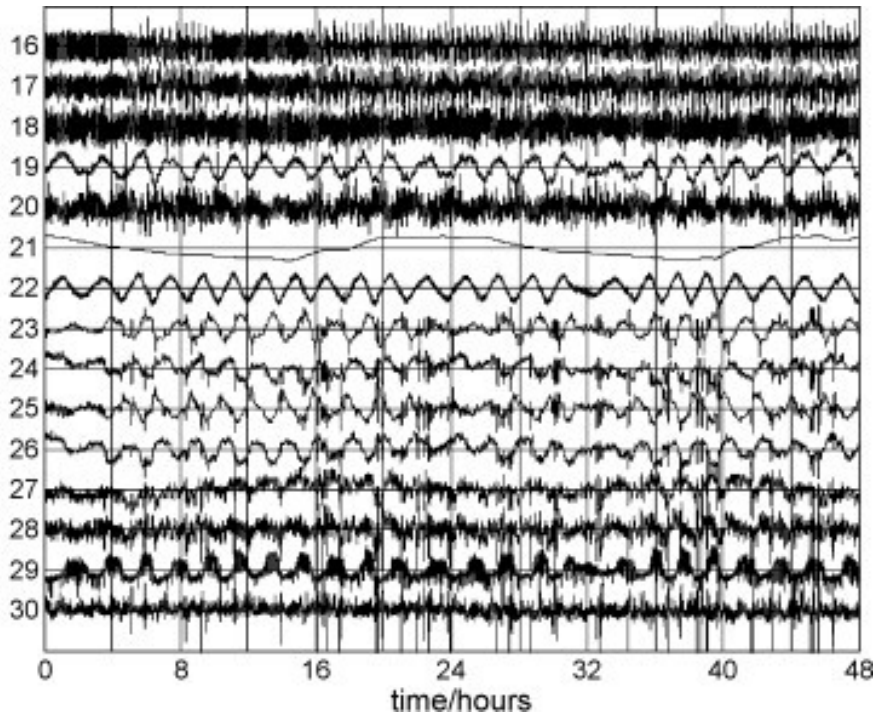


Figure 1.1: Examples of persistent and abrupt disturbances. Tag 25 is the controlled temperature. Tag 29 is column feed. Tag 30 is the trend of the steam flow (picture from Thornhill et al. (2003)).

Fig. 1.1 shows real industrial examples of what it is meant in this thesis as fast and complex disturbances. Such disturbances show repeating patterns evolving over minutes or hours rather than weeks or months. Furthermore, they are characterised by complex and contorted oscillations or abrupt spikes, rather than simple deviations such as steps.

The characteristics of such patterns depends on the causes of the disturbance, which can be, for example, a malfunctioning component, a poorly tuned controller, or a disturbance external to the control loop. More important however, and fundamental characteristic to be noticed for the rest of the work, is that each measurement shows patterns that repeat themselves with a certain similarity.

1.1.2 Economic impact of disturbances

A disturbance can have economic impacts. Such impacts are for example mentioned in a real case study described in Thornhill et al. (2003), from which the trends over time of Fig. 1.1 were taken. Each trend is associated to a tag number, where a tag is a point of measurement in the plant. The Eastman Chemical Company provided this case study, and Figure 1.2 shows the plant flowsheet. In this plant, a malfunctioning valve caused a persistent oscillation of the outflow of a decanter (Tag

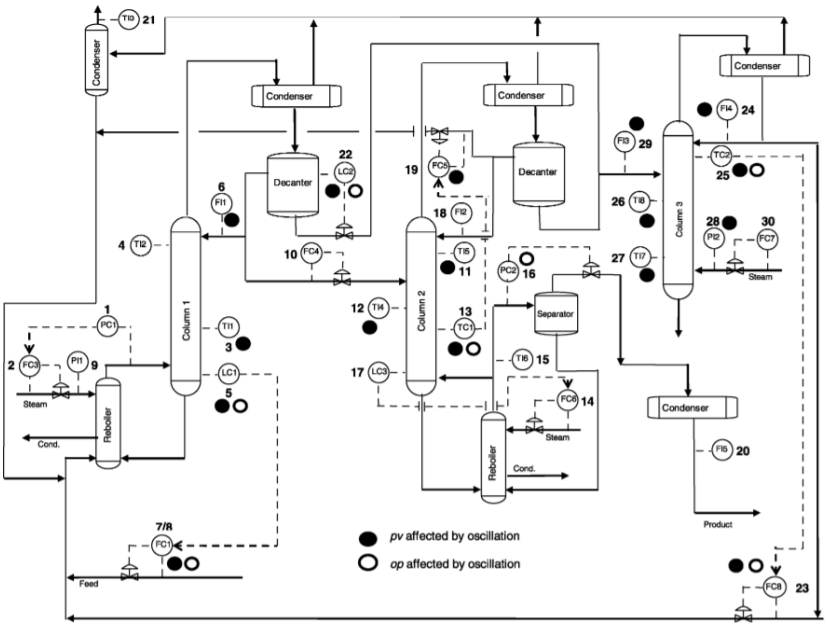


Figure 1.2: Flow sheet of Eastman Chemical Company case study (from Thornhill et al. (2003)).

29), the decanter outflow was the feed of Column 3, the oscillation of such feed caused variations of the controlled temperature of the column (Tag 25).

Since the change of temperature is a symptom of a change in the product composition, the change of the product composition was the first economic impact of the column. Furthermore, the production rate was affected, because the column load was changing periodically. This was the second economic impact.

1.1.3 The role of control systems in disturbance propagation

In the above example, the disturbance propagated further because of the intervention of control systems. This is common, as Section 1.3 will explain further. In this case, the temperature of column 3 was controlled with the recycle (Tag 24). To compensate temperature variations, the recycle deviated from its steady value causing a variation of the level of Column 1 (Tag 5). The disturbance propagated further and affected other manipulated and controlled variables through similar mechanisms. Indeed, Figure 1.1 shows that the variations of the variables around their set points follow a similar pattern.

Because of the control system, such disturbance phenomenon was, therefore, a *plant-wide disturbance*. In these situations, operators often prefer switching controllers off and controlling a plant section manually to avoid a propagation of the disturbance. However, operating a plant manually is more strenuous and might limit the potential of reaching the optimal operating conditions, taking the plant conditions into account. Furthermore, solving the cause of a disturbance is time consuming, and it can take even months according to the experience of present author. This means that some sections of a plant can be operated manually for some time.

Increasing automation in presence of such disturbances is the research aim of this thesis. To increase the automation of process plant and optimise them constantly, the control system should be able to find the optimal control strategy that, given the constraints and condition of the plant, avoids the propagation of a disturbance but limits as well its undesired effects on the most critical process variables. A trade-off has to be found between these two objectives, as Section 1.3.2 will explain. Expert operators can properly evaluate this trade-off considering also the disturbance occurring and its recurring pattern. On the contrary, current control systems might misjudge the situation.

Managing this trade-off using automation systems and providing controller system the capability to judge the impact of disturbances on processes are two technical objectives of this PhD project. Achieving these objectives will enable the overall research aim to be met.

1.1.4 Propagation of disturbances within a production site

The site utilities are sections of the production site which provide or distribute energy and, more rarely, materials necessary for the correct functioning of the production plants. Site utilities are often connected to more plants with energy and mass flows. Since a disturbance propagates through the exchange of energy and mass, a disturbance can propagate to more plants of a production site through the site utilities.

When a disturbance propagates to more plants, its economic impact increases. Product quality and production rate can be affected at more points of a production site. Furthermore, the diagnosis is more complicated for three reasons. Firstly, more variables and more propagation paths must be analysed. Secondly, it is more likely that more disturbances enter in a process unit and affect a

variable at the same time. Finally, different groups within a company can be responsible for different plant sections, be they production plants or site utilities. The analysis of a disturbance propagation can be difficult because of lack of exchange of information between technical departments.

Assessing the presence of disturbances and stopping their propagation is therefore beneficial. To stop the disturbance propagation, it would be important to understand which are the most relevant cases to analyse and how the system can be controlled to avoid a disturbance propagation.

This thesis will analyse the interaction between production plants, steam utility and electric utility, where the steam and electric utility produce and distribute respectively steam and electricity at the production site. The reason is that a detailed review of the mechanisms for disturbance propagation between plants, steam utilities, and electrical utilities is missing in the literature.

1.1.5 The aim of the PhD

The research aim of this PhD thesis is '*Increasing the level of automation in various areas of a process site by optimizing, given the constraints applied to the process, the response to fast complex disturbances, examining the trade off between rejection of the disturbance on controlled variables and avoidance of disturbance propagation*'.

As Section 1.1.2 mentioned, expert operators can evaluate this trade-off and implement a control strategy manually. To have a similar capability, a control system should be able recognize the disturbance occurring, specifically its trend over time, and implement the best possible solution taking the constraints of the process into account. This is facilitated by the fact that disturbances are often characterized by a recurring pattern that shows strong similarities between one occurrence and another. The rest of the chapter will argue that the solution that is proposed is integrating a multi-step time series forecasting of the disturbance affecting the controlled area of the production site in a Model Predictive Control (MPC) framework.

The work reported in this thesis proposes a control method that is implementable in different areas of the production site. However, as mentioned in Section 1.1.4, there is little work in literature reviewing the types of disturbances propagating between site utilities and process production plants. This is another task that the thesis will face in order to select the case studies of interest and understanding how the system can be controlled.

Since the focus of the thesis is on process units present in the whole production site, the methods developed will be applied on time series of real disturbances and with realistic case studies. The case studies considered in the thesis are a laboratory Continuous Stirred Tank Heater (CSTH), an industrial 160 MW steam boiler and a non-linear distillation column.

1.2 DISTURBANCES IN SITE UTILITIES

1.2.1 SITE UTILITIES

Site utilities provide services for the basic functioning of the connected chemical plants. Utilities and plants exchange energy flows and, sometimes, mass flows (Cecilio, 2014). For example, site utilities produce steam, or they warm the hot oil that is used for the heating in reactions and distillations, they produce electricity for the functioning of the site, they chill water or cool down brine needed by plants for cooling processes. Hydrogen distribution networks are an example of utility exchanging mass flows with the plants. They distribute hydrogen to different units in refineries, and they are considered utilities in the oil processing industries (Alves and Towler, 2002).

Generally, for example in case of steam generation utility, utilities are connected to more than one section of a chemical plant. Furthermore, they can often be connected not only to more sections of a plant but also to more plants. Understanding the disturbances occurring and propagating between site utilities and production plants is of primary importance for this PhD project, because in this way the requirements and potentialities to stop such disturbances from propagating within a production site with automation systems can be analysed.

In this thesis, as it will be discussed shortly, the focus will be on steam utility (generation and distribution of steam to units in a production site), and electric utility (generation and distribution of electricity).

1.2.2 Disturbances

1.2.2.1 Definition of disturbance

In process control engineering, a disturbance is an unwanted deviation of a process variable from its desired set point or desired value (Thornhill, 2005a). In electrical engineering, the definition of *electric power quality disturbance* is the closest to definition of disturbance in process control. An electric power quality disturbance is defined by Santoso et al. (1994) as any deviation from a reference sinusoidal voltage waveform with a specified rated amplitude and frequency.

From now on, the term *disturbance* will define any unwanted deviation of a variable from its desired reference signal. This includes the definition of disturbance in the process control domain, where the values of process variables are constant over time most of time, and in electric domain, where the values of voltage and currents are not constant over time. However, in control theory, the term *disturbance* has a further meaning, referring to the external input of a system, different from the manipulated variables, that causes the deviation (Cecilio, 2014; IEC, 2017). Here, the term *external disturbance* is used for this concept.

1.2.2.2 Possible causes and impacts of disturbance

The deviation of one controlled variable from its set point has three possible reasons:

- A controller is not correctly tuned, or the control action is saturated.
- A component in the control loop is malfunctioning. Examples are a sticking valve, a faulty sensor or a trip of an electric motor.
- An external disturbance is entering the system with a frequency and amplitude that the controller cannot reject.

A disturbance can pose issues regarding the observance of strict product specifications, making the final product unsellable (Downs and Caveness, 2012). However, a plant operating close to its limits is often more profitable than a plant that has to stay away from its limits because of the possible impacts of the occurring disturbances (Thornhill et al., 2003).

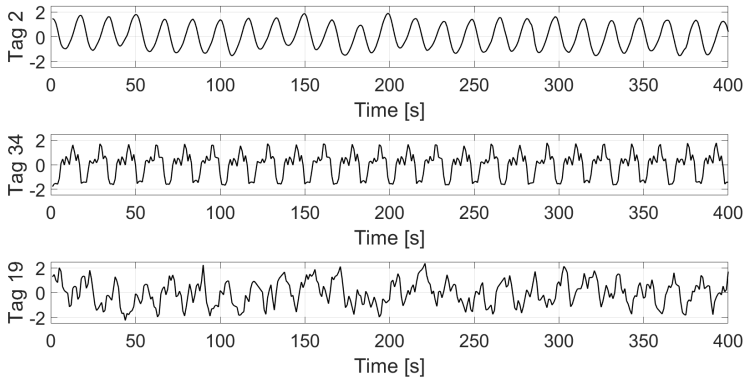


Figure 1.3: Examples of persistent disturbance.

Furthermore, a disturbance often propagates to other plant sections, as Section 1.3 will describe. When it affects more variables of a plant, it is called a plant-wide disturbance. When it also affects the site utility, it is called site-wide disturbance (Horch et al., 2007).

In electrical engineering, a disturbance can often cause a malfunctioning of a device, but it can also immediately and permanently damage the device. For this reason, protection systems might trip the electrical devices before the disturbance damages the component. Trips of electromechanical devices have definitely an impact on the process. Nonetheless, the control system can do little against such trips and therefore the primary interest is analysing the interactions between processes, rotating machines, and electric grids - that is on electromechanical phenomena - that do not cause a trip of the device.

1.2.2.3 Classification of process disturbances

The classification of disturbances in the process industry is made based on the time scale of the disturbance. Thornhill and Horch (2007) classify the disturbances in three categories:

1. Slowly developing disturbances.
2. Persistent, dynamic disturbances.
3. Abrupt disturbances.

Slowly developing process disturbances The variable deviates slowly, over months, from its desired value. For example, the fouling of a heat exchanger and the degradation of a catalyst belong to this category. Such problems are mostly known, and the operators keep on operating the plant until its operation is too compromised. At this point, maintenance action is needed. This category is not of interest for this PhD because control systems can do very little against these disturbances. Secondly, plant operators can take actions to compensate their effects without time pressure.

Persistent, dynamic process disturbances A continuously repeating pattern characterises the persistent disturbances. A non-linear element, for example a sticking valve in a feedback control loop, can often cause the pattern. In this case, the measurements of such variables are non-linear time series, following the definition of Bauer (2005) who states that a time series is non-linear if the process that generates the time series is non-linear.

However, there are no specifications for the pattern shape and its duration, which can span from some seconds to minutes or hours. Figure 1.3 shows three measurements of variables in a refinery section affected by a disturbance. The disturbance pattern of Tag 2 is an oscillation, similar to a sinusoid. The disturbance pattern of Tag 34 is a regular oscillation although it is not a sinusoid. The pattern of tag 19 is an oscillation, but it is also very irregular.

In many cases, however, the pattern of a disturbance is regular. If a regular pattern characterises a time series, it is possible to predict its future evolution based on the past observation of its pattern. Therefore it is self-predictable. If the future trend of disturbance and its effects on the controlled variables are known, then a control action might optimally compensate the disturbance. Creating an optimal control framework that predicts a disturbance evolution and reacts optimally to that disturbance is one of the contributions of this PhD.

Abrupt disturbances Abrupt disturbances belong to those disturbances caused by fast discontinuous events. In some situations, such events are unexpected. In other situations, such events are planned.

For example, a slugging flow or a compressor trip is an unexpected abrupt disturbance. The compressor trip can be caused by a mechanical breakage of the compressor but also by an interruption of

the electricity for the electric motor connected to the compressor. The interruption can be caused, for example, by a short circuit in one point of the industrial electric grid.

Unloading of wastes is an example instead of planned disturbances. In some plants, a certain amount of waste must be gathered before being sent together to burn in the furnace for steam generation. The addition of waste can cause the composition of the fuel to change suddenly, causing an abrupt disturbance in the steam generation unit.

The pattern of the time series of an abrupt disturbance tend to be different at each occurrence, especially when the disturbance is unplanned. Therefore, it might be more difficult to predict the future trend of an abrupt disturbance based on past instances. Nonetheless, this thesis shows that it is still possible. The reason is that even unwanted phenomena can have patterns that repeat similarly over time.

1.2.2.4 Classification of electrical disturbances

Unlike process disturbances, the electrical disturbances are classified not only according to the time scale of the disturbance event but also according to amplitude, frequency and waveform of the sinusoidal signal affected by a disturbance. Standards EN 50160 and IEEE 1159 define the electrical disturbances according to such elements.

However, Cecilio (2014) tried to unify the classification of the process and electrical disturbances, and she noticed that an electric disturbance is considered of long duration when it lasts between one to three minutes. Therefore, she argued that electrical disturbances would always belong to the abrupt disturbances with the time scale used for the disturbance classification in process control engineering.

1.3 PROPAGATION OF DISTURBANCES

1.3.1 Possible disturbance propagation paths in a production site

If a variable is affected by a disturbance, other variables will be probably affected by a disturbance with a similar pattern as well. The propagation of a disturbance happens through the exchange

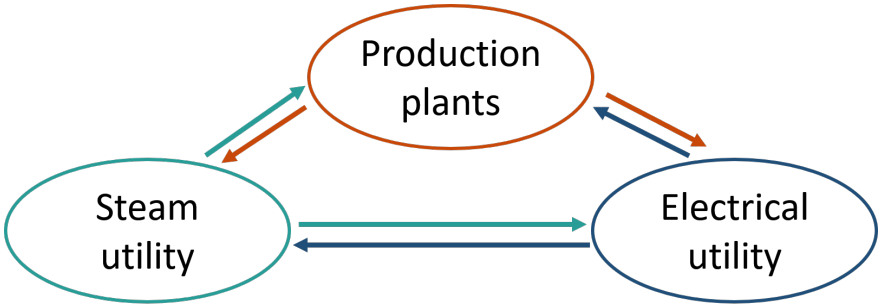


Figure 1.4: Possible paths of disturbance propagation.

of material and energy flows, and control signals. The examples in sections 1.3.3, 1.3.4 and 1.3.5 describe how the propagation might happen. The examples will argue that disturbances can propagate:

- Through a plant
- From the plant to a utility
- From a utility to a plant

Therefore, the scheme in Figure 1.4 can be drawn. The scheme shows that production plants, steam utility and electric utility can be considered the vertices of a triangle. The triangle represents the possible propagation paths of a disturbance in a production site. Since disturbances can propagate from each vertex to the other two, there are two directions for each side of the triangle.

This PhD reviews the most common scenarios of propagation of disturbance between these three actors in Figure 1.4. The research community has not investigated in detail the comprehensive paths used by disturbances to propagate between plants through utilities. Cecilio et al. (2011) deduced a relationship between plant and utility in two case studies. The utilities considered were a cooling water utility and an electric utility. However, the authors did not demonstrate the disturbance propagation mechanisms. Furthermore, Cecilio (2014) highlighted that academia and industry consider electromechanical systems and process systems as separate, even though she argued that they should be considered together for analysing process disturbance. Therefore, there is a need to investigate which disturbances can propagate between utilities and plants, where they originate, which patterns they exhibit, and how their impact and propagation can be limited.

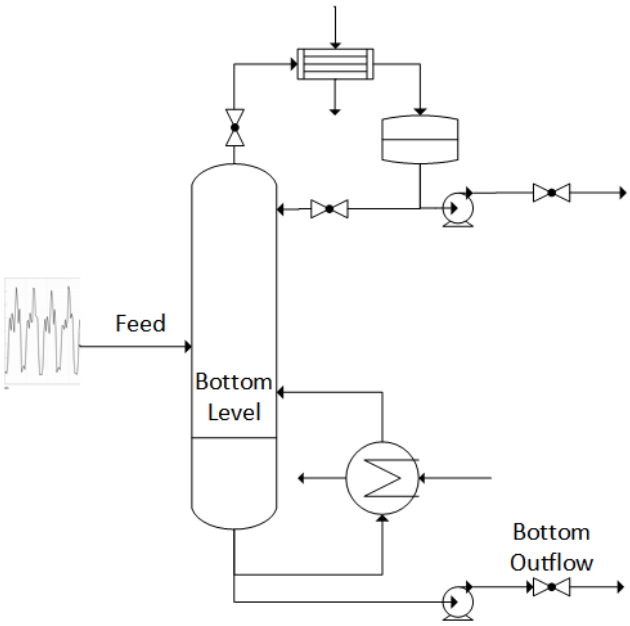


Figure 1.5: Example of propagation of a disturbance. A change of the feed can have effects on other variables such as the bottom level and thebottom outflow.

1.3.2 The role of controllers in disturbance propagation

As the following examples will highlight, the controllers have a role in the propagation of a disturbance. To reduce the variability of the controlled variable, a controller can propagate a disturbance further by diverting the disturbance to the manipulated variable. For example, to keep a level in a tank constant despite the fluctuations of the feed, the controller of the level manipulates the outflow of the tank, which is the feed of a downstream unit.

Sometimes the controllers should understand how much they should intervene. They should find an optimal trade-off between using the manipulated variable to keep the controlled variable within a specific range, and not using the manipulated variable to avoid the disturbance propagation.

Developing an optimal control that satisfies this trade-off is one of the technical objectives of the present PhD.

1.3.3 Example: disturbance propagation through a plant

Figure 1.5 show a distillation column. Supposing that the feed is the disturbance because it is controlled by a sticking valve, this section focuses on the reaction of the controller of the level of the column.

- The column feed oscillates.
- The bottom level of the column starts varying because the feed variation has changed the mass balance in the column, while the outlet flow is initially constant.
- The level sensor measures a deviation of the level from its set-point. The information is provided to the level controller.
- The controller intervenes, changing the set-point of the outlet flow.
- The controller of the outlet flow reacts to a change of the set-point, acting on the valve (the actuator).
- The outlet flow changes. The outlet flow is the inlet flow of a second column, which notices a varying inlet flow as input.

Mass flows and control signals (sensor measurement, set-point reference and control action) propagate the disturbance to the following column of the plant in this case. A human operator would probably set the level controller in manual mode and keep the position of outflow valve constant. The level oscillates but the outflow, to the eye of the operator, should be constant and therefore the process unit downstream should not be affected.

This manual approach has however some drawbacks. First, the operator is very likely to change the valve position from time to time. Secondly, the variations of the level become variations of the inlet pressure of the valve and therefore the flow would still oscillate. A good operator would set instead the set-point of outflow constant. Still, in practice having a uniform way of operating plants among operators is not always achieved as not all operators drive the plant in the same way.

Automating the response of the controllers to such disturbances might help finding an optimal and standard response.

1.3.4 Example: disturbance propagation between a plant and a steam utility

Considering the column in Figure 1.5 again, not only the mass flows but also the energy flows have a role in disturbance propagation. Indeed, supposing that the feed of the column oscillates because of valve stiction and that the column temperature is controlled using the steam:

- The column feed oscillates.
- The controlled temperature starts varying because the variation of feed has changed the energy balance inside the column, while the steam flow is initially kept constant.
- The temperature sensor measures a deviation of the temperature from its set-point. The information is provided to the temperature controller.
- The controller intervenes, changing the set-point of the steam flow.
- The controller of the steam flow reacts to a change of the set-point, acting on the valve (the actuator).
- The steam inflow of the reboiler changes.
- This steam flow variation is a change of the outflow for the steam header. The pressure in the steam header starts varying.

In the example the column in Figure 1.5, the disturbance started from a valve stiction and propagated not only to the following column but also to the steam utility.

1.3.5 Example: disturbance propagation between plant and electric utility

Cecilio et al. (2011) provided an example with a disturbance of a plant affecting the electric utility. The authors considered the recompression area represented in Figure 1.6 and the trends of the variable measurements during a disturbance of the process shown in Figure 1.7. The measurements include:

- Process variables such as the pressures before compression ($PC1_X$,$PC2_X$) and after compression (P1,P2), and temperatures (T1,T2,T3,T4)
- Manipulated variables such as the control outputs of pressure control ($PC1_Y$,$PC2_Y$) and the set-point for motor speed control ($SC1_Y$)
- Electromechanical variables such as electric motor speed (S1), current (I1), power (J1), and compressor vibrations (V1,V2,V3,V4)

The authors noticed that process, control, and electromechanical measurement in Figure 1.7 are affected by similar oscillations between the day 1.5 and the day 3. Furthermore, they noticed that the oscillations of the process variable $PC2_X$ are opposite in phase to the oscillations of the control output $PC2_Y$ and other electromechanical variables such as S1, I1 and J1. Therefore, the authors deduced that first the controller reacts to a process disturbance and after the disturbance propagates to the electric utility.

1.4 OPERATING A PROCESS IN CASE OF PLANT-WIDE DISTURBANCES

Disturbances can affect the product quality, the production rate and can accelerate the wear of machinery. Therefore, plant personnel want to minimise the effects of disturbances.

Indeed, despite the presence of a disturbance, the operator must ensure the quality of the product and avoid hazards. Safety systems shut down the plant in risky situations. However, the shut-down is a cost that the operator should avoid. In such situations, the operators deactivate some control loops

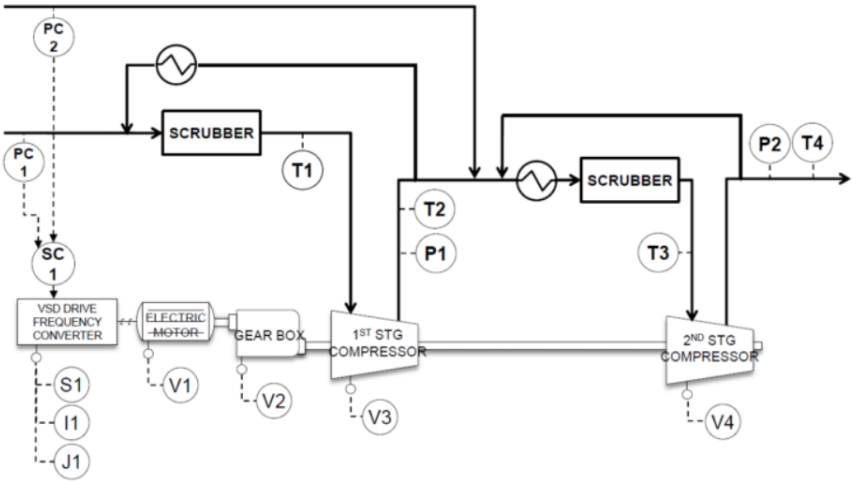


Figure 1.6: Schematics of the process and mechanical components considered by Cecilio et al. (2011) (picture from Cecilio et al. (2011))

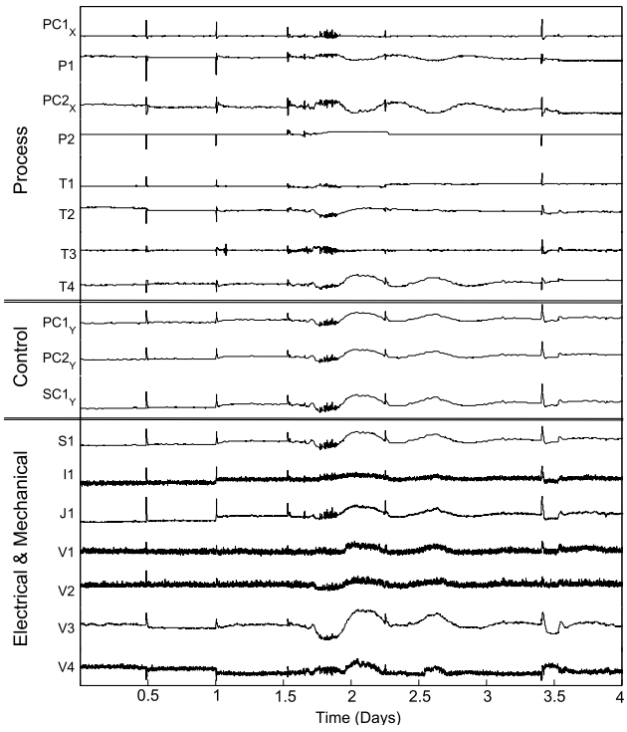


Figure 1.7: Time trends of process, control, electrical and mechanical measurements (from Cecilio et al. (2011)).

and operate a section of the plant manually. The reason is that the control systems contribute to the propagation of the disturbances, as explained before in Section 1.3.2. Moreover, the controllers might react too slowly, or too aggressively. In the latter case, the controlled variables can manifest continuous oscillations or limit cycles. Therefore, the operator must decide which controls to

deactivate, control their respective variables manually and act so that the plant can slowly settle and work again in a stable region. At this point, the control systems can be activated again. The difficulty for the operator is to watch and supervise many variables, to understand how the plant reacts and how aggressive his manual control should be to avoid further problems. The recovery from a disturbance can last hours, can involve more shifts and more operators that together watch and manually control the plant.

However, sometimes the procedure of the operator is not even resolutive. The source of the disturbance can be also, for example. a broken component. In this case, the operator must understand how to block the propagation of the disturbance so that it does not reach other sections of the plant. Until a repair is possible, the operator has to work with a plant, which is partly malfunctioning. Diagnosing a disturbance and solving its cause can be a long process, taking even months

Such events are not infrequent. Therefore, it would be useful to have a control system that works during normal operations as well in presence of disturbances, that can automate the reaction to such disturbances, stopping their propagation and keeping the process variables within their given constraints or close to their set-points.

Increasing the level of automation in case of disturbance is the aim of this PhD.

1.5 MODEL PREDICTIVE CONTROL

This section focuses on a type of control system available in the process industry, which is the Model Predictive Control (MPC). It proposes an extension to the MPC framework that might stop the disturbance propagation, keep the most critical controlled variables within their constraints, and help the operators in handling plant-wide or site-wide disturbances.

1.5.1 Use of MPC in process industry

In comparison to the PID (Proportional Integral Differential) control, the MPC is less used in process industry. However, MPC is widely implemented in the refining and petrochemical industry, and indeed every refinery has an MPC application according to the ARC Advisory Group (2006). Other than in the petrochemical industry and refining, the MPC has not been widely used until fairly

recently. However the trend is changing, and chemical companies such as BASF (Kapp, 2015) or Evonik (Process Engineering, 2009) have installed MPC controllers in their plants. Companies install MPC controllers in certain plant sections because MPC controllers can push the constraints of a plant and optimise it. This increases the profitability.

1.5.2 Features of MPC for disturbance handling

The MPC is an optimal, multivariable, model-based control technique. Using a model of the system, the controller can predict the behaviour of the controlled system under the influence of the manipulated variables. Furthermore, the controller can calculate the control action that minimises or maximizes a defined objective function subject to maintaining controlled and manipulated variables within their constraints. These characteristics make the MPC an interesting tool for handling disturbances. Indeed, keeping the controlled variables within their constraints during a disturbance is important. Furthermore, an objective function might be formulated so that the control action achieves a trade-off between rejecting a disturbance from the most critical controlled variables and avoiding the disturbance propagation. Reaching this trade-off is one of the aims of this PhD that Section 1.1.5 has mentioned. This PhD investigates and shows how an MPC can reach the scope.

1.5.3 Current limitations of industrial MPCs for disturbance handling

Based on his industrial professional experience, the present author thinks that one of the main limitations of the MPC in industrial practice is the way the disturbances are handled. Indeed, plant-wide disturbances are characterized generally by a repeating pattern. This might allow a prediction of their future values of the disturbance based on the evolution of their past patterns. Instead, in industrial MPC the future values of measurable disturbances are assumed to be the same as the current value (Binder et al., 2019; Camacho and Bordons, 2008; Havlena, 2011). Therefore, an MPC does not calculate a control action which is optimal for the current disturbance pattern.

Figure 1.8 shows the problem by plotting the time trend of a hypothetic feed of a distillation column affected by a persistent disturbance. Camacho and Bordons (2008), Havlena (2011) and Binder

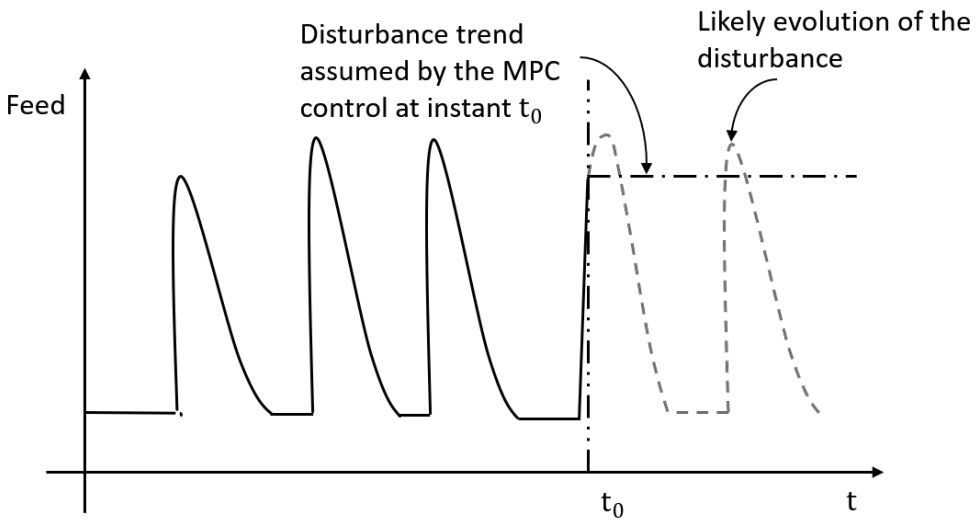


Figure 1.8: Example of a feed disturbance

et al. (2019) explain that the standard way of treating disturbances in an industrial MPC is supposing at instant t_0 that the feed has changed in the last instants of time nearly as a step. However, it is possible to guess that the feed will keep on evolving as a sequence of spikes also in the future. The effects of the feed on the controlled variables in the latter case is different from the case where the feed is considered constant over the future. Therefore, the control action would be appropriate for the specific disturbance.

The next Chapter 2 will describe the state of the art for dealing with plant-wide disturbances. However, Chapter 2 will show that while in other applications, for example control of wind turbines, it is common to provide to an MPC controller the predicted future values of the disturbance to improve the controller response, this is not common in research applications to predict persistent and abrupt but predictable plant-wide disturbances.

Nonetheless, there is some evidence of the effects of disturbances on MPC controllers. Darby and Nikolaou (2012) state that the performance degradation of an MPC in a process plant is often linked to the presence of an oscillating disturbance entering in the plant section controlled by the MPC. A patent of Honeywell (Havlena, 2011) affirms that for disturbances with a 'high frequency' (a precise value is not provided) the standard approach of handling disturbances results in an oscillatory behaviour of the predicted trajectories of the controlled variables and in significant variations over time of the values of the manipulated variables.

A technical objective of the present thesis is to show that doing a multi-step prediction of the time

series of a real industrial disturbance, of persistent as well of abrupt type, is first of all possible. Furthermore, a requirement is that the method used to forecast such disturbances should be fast in recognizing and starting predicting the right disturbance pattern.

A further technical objective is to show than an MPC that uses a detailed multi-step prediction of the disturbance for a certain horizon does improve its performance compared to a similar MPC that does not use such prediction.

Finally, statistical metrics are required to compare quantitatively more controllers so that such controllers can be compared in terms of disturbance propagation, violation of constraints and set-point tracking of controlled variables.

1.6 RESEARCH STATEMENT AND TECHNICAL OBJECTIVES OF THE THESIS

The research aim for the thesis presented in Section 1.1.5 was '*Increasing the level of automation in different areas of a process site by optimizing the response to fast complex disturbances, examining the trade off between rejection and avoidance of disturbance propagation*'.

Following the discussions in this chapter, it is suggested that the aim can be achieved if the following technical objectives are achieved:

1. Review the most important persistent and abrupt disturbances, and their causes, propagating in a chemical and oil process site with a focus on propagation in steam and electrical utilities
2. Show whether a multistep prediction of persistent or abrupt disturbances is possible using an amount of industrial data smaller than a few hours, and provide a term for the forecastability of the time series
3. Propose an MPC with a data-driven multi-step forecasting and test whether the disturbance forecasts obtained in point 2 are good enough in conjunction with MPC for realistic case studies with industrial disturbances.
4. Analyse with new metrics the controller action of MPC controllers used in industrial settings in terms of disturbance handling and set-point tracking for persistent and spiky abrupt disturbances (fast complex disturbances)

The first technical objective supports the research aim because it defines the cases and the areas within a production site where the proposed MPC framework might help. Such an MPC framework should help in stopping the propagation of the disturbance while keeping the process variables close as much as possible to their set-points or, depending on their function, within given constraints. Chapter 3 focuses on this aspect, arguing that the most relevant disturbance propagation mechanisms occur within a production plant or between a production plant and steam utility, whereas the interactions between electric utility and production plants cannot be attenuated by a controller system.

The second technical objective aims to prove whether it is feasible to provide a multi-step forecast of the disturbance time series to a controller. This is the focus of Chapter 4, which proposes a metrics to measure the predictability of a disturbance and proposes a modified k-NN algorithm to predict both persistent and abrupt industrial disturbances.

Once such forecast has been proved to be feasible, the third technical objective is to show that an MPC controller benefits from having a detailed multi-step forecast in process applications, where the disturbance propagation should be stopped while controlling the values of the process variables. The chapters 5 shows how the disturbance forecast is implemented in the MPC controller and how a trade off between avoiding disturbance propagation and rejection of the effects of the disturbance on the controlled process variable is achievable. Chapter 6 tests the proposed solution on three simulated case studies (two of them industrial) and shows the impact of the length of the multi-step prediction and of MPC controller tuning on the performance achievable. The chapter shows that for most of the tunings, combining a disturbance forecast with an MPC controller is highly effective in stopping a disturbance from propagating further and in keeping the process variable within its given constraint or close to its set-point. However, Chapter 6 shows also the counter-intuitive result that long horizons of the multi-step prediction can cause instabilities of the controller and defines how the prediction horizon must be set in relation to the controller tuning parameters.

Still, to judge quantitatively whether and how much the proposed solution improves the level of automation of controllers in handling persistent and abrupt disturbances compared to other solutions, a set of metrics is required and this the reason behind the fourth technical aim. Chapter 5 proposes a set of metrics and Chapter 6 implements them. Indeed, Chapter 6 compares the solution

proposed of combining the forecasting of plant-wide disturbances with an MPC controller with other two strategies commonly used in practice to handle disturbances with MPC controllers.

The author of the thesis wanted the research project to be applied oriented. Therefore, the proposed controller has been tested on simulators of real or realistic process units: a laboratory water tank (Thornhill et al., 2008) but also a 160 MW steam boiler for power generation (Åström and Bell, 1998) and an azeotropic highly non linear distillation column (Luyben and Tyréus, 1998). Furthermore, industrial datasets of disturbances from oil and chemical plants have been used.

1.6.1 Publications

The work of the thesis has been published in the following articles:

- F. Borghesan, M. Chioua, and N. F. Thornhill. Forecasting of process disturbances using k-nearest neighbours, with an application in process control. *Computers and Chemical Engineering*, 128:188 – 200, 2019a. ISSN 00981354
- F. Borghesan, M. Chioua, and N. F. Thornhill. Forecast of persistent disturbances using k -nearest neighbour methods. In *Computer Aided Chemical Engineering, Volume 44*, pages 631–636, 2018a
- F. Borghesan, M. Chioua, and N. F. Thornhill. An MPC with disturbance forecasting for the control of the level of a tank with limited buffer capacity. In *2018 26th Mediterranean Conference on Control and Automation (MED)*, pages 1–9, 2018b

1.7 SUMMARY

This chapter has explained the industrial problem that this project aims to solve, which is increasing the level of automation of process plants in dealing with plant-wide and site-wide disturbances. Furthermore, the chapter has defined the technical objectives to reach this research aim.

The chapter has started with an overview that has described briefly the background and motivation. After the brief overview, the chapter has analysed the problem in detail. Section 1.2 has described the concepts of site utilities and of disturbances, stating the interest of this thesis for the persistent

and abrupt disturbances propagating between production plants, steam utility and electrical utility. Section 1.3 has explained scenarios where a disturbance can propagate further, underlining the role of controllers in the rejection of the disturbances from the controlled variables but also in the propagation of a disturbance. Section 1.4 described how operators intervene manually when disturbances propagate in a production site, and why it would be beneficial to create a control system able to react automatically to disturbances. Section 1.5 has proposed a framework that might mitigate the problems caused by a propagating disturbance. The framework consists of a Model Predictive Control (MPC) that works in conjunction with an algorithm to forecast the time series of persistent and abrupt plant-wide disturbances. The chapter argued that this would attenuate the propagation of disturbances and keep the key controlled variables close to their set-points. Finally, Section 1.6 stated the research aim and technical objectives, indicating the chapters of the thesis where such technical objectives are treated.

Chapter 2

LITERATURE REVIEW

This chapter provide a review of the literature relevant to the Model Predictive Control (MPC) and time series forecasting. These topics are relevant for the framework proposed in this thesis of an MPC with disturbance forecasting with applications in process control.

The focus of the review for the MPC is about the approaches for handling external disturbances. Regarding time series forecasting, the main focus of the review is about the potential ability in predicting persistent and abrupt disturbances, training time and simplicity of the methods.

2.1 INTRODUCTION

Chapter 1 described the background and motivation of the project, declaring the research aim and the technical objectives of the thesis. The research aim was *'Increasing the level of automation in different areas of a process site by optimizing the response to fast complex disturbances, examining the trade off between rejection and avoidance of disturbance propagation'*. The identified framework has been an MPC that exploits the forecast of a disturbance to adjust its control action. Two resulting technical objectives are providing a method for predicting a disturbance and implementing such disturbance forecast in a Model Predictive Control (MPC) framework. Therefore, this chapter provides a review of literature relevant to the MPC and time series forecasting.

Section 2.2 describes the common frameworks to handle external disturbances in an MPC, focusing specifically on frozen time MPC, preview MPC, robust MPC, stochastic MPC and deterministic MPC. The section ends choosing the framework to be used in this thesis.

Section 2.3 discusses time series forecasting, reviewing statistical and machine learning methods. The review provides the basis on which to choose an appropriate method to forecast the types of disturbances encountered in a production sites.

2.2 MODEL PREDICTIVE CONTROL

2.2.1 Introduction

Model Predictive Control (MPC) is a discrete-time and model-based control technique. It uses a model of the system to predict the future evolution of the controlled variables under a specific sequence of manipulated variables. The MPC works by finding the sequence of the manipulated variables that minimises a certain cost function over a future period, called prediction horizon, in presence of disturbances and constraints on the controlled and manipulated variables.

Once the control sequence has been found, the controller applies the first sample of the control sequence. At the following time step, the controller finds again the control sequence that minimises the objective function and applies the first sample of the new control sequence. The cost function for a state x at instant t is defined in Mayne et al. (2000) as

$$V_N\left(x, t,\ \boldsymbol{u}\right) := \sum_{i=t}^{t+\ p-1} l(x\left(i\right), u\left(i\right)) + V_f(x\left(t+p\right)) \tag{2.1}$$

where $\boldsymbol{u} = \{u(t),\ u\left(t+1\right), \ldots,\ u\left(t+p-1\right)\}$ is the sequence of controller outputs $u\left(i\right)$.

Each $u\left(i\right) \in \mathbb{U}$ is the value of the controller output at discrete time instant i. The set $\mathbb{U}$ is a compact, convex subset of $\mathbb{R}^m$. The variable $x\left(i\right) \in \mathbb{X}$ is the state of the system at instant i, where $\mathbb{X}$ is a convex, compact subset of $\mathbb{R}^n$. The prediction horizon is p and $l(x\left(i\right),\ u\left(i\right))$ represents the cost at instant i, dependent on the values of the state and the values of the manipulated variables. The costs $l(\cdot)$ at different instants i, called also stage costs, are summed over the prediction horizon. The term $V_f(x\left(t+p\right))$ represents the terminal cost. Unlike the stage cost, the terminal cost is dependent only on the state of the system at the end of the prediction horizon.

The reviews of MPC by Afram and Janabi-Sharifi (2014), Darby and Nikolaou (2012) and Farina et al. (2016) highlight the following features of the MPC, which are of interest for this project:

- It is a multivariable control, able to capture and control the influences between different sections of the controlled system.
- It can handle constraints on manipulated and controlled variables, allowing the system to be at a safe and economical operating point in case of a disturbance.

- It is considered by some researchers to be the most appropriate control method to benefit from an apriori knowledge of future and predictable disturbance.

2.2.2 Handling of external disturbances

2.2.2.1 Definition of external disturbance

The term *external disturbance* is used in this thesis to indicate the inputs of the system that the controller cannot manipulate. The term $d(t)$ in the following system of equations represents the external disturbance

$$\begin{aligned} x\,(t+1) &= Ax(t) + Bu(t) + B_d d(t) \\ y(t) &= Cx(t) + Du(t) + D_d d(t) + d_s(t) \\ B_d &= [B_m\ B_u]\,,\quad d = [d_m\ d_u]^T \end{aligned} \tag{2.2}$$

where $x(t)$ is the state of the controlled system at instant t, $y(t)$ is the vector of the controlled measurable variables, $u(t)$ is the vector of the manipulable inputs, $d_s(t)$ indicate the noise of sensors. A, B, B_d, C, D, D_d are matrices that represent the relations between inputs of the system, system state and controlled variable.

The vector of the external disturbances at instant t can be considered as $d(t) = [d_m(t)\ d_u(t)]^T$, where $[\cdot]^T$ stands for the transpose of a matrix. The vector of the external disturbances is $d_m(t)$ which can be measured by a sensor in a system, while d_u is the vector of the external disturbances which cannot be measured. For example, the mass flow of the feed to a column is an external measurable disturbance for the temperature controller of the column. Similarly, the matrix B_d, that describes the relations between external disturbances, state and outputs of the system, is composed of a part related to the measurable external disturbances and a part related to the unmeasurable ones. The focus in this thesis is on measurable time varying disturbances and hence $d = d_m$ in Eq. 2.2.

Therefore, this work distinguishes itself from other works such as the one of Muske and Badgwell (2002) and Carrasco and Goodwin (2011). Those works focus on unmeasured disturbances, which are also considered constant over a specified interval.

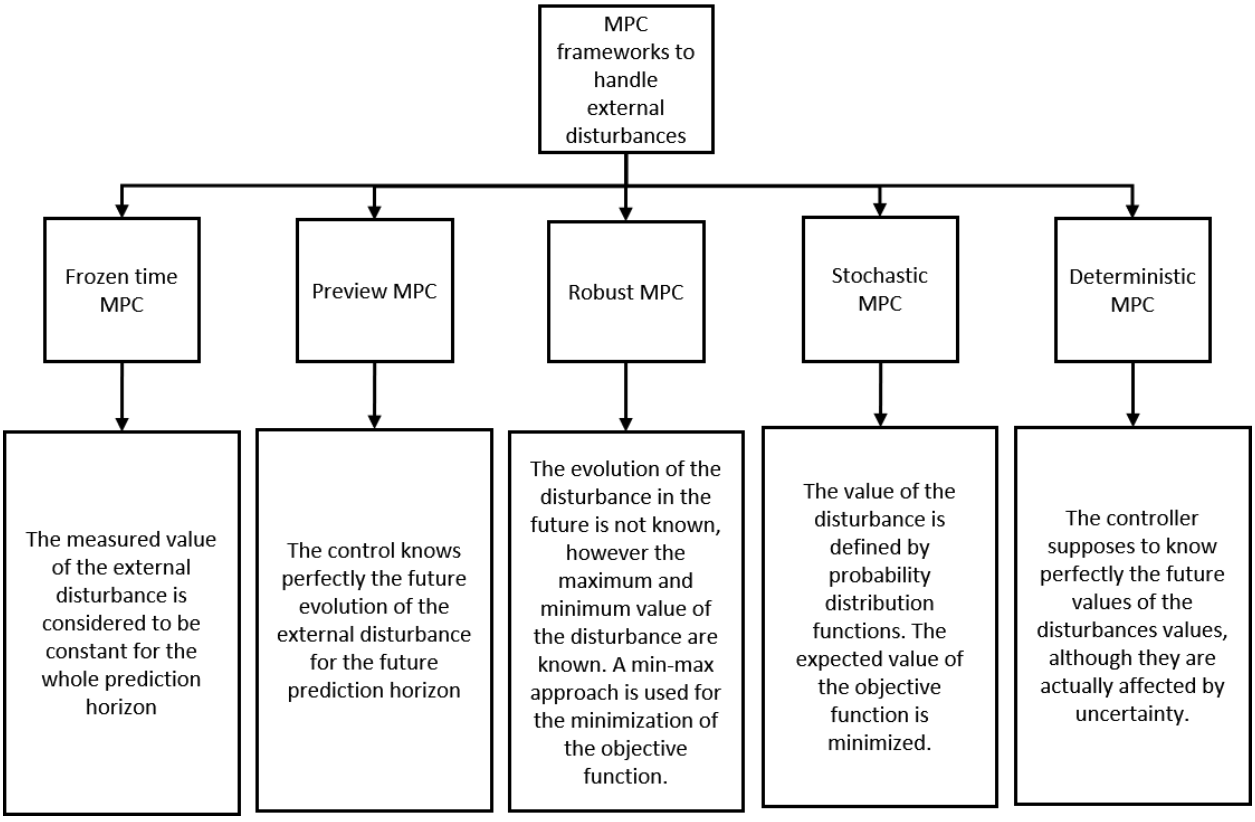


Figure 2.1: MPC frameworks to handle external disturbances

2.2.2.2 MPC FRAMEWORKS TO HANDLE DISTURBANCES

Five common MPC frameworks exist to handle external disturbances. Figure 2.1 lists the methods and provides a short description for each of them. Following Mayne (2016), Table 2.1 shows the objective functions and the constraints of each framework.

SYMBOLOGY In Table 2.1, $l(\cdot,\ \cdot)$ represents the stage cost for a certain state and control action. The variable $x^u(i, x, \hat{d}) \in X \subseteq R^n, i = 0, \ldots, p-1$ is the value of the state at instant i, given an initial state x at instant $i = 0$, when a series of controller output $\boldsymbol{u} = \{u(i),\ \ldots,\ u(p-1)\}$, $u\,(i) \in \mathbb{U} \subseteq \mathbb{R}^m$, and a disturbance sequence $\hat{\boldsymbol{d}} = \left\{\hat{d}(i),\ \ldots,\ \hat{d}(p-1)\right\}$, $\hat{d}(i) \in \mathbb{D} \subseteq \mathbb{R}^l$ is assumed to have been applied to the system.

The state space is $\mathbb{X}$, while $\mathbb{X}_f$ is the space of the terminal state, $\mathbb{U}$ is the space of the controller outputs, $\mathbb{D}$ is the space of the disturbance at an instant i while $\mathbb{D}^p$ represents the space of the disturbance sequence $\hat{\boldsymbol{d}}$, $\mathbb{I}_{0:p-1}$ is the set of values that i can assume, n is the dimension of the state, m is number of manipulated variables of the controller, l is the number of disturbances considered. Finally, $u(i, \hat{\boldsymbol{d}})$ indicates that the control action at instant i takes explicitly into account the disturbance sequence $\hat{\boldsymbol{d}}$.

Table 2.1: Cost functions and constraints for various MPC formulations

MPC Type	Cost function	Constraints
Frozen time MPC	$V_N(x,\ \boldsymbol{u}) = \sum_{i=0}^{p-1} l(x^{\boldsymbol{u}}(i,x,\hat{\boldsymbol{d}}), u(i,\hat{\boldsymbol{d}})) + V_f(x^{\boldsymbol{u}}(p,x,\ \hat{\boldsymbol{d}}))$	$u(i,\hat{\boldsymbol{d}}) \in \mathbb{U} \subseteq \mathbb{R}^m$, $x^u(i,x,\hat{\boldsymbol{d}}) \in \mathbb{X} \subseteq \mathbb{R}^n$, $\forall i \in \mathbb{I}_{0:p-1}$ $x^u(p,x,\hat{\boldsymbol{d}}) \in \mathbb{X}_f$
	$\hat{\boldsymbol{d}} = \left[\hat{d}(0)\dots\hat{d}(p-1)\right],\ \hat{d}(i) = d(0) \in \mathbb{D} \subseteq \mathbb{R}^l \in \mathbb{R}^l,\ i = 0\dots p-1$ l is the number of disturbances. The values over time of the disturbances are constant and equal to the initial value $d(0)$	
Preview MPC and deterministic MPC	$V_N(x,\ \boldsymbol{u}) = \sum_{i=0}^{p-1} l(x^u(i,x,\hat{\boldsymbol{d}}), u(i,\hat{\boldsymbol{d}})) + V_f(x^u(p,x,\hat{\boldsymbol{d}}))$	$u(i,\hat{\boldsymbol{d}}) \in \mathbb{U} \subseteq \mathbb{R}^m$, $x^u(i,x,\hat{\boldsymbol{d}}) \in \mathbb{X} \subseteq \mathbb{R}^n$, $\forall i \in \mathbb{I}_{0:p-1}$ $x^u(p,x,\hat{\boldsymbol{d}}) \in \mathbb{X}_f$
	$\hat{\boldsymbol{d}} = \left[\hat{d}(0)\dots\hat{d}(p-1)\right],\ \hat{d}(i) \in \mathbb{D},\ i = 0\dots p-1$ The values $\hat{d}(i)$ are perfectly known in the preview MPC. They are supposed to be known in the deterministic MPC	
Robust MPC	Robust MPC Nominal case: $V_N(x,\ \boldsymbol{\pi}) = \sum_{i=0}^{p-1} l(x^{\pi}(i,x,\mathbf{0}\ ), \mu_i(i,\mathbf{0})) + V_f(x^{\pi}(p,x,\mathbf{0}))$ $\mathbf{0} = [0,\ \dots, 0]$ is a sequence of zero vectors	$\mu_i(x^{\boldsymbol{\pi}}(i,x,\hat{\boldsymbol{d}})) \in \mathbb{U}$, $x^{\pi}(i,x,\hat{\boldsymbol{d}}) \in \mathbb{X}$, $\forall(i,\hat{\boldsymbol{d}}) \in \mathbb{I}_{0:p-1} \times \mathbb{D}^p$ $x^{\pi}(p,x,\hat{\boldsymbol{d}}) \in \mathbb{X}_f$, $\forall \hat{\boldsymbol{d}} \in \mathbb{D}^p$
	Robust MPC Worst case: $\mu_i(x^{\boldsymbol{\pi}}(i,x,\hat{\boldsymbol{d}})) \in \mathbb{U}$, $P(x^{\pi}(i,x,\hat{\boldsymbol{d}}) \in \mathbb{X}) \geq 1-\varepsilon$ $P(x^{\pi}(p,x,\hat{\boldsymbol{d}}) \in \mathbb{X}_f) \geq 1-\varepsilon$, $\forall i \in \mathbb{I}_{0:p-1}$, $\forall \hat{\boldsymbol{d}} \in \mathbb{D}^p$	
	$\hat{\boldsymbol{d}} = \left[\hat{d}(0)\dots\hat{d}(p-1)\right],\ \hat{d}(i) \in \mathbb{D} \subset \mathbb{R}^l,\ d_{\text{Min } i} \leq \hat{d}(i) \leq d_{\text{Max } i},\ i = 0\dots p-1$ The values of $\hat{d}(i)$ are not known but $d_{\text{Min } i}$ and $d_{\text{Max } i}$ are known.	

Table 2.0: Cost functions and constraints for various MPC formulations

MPC Type	Cost function		Constraints
Stochastic MPC	$V_N(x,\ \boldsymbol{u}) =$ $E_w\left\{\sum_{i=0}^{p-1} l(x^{\pi}(i,x,\hat{\boldsymbol{d}}),\mu_i(i),\hat{\boldsymbol{d}}) + V_f(x^{\pi}(p,x,\hat{\boldsymbol{d}}))\right\}$	Hard version	$\mu_i(x^{\pi}(i,x,\hat{\boldsymbol{d}})) \in \mathbb{U}$, $E_w(x^{\pi}(i,x,\hat{\boldsymbol{d}})) \in \mathbb{X}$, $\forall(i,\hat{\boldsymbol{d}}) \in \mathbb{I}_{0:p-1} \times \mathbb{D}^p$ $E_w(x^{\pi}(p,x,\hat{\boldsymbol{d}})) \in \mathbb{X}_f$ $\forall\hat{\boldsymbol{d}} \in \mathbb{D}^p$
		Soft version	$\mu_i(x^{\pi}(i,x,\hat{\boldsymbol{d}})) \in \mathbb{U}$, $E_w(x^{\pi}(i,x,\hat{\boldsymbol{d}})) \in \mathbb{X}$, $\forall(i,\hat{\boldsymbol{d}}) \in \mathbb{I}_{0:p-1} \times \mathbb{D}^p$ $E_w(x^{\pi}(p,x,\hat{\boldsymbol{d}})) \in \mathbb{X}_f$ $\forall\hat{\boldsymbol{d}} \in \mathbb{D}^p$
	$\hat{\boldsymbol{d}} = \left[\hat{d}(0)\ldots\hat{d}(p-1)\right],\ \ \hat{d}(i) \sim D_i,\ \ \hat{d}(i) \in \mathbb{D} \subseteq \mathbb{R}^l,\ \ \ i = 0\ldots p-1$ The values $\hat{d}(i)$ are not constrained and follow a probability distribution D_i that is defined according the probabilistic model of the disturbance.		

Using the term $x^{\pi}\left(i,x,\hat{\boldsymbol{d}}\right)$ instead of $x^{\boldsymbol{u}}\left(i,x,\hat{\boldsymbol{d}}\right)$ highlights that an explicit offline solution has been used. The formulation with an explicit offline solution is preferred in the case of robust and stochastic MPC. The reason is that finding a solution online might be computationally expensive (Bernardini and Bemporad, 2012; Farina et al., 2016; Mayne, 2016). The control action u is defined by a policy μ. The policy depends on the value of the state x at an instant of time i, and it is stored in a look-up table. The control action is defined as $u = \mu(i,x) = F(x(i)) \cdot x(i) + G(x(i))$ (Bemporad et al., 2002a,b). The term $x^{\pi}\left(i,x,\hat{\boldsymbol{d}}\right)$ is the value of the state at instant i, given an initial state x at instant $i = 0$, when a series of controller policies $\boldsymbol{\mu} = \{\mu(i,\ x),\ \ldots,\ \mu(p-1,x)\}$, $\mu\,(i,x) \in \mathbb{U} \subseteq \mathbb{R}^m$ and a disturbance sequence $\hat{\boldsymbol{d}}$ would have been applied to the system.

A distinction has to be made between the values d that have been really applied to the system and the values $\hat{d}$ that the controller uses for the calculation of the objective function. There can be a mismatch that has an impact on the calculations of the controller. For example, assuming in the Frozen Time MPC that the values of disturbance $\hat{d}$ are equal to the $d(0)$ over the whole prediction

horizon p does not mean that the value of the disturbance applied to the system is going to be constant. This section discusses the assumptions of different MPC formulations on values of the disturbance sequence $\hat{\boldsymbol{d}}$.

Frozen Time MPC In Frozen Time MPC (FTMPC), the measured value of the external disturbance is considered to be constant also for the whole prediction horizon. This is the most used approach to handle external disturbances in commercial MPC, according to Camacho and Bordons (2008). This way of handling disturbance is called Frozen Time MPC (FTMPC) by Cairano et al. (2014). In the formulations in Table 2.1, the disturbance is assumed to be equal to the value of the disturbance measured at instant zero, therefore $d\,(i) = d(0),\ \ i = 0, \ldots, N$.

Preview MPC In Preview MPC, the controller receives and uses the actual future evolution of the external disturbance for the length of the prediction horizon (Carrasco and Goodwin, 2011; Mehra et al., 1997). Preview MPC can be considered a subset of optimal preview control. Optimal preview control is characterized by a perfect knowledge of the disturbance future evolution, but different control techniques can be used (Birla and Swarup, 2015). The formulations in Table 2.1 are like those of the Frozen Time MPC but the elements $\hat{d}\,(i)$ are allowed to vary over time.

Robust MPC In Robust MPC, the disturbance evolution in the future is not supposed to be known. However, the maximum and minimum values of the disturbance are known. The controller should consider all possible evolutions of the disturbance in a bounded set $\mathbb{D} \subset \mathbb{R}^l$ (Farina et al., 2016; Mayne, 2016, 2014). Therefore, Table 2.1 indicates that the controller actions and states should stay within their constraints over the prediction horizon, for all possible evolutions of the disturbances ($u \in \mathbb{U},\ x \in \mathbb{X},\ x_f \in \mathbb{X}_f, \forall \left(i, \hat{\boldsymbol{d}}\right) \in \mathbb{I}_{0:p-1} \times \mathbb{D}^p$). Two cases are often considered for the objective function: the nominal case, that does not consider the presence of disturbances, and the worst case scenario. For the worst case-scenario, a min-max approach is used and the controller considers the action that minimizes the objective function in the case of the worst possible disturbance instance (Bernardini and Bemporad, 2012).

Stochastic MPC In Stochastic MPC, there may not be upper and lower bounds of the disturbance. Therefore, the disturbances can potentially assume any possible value in the real

coordinate space of dimension l, in mathematical terms $\mathbb{D} \subseteq \mathbb{R}^l$. This is different from the case of robust MPC where the possible values of the disturbances are necessarily a subset of $\mathbb{R}^l$, or in mathematical terms $\mathbb{D} \subset \mathbb{R}^l$. In stochastic MPC, the value of the disturbance is defined by a probability distribution function. The MPC minimizes the expected value of the objective function for all possible disturbance sequences $\hat{\boldsymbol{d}}$. Hard constraints for the controller outputs are always present. However, the constraints on the controlled variables can be hard or probabilistic.

In the hard formulation of the problem, the expected value of the state $E_w\left(x^\pi\left(i, x, \hat{\boldsymbol{d}}\right)\right)$ should be within the constraints $\mathbb{X}$ for all values that the disturbances $\hat{\boldsymbol{d}}$ can have over the prediction horizon until the instant $p-1$. Additionally, such constraint should be valid also at the end of the prediction horizon, where terminal constraints enter into force, which are possibly different from those valid over the prediction horizon, and oblige the expected value of the state to be within a space $\mathbb{X}_f$. In mathematical terms, this is translated in the conditions $E_w\left(x^\pi\left(i, x, \hat{\boldsymbol{d}}\right)\right) \in \mathbb{X},\ \forall \left(i, \hat{\boldsymbol{d}}\right) \in \mathbb{I}_{0:p-1} \times \mathbb{D}^p$ and $E_w\left(x^\pi\left(N, x, \hat{\boldsymbol{d}}\right)\right) \in \mathbb{X}_f,\ \forall \hat{\boldsymbol{d}} \in \mathbb{D}^p$ (Mayne, 2016). However, in case of potentially unlimited disturbances, a hard constraint for the controlled variables is not possible because no feasible solutions can be found. Chance constraints are used in these cases. In chance constraints, the probability $P(\cdot)$ that the state $x^\pi(i, x, \hat{d})$ is within its constraints is defined. Then, the constraint is that such probability is bigger than a certain value. The value is generally slightly smaller than one. This means that with a very high probability, almost equal to one, the limits imposed to the controlled variables are respected (Farina et al., 2016; Mayne, 2016). The mathematical conditions $P\left(x^\pi(i, x, \hat{d}) \in \mathbb{X}\right) \geq 1-\varepsilon$ and $P\left(x^\pi\left(N, x, \hat{\boldsymbol{d}}\right) \in \mathbb{X}_f\right) \geq 1-\varepsilon$ are therefore used, where ε is a small number to be defined.

Deterministic MPC In Deterministic MPC, the controller does not have information on the probabilities of the values that a disturbance can have. The assumption is that the future values of the disturbances that are provided to the controller are certain, although they are not. This approach is a simplification of the stochastic MPC. The formulations of objective functions are identical to those of preview MPC

The approaches further analysed Of the four approaches that consider a disturbance as evolving in the future (preview, robust, stochastic MPC and deterministic MPC), the approach of

the robust MPC has not been considered further.

Indeed, the robust MPC controller must find a sequence of controller outputs that satisfies all constraints for all possible sequences $\hat{\mathbf{d}}$ of the disturbance $\hat{d}(\cdot)$ between the upper and lower bounds. This is a stricter requirement than those of the other approaches, that are more precise in knowing the future evolution of the disturbance for each instant of time over the prediction horizon.

For this reason, if the uncertainty of the disturbance is high (the upper and lower bounds of the disturbances are far from each other), the robust MPC might not be able to calculate a solution that satisfies all constraints, although there might be one if a more precise knowledge of the future disturbance evolution were used. Therefore, the controller does not intervene or it stops working. However, such an action contradicts the aim of the research in this thesis, which is to increase the level of automation of process plants in presence of disturbances. Furthermore, violations of some constraints during a disturbance are very likely and also relatively acceptable if short in time, according to the professional experience of the present author. The focus of this PhD has been posed therefore on Frozen Time MPC (FTMPC), preview MPC, stochastic MPC and deterministic MPC.

2.2.3 Frozen Time MPC (FTMPC)

2.2.3.1 FTMPC in process industry

FTMPC is the basic strategy to handle disturbances in an MPC (Binder et al., 2019; Camacho and Bordons, 2008; Havlena, 2011). It is also the one available in commercial implementations of MPC controllers as Havlena (2011) stated while working for Honeywell, and as the present author experienced more recently (until 2016, while employed in industry) with the products from Aspentech. The value of the disturbance is assumed constant over the prediction horizon and equal to the measured value at the current instant of time.

Majanne (2005) compared a FTMPC with a control scheme based on PI controllers to control the steam pressures at various points in steam distribution network. The rates of the mass flows of steam were used as measured disturbances for the feed-forward action of the FTMPC. According to the author of the paper, the FTMPC provided a slight improvement of the set-point tracking over

the scheme with PI controllers. The author stated that the main advantages are a simplified control structure (the MPC replaces six PI controllers) and ease of tuning.

Olsen et al. (2005) implemented an FTMPC to control the distillation column of the benchmark model of a VAc production plant developed by Luyben and Tyréus (1998). The controller had to keep at their set-points the level of the reboiler and the concentration of water in the outflow from the bottom of the column. The feed of the column was used as disturbance variable for the feed-forward action. The authors considered two cases. In one case the composition of the feed changed as a step, and the authors of the paper considered the response of the controller as unacceptable because the concentration of water violated its constraints. In the other case, the pump serving feed of the column has been temporarily shut-off for five minutes and the reaction of the controller was considered only acceptable. The authors thought that the controller was aggressive. In addition, the sampling of the measurements of the concentration of water was much larger than the sampling of controller. In their opinion, the aggressiveness and the delays of the measurements led to poor performance.

Shen et al. (2009) implemented an FTMPC for a water treatment plant. The controller should keep the quality of the effluents constant while minimizing the energy consumption. The measured disturbance is a nearly periodic oscillation of the concentration of pollutants. The authors of the paper considers the FTMPC a failure because it worsens the performance of the controller compared to the situation where no feed-forward action is used in the MPC. To improve the controller action, the authors filter the values of the measured disturbance by using a moving average filter.

2.2.3.2 Conclusions on the FTMPC

FTMPC is the most common approach used to handle external disturbances in an MPC. The disturbance is assumed constant in the future and its values is equal to the one measured at current time. It is a simple technique to implement but its real benefits are questionable. There might be a slight improvement of performance with FTMPC but unsatisfactory performance has been reported in a few papers because the control action can be too aggressive.

2.2.4 Preview MPC

2.2.4.1 Preview of set-points

In case of a preview of set-points, the set-points are provided in advance to the controller. Therefore, the controller has the information that the set points will change to a new value in a specific time τ_{sp}. In this case, the controller might change the controller outputs before the set-point changes. In this way the controller outputs are not changed abruptly when the set-point changes and a better tracking of the set-points can be reached in case of slow systems.

2.2.4.2 Preview of external disturbances

In case of a preview of external disturbances, the disturbances are measured before they enter into the system. At first, this might seem similar to classical control with a feedforward framework (Liptak, 2005). However, classic feedforward control is not an optimal control framework. Furthermore, they do not allow handling of constraints on the controlled variables, as a preview MPC can. It is necessary to measure the disturbance well in advance, before it has an impact on the controlled variable. If τ is the delay between the instant the disturbance is measured and the instant the disturbance enters in the system, then the controller has information about the value of the disturbance at instant t, that is $d(t)$, and all other values $d\,(i)\,,\ i = 0, \ldots, \tau$ as well. Therefore, a disturbance sequence $\hat{\boldsymbol{d}}$ is available to the controller.

2.2.4.3 Preview MPC in fields different from process industry

Mehra et al. (1997) developed an MPC control that takes into account the irregularities of the street to improve the control of the suspensions of the vehicle. A sensor positioned at the very front of the car measures the irregularities of the road. With information from this sensor and from the speed of the car, the controller quickly calculates the profile of the road that the suspensions will have to compensate and sends appropriate commands to the active suspension.

Takaba mentioned the industrial case of a cold mill steel plant. The strips must have a uniform thickness at the end of the process. However, a control action that is not adequate to the thickness of the strips at the beginning of the process can ruin the strips. A sensor can measure the thickness of the strips upstream and provide such information as disturbance preview to the controller that adjusts the force applied on the metal bars.

Koerber and King (2013) used an MPC with preview to control a wind turbine. By adjusting the position of blade, the controller has to keep the rotational speed of the turbine below a certain mechanical constraint and keep structural oscillations of the wind tower within certain amplitudes. The disturbance previewed is the wind speed, measured some hundred meters far from the tower. The authors tested the control both in normal turbulent conditions and in presence of abrupt events such as gust. Compared to other MPC solutions without preview and to a solution based on classical control, the MPC with preview shows better performance in keeping the controlled variables far from their safety constraints.

2.2.4.4 Preview MPC in process industry

The reason for reviewing other industrial domains is because there are not many reported applications of preview control in the process field. However, there were applications in the Japanese industry in the late 1990s. Nunokawa et al. (1997) applied unconstrained preview optimal control, but with no MPC, to a coke oven plant. In this process the coal is charged in the furnace regularly, coke is distilled, the produced coke is removed from the furnace, and new coal is charged in the furnace. New coal charges cause variations of the furnace temperature. The resulting temperature overshooting can be minimized by knowing when new coal will be charged in the furnace. The problem formulated is not constrained, and there is no disturbance propagation issue that must be considered. Also Yoshitani and Hasegawa (1998) considered a problem related to steel manufacturing. The process considered is called annealing and consists of the heating, the soaking, the cooling and the overaging furnace. The temperature of the strips at the outlet of the process must be constant. However, the desired thickness of the strip has an impact on the temperature. Reducing the temperature variations is possible if the controller knows in advance the thickness of the strip and the instant when the set-point of the thickness will be changed.

2.2.4.5 Conclusions on Preview MPC

The primary applications of Preview MPC that have been reported are not in process engineering. However, the examples from Japan show the feasibility of applying preview MPC also in the process industry. The main issue of preview MPC is that there should be a sufficiently long delay τ between the instant the disturbance is measured and the instant the disturbance enters into the system.

If the delay τ is too small, preview MPC cannot be used and a prediction of the disturbance should be used instead. In case of process plants, it might be hard to have transport delays which are large enough because the process units tend to be close to each other.

2.2.5 Stochastic MPC

2.2.5.1 Stochastic MPC in process industry

As of 2016, Farina et al. (2016) reported that they had not found any implementation of stochastic MPC in real processes. However, some research papers applied stochastic MPC and stochastic optimisation to industrial processes. In this research area, the uncertainties considered are classified in external uncertainties, such as feeds or throughput requests, or internal uncertainties, such as model uncertainties (Henrion and Möller, 2003; Li et al.).

The external uncertainties are the interest of this thesis section, and they can be considered similar to the external disturbances. The aim of the papers that have been considered in the field of process control was to find the optimal set-points of the flows inside a petrochemical plant. The feeds and the requests of final product are the disturbances. The problem can be analysed from a steady state or a dynamic point of view (Li et al.). In the steady state case, the disturbance is considered constant, but its exact value is not known. The problem is to find the set-points in the process that maximise the profits of a plant and be sure that the controlled variables remain within their constraints (Li et al.; Mesfin and Shuhaimi, 2010). In the dynamic case, the disturbance is not constant over the prediction horizon, and it is affected by uncertainty. The aim can be economical, for example reducing the steam energy consumption of a distillation column in case of feed disturbances (Li et al., 2002), or more process related, such as reducing the variations of the outlet flow of a tank whose inlet feed is not constant (Li et al.).

Since such studies are done in a design phase, the disturbance model is not learnt by the control system, instead, it is defined by the user. The approach found in Li et al. (2002), Li et al. and in Bahakim and Ricardez-Sandoval (2014) is to define the disturbance over the prediction horizon as a vector composed of stochastic variables, one variable for each time step. Each stochastic variable is defined by a mean value and variance. In Li et al. (2002) and in Li et al. the variables are considered Gaussian. In Bahakim and Ricardez-Sandoval (2014) the approach is that the user can choose which distribution to use.

2.2.5.2 Stochastic MPC in other fields and learning MPC

Stochastic MPC has also been used in fields different from process industry. Cairano et al. (2014) employed stochastic MPC to control the charge and discharge power which regulate the state of charge of the battery of a hybrid electric vehicle. The disturbance is the driving style of the driver, more precisely the power requested by the driver. An FTMPC was used as term of comparison. In real-world scenarios, the approach based on stochastic MPC reduced the vehicle fuel consumption by 8%-12% compared to the FTMPC. The disturbance model is created using a Markov chain. A Markov chain model defines a set of probabilities

$$P\left(d(t+1) = b \mid d(t) = a\right), \ \forall a \in \mathbb{D}, \ \forall b \in \mathbb{D} \tag{2.3}$$

which are the probabilities that the disturbance d has a value b in the instant $t+1$ if the disturbance was equal to a in the former instant of time t. Using a probabilistic model of the disturbance, the MPC can optimally controls the system. This paper is interesting for the current PhD project because the controller updates the model of the disturbance autonomously. Such MPC frameworks that learn and update the model of the disturbance or the model of the controlled system are called learning MPC (Aswani et al., 2013; Cairano et al., 2014; Klenske et al., 2016).

2.2.5.3 Conclusions on the stochastic MPC

Stochastic MPC has been used in research projects related to process industry to analyse how a disturbance might affect the process and the control. However, such studies were done for the design phase of a plant and not for a plant in operation. In the automotive field, Cairano et al. (2014) proposed a learning MPC framework that updates the model of the disturbance. Including a disturbance forecast in an MPC framework brings advantages also for stochastic MPC.

The main issue is defining a probabilistic model of the disturbance and this requires prior knowledge or a set of data from which to derive the probabilistic model. Prior knowledge is often hard to have when dealing with plant-wide disturbances because the causes of a disturbance can be diverse and it can also be difficult to have probabilistic first principle models of each part of the plant. If the probabilistic model is based on data, the problem can be having enough data to start predicting the time series and managing the amount of data in an efficient way.

A second issue with stochastic MPC is the computational costs of considering the probabilities in the calculations of the optimal decision. This might force the use of explicit formulations of the MPC.

2.2.6 Deterministic MPC

2.2.6.1 Deterministic MPC in process industry

Deterministic MPC receives a multi-step prediction that does not include any uncertainty measure, unlike stochastic MPC. The mathematical formulation of deterministic MPC is equivalent to the one of the preview MPC. The difference is that the disturbance forecast is measured in preview MPC, while it is predicted and generally more uncertain in deterministic MPC.

The review of literature revealed there are not many papers using deterministic MPC in process control. Honeywell, a supplier of automation solutions, deposited a patent in the USA in 1995 called "Neural net based disturbance predictor for model predictive control" (Mathur and Ravi, 1995). The patent proposed to use an MPC together with an Artificial Neural Network (ANN). The ANN should predict the evolution of the disturbance, and the MPC should compensate that specific disturbance. The patent describes the idea and the advantages of predicting plant wide disturbances for control purpose. However, it does not describe in detail the possible implementation. Honeywell deposited a second patent in 2011. The title is "System and method for predicting future disturbances in model predictive control applications" (Havlena, 2011). In this case, they suppose that a mathematical model of the disturbance is available, but they do not provide any possible mathematical formulation of the model.

Bordons and Cueli (2004) implemented a deterministic MPC in a real olive oil mill. This mill has an on-off controller to regulate the feed of fresh olives in a device called thermomixer. The on-off controller is the source of disturbance considered. The thermomixer has three tanks and the temperature of the last tank must be kept constant. However, the temperature is affected by the varying level which oscillates due to the on-off controller that has been mentioned before. The oscillations are very regular and the authors tuned an Auto Regressive model (AR model) to predict them. By adjusting the heating, the MPC uses the prediction of the disturbance to keep the temperature of the olive oil more constant. The authors compared such controller to an

FTMPC and an MPC controller which does not include any information about the future values of the disturbance. The proposed controller shows the best set-point tracking. The worst controller is the one without any disturbance information. Although Bordons and Cueli (2004) focused on plant-wide disturbances, they did not focus also on the role of the controller in the disturbance propagation. Also, they consider only persistent disturbances and not abrupt disturbances. Finally, the persistent disturbance they consider resembles a sinusoidal disturbance and does not have a complex repeating pattern.

More recently, Binder et al. (2019) use as well an Auto Regressive model (AR) for predicting process disturbances in conjunction with an MPC. The authors highlight that there are very few works where the disturbance is predicted in process control, and cite only Bordons and Cueli (2004) as example. Their case study is an oil production well with an electric submersible pump (ESP) installed. The disturbance is the pressure of the oil well, which is the back-pressure of the ESP. The manipulated variables are the speed of the pump and the opening of a valve. The controlled variables are the mass flow rate through the ESP, the outlet pressure and the electric current flowing in motor of the pump. The authors compare their proposed MPC working in conjunction with AR model with an FTMPC. The proposed solution improves the performance in set-point tracking of the controller. By contrast, the aggressiveness of manipulated variables remains unchanged. Although such work is about process control applications, it does not focus on plant-wide disturbance and their propagation.

2.2.6.2 Deterministic MPC in other fields

Including weather forecast in a deterministic MPC is common in building automation, according to the review of Afram and Janabi-Sharifi (2014). Oldewurtel et al. (2012) compared a stochastic MPC with a deterministic MPC for building automation. They used a stochastic MPC to minimise the energy consumed to keep the temperature inside a building within desired constraints. The external disturbance was the outside temperature. The profile of the outside temperature is the sum of two components. These two components are a temperature profile provided by the forecasting agency and considered certain, and an uncertain noise. By considering only the temperature profile provided by the forecasting agency, the authors formulated the deterministic version of the MPC problem. This is interesting because it shows that the disturbance forecasting is independent of

the MPC formulation and solution in the deterministic approach. However, the stochastic MPC was superior to the deterministic MPC regarding energy consumption and number of times the temperature of the building violated the constraints.

2.2.6.3 Conclusions on deterministic MPC

Some works applied deterministic MPC to process control. Honeywell filed two patents for the use of time series forecasting in conjunction with MPC to handle plant-wide disturbances (Havlena, 2011; Mathur and Ravi, 1995). However, the patents do not provide details for an implementation.

Bordons and Cueli (2004) implemented a deterministic MPC that improves the set-point tracking of a system affected by a plant wide disturbance in a real olive oil mill. However, the authors focused only on very regular persistent disturbances and they did not focus on propagation of disturbances. A more recent paper by Binder et al. (2019) applied deterministic MPC to improve the set-point tracking of a pump used for extraction of oil from a well. Although, it is not a work related to plant wide disturbances, Binder et al. (2019) confirmed there have not been apparently many other works using deterministic MPC in process control.

Deterministic MPC has been used more in building automation, where the weather condition is the disturbance that can be forecasted. A paper in the field of building automation written by Oldewurtel et al. (2012) showed that the performance of a deterministic MPC can be poorer than the performance obtainable with a stochastic MPC.

However, the formulation of deterministic MPC is independent from the method used for the disturbance forecasting. This simplifies the problem.

2.2.7 Conclusions on model predictive control

This section reviewed common frameworks used in MPC to take into account information about the future evolution of external disturbances. Four main approaches have been considered.

The most common approach is Frozen Time MPC (FTMPC), where the disturbance is assumed to be constant over the prediction horizon and equal to the value of the disturbance measured at the current time. This approach might improve slightly the performance of a controller in some cases. However, a few papers reported that the behaviour of a controller using this approach can be aggressive, leading to very poor performance.

Instead, several papers showed that providing information of the future trend of an external disturbance improves the reaction of an MPC controller to disturbance.

In preview MPC the disturbance is measured τ time instants before it enters in the system. Therefore, the controller has information of the values of disturbance sequence $d(i)$, $i = 0, \ldots \tau$. An issue for preview MPC in process plants is that it might be hard to have values of τ that are large enough because the process units tend to be close to each other and the transport delays are relatively small.

In stochastic MPC the disturbance is affected by uncertainty, and the MPC minimizes the expected value of the objective function and the constraints are formulated as chance constraints.

The deterministic MPC uses a simplified assumption compared to the stochastic approach. The disturbance sequences are predicted and the prediction is affected by uncertainty. However, the controller assumes that the values of the disturbance are certain. The formulation of the objective function and of the constraints is identical to that of the preview MPC control. Although the performance of a deterministic MPC might be inferior to the performance of a stochastic MPC, the advantage of a deterministic MPC is that the problem of disturbance forecasting is independent of the formulation and solution of the MPC problem. For this reason, the deterministic MPC seems to suit better the needs of this thesis for this initial work.

Furthermore, this section introduced the concept of learning MPC. Learning MPC is a control framework that learns and updates online the model of the disturbance or the model of the system and provides such model to the MPC (Aswani et al., 2013; Cairano et al., 2014; Klenske et al., 2016).

2.3 TIME SERIES FORECASTING

2.3.1 Introduction

Searches of the literature during the PhD studies did not reveal many papers related to time series forecasting for process disturbances. Therefore, the current section investigates time series forecasting in the following research areas: wind speed and wind power forecasting (Hu et al., 2016; Jung and Broadwater, 2014; Li and Shi, 2010), electric load forecasting (Hong and Fan, 2016; Khotanzad et al., 1998), finance and business (Cavalcante et al., 2016; Patel et al., 2015;

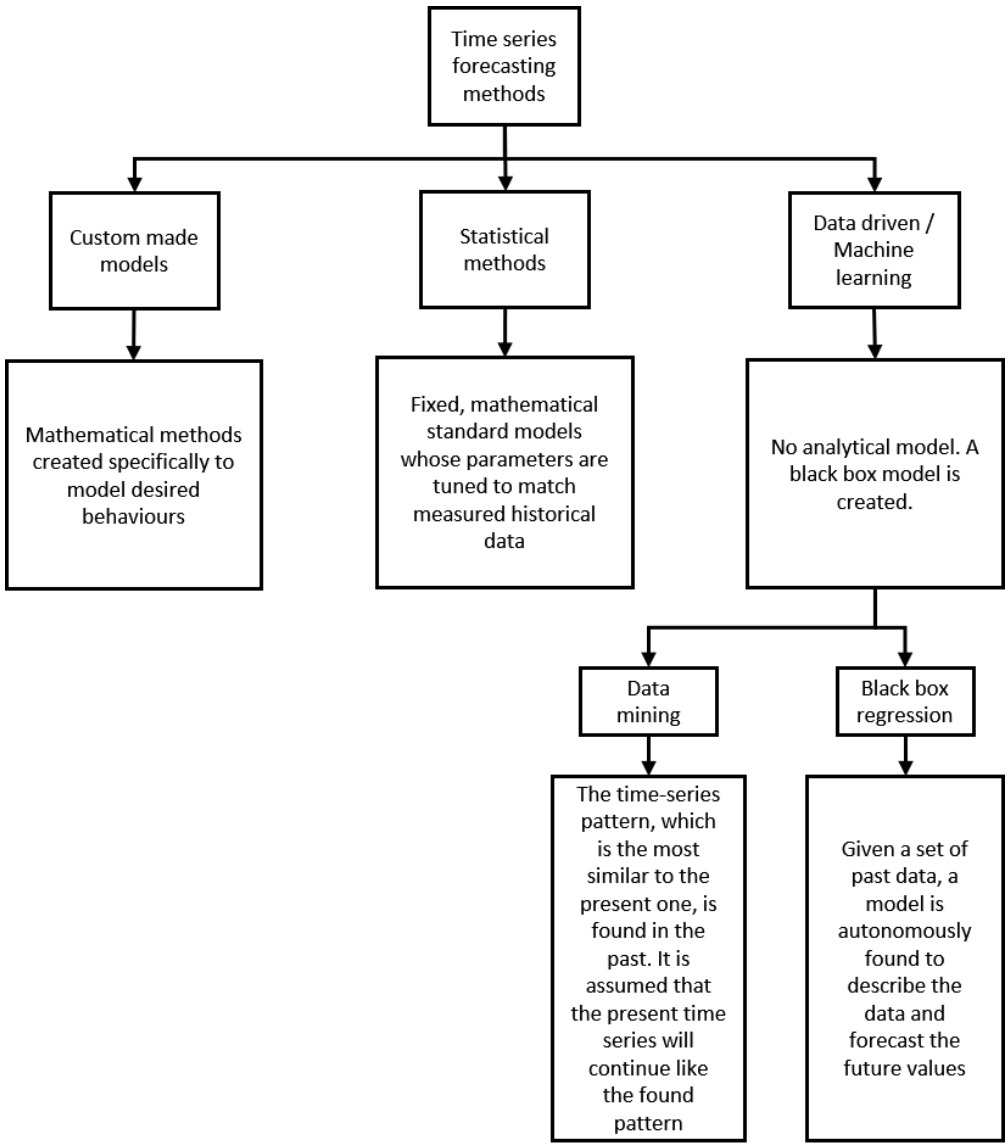


Figure 2.2: Depiction of available time series forecasting methods

Taylor and Letham, 2018), traffic forecasting (Vlahogianni et al., 2014).

There are three main types of time series forecasting methods, as Figure 2.2 shows

1. Methods based on purpose-built models
2. Statistical methods
3. Machine learning methods, also called black-box or data-driven models

Purpose-built models are created relying on knowledge rather than on past data. This class might include, for example, first principle models, which use equations based on fundamental physical principles (Jung and Broadwater, 2014; Yesilbudak et al., 2013), but also economic models that describe the fundamental laws of demand and supply. These models were not reviewed further for this PhD because they are out of the scope.

Conventional statistical methods for time series forecasting use standard mathematical models to represent the relationship between inputs and outputs. A generic model is defined, and its parameters are tuned to fit the existing relationships, in contrast to purpose-built models which describe mathematically those relationships based on physical first principles. The statistical methods are represented by Markov chain models, exponential smoothing methods and the family of Autoregressive Integrated Moving Average models with eXogenous inputs (ARIMAX), which includes its subtypes autoregressive moving average (ARMA), autoregressive (AR) and moving average (MA). Section 2.3.2 describes these models.

Unlike statistical methods, machine learning methods do not have a strongly pre-defined structure. Through a training process which uses past data, machine learning method are able to represent the relationship between inputs and outputs. The models resulting from most of the machine learning methods are not analytical. In these cases, it is not possible to analyse the impact of the parameters on the model. For this reason, the models created are defined as "black box models".

There are two main approaches for time series forecasting within machine learning. The first one is the same approach used by the time series forecasting community for statistical methods, which is finding a model, given a set of past data, that describes the data and forecasts the future values. The other approach is the one of data mining community. In that approach, the aim is finding the time series pattern in the past which is the most similar to the present one, assuming that the present time series will continue as the found pattern.

2.3.1.1 A HISTORICAL POINT OF VIEW

According to Bontempi et al. (2013), linear statistical methods, and specifically ARMA models (described in paragraph 2.3.2.2) were predominant until early 80s. The authors state that the linear statistical methods showed their limits in real applications often characterised by non-linear

behaviour and this led to a focus on non-linear time series models. However, De Gooijer and Hyndman (2006), and Bontempi et al. (2013) said that the theory behind non-linear statistical methods does not yet have such a solid basis as the theory behind linear models. In particular, De Gooijer and Hyndman (2006) state that non-linear methods do not allow the writing of a closed form analytical expression for multi-step forecast. The result is that starting from the early 90s machine learning methods became a competitor of classical statistical methods.

This move of researchers from the statistical perspective to machine learning methods, in particular computational approaches using Artificial Neural Networks (ANN), has been confirmed by Patel et al. (2015) for the financial field, and by Vlahogianni et al. (2014) for the traffic forecasting field. For the field of traffic forecasting, Vlahogianni et al. (2014) state that the classical statistical methods show their limits in the presence of structured and unstructured data, complex road setting or unstable traffic conditions.

Bontempi et al. (2013) mentioned cases where ANN outperformed statistical methods based on linear regression and Box- Jenkins methods (ARMA-ARIMA methods). However, there are more cautious views. In a recent critical review of methods for electricity load forecast, Hong and Fan (2016) state that there is "the myth of the best technique". In their view, a technique should be chosen case by case. There is an additional problem, which is that there is a lack of benchmarks that would allow a fair comparison of the methods for specific cases. This is the opinion of Hong and Fan (2016) for electric load forecasting, Weron (2014) for electricity price forecasting, Vlahogianni et al. (2014) for traffic forecasting, and Jung and Broadwater (2014) for forecasting of wind speed and electric power generated by wind turbines.

2.3.2 Statistical methods

Statistical methods use standard models that assume that the time series to be forecasted derives from a stochastic process. Indeed, such models can be considered standard because they have not been developed starting from physical first principles, rather trying to represent a variety of common responses of systems found in real situations. However, within a class of models the exact response of the model changes depending on the number and on the values of parameters used for the specific model.

Table 2.1: Commonly used statistical models for time series forecasting

Models	Description	Comments
Exponential smoothing	Examples of exponential smoothing models discussed by Hyndman et al. (2005) Example 1 $y(t) = H\boldsymbol{x}(t)z^{-1} + \varepsilon(t)\boldsymbol{x}(t) = F\boldsymbol{x}(t)z^{-1} + G\varepsilon(t)$ Example 2 $y(t) = H\boldsymbol{x}(t)z^{-1}(1 + \varepsilon(t))\boldsymbol{x}(t) = (F + G\ \varepsilon(t))\ \boldsymbol{x}(t)z^{-1}$ $H,\ F,\ G$ are matrices, $y(t)$ is the output state at time t, $x(t)$ is an unmeasured state, $B^{(-i)} = [z^{-i}, \ldots, z^{-i-p}]$, where z^{-i} is the shift operator, $\varepsilon(k)$ are samples of i.i.d $\mathcal{N}\left(0, \sigma^2\right)$, noise with independent and identically distributed Gaussian samples	It is popular in academia but in the electric load forecast is not used in practice (Hong and Fan, 2016). It cannot handle well cycles which are not periodic.
ARIMAX and derived models	$y(t) = \frac{\beta\,(b)}{\phi\,(p)\,\nabla\,(d)}u(t) + \frac{\theta(q)}{\phi\,(p)\,\nabla(d)}\varepsilon(t)$ u is an exogenous input, $\varepsilon(t)$ is white noise, z^{-i} is the shift operator. $\phi\,(p) = 1 - \phi_1 z^{-1} - \ldots - \phi_{pz^{-p}}$ $\nabla\,(d) = \left(1 - z^{-1}\right)^d$ $\theta\,(q) = 1 + \theta_1 z^{-1} + \ldots + \theta_{qz^{-q}}$ $\beta\,(b) = \beta_1 + \beta_2 z^{-1} + \ldots + \beta_{bz^{-b+1}}$	The predicted variable can take only discrete values.
Markov chain	The model defines the probabilities $\Pr\,(y(t) = y_0 \mid\ y(t-1) = y_1,\ \ldots, y(t-n) = y_n),$ $\forall y_0, y_1, \ldots, y_n \in S$ where S is a discrete space state and n is the order of the Markov chain	The predicted variable can take only discrete values.

Therefore, the forecaster chooses a class of models and sets the number of parameters, according to his ability and experience. The parameters of the model, sometimes called coefficients, are then optimised to match the behaviour to the behaviour observed in the real system. Table 2.1 provides the structure of the models presented in this section. For example, the functions describing the ARIMAX class of methods link the previously recorded value of a time series, external inputs and noise to the predicted value of the time series. In case of a significant mismatch between the value predicted and the actual value, the forecaster can change the structure of the model, removing or adding some relationship between input and output described by the blocks in the ARIMAX block of the Table. To obtain good predictions with statistical methods, Weron (2014) says that the quality of the data is important. Good data have, for example, a high signal-to-noise ratio, defined as the ratio between the variance of the signal and the variance of the noise. The experience and ability of the forecaster to choose the right model structure plays a role according to Weron (2014), and Hong and Fan (2016).

Table 2.1 describes the statistical methods that have been investigated for this thesis. The names of the methods are in the first column of the table. The second column provides a mathematical description of the model to calculate the value $x(t)$ of a generic time series at instant t. The third column gathers the comments found in the literature. The notation with the back-shift operator z^{-i} has been used. With a such notation $z^{-i}x(t) = x(t-i)$, where $x\,(t-i)$ is the value of x at instant $t-i$.

2.3.2.1 Exponential smoothing models

The exponential smoothing models are those listed in the first row of Table 2.1. It is a class of methods where one or more values in the past contribute to the calculation of the forecasted value. Table 2.1 shows two examples of exponential smoothing methods that were analysed by Hyndman et al. (2005). The first is an example of an additive exponential smoothing model. In the second example, the past data are linked to the new value in a multiplicative way. Hyndman et al. (2005) showed that only the first example has an equivalent ARIMA model.

One disadvantage of the exponential smoothing methods is that they are not always able to handle cycles who do not have an precise periodicity (Hyndman, 2011).

2.3.2.2 ARIMAX models

The model in Table 2.1 is an ARIMAX (Auto Regressive Integrative Moving Average with eXogenous inputs) model for linear systems. It is a general model composed of four components, which are the AR (autoregressive), the I (integrative), the MA (moving average), the X (eXogenous inputs) components. Each component has a different contribution to the predicted value $x(t)$ of a time series. In the table, $\phi(p)$ represents the Auto-Regressive (AR) component, which models the effect of the past p values $x(t-1), \ldots, x(t-p)$ of a time series on the last value of the time series $x(t)$. $\nabla(d)$ represents the integrative (I) component, which models the effect of applying d times the differencing operation (which is used to remove trends and patterns for the preprocessing of data) on the values $x(\cdot)$. The term $\theta(q)$ is the Moving Average (MA), which models the effect of last $q+1$ samples of white noise $\varepsilon(t),\ \varepsilon(t-1), \ldots, \varepsilon(t-q)$ on the variable $x(t)$. The term $\beta(b)$ represents the eXogenous component and models the effect of the last b external inputs $u(t),\ u(t-1), \ldots, u(t-b+1)$ on $x(t)$.

Other models can be derived from the general ARIMAX model, by choosing only some of the mentioned components. For example, Bordons and Cueli (2004) and Binder et al. (2019), the two works found which used predictions of process disturbances in conjunction with MPC, used AR models to predict such disturbances. However, they showed the applications of AR models only on persistent disturbances and not on abrupt disturbances.

Venkatasubramanian et al. mention the use of ARMA models for fault diagnosis. For fault diagnosis, an ARMA model of the system of interest is created and validated. Later, if there is a mismatch between the values predicted by the model and the real data of the system, the mismatch is a symptom of a fault in the system.

ARIMA models are used, for example, for electric load forecasting. Hong and Fan (2016) state that the ARIMA models are in such field the most common univariate models together with the exponential smoothing models, where univariate models are those that do not rely on exogenous variables such as weather variables.

The class of ARIMAX and its derivate models is popular. However, there are two drawbacks. This class of model was designed to model linear systems or approximate non-linear systems around a given operating point. Instead, the time series of disturbances in process industry are often

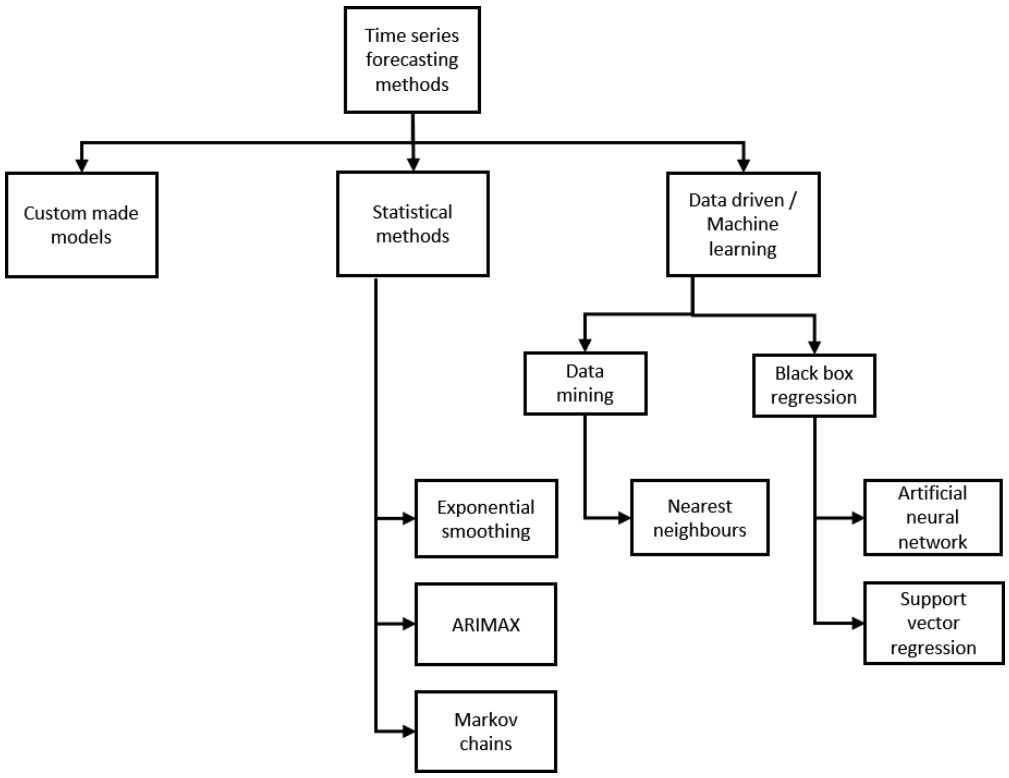


Figure 2.3: List of considered time series forecasting methods

non-linear. Furthermore, according to Hyndman (2011), this class of model can predict time series characterised by oscillations but -the quality of the prediction can decrease when the period of such oscillations is not constant. This might a problem when the time series of a persistent disturbance is not regular, but especially when dealing with abrupt disturbances.

2.3.2.3 Markov chains

Markov chains are discrete probabilistic models. Saying that the model is discrete means that $x(t) \in S,\ \forall k$ where the set S is a discrete set. The model provides the probability that a time series has a certain value within a set at instant t, given the values of the time series in the past, as Table 2.1 describes. These conditional probabilities are called transition probabilities. The order of the Markov chain, the number n is the description in the Table 2.1, is the number of values that are observed by the model to provide the transition probabilities (Shamshad et al., 2005).

Guo et al. (2008) used Markov chains the predict the residence time of synthetic gas in a gasifier, that is the time, on average, that a particle of synthetic gas spends inside the gasifier. The transition probabilities described the probability that the flow through the gasifier could change from one instant of time to an other.

Cheng and Duran (2004) focused on the problem of worldwide supply of crude oil. They created a model that describes the levels of the oil reservoirs at different locations over time. The levels of such reservoirs are affected by the stochastic request and supply of oil. Oil is supplied through tankers, which might need a variable amount of time for their navigation. Their final aim was to optimally dispatch the tankers at several locations, minimising the cost of the fleet and taking into account the uncertainties.

Markov chains have also been used for wind speed forecasting (Shamshad et al., 2005), electricity price forecasting (Weron, 2014) and they have been particularly successful for the time series forecasting used in speech recognition (Längkvist et al., 2014).

The main advantage of the Markov chains is that they provide a probabilistic model. This permits taking the probabilistic nature of the disturbance into account in a stochastic MPC.

The main drawback of Markov chains is the discretization of the predicted variable. For example, if the feed of a column is affected by a disturbance, only some discrete values of the feed would be considered by the Markov chain for forecasting. The question would be, which values should be considered.

2.3.3 Machine learning methods

Figure 2.3 shows the examined methods. Machine learning methods use two approaches to do time series forecasting. In the black box regression approach, the machine approximates the model behind the system (Sapankevych and Sankar, 2009).

By contrast the data mining approach, consists of finding which parts of the past time series are similar to the present one. Once a similar trend has been discovered in the past, the present time series is assumed to evolve as the similar past ones (Aghabozorgi et al., 2015; Fu, 2011; Yesilbudak et al., 2013).

The following sections will examine selected machine learning methods. The list of methods is not exhaustive, still there is a reason they have been chosen. The k-NN is arguably one of the simplest machine learning techniques, used to analyse non-linear time series (Kantz and Schreiber, 2004) and specifically plant-wide disturbances (Thornhill, 2005b). The Artifical Neural Networks

Table 2.2: Machine learning methods for time series forecasting

Method	Description	Comments
Nearest neighbours	Given a time series $\boldsymbol{y} = [y(1) \dots y(t)]$, $\boldsymbol{y}_E = [y(t-m+1), \dots, y(t-m+1)]$ is the subsegment of $\boldsymbol{y}$ made of the last m samples. The algorithms finds the nearest neighbour of $\boldsymbol{y}_E$, that is the subsegment $\boldsymbol{y}_1$of length m of $\boldsymbol{y}$ which minimizes a certain distance (generally Euclidean) with $\boldsymbol{y}_E$ (Yesilbudak2013). The algorithm supposes that $\boldsymbol{y}_E$ will evolve as $\boldsymbol{y}_1$ did. The $k-$Nearest neighbours is a variant of Nearest neighbour. It finds the k time subsegment $\boldsymbol{y}_j$ that minimize the distance with $\boldsymbol{y}_E$.	Easy to implement. However, it is not robust against noise because two subsegments might look similar in noise rather than similar in pattern shape (Aghabozorgi et al., 2015). If the time series is not regular, the prediction might deteriorate. Searching segments which are similar to the present one can be computationally expensive (Fu, 2011)
Support vector regression	Support vector regression supposes that prediction $\hat{y}(t+h)$ at h steps ahead is $\hat{y}(t+h) = d^T \phi(\boldsymbol{y}(t)) + b$ where $\boldsymbol{y}(m) = [y(t)\ y(t-1) \dots y(t-m)]$ is the vector made of the last m samples of the time series, and d and b are parameters to be found through a minimization process. Such relationship is not found in a dimensional space of size m rather in a high dimensional space of size d. Indeed, $\phi(x)$ in the former expression is a non-linear function $\phi : \mathbb{R}^m \rightarrow \mathbb{R}^d$.	Among the most used machine learning techniques for time series forecasting for the electric load (Weron, 2014). It is very robust against noise present on the time series. The optimisation problem always has one solution because the objective function is convex. The choice of the kernel is arbitrary. It takes less time than Artificial Neural Network to be trained (Weron, 2014) The training phase is done offline.
Artificial neural network	An artificial neural network is composed of nodes (neurons) disposed in layers and connected each other through weighted arcs. The output of one node j is $y_j = f\left(\sum_{i=1}^{n} w_{i,j} y_i\right)$ where $d_{i,j}$ is the weight of the arc that connect the node i to the node j, y_i are the outputs of other nodes connected to j and $f(\cdot)$ is a non-linear function, for example a sigmoid function $f(x) = \dfrac{1}{1+\exp(-x)}$ The prediction $\hat{y}(t+h)$ is the result from the last nodes of a network.	Among the most used machine learning technique for time forecasting. It is capable of modelling non-linearity. It is a black box model, it cannot provide any insight into the model and show the most important relationships in a system. It requires a significant amount of training data, done offline

(ANN) are consistently present in the reviews considered (Cavalcante et al., 2016; De Gooijer and Hyndman, 2006; Jung and Broadwater, 2014; Weron, 2014). The Support Vector Regression (SVR) receive maybe less attention than ANN but are still part of the most used techniques for time series forecasting (Jung and Broadwater, 2014; Suganthi and Samuel, 2012; Weron, 2014) and were also used in solutions that won forecasting competitions (Chen et al., 2004) while providing some advantages over ANN.

2.3.3.1 Nearest neighbours

The nearest neighbour method, explained in the first row of Table 2.2, supposes that the current time series segment will evolve in future as a past time interval, similar to the present one according to a specific norm, evolved in the past (Kantz and Schreiber, 2004).

The similarity between the present and the past segment is evaluated through a distance function. Although the Euclidean distance is commonly used, several distance metrics are available in the literature and, apparently, there are no formal methodologies to choose a priori the best one for each case (Yesilbudak et al., 2013).

Next to the nearest neighbour method, there is the k-nearest neighbours method (k-NN). The k-NN method selects, instead of one segment, the k most similar segments. The algorithm considers the segments of length h, which follows each nearest neighbour, where h is the desired length of the prediction. Averaging these k time segments of length h, the algorithm obtains the prediction vector.

A consistent advantage of the k-NN is that it has been already used for predicting process disturbances. Indeed, Thornhill (2005b) used such method to do one-step predictions of persistent process disturbances. Figure 2.4, taken from Thornhill (2005b), visualises the approach. The repeating pattern, identified by the k-NN, is highlighted. The little circle next to each highlighted pattern indicates how each nearest neighbour continued one step further. Averaging these values, the prediction $\hat{y}(t+1)$ is obtained. Furthermore, Figure 2.4 suggests that a possible advantage of the k-NN is is that it does not need a training to predict new patterns. Once a new pattern appears in a time series, it can be predicted once it reappears.

Nonetheless, it is not sure that the k-NN would suit the needs of this thesis. The prediction obtained

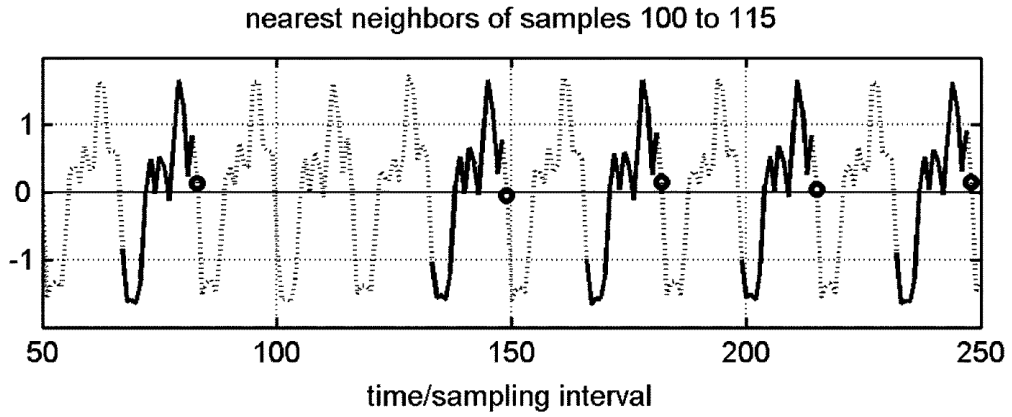


Figure 2.4: Depiction of available time series forecasting methods (from Thornhill (2005b)).

in Thornhill (2005b) was not a multi-step prediction, and the aim was not to obtain the best possible prediction rather to identify the source of the disturbance by comparing the quality of disturbances using the same method on different time series. Also, Thornhill (2005b) did not test the method on abrupt disturbances.

An issue with the k-NN is that the method might not be robust against noise. The distance between two segments might be small because the time series are noisy and not because the underlying pattern is similar (Aghabozorgi et al., 2015). Furthermore, it can be computationally expensive to search the nearest neighbours when the dataset increases in size (Fu, 2011).

In summary, the nearest neighbour method can be promising because it is simple to code. It is based on the concept of self-predictability and the disturbances in a process site are generally characterised by a repeating pattern. It might be able to predict new patterns of a disturbance as soon as they appear. Despite the fact that it is a method which is not mentioned in the reviews analysed for the forecasting of wind speed (Jung and Broadwater, 2014), electric load (Hong and Fan, 2016), electricity price (Weron, 2014) and finance (Patel et al., 2015), it has been used for one-step prediction of time series of process disturbances. This thesis will show it provides good results also for multi-step predictions and not only for persistent but also for abrupt process disturbances.

2.3.3.2 Support vector machines / Support vector regression

There are two main types of support vector machines (SVM) for time series forecasting in the literature (Patel et al., 2015): the support vector classification (SVC) and the support vector

regression (SVR) method. The SVC is used for a qualitative forecasting, such as indicating whether a price stock might increase or decrease. By contrast, SVR provides a quantitative prediction and hence is of more interest for this thesis.

As shown in Table 2.2 on page 69 describes, SVR aims to find a linear relationship between the value to be predicted and former samples of a time series. Since the relationships between inputs and outputs of many systems might be not linear, the inputs are transformed to a higher dimensional feature space using a function $\phi(x) : \mathbb{R}^m \rightarrow \mathbb{R}^d$, where $\mathbb{R}^d$ is the high dimensional space. Then, through an optimization problem, it is possible to find the parameters that describe the linear relationship in the high dimensional space between input and output.

An advantage of SVR is that such optimisation problem is always solvable because the problem formulation is convex. Moreover, the found solution is also the global optimum (Patel et al., 2015). Instead, other methods, such as ANN, might not find converging parameters through their optimization problem. Furthermore, the SVR is also considered resistant to the problem of over-fitting (Hong and Fan, 2016; Huang et al., 2005).

SVR has been applied for the forecasting of stock prices and electric load forecasting (Sapankevych and Sankar, 2009). In electric load forecasting, the SVR method has been effective for real problems. It attracted attention, according to Sapankevych and Sankar (2009), and Hong and Fan (2016), because it was the method which won the EUNITE 2001 competition for electric load forecasting, which was based on real data. Chen et al. (2004) described the winning algorithm.

A drawback of SVR is that the optimisation phase must use a function called kernel to transform the data in a high dimensional space. Unfortunately, the choice of the kernel is arbitrary Sapankevych and Sankar (2009).

Furthermore, since the training of SVR is made offline, further training is needed whenever a new disturbance pattern occurs.

2.3.3.3 Artificial neural networks

Artificial neural networks are widely used for time series forecasting and are the only machine learning technique that has been constantly mentioned in the analysed reviews of methods for time series forecasting (Cavalcante et al., 2016; De Gooijer and Hyndman, 2006; Hong and Fan, 2016;

Jung and Broadwater, 2014; Patel et al., 2015; Vlahogianni et al., 2014; Weron, 2014).

An ANN contains several nodes, each representing a non linear function that takes as inputs the output of other nodes. The nodes are generally distributed in layers. The inputs of the input layer are the most recent values of the time series. The outputs of the nodes of the output layer are the predicted values.

Furthermore, ANN have been implemented in real cases for time series prediction. Khotanzad et al. (1998) developed on ANN to do a multi-step forecast of electric load. As of 1997, thirty-five companies focusing on electricity generation in North America used this tool.

An advantage of the ANN is that they are capable of modelling non-linear and complex behaviours (Cavalcante et al., 2016; Hippert et al., 2001; Jung and Broadwater, 2014; Li and Shi, 2010). However, ANNs do not provide the user with an insight into the functioning of the system once the model has been identified, since they are black-box models (Hong and Fan, 2016). The lack of interpretability of the model is judged as a drawback by some, as mentioned in Hong and Fan (2016), because it does not allow the user to understand which changes must be done to improve a prediction. Finally, as with SVR, they do need a new training whenever a new disturbance pattern might appear in the process. Furthemore, an ANN needs more training data compared to the SVR method, limiting the ability to adapt to new disturbance patterns.

A further disadvantage is that the weights found after the training might not be optimal (Li and Shi, 2010; Sapankevych and Sankar, 2009). The reason is that the function to be minimized for training might have more local minima: the optimisation procedure might finish in a point which is not a global minimum. Finally, ANN require a large amount of data for the training.

Starting from 2006 large (deep learning) ANNs started to receive attention for their results in computer vision, speech recognition and text translation (LeCun et al., 2015). Deep learning ANNs have more layers and far more nodes compared to the networks developed before 2006. This was became possible due to advances in computational power and use of different activation functions.

Despite the considerable benefits of deep neural networks in other sectors, the application of deep neural networks to time series has been limited, according to the review of Längkvist et al. (2014).

Cavalcante et al. (2016) confirmed it for the time series forecasting for the financial sector, and Hu et al. (2016) confirmed it for wind speed forecasting.

2.3.4 Conclusions on time series forecasting

This section described some methods for time series forecasting. This is relevant for one of the technical objectives consisting in providing a multi-step prediction of a process disturbance.

The section started with an introduction to three approaches for time series forecasting: purpose-built models, statistical methods, and machine learning methods. The focus was later on the statistical methods and machine learning methods.

Exponential smoothing, ARIMAX and Markov chain models belong to the statistical methods. Exponential smoothing and ARIMAX are popular methods. AR models have also been used to predict very regular persistent disturbance in process control applications. This is promising. However, exponential smoothing and ARIMAX models can have issues in modelling time series characterised by oscillations which are not strictly periodic. This can be a problem not only in case the time series of a persistent disturbance is not extremely regular, but especially for abrupt disturbances. Furthermore, ARIMAX models are designed to model linear time series, whereas the disturbances occurring in industrial plants are often non-linear.

Markov chains provide a probabilistic model, and this is an advantage if a stochastic MPC will be implemented. However, Markov chains need to discretise the space state of the predicted variable.

After the statistical methods, the machine learning methods were introduced. The machine learning methods were classified as those using a black-box approach and those using a data mining approach.

The data mining approach, based on the research of similarities and patterns in the time series, is very intuitive and it can be easily implemented. On the other hand, the methods based on the black box regression might provide better predictions. However, they must be trained offline and are not adaptive to new disturbance patterns, and they need a significant amount of data for the training. The latter points were considered a barrier and therefore the k-Nearest neighbours method seems more promising.

However, the review of literature showed that the k-Nearest neighbours approach has some drawbacks. The concept of similarity based on a distance function can be misleading in the presence of noise. Two time series segments might look similar because of the noise and not because of the real underlying signal (Aghabozorgi et al., 2015). Furthermore, an algorithm based on the data mining approach looks back through a time series to search segments which are similar to the present one. This operation can be computationally expensive (Fu, 2011).

2.4 SUMMARY

This thesis proposes a framework where an MPC uses predictions of a plant-wide disturbance to reject and stop the propagation of this disturbance. This chapter provided a literature review of MPC and time series forecasting. The aim was to identify the techniques that seem more appropriate to achieve the research objective of the PhD.

The section regarding MPC described the common frameworks used to handle external disturbances. The focus was to analyse the difference between how an external disturbance might evolve in reality and how, instead, the considered MPC frameworks assume that the disturbance will evolve. The frameworks that have been considered are frozen time MPC (FTMPC), preview MPC, robust MPC, stochastic MPC and deterministic MPC.

The review showed that the commonly used framework to handle disturbances is the FTMPC. Although the FTMPC can improve the set-point tracking of controlled variables, it can also lead to very poor performance in some cases because the control action is too aggressive. Providing a multi-step prediction or preview of the disturbance to an MPC controller improves the performance.

Over the frameworks considered, deterministic MPC seems to be promising at this stage. Although the performance achievable might be inferior to stochastic MPC, such framework leads still to an improvement of performance. Furthermore, the problem of disturbance prediction is independent of MPC formulation and this simplifies the problem.

The present chapter also described the problem of doing a multi step prediction of the time series of process disturbances. Since the prediction of process disturbances had few applications, the review focused rather on methods to predict time series independently from the specific sector of application, focussing on statistical methods and machine learning methods for time series

forecasting. The arguments in this chapter suggest that machine learning methods might suit better the needs of predicting process disturbances. Within the machine learning methods analysed, the k-nearest neighbours seems the most promising because of limited amount of data required for training, for ability to adapt to new disturbance patterns without needing new offline training, and simplicity.

Chapter 3

DISTURBANCE PROPAGATION IN A PRODUCTION SITE

This chapter describes the structure of a production plant, steam utility and electrical utility present in a production site. Then it investigates and describes the mechanisms of disturbance propagation within these areas of a production site.

By understanding the disturbances propagating in a production site and how they propagate, the analysis in this chapter identifies the problems that can be solved or attenuated with the control technique proposed in this thesis.

3.1 INTRODUCTION

This chapter deals with the first of the technical objectives listed in Section 1.6. The aim is to review and highlight the causes of the most important persistent and abrupt disturbances propagating in chemical and oil process sites.

The areas of a production site that Chapter 1 considered relevant are the production plants, the steam utility and the electrical utility. Fig. 3.1 represents each of these areas with a bubble, each

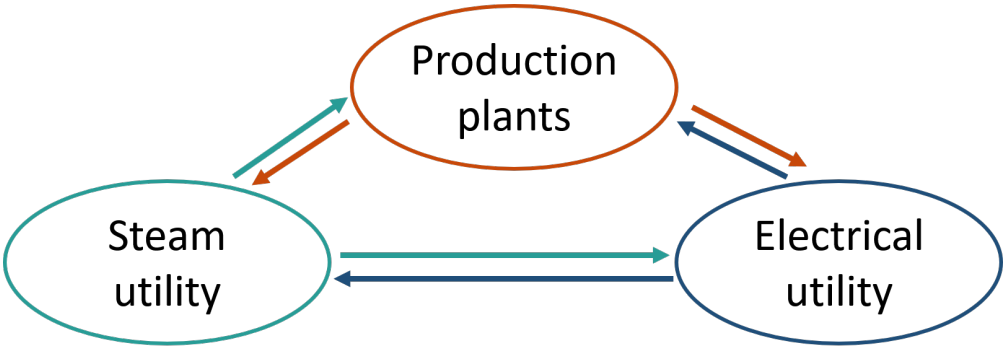


Figure 3.1: Possible path of disturbance propagation

connected to another with two arrows, underlining that possibly a disturbance can propagate in both directions.

Production plants have caught most of the attention in the past in the field of disturbance propagation. However, utilities can be the source of disturbances. Thornhill (2005a), Chioua et al. (2016) and Zhou et al. (2019) reported cases of sticking valves controlling steam and ultimately variables in a process. Cecilio et al. (2011) deduced a relationship between plant and utility in a case study with a cooling water utility and in a case study with an electric utility. However, there is a lack of knowledge about the causes of the disturbances that originate from site utilities in the literature relative to plant-wide disturbances. Furthermore, the research community has not investigated in detail the comprehensive paths used by disturbances to propagate between plants through utilities.

Literature shows a lack of examples showing specifically persistent and abrupt disturbances propagating in utilities. In these cases, the chapter reviews the interactions that might lead to a propagation of a disturbance, and the analysis is qualitative. However, Chapter 5 and Chapter 6 provide later a quantitative analysis using certain case studies to test the idea proposed in this thesis of an MPC with disturbance forecasting.

Presenting the material, there are conditions that can lead to a sudden breakage or to a controlled trip of the unit described. Trips are a major disturbance. However, this chapter is going to describe the conditions that lead to a trip only when the control can prevent the trip. Otherwise, trips of units are not relevant for this thesis. Indeed, if the whole production has to stop after a trip of a unit, then the control cannot do much . If only a unit has to stop, the disturbance for other units, for example in terms of a flow or pressure variation, is a simple step. In the latter case there is no need of a controller with a detailed multi-step prediction of the disturbance.

The chapter starts describing in Section 3.2 the structure and functioning of a process production plant, steam utility and electrical utility. The chapter continues explaining the disturbance propagation mechanism between these areas. Section 3.3 focuses on the disturbance propagating within a production plant. Section 3.4 focuses on the disturbance propagation between electrical utility and production plant. Section 3.6 ends the discussion describing the interactions between steam utility and production plant. The chapter finishes with a summary at Section 3.7.

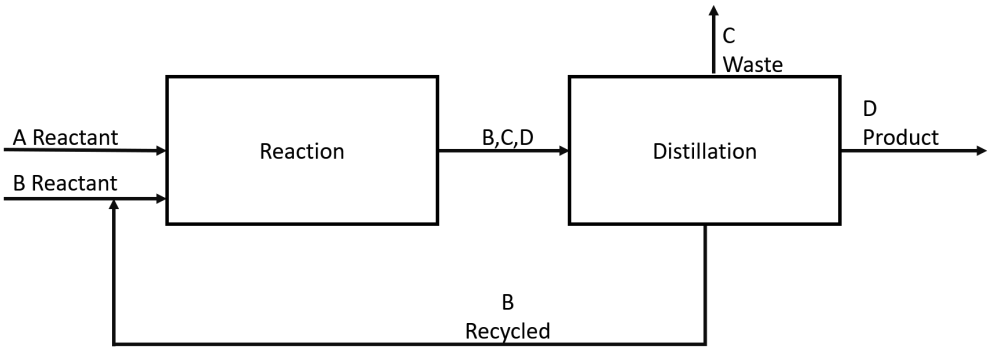


Figure 3.2: The principle of recycling in chemical plants

3.2 DESCRIPTION OF THE SYSTEMS CONSIDERED

3.2.1 Process plant

The present work is mainly interested in the plants of the chemical and oil industries. The process plants of oil and chemical industries show similarities, sharing the same type of machinery and often the same process units.

3.2.1.1 The structure of a chemical plant

In a chemical plant, the reaction stage involves the conversion of reactants into a mixture of components that must be separated. The separation can be achieved through several techniques such as filtration, evaporation and absorption but the predominant one is distillation. The mixture exiting from the reactor is made of the final product (or products), material and residual of reactants that can be recycled. Fig. 3.2 shows this structure.

3.2.1.2 The structure of an oil refinery

By contrast with a chemical plant, oil refineries tend to lack recycles. The extracted oil is first filtered removing water and salts, then it is distilled using a crude oil distillation unit. The crude oil distillation unit is a distillation columns where the crude oil enters and it is split into the different components. The components can be further processed downstream but the important point is the there is no recycle as the product move downstream.

3.2.1.3 The plant configurations that lead to disturbance propagation

There are elements that lead the propagation of disturbances. One element is the presence of recycles in the plant (Luyben et al., 1998), which is predominant in chemical plants. A disturbance reaching the end of the process can propagate to the initial part of the process and propagate further downstream, following a loop while affecting the whole plant.

Another element, common to chemical plans and oil refineries, is the presence of process-to-process heat exchangers, leading to heat integration. While a utility exchanger allows the importing of heat from heat sources or the discarding of heat to the environment, process-to-process exchangers are used to transfer heat from one part of the process to another, or between different plants in a production site (Luyben et al., 1998).

A further element is that process plants often lack buffer tanks in order to reduce the capital costs. However, buffer tanks can stop the propagation of disturbances downstream, as Section 3.3 will explain.

3.2.2 Steam system

Typical uses for steam in a production site include:

- Heating applications
- Chemical reactions, stripping of contaminant, fractioning of hydrocarbons
- Mechanical drive in place of or in conjunction with electric motors
- Mechanical drive for electrical generation
- Steam ejectors, used to create vacuum
- Pressure regulation in a reaction (especially when the reactants have low solubility in water)

Units in a production site have different requirements. For example, turbines require superheated steam while reboilers require saturated steam. Furthermore, the specifications for pressure and temperature of steam is not the same for every unit.

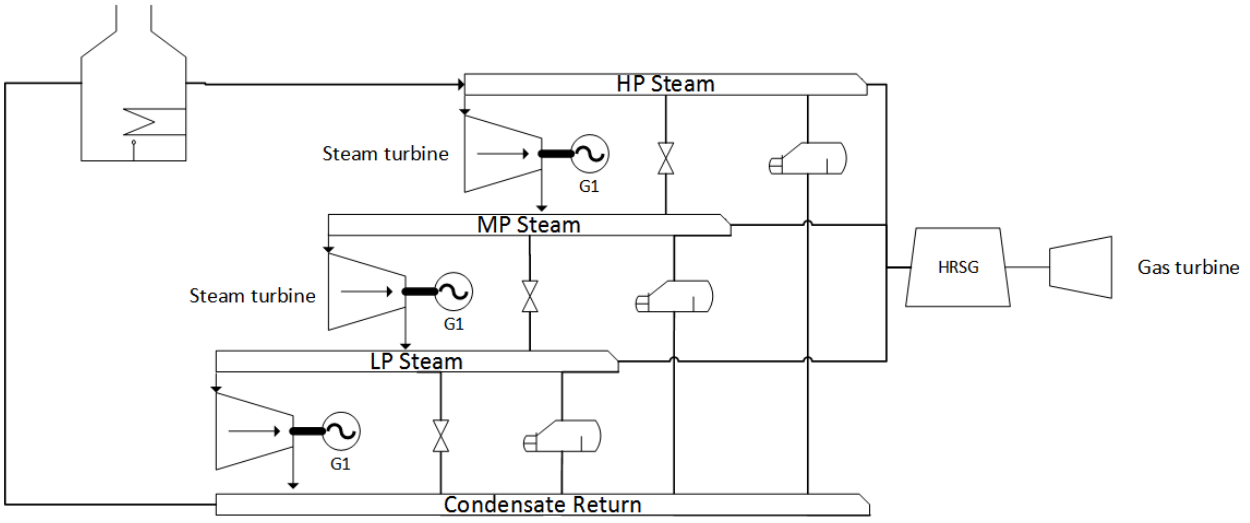


Figure 3.3: Distribution in a steam utility.

3.2.2.1 Levels of pressure of steam

Steam utilities are made of a network of headers supplying steam to one or more units at generally three or more pressure levels, as Fig. 3.3 shows. Such pressure levels are not defined by standards but Towler and Sinnott (2013) mention:

- High Pressure (HP) steam at around 40 bar
- Medium pressure (MP) steam at around 20 bar
- Low Pressure (LP) steam at around 3 bar

One or more steam generators can provide steam to the network. There is at least one steam generator producing steam at highest pressure. Other generators, if present, might produce steam at lower pressure. The pressure at each header is controlled taking steam from the upper level or venting steam. Depending on the network, the pressure can be controlled also redirecting steam to steam turbines or controlling the steam generators present at that pressure level (Dzedzemane et al., 2018; Majanne, 2005).

3.2.2.2 Propagation of disturbance between different headers

Disturbances propagate from one level of pressure to another. Rejecting disturbances from a lower level implies that the flow rate of steam from the header at higher pressure changes. This impacts

the pressure of this header, propagating the disturbance further (Dzedzemane et al., 2018; Majanne, 2005).

The other way round, variation of pressure from an upper level impact the amount of steam flowing through let-down valves to the lower levels and consequently the pressure.

3.2.2.3 Propagation of disturbance along one header

Disturbances propagate along one header. Since pressure is the same for one header, all units connected to that header are affected by a possible disturbance (Adams et al., 2008). The units can belong to different production plants. Through the headers, disturbances can become site-wide disturbances.

However, the propagation of disturbances along one header can be mitigated by controllers regulating the flow of steam. Variations of pressure of a header implies a variation of mass flow rate through the valve regulating the inlet of steam to a unit. Using flow rate controllers in cascade to the main controller of a unit, for example a temperature control of a unit, can reject the effects of variations of pressure on the flow of steam.

3.2.2.4 Disturbances from Heat Recovery Steam Generators (HRSG)

Some of the steam generators in steam distribution network can introduce disturbances because their production of steam is not constant (Dzedzemane et al., 2018). This is the case of Heat Recovery Steam Generators (HRSGs). HRSGs recover the available heat from the exhausts of other processes to produce steam.

Examples of such a process can be, for example, the burning of waste products from production or the exhaust of a gas turbine used for electricity generation. The heat available for recovery fluctuates over time and so fluctuates the heat produced by HRSGs. This is the cause of the disturbance.

In some cases HRSGs have an additional firing (Kehlhofer et al., 2009; Working Group CIGRE, 2003). The additional firing can compensate the fluctuations of the recovered heat.

3.2.3 Electrical utility and electromechanical loads

Most process production sites are connected to the public electrical grid. Still, it might be economical beneficial to have generation units in-site (Khan, 2008). In some cases having an in-site electrical generation is necessary because public grid is unavailable for example in oil platforms, LNG plants, and ore mines.

Most electric loads in oil and chemical plants are electric motors connected to rotating machines, such as compressors or pumps. Such machines are the interface between electric utility and process.

For this reason, this chapter analyses the electric motors and the compressors, which are particularly interesting for the industrial partners of this PhD project. Nonetheless, other industries might have different types of loads that are important. For the steel making industry, for example, electric furnaces have a relevant role.

3.2.3.1 Overview of an industrial distribution network

Fig. 3.4 shows the diagram of an example of industrial distribution grid, made of the main substation, a primary distribution grid, a secondary distribution grid and an on site generation unit (Mohd Noor, 2018).

In the main substation, the electricity through the transmission lines arrives from the public electricity grid to the production site. Large loads, such as electric motors are connected to the primary grid. Loads requiring little power, such as instrumentation and controllers, are connected to the secondary grid.

Electricity has the highest voltage in the electrical distribution network at the main substation, connected to the transmission line. Larger loads require generally larger voltages. Therefore, voltage is gradually stepped down using transformers. One or more loads share a feeder at a specific voltage.

Frequency is equal all over the grid. The speed of electric motors (with the exception of DC motors, not so common in industrial settings any more) depends on the frequency of grid. Some motors have to run at constant rotational speed and are installed connected directly to a feeder. For other applications, motors need to change their speed. In these cases a variable speed drive is installed

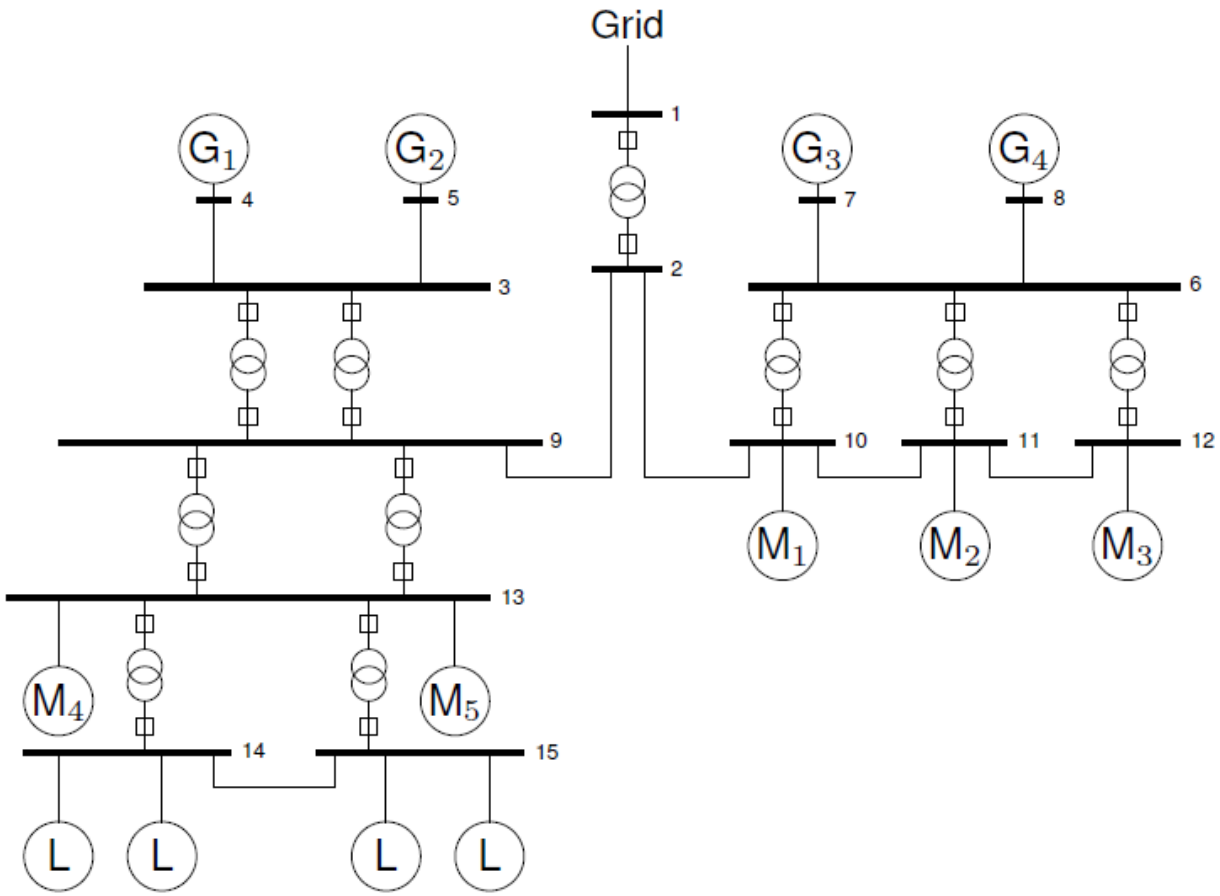


Figure 3.4: Example of an industrial distribution grid (from Mohd Noor (2018)).

between feeder and motor, which is a power electronics device whose function is to modulate the voltages or currents entering the motor to control its rotational speed.

There are two types of electric AC motors. According to TMEIC (2019), a joint venture between Toshiba and Mitsubishi, synchronous motors are prevalent for loads larger than 30 MW. Asynchronous motors are otherwise preferred. However, these limits have changed in the last years. In 2010, synchronous motors were preferred for loads larger than 1.5-2 MW according to experts from ABB (Steimer et al., 2010). Asynchronous motors are cheaper and need less maintenance than synchronous motor. However, they are less efficient. In this thesis, the focus is on asynchronous motors which are more common.

3.2.3.2 Propagation of voltage disturbances

Disturbances of the voltage are caused by variations of the currents. For the same power delivered, an increase of currents decreases the voltage. For example, during short circuits and starting of loads the inrush currents can be very high and the voltage can drop.

Disturbances of the voltage can come from the grid and propagates through the electric distribution network, or propagate from any point of the electrical distribution network. In the latter case, the magnitude of the variation of the voltage diminishes generally the further the point of measurement is from the source of disturbance. because the impedance between these two points is larger (Khan, 2008).

3.2.3.3 Propagation of frequency disturbances

The main frequency is the same all over the electric distribution network and it is equal to the frequency of the public grid. It changes because of the imbalance between active power produced and consumed. Since the balance is never perfect, the frequency changes continuously within two limits.

On the top of the sinusoidal signal with the fundamental harmonic, the electric signal can be affected by harmonics. The IEEE Industry Applications Scoiety (1999) defines a harmonic as "a sinusoidal component of a periodic wave or quantity having a frequency that is an integral multiple of the fundamental frequency". The harmonics are a main problem and they can propagate. However, according to interviews with experts from ABB reported by Borghesan et al. (2019b), they pose mechanical issues to process units but they are not sources of propagation of process disturbances.

3.2.3.4 Compressors

A compressor is a device that increases the pressure of a gas. A way to control the pressure is by changing its rotational speed.

Using variable speed drives has maintenance and control advantages over using gas or steam turbine to drive the compressor. Electric motors are more robust than turbines and can change their speed faster.

However, electric motors have some disadvantages. There must be always a very close balance

between electrical energy produced and consumed. Using electric motors on an offshore platform can be an issue because any imbalance of power, even short, in such a small electric system can lead to a trip of all loads (Lerch, 2016).

Furthermore, short disturbances of power delivered can lead the compressors into surge. Indeed, in such cases the speed of an electric motor decreases rapidly, bringing the connected compressors into surge. Anti-surge system can be activated to try to avoid the trip. Still, in some case a trip is unavoidable as this chapter will discuss later.

3.3 PROPAGATION OF DISTURBANCES WITHIN A PLANT

3.3.1 Overview of propagation mechanisms

The unit chosen to illustrate the effects of a disturbance within a plant is a distillation column, which is a key unit in chemical plants and refineries. The separation phase of such plants is often made by a distillation train, where a disturbance can propagate from one column to the following.

Figure 3.5 shows the scheme of a column and its main items of equipment. There are three main disturbances considered, shown on the left side of the graphic in Fig. 3.6:

- Variation of the pressure
- Variation of the energy entering or exiting the column
- Variation of the inflow rate and its composition of the feed

The graphic in Fig. 3.6 shows how a disturbance from one of the mentioned sources can propagate within a distillation column. The graphic shows the mentioned causes on the left in blue boxes, the impact on energy and mass balance of a column, which are the first-principle phenomena that regulates the functioning of a column, in yellow boxes, the visible phenomena that manifest themselves in disturbances characterized by fast and complex characteristics in green boxes, and final effects on the process in red boxes.

Purple boxes are used to highlight the interactions between utilities and production plants. Steam utility can affect the energy inside the column. Steam utility can also affect the vacuum system

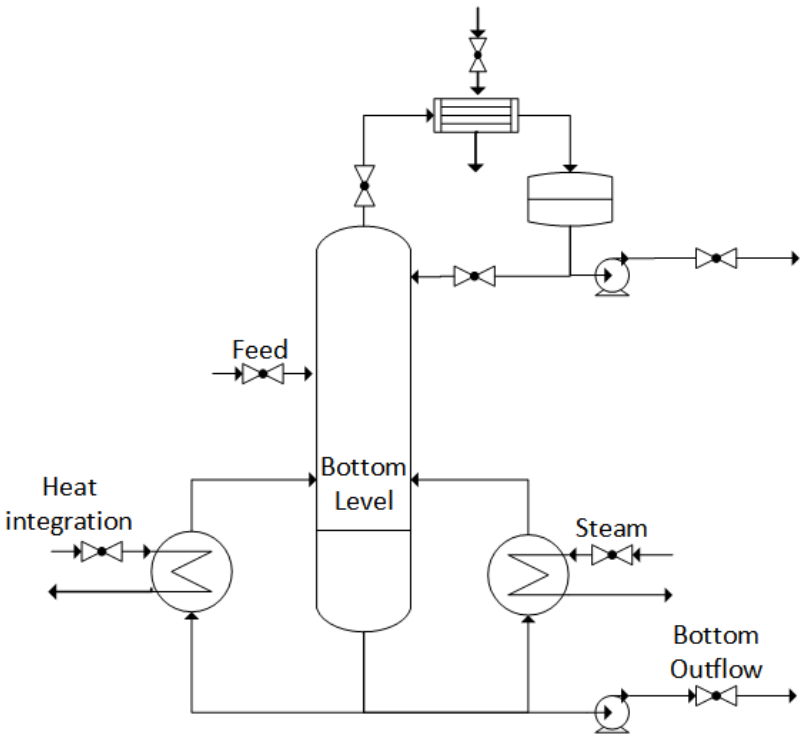


Figure 3.5: Depiction of a distillation column.

and therefore the pressure of a column. Electrical utilities can potentially impact flow rates and pressures through rotating machines such as compressors and pumps. However, Section 3.5 will argue that the impact might not be so strong as for the impact of steam utility. Therefore, the present author decided to not state that variations of the inflow mass rate is caused by interactions with utilities by not using a purple box.

The following subsections analyse the elements of the graphic in Fig. 3.6, starting describing the initial causes considered which are on the left.

3.3.2 The three cases considered and possible causes

The left side of the graphic of Fig. 3.6 shows the sources considered for possible disturbances in a column.

A variation of the overhead pressure of a column can occur, in the experience of the present author, because of a sluggish pressure controller, because of an obstruction in the column, because of pressure variations from steam affecting the vacuum system, or issue in a compressor that adjusts the pressure.

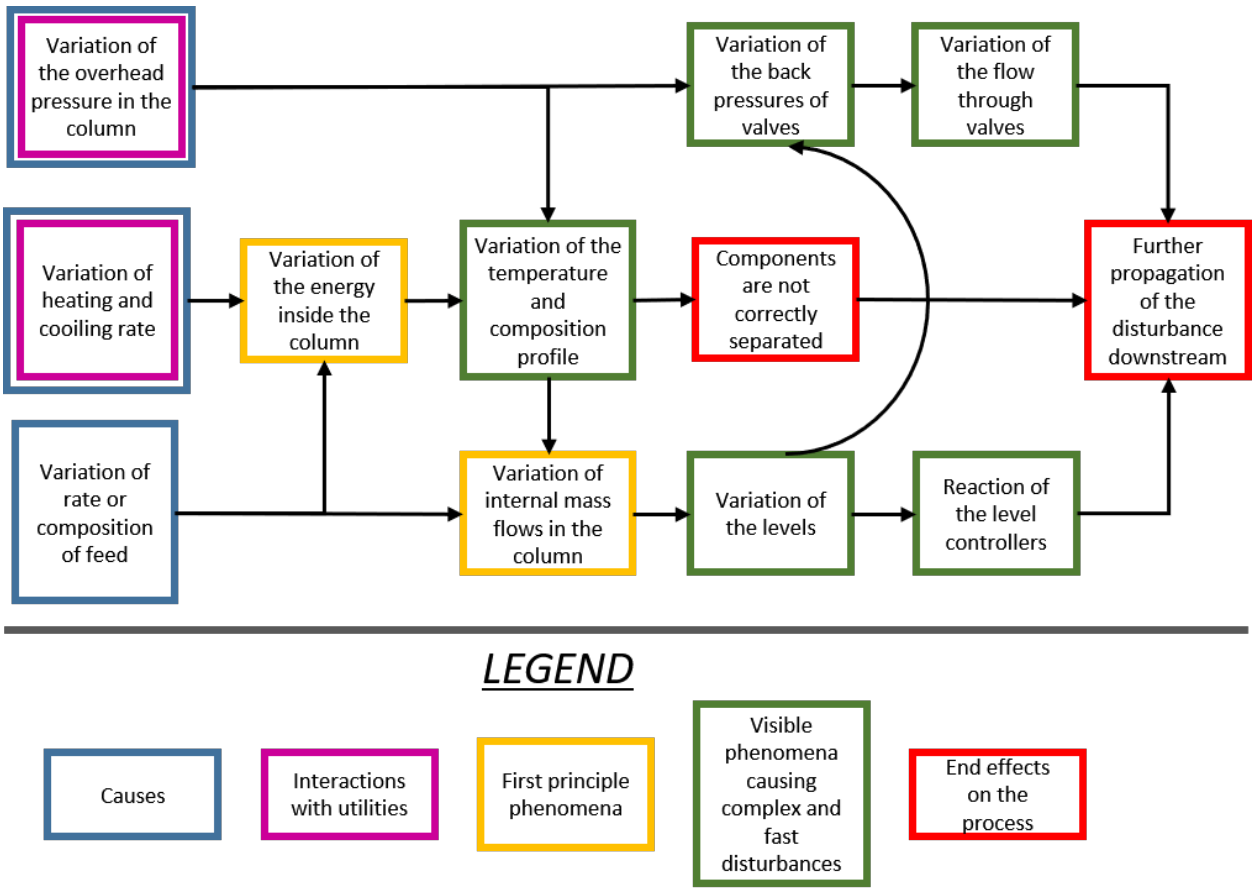


Figure 3.6: Considered paths of disturbance propagation in a distillation column

A variation of heating or cooling rate can come from the utility. Thornhill (2005a), Chioua et al. (2016), and Zhou et al. (2019) published case studies where sticking valves affected the inlet of steam in reboilers of distillation columns and heat exchangers of paper production plants. Section 3.5, dedicated to the propagation of disturbances between production plants and steam utility, will describe further cases. However, a problem with the steam boiler or cooler can also come from heat integration. If the temperature or flow rate of the fluid used for heat integration changes, then there is a variation of energy given or removed from the unit.

A variation of the flow rate of the feed to a column can happen, for example, because of a sticking valve (Bauer et al., 2016; Choudhury et al., 2008) or because of controls not working properly (Bauer et al., 2016; Choudhury et al., 2008). A variation of the composition can occur because of a variation of the material coming from the reactor, an incorrect separation in an upstream unit, or because there is an accumulation of some reactants plantwide (Downs and Skogestad, 2011; Luyben et al., 1998).

3.3.3 Energy balance

The yellow box in the second column from the left of the graphic in Fig. 3.6 suggests that variations of inflow rates, heating and cooling rates affect the energy balance inside a column. Specifically:

- An increase in heating increases the energy in the column.
- An increase in cooling decreases the energy in the column.
- An increase in feed flow rate can increase or decrease the energy in the column depending on the specific enthalpy of the feed.

3.3.4 Variation of temperatures and composition profile of a distillation column

Here, the green box in the third column of the graphic in Fig. 3.6 is analysed.

Each tray in a column holds a boiling mixture characterized for a certain composition and pressure by a boiling temperature. A temperature and composition profile for the column can be built for the entire column.

Changing the overhead pressure affects the temperature and composition profile. The composition profile changes also because of variation of the internal energy, which affects the vapour flow (called also boil up). Increasing the rate at which energy is supplied, more heavy components flow up and less light components condense. The composition profile and temperature profile change.

At this point, the control system of the column should intervene adjusting the energy rate in the column, for example adjusting the steam flow rate and adjusting the cooling rate through the condenser. This might propagate the disturbance to utilities, which should be robust enough to not be affected.

3.3.5 Incorrect separation of components

Here, the first end effect of a disturbance propagating in column is described, which is represented by the red box in fourth column from the left of the graphic in Fig. 3.6.

Changes in the composition profile can cause impurities to be present in the outflows from the top and bottom of the column. Impurities can represent a disturbance for the functioning of the following process units and they might not be removed in following units. Depending on the amount of impurity present after the disturbance, the final product might be out of specification and not saleable.

3.3.6 Variation of internal mass flows in the column

Here, it is described that the internal flows in a column depend on the mass and energy balance. The mass balance determines the amount of light and heavy components. The energy balance determines how such components are split between components that fall in the bottom of the column and those that flow in reflux drum.

In this way, the rates of the inflows to the levels of the bottom of the column and of the reflux drum change.

3.3.7 Effects on the levels of the units

In a distillation column there are two liquid levels which should be considered. These are the level of the bottom of the column and the one of the overhead drum. The control of such levels propagate a disturbance further, as the two green boxes on bottom-right corner of Fig. 3.6 indicate.

3.3.8 Reaction of the level controllers

The manipulated variables of the levels of the overhead drum and bottom of a column are outflows. Depending on the structure of the plant, the outflow of the overhead drum or the outflow of the column might enter in a new unit. Therefore, a variation of the level that is compensated by the level controller manipulating the outflow represents an important example of disturbance propagation to a further unit.

3.3.9 Variations of flow through a valve

The standard ISA S75.01 (ISA, 2007) describes the equations to model the mass flow through a valve according to the different conditions of the flow, for liquids and compressible gases. Although the formulations are different, they all show a dependence on the back pressure of the valve.

The back pressure of a valve can change because of variation of the overhead pressure of a unit or also because of variations of the level of liquid. For example, the mass flow vented from the top of a column to keep the pressure constant is affected by the overhead pressure. The outflow from the bottom a column is affected both by the overhead pressure than by variations of the bottom level.

A flow controller in cascade can keep the flow at the desired value despite disturbances of the pressure. However, the present author experienced in one occasion pressure oscillations that were so fast that were not rejected by a flow controller.

3.3.10 Further propagation of disturbance downstream

A disturbance can propagate to the following process unit because of variation of the outflow mass flow rates or because pf variation of the composition of such outflow.

Therefore, to avoid a disturbance propagation the level controllers should try to keep the outflows as constant as possible, flow controllers in cascade to the level controllers should be used so that variations of backpressure do not impact the outflow mass flow rates, and composition control of a column should be tight.

3.3.11 Conclusions on disturbance propagation within a plant

This section analysed mechanisms of propagation of disturbances within a distillation column. A distillation column is a key unit in chemical plants and refineries. In distillation trains, a disturbance can propagate from one column to the following.

A possible disturbance of the overhead pressure, of the heating and cooling rate, and of rate and composition of the feed have been considered. The connections there might be with utilities have been highlighted.

The section described the steps that might lesd a disturbance to propagate downstream within a plant through a variation of rate and composition of the outflows of a column.

3.4 PROPAGATION OF DISTURBANCES BETWEEN ELECTRICAL UTILITY AND PROCESS PLANT

3.4.1 Overview of the propagation mechanisms

The book edited by Baggini Baggini (2008) gives a comprehensive review of the effect of electric disturbances on individual electrical devices. However, literature has not analysed and categorized the effects of electrical disturbances on process plants. This section addresses this open topic.

To complete this section, a cycle of interviews with professionals within ABB Energy Industries in Oslo, Norway, has been conducted (Borghesan et al., 2019b). The aim was to understand which are the most relevant phenomena in industrial practice.

The investigation showed that the most important types of interactions between electrical utilities and plants are:

- Variation of frequency
- Voltage dips
- Protection tripping

To analyse these relationships, this section considers an asynchronous motor, in the case it is connected directly or with a variable speed drive to the feeder. Asynchronous motors are the most common type of electric motors for middle range power and high power up to 30 MW TMEIC (2019).

3.4.2 Variation of the frequency

3.4.2.1 The magnitudes and durations of frequency changes

The frequency of an electric grid changes because of imbalances between the power generated and the power consumed by the loads and power generated. A perfect balance is impossible and the frequency of the grid varies continuously. However, the frequency remains most of the time between the maximum and minimum allowed frequencies. Outside these constraints, the balance between power generated and consumed is restored by tripping loads or generators. The MPC framework proposed in this thesis cannot do anything against a trip. Therefore, the interest of this section is defining the largest disturbance in frequency that does not lead to a trip of units.

Baggini (2008) mentions the European standard EN 50160/2006 (in developing countries the limits might be more loose (Borghesan et al., 2019b)). The standard states that the frequency of a system connected to the public main grid must stay within:

- 50 Hz ±1% (49.5 − 50.5 Hz) for 99.5% of the year
- 50 Hz +4%/−6% (47 − 52 Hz) for 100% of the time

In the rare case the frequency varies more than 0.5 Hz, the duration of the disturbance should be short. British National Grid states that any frequency deviation below 49.5Hz should not persist for more than 60 seconds (National Grid, 2006).

If the system is in island mode, as in the case in off-shore platforms, the limits are more stringent. For the case study of an offshore LNG platform, Siemens (Lerch, 2016) reports that decreases of the frequency in the order of 0.5 Hz can last only up to 10 s before causing a trip of the generators, as Table 3.1 reports.

3.4.2.2 Effect of frequency changes on an asynchronous motor

Depending on the connection of the motor to the grid, a variation of the frequency can cause a variation of the rotating speed because the torque applied by the motors can be related to the frequency of the voltage of the grid. If the motor is connected through a drive, the frequency seen by the motor is not the same of the frequency of the grid affected by the disturbance. Conversely, if

Table 3.1: Manufacturer standard settings for the Siemens steam turbine SST-400 connected to the generator in Lerch (2016).

Frequency variation from nominal	Protection settings
f = +2.5 Hz	10 s delay
f = −0.5 Hz	10 s delay
f = −2.5 Hz	5 s delay
f = −3 Hz	3 s delay

the motor is connected directly to the grid, the frequency of the electric supply to the motor is the one of the grid. Consequently, professionals of ABB Energy Industries (Borghesan et al., 2019b) stated that a drive can be considered a protection for the motor and process to frequency variations, but only if the frequency variations are small in magnitude.

3.4.2.3 Effects of frequency changes on the process

The system made of compressor and electric motor described in Cortinovis et al. (2014, 2015, 2016) has been modelled and simulated in collaboration with M. Zagorowska within the Horizon 2020 PRONTO project. However, the drive has not been modelled to analyse the effects of variations of frequency in the case of a motor connected directly to the grid.

Fig. 3.7 shows the trajectory made by the system after a decrease of the frequency of the grid. The frequency decreases step-wise of 0.5 Hz from a nominal value of 50 Hz. This is the variation of frequency allowed in a public electricity grid for 99.5% of the time. In such conditions, first the mass flow is reduced and only thereafter the pressure ratio falls, while the mass flow rate slightly increases again at the end of the transient.

The values of the variables considered have been normalised over their nominal values. The excursion of the mass flow rate is higher than the one of the pressure ratio. This occurs because the pressure depends on the amount of gas present in the pipelines and vessels connected to the compressor. The volumes of such elements act as buffer. Such a fast transient of the mass flow rates does not change considerably the mass balance and the pressure inside these volumes. Figure 3.9 shows that the compressor goes closer to the surge line during the transient.

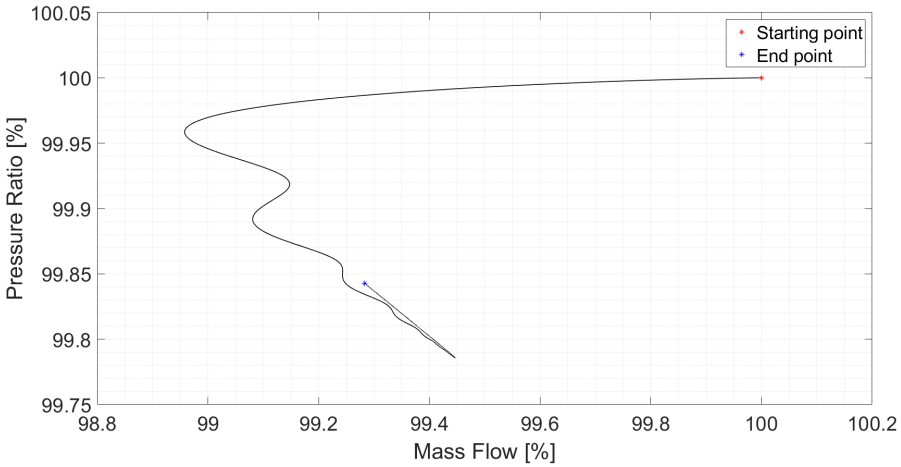


Figure 3.7: Evolution of the system over the plane representing mass flow and pressure ratio of the compressor after a decrease of 0.5 Hz of the frequency of the grid from 50 Hz.

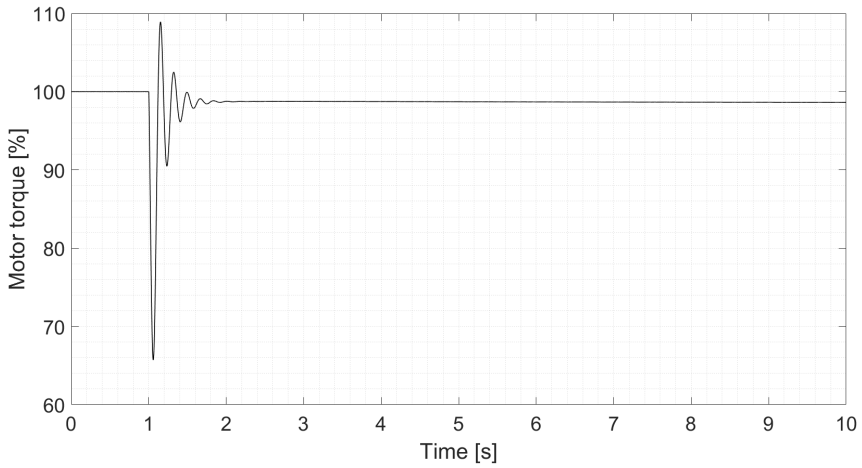


Figure 3.8: Motor torque response after a decrease of 0.5 Hz of the frequency of the grid from 50 Hz

However, the excursion is very limited at least for this test compressor and for this limited variation of the frequency. Furthermore, at steady state, the control system of the compressor will reject the effects of such electric disturbance on the compressor. Consequently, the only relevant effect might be the mechanical stress on the shaft of the motor caused by the large variation of the torque that Fig. 3.8 shows.

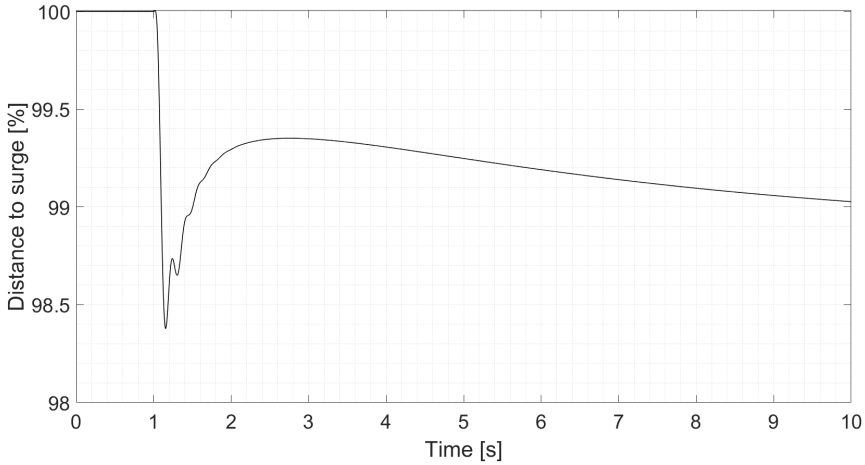


Figure 3.9: Distance to surge response after a decrease of 0.5 Hz of the frequency of the grid from 50 Hz

3.4.3 Voltage variations and voltage dips

3.4.3.1 The magnitudes, durations and causes of voltage changes

The European norm EN 50160 defines the standards that European energy suppliers should provide. According to this norm the amplitude of the voltage of the electrical power supply should be within a range of ±10% of the nominal value when measured at connection between the public electricity grid and the industrial distribution network (Markiewicz and Klajn, 2004). Voltage disturbances in this range are called voltage fluctuations (Baggini, 2008).

However, the voltage at the terminal of an electric machine can be influenced by the equipment surrounding it. This voltage is called *utility voltage* and the European norm EN 61000 defines its allowed variations. The amplitude of such variations should not exceed 3% in normal operation, although in case of a large load change or switching operations they can reach 10% and the duration can be a few tens of seconds (IEC, 2002a).

A voltage dip is a voltage reduction of more than 10% of the nominal value. Such voltage changes often occur due to environmental reasons, such falling trees and weather conditions that can break a cable and cause a short circuit (Baggini, 2008; Bakken et al., 2016). The voltage dip lasts until the protection system of the grid is able to isolate the short circuit from the rest of the grid. The technological level of the grid and configuration of the grid have an impact on the duration, while the proximity of the place of measurement from the place of the fault has an impact on the depth of the voltage dip (Bakken et al., 2016; IEC, 2002b).

Table 3.2: Average duration and depth of voltage dips in two surveys

Location	Duration	Depth	Source of information
Europe	50-150 ms	0-100 %	IEC (2002b)
Kollsnes and Kårstø, Norway	50-150 ms	15-50 %	Bakken et al. (2016)
USA	65-165 ms	80 %	Gunther and Mebta (1995)

Table 3.2 lists the average characteristics of a voltage dip according to three surveys done in Europe, in two production sites of Equinor in Norway, and across USA. The location and the weather of a specific season and year has also an impact on the frequency of such events. As example of critical conditions, Bakken et al. (2016) registered 26 events of voltage dip over a period of four years between the production sites of Equinor in Kollsnes and Kårstø, Norway.

3.4.3.2 Effect of voltage change on an asynchronous motor

Fluctuations of voltage (voltage variations within ±10% of the nominal value) applied to a motor have little impact on the speed and general functioning of a motor. The variation of the torque of a motor is relatively small in such cases while the inertia is high (IEEE Industry Applications Scoiety, 1999; Stein and Ghassemi, 2019).

Instead, voltage dips (voltage reductions larger than 10% of the nominal value) might cause a trip of the motor, of the drive or of the machine connected to the motor. Regarding the motor and the drive, the problem is that high currents can flow in such elements once the voltage amplitude recovers after a voltage dip (Bollen, 1995; Gomez et al., 2002; Wang et al., 2012). Such high currents can damage the motor and the power electronics. Therefore, it is better to trip motor and drive, and restart them with a dedicated procedure that limits the currents flowing.

3.4.3.3 Effects of voltage changes on the process

In addition to the trip of a motor or drive, a voltage dip can cause a controlled trip of the machine connected to the electric motor because the machine is going to enter in an operating area that can damage it. An example is when a compressor is connected to a motor. The reduction in rotational speed leads to a reduction in mass flow rate through the compressor, which in turn leads the system

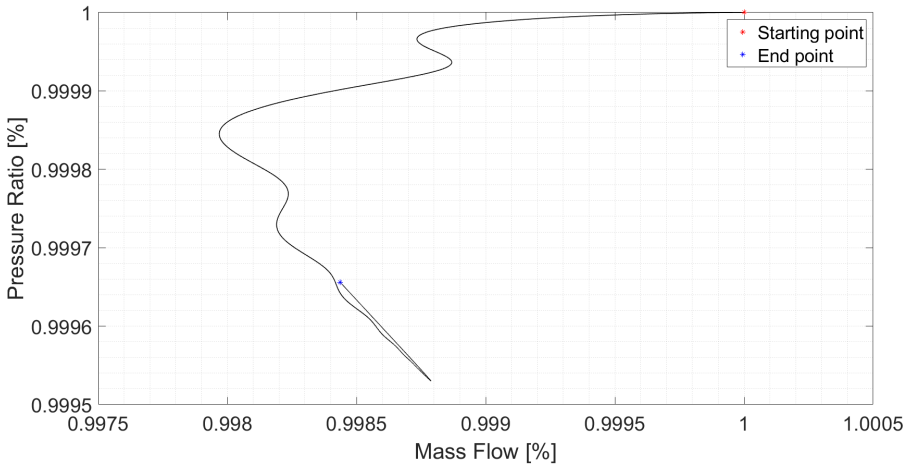
into surge. If surge cannot be avoided by using the anti-surge valve (which recycles gases flowing in a compressor), the compressor is tripped in a controlled way. In case of a trip, the MPC framework proposed in this thesis cannot help, as explained in the introduction.

Still, commercial solutions have been made available with so called ride through capabilities that prevent a trip of compressor and drive (Besselmann et al., 2016; Cortinovis et al., 2015, 2019; Wymann and Jorg, 2014). The solution described in Bakken et al. (2016), Besselmann et al. (2016), and Cortinovis et al. (2015, 2019) decides whether a limited amount of torque should be provided to the compressor connected, to prevent it entering into surge. The following analysis determines the effect on the process of a voltage variation, assuming that such voltage variation do not cause a trip of the unit. The cases of a motor connected to a drive and of a motor connected directly to the grid are both considered.

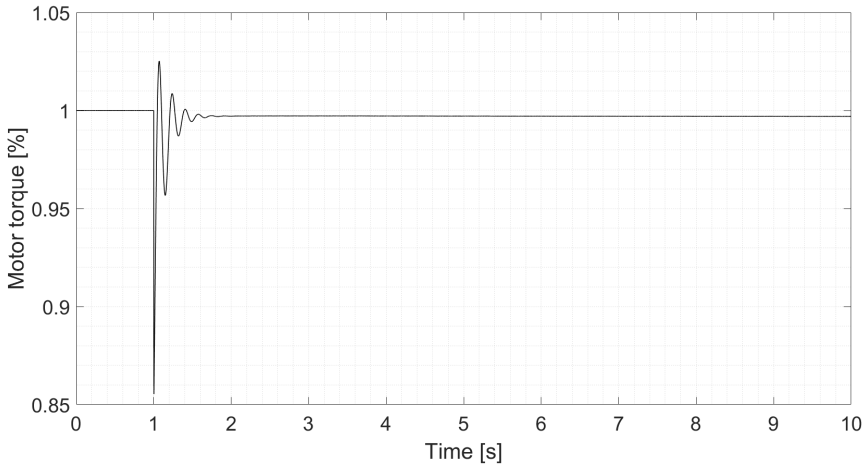
To analyse the effects on a system with a motor connected to a grid, the same system considered in Section 3.4.2 has been used. Two cases have been analysed. Fig. 3.10 shows the trajectory of mass flow and pressure ratio, and the trend over time of the torque for a voltage fluctuation of -3% from the nominal voltage for a duration of 10 s. Fig. 3.11 shows the corresponding plots for a voltage reduction of -50% of nominal voltage for a duration of 350 ms. For the voltage fluctuation, Fig. 3.10b shows that the variations of the torque are large (almost -15%). This might cause mechanical problems. Nonetheless, the variations of pressure ratio and mass flow rate shown in Fig. 3.10a are minimal. They are more severe for a voltage dip, shown in Fig. 3.11a. Both cases show however that the magnitude of the disturbance on the process side is largely reduced. For example, a reduction of 50% of voltage causes a reduction of mass flow of 6%.

The results do not change when a motor is connected to an electrical drive instead of being connected directly to the grid. Cortinovis et al. (2016) published and described the trend over time of discharge pressure after a dip lasting 150 ms and a ride through system in action. If the pressure stayed nearly constant, the compressor flow saw a reduction of maximum 6% with a transient of 4s. Also in this case the effect on the process is limited. According to the author of this thesis, the probable reason is that the torque changes for a very limited amount of time and the inertia of such system is relatively high.

To conclude, a voltage dip can lead to a trip of the compressor or of the connected motor and drive.



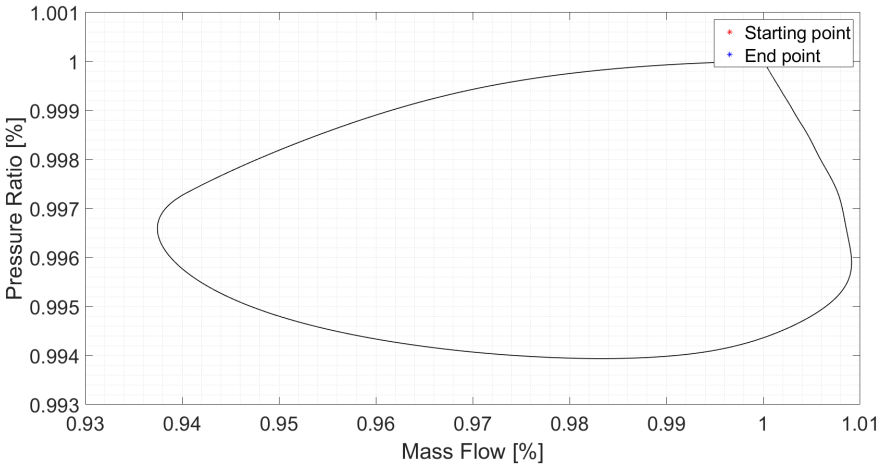
(a) Response of mass flow rate and pressure ratio



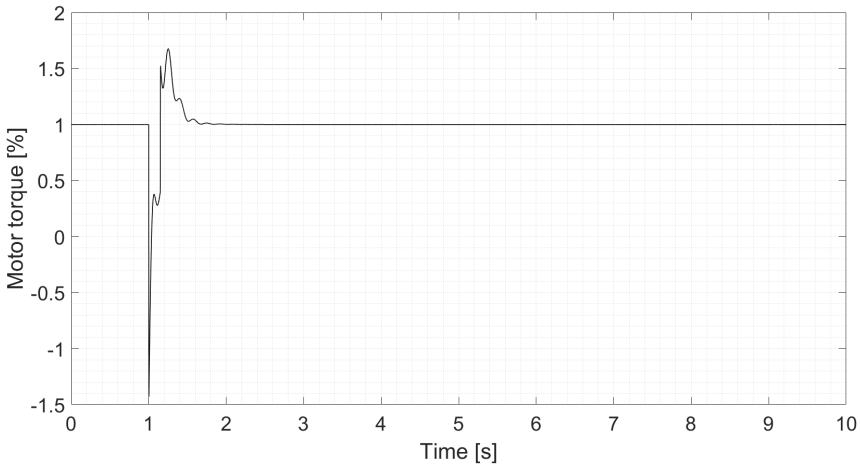
(b) Response of the motor torque over time

Figure 3.10: Voltage variation of -3% of the nominal value for 10 s

It can also reduce the mass flow rate flowing through the compressor. This reduction might upset the process but it depends on the process whether a sudden and short change of the mass flow is important. Furthermore, as discussed earlier, the work of Bakken et al. (2016) reported 26 voltage dips over a period of four years between the production sites of Equinor in Kollsnes and Kårstø, Norway. While this is a relevant number if the consequence is a stop of production, it does not seem relevant if the consequence is a short fluctuation of the mass flow rate for few seconds.



(a) Response of mass flow rate and pressure ratio



(b) Response of the motor torque over time

Figure 3.11: Voltage variation of -50% of the nominal value for 350 ms

3.4.4 Disturbances propagating from the process to the electric grid

Apart from the known step variations of load, the present author did not find many examples of plantwide disturbances propagating from the process to the grid. A problem which might occur are sub-synchronous oscillations, which are mechanical and grid oscillations at a lower frequency than the frequency of the grid.

The work of General Electric (GE) showed in Rotondo et al. (2015) is the only discussion of this problem found. The authors discussed a compressor whose anti surge valve was affected by stiction.

The sticking valve caused an oscillation of the compressor flow which excited the first of the natural frequencies of the system at 10 Hz, resulting in vibrations of the gear connecting the electric drive to the compressor, ripples in the torque delivered by the drive and in the currents (which are related to the torque) flowing in the drive. However, the authors do not mention whether such disturbance propagated through the distribution network to other electromechanical units. This was an example that the authors wanted to present to the oil and gas community to make it aware of the possible interactions between process and electromechanical systems.

The experts interviewed in ABB Energy Industries in Oslo, Norway (Borghesan et al., 2019b) were asked to provide examples of disturbance propagation from the process to the grid (other than planned load variations). One of them noted that the compressors are particularly prone to induce the trip of their connected motors, whereas pumps (e.g. water pumps) do not create such problems. It is however difficult to say whether the problem of such trips comes from the process, or rather from the integration of compressors and electric drive.

Centrifugal compressors are affected by unstable transients of pressure and flow leading to a compressor trip, when excited with torsional vibrations at sub-synchronous frequencies from 5 to 50 Hz (Wachel and Szenasi, 1980). Such vibrations are known to be caused by the drive (Hütten et al., 2013; Jorg et al., 2013; Kita et al., 2007; Wachel and Szenasi, 1993), but apparently they can be also caused by the process as in the former example of GE (Rotondo et al., 2015).

To conclude, plantwide disturbances are not widely acknowledged to be source of disturbances propagating to the grid, although they can create mechanical issues and might cause a trip of the motor and load.

3.4.5 Conclusions on disturbance propagation between electrical utility and plant

The analysis reviewed the possible interactions between electromechanical systems and processes. It results that the effects of such interactions are short abrupt process disturbances, or mechanical damage and trips of the units.

When electrical disturbances do not cause a trip, their effects on a process seem limited to few

seconds and the amplitude of a disturbance on the process side is far smaller than on the electric side. This is due to the inertias of rotating machineries which dampen the effects of an electrical disturbance and due to the limited duration of electrical disturbances. Furthermore, the presence of large electrical disturbances which might have an impact on a process, although limited if does not lead to a trip, are rare when the industrial site is connected to a public electricity grid.

The analysis in Section 3.4.4 found very little awareness of propagation of plant-wide disturbances to electrical utility. However, GE (Rotondo et al., 2015) showed a case study where the ripples caused by a sticking valve can propagate up to the electric drive. The aim of the paper was to make the oil and gas community aware of the interactions between process and electromechanical systems.

Interviewed on the topic, experts of ABB commented they do not typically see disturbances propagating from the process to the grid. One expert noted that compressors are prone to cause trips of motors for reasons unknown and to be investigated. However, centrifugal compressors are known to trip following vibrations that can be caused by the electric drives and in some situations, according to the case study of GE mentioned before, by the process. Therefore, the process is likely not the only and major cause of such trips of compressors.

To conclude, the interactions between electrical utility and process do exist. However, when they do not cause a trip of the motor or of the machine, they represent problems that have a limited and infrequent impact on the process. Instead, when they cause a trip of the unit, the control framework proposed in this thesis cannot alleviate the situation. A trip of a machine can lead to a stop of a production or it represents for the rest of the system a simple step disturbance. In the latter case, the control system would not benefit from a multi-step prediction.

3.5 PROPAGATION OF DISTURBANCES BETWEEN STEAM UTILITY AND PROCESS PLANT

3.5.1 Overview of the propagation mechanisms

Fig. 3.12 shows the sources and the mechanisms of propagation of disturbances within a steam utility, and between a steam utility and production plants. The sources of disturbances are on the

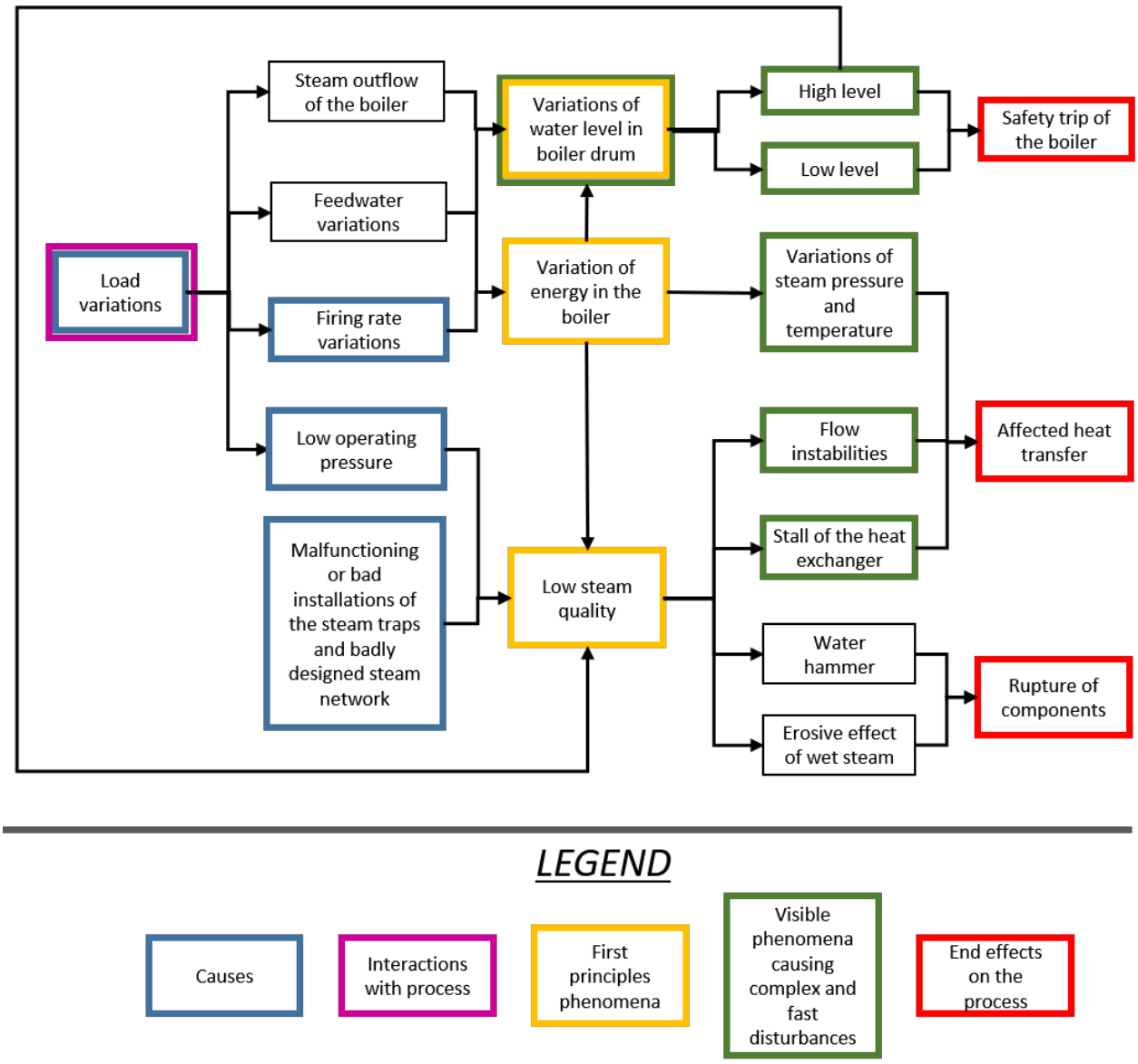


Figure 3.12: Considered paths of disturbance propagation in a steam utility connected to a plant

left of the graphic. Some sources are endogenous to the steam utility such as malfunctions or changes of the fuel used. Other disturbances are exogenous and caused by variations of request for steam from the loads.

All sources have three types of outcome, represented on the right of Fig. 3.12.

- Heat transfer with the process deviates from its desired value, propagating the disturbance to the process.
- A component breaks, affecting the production.

- A boiler is forced to trip.

The control framework proposed in this thesis can mitigate the disturbance propagation caused by heat transfer deviating from its desired value. It cannot do anything once a unit of the plant breaks or trips. However, it might avoid a safety trip of the boiler in some circumstances and it should avoid the conditions that will lead later a device or a process unit to break.

This section describes the main phenomena and interactions between the elements of Fig. 3.12. There are three main first-principle phenomena, highlighted in yellow in Fig. Fig. 3.12, which are present in a steam utility. These are:

- Low steam quality (where the steam quality is an indicator of the amount of water in the steam)
- Variation of energy in the boiler
- Variation of level of water in the drum of the boiler

The first-principle phenomena give rise to a series of other phenomena, highlighted in green in Fig. 3.12, which are visible and measurable.

The section is organized so that Section 3.5.2 describes the problem of low steam quality, Section 3.5.3 describes the variation of energy in a boiler, while Section 3.5.4.2 focuses on the variation of level in a boiler.

3.5.2 Low steam quality

3.5.2.1 Causes of low steam quality and condensate in the steam network

Fig. 3.13 highlights the paths considered for the low steam quality. The phenomenon of low steam quality, often called wet steam or carryover, refers to the saturation of steam and therefore to the presence of small drops of water condensate in the steam. Low quality means that a high amount of water is entrained in the steam.

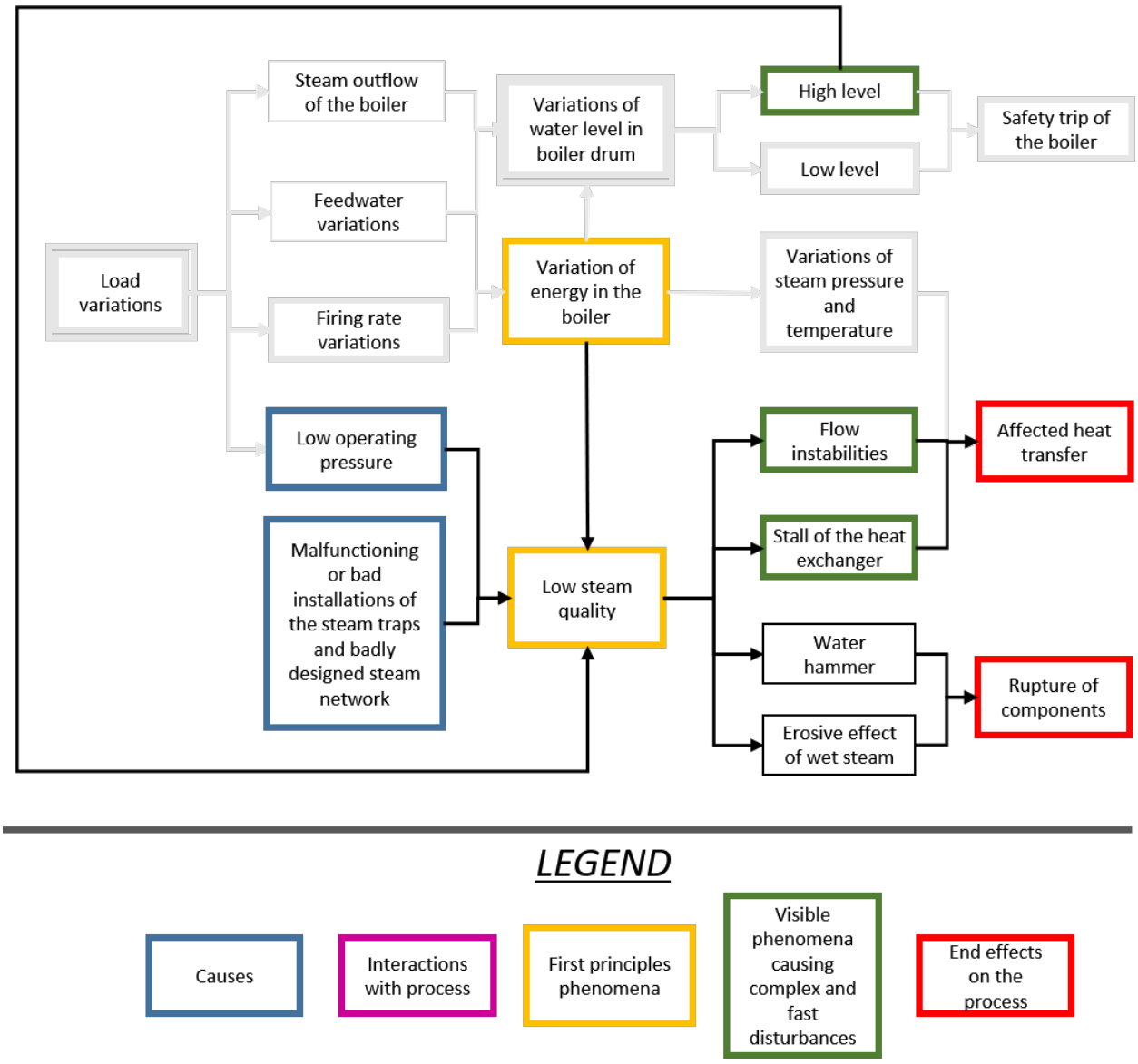


Figure 3.13: Considered paths of low steam quality

The reasons for a low quality of steam can lie in the boiler, in the distribution network, or in both. Fig. 3.13 highlights four sources, which are the variation of energy in the boiler, the low operating pressure, the high level of water in the boiler and malfunctioning of steam traps.

Heat losses along the pipelines are present in the steam distribution network and the presence of condensate is normal (TLV, 2019). For this reason, the steam distribution network must be designed so that the condensate is removed through steam traps and does not accumulate in specific spots (Swagelok Energy Advisors, 2019). Nonetheless, the steam distribution network might be badly designed, because it collects pockets of condensate in certain points, or some traps might not be

working properly. In addition, the problem can lie in the boiler because not only steam but also unexpected condensate is carried over.

Low pressure increases turbulence in the drum of a boiler. This makes more likely that water in place of steam enters in the steam distribution network. The pressure can be permanently low because that is its operating point. In this case, the wrong set point is the source of the problem. Alternatively, it can be only temporarily low as a consequence of the increasing outflow of steam due to an increasing request of steam.

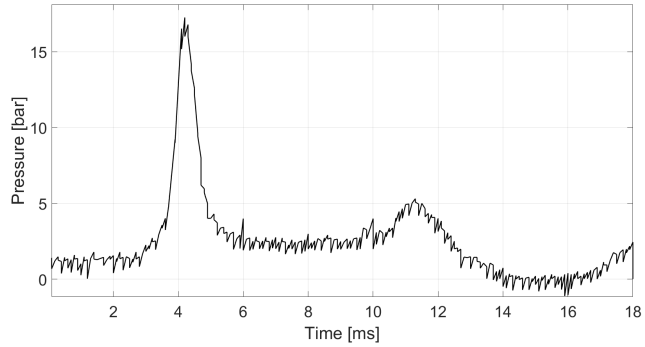
As with low pressure, a high level of water in the steam drum increases the possibility that turbulent water spills and enters in the steam distribution network. Finally, variation of energy is especially problematic when the flow rate of feedwater to the drum suddenly rises. This rise reduces the energy in the steam drum and creates small drops entrained in the evaporating steam. These reduce the quality of the steam.

3.5.2.2 Effects of low steam quality

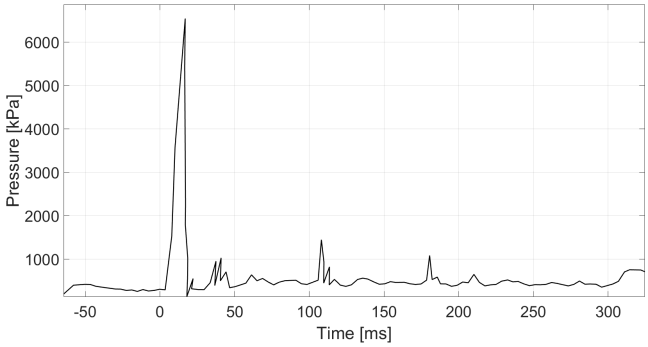
A problem caused by steam with low quality is that the entrained droplets are abrasive, damaging valves and steam turbines (Swagelok Energy Advisors, 2009). Furthermore, low steam quality can reduce the heat transfer efficiency(Swagelok Energy Advisors, 2009). However, these two effects are not relevant for this thesis because they do not represent disturbances that can be solved by the proposed control system.

It is is relevant that drops of water can build up and fill with condensate the pipes of the distribution network and of reboilers. The presence of condensate within a steam system can cause the following issues:

- Water hammer
- Flow instabilities showing disturbances of the flow and pressure of the steam with both
  - Oscillating patterns
  - Abrupt patterns
- Limit cycles due to the interaction with the control system of the heat exchangers



(a) Pressure variation in a pipe during an experimental water hammer caused by a sudden movement of water condensate. Data from McDonald (2000)



(b) Pressure variation in a pipe during an experimental water hammer caused by condensation. Data from Gruel et al. (1981)

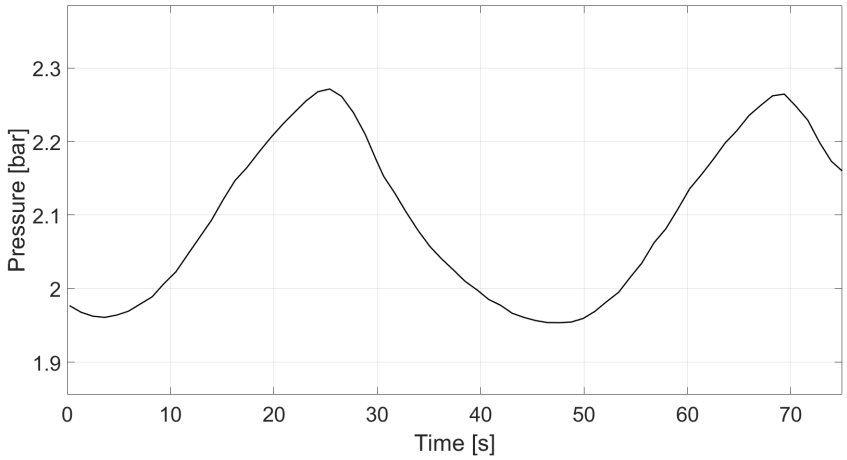
Figure 3.14: Two examples of experimental water hammers

3.5.2.3 Water hammer

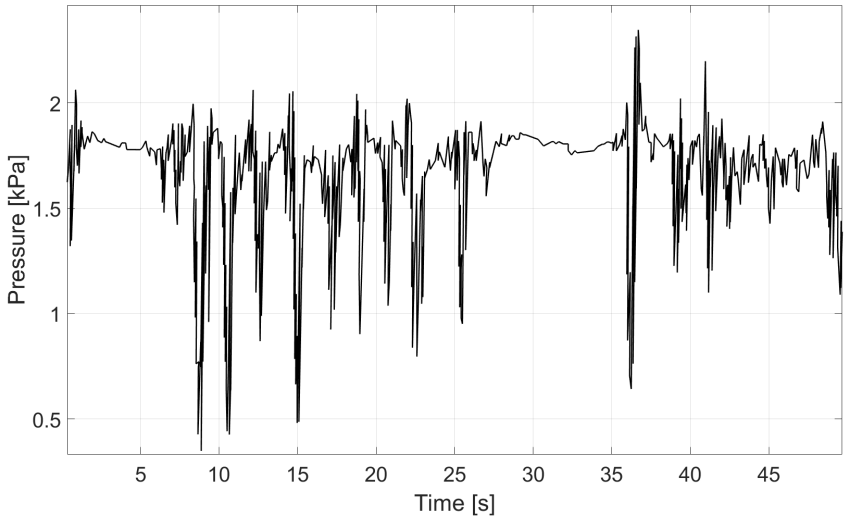
Water hammer is an abrupt pressure variation inside the pipes of a system, causing a loud sound which reminds the one of a hammer. Water hammer is caused by two phenomena (TLV, 2019).

One phenomenon occurs when high speed steam draws the condensate inside pipes, forming slugs of condensate. When the pipe curves, the turbulent condensate can strike against the curve or a valve. The other phenomenon occurs when pockets of steam are encircled by colder condensate. The pocket of steam condenses suddenly, implodes reducing its volume, creates a vacuum, and a strong, spiky, pressure variation occurs. Fig. 3.14 shows examples of water hammer.

While the phenomenon of water hammer is well known to pose mechanical issues in pipelines and heat exchangers, the present author did not find sources linking water hammer to disturbances of



(a) Example of pressure variation due to steam and condensate interactions. Data from Kakac and Bon (2008).



(b) Trend over time of the pressure of a steam flow affected by geysering. Data from Jiang et al. (1995)

Figure 3.15: Oscillatory and abrupt flow instabilities.

the controlled process variables of the plant. In addition, the phenomenon seems to develop in a time of milliseconds in some experimental papers (Gruel et al., 1981; McDonald, 2000) and it might be too short to have an impact in the process.

3.5.2.4 Flow instabilities

If condensate is present, the liquid and vapout phase can interact for certain conditions of pressure, rate of mass flow and external heating. Such interactions can manifest themselves as oscillations or abrupt variations of pressure and rate of mass flow. These are called flow instabilities and have been extensively studied in the field of nuclear engineering for steam generation with Boiling Water Reactors (BWRs), for example in Durga Prasad et al. (2007), Jiang et al. (1995), Kakac and Bon (2008), Rouhani and Sohal (1983), and Zhang et al. (2020). The reason is that such disturbances also affect the power produced by a plant and pose problems to control systems, although the authors do not specify which ones. Fig. 3.15a shows an example of an oscillating disturbance and Fig. 3.15b shows an example of an abrupt disturbance.

By contrast with the literature on nuclear plants, there are very few works on the effects of such oscillations in process plants. The works found (Agunlejika et al., 2016; Alane and Heggs, 2011; Kessler, 2014; Kister, 1990) focus on reboilers of distillation columns functioning through natural recirculation. This is the same principle of circulation of a BWR. As for the BWRs, such disturbance occurs at start up or at low heating power. However, the fluid which exhibits first this type of disturbance is the process fluid in case of reboilers of columns, whereas it is water in the case of BWRs.

In case of reboilers of columns, the pressure and temperature of the steam flowing in the reboiler can be affected (Agunlejika et al., 2016). However, this paper does not discuss whether the disturbance can propagate further in the steam utility.

The next case study might suggest that flow instabilities might occur also the steam side. Fig. 3.15b shows an example of pressure variations of pipes affected specifically by geysering published in Jiang et al. (1995). Geysering is a phenomenon where a bubble of steam originates at the bottom of a column of liquid, becomes bigger and then implodes (Durga Prasad et al., 2007; Jiang et al., 1995). The example mentioned is similar to the trend plotted in red in Fig. 3.16, which plots the pressure of the steam serving the distillation column number 3 of the Eastman plant described in Thornhill et al. (2003).

The case in Thornhill et al. (2003) is different from the one mentioned previously in Agunlejika et al. (2016) because there is no reboiler. The steam is injected in the column, which is stripper.

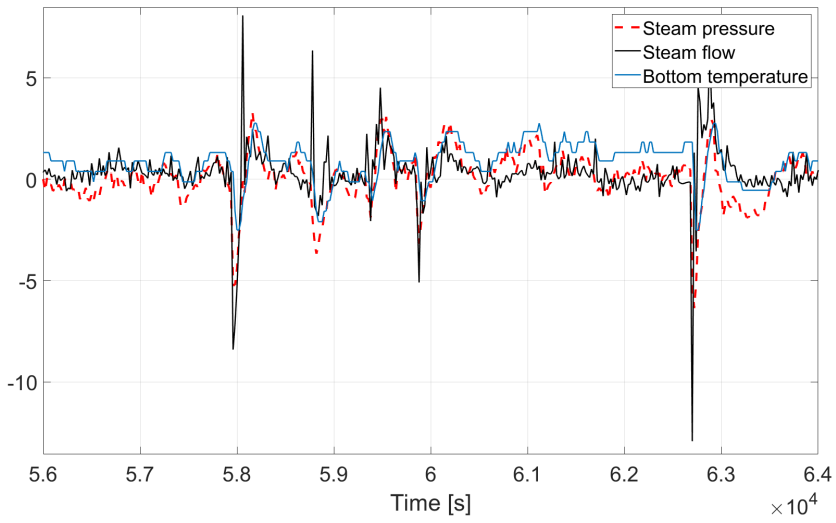


Figure 3.16: Effect of abrupt disturbances, maybe caused by water hammer or geysering, or temperature of the process fluid. Trend over time of Tag 27 (bottom temperature of a column), Tag 28 (steam pressure in the reboiler of the column) and Tag 30 (steam flow) of the dataset used in Thornhill et al. (2003)

Fig. 3.16 plots temperature of the bottom of the column, mass flow rate and pressure of steam. The temperature follows qualitatively the trend of the other two variables.The disturbance might originate from the steam.

3.5.2.5 Stall of a reboiler

Stall of a reboiler occurs when the condensate builds up and drain periodically, thus affecting the heat exchange area and, eventually, the heat transfer to the process, and causing persistent disturbances propagating to the process.

The documentation of Spirax Sarco (2019), a company focusing on steam systems, describes the phenomenon. When the load for a reboiler reduces, the inlet steam valve closes, reducing the pressure inside the reboiler. The pressure can reduce so much that the steam trap locks and cannot drain the condensate. Indeed, the steam traps need a minimal differential pressure to work.

The increasing level of condensate in the reboiler reduces the heat transfer area. Therefore the temperature of the process liquid decreases below the required set-point after a while. When the controller opens the steam inlet valve again, the pressure inside the reboiler increases and the condensate is soon drained. However, the temperature of the process liquid increases and the steam valve must be closed again. Therefore, the cycle restarts.

The TLV Corporation (TLV) has an animated webpage showing how such cyclic variations propagate to the process: `https://www.tlv.com/global/ME/steam-theory/stall-phenomenon-pt1.html`. To the knowledge of the present author, there are no example in the academic literature of disturbances caused by stall of heat exchangers.

3.5.3 Variation of the energy in the boiler

3.5.3.1 Causes of variation of the energy in the boiler

The control system of the level of water in the boiler can vary the energy in a boiler. This is particularly true for old plants, with on-off control systems (Oram and Borghesan, 2019). Variation of energy may be also caused by variation of the firing rate, which is the heat provided by burning fuels, as Section 3.5.3.4 will discuss. Additionally, variations of load change the net energy in the distribution network and in the steam drum and this is the topic of the Section 3.5.4.2.

3.5.3.2 Effects of variation of the energy in the boiler

Water evaporates when a certain level of energy per mass of water is reached. Consequently variation of energy provided to water acts on the production rate of the steam. A change of production rate affects the pressure in the steam header, as Fig. 3.17 suggests. The change of the pressure of the steam propagates to the process liquid. Furthermore, sudden reductions of the energy provided to the boiler, for example by increasing the colder feed of water, can also influence the steam quality because the steam might slightly condense, entraining small drops of water.

3.5.3.3 Variations of the feed of water in the boiler

The level of water in the steam drum is controlled using a feed of water, which is necessarily colder than water in steam drum, even if pre-heated (Dukelow et al., 2005). Therefore, whenever the feed changes, this disturbs the amount of energy in the steam drum. In particular, an on-off type of control of the level of the drum was common in the past and it is a known source of disturbances (Dukelow et al., 2005; Hahn, 1998). However, such disturbances are often overlooked by the companies operating the plants, according to Spirax Sarco (2014).

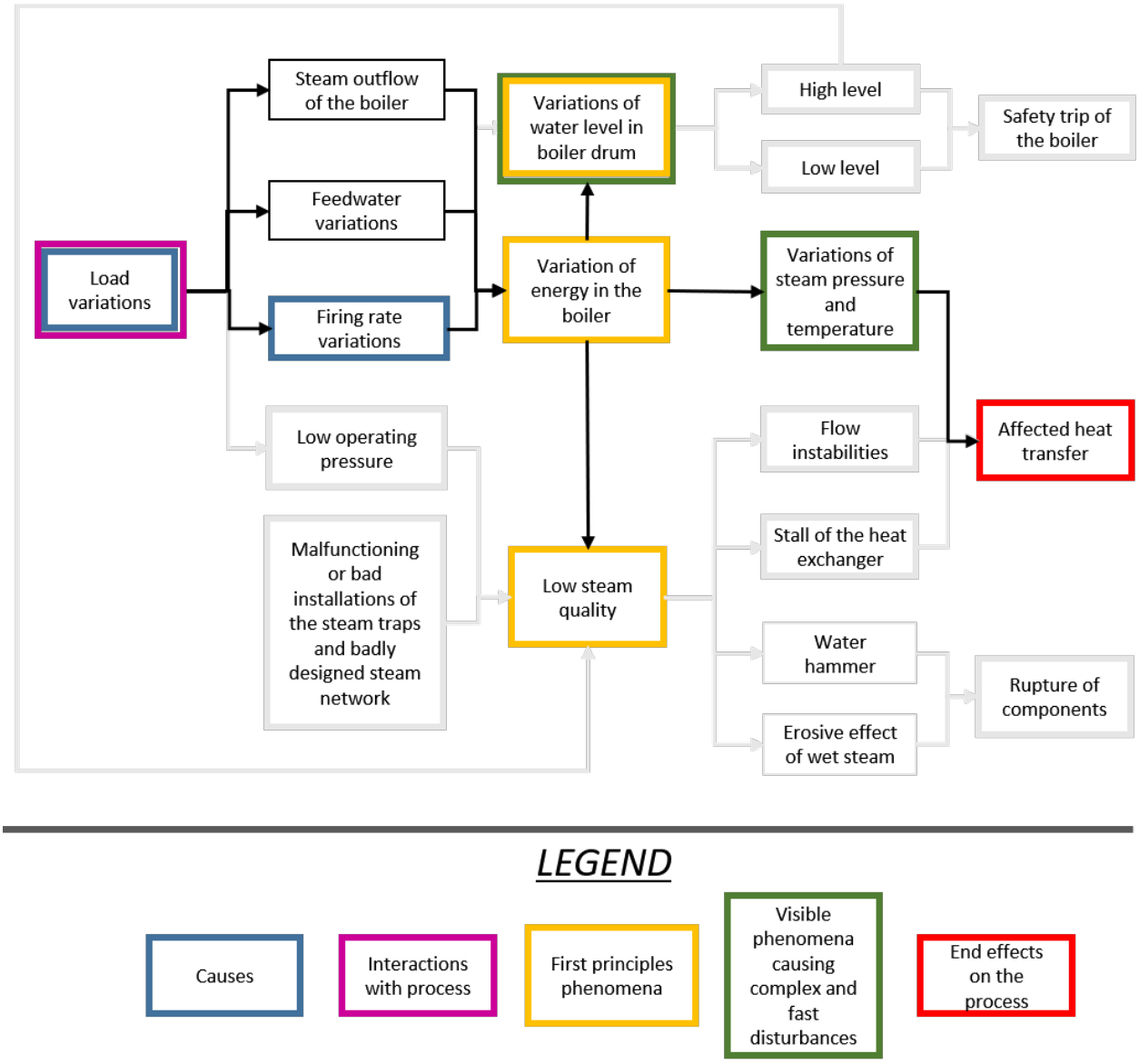


Figure 3.17: Considered paths for a variation of energy in a boiler.

Hahn (1998) explains what occurs when the feed is suddenly raised. Initially, since the drum is not a perfectly mixed volume, the feed of water first creates a cold layer of water within the drum. The interaction between the steam bubbles rising in the drum and the colder layer of water causes some of the steam in the bubble to condense. This causes two problems.

The most important problem from a control point of view is the suppression of the rate of steam production (Dukelow et al., 2005; Hahn, 1998; Spirax Sarco, 2014). Indeed, the colder water reduces the steam production until saturation temperature of water is reached again (Hahn, 1998). Reducing the steam flow, the pressure in distribution network reduces as well.

The other problem is that the contact of colder water with steam causes fog in the drum (Hahn, 1998; Spirax Sarco, 2014). This means steam entrains water and therefore the steam quality deteriorates.

These problems can be attenuated by using a continuously modulated feed of water in place of an on-off controller (Dukelow et al., 2005; Hahn, 1998; Spirax Sarco, 2014).

The present author himself experienced site wide disturbances in a production site in Germany caused by an on-off control level of the steam drum. The pressure of the steam exhibited oscillations with a period of one hour which propagated further in the process. The distillation columns served by this system showed, for example, oscillations of the controlled temperature and of the levels of the bottom of the column with the same period.

3.5.3.4 Variability of the firing rate

In a boiler, the firing rate determines the heat provided through the furnace to water. Such heat depends on the mass flow of fuel, on its calorific value and the ratio between air and fuel in the burning process. Any change of these parameters is a disturbance for the heat, impacting steam production, pressure and level of a boiler (Elguindy, 2013). These changes can be more problematic if they are not measurable (Dukelow et al., 2005; Kortela and Lautala, 1984).

The mass flow rate of a solid fuel like coal can be difficult to measure. Therefore, the control works in open loop and disturbances on the final controlled variable are less likely to be compensated on time (Dukelow et al., 2005). Even if the flow rate of fuel is measured, the calorific values of the fuels can still change. This occurs when the burner accepts different fuels but it can also occur because the intrinsic quality of fuel is not constant, as in the case of coal, biomass, municipal waste or industrial by-products (Dukelow et al., 2005; Kortela and Lautala, 1984; Woodward, 2006).

In these cases, adding additional firing can be a solution (Dukelow et al., 2005). To control the additional firing and compensate for the disturbances, the calorific value of the variable sources might be retrieved through other parameters. The oxygen consumption (Kortela and Lautala, 1984), or variations in the steam pressure (Dukelow et al., 2005) can be measured and used to calculate variations of the energy provided to the boiler. Once that the energy coming from the disturbed sources is known, the additional fire can compensate for that.

Finally, the ratio between air and fuel can be influenced by variation of the fuel but also by variations

of the air flow in the burning process. The latter is influenced by the pressure control inside the furnace. Dukelow et al. (2005) mentions possible interactions between pressure control and air/fuel ratio.

3.5.3.5 Variations of the load

For batch processes, starting and shutting down units requiring steam is a frequent operation (Hahn, 1998). Steam valves are often opened at once when a batch process starts. The initial request of steam during start-up can be three times higher than in the steady state regime (Hahn, 1998).

Adams et al. (2008) reported non-linear oscillations of the flow of steam in a sugar mill. The oscillations had a period of 10 minutes and were caused by the continuous switching of loads in the production site. The disturbance propagated affecting levels and concentrations of juice in the units in operation. The authors did not analyse however the impact of the disturbance on the rest of the steam utility.

Majanne (2005) explained that also paper industry is characterized by frequent switching of loads. This has an impact the pressure of steam in the steam distribution network. Switching of a unit can represent 20-40% of the nominal load of the boiler and the control of the system has to keep the pressure within limits. However, Majanne (2005) considered only step variations in its simulations and did not mention possible oscillations in such systems.

Another possible cause of variation of load that can impact the pressure in the system is a valve stiction. Adams et al. (2008) mentioned also oscillations of steam flowing into loads due to a sticking valve. Sticking valves impacting pressure of steam in the steam headers are reported also by Chioua et al. (2016), Thornhill (2005a), and Zhou et al. (2019).

The present author did not find publications describing the impact of stall of reboilers on the rest of a steam utility. Still, this phenomena might have an impact similar to that of sticking valve.

3.5.4 Variations of level of water in the drum of a boiler

The level of water in a boiler has to stay between upper and lower limits. When the level is below the lower limit, mechanical damage can occur because boiler tubes are uncovered and can overheat. When the level is above the upper limit, splashes of boiling water might enter in the steam distribution network causing low steam quality (Dukelow et al., 2005; Hahn, 1998; Kehlhofer et al., 2009; Spirax Sarco, 2014). In both scenarios, the boiler is tripped, causing a major impact on the production site.

The variation of the level of water in a drum of a boiler depends on the total volume, given as the sum of the volume of water in the drum and the volume of steam bubbles entrapped in the water (Åström and Bell, 2000). The volume of the bubbles of steam depends on the pressure in the boiler. The coupling between pressure and volume makes the control of the level hard in case of disturbances that affect pressure and mass of water inside the drum (Åström and Bell, 2000).

3.5.4.1 The causes of level variations

The heating provided to the boiler, the steam outflow and the feed of fresh water all affect the pressure and mass of water in the drum, and consequently the level of the drum (Åström and Bell, 2000).

Dukelow et al. (2005) explained the initial response of level of water through variations of the rate of feed water. In Elguindy (2013), the disturbance is the heat provided to the boiler. The heat comes from the exhaust of gas burnt in a gas turbine for generation of electricity. The disturbances of the heat affect pressure and level in the drum of the boiler. Hahn (1998) considered the case where the disturbance is the load request which changes abruptly because of starting of units for batch processes.

According to Hahn (1998), the variations of steam request are particularly problematic for the level of water in a drum because steam valves are often opened at once when a batch process starts. This causes an overshoot in steam request. He stated as example that although the unit started might represent a 5% of the load of the boiler in steady-state, the initial overshoot can be 15% of the nominal load of a boiler. These magnitudes are problematic for the level of a boiler.

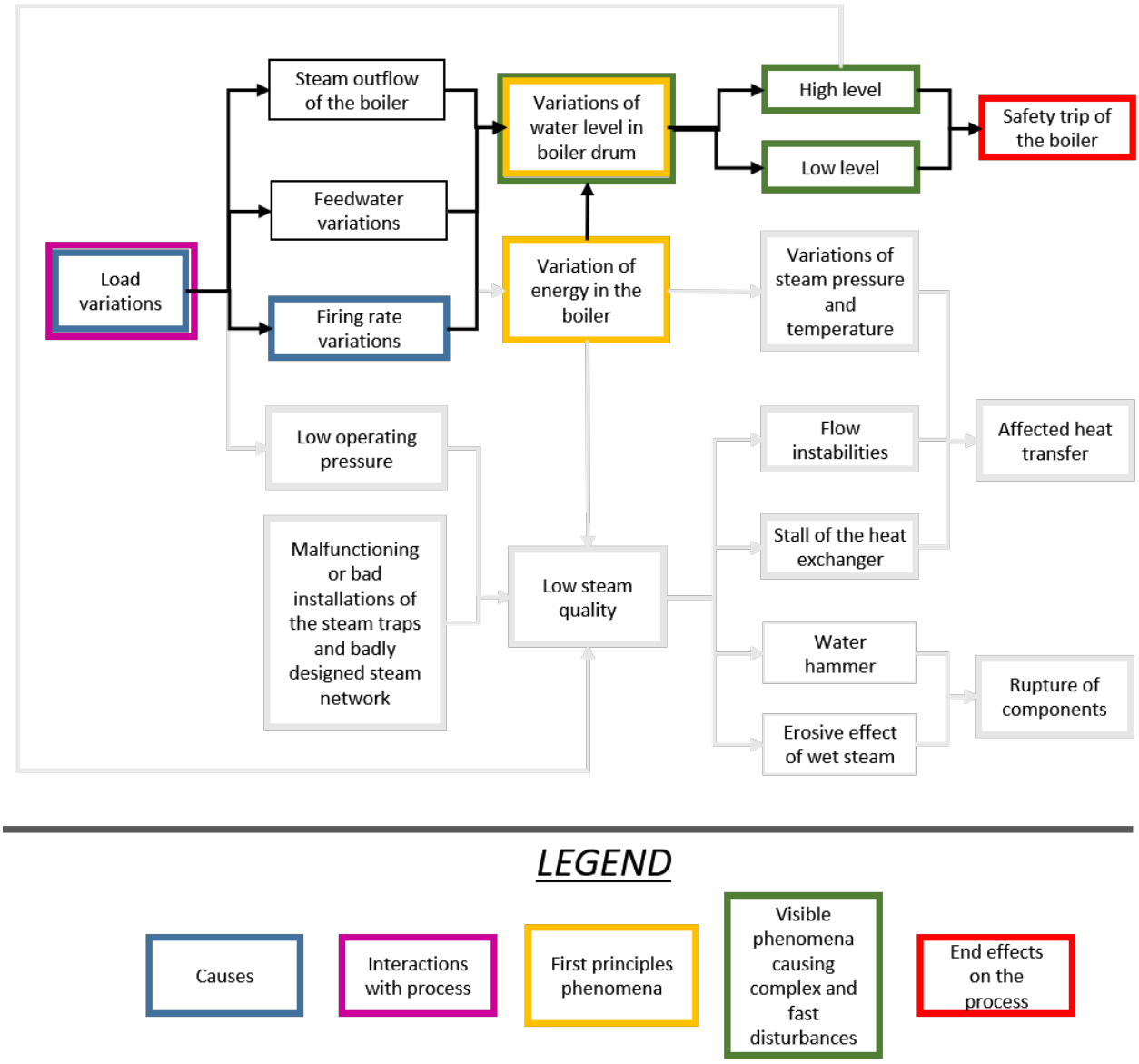


Figure 3.18: Considered paths for variations of the level.

3.5.4.2 The effects of fast changes of steam demand on level variations

Opening the steam valve causes the pressure to drop rapidly. With a lower pressure, more drops of water are entrained in the steam and brought to the steam distribution network. Also, the bubbles of the boiling water become bigger, increasing the volume and level of water. This phenomena is called *swell* (Dukelow et al., 2005; Hahn, 1998). Low pressure leads also to a higher turbulence of water (Spirax Sarco, 2014). Hahn (1998) and Spirax Sarco (2014) stated that water is sucked in the steam line in such conditions. This leads to the problem of poor quality of steam. If the level of water crosses the upper limit, the boiler will trip.

Another problem caused by a change of the steam request is that during swell, measurement of the level of water gives an overestimate of the mass of water present in the drum. Furthermore, the measurement is imprecise when water is turbulent and can be worsened in the presence of a thick layer of foam. This foam is caused by salts dissolved in water that are not removed by a proper desalination (Hahn, 1998; Spirax Sarco, 2014). In these conditions, the control of the level might not add enough fresh water in the boiler. However, the level can drop below its lower limit once the pressure increases again. Decreasing below the lower limit, tubes used for heating the water in the drum are uncovered, can overheat and damage. To avoid the damage, the boiler is tripped when the level is below the lower limit. Therefore, disturbance of the load can propagate to the level of the boiler, and lead to a trip of the unit.

Relatively similar dynamics occur when there are changes in the flow rate of the feed of water, or in the rate at which heat is provided. Åström and Bell (2000) and Dukelow et al. (2005) describe them in detail.

3.5.5 Conclusions on disturbance propagation between steam utility and production plant

This section reviewed the interactions between steam utility and production plants. The analysis showed that persistent as well as abrupt disturbances can occur in the interaction between steam utilities and process plants.

Presence of water condensate in the steam pipelines is mainly considered as a cause of mechanical damage. Nonetheless, this thesis argues that the presence of condensate might have also impacts on the process. Flow instabilities can occur when steam and condensate interact and these might impact the process.

Another source of disturbance is the stall of reboilers, occurring for low loads of the reboilers. Stall causes persistent disturbances to the loads and, apparently, it has not been studied much by academia.

The section presented also the effects that variations of load requests, firing rate and feed of fresh water have on steam pressure and level of water in the drum of a boiler. The steam pressure has an

impact on functioning of loads. Variations of level of water in the drum can lead to a trip of the boiler if outside certain limits.

3.6 PROPAGATION OF DISTURBANCES BETWEEN STEAM UTILITY AND ELECTRICAL UTILITY

3.6.1 Overview of the propagation mechanisms

Many of the problems considered in the former section while analysing the interactions between steam utility and production plants apply also to the case of propagation of disturbances between steam utility and electrical utility. In particular, the problem of low steam quality has been already described. Also the former section analysed the effects that a change of request of steam, independently whether from a production plant or a turbine, causes to the steam utility.

This section addresses two points that have not been discussed before. The first discusses what are the disturbances considered for the steam utility when a system is in island mode. The second regards the limitations of the interactions between the control of steam turbines for electricity generation and steam utility. The latter point is analysed comprehensively in references like Kundur and Balu (1994) and Machowski et al. (2011).

3.6.2 Disturbances in island mode caused by an imbalance between power generated and consumed

The variation of load for the steam turbines requires an intervention of the steam utility. However, when the production site is connected to a public electricity grid, the intervention of the industrial steam utility will be minimal (Lerch, 2013). The frequency will vary slowly thanks to a large inertia given by the public electricity grid.

On the other hand, when a production site is in island mode, there are few generators of steam and few electric loads. Therefore, any power imbalance has to be compensated by sharing among few steam generators. A series of papers by Siemens (Lerch, 2013, 2016; Loscha et al., 2016) dealt with this problem. They designed an LNG offshore platform analysing a scenario where a gas turbine trips. The trip of a gas turbine represents a loss of electrical generation and of steam generation (through the gas exhausts). The control system has to manage both. They also considered a scenario

where a compressor, which is a load, trip.

In both cases however, the scenario is a case where the trip of a unit represent a simple step disturbance for the other units. This does not require multi-step prediction of the prediction. Therefore, it is not a case of interest for the framework proposed in this thesis.

3.6.3 Limits of pressure variation for a boiler and a steam turbine

Steam temporarily in excess in the steam distribution network can be redirected to steam turbines for electricity generation, if the turbine has availability to extract further energy. However, this can be a problem for the grid because the frequency can increase too much. In this case, steam can also be vented (Majanne, 2005).

Some steam turbines, called back-pressure turbines, are turbines whose outflow is not condensate rather steam. They can be used to control the pressure at medium pressure (MP) or at low pressure (LP). Majanne (2005) explains that a back-pressure steam turbine is faster in adjusting the pressure at MP and LP level than a boiler, thanks to its faster dynamic.

However, the steam turbine can propagate a disturbance at MP or LP level to the boiler. According to Majanne (2005), disturbances within ±5% of the nominal value of the steam pressure are acceptable. Above this limit, trips of the boiler or turbines can occur, due to violations of constraints of the levels in the drum of a boiler or due to excessive temperatures of the steam that can damage a steam turbine.

3.6.4 Conclusion on the disturbance propagation between steam utility and electrical utility

The section pointed out that some problems considered while analysing the interactions between steam utility and production plants apply for the interaction between electrical utility and steam utility. In particular the problem of quality of steam and the response of a steam utility to a load change have been considered.

This section adds that problems where the steam utility has to react to disturbances from the electric side are not of interest for this project. Most of these problems involve trips of units, which can be modelled through step rather than a complex future disturbance to be predicted. Finally, the interactions between steam turbines and boilers have been mentioned and a reference stating the acceptable limits of such interactions has been provided.

3.7 SUMMARY

This chapter has investigated and described how disturbances might propagate within a production site. The areas considered of a production site are the production plants, the steam utility and the electrical utility.

The aim was understanding what disturbances arise in a production site, their impact on the process and how they propagate. This allows defining which are the disturbances that have an impact on the production site and that can be potentially attenuated by the control system proposed in this thesis.

This review shows that the areas of most interest for this project are the production plant, the steam utility, and the interconnection between these two. The chapter described the propagation mechanisms within a chemical and oil refinery plant, taking a distillation column as an example to describe the physical mechanisms of disturbance propagation.

Disturbances can enter in the plant from the steam utility through reboilers for a variety of reasons. As example, sticking valves or the phenomenon of stall of a reboiler can cause persistent disturbances in the production plant. Analysing an industrial dataset, this chapter showed that abrupt, spiky, disturbances of the steam pressure and mass flow might also affect a process. The hypothesis is that such disturbances are caused by flow instabilities, occurring when condensate and steam in the pipelines of the steam distribution interact.

A plant can also upset a steam utility with load variations. Following such load variations, the utility should not only keep pressure and mass flow rate of steam within constraints, but it must also keep the level of water in the drum of boiler within two constraints. If not, a safety trip of the boiler occurs, with consequences for the whole production site.

The review showed that there are disturbances propagating from an electric utility to production

plants. Nonetheless, they are not of interest for this thesis. The disturbances from the electric utility to a production plant often cause a safety trip of a electric motor or of the connected rotating machine. Such problems would not benefit from a control system able to do a multi-step prediction of a disturbance. Indeed, once the machine is shutdown, the disturbance can be seen as a simple step rather than a disturbance with a complex pattern to be predicted.

Instead, the events that do not cause a trip of motor or machine, seem to not have a considerable impact on the process and they are also relatively rare. This was assessed using a model of a laboratory-scale compressor used by ABB.

Finally, the chapter analysed interactions between electrical and steam utility. The impact that an electric utility has on a steam utility are similar to those of a variation of load from a production plant has on a steam utility. Regarding the impact that steam disturbances can have on an electrical utility, the dedicated section provided limits for allowed steam variations that have been found in literature.

Chapter 4

DISTURBANCE PREDICTION

This chapter examines the prediction of disturbances based on their past measurements using k-nearest neighbours. This prediction method works in a semi-supervised way, it is robust against changes of the characteristics of the disturbance, and its functioning is simple and transparent.

Specifically, it shows how prediction of a disturbance can be obtained using two $k-$nearest neighbour methods. Previous uses of $k-$nearest neighbours for time series prediction have typically predicted just one sample a few steps ahead. Instead, this chapter shows it is possible to achieve the more challenging task of predicting the future evolution of the time series. A condition for a good prediction is the regularity and predictability of the time-series. The chapter shows a qualitative and quantitave method to analyse the predictability. Further, it compares the prediction performance of the $k-$nearest neighbours method with the one obtainable with an autoregressive model, and highlights the capability of the $k-$nearest neighbours to learn new disturbance patterns

4.1 INTRODUCTION

The chapter focuses on the second of the technical objectives listed in Section 1.6. The technical objective is showing whether a multistep prediction of a persistent and abrupt type of disturbance is possible using an amount of industrial data smaller than a few hours and provide a term for the forecastability of the time-series. Once a prediction is obtainable from industrial data, the prediction can be used in an MPC framework as the thesis will discuss in next chapters.

The algorithm chosen is the $k-$Nearest Neighbours for its simplicity and capability to work with few training data. The chapter proposes next to the basic $k-$nearest neighbours also another version of the algorithm. The additional version, called here weighted $k-$nearest neighbours, has been created to provide the algorithm more robustness.

An interest of the chapter is showing whether the algorithm is able to provide a good multi-step prediction of a time series of a disturbance, and in seeing whether the performance are good both in case of persistent and abrupt disturbances. Given the algorithm, there is an interest in seeing how the quality of the prediction can be assessed and how the parameters of the algorithm affect the quality of the prediction. Since the interest is in creating an algorithm that works with minimal human intervention, the tuning parameters should be found automatically. Here the tuning parameters are found through a grid search algorithm. Furthermore, not all time series are predictable because they lack of regularity. The forecastability has to be assessed. This chapter proposes answers to these questions and it is based on the publication Borghesan et al. (2019a), which is part of a special issue in the journal *Computer and Chemical Engineering* dedicated to selected works presented at the *PSE 2018* conference in San Diego, USA.

The structure of the chapter is the following. Section 4.2 describes the algorithms, Section 4.3 focuses on assessing the quality of the prediction, Section 4.4 explains the method to find the optimal parameters of the k-nearest neighbours, Section 4.5 describes a qualitative and quantitative method to assess the predictability of a time series, Section 4.6 presents the autoregressive model used as alternative method for comparison, Section 4.7 describes the time series of the industrial time series used for testing, Section 4.8 to Section 4.10 present the results. The chapter ends with the summary in Section 4.11

4.2 $k-$NEAREST NEIGHBOURS

4.2.1 Basic concepts of nearest neighbour prediction

The $k-$nearest neighbours method supposes that the current time series segment will evolve in future like a past time series segment (not necessarily a recent one) evolved previously (Kantz and Schreiber, 2004). The task therefore is to identify past segments of the time series which are similar to the present one according to a certain norm.

At current sample time t, the algorithm considers a measurement time series made of t samples $\mathbf{y}_M(t) = [y(1)\ y(2) \dots y(t)]$, termed 'memory'. The size t of the memory increases as more samples $y(\cdot)$ are recorded. The segment made of the last m samples of $\mathbf{y}_M(t)$ is $\mathbf{y}_E(t) =$

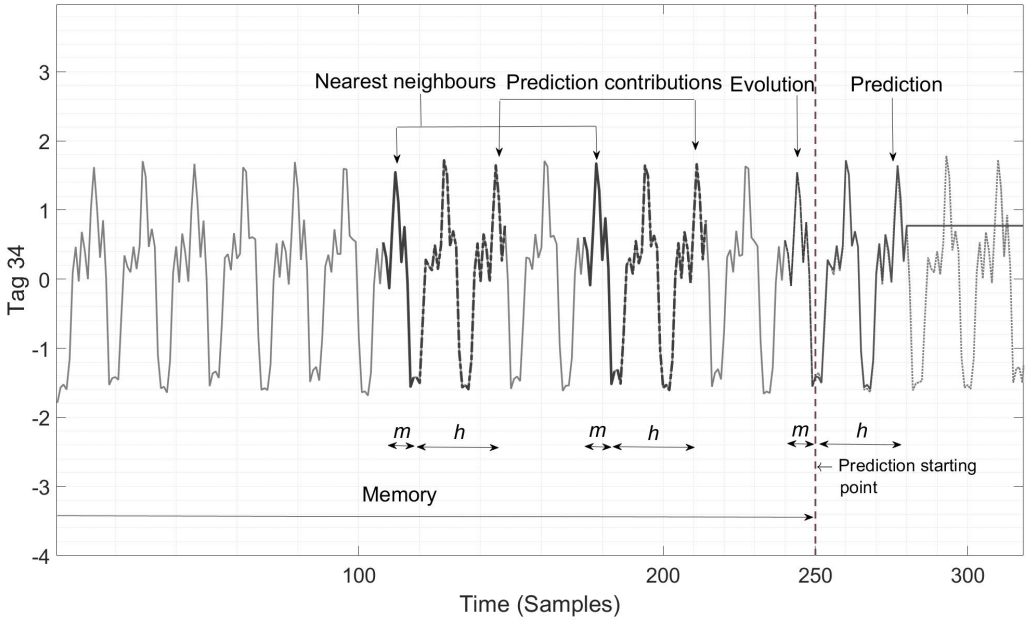


Figure 4.1: An example of a persistent disturbance and representation of terminology (from Borghesan et al. (2019a))

$[y\,(t-m+1)\quad y\,(t-m+2)\ldots y(t)]$. This segment represents the current evolving disturbance pattern and is called $\mathbf{y}_E(t)$ 'evolution', while m is known as the 'embedding dimension' (Kantz and Schreiber, 2004). The algorithm searches within the memory $\mathbf{y}_M(t)$ for the k time series intervals of length m that are most similar to $\mathbf{y}_E(t)$. The similarity is measured in this work with the Euclidean distance, D (Eq. 4.1). These k time series intervals $\mathbf{y}_j,\ j = 1,\ldots,k$ are the $k-$nearest neighbours and are those k time series intervals within $\mathbf{y}_M(t)$ with smallest Euclidean distances:

$$D\left(\mathbf{y}_E(t),\mathbf{y}_j\right) = \sqrt{\sum_{i=1}^{m}\left(y_E\,(i) - y_j\,(i)\right)^2} \tag{4.1}$$

As depicted in Fig. 4.1, each nearest neighbour $\mathbf{y}_j$ is followed by a time series of length h, where h is the desired prediction horizon. These time series of length h are called the 'prediction contributions' $\mathbf{y}_{P\,j}, j = 1,\ldots,k$. They show how their corresponding nearest neighbours evolved over an interval of length h. Therefore, they are the basis for building the prediction vector, as will be described in Section 4.2.2. Since all prediction contributions must stay within the memory

$\mathbf{y}_M(t)$, there is a constraint for the starting points r_j of the nearest neighbours $\mathbf{y}_j$

$$\begin{aligned} \mathbf{y}_j &= \left[y\left(r_j\right) \quad y\left(r_j+1\right) \ldots \quad y\left(r_j+m\right)\right], \\ j &= 1, \ldots, k, \\ r_j &\in [1; t-h-m+1] \end{aligned} \tag{4.2}$$

Consequently $\mathbf{y}_{Pj}$ is defined as

$$\begin{aligned} \mathbf{y}_{Pj} &= \left[y\left(r_j+m+1\right) \quad \ldots \quad y\left(r_j+m+h\right)\right] \\ j &= 1, \ldots, k \end{aligned} \tag{4.3}$$

4.2.2 Two versions of the algorithm

Unweighted and weighted versions of the algorithm differentiate themselves at this step. For the unweighted version, the prediction is an average of the prediction contributions. The prediction is a vector $\hat{\mathbf{y}}(t) = [\hat{y}\,(t+1) \ldots\ \hat{y}\,(t+h)]$ where:

$$\hat{y}(t+i) = \frac{1}{k} \sum_{j=1}^{k} y_{P\ j}(i), \quad i = 1, \ldots, h \tag{4.4}$$

In the weighted version of the algorithm, the nearest neighbours contribute to the prediction proportionally to their distance from the evolution. First a weight w_j for each nearest neighbours is calculated. The weight $w_j = 1$ if the nearest neighbour $\mathbf{y}_j$ has the smallest distance with $\mathbf{y}_E(t)$. Conversely, $w_j = 0$ if the corresponding nearest neighbour $\mathbf{y}_j$ is the most distant from $\mathbf{y}_E(t)$.

$$w_j = \begin{cases} \dfrac{\max\limits_{\ell=1\ldots k} \left(D(\mathbf{y}_E(t), \mathbf{y}_\ell)\right) - D(\mathbf{y}_E(t), \mathbf{y}_j)}{\max\limits_{\ell=1\ldots k} \left(D(\mathbf{y}_E(t), \mathbf{y}_\ell)\right) - \min\limits_{\ell=1\ldots k} \left(D(\mathbf{y}_E(t), \mathbf{y}_\ell)\right)} & \text{with } j = 1, \ldots, k \quad \text{if } k \geq 2 \\ 1 & \text{with } j = 1 \qquad \text{if } k = 1 \end{cases} \tag{4.5}$$

The prediction vector $\hat{\mathbf{y}}(t) = [\hat{y}\,(t+1) \ldots\ \hat{y}\,(t+h)]$ is a weighted average of the prediction contributions, where:

$$\hat{y}\,(t+i) = \frac{1}{\sum_{j=1}^{k} w_j} \sum_{j=1}^{k} w_j\ y_{P\ j}(i) \quad i = 1, \ldots,\ h \tag{4.6}$$

The weighted method has been developed to guarantee a higher robustness and precision of the prediction, since it is able to partially ignore the nearest neighbours that are too distant from the evolution. This is interesting when the algorithm works over an interval of time and the possibility of finding exactly k good nearest neighbours can change over time.

4.2.3 A FIXED NUMBER OF NEIGHBOURS VERSUS A MAXIMAL NEIGHBOURS DISTANCE

Concerning the number of nearest neighbours to be found, a possibility is setting a fixed number k, indipendently from the instant of time t in which the prediction should start. Kantz and Schreiber (2004) proposed to choose the maximal distance $D_{\max}$ between evolution and a neighbour, for which the neighbour can be considered as one of the nearest neighbours that will evolve as the evolution $\mathbf{y}_E(t)$.

Indeed, if the distance $D(\mathbf{y}_E(t), \mathbf{y}_j)$ in Eq. 4.1 is too large, then it is likely that the time segment $\mathbf{y}_j$, chosen as nearest neighbour of $\mathbf{y}_E(t)$, will not evolve in the future as the evolution $\mathbf{y}_E(t)$ will do because the chosen nearest neighbour does not capture the same dynamic occurring to the evolution. In this case, the time segment $\mathbf{y}_j$ can be defined as false nearest neighbour. Choosing constantly a number k of nearest neighbours, without taking into account their distance from the evolution, has the risk of selecting false nearest neighbours.

On the other hand $D_{\max}$ cannot be too small. For example, some time series segments might be affected by noise in the measurement. This implies that although such time series segments are relatively distant from the evolution because of noise, they reflect the same dynamic. In a such case, averaging more prediction contributions (without considering false nearest neighbours) can have the beneficial effect of finding the expected value of the prediction.

Using the approach of $D_{\max}$, k is chosen at each sample t as

$$\begin{aligned} k(t, D_{\max}) &= |Y_{NN}(t, D_{\max})| \\ Y_{NN}(t, D_{\max}) &= \{\mathbf{y}_1, \ldots, \mathbf{y}_k : D(\mathbf{y}_E(t), \mathbf{y}_j) \leq D_{\max}\} \end{aligned} \tag{4.7}$$

In the above expression, $|\cdot|$ has been used to indicate the number of items in the set. Setting a fixed $D_{\max}$ is different from setting a fixed k only if $D_{\max}$ and k are constant over a certain interval of time. Instead, considering a prediction starting at a certain instant of time, certain values of $D_{\max}$ correspond to a specific value of k.

4.3 MEASURING ACCURACY

4.3.1 Measuring the accuracy of the prediction for varying values of k and m at an instant of time t

For a given starting point of the prediction t, the tuning parameters of the methods are m and k. Varying m and k causes the average prediction distance to change. The prediction distance E_{av} is the Euclidean distance between the prediction and the corresponding segment of the actual future time series (not known in advance to the algorithm) divided by the chosen prediction horizon h so that the value does not depend on the length of the prediction horizon.

$$E_{av}(t,k,m) = \frac{1}{h} D(\hat{\mathbf{y}}\,(t,k,m)\,,\ [y\,(t+1)\ldots y\,(t+h)]) \tag{4.8}$$

The smaller $E_{av}(t)$ is, the more accurate the prediction is.

4.3.2 Measuring the accuracy of the prediction for varying values of k and m over an interval of time

Eq. 4.8 measures the error made at one sample time t. However, the optimal parameters m and k change for different sampling times. Consequently, it is important as well to measure the performance of a fixed m and k over an interval of time. This work introduces the measure

$$E^{k_{\max}}_{av\ \mathrm{int}}(t_1,t_2,k,m) = \frac{1}{t_2-t_1}\sum_{t=t_1}^{t_2} E_{av}(t,k,m) \tag{4.9}$$

The superscript $k_{\max}$ means the number of nearest neighbours is constant over time. The subscripts 'av int' means that this measure is an average of the prediction error over an interval.

Similarly, it is possible to fix a value $D_{\max}$ and m over a certain interval. In this case k might change but depends on a fixed $D_{\max}$, as Eq.4.7 described.

$$E^{D_{\max}}_{av\ \mathrm{int}}(t_1,t_2,D_{\max},m) = \frac{1}{t_2-t_1}\sum_{t=t_1}^{t_2} E_{av}\,(t,k(t,D_{\max}),m) \tag{4.10}$$

To not overload the notation, the following expression in introduced when the discussion refers to both $E^{k_{\max}}_{av\ \mathrm{int}}$ and $E^{D_{\max}}_{av\ \mathrm{int}}$ and the main focus is the interval of time $t_1 \rightarrow t_2$.

$$E_{av\ \mathrm{int}}(t_1,t_2) \tag{4.11}$$

4.4 TRAINING OF THE OPTIMAL PARAMETERS

4.4.1 Finding the tuning parameters through an optimization problem

A rule of thumb is to set the embedding dimension m to $\lfloor \frac{1}{f_0} \rfloor$, where $\lfloor \cdot \rfloor$ is the floor function that provides the smaller or equal integer of a real number, and f_0 is the main frequency of the persistent disturbance. In this case m is close to the length of one instance of the repeating pattern of the persistent disturbance. The number of nearest neighbours k should be $k = \lfloor \frac{t}{m} \rfloor$, which means equal to the number of occurrences of the repeating pattern. This strategy will be called *base strategy* in the rest of the work.

The present work proposes to find the parameters through a training algorithm based on a search grid. This involves enumerating the possible combinations within a range of the parameters k and m, or $D_{\max}$ and m depending on the strategy used, and choosing the pair of parameters that minimises $E_{av\,\mathrm{int}}(t_1^{\mathrm{tr}}, t_2^{\mathrm{tr}})$ with $t_2^{\mathrm{tr}} < t - h$, where t is the current instant of time. The interval $t_1^{\mathrm{tr}} \rightarrow t_2^{\mathrm{tr}}$ is the training interval and corresponds to values $y(t_1), y(t_1 + 1)...y(t_2)$ that have been already measured at instant t. Since these values are known, the training algorithm can compare what the prediction would be for each instant of the training interval and what it was in reality. The condition $t_2^{\mathrm{tr}} < t - h$ is set because the algorithm had to measure the values of the time series to calculate the value of $E_{av}(t_2)$ used to calculate thereafter $E_{av\,\mathrm{int}}(t_1^{\mathrm{tr}}, t_2^{\mathrm{tr}})$. The length of the interval $t_1^{\mathrm{tr}} \rightarrow t_2^{\mathrm{tr}}$ is set to be long enough to cover some instances of the pattern of the disturbance. The training should not be conducted at every sample t, rather at discretion when, for example, new disturbances patterns are visible or when the noise level of the measurement is changing because of a change of the operating point of the plant.

4.4.2 Evaluating the accuracy of the training process for the choice of the tuning parameters

The parameters obtained from the training are $\left(k_{\mathrm{opt}}^{\mathrm{tr}}, m_{\mathrm{opt}}^{\mathrm{tr}}\right)$ or $\left(D_{\mathrm{max\,opt}}^{\mathrm{tr}}, m_{\mathrm{opt}}^{\mathrm{tr}}\right)$, depending whether a fixed k or $D_{\max}$ was defined.

To measure how accurate the training was, the prediction obtained from such parameters should be evaluated over a test interval $t_1^{\text{test}} \rightarrow t_2^{\text{test}}$. The term of comparison is the value of $E_{av\,\text{int}}\left(t_1^{\text{test}}, t_2^{\text{test}}\right)$ obtained with the parameters $k_{\text{opt}}^{\text{test}}$, $m_{\text{opt}}^{\text{test}}$, $D_{\text{max opt}}^{\text{test}}$ that are the optimal ones for the testing interval $t_1^{\text{test}} \rightarrow t_2^{\text{test}}$.

The metric γ is the ratio between the value of $E_{av\,\text{int}}\left(t_1^{\text{test}}, t_2^{\text{test}}\right)$ obtained using the parameters $k_{\text{opt}}^{\text{tr}}$, $m_{\text{opt}}^{\text{tr}}$, $D_{\text{max opt}}^{\text{tr}}$ and the one obtained using $k_{\text{opt}}^{\text{test}}$, $m_{\text{opt}}^{\text{test}}$, $D_{\text{max opt}}^{\text{test}}$. Two versions $\gamma_{k_{\max}}$ and $\gamma_{D_{\max}}$ of γ are defined, according to the strategy used:

$$\begin{aligned}\gamma_{k_{\max}} &= \frac{E_{av\,\text{int}}^{k_{\max}}(t_1^{\text{test}}, t_2^{\text{test}}, k_{\text{opt}}^{\text{test}}, m_{\text{opt}}^{\text{test}})}{E_{av\,\text{int}}^{k_{\max}}(t_1^{\text{test}}, t_2^{\text{test}}, k_{\text{opt}}^{\text{tr}}, m_{\text{opt}}^{\text{tr}})} \\ \gamma_{D_{\max}} &= \frac{E_{av\,\text{int}}^{D_{\max}}(t_1^{\text{test}}, t_2^{\text{test}}, k_{\text{opt}}^{\text{test}}, m_{\text{opt}}^{\text{test}})}{E_{av\,\text{int}}^{D_{\max}}(t_1^{\text{test}}, t_2^{\text{test}}, k_{\text{opt}}^{\text{tr}}, m_{\text{opt}}^{\text{tr}})}\end{aligned} \tag{4.12}$$

4.5 ASSESSING THE PREDICTABILITY OF A TIME SERIES

4.5.1 Qualitative method to assess the predictability

To distinguish a time series with some recurring and deterministic patterns from a stochastic time series, the predictability of the time series should be assessed. Here, this is done with a qualitative method.

A practical qualitative method to estimate the predictability of a time series is to plot its phase space plot. The phase space plot associates to a value $y(t)$ of the time series the corresponding value $y(t-\tau)$, where τ is a delay. It possible also to draw a 3D plot where two values $y(t-\tau_1)$ and $y(t-\tau_2)$ are associated to $y(t)$. These plots highlight the presence of recurrent patterns in the time series and consequently their self-predictability, explained in Section 4.2.1.

4.5.2 Quantitative method to assess the predictability

The quantitative method that this thesis proposes derives from the Harris index described in Desborough and Harris (1992). The Harris index was developed for control loop performance assessment. The principle is that if the time series of the error of a controller is predictable, then the control has poor performance. Instead of being used on the time series of the error of a controller, here the procedure is used on the time series of a disturbance to assess the predictability of the time

series. The procedure is to tune an autoregressive (AR) model of the time series.

$$\hat{y}\,(t+h) = a_0 + a_1 y(t) + a_2 y(t-1) + \cdots + a_m y(t-q+1) \tag{4.13}$$

where the horizon h and the order q of the AR model can be chosen as described in Thornhill et al. (1999).

To tune the coefficients, a section of the time series with constant characteristics as the mean value must be provided. The coefficients of the model are found so that the residuals $r(t) = y(t) - \hat{y}(t)$ of the prediction are minimized for the training time series. The variance of the residuals is compared to mean square of the time series and this gives the Harris index.

$$H_{index} = \frac{\sigma_r^2}{\mathrm{mse}(y)} \tag{4.14}$$

where σ is the variance of the residuals and $\mathrm{mse}(y)$ is the mean square of the time series. If the residuals (and their variance) are large compared to the values of the time series (and consequently to their mean square), then the AR model is not able to capture fully the dynamic of the time series and, consequently, the time series has a low predictability. A value of $H_{index} = 0$ corresponds to a highly predictable time series. Therefore, a predictability index can be derived as

$$P_{index} = 1 - H_{index} \tag{4.15}$$

where $P_{index} = 1$ indicates that the time series is highly predictable and $P_{index} = 0$ indicates that the time series is not predictable.

A high value of the predictability index is a guarantee that the prediction will work. In case of a persistent disturbance, a value of predictability index smaller than 0.5 makes questionable the use for an application in process control.

For abrupt disturbances instead, a low value of the predictability index means that the abrupt event is not predictable before occurring. However, once it starts, its future evolution might be predicted.

4.6 THE AUTOREGRESSIVE MODEL AS REFERENCE OF COMPARISON

The widely used AR model, employed for the predictability index can also be used as comparison for the $k-$nearest neighbours methods presented in this work.

To compare the performance between the two methods, the same intervals of time are used for the training of the two methods. When the $k-$nearest method is trained on an interval $t_1^{\text{tr}} \rightarrow t_2^{\text{tr}}$, a memory, starting from the first recorded instant, should be provided to the algorithm. Consequently, to compare fairly the training done on the two methods, the AR model uses the interval $1 \rightarrow t_2^{\text{tr}}$ for the training.

The training and the prediction of the model is done using the routines in Matlab *estimate* and *forecast*. Once the prediction with the trained autoregressive model is obtained, the quality of the prediction can be obtained.

$$E_{av}^{\text{AR}}(t, AR_{\text{model}}) = \frac{1}{h} D(\hat{\mathbf{y}}\,(t, AR_{\text{model}})\,,\ [y\,(t+1)\ldots y\,(t+h)]) \tag{4.16}$$

$$E_{av\ \text{int}}^{\text{AR}}(t_1, t_2, AR_{\text{model}}) = \frac{1}{t_2 - t_1} \sum_{t=t_1}^{t_2} E_{av}^{\text{AR}}(t, AR_{\text{model}}) \tag{4.17}$$

where AR_{model} refers to the autoregressive model with its coefficients and previous time series elements.

A coefficient γ^{AR} can be introduced. Previously, in Section 4.4.2, the aim of γ is to understand how good the parameters for the $k-$nearest neighbours are. Here the aim of γ^{AR} is to understand how good is, over the testing interval, the trained autoregressive model $AR_{\text{opt}}^{\text{tr}}$ compared to the model $AR_{\text{opt}}^{\text{test}}$ that would result from the training on the testing interval.

$$\gamma_{\text{AR}} = \frac{E_{av\ \text{int}}^{\text{AR}}(t_1^{\text{test}}, t_2^{\text{test}}, AR_{\text{opt}}^{\text{test}})}{E_{av\ \text{int}}^{\text{AR}}(t_1^{\text{test}}, t_2^{\text{test}}, AR_{\text{opt}}^{\text{tr}})} \tag{4.18}$$

4.7 REAL INDUSTRIAL DISTURBANCES

Fig.4.2 shows the time series used to analyse the prediction methods. The upper and second panel of the figure show Tag 33 and Tag 34 from a SE Asian refinery. These time series have been presented previously, for instance in Thornhill (2005b).

Tag 33 has a persistent and regular oscillation. However, the repeating pattern is not so regular as the one of Tag 34. Further, there is a step change around sample 500, as shown in the arrow in the top panel of Fig.4.2. The first 500 samples have different values than the later samples, even though the pattern of oscillation is similar. Therefore, one can expect lower predictability just after the step change since there will be no nearest neighbours in the memory on which to base the prediction.

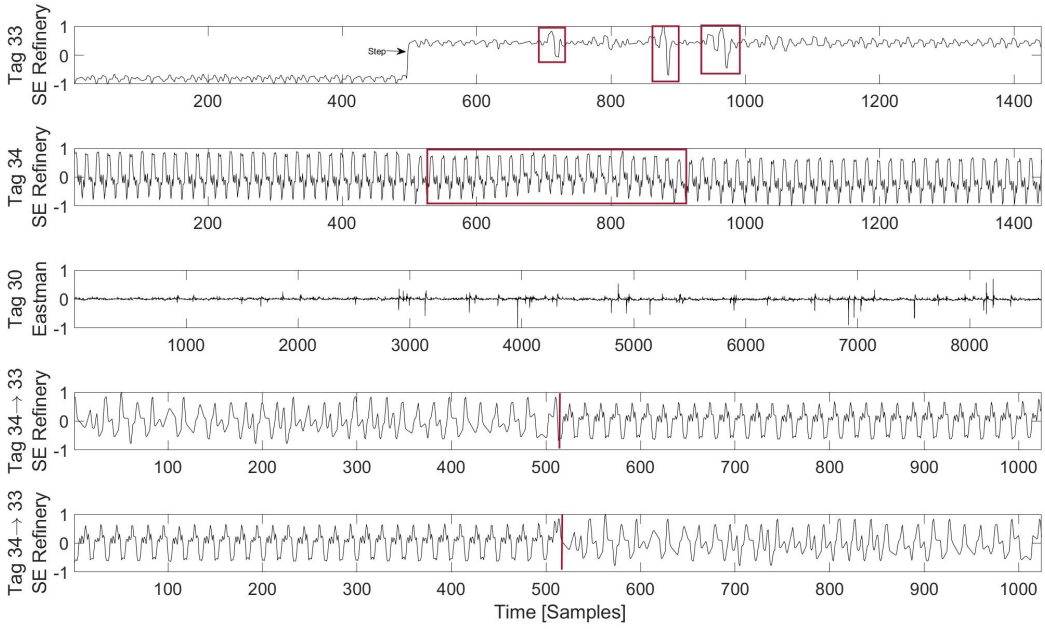


Figure 4.2: The time series considered for the section regarding the results of the prediction methods.

There are also three abrupt transient disturbances within the red rectangles shown on the figure that also will present challenges for prediction.

Tag 34 has a very regular and persistent oscillation, and it is expected to be highly predictable. However, the local mean value is not constant between sample 500 to 900, and this will reduce its predictability to an extent.

The third panel in Fig.4.2 shows Tag 30 of the dataset from the Eastman Chemical Company described in Thornhill et al. (2003). This time series is affected by phenomena of abrupt disturbances that take the form of short spikes of varying amplitude with durations of 3 to 5 samples.

The time trend of Tag 30 is affected by noise between the abrupt disturbances, and random noise is inherently unpredictable. Moreover, the occurrence of an abrupt disturbance is not predictable. However, the results will show that once the abrupt phenomenon starts, the k-nearest neighbours algorithm can detect the phenomenon and provide useful predictions.

The fourth panel shows a time series created by concatenating a section of the Tag 33 with one of the Tag 34. The time series in the fifth panel is built concatenating the same two time series but in the opposite order compared to the order of the fourth panel. These two time series, built

Table 4.1: Predictability index for the three main time series considered with $h = 15$ and $m = 30$

	Tag 33	Tag 34	Tag 30
P_{index}	0.610	0.984	0.001

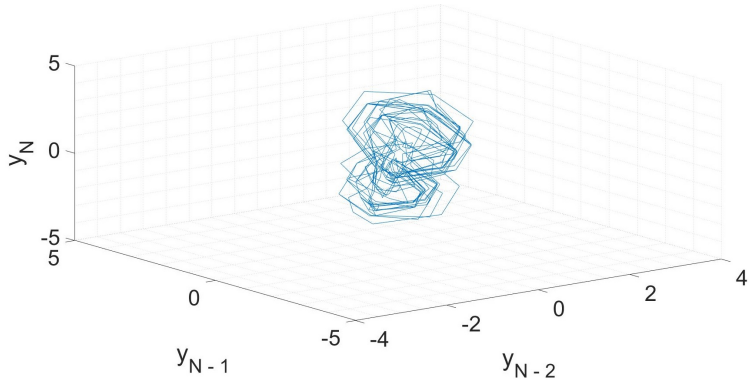
on-purpose, are used in Section 4.9 to show the effects of a time changing disturbance pattern on the prediction performances.

4.7.1 Qualitative assessment the predictability

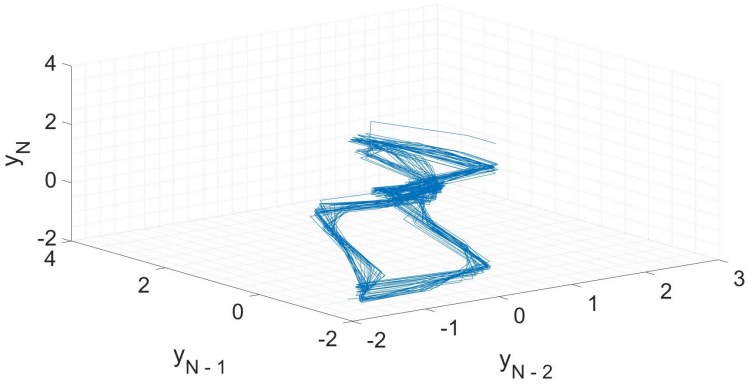
Fig.4.3 shows phase plots for the three main time series considered. Of the three phase plots, the plot in Fig.4.3b, corresponding to Tag 34, is far more well defined than the other two. Tag 34 shows how the $k-$nearest neighbours method can give good predictions because the trajectory tends to evolve in the same way from any given point. Tag 33 shows also some repeating trajectories but, qualitatively, the pattern is not well defined. The confused pattern at the centre of the plot for Tag 30 suggests that tag 30 has generally low predictability. However, there are spikes radiating from the centre. Once the $k-$nearest neighbours method has identified a spike, then Fig 4.3c shows that a return to the centre can be predicted.

4.7.2 Quantitative assessment the predictability

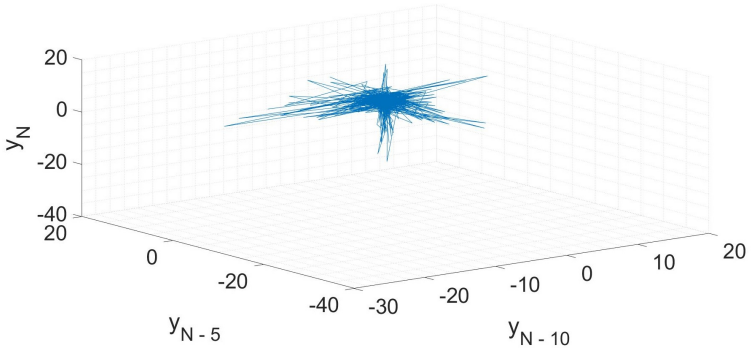
Section 4.5.2 described how to assess quantitatively the predictability of time series. The method is applied to the three industrial disturbances. The prediction horizon is set to $h = 15$ and the order is $m = 30$. Table 4.1 shows the predictability index for the three main time series considered. The quantitative analysis reflects what was already understandable from the qualitative analysis. The time series of the Tag 34 is extremely regular and predictable. However, the time series of Tag 33 and especially the time series of Tag 30 are harder to predict.



(a) Tag 33 SE Asian refinery



(b) Tag 34 SE Asian refinery



(c) Tag 30 Eastman Chemical Company

Figure 4.3: Phase space plots of sections of the considered time series

4.8 RESULTS: EFFECT OF k AND m ON $E_{av\,\mathrm{int}}$

4.8.1 Choice of settings of parameters

Fig.4.4 shows the effects of k and m on $E_{av\,\mathrm{int}}$ over an interval of time $t_1 \rightarrow t_2$. Indeed, it plots the values of $E_{av\,\mathrm{int}}$ for several combinations of k and m using the weighted and unweighted method for the three main considered time series. In all cases, the length of the interval $t_1 \rightarrow t_2$ is 1000 samples.

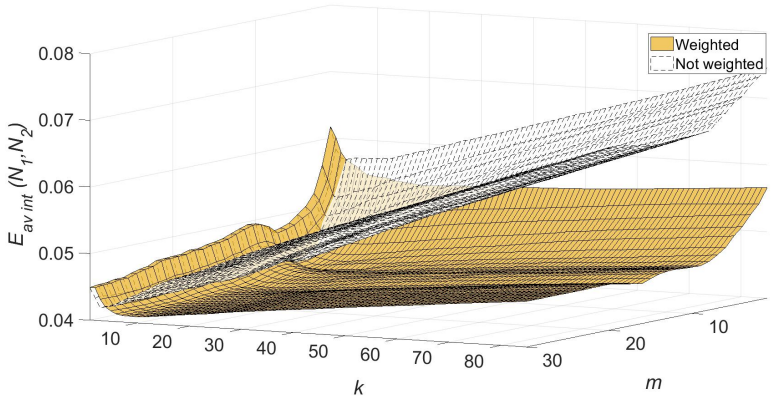
For the Tags 33 and 34 from the SE Asian refinery the prediction horizon is $h = 15$, roughly the period of the oscillation. The period of oscillation varies between 15 and 17 for Tag 33 and Tag 34. Tag 30 is affected by abrupt disturbances and once an abrupt disturbance starts, it is possible to predict its future values until the end of the disturbance pattern. The abrupt disturbance pattern of Tag 30 lasts generally 15 samples. Therefore, $h = 15$ as well for Tag 30.

For such sensitivity analysis, the maximal embedding dimension m has been chosen as roughly two times the period of one oscillation. Considering the period of oscillation for the Tags 33 and 34 equal to 17 samples then $m \approx 35$. The reason is that the most recent cycles are likely to be the most important to understand the future trend of a disturbance. However, there is no oscillation in Tag 30 but there are roughly six phenomena of abrupt disturbances every one thousand samples, although not at regular intervals (with a periodicity of about $\frac{1000}{6} \approx 165$). Given a periodicity of about 165 samples, the maximal possible value of m is 330, following the same principle used for the Tags 33 and 34.

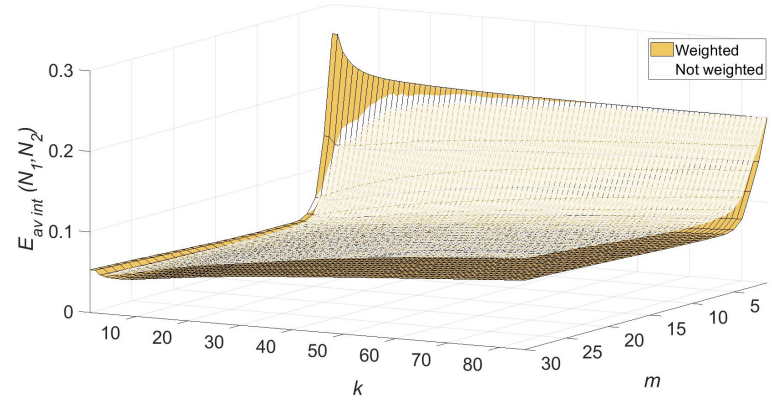
The maximal number of neighbours has been set as the number of samples t in the maximal memory t_2 over the interval divided by the length of one oscillation. Indeed, the maximal number of nearest neighbours that can be found in a series is equal to the number of cycles of oscillations in the memory. Consequently $k_{\max} = \frac{1420}{17} \approx 85$ for Tags 33 and 34 and $k_{\max} = \frac{7000}{165} \approx 50$.

4.8.2 The effect of m on $E_{av\,\mathrm{int}}$

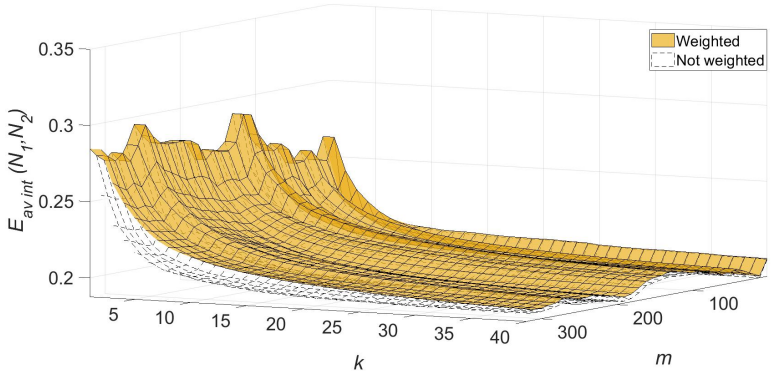
Fig. 4.4a and Fig. 4.4b shows that the value of $E_{av\,\mathrm{int}}$ can be high for very small values of the embedding m regardless of the value of k for the Tags 33 and 34, which characterized by a persistent disturbance. This is because an embedding dimension that does not capture a significant portion of the period of oscillation does not correctly identify the shape of the disturbance. For example,



(a) Tag 33 SE Asian refinery



(b) Tag 34 SE Asian refinery



(c) Tag 30 Eastman Chemical company

Figure 4.4: Effect of parameters k and m on prediction of Tags 33 and 34 with $t_1 = 400, t_2 = 1425$ and $h = 15$. Effect of parameters k and m on prediction of Tag 30 with $t_1 = 6000, t_2 = 7000$ and $h = 15$.

two points might have similar values in the ascending or descending phase of an oscillation but the prediction contributions $\mathbf{y}_P$ could be very different, thereby worsening the prediction. Tag 34 is more predictable and gives high values of $E_{av\,\mathrm{int}}$ when m is less than about 5 ($m \leq 5$). Tag 33 is less predictable and gives high values of $E_{av\,\mathrm{int}}$ for m smaller than about 7 ($m \leq 7$). Consequently, given in these cases a duration of pattern of about 17 samples, it is possible to say that m should be higher than a third of the duration of the repeating pattern for persistent disturbances. This limit is inserted in the search grid algorithm for the training of optimal parameters which has been described in Section 4.4.1.

However, Fig. 4.4c shows that the prediction error for Tag 30 seems to be largely independent from the value of m, with a slight tendency of improvement for small values of m. The reason of this slight improvement is that in case of an abrupt phenomena only a short time segment is needed to evaluate the distance between evolution and nearest neighbours. However, the measure $E_{av\,\mathrm{int}}$ is an average of the values E_{av} for the different instants t. The time series shows noise, except for few instants, precisely during the abrupt phenomena. Consequently, it is not very relevant which are the nearest neighbours picked for the prediction and consequently their embedding dimension. Since the aim for the Tag 30 is to predict the short abrupt phenomena, then the embedding dimension should not be chosen too large. Indeed, if the length of the evolution is too long, then the part of the evolution occurring before the abrupt event contributes considerably more in calculating the distance $D\left(\mathbf{y}_E(t), \mathbf{y}_j\right)$ (from Eq.4.1) than the short abrupt event.

4.8.3 The effect of k on $E_{av\,\mathrm{int}}$

For all the time series considered, choosing very few nearest neighbours (parameter k) is not good for the performance. Even Tag 34 benefits from having $k \geq 4$, as shown by Fig.4.4c where there are low values of $E_{av\,\mathrm{int}}$ even for very small of k. Indeed, the minimum value of $E_{av\,\mathrm{int}} = 0.38$ for Tag 34 is obtained for $k = 6, m = 10$. For the same m but $k = 2$, the error $E_{av\,\mathrm{int}}$ becomes 0.42 instead. The reason is that even persistent disturbances have some randomness. By averaging over more prediction contributions, the resulting prediction is closer to the true value.

Especially for noisy time series, such as Tag 33 and even more Tag 30, k cannot be too small. By using many nearest neighbours, the resulting prediction is filtered and is closer to the time series

underneath the hidden signal. For Tag 30 the graph suggests that the a high number of nearest neighbours should be used for the prediction. The presence of noise is the likely explanation of this behaviour. In this specific case k must be higher then 15 as Fig.4.4c suggests.

However, after a threshold, high values of k are not beneficial for more regular time series like Tags 33 and 34. Increasing k too much results in choosing time series intervals, called false neighbours, that are considered as nearest neighbours even though they are not very similar to the evolution $\mathbf{y}_E(t)$ and do not develop in the same way. To conclude, the minimal values of E_{av} are roughly given for values of $4 \leq k \leq 10$ for Tag 34 and $4 \leq k \leq 20$ for Tag 33 using the weighted algorithm.

4.8.4 Effects of weighted and unweighted method on E_{av}

Figures 4.4a and 4.4b show that the weighted method has the advantage of making the value of $E_{av\,\mathrm{int}}$ less sensitive to the choice of k for Tags 33 and 34 respectively. Therefore, the value of k is robust even when the characteristics of the disturbance are changing.

However, the unweighted method is generally better for Tag 30 for a certain value of k because the hypothesis on which the weighted method is based is not valid any more in presence of noise. Indeed, the weighted method assumes that the closer a nearest neighbour is to the evolution, the closer the corresponding prediction contribution will be to the future values of the time series.

4.9 RESULTS: COMPARISON OF THE TECHNIQUES CONSIDERED FOR DISTURBANCE FORECASTING

4.9.1 Overview

One interest of this section is analysing how good is the performance achieved by various techniques used to find the parameters for the $k-$nearest neighbours method in the prediction of the time series.

Section 4.4.1 stated that possible choices of the memory m and of the number of nearest neighbours k is to set $m = \lfloor \frac{1}{f_0} \rfloor$ and $k = \lfloor \frac{t}{m} \rfloor$. However, this is a rule of thumb and, furthermore, the choice of f_0 for a time series affected by abrupt disturbances is not trivial. This strategy for the choice of m and k is compared here with the strategies based on the grid search method explained in Section

4.4.1. To provide terms of comparison, the best predictions available at each instant of time t using the weighted and unweighted algorithm are used.

The other interest of this section is to highlight the advantages of the $k-$nearest neighbours in comparison to the autoregressive model.

4.9.2 The searching grid, training and testing interval

The optimal parameters are found with a grid search algorithm, which means that the parameters are chosen by testing combinations of the parameters that are within a range. Table 4.2 shows the extremes of such ranges and the discretization step.

The training time has been chosen so that several instances of the patterns of the disturbances are present. For the tags from the SE Asian refinery the length of the training interval $t_1^{\text{tr}} \rightarrow t_2^{\text{tr}}$ was 70 samples. For Tag 30, the length of the training interval was 985 samples.

The testing interval for the tags from the SE Asian refinery includes the transitory variations, such as the step change for Tag 33. For Tag 30 the testing interval encompasses eight instances of abrupt disturbances of varying amplitude.

Furthermore this section analyses also the composed time series called Tag 33→34 and Tag 34→33, which have been described in Section 4.7. In these two cases, the parameters obtained from the training on the first section of the time series are tested on the second half. This simulates the case when the pattern of the disturbance is changing and the method must learn how to predict this new pattern.

4.9.3 Performance of various strategies

Table 4.3 shows the values of $E_{av\,\text{int}}$ for the time series considered over their testing interval with different strategies. The strategies are listed below.

- 'Opt': the best prediction available at each sample time t with a value of $k_{\min} \leq k \leq k_{\max}$ and $m_{\min} \leq m \leq m_{\max}$. This is a term of comparison, since it is not possible at an instant t to know already the optimal parameters k and m for calculating the prediction

Table 4.2: Range of the parameters for the search grid optimization algorithms

	SE Asian refinery			Eastman Chemical Company		
	Tag 33 and Tag 34			Tag 30		
	k	$D_{\max}$	m	k	$D_{\max}$	m
Min	4	0	5	4	0	1
Discretization Step	1	0.001	1	1	0.01	10
Max	85	0.5	30	50	1	50
Prediction Horizon	15					

- 'Base': the prediction obtained using the parameters $k = \lfloor \frac{t}{m} \rfloor$ and $m = \lfloor \frac{1}{f_0} \rfloor$
- 'Opt k': The prediction obtained using the weighted method training the algorithm to find the fixed parameters k and m that minimized $E_{av\ \mathrm{int}}(t_1^{\mathrm{tr}}, t_2^{\mathrm{tr}})$
- 'Opt $D_{\max}$': The prediction obtained using the weighted method and training the algorithm to find the fixed parameters $D_{\max}$ and m that minimized $E_{av\ \mathrm{int}}(t_1^{\mathrm{tr}}, t_2^{\mathrm{tr}})$
- 'AR': The prediction obtained using the AR model fitted on the interval $1 \rightarrow t_2^{\mathrm{tr}}$

For each of the strategies considered (excluding the AR model) the values $E_{av\ \mathrm{int}}$ using the weighted method are given. Further, the ratio

$$\Xi = \frac{E_{av\ \mathrm{int}}^{\mathrm{weighted}} - E_{av\ \mathrm{int}}^{\mathrm{unweighted}}}{E_{av\ \mathrm{int}}^{\mathrm{unweighted}}} \cdot 100 \tag{4.19}$$

is provided. This ratio shows the improvement on $E_{av\ \mathrm{int}}$ using the weighted method instead of the unweighted one. A negative value of Ξ ($\Xi < 0\%$) indicates that that the weighted method had better performance compared to the unweighted method for the interval of time considered. The opposite occurs for a positive value of Ξ ($\Xi > 0\%$). Furthermore, the magnitude of the index Ξ shows how large the improvement (or deterioration) was.

Table 4.3: Values of $E_{av\ \mathrm{int}}$ obtained with the considered strategies, values of the metric γ to measure the accuracy of the training and values of the metric Ξ to evaluate the performance of weighted method in comparison to the unweighted one

		Tag 33	Tag 34	Tag 30	Tag 33→34	Tag 34→33
Opt	Weighted	0.031	0.025	0.168	0.026	0.112
	Ξ	-3.13 %	0.00 %	+3.07 %	-16.1 %	+9.80 %
Base	Weighted	0.044	0.070	0.195	0.068	0.153
	Ξ	-17.0 %	-21.4 %	+1.56 %	-33.3 %	-10.5 %
Opt k	Weighted	0.041	0.039	0.186	0.047	0.157
	Ξ	-10.9 %	-7.14 %	-1.59 %	-29.9 %	-5.42 %
$\gamma_{k_{\max}}$	Weighted	1.000	0.974	1.000	0.766	0.892
	Unweighted	0.913	0.976	0.989	0.642	0.867
Opt $D_{\max}$	Weighted	0.042	0.042	0.193	0.052	0.184
	Ξ	-2.33 %	0.00 %	0.00 %	-11.86 %	0.00 %
$\gamma^{D_{\max}}$	Weighted	1.000	0.952	1.000	0.731	0.788
	Unweighted	0.977	0.976	1.000	0.661	0.793
AR	-	0.878	0.160	0.199	0.148	0.162
γ^{AR}	-	0.056	0.375	0.938	0.338	0.864

The table show also the metric γ that has been introduced in Eq. 4.12 for evaluating the accuracy of the training process.

4.9.4 Comparison of the performance between the Base strategy, and the Opt k and Opt $D_{\max}$ strategies

Comparing the rows of Table 4.3 relative to the Opt k and Opt $D_{\max}$ strategies with the rows relative to the Base strategy shows that the impact of the choice of the parameters depends on the predictability of the time series.

If the time series is highly predictable, then the strategies based on grid search algorithms explained in Section 4.4.1 improve the quality of the prediction compared to the base strategy. Indeed, Tag

34 is highly predictable and one can get very good results by careful tuning. Tags 33 and 30 are less inherently predictable and the achievable performance of the prediction are less sensitive to the tuning parameters. This can also be seen comparing Fig. 4.4a with Fig. 4.4b, which show the values of $E_{av\text{int}}$ for the Tag 33 and Tag 34. The surface graph for Tag 34 changes in magnitude more that the graph for Tag 33 when parameters k and m are varied. Tag 30 in Fig. 4.4c changes for varying values of k but not too much for varying values of m.

4.9.5 Comparison of the performance between the Opt k and Opt $D_{\max}$ strategies

The results show that setting a certain value of k instead of a certain value of $D_{\max}$ makes no difference in most cases or it is even better in some of the cases. The major difference is in the computational time needed to obtain the optimal parameters. Indeed, the grid used to find the optimal parameters should be very fine along the values of $D_{\max}$ in order to obtain good results. The consequence is that the method that uses $D_{\max}$ needs to compute far more combinations of the parameters for the search grid algorithm. Therefore, this approach is not recommended.

4.9.6 Analysis of the metrics γ about the quality of prediction in the test interval

For Tags 33, 34 and 30, where the pattern in the time series is repeating itself, there is not a significant difference of performance between using the parameters obtained from the training of the algorithm and best results obtainable for the interval considered. Table 4.3 shows indeed high values of γ for these Tags. Consequently the conducted training has been enough to nearly reach the optimal performances available from the strategy.

Instead, there is a decrease of performance in case of the two synthetic time series Tag 33→34 and 34→33, especially in the case of Tag 33→34. However, γ for the Tag 33→34, using the weighted method, is 0.76. In comparison the AR model shows a γ of just 0.33. Therefore the $k-$nearest neighbour method shows a far higher robustness.

4.9.7 Comparison between the weighted and unweighted method

The prediction performance obtainable with the unweighted method, if k and m are allowed to change over time, is in some cases slightly better than the performance with the weighted method. This is can be seen from the values $E_{av\,\mathrm{int}}$ corresponding to the strategy 'Opt'. However, the strategy 'Opt' is a term of comparison. It is not possible to know at an instant t what are the optimal parameters to be chosen for the $k-$nearest neighbour method.

Looking at the ratio Ξ (Eq.4.19) for the different strategies, it is possible to see that the weighted method improves the prediction, except for Tag 30, where the 'Base unweighted' strategy is slightly better than the weighted one.

Therefore, the recommendation is to use the weighted method because it provides generally better results.

4.9.8 Comparing the behaviour of the $k-$nearest neighbour method with the linear AR model

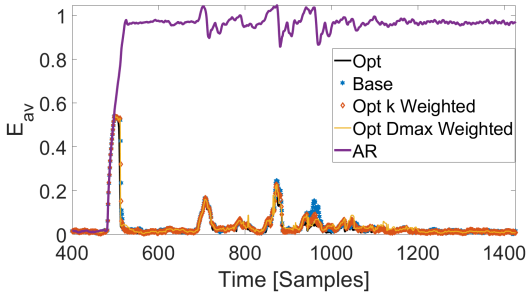
Table 4.3 shows that the values of $E_{av\,\mathrm{in}}$ are far higher for the predictions obtained by the autoregressive model than the $k-$nearest neighbours for Tags 33,34 and 33$\rightarrow$34. Furthermore, the values of γ^{AR} are very low, meaning that a retraining of the model would be necessary. Instead, the values of γ for the $k-$nearest neighbours are high, meaning that the the $k-$nearest neighbours does not need a retraining.

This observation highlights one of the advantage of the $k-$nearest neighbours, which is the capability to learn new patterns, without new training and human intervention for the choice of the parameters.

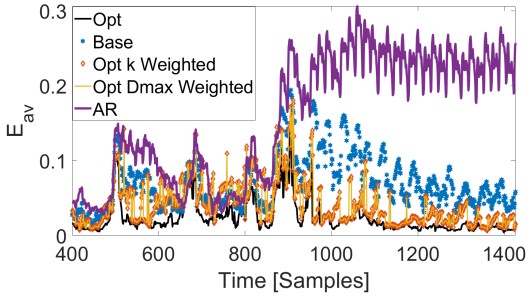
4.9.9 Variation of the values of E_{av} over time

Fig. 4.5 plots the values of E_{av} over time using the strategies discussed above. Given the analysis done in Section 4.9.7, only the weighted method is plotted.

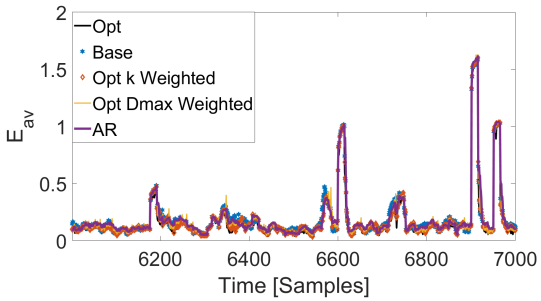
From Fig. 4.5, it is visible that the best performance available, indicated as 'Opt', vary over time.



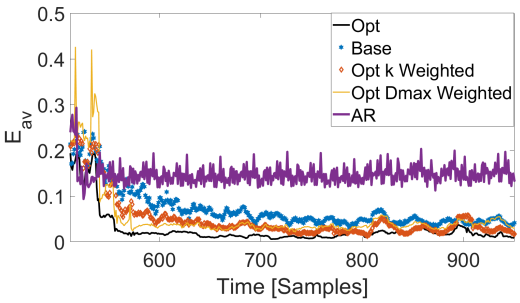
(a) Tag 33 SE Asian refinery



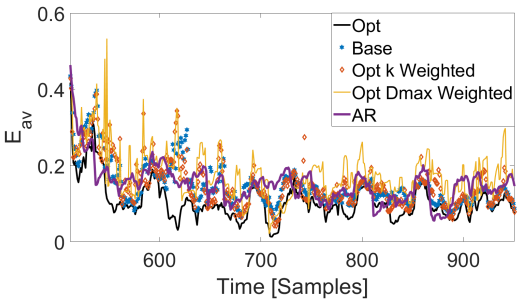
(b) Tag 34 SE Asian refinery



(c) Tag 30 Eastman Chemical Company



(d) Tag 33→34 SE Asian refinery



(e) Tag 34→33 SE Asian refinery

Figure 4.5: Optimal distances achievable over time for various strategies

Furthermore, some strategies might appear better than other in some intervals of time and worse in other intervals. Therefore, a performance metric that takes an interval of time into account is needed. This is the reason behind the metric $E_{av\,\mathrm{int}}$ explained in Section 4.3.2.

Regarding the $k-$nearest neighbours, some plots exhibit a peak of E_{av} when the time trend has events or disturbance patterns that do not resemble events present in the memory of the algorithm. This is the case of the step present in the Tag 33, for example, in Fig. 4.5a. This event highlights also the time that the $k-$nearest neighbours algorithm needs to acquire new data at the new operating condition and be able to provide reliable predictions again. The strategies based on $k-$nearest neighbours need circa 50 samples to learn again how to predict the time series of the disturbance after the step present in Tag 33. This is equivalent to 50 minutes of measurements. Fig. 4.5d shows similar results for the time series Tag 33→34. The technical objective that this chapter pursues is to use an amount of industrial data smaller than a few hours to provide to multi-step prediction of a time series.

The AR model instead after a transient is not able to learn a new model unless it is retrained. Consequently an offset might be visible on the value of E_{av} for the AR model. Of course, an AR model is intended for stationary time series, but in process plants it might be common that the time series of the measured disturbances are not stationary and in this case the $k-$nearest neighbours has an advantage.

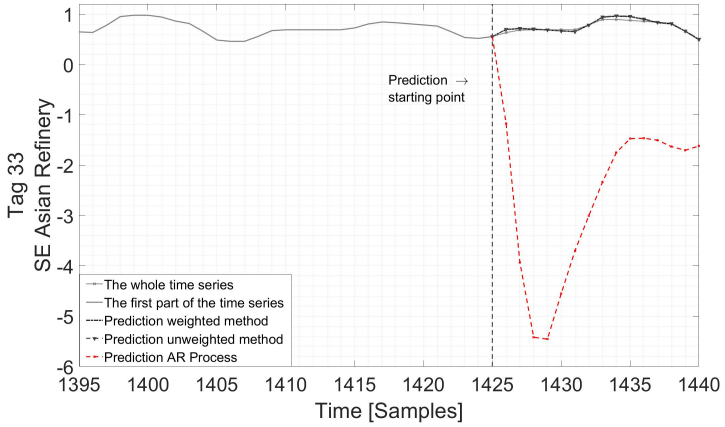
Finally, the values of E_{av} of different strategies overlap for the Tag 30, which is the least predictable of the all time series considered. Instead, for the other Tags 33 and 34, and their composite time series 33→34 and 34→33, there is a visible distinction between the different strategies. Highly predictable time series benefit more from an accurate choice of the parameters of the k-nearest neighbours.

4.10 RESULTS: EXAMPLES OF PREDICTION AT ONE INSTANT OF TIME

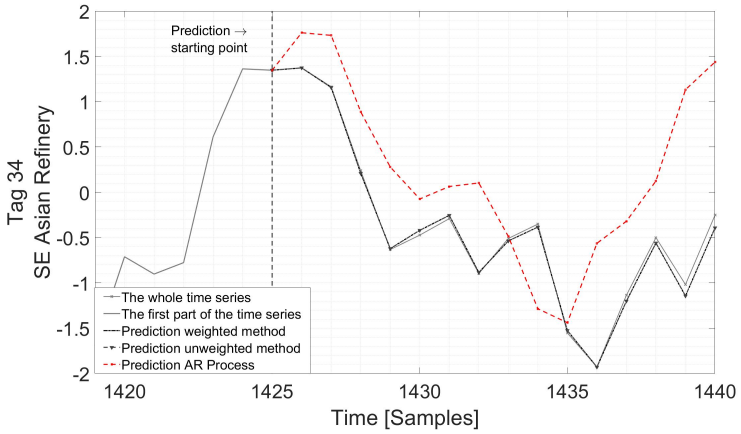
Fig. 4.6 provide examples of possible prediction obtainable using the parameters and the AR model resulting from the training process. For the Tags 33 and 34 the prediction starts at instant $t = 1425$, using a prediction horizon $h = 15$. This instant of time lies in the region where the AR models for the two time series show a deterioration of the prediction performance. For Tag 30 the prediction starts from the Eastman Chemical company $t = 6615$ and $h = 15$.

As regards the two Tags 33 and 34, the AR model shows qualitatively the deterioration of the performance of the AR model compared to the prediction obtained by the $k-$nearest neighbour method.

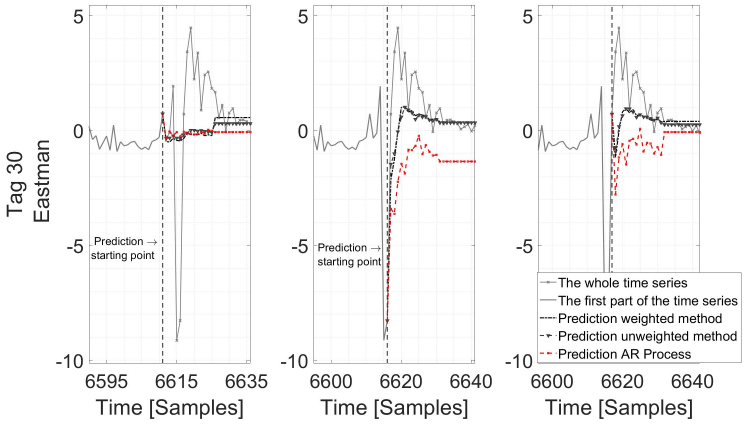
As regards Tag 30, Fig.4.6c shows that neither the k-nearest neighbours nor the autoregressive model predict the abrupt disturbance just before it happens. However, once it happens they can forecast the future trend and, nonetheless, the $k-$nearest neighbours shows better performance.



(a) Tag 33 SE Asian refinery



(b) Tag 34 SE Asian refinery



(c) Tag 30 Eastman Chemical Company

Figure 4.6: Examples of predictions obtained with the weighted and unweighted k-nearest neighbours methods using the parameters obtained from the training and with the AR model

4.11 SUMMARY

This chapter has focused on the prediction of persistent and abrupt process disturbances. Predicting these process disturbances is the second of the technical objectives of the thesis which have been presented in Section 1.6. Once this technical objective has been achieved, the prediction can implemented in the MPC framework proposed in this thesis for handling propagating disturbances.

The chapter proposed two versions of the k-nearest neighbours method to predict the future values of process disturbances. The methods have been able to provide good predictions of three time series of real plants, affected by persistent oscillating disturbances or spiky abrupt ones. The work shows also how to assess the predictability of a time series, analyses the impact of the parameters k, $D_{\max}$ and m on the predictions. The chapter provides guidance in their choice and compares different strategies to obtain the parameters. It concludes that the weighted method is more robust, and that using a fixed number of neighbours k in place of a fixed distance $D_{\max}$ leads to no deterioration of performance and it is computationally faster to find its optimal parameters. Furthermore, when a strong self-predictability is present, an algorithm that optimizes the choices of the tuning parameters is beneficial for the quality of the prediction. On the other hand, when a strong self-predictability is not present, the method is robust to a wide range of values of the parameters.

The work has also analysed the effect of changing characteristics of the disturbance in the prediction performance and does a comparison of the $k-$nearest neighbours method with the predictions obtained with an autoregressive model. This analysis shows that the $k-$nearest neighbours is better because it is able to learn fast to predict the changing characteristics of the disturbance in an unsupervised way. The $k-$nearest neighbours required less than one hour of new collected data to be able to predict the disturbances again with good accuracy, once the pattern of the disturbance changed.

Chapter 5

MPC WITH DISTURBANCE FORECASTING WITH APPLICATIONS

This chapter discusses how a prediction of a measured process disturbance can be used by an MPC controller to bring advantages for the controlled process. The advantages are measured in terms of capability of the controller to avoid a propagation of the disturbance, to reduce the variability of the key controlled variables, and to avoid violations of constraints. The chapter discusses technical aspects of the MPC and the use of such MPC on specific case studies.

The technical aspects that are examined are the tuning, implementation and evaluation of the controller. In particular, using a prediction of a disturbance adds a new tuning parameter to an MPC controller, which is the length of the prediction. This chapter discusses how this parameter should be tuned.

The tuning of the controller is presented for three case studies, explaining how the controller can dampen the propagation of a disturbance through mass and energy flows, while the key controlled variables are at their set-points. The case studies simulate a laboratory Continous Stirred Tank Heater (CSTH), a 160 MW power generation boiler, and an industrial azeotropic distillation column.

5.1 INTRODUCTION

The chapter focuses on the last two technical objectives listed in Section 1.6. These technical objectives are the implementation and the evaluation of an MPC controller that uses a multi-step forecast of a measured disturbance in order to avoid a propagation of the disturbance, and to reduce the variability of the key controlled variables.

To achieve this, three aspects are now considered. One aspect requires to define which are the variables of the controlled system that can propagate a disturbance, which are the key variables that have to follow strictly their set-points, and which can act as buffer.

Another aspect is understanding how to implement and tune the proposed MPC controller properly, considering that the presence of a disturbance prediction introduces an additional parameter. Specifically, this thesis investigates how the disturbance horizon of the prediction affects the performance of a controller that uses this prediction. A key-point is also tuning the MPC so it handles buffer variables properly. The aim is that certain manipulated variables vary minimally and do not propagate a disturbance, while their corresponding controlled variables can act as buffer by staying within constraints and without following strictly a set-point.

Furthermore, the chapter provides a set of metrics that assess in three aspects the performance of a controller:

- Avoidance of a propagation of the disturbance
- Reduction of the variability of the key controlled variables
- Avoidance of violations of the constraint

The chapter examines three case studies, which are a laboratory CSTH tank, a steam generation boiler and a distillation column. These systems have an increasing level of complexity and describe different scenarios that might occur in a production site. In particular, the steam boiler and the distillation column represent units respectively of the steam utility and the production plant. Chapter 3 concluded that these areas are the most relevant for disturbance propagation within a production site.

The chapter starts with Section 5.2 on the background and motivation, which describes the MPC formulation used, discusses the implementation issues that can arise, and explains the needs of metrics for the evaluation of the performance in handling plant-wide and site-wide disturbances. Section 5.3 explains how the implementations issues have been solved and Section 5.4 defines the metrics for the assessment of a controller. Section 5.5 clarifies what is the purpose of each case study within the thesis. The subsequent Section 5.6, Section 5.7 and Section 5.8 describe the three case studies, laying out the strategy that the controller should pursue and how this is translated in tuning parameters of the controller.

5.2 BACKGROUND AND MOTIVATION

5.2.1 MPC formulation

An MPC controller needs a model of the controlled system. The model is used to calculate the response of such system if a certain sequence of the manipulation variables would be applied. The aim is to find a sequence that minimises a certain objective function. The value of the objective function is obtained from the response of the system and from the sequence of the control action applied, as it will be explained later. Once the optimal sequence of the control action is calculated, the first element of the sequence for each manipulated variable is applied.

5.2.1.1 The model assumed

In linear MPC, the model used to calculate such response is discrete and linear.

$$\begin{aligned} x\,(t+1) &= Ax(t) + Bu(t) + B_d\hat{d}_{\mathrm{MPC}}(t) \\ y(t) &= Cx(t) + Du(t) + D_d\hat{d}_{\mathrm{MPC}}(t) \end{aligned} \tag{5.1}$$

where $x(t)$ is the state of the controlled system at instant t, $y(t)$ is the vector of the controlled measurable variables, $u(t)$ is the vector of the manipulable inputs, $\hat{d}_{\mathrm{MPC}}(t)$ is the vector of the measured disturbances. A, B, B_d, C, D, D_d are matrices that represent the relations between inputs of the system, system state and controlled variables.

5.2.1.2 The prediction, the control and disturbance horizons

The responses of the controlled and manipulated variables are calculated for a certain time in the future. In MPC, this period of time is called prediction horizon. Fig. 5.1 shows that over the prediction horizon, the manipulated variables are allowed to change only for a certain horizon, which is called control horizon. The control horizon is always smaller or equal than the prediction horizon. Its length is at discretion of the designer of the controller, as for the prediction horizon. After the end of the control horizon, the value of the control action remains constant and equal to the value at the end of the control horizon.

If the response of the model should take also the predicted values of a disturbance into account, the values of the disturbance that are provided to the MPC controller have to be determined over the whole prediction horizon. However, the length of the prediction, called the disturbance horizon

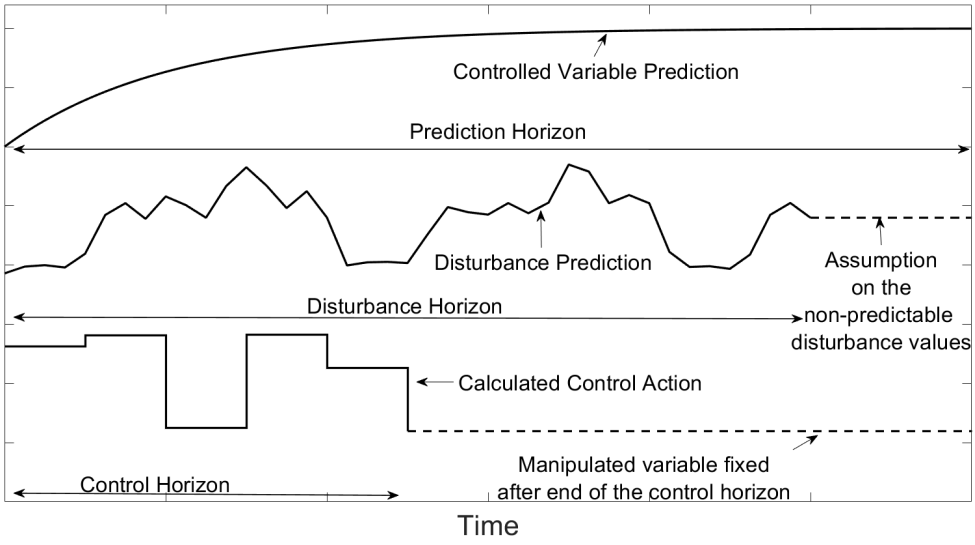


Figure 5.1: Representation of the prediction, disturbance and control horizons

in the former Chapter 4, is limited and might be equal or smaller than the prediction horizon. A question is defining how long the disturbance horizon should be in relation to the control horizon. Another issue is defining the values of the disturbance in the interval between the end of the disturbance horizon and the end of the prediction horizon. Fig. 5.1 represents the issue. The figure shows that the disturbance sequence provided to the controller is made of two parts. A first part is made of the values of the prediction and a second part, represented by a dashed line, is constant and equal to a default value that must be determined.

5.2.1.3 The optimization problem

The MPC has to minimize the optimization problem with soft constraints in Eq. 5.2. The optimization problem considered is the one of the MATLAB® Model Predictive Control Toolbox (Mathworks), which has been developed by Bemporad, Ricker and Morari.

$$\min_{\mathbf{u},\varepsilon} \quad J_y + J_u + J_{\Delta u} + J_\varepsilon \tag{5.2a}$$

$$\text{s.t.} \quad \frac{u_{j,\text{Min}}}{s^u_j} \leq \frac{u_j\,(t+i \mid t)}{s^u_j} \leq \frac{u_{j,\text{Max}}}{s^u_j} \qquad \text{for } 1 \leq j \leq N_u, \quad \text{for } 1 \leq i \leq p \tag{5.2b}$$

$$\frac{\Delta u_{j,\text{Min}}}{s^u_j} \leq \frac{\Delta u_j\,(t+i \mid t)}{s^u_j} \leq \frac{\Delta u_{j,\text{Max}}}{s^u_j} \quad \text{for } 1 \leq j \leq N_u, \quad \text{for } 1 \leq i \leq p \tag{5.2c}$$

$$\begin{aligned} \frac{y_{j,\text{Min}}}{s^y_j} - \varepsilon \Psi^y_{j,\text{Min}} \leq \frac{y\,(t+i \mid t)}{s^y_j} \leq \qquad & \text{for } 1 \leq j \leq N_y, \quad \text{for } 1 \leq i \leq p \\ \leq \frac{y_{j,\text{Max}}}{s^y_j} + \varepsilon\ \Psi^y_{j,\text{Max}} & \end{aligned} \tag{5.2d}$$

$$u_j\,(t+i \mid t) = u_j(t+c \mid t) \qquad \text{for } 1 \leq j \leq N_u, \quad \text{for } c \leq i \leq p \tag{5.2e}$$

The decision variables of this optimization problem are the sequences of control actions $u_j = [u_j(t)\ \ u_j(t+1) \ldots u_j(t+p-1)]$ for the N_u manipulated variables over the prediction horizon p, and the slack variable ε which defines the violation of the nominal constraints of the controlled variables. Both the controlled and manipulated variables are normalised over their range with the terms s^y_j and s^u_j.

Eq. 5.2a is the objective function of the MPC. Eq. 5.2b defines the hard constraints on the manipulated variables. Eq. 5.2c defines the hard constraints on the rate of change of manipulated variables. Eq. 5.2d defines the soft constraints on the controlled variables. Eq. 5.2e states that the control action remains constant after the end of the control horizon. The former equations are dealt in details in the following text. Table 5.1 describes the variables and parameters encountered.

The objective function The objective function is the sum of four terms:

$$J = J_y + J_u + J_{\Delta u} + J_\varepsilon \tag{5.3}$$

The terms J_y and J_u, called *output reference tracking* and *manipulated variable tracking*, penalize the deviation of controlled and manipulated variables from their reference values over the prediction horizon with respectively the weights w^y_j and w^u_j. The term $J_{\Delta u}$ is the *manipulated variable move suppression* and penalizes through the weights $w^{\Delta u}_j$ the variations of the manipulated variables at

sample t from their values in the former sample at sample $t-1$. The term J_ε is the term associated to the *constraint violation* which penalizes violations of the constraints set for the controlled variable.

$$
\begin{aligned}
J_y(\mathbf{u},\varepsilon) &= \sum_{j=1}^{N_y}\sum_{i=1}^{p}\{\frac{w_j^y}{s_j^y}[r_j\,(t+i\mid t)-y_j\,(t+i\mid t)]\}^2\\
J_u(\mathbf{u},\varepsilon) &= \sum_{j=1}^{N_u}\sum_{i=0}^{p-1}\{\frac{w_j^u}{s_j^u}[u_j\,(t+i\mid t)-u_{j,target}\,(t+i\mid t)]\}^2\\
J_{\Delta u}(\mathbf{u},\varepsilon) &= \sum_{j=1}^{N_u}\sum_{i=0}^{p-1}\{\frac{w_j^{\Delta u}}{s_j^u}[u_j\,(t+i\mid t)-u_j(t+i-1\mid t)]\}^2\\
J_\varepsilon(\mathbf{u},\varepsilon) &= \rho_\varepsilon\varepsilon_t^2
\end{aligned}
\tag{5.4}
$$

The value of the objective function does not depend explicitly on the disturbances. However, the response of a controlled variable $[y_j(t)\;\; y_j(t+1)\ldots y_j(t+p)]$ does depend on the disturbance.

The hard constraints on the manipulated variables The constraints described by Eq. 5.2b and Eq. 5.2c are hard. This means that the manipulated variables are always within their respective constraints and the rate of change cannot be faster than a certain limit.

The soft constraints on the controlled variables The constraints on the controlled variables are soft. It means that a violation of the constraints is possible although strongly penalized. The soft constraints on the controlled variables are defined as (Mathworks, 2020c)

$$
\frac{y_{j,\mathrm{Min}}}{s_j^y}-\varepsilon_t\Psi^y_{\mathrm{Min}}\le y\,(t+i\mid t)\le\frac{y_{j,\mathrm{Max}}}{s_j^y}+\varepsilon_t\,\Psi^y_{\mathrm{Max}}
$$

where y_{Min} and y_{Max} are the nominal constraints for the $j-$th controlled variable. The parameters $\Psi^v_{j,\mathrm{Min}}$ and Ψ^v_{Max} are tunable, and are called ECR values in the documentation. These values define in conjunction with ρ_ε how much the MPC can violate the nominal constraints. If $\Psi^v_{j,\mathrm{Min}}$ and $\Psi^v_{j,\mathrm{Max}}$ are set to zero, the constraints are hard constraints. However, the values Ψ^v_{Min}, Ψ^v_{Max} and ρ_ε have been left to their defaults values that define a soft constraints formulation.

The tuning parameters The tuning parameters of an MPC controller are the prediction horizon p and the control horizon c, the weights on controlled and manipulated variables w_j^y, w_j^u, $w_j^{\Delta u}$,

Table 5.1: Variables and parameters in the optimization problem of the MPC.

t	Current control interval	N_y	Number of controller variables
N_u	Number of manipulated variables	p	Prediction horizon
c	Control horizon	h	Disturbance horizon
y_j and r_j	Value and set-point of the $j-$th controlled variable	u_j and $u_{j,target}$	Value and target of the $j-$th manipulated variable
$y_{j,\text{Max}}$ and $y_{j,\text{Min}}$	Upper and lower constraint on the $j-$th controlled variable	$u_{j,\text{Max}}$ and $u_{j,\text{Min}}$	Upper and lower constraint on the $j-$th manipulated variable
w_j^y	Tuning weight for the set-point tracking of the $j-$th controlled variable	$\Psi^y_{j,\text{Min}}$ and $\Psi^y_{j,\text{Min}}$	Equal concern for relaxation (ECR) parameter for the upper and lower constraint on the $j-$th controlled variable
w_j^u	Tuning weight for the target tracking of the $j-$th manipulated variable	$w_j^{\Delta u}$	Tuning weight for the move suppression of the $j-$th manipulated variable
s_j^y	Scale factor for the $j-$th controlled variable	s_j^u	Scale factor for the $j-$th manipulated variable
ρ_ε	Weight for the penalization of the constraints violation	ε	Slack variable which quantifies the worst-case constraint violation

and the penalty weight on the constraint variation ε. Although it is not explicitly in the optimization problem, the sampling is another tuning parameter which improves the rejection of disturbances at expense of the of computational power. Also the disturbance horizon h does not appear explicitly in the optimization problem, however it is an additional tuning parameters since it influences the values of output response $y_j(t+i|t)$ and therefore J_y.

When the MPC has constraints, choosing the parameters to obtain a certain behaviour of the controller is not possible analytically (Alhajeri and Soroush, 2020). Here, the approach used is setting the weights $w_j^y, w_j^u, w_j^{\Delta u}$ to define priorities for the set-point tracking of the controlled variables, and for the movement of the manipulated variables which are linked to disturbance propagation. The prediction horizon has been set so that is longer than the settling time of the process (Alhajeri and Soroush, 2020; Mayne et al., 2000).

Table 5.2: How the disturbance horizon is set in academic literature.
Legend: p - Prediction Horizon, c - Control Horizon, h - Disturbance Horizon

How to set the disturbance horizon	Works	Comments
$h = c = p$	*Control of wind turbines* Bottasso et al. (2014); Laks et al. (2011); Madsen et al. (2012); Schlipf et al. (2012); Sinner and Pao (2019) *Control of Hybrid Electric Vehicles* Cairano et al. (2014); Debert et al. (2010); Xie et al. (2019) *Building automation* Oldewurtel et al. (2012)	• These works do not explain the reason of this setting • The maximal disturbance horizon can change depending on the disturbance characteristics • The maximal disturbance horizon can limit the prediction horizon to very small values • Short prediction horizons can affect stability and performance • Setting long prediction horizon would force the control horizon to be long, resulting in computationally expensive solutions • Debert et al. (2010) found an improvement using long horizons • Bottasso et al. (2014); Sinner and Pao (2019); Xie et al. (2019) found more aggressive behaviour of the controllers using longer horizon. The causes were supposed to be model mismatches or degradation of prediction and preview for long horizons.
$h = c < p$	*Theoretic works with preview of the set-point* Dughman and Rossiter (2020); Valencia-Palomo et al. (2014) *Control of wind turbines* Lio et al. (2017) *Process control* Borghesan et al. (2019a)	• Except Borghesan et al. (2019a), the other works are from the group of Rossiter. • Dughman and Rossiter (2020); Valencia-Palomo, Rossiter, and López-Estrada (2014) explained that a preview horizon of the set-point longer than the control horizon can make the controller response aggressive. • Lio, Jones, and Rossiter (2017) set control horizon and disturbance horizon equal without explaining why. • Borghesan et al. (2019a) noted independently that the control horizon and disturbance horizon should be equal although not doing a strict analysis

5.2.2 Tuning the disturbance horizon

Table 5.2 briefly reviews previous publications on using a multi-step prediction or preview of a disturbance with an MPC controller. *Preview* means that a disturbance is measured before it enters into the system or when the future values of set points are known, and such information is provided to the controller (Section 2.2.2.2).

The table divides the publications depending on how the authors set the disturbance horizon h, the prediction horizon p and the control horizon c.

Most of these works set the three horizons equal as $h = c = p$. Only few articles, related mainly to one research group, set such horizons differently, namely setting $h = c \leq p$.

In the followings, three topics are discussed:

- Why setting $h = c = p$ has drawbacks for process control
- Why a long disturbance horizon might render the controller aggressive
- What is the condition to set h and c shorter than p

5.2.2.1 The drawbacks in setting equal the prediction, control and disturbance horizons

Setting the three horizons equal to each other poses problems in process control. Indeed, the maximal possible disturbance horizon is limited by the duration of the repeating pattern characterising the time series of the disturbance, as previous Chapter 4 described. This means that the disturbance horizon can be as short as few minutes. By contrast, the prediction horizon should be long enough to cover the settling time of the system in order to avoid stability problems and avoid poor control performance (Alhajeri and Soroush, 2020; Mayne et al., 2000). However, the settling time of industrial processes is generally longer than a few minutes, and in the order of some hours for distillation columns.

Furthermore, setting very long control horizons is computationally expensive. It can be concluded that the disturbance horizon h and the control horizon c are likely to be shorter than the prediction horizon p in process control applications.

5.2.2.2 The drawbacks of setting long disturbance horizons

Analysing the articles where the three horizons are equal, there is a contradiction in the literature regarding the effect of having long horizons. Debert et al. (2010) found that with an increasing horizon, the performance metrics of their controller improved. However, the improvement was strong at the beginning, for small values of preview, and marginal after a certain threshold.

Instead, Bottasso et al. (2014); Sinner and Pao (2019); Xie et al. (2019) found that using longer horizons caused the performance of the controller to deteriorate making it more nervous and aggressive. Sinner and Pao (2019) were not able to explain the reasons and guessed it was due to model mismatch between the model of the system and model used by the controller for predictions. Such differences, they guessed, were amplified for longer horizons. Bottasso et al. (2014) thought that long preview times might impoverish the quality of the preview measurement. However, none among Bottasso et al. (2014); Sinner and Pao (2019); Xie et al. (2019) showed results where a perfect knowledge of the prediction is assumed. To fill this gap, results presented in this thesis will show the same MPC tuning using a prediction as well as using the exact future signal of the disturbance.

5.2.2.3 Conditions to set the control and disturbance horizon shorter than the prediction horizon

There are few papers that have investigated the relationship between disturbance horizon, control horizon and prediction horizon when they are not set equal (Dughman and Rossiter, 2020). Rossiter and his co-authors focused on the topic.

This research group analysed two cases of preview. One case is when the set-point of a controlled variable is previewed to the controller. In Dughman and Rossiter (2020) and in Valencia-Palomo, Rossiter, and López-Estrada (2014) they found that a disturbance horizon longer than the control horizon can cause the response of the controller to deteriorate. They state that the controller has c degrees of freedom because it can modify c times the control action over that control horizon. If $c < h$, it may happen that the degrees of freedom are not enough to compensate the information coming from the preview and the solution can be unfeasible or too aggressive.

The other case is when a disturbance, rather than a set-point, is previewed. This is presented in Lio,

Jones, and Rossiter (2017). Although the authors do not explain the reason, they set also in this case $h = c < p$. The leads to the question on how to pad the values of the disturbance $d(i)$ in the interval between the end of the disturbance horizon and the end of the control horizon. Lio et al. (2017) set the disturbance values $d(i) = 0, \forall h \leq i \leq c$. The same solution has been found independently by Borghesan et al. (2019a) using a prediction of the disturbance, rather than a preview.

5.2.3 The metrics for performance monitoring

Metrics are needed to compare quantitatively different MPC structures and tuning for a process considered. The controller should minimize the disturbance propagation, keep the most important variables of plant at their set-points, and avoid violations of constraints.

Although there is a large literature in process monitoring, these works do not fit the purpose of this thesis. Indeed, the main objective of process monitoring has been detecting whether the performance of controllers degrade over time (Gao et al., 2016). Such works compare the performance of the controller to an ideal controller or to a situation recorded in the past which is considered ideal (Harris, 1989; Horton et al., 2003; Huang et al., 2000; Julien et al., 2004). This thesis, instead, wants a comparison between different controllers without considering one as reference. Furthermore, these published metrics consider the controller inadequate when the set-point is not followed. This principle is irrelevant for variables that should act as buffer.

By contrast, the works of Downs and Caveness (2012), Vasudevan and Rangaiah (2012) and Horton et al. (2003) are relevant for this thesis. Downs and Caveness (2012) from Eastman Chemical Company argued that the standard deviation of the compositions of products is a valid way to measure the effects of plant-wide disturbances on the process. Downs and Caveness (2012) used standard deviation also for assessing the propagation of disturbances through certain manipulated variables. However, the authors do not normalise the variables over their range. In this way, it is not possible to compare the metrics for various variables, which is important in a multi-variable system.

Horton et al. (2003) also used the standard deviation of the manipulated variable, in this case the outflow, to assess the quality of a controller for a buffer tank. However, the authors did not consider the possible constraints violation in their metric.

In place of the standard deviation, Vasudevan and Rangaiah (2012) use the total variation $TV = \sum_{i=0}^{\infty} u(t+1) - u(t)$ as measure for the performance of the controllers during a disturbance. The type of disturbance they consider is a step change of inflows and compositions instead of persistent and spiky abrupt disturbances. However, in the case of persistent and abrupt disturbances, the terms $u(t+1) - u(t)$ do not have the same sign over the interval of time considered. Therefore, the positive differences cancel the negative differences. Using the absolute value $|u(t+1) - u(t)|$ would have solved the problem.

In conclusion, these solutions are not normalized over the ranges of the manipulated variables, so that the actions of a multiple input- multiple-output controller on several controlled and manipulated variables cannot be compared. Furthermore, these metrics do not consider the violations of constraints for buffer variables. New metrics should solve these issues.

5.3 IMPLEMENTATION OF THE MPC WITH DISTURBANCE FORECASTING

5.3.1 Implementing the disturbance forecast in the MPC framework

The former section explained that the longest disturbance horizon for a certain disturbance might be shorter than the prediction horizon. However, it is necessary to provide the model of the MPC controller of a vector with the values of the disturbance that covers the duration of the prediction horizon. Therefore, the issue is defining the default values of such vector for the values between the end of the disturbance horizon and the end of the prediction horizon.

The vector $\hat{\mathbf{d}}_{\mathrm{MPC}}(t)$ indicates the vector of length p, which is provided to the MPC controller. It is a concatenation of three parts. The first part is made by only one value, which is the measurement of the current disturbance value $d(t)$. The second part is the prediction vector $\hat{\mathbf{d}}(t, h)$ with the h predicted values of the disturbance. The third part is a vector $\mathbf{0}^{p-h-1}$ composed of $p - h - 1$ zeros

that fills the remaining elements of $\hat{\mathbf{d}}_{\text{MPC}}(t)$. Therefore, $\hat{\mathbf{d}}_{\text{MPC}}(t)$ can be written as

$$\begin{aligned}\hat{\mathbf{d}}_{\text{MPC}}(t) &= [d(t) \quad \hat{\mathbf{d}}(t,h) \quad \mathbf{0}^{p-h-1}] \\ &= [\hat{d}_{\text{MPC}}(t) \;\; \hat{d}_{\text{MPC}}(t+1) \;\; \ldots \;\; \hat{d}_{\text{MPC}}(t+p-1)]\end{aligned}$$

The reason for filling the end of the vector $\hat{\mathbf{d}}_{\text{MPC}}(t)$ with zeros is the following. If the last part of such vector would be filled with a value different from zero, that is $\hat{d}_{\text{MPC}}(t+i) \neq 0, \;\; i = h, \ldots, p-1$, this would imply that there is a permanent change of the disturbance at steady state. If this had been true, the manipulated variables should probably change their steady state value to compensate this new condition. This can make the response of the controller aggressive because the controller might start changing the steady state of the manipulated variables at every sampling time. Instead, the disturbances considered, which are persistent or abrupt spiky disturbances, deviate around their origin.

The present author found in a former work (Borghesan et al., 2019a) that the length of disturbance forecasting should equal the control horizon, $h = c$ so that the controller can counteract the known disturbance. The Section 5.2.2.3 explained the reason found for this behaviour and highlighted that still few researchers investigated this problem. Next chapter investigate the problem further, showing what happens varying the control and disturbance horizon.

5.3.2 The difference between sampling of the MPC controller and sampling of the disturbance time series for time-series forecast

The MPC controller has a certain sampling. Generally speaking, the faster is the sampling the better is the rejection of the controller to disturbances but the higher is the computational power requested (Alhajeri and Soroush, 2020).

Separately, the forecasting algorithm has its own sampling to record the past values of the disturbance. If such sampling is too slow, fast dynamic part of the time series can be missed and the search of nearest neighbours can fail. For example, the spikes of Tag 30 used in Chapter 4 last roughly 60-120 seconds. The original time series was sampled every 20 seconds. If the sampling

used were 60 seconds, some spikes might not be recorded and/or the forecasting algorithm might not find the right nearest neighbours of such spikes. Consequently the algorithm might not forecast these spikes when they occur.

Hence, the time series of the disturbance should be ideally sampled at high frequency and the forecasts should be calculated based on this high frequency time series. Thereafter, the prediction obtained should be resampled with the the sampling of the MPC controller. This procedure is nonetheless computationally expensive and poses also the problem of how to adjust the sampling time when different disturbances occur.

In this work the sampling time of the disturbance is equal to the sampling time of the MPC controller if not stated otherwise. The case study of the boiler will be used to investigate the effect of the choice of the sampling.

5.3.3 The tuning of the controlled variables acting as buffer

A controlled variable acting as buffer is a controlled variable whose priority is to stay within an upper and lower constraint. The manipulated variables controlling such buffer variable should ideally stay as constant as possible and intervene when the buffer variable is going to cross its constraints. The ultimate aim is breaking the propagation of a disturbance.

Although the priority for the variables that act as buffer variable is staying within the constraints, following a set-point has some relevance, especially for abrupt disturbances which are unexpected before they manifest themselves. It has been found, while working for this thesis, that a buffer variable should slowly return to the middle of its range (which can be set as set-point).

In this way, when an expected abrupt disturbance enters again the system, the buffer variable is equally distant from the upper and lower constraint. Instead, if the buffer variable found itself close to one of the constraints, the action of the corresponding manipulated variables would be stronger, propagating the disturbance.

The solution found has been using weights for such controlled variables that change over time.

$$w_j^y(t) = \begin{cases} 0 & \text{if } t \leq c \\ \epsilon & \text{if } c < t \leq p \end{cases} \tag{5.5}$$

where ϵ is a small number. For example, the value of ϵ has been set equal to 1×10^{-3} in this thesis.

The reasoning behind this formulation is that the controller can use fully the buffer capacity of the controlled variable for the initial instants corresponding to the control horizon m, so that the disturbance is potentially attenuated.

However the weight on such buffer variables increases after, so that the solutions found at steady state for the manipulated variables aim to bring the buffer variables gradually at their nominal values, centred in the middle of the admissible range.

5.4 EVALUATING THE MPC PERFORMANCE

This section describes the metrics that have been developed to compare quantitatively different MPC tuning or structures for the processes considered. These are the aspects that should be analysed:

- Whether constraints on buffer variables have been violated
- Whether the set-point is tracked properly for other variables
- Whether the manipulated variables associated to disturbance propagation are kept constant

The list above leads to three metrics. The metric $\Theta_{y_j}^{\text{Area}}$ evaluates violations of the constraints of a $j-$th buffer variable. It quantifies the integrated excursion of the process variable beyond the constraints, normalized over an interval $t_1 \rightarrow t_2$ and the width of constraints range $y_{j,\text{Max}} - y_{j,\text{Min}}$ to have a value in percent.

$$\Theta_j^{\text{Area}}(t_1, t_2) = \frac{\sum_{t=t_1}^{t_2} \left(\max\left(y(t) - y_{\text{Max}}, y_{\text{Min}} - y(t), 0\right) \right)}{t_2 - t_1} \cdot \frac{100}{y_{j,\text{Max}} - y_{j,\text{Min}}} \tag{5.6}$$

The metric Γ_j^y is used to evaluate the tracking of the set-points. It is the standard deviation of the $j-$th controlled variable, normalized over the interval of time considered and the width of

constraints range $y_{j,\text{Max}} - y_{j,\text{Min}}$ to have a value in percent.

$$\Gamma_j^y(t_1, t_2) = \sqrt{\frac{\sum_{t=t_1}^{t_2} \left(y_j(t) - \bar{y}_j\right)^2}{t_2 - t_1}} \cdot \frac{100}{y_{j,\text{Max}} - y_{j,\text{Min}}} \tag{5.7}$$

The metric σ_j^u measure the movement of a manipulated variable. It is the standard deviation of $j-$th manipulated variable u over an interval of time $t_1 \rightarrow t_2$, normalized over the range of the manipulated variable.

$$\sigma_j^u(t_1, t_2) = \sqrt{\frac{\sum_{t=t_1}^{t_2} \left(u(t)_j - \bar{u}_j\right)^2}{t_2 - t_1}} \cdot \frac{100}{u_{j,\text{Max}} - u_{j,\text{Min}}} \tag{5.8}$$

A smaller standard deviation implies that there is less propagation of the disturbance through that manipulated variable.

The length of time horizon $t_2 - t_2$ considered for the metrics is not relevant when a persistent disturbance with a regular pattern is occurring. However, it is more important when abrupt disturbances occur because such phenomena do not occur regularly. More events of the disturbance can occur in one interval of time than in another.

When the aim is understanding the impact of abrupt disturbances on the compositions of the product, it might be reasonable to set such interval equal to the residence time of the lot tanks at the end of the production, where the product is collected before being unloaded for shipment, for example in tracks or ships (Downs and Caveness, 2012). In this way, the impact of the abrupt disturbance is averaged over the corresponding shipment lot.

In this work however, the duration of the interval is simply equal to the duration of the simulation because the case studies considered do not include lot tanks.

5.5 INTRODUCTION TO THE CASE STUDIES

Table 5.3 lists the case studies used and the objectives of the tests run on these case studies. There two main types of objectives:

- Testing the tuning and implementation of the proposed MPC with systems of increasing complexity

Table 5.3: The relationships between the three case studies
Legend. DV stands for Disturbance Variable. MV stands for Manipulated Variable. CV stands for Controlled Variable.

Case study	Number of disturbance variables	Dimension	Objectives of the test
Continuous Stirred Tank Heater	1 DV	SISO	• Testing the idea of buffer with an MPC with disturbance forecasting.
Boiler		MIMO (2 MV $\times$ 2 CV)	• Expanding the idea of buffer to CV different from level. • Testing rules for defining the length of the disturbance horizon. • Analysing the impact of the sampling time on the controller and predictor.
VAC Distillation Column		MIMO (5 MV $\times$ 8 CV)	• Proofing the rules for tuning the disturbance horizon. • Testing an MPC where both variables that must follow a set-point and variables that act as variables are present.

- Testing the proposed MPC in the areas of a production site that Chapter 3 considered relevant, which are the steam utility and production plants

The simplest case study is the Continous Stirred Tank Heater (CSTH), which is a SISO system. The most complex is the VAc distillation column which has 5 Manipulated Variables (MVs) for 8 Controlled Variables (CVs). The increasing complexity reflects the work done in the PhD in testing the proposed MPC framework. In particular, the CSTH model has been the first model on which to test the idea for a better management of the buffer variables in a process unit.

The steam boiler represents the first Multiple Input - Multiple Output (MIMO) system considered (2 MV $\times$ 2 CV) and it is the first model considered based on a real industrial system. It has two possible configurations. One where the objective is only following the set-points of the controlled variables and one where the controlled variables act as buffer. The latter case shows that it is possible to extend the concept of buffer to controlled variables that are not levels.

The VAc distillation column is the largest case (5 MV × 8 CV) characterized by controlled variables that act as buffer and other controlled variables that must strictly follow their set-points. A key objective is testing whether the proposed framework is able to provide good performance for both types of variables.

The boiler and the VAc column represent the steam utility and process using the the utility. Hence it will be seen how the proposed framework works in two areas of a production site that Chapter 3 considered relevant for the propagation of site-wide disturbances.

5.6 CASE STUDIES: THE CONTINUOUS STIRRED TANK HEATER (CSTH)

5.6.1 Objective of the case study of the CSTH

This is the first case study considered and the aim was to test how the MPC exploits a buffer when a detailed information about the future evolution of the disturbance is provided. Exploiting a buffer means keeping the controlled variable within constraints while minimizing the outflow variations.

5.6.2 Physical model of the CSTH

Fig. 5.2 shows the considered case study for the Continuous Stirred Tank Heater (CSTH) case study, which has been derived from Thornhill et al. (2008). The case study consists of a simulated tank filled with water, a cold-water inflow and a water outflow. The level is the only controlled variable and the outflow valve of the tank is the only manipulated variable available to the controller. The heating system and the controlled temperature of the original model are not considered to keep this case study simple.

In Thornhill et al. (2008), the outflow valve was modelled to be fixed at 50% of its maximal aperture. Here, it is modelled as a control valve instead. The outflow is modelled as in Eq. 5.9

$$F_{\text{out}}(z, x) = \frac{0.1013 \times 10^{-4}}{50} z\sqrt{55 + x} \tag{5.9}$$

where $0 \leq x \leq 41$ is the level of water in cm and $z \in [0; 100]$ is the valve position. The valve

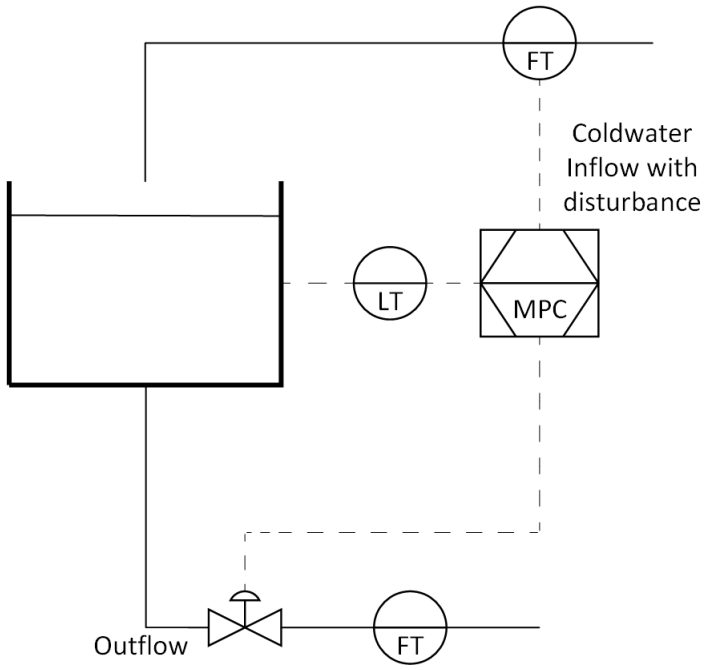


Figure 5.2: Case study of the CSTH.

position z has the following dynamic characterised by a delay of 1s and a time constant of 3.8s. This can be expressed in the frequency domain as

$$\begin{aligned} z(s) &= S\left(\hat{z}\left(s\right)\right) \\ \hat{z}(s) &= \frac{e^{-s}}{(3.8s+1)}u(s) \end{aligned} \tag{5.10}$$

where $u(s)$ is the output of the controller in the range 4-20 mA, and the nonlinear function $S(\cdot)$ converts the signal $\hat{z}(s)$ in 4-20 mA into the valve position z with values between 0% and 100%.

The inflow of the tank is considered constant in the nominal case. In the model, the disturbance d is added to the nominal value of the cold water flow rate and it is considered measurable.

5.6.3 Strategies of the MPC for the CSTH

The MPC controller regulates the measured level of the water y in mA in the tank (whereas x is the level of the water in cm) by manipulating the valve position z by means of u , as described in Eq. 5.10.

The strategy of the controller is to keep the outflow as steady as possible and to intervene only if the level has violated the constraints or if the controller predicts that it is going to violate the constraints.

Table 5.4: Tuning parameters of the MPC for the CSTH case study

Tuning parameter	Value
w_j^y - Output reference tracking	0
w_j^u - Manipulated variable tracking	0
$w_j^{\Delta u}$ - Move suppression	2
Controller sampling time	1 s
p - Prediction horizon	1200
c - Control horizon	15
Ψ_{Min} and Ψ_{Min} -ECR controlled variable	1
ρ - ECR weight	100000

Table 5.5: Constraints of the MPC for the CSTH case study

Constraint	Value	Constraint	Value
v_{Min}	12 mA	v_{Max}	12.5 mA
u_{Min}	4 mA	u_{Max}	20 mA
Δu_{Min}	-1 mA s^{-1}	Δu_{Max}	$+1$ mA s^{-1}

5.6.4 Tuning of the MPC

The Section 5.2.1 describes the optimization problem solved to calculate the control action of MPC. Table 5.4 lists the tuning parameters. The sampling time of 1s is short, because the tested disturbances have a high frequency. The prediction horizon $p = 1200$ is more than the settling time of the system (900 s). To limit the aggressiveness of the MPC, the control horizon is set equal to few steps, as suggested by Seborg et al. (2004). Finally, it was found during the tests that the disturbance horizon should be equal to the control horizon, $h = c$, to have good performance, but this topic will be analysed in detail in the next case studies.

The resulting objective function is:

$$J = J_{\Delta u} + J_{\varepsilon} = \sum_{i=0}^{p-1} \{ \frac{w^{\Delta u}}{s^u} [u\,(t+i) - u(t+i-1 \mid t)] \}^2 + \rho_{\varepsilon} \varepsilon_N^2 \tag{5.11}$$

Table 5.5 lists the constraints imposed on the controlled and manipulated variables. The constraints of the level, y_{Min} and y_{Max}, are tight. The aim is to show how even a little buffer capacity can reduce the disturbance propagation with adequate control.

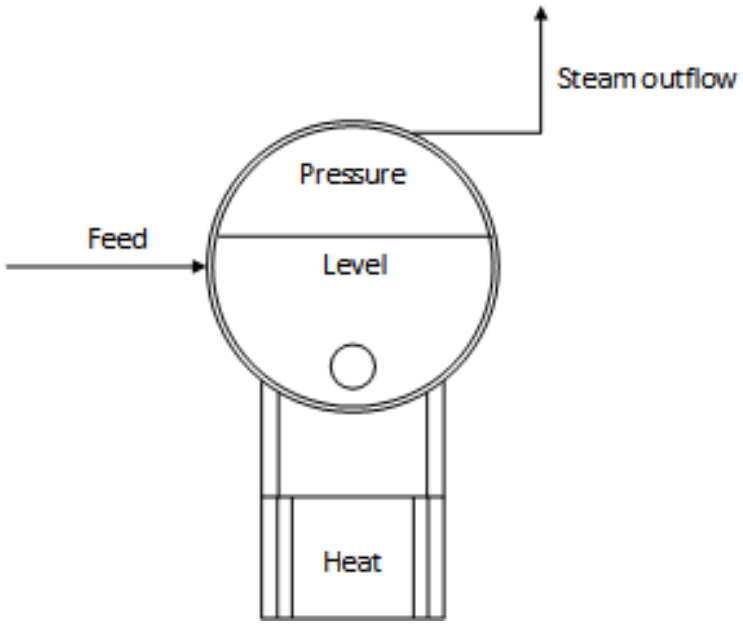


Figure 5.3: Case study of the steam boiler.

5.7 CASE STUDY: THE STEAM BOILER

5.7.1 Objective of the case study of the steam boiler

The second case study represents a simulated industrial application related to the topic of disturbances propagating to and from a steam utility. Furthermore, this case study is a multi-variable controlled system and shows more complex dynamics than the CSTH, such as inverse responses and initial overshoots. This realistic case study demonstrates the impact of various tuning parameters on the controller performance. This leads to indications on how to set the disturbance horizon in the proposed MPC as well as indications of the impact of sampling time on the prediction algorithm and MPC controller.

5.7.2 Physical model

The case study uses the model of a boiler of a 160 MW power plant located in Sweden, which has been developed by Åström and Bell (1998). The model has been able replicate the results of experiments done on the real plant and the authors provided the full code of the model.

The model has the following inputs, shown in Fig. 5.3:

- Inflow of feed water F_f
- Heat H
- Steam outflow F_s

The outputs are:

- The pressure P
- The level L

By using flows in place of positions of valves, the authors of the model decoupled the interactions between pressure and flow through the valves. If positions of valves had been used, the pressure inside the drum would have influenced the inflow of fresh water and the outflow of steam, which in turn would have influenced the pressure inside the drum.

Fig. 5.4 shows the comparison between the response of the nonlinear model, that the controller controls, and the linearised model used by the MPC controller for its internal calculations. The response of the pressure of the two models overlap. There a slight mismatch of the response of the level due to non-linearities. This is visible in the response of the level to a step variation of heat and steam, which are shown in the second row from the top in the first two columns on the left. Still the mismatch has not been considered relevant because it is not large and the controller is in a closed loop.

5.7.3 Disturbances and configurations considered

5.7.3.1 Overview of the possible configurations of the boiler

The model of the boiler has three inputs for two outputs. The outputs of the model, which are the pressure and level, are always controlled variables. However, depending on the configuration of the steam utility, one of the inputs is the disturbance and the other two are the manipulated variables. Consequently, three possible cases can be considered. Fig. 5.4 shows that all inputs have an impact on the controlled variables. For each configuration, the manipulated variables have to compensate the effects of the disturbance.

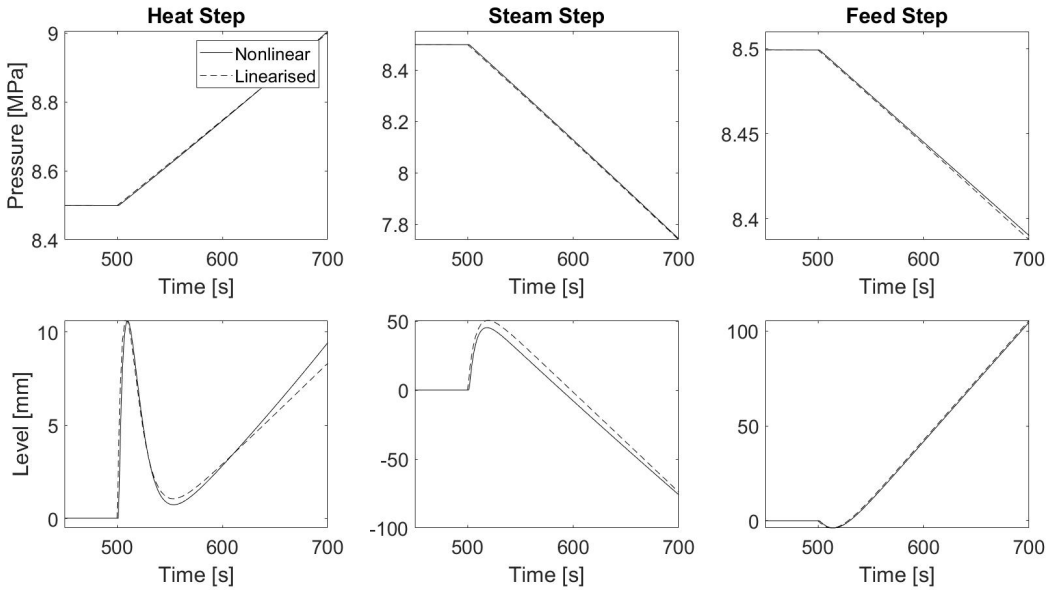


Figure 5.4: Step test response of the nonlinear model of the steam boiler and of the linearised model used by the corresponding MPC controller

5.7.3.2 Disturbances from the steam outflow

In this configuration, the disturbance is the outflow of steam from the boiler. Changes of the steam outflow affect the energy and mass balance inside the boiler, and eventually pressure and level. The heat flow rate and the feed of fresh water in the boiler should compensate for such effects.

Steps and ramps are the typical types of disturbances used to test real steam boilers or simulators (Åström and Bell, 1998; Elguindy, 2013; Hultgren et al., 2019; Luyben, 2004; Majanne, 2005; Sabia et al., 2019; Spinelli et al., 2020). The reason is that most of the articles that have been found focus on boilers used for generation of electricity (Åström and Bell, 1998; Elguindy, 2013; Hultgren et al., 2019; Sabia et al., 2019; Spinelli et al., 2020). In these articles, step responses are then representative of sudden electric load changes. Ramps represent soft-starts of electric units or daily trends of electricity consumption. Fewer articles focus on steam generations for processes. Luyben (2004) and Majanne (2005) focus on applications for industrial loads and, nonetheless, also considered disturbances from the steam outflow as steps, because their focus is on the starting and trip of process units.

The article of Prasad et al. (2002) is the only article found which focuses on the reaction of steam boiler to plant-wide disturbances. The plant-wide disturbance that the authors considered is a

random width square wave. However, Chapter 3 reported that the possible plat-wide disturbances can be more complex. Persistent disturbance of the steam provided to the load can be caused, for example, by the phenomenon of stall of the heat exchangers or by stiction of valves. Abrupt changes with a spiky shape can be thought as phenomena of geysering. Therefore, it is assumed for this case study that the disturbances can be persistent or abrupt.

5.7.3.3 Disturbances from the heat provided

If the heat provided to the boiler is the disturbance, then the steam outflow and the feed of water are the manipulated variables.

The heat provided to the boiler is commonly a disturbance because the calorific value of the fuel burnt can change (Dukelow et al., 2005; Kortela and Lautala, 1984; Wu et al., 2015). However, the predictability of the time series of a disturbance is limited in these cases, because the calorific value of the fuel cannot always be measured and because there are not repeating patterns, as Section 3.5.3.4 discussed. The low predictability of a disturbance does not permit to use the proposed MPC frameworks.

The predictability of the disturbance is higher if regular events occur, such as burning intermittently side products of the process. In this case, abrupt disturbances of the heat provided to the boiler occur, as the present author experienced. Also poor controls or sticking valves can potentially affect the feed of fuel to the boiler, causing persistent disturbances. In these cases, the proposed MPC framework can be potentially used.

5.7.3.4 Disturbances from the feed water

A further possible scenario is when the disturbance is from the feed water. Then the heat and steam outflow are the manipulated variables. However, this scenario is not considered because it is not so common any more. It used to be common when on-off controllers were implemented to control the level of a boiler and they caused persistence disturbance site-wide (Section 3.5.3.3). Such controllers are largely obsolete and analysing this third case would not bring consistent advantages for studying the implementation of the MPC.

5.7.4 Strategies for MPC controller

5.7.4.1 The key controlled and manipulated variables

Section 3.5 explained that the level of a boiler must stay within two very tight limits in the order of +/−100 mm to +/−150 mm (Basu and Kumar, 2019; Chen and Shamma, 2004; Elguindy, 2013). Dukelow et al. (2005) state that boilers drums are generally designed to follow a constant set-point. However, some authors who have used this case study consider observing tight constraints more important than tracking a specific set-point (Chen and Shamma, 2004; Ghabraei et al., 2018; Ławryńczuk, 2017).

The set-point of the pressure is more relevant than the one of the level because the pressure is strictly related to the enthalpy of the saturated steam leaving the boiler. Furthermore, the change of pressure of steam in the drum affects the change of the rate of the outflow of steam and of the inflow of feedwater flowing through a valve following square root relationships as described in Section 3.5. However, the model developed by Åström and Bell (1998), which is used in this thesis, neglects the position of valves and considers the inflow of feedwater and outflow of steam as independent from the pressure of the drum.

5.7.4.2 The dependency of the power delivered by steam on pressure and mass flow rate

Although the pressure of the steam influences the specific enthalpy of the steam, the power delivered from a boiler through the steam depends more strongly on the mass flow rate than on the pressure. To show this, the gradient of the function describing such delivered power is computed.

The power delivered to a load by a boiler through the steam is the following.

$$\dot{W}\left(p_{\mathrm{st}}, \dot{m}_{\mathrm{st}}\right) = \left(h_{\mathrm{st}}\left(p_{\mathrm{st}}\right) - h_{\mathrm{cond}}\left(p_{\mathrm{cond}}\right)\right) \cdot \dot{m}_{\mathrm{st}} - Q_{\mathrm{loss}} \tag{5.12}$$

where $\dot{W}$ is the power delivered, h_{st} is the specific enthalpy of the steam leaving the boiler which depends on p_{st}, which is the pressure of saturated steam. The specific enthalpy of the condensate leaving the load is h_{cond}. Such specific enthalpy depends on p_{cond}, which is the pressure of the condensate. The variable $\dot{m}_{\mathrm{st}}$ is mass flow rate of the steam, and Q_{loss} is the loss of energy to the environment.

The interest is calculating the gradient only for the part of the above equation that depends on the values of p_{st} and $\dot{m}_{st}$, because these are the variables that can be influenced by the boiler and its controller. On the contrary, the variables Q_{sh}, Q_{loss}, h_{cond} and p_{cond} are independent. Furthermore, the value of $\dot{m}_{st}$ is assumed to be controlled by a mass-flow controller so that possible disturbances and dependencies on the value of p_{st} can be assumed to be compensated by the intervention of the controller through valve adjustments.

Consequently, the gradient results to be:

$$\begin{aligned} \nabla \dot{W}\left(p_{st}, \cdot \dot{m}_{st}\right) &= \frac{\partial\left(h_{st} \cdot \dot{m}_{st}\right)}{\partial p_{st}} \hat{p}_{st} + \frac{\partial\left(h_{st} \cdot m_{st}\right)}{\partial \dot{m}_{st}} \hat{\dot{m}}_{st} \\ &= \frac{\partial h_{st}}{\partial p_{st}} \cdot \dot{m}_{st}^{(nom)} \cdot \hat{p}_{st} + h_{st}^{(nom)} \cdot \hat{\dot{m}}_{st} \end{aligned} \tag{5.13}$$

In the above equation the term ∇ defines the gradient, the terms $h_{st}^{(nom)}$ and $\dot{m}_{st}^{(nom)}$ denote the nominal values of enthalpy and mass outflow of steam at the operating point, the terms $\hat{\dot{m}}_{st}$ and $\hat{p}_{st}$ indicate a unitary variation of the pressure and mass flow rate of steam.

The values of mass flow of steam and pressure at the considered operating point are $\dot{m}_{st}^{(nom)} = 49.95\ \mathrm{kg \cdot s^{-1}}$ and $p_{st}^{(nom)} = 85$ bara. Using steam tables, the coefficients of the Eq. 5.13 can be calculated and later such coefficients can be normalised over the nominal values of the pressure and steam outflow. In this way, the equation becomes

$$\begin{aligned} \nabla \dot{W}\left(p_{st}, \cdot \dot{m}_{st}\right) &= -0.078 \cdot \frac{\mathrm{MW}}{\mathrm{bar}} \hat{p}_{st} + 2.75 \cdot \frac{\mathrm{MJ}}{\mathrm{kg}} \hat{\dot{m}}_{st} \\ &= -0.078 \cdot \frac{\mathrm{MW}}{\mathrm{bar}} \cdot 85 \cdot \mathrm{bar} \cdot \underline{\hat{p}_{st}} + 2.75 \cdot \frac{\mathrm{MJ}}{\mathrm{kg}} \cdot 49.54 \cdot \frac{\mathrm{kg}}{\mathrm{s}} \cdot \underline{\hat{\dot{m}}_{st}} \\ &= -6.6822 \cdot \mathrm{MW} \cdot \underline{\hat{p}_{st}} + 137.4 \cdot \mathrm{MW} \cdot \underline{\hat{\dot{m}}_{st}} \end{aligned} \tag{5.14}$$

where $\underline{\hat{p}_{st}}$ and $\underline{\hat{\dot{m}}_{st}}$ define the normalised unitary variation of the pressure and mass flow rate of the steam.

The last line of the above equation 5.14 shows that a change of steam mass flow has an effect which is two orders of magnitude bigger than the effect obtained with a change of the same proportion of the steam pressure.

From previous analysis, if the power delivered to loads must be kept as constant as possible, then it is by far better to keep the mass outflow load constant, rather than the pressure constant. If the

steam outflow is used to keep the pressure at its set-point, then the power variations at load side can be relatively large.

5.7.4.3 Summary of MPC strategies

To summarize, there two strategies depending on where the disturbance comes from.

- **The disturbance comes from the heat provided to the boiler**
  The controller has to avoid further propagation of the disturbance. Consequently, it must reduce the changes of the power delivered downstream by moving the steam outflow only when strictly necessary. The controller is configure in the following way:
  - The movement of the steam outflow is penalized
  - The movement of the water feed is not penalized
  - The level and the pressure of the boiler act as buffer variables
- **The disturbance comes from the request of steam**
  The controller can only try to keep the pressure of steam as steady as possible to avoid further effects on the temperature and power delivered by the steam.
  - The movement of manipulated variables, the feed of water and the heat provided, are not penalised
  - The tracking of the set-point of the pressure is enforced
  - The level follows gently a set-point to keep the system at its steady-state operating point

The next section describes how the this strategy is implemented in the controller tuning.

5.7.5 The tuning and the constraints on the controlled variable

5.7.5.1 The tuning parameters

The parameters on Table 5.6 and Table 5.7 are used in the objective function of the optimization problem of Eq. 5.2 in Section 5.2.1.3, which is repeated here for convenience.

$$
\begin{aligned}
\min_{\mathbf{u},\varepsilon} \quad & J_y + J_u + J_{\Delta u} + J_\varepsilon \\
\text{s.t.} \quad & \frac{u_{j,\text{Min}}}{s^u_j} \le \frac{u_j\,(t+i \mid t)}{s^u_j} \le \frac{u_{j,\text{Max}}}{s^u_j} && \text{for } 1 \le j \le N_u, \quad \text{for } 1 \le i \le p \\
& \frac{\Delta u_{j,\text{Min}}}{s^u_j} \le \frac{\Delta u_j\,(t+i \mid t)}{s^u_j} \le \frac{\Delta u_{j,\text{Max}}}{s^u_j} && \text{for } 1 \le j \le N_u, \quad \text{for } 1 \le i \le p \\
& \frac{y_{j,\text{Min}}}{s^y_j} - \varepsilon \Psi^y_{j,\text{Min}} \le \frac{y\,(t+i \mid t)}{s^y_j} \le && \text{for } 1 \le j \le N_y, \quad \text{for } 1 \le i \le p \\
& \qquad \le \frac{y_{j,\text{Max}}}{s^y_j} + \varepsilon\ \Psi^y_{j,\text{Max}} \\
& u_j\,(t+i \mid t) = u_j(t+c \mid t) && \text{for } 1 \le j \le N_u, \quad \text{for } c \le i \le p
\end{aligned}
$$

where the objective function in Eq. 5.4 is:

$$
\begin{aligned}
J_y(\mathbf{u},\varepsilon) &= \sum_{j=1}^{N_y}\sum_{i=1}^{p}\{\frac{w^y_j}{s^y_j}[r_j\,(t+i \mid t) - y_j\,(t+i \mid t)]\}^2 \\
J_u(\mathbf{u},\varepsilon) &= \sum_{j=1}^{N_u}\sum_{i=0}^{p-1}\{\frac{w^u_j}{s^u_j}[u_j\,(t+i \mid t) - u_{j,target}\,(t+i \mid t)]\}^2 \\
J_{\Delta u}(\mathbf{u},\varepsilon) &= \sum_{j=1}^{N_u}\sum_{i=0}^{p-1}\{\frac{w^{\Delta u}_j}{s^u_j}[u_j\,(t+i \mid t) - u_j(t+i-1 \mid t)]\}^2 \\
J_\varepsilon(\mathbf{u},\varepsilon) &= \rho_\varepsilon \varepsilon_t^2
\end{aligned}
$$

This case study serves to analyse the effects on the performance of varying controller sampling in addition to prediction, control and disturbance horizons of the controller. Therefore, various sets of values are tested for such parameters.

Table 5.6: Tuning parameters of the MPC for the steam boiler

Tuning parameter	Disturbance from the heat		Disturbance from the steam outflow	
w_j^y - Output reference tracking	Pressure	[0 - 1×10^{-3}]	Pressure	20
	Level	[0 - 1×10^{-3}]	Level	0.05
w_j^u - Manipulated variable tracking	Steam outflow rate	0	Heat flow rate	0
	Feed water flow rate	0	Feed water flow rate	0
$w_j^{\Delta u}$ - Move suppression	Steam outflow rate	0.5	Heat flow rate	0.1
	Feed water flow rate	0.1	Feed water flow rate	0.1
$\Psi^y_{j,\text{Min}}$ and $\Psi^y_{j,\text{Max}}$ ECR controlled variable	Pressure			
	1			
	Level			
	1			
Controller sampling time	[5,30,60] s			
p - Prediction horizon	1500 s			
c - Control horizon	3 samples, 420 s			
h - Disturbance horizon	3 samples, Control horizon, Max forecastability			
ρ - ECR Weight	1×10^5			

The weights on the CVs and MVs The tuning parameters have been set up using the guidelines in Mathworks (2020b). Following those guidelines, in the case of the disturbance originating from the steam outflow the 'Output reference tracking' weight w_j^y for the pressure is 20 because this indicates a controlled variable that must follow strictly its set-point. On the other hand the same weight relative to the the level is 0.05 because this indicates that the controlled variable should follow the set-point but large excursions are allowed.

Table 5.7: Constraints of the MPC for the steam boiler

Constraint	Variable	Value	Constraint	Variable	Value
y_{Min}	Pressure	83.3 bara	y_{Max}	Pressure	86.7 bara
	Level	-100 mm		Level	100 mm
u_{Min}	Heat flow rate	0 MW	u_{Max}	Heat flow rate	160 MW
	Steam outflow	0 $\text{kg} \cdot \text{s}^{-1}$		Steam outflow	93.38 $\text{kg} \cdot \text{s}^{-1}$
	Feed water	0 $\text{kg} \cdot \text{s}^{-1}$		Feed water	93.38 $\text{kg} \cdot \text{s}^{-1}$
Δu_{Min}	Heat	-0.007 $u_{\text{Max}} \cdot \text{s}^{-1}$	Δu_{Max}	Heat flow rate	0.007 $u_{\text{Max}} \cdot \text{s}^{-1}$
	Steam outflow rate	-2 $u_{\text{Max}} \cdot \text{s}^{-1}$		Steam outflow rate	0.02 $u_{\text{Max}} \cdot \text{s}^{-1}$
	Feed water flow rate	-0.05 $u_{\text{Max}} \cdot \text{s}^{-1}$		Feed water flow rate	0.05 $u_{\text{Max}} \cdot \text{s}^{-1}$

When the disturbance comes from the heat provided, the pressure and the level act as buffer. A time-varying weight w_j^y on the reference tracking has been added as described in Section 5.3.3. The notation [.. − ..] indicates the two values that a weight w_j^y takes over time.

The sampling times Three discretionary sampling times have been chosen. The shortest of 5s has been chosen because of the fast initial transients of the level of boiler. However, this fast sampling time is computationally expensive. Therefore, also longer sampling of 30s and 60s have been tested to test whether performance would degrade considerably.

Prediction horizon The prediction horizon is fixed, using the rule found in Dougherty and Cooper (2003) for integrating process. The authors state that the response of the system should be approximated with an integrator system with a delay. The prediction horizon is calculated based on the biggest response delay of the system θ_p. Looking at the responses depicted in Fig. 5.4, there are not clear delays but rather initial overshoots or inverse responses. The maximal registered duration of such initial responses is considered the response delay and it is equal to $\theta_p = 88$ s.

Control horizons A choice for the control horizon is using only three samples (independent from the sampling time). Such a choice is often used in real applications and might make the controllers less aggressive and improve the stability of the controllers, as suggested by Mathworks

(2018) and Seborg et al. (2004). However, other researchers show that longer control horizons can be beneficial (Alhajeri and Soroush, 2020; Dougherty and Cooper, 2003; Rossiter, 2014). According to the tuning rules of Dougherty and Cooper (2003), the control horizon should be 420s. So an additional control horizon of 420s is chosen. Depending on the sampling rate of the controller, this control horizon is converted in samples.

Disturbance horizons Three possibilities have been chosen for the disturbance horizon. A very short disturbance horizon of three samples (independent from the sampling time), the length of the control horizon or, finally, the maximal forecastability. The maximal forecastability is considered as the duration of one cycle of a repeating disturbance, or as the duration of one pattern of a persistent disturbance.

5.7.5.2 The constraints

Table 5.7 shows the constraints for the controlled and manipulated variables. Åström and Bell (1987) provided the constraints for the manipulated variables but not for the controlled variables.

The constraints on the level have been taken from Ławryńczuk (2017), who used the same case study. However, such limits are 30% tighter than those presented in the handbook of Basu and Kumar (2019) and in the case study of Elguindy (2013). The stricter constraints of Ławryńczuk (2017) were chosen to test the ability of the proposed controller to exploit limited buffers.

The nominal pressure is 85 bara and the limits are set to ±2%. These values for the percent limits have been taken by Majanne (2005) who described a plant with a maximum pressure of 100 bar. Elguindy (2013), instead, sets limits of the pressure at ±3.3% for his 9 bar plant. However, the more restrictive set of limits of Majanne (2005) has been chosen to test the controller in harder conditions.

5.8 CASE STUDY: THE VAc COLUMN

5.8.1 Physical model of the azeotropic column

The VAc column case study is the final distillation column of the vinyl-acetate benchmark model described by Chen et al. (2003), Luyben and Tyréus (1998), Luyben et al. (1998), and Luyben

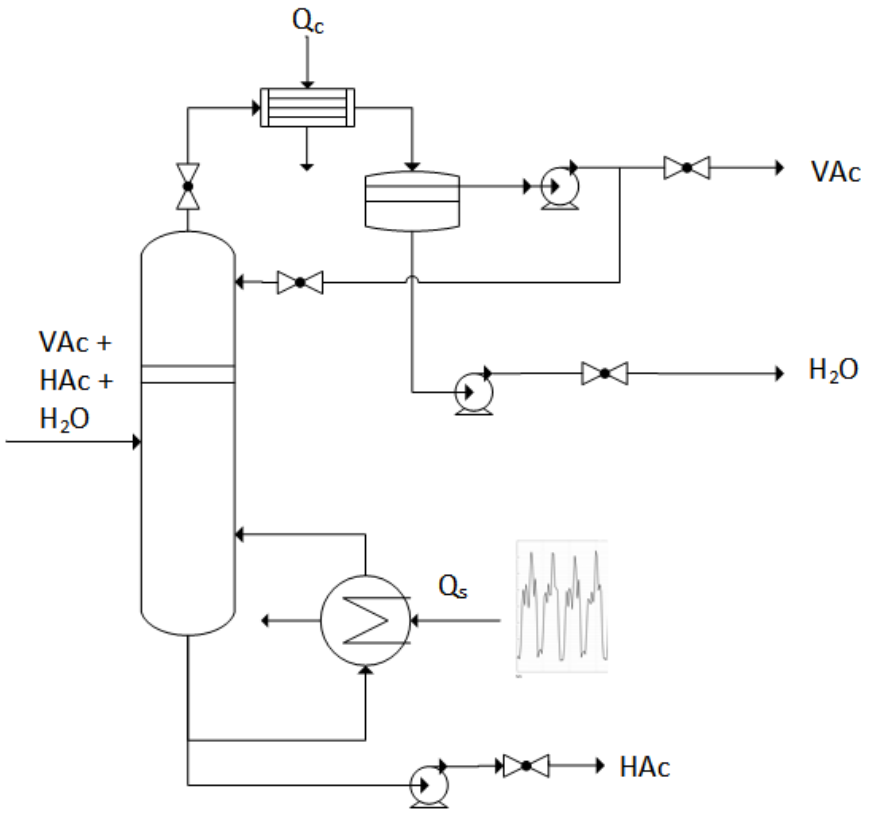


Figure 5.5: Case study of the VAc distillation column.

(2002). The vinyl-acetate process is made of a reaction phase, and a separation phase based on a separator, an absorber and the distillation column which analysed here. The case study is depicted in Fig. 5.5.

The feed to the column is a mixture of Vinyl Acetate (VAc), Water (H_2O) and Acetic Acid (HAc). The column separates the mixture in two streams. The stream out of the bottom of the column is principally HAc. The HAc is used for the main reaction of the plant and it is therefore recycled to the reactor. To stop the propagation of disturbances, Luyben et al. (1998) stated that the flow rate of this stream should be kept constant. The vapour from the top of the column is instead a mixture mainly of VAc and water. The vapour is condensed and enters in a decanter, where the organic and aqueous phases can separate. The upper layer is VAc, while the lower layer is water. Consequently, the level of the water influences the level of the organic phase. The water is taken from a lower flange and discarded. The organic phase is in part refluxed into the column and in part is the final product of this section of the plant. Indeed, there is a distillation train which should process the VAc but which has not been described by Luyben and Tyréus (1998).

Table 5.8: The steady state values of the flows, reboiler heat and condenser duty of the original model and the one developed

	Column Feed (original/ modelled)	Column Bottom (original/ modelled)	Organic Product (original/ modelled)	Aqueous Product (original/ modelled)
Flow ($mol\,min^{-1}$)	3820/3820	2160/2160	826/829	831/831
Temperature (°C)	42.5/42.5	137.2/137.2	40/40	40/40
Pressure (psia)	84/84	30/30	18/18	18/18
VAc (mol frac)	0.206/0.206	11×10^{-6}/ 11×10^{-6}	0.950/0.944	0.002/0.005
H_2O (mol frac)	0.281/0.281	0.093/0.0927	0.050/0.055	0.998/0.995
HAc (mol frac)	0.513/0.513	0.907/0.907	370×10^{-6} / 18×10^{-6}	370×10^{-6}/ 16×10^{-6}

Reboiler duty ($kcal\,hr^{-1}$) (original/modelled)	4×10^6/ 4.19×10^6	Condenser duty ($kcal\,hr^{-1}$) (original/modelled)	3.9×10^6/ 3.82×10^6

5.8.1.1 Comparison with the original model

The model of the system has been developed using Aspen Plus v11 following Luyben (2002). The UNIF-HOC physical property package is used for the column and the Aspen NRTL for the decanter as Luyben did in a later paper using Aspen Plus (Luyben, 2011). Table 5.8 compares the steady state values of the flows, their compositions, the heat provided through the steam reboiler and the condenser cooling duty of model with the original model developed in Luyben et al. (1998). The values mainly overlap but there are some significant differences regarding the presence of spurious components of HAc and VAc in the organic and aqueous stream. Such difference is probably due to the use of the NRTL package for the modelling of the two phase separation process in place of the Wilson package, used in the original paper Luyben et al. (1998).

The temperature profile is depicted in Fig. 5.6 and it reflects the qualitative trend of the one published originally. The temperature of the sixteenth stage, which is the temperature controlled, is slightly shifted being 115 °C instead of 110°C.

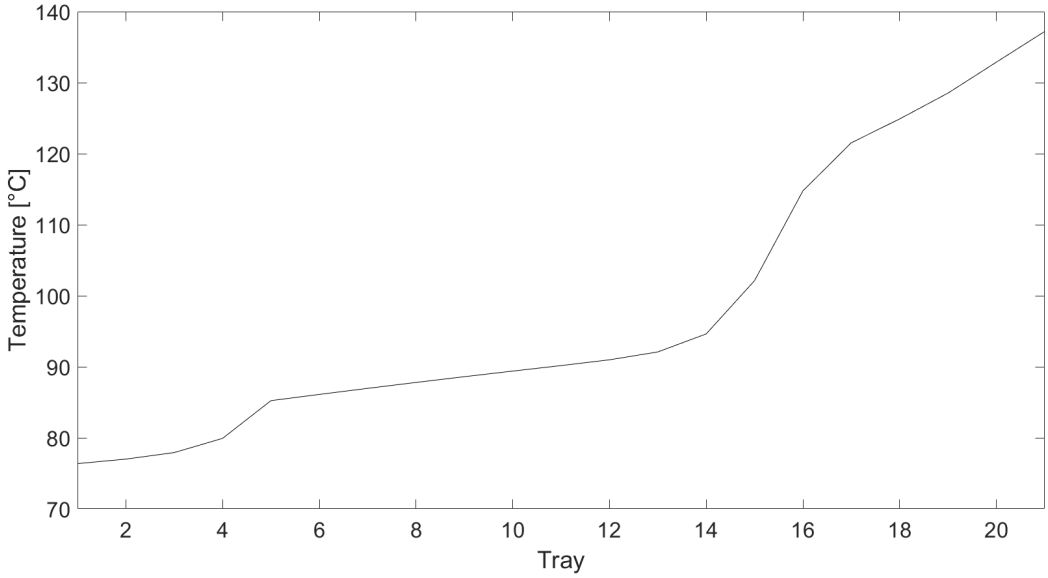


Figure 5.6: The temperature profile found for the VAc distillation column

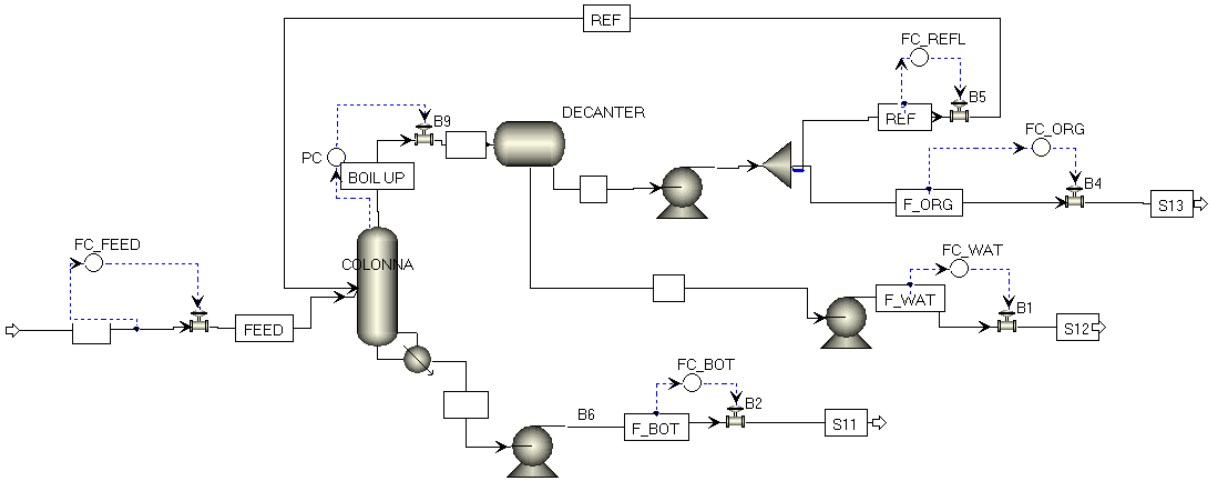


Figure 5.7: The structure of the VAc distillation column

The model, inclusive of base-level PI-based controllers (Proportional-Integral) for flow control, is then exported in Aspen Dynamics. Fig. 5.7 shows a screenshot of such model. The Aspen Dynamics model is connected with Simulink using the procedure explained in Mathworks (2020a). The result is a co-simulation where Aspen simulates the behaviour of the column, subject to the control actions of the MPC controller which are calculated in the Simulink/Matlab environment.

Table 5.9: Controlled and manipulated variable of the case study of the VAC distillation column.

Controlled variables			
T_c	Temperature of the 16th stage counted from the top	L_{bot}	Level of the bottom
L_{acq}	Level of the aqueous phase in the decanter	L_{org}	Level of the organic phase in the decanter
T_{org}	Temperature of the organic phase in the decanter	C_{HAc}^{top}	Impurities of HAc in the organic outflow from the decanter
C_{VAc}^{bot}	Impurities of VAc in the outflow from the bottom of the column	C_{wat}^{bot}	Impurities of water in the outflow from the bottom of the column
Manipulated variables			
F_{org}	Set-point of the organic outflow from the decanter	F_{acq}	Set-point of the aqueous outflow from the decanter
F_{bot}	Set-point of the outflow from the bottom of the column	F_{refl}	Set-point of the reflux flow
Q_c	Condenser cooling power		
Disturbance variable			
Q_r	Reboiler heating power		

5.8.2 Control configuration considered

The Table 5.9 lists the controlled and manipulated variables of the MPC, and the disturbance. All measurements are updated every second except the measurements with online analysers of the impurities. Such analysers update their measurements every minute.

In addition to online analysers, temperature is used for inferential control of the concentrations. The temperature profile of the column is plotted in Fig. 5.6. The temperature of the 16th stage is the one chosen to be controlled, which is the same temperature controlled in the original model (Luyben and Tyréus, 1998) . The 16th stage is the stage where the temperature profile is steepest and whose temperature changes most in response to variations in the manipulated variables and disturbance. These are common heuristics to choose the tray to be controlled in a column for inferential control (Luyben, 2006; Luyben et al., 1998; Skogestad, 2007).

The pressure at the top of the column is controlled with a PI controller. The reason is that the sampling of the MPC is 1 minute. To obtain a tighter control, a PI controller is preferred because of its a higher sampling rate.

The MPC controller provides the set-points to the base-layer PI-controllers regulating the flows, rather than acting directly on the valves. This is necessary because the levels in the column are going to fluctuate, since they are acting as buffer, and these fluctuations cause a variation of the back-pressure of the valves. If an MPC acts directly on the valves, the valve position is kept constant for the duration of the sampling time of the MPC, and the flow through a valve can fluctuate.

5.8.3 Disturbances considered

It is assumed that the disturbance comes from the steam utility through the reboiler of the column. The scenario represents a propagating site-wide disturbance, reflecting the interest of this thesis on this type of disturbance. Furthermore, this scenario is problematic from a control point of view because steam is generally an important manipulated variable used to compensate disturbances coming from elsewhere. In this case, the controller needs to coordinate the remaining manipulated variables to compensate the effects of the disturbance from the steam.

Figure 5.8 represents the step responses between disturbance and manipulated variables (column headings), and controlled variables (row headings). Such plots show that the reboiler duty Q_r affects all controlled variables.

5.8.4 The strategy of the MPC controller

The MPC controller has to avoid a propagation of the disturbance and keep the most important variables at their set-point.

If the level controllers are tightly tuned, variations of the levels caused by the steam are reflected on the variations of the mass outflows. The MPC controller should therefore keep the outflows from the bottom of column and from the organic phase of the decanter constant, while letting the corresponding levels act as buffer.

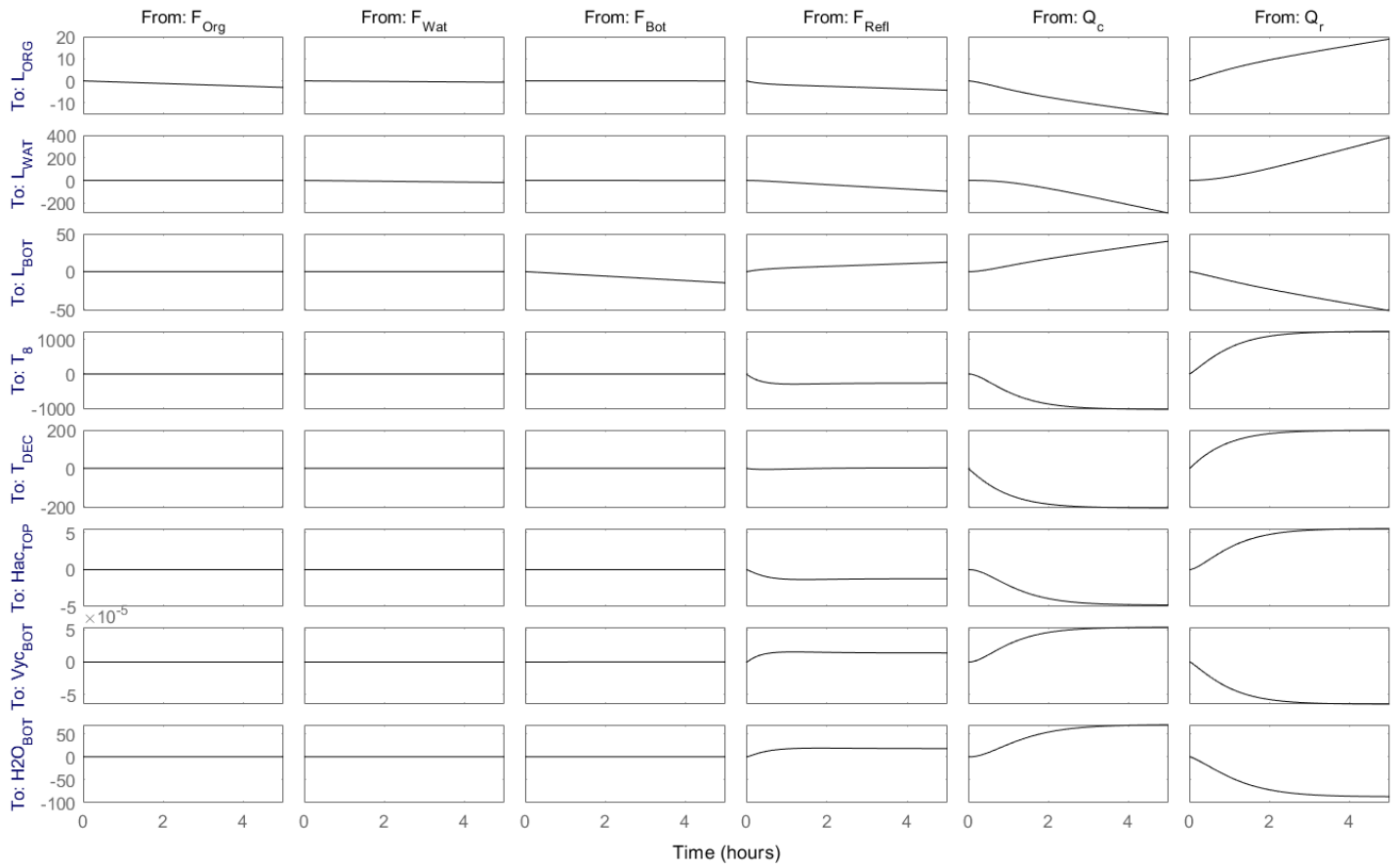


Figure 5.8: The step responses of the model of VAc distillation column linearised at the operating point defined in Table 5.11. The model has been scaled over the span of its manipulated and controller variables, where the span is the difference between maximum and minimum value of the variable considered. The step responses show the variations in spans of the controlled variables for a variation of one span of the manipulated variable. Therefore, the step responses provide only a qualitative information given the high non-linearity of the distillation column.

Variations of the outflow of the aqueous phase are not relevant for the rest of the process. Since the level of the aqueous layer in the decanter affects the level of the organic material, the level of the aqueous phase should rather be controlled at a set-point.

Variations of the temperature of the organic phase flowing out of the decanter represent variations of the liquid enthalpy, which are propagated to the following distillation train. Therefore, the MPC controller has to keep the temperature of organic outflow constant. The condenser duty is the only manipulated variable which can compensate the disturbance of the steam on this variable.

The concentrations of impurities should be strictly close to their nominal values. Although the constraints provided originally by Luyben and Tyréus (1998) for such controlled variables are relaxed, chemical companies have been more prone to reduce the variability of their products in the later years to provide the customers with consistent product quality (Downs and Caveness, 2012). Therefore, reducing the variations of such concentrations has been set as a priority.

5.8.5 Tuning of the MPC controller

5.8.5.1 The tuning parameters

Table 5.10 lists the parameters chosen for the MPC. The levels of the organic phase of the decanter and the bottom of the column are free to move within their constraints because their corresponding outflows must avoid a propagation of disturbance. Section 5.3.3 describes how they have been tuned. The weights 'Manipulated suppression' of such outflows have been consequently increased compared to others. The reference tracking weights on the other variables are instead different from zero, with the highest priority given to the concentrations of the chemical components.

As it regards the parameters of the controllers, the sampling time has been chosen equal to 1 minute which is common for process applications with long horizons and does not make the computational time too long. The prediction horizon of 5 hours resulted from applying the guidelines of Dougherty and Cooper (2003) to the present case study. The same guidelines of Dougherty and Cooper (2003) suggested a control horizon equivalent to 90 min. However, Seborg et al. (2004), Mathworks (2018) and Alhajeri and Soroush (2020) suggest to use a short controller horizon controller to limit the aggressiveness of the controller. Specifically, these references suggest values of the control

Table 5.10: Tuning parameters of the MPC for the VAc distillation column

Tuning parameter	Variable	Value	Variable	Value
w_j^y - Output reference tracking	Level organic phase	[0 - 1×10^{-3}]	Level aqueous phase	1
	Level bottom	[0 - 1×10^{-3}]	Temperature 16$^{\text{th}}$ tray	0.7
	Temperature decanter	1	HAc molar fraction top	1
	VAc molar fraction bottom	1	Water molar fraction bottom	1
w_j^u - Manipulated variable tracking	Flow organic stream	0	Flow aqueous stream	0
	Flow bottom stream	0	Reflux	0
	Condenser duty	0		
$w_j^{\Delta u}$ - Move suppression	Flow organic stream	0.5	Flow aqueous stream	0.1
	Flow bottom stream	0.5	Reflux	0.1
	Condenser duty	0.1		
Ψ^y_{Min} and Ψ^y_{Max} ECR controlled variable	Level organic phase	1	Level aqueous phase	1
	Level bottom	1	Temperature 16$^{\text{th}}$ tray	1
	Temperature decanter	1	HAc molar fraction top	1
	VAc molar fraction bottom	1	Water molar fraction bottom	1
Controller sampling time	1 min			
p - Prediction horizon	5 hr			
c - Control horizon	3 min, 15 min, 90 min			
h - Disturbance horizon	3 minutes, Control horizon, Max forecastability			
ρ - ECR Weight	1×10^5			

Table 5.11: Nominal values of the MPC for the VAc distillation column

Nominal values			
Temperature 16^{th}	114.766 °C	Temperature decanter	40 °C
HAc molar fraction in org. flow	$1.8{\cdot}10^{-5}$	VAc molar fraction bottom	$11 \cdot 10^{-5}$
Water molar fraction bottom	0.0927		
Flow organic stream	4093.7 kg·hr^{-1}	Flow bottom	7277.5 kg·hr^{-1}
Flow aqueous phase	914.7 kg·hr^{-1}	Flow reflux	26074.5 kg·hr^{-1}
Condenser duty	3.82 Mkcal·hr^{-1}		

horizon between 3 and 15 steps, independently from the dynamics of the system. Therefore, such values of the control horizon are tested in addition to a control horizon of 90 steps (equivalent to 90 minutes). The values of the disturbance horizon are chosen as for the boiler case study. The options are setting the disturbance horizon equal to three samples, equal to the control horizon or, setting it equal the length of the maximal forecastability for that signal. The max forecastability is considered as the duration of one pattern of the the disturbance.

5.8.5.2 The constraints

Table 5.11 shows the nominal values for the controlled and manipulated variables that the MPC should track, and Table 5.12 shows the constraints. The constraints on the controlled and manipulated variables come from Chen et al. (2003). However, the authors did not stated the limits on the rates of opening and closing of the manipulated variables Δu_{Min} and Δu_{Max}. The values of the limits of these rate were found in the 'Control Valve Handbook' of Emerson Automation Solutions (2019), and reduced by a tenth. In this way the actuators are not stressed.

Table 5.12: Constraints of the MPC for the VAc distillation column

Constraint	Variable	Value	Constraint	Variable	Value
y_{Min}	Level organic material	10%	y_{Max}	Level organic material	90%
	Level aqueous phase	10%		Level aqueous phase	90%
	Level bottom column	10%		Level bottom column	90%
	Temperature 16$^{\text{th}}$ stage	T_{sp} -3 °C		Temperature 16$^{\text{th}}$ stage	T_{sp} +3 °C
	Temperature decanter	35 °C		Temperature decanter	45 °C
	HAc molar fraction top	0		HAc molar fraction top	600 ppm
	VAc molar fraction bottom	0		VAc molar fraction bottom	100 ppm
	Water molar fraction bottom	0		Water molar fraction bottom	0.2
u_{Min}	Organic flow	0 kg·hr^{-1}	u_{Max}	Organic flow	8187.9 kg·hr^{-1}
	Aqueous flow	0 kg·hr^{-1}		Aqueous flow	1818.7 kg·hr^{-1}
	Bottom flow	0 kg·hr^{-1}		Bottom flow	14560 kg·hr^{-1}
	Reflux flow	0 kg·hr^{-1}		Reflux flow	48136 kg·hr^{-1}
	Condenser duty	-4.2 Mcal·hr^{-1}		Condenser duty	0 Mcal·hr^{-1}
Δu_{Min}	Organic flow	$-0.02 u_{\text{Nom}} \cdot \text{s}^{-1}$	Δu_{Max}	Organic flow	$+0.01 u_{\text{Nom}} \cdot \text{s}^{-1}$
	Aqueous flow			Aqueous flow	
	Bottom flow			Bottom flow	
	Reflux flow			Reflux flow	
	Condenser duty			Condenser duty	

5.9 SUMMARY

This chapter focused on the last two technical objectives of the thesis, which are the implementation and the evaluation of performance of the proposed MPC with disturbance forecasting for process control applications. The MPC solution should be able to keep the key controlled variables at their nominal values and avoid a propagation of the disturbance by exploiting the capability of certain variables to act as buffer. To reach this objective, the problem is dealt in terms of implementation of the MPC controller and in terms of designing a controller strategy for the controlled system.

A review of literature found that the length of the disturbance prediction needed to obtain desired performances is an open question. Furthermore, there is room of improvement for metrics evaluating performance of controllers in handling site and plant-wide disturbances.

The key issues for inclusion of a disturbance forecast are the duration of the disturbance prediction (here called disturbance horizon), the possible different sampling between prediction algorithm and MPC controller, the tuning of those variables that should act as buffer, the metrics for the evaluation of the performance.

Three case studies in process engineering were presented which are a laboratory CSTH tank, an industrial steam boiler, and a distillation column. Each case study will test different aspects of the implemented solutions, and serves to show the abilities of the proposed MPC framework in different areas of a production site.

A controller strategy was devised for each case study to define the controlled variables that must be close to their set-point, the manipulated variables that can propagate further a disturbance, and the controlled variables that can act as buffer. The strategies are finally translated into a choice of the weights for tuning the controller.

Chapter 6

MPC WITH DISTURBANCE FORECASTING: RESULTS

This chapter presents the results of the implementations of the MPC with disturbance forecasting proposed in this thesis. An aim of the chapter is to show whether the proposed MPC with disturbance forecasting provides good performance for realistic case studies with industrial disturbances. This is the third of the technical objectives of the thesis. The chapter shows also the use of new metrics for assessing the performance of the controller in in three aspects, which are capability of the controller to avoid a propagation of the disturbance, capability to reduce the variability of the key controlled variables, and capability to avoid violations of constraints. This is the last technical objective of the thesis.

The MPC is tested on the three case studies described in Chapter 5, which are a laboratory CSTH, an industrial steam boiler, and an industrial distillation column. Using the same metrics the proposed MPC is compared to other two other strategies used in industrial applications to deal with disturbances in MPC frameworks. The strategy are called here Prediction OFF and Frozen Time MPC (FTMPC).

The chapter provides insights about the impact that the tuning of the disturbance horizon, the sampling of prediction and controller algorithms, and the prediction algorithm have on the performance achievable by the MPC framework.

6.1 INTRODUCTION

This chapter focuses on the last two technical objectives listed in Section 1.6, which are implementing and evaluating an MPC controller in realistic case studies that uses a multi-step forecast of a measured disturbance to avoid a propagation of the disturbance and to reduce the variations of the key controlled controlled variables.

Table 6.1: The three MPC strategies compared for dealing with the disturbance values.

Model of the MPC		
The model used by the MPC for the calculation of the objective function is: $$x(t+1) = Ax(t) + Bu(t) + B_d\hat{d}_{\text{MPC}}(t)$$ $$y(t) = Cx(t) + Du(t) + D_d\hat{d}_{\text{MPC}}(t)$$ The values of the disturbance $\hat{d}_{\text{MPC}}$ over the prediction horizon p have an impact on the predictions made by the model and on the objective function of the MPC (Section 5.2.1.2 at page 151).		
Strategy	Description	Mathematical formulation
Prediction ON	Framework proposed in this thesis and explained in Section 5.3.1. Predicting the future values $\hat{d}$ of the disturbance for a horizon h. Set remaining values to zero.	$\hat{d}_{\text{MPC}}(t) = \begin{cases} d(t), & \text{for } i = 0 \\ \hat{d}(i), & \text{for } 1 \leq i \leq h \\ 0, & \text{for } h < i < p \end{cases}$
Prediction OFF	Ignoring the presence of the disturbance, which means setting to zero the values of the disturbance over the prediction horizon p	$\hat{d}_{\text{MPC}}(t+i) = 0, 0 \leq i < p$
Frozen Time MPC (FTMPC)	Setting the values of the disturbance of the disturbance over the prediction horizon equal to the current measured value $d(t)$	$\hat{d}_{\text{MPC}}(t+i) = d(t), 0 \leq i < p$

A key-objective of this chapter is determining whether using a disturbance forecast improves performance of an MPC in dealing with process disturbances, and for which conditions.

The improvement is assessed comparing the proposed MPC with two other MPC controllers. While the tuning of all controllers is the same, they differentiate themselves in the way they fill the values of the disturbance $\hat{d}_{\text{MPC}}$ assumed over the prediction horizon p. Table 6.1 gives a reminder of the problem explained in Section 5.2.1.2 and describes the strategies. The strategies called Prediction OFF and FTMPC are commonly used in industrial settings (Camacho and Bordons, 2008). The results presented here are also going to highlight their limits.

The controller strategies are evaluated according to ability to avoid violations of constraints, ability to reduce the variability of the key controlled variables, and ability of the controller to avoid a propagation of the disturbance. Table 6.2 describes the metrics used for evaluate these three aspect. These metrics were explained in Section 5.4 of the former chapter.

Table 6.2: Metrics for the evaluation of a controller

Method	Description
$\Theta_j^{\text{Area}}(t_1, t_2)$	$\frac{\sum_{t=t_1}^{t_2} \left(\max\left(y(t) - y_{\text{Max}}, y_{\text{Min}} - y(t), 0\right)\right)}{t_2 - t_1} \cdot \frac{100}{y_{j,\text{Max}} - y_{j,\text{Min}}}$
The metric evaluates the constraints violation of a $j-$th buffer variable. It quantifies the integrated excursion of the process variable beyond the constraints, normalized over an interval $t_1 \rightarrow t_2$ and the width of constraints range $y_{j,\text{Max}} - y_{j,\text{Min}}$ to have a value in percent.	
$\Gamma_j^y(t_1, t_2)$	$\frac{\sum_{t=t_1}^{t_2} \left(\max\left(y(t) - y_{\text{Max}}, y_{\text{Min}} - y(t), 0\right)\right)}{t_2 - t_1} \cdot \frac{100}{y_{j,\text{Max}} - y_{j,\text{Min}}}$
The metric evaluates the tracking of the set-points. It is the standard deviation of the $j-$th controlled variable, normalized over the interval of time considered and the width of constraints range $y_{j,\text{Max}} - y_{j,\text{Min}}$ to have a value in percent.	
$\sigma_j^u(t_1, t_2)$	$\sqrt{\frac{\sum_{t=t_1}^{t_2} \left(u(t)_j - \bar{u}_j\right)^2}{t_2 - t_1}} \cdot \frac{100}{u_{j,\text{Max}} - u_{j,\text{Min}}}$
The metric measures the movement of the $j-$th manipulated variables associated to disturbance propagation. It is the standard deviation of $j-$th manipulated variable u over an interval of time $t_1 \rightarrow t_2$, normalized over the range of the manipulated variable.	

When assessing for which conditions the proposed MPC has benefits, this chapter analyses:

- The impact of the speed of the pattern of the disturbance on the performance.
- The performance when controlling variables acting as buffer.
- The performance when controlling variables that must follow a set-point.
- The possible trade-offs in controlling variables acting as buffer as well as variables that must follow a set-point.
- The difference in performance when the controller uses a prediction compared to a perfect knowledge about the future values of the disturbance.

Table 6.3: List of questions solved in this chapter and where they are treated.

Questions	Case study			
	CSTH tank	Steam boiler		VAC column
		Disturbance from the load	Disturbance from the heat	
	Process dependent questions			
Impact of disturbance frequency on performance of controllers	✓			
Performance with variables that must follow a set-point		✓		✓
Performance with variables that act as buffer	✓		✓	✓
Trade-offs when a system has CV acting as buffer and CV which must follow a set-point				✓
	MPC dependent questions			
Length of the disturbance horizon		✓	✓	✓
Impact of the disturbance sampling on performance			✓	✓
Impact of prediction algorithm on control performance	✓		✓	✓

Additionally, Chapter 5 highlighted issues specific of the MPC with disturbance forecasting to be analysed:

- Determining the impact on performance of the length of the disturbance horizon and its relationship with the control horizon.
- Analysing the impact of the predictor and controller sampling on performance.

Table 6.3 lists which case studies will analyse such questions. There are three simulated systems, which are a laboratory scale CSTH tank, an industrial steam boiler and an industrial distillation

column. The steam boiler is tested in two configurations leading to a total of four scenarios analysed. Chapter 5 provided a detailed description of the systems and of the tuning of the MPC controllers.

Section 6.2 introduces the time series that are used as disturbances for the tests. Section 6.3 presents the results for the CSTH tank, Section 6.4 shows the results for the two configurations of the steam boiler, and Section 6.5 focuses on the results of the VAc distillation column. The chapter ends with the summary in Section 6.6.

6.2 THE REAL INDUSTRIAL DISTURBANCES

This chapter uses mainly time series of disturbances in real industrial plant. Such time series are those used in Chapter 4 for comparing algorithms for time series forecating and described in Section 4.7. They are Tags 33 and 34 from the a SE Asia refinery (Thornhill, 2005b), characterized by a persistent oscillatory behaviour, and Tag 30 from the Eastman Chemical Company (Thornhill et al., 2003), characterized by abrupt patterns.

The original sampling time of Tag 33 and Tag 34 was 60s whereas it was 20s for Tag 30. The original sampling time have been used for the industrial cases represented by the steam boiler and the VAc distillation column. However, a reasonable time scale for the laboratory-scale CSTH simulator (Thornhill et al., 2008) would be much shorter. Therefore, the time series of the disturbances derived from Tags 33 and 34 that are to applied to the CSTH use the same waveform but have a sampling interval of 5 s instead of 60 s. Similarly, the time series of the disturbance derived from Tag 30 uses a sampling interval of 1 s instead of 20 s.

In the present chapter, the prediction is obtained using the weighted k-NN algorithm described in Section 4.2.2 with the parameters optimized using the grid-search method described in Section 4.4.1. However, an exact prediction of the disturbance is used for certain scenarios to remove the error caused by the prediction algorithm.

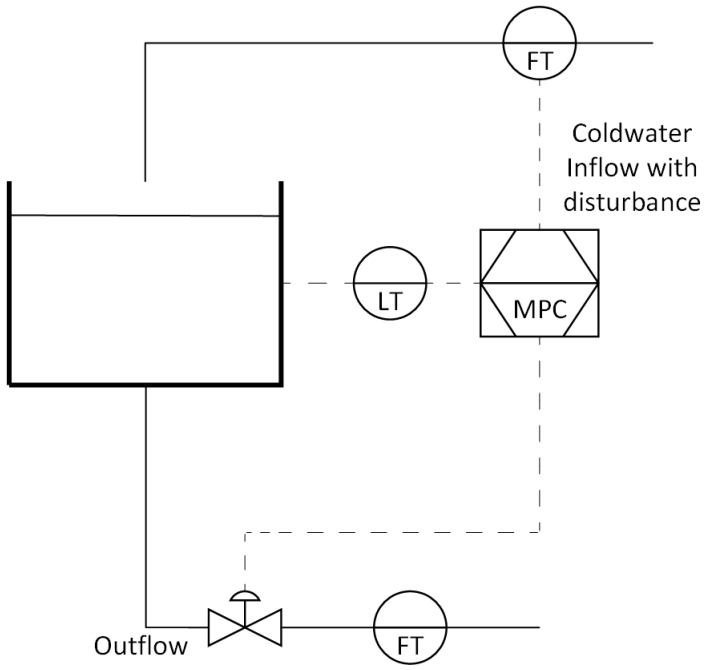


Figure 6.1: Case study of CSTH. Duplicated from Fig. 5.2.

6.3 RESULTS: THE CSTH

6.3.1 Introduction

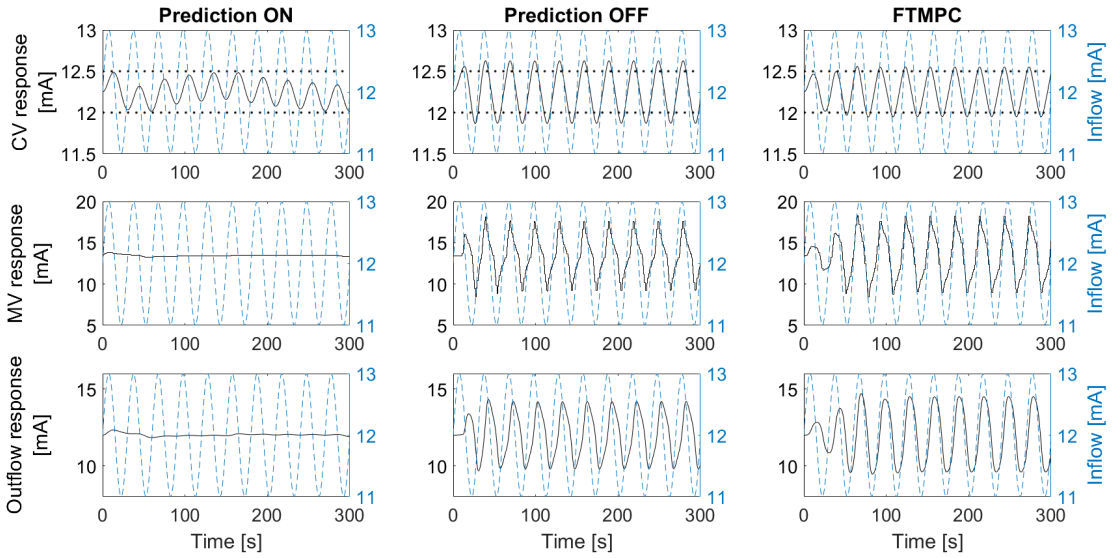
This section analyses the results with the CSTH tank, that was presented in Section 5.6 and it is shown in Fig. 6.1. The aim of the controller is to keep the level within the constraints, and to attenuate the disturbance propagation by reducing the variation of the outflow.

The section compares the proposed MPC framework with the strategies listed in Section 6.1 in two experiments. Section 6.3.2 considers sinusoidal disturbances. The assumption is that the controller knows exactly the future evolution of the disturbance over the disturbance horizon. The aim of this test is to understand the behaviour of the MPC with very regular disturbances at various frequencies.

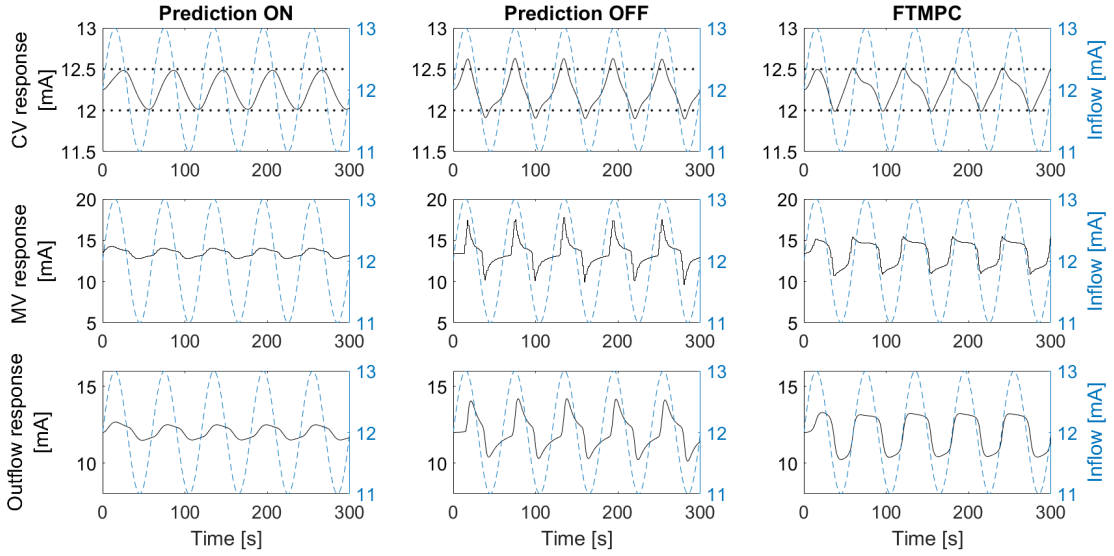
Section 6.3.3 considers as disturbance the time trends of Tags 33 and 34 from the SE Asian refinery, and Tag 30 of the Eastman Chemical company.

6.3.2 Simulated sinusoidal disturbances

The controller has been tuned so that it moves the outflow valve (the manipulated variable) either when the level (the controlled variable) has violated the constraints or when the constraints are



(a) Frequency 1/30 Hz

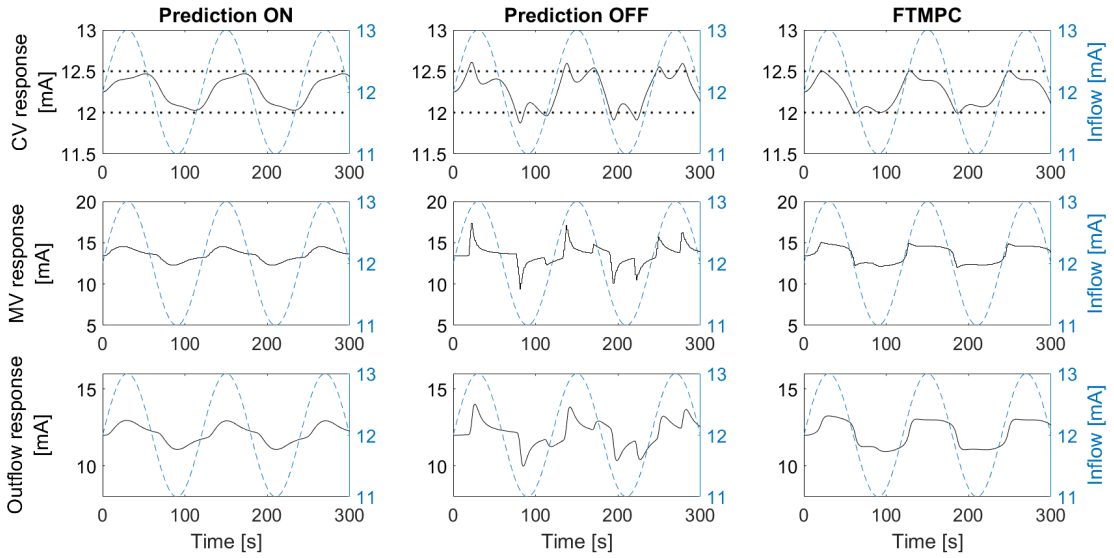


(b) Frequency 1/60 Hz

Figure 6.2: Results of the responses of the level (CV), of the set-point of the valve position (MV), and of the outflow for a sinusoidal disturbance of the inflow (dashed in blue in the pictures).

going to be violated. The controller predicts whether the constraints are going to be violated based on the values of the disturbance that have been set over the prediction horizon.

Fig. 6.2a, Fig. 6.2b and Fig. 6.2c show the trend over time of the controlled variable (the level), the manipulated variable (the valve position), the outflow from the tank, and dashed the disturbance (the inflow to the tank) using the MPC strategies described in Section 6.1 for various



(c) Frequency $1/120$ Hz

Figure 6.2: *(continued)* Results of the responses of the level (CV), of the set-point of the valve position (MV), and of the outflow for a sinusoidal disturbance of the inflow (dashed in blue in the pictures).

sinusoidal disturbances of the water inflow. The MPC strategies are the MPC capable of predicting the disturbance (Prediction ON), the MPC that ignores the presence of a disturbance in its model (Prediction OFF), and the frozen time MPC (FTMPC). The disturbance is $d = \sin(2\pi f t)$, where $f \in \left\{\frac{1}{30}\text{Hz}; \frac{1}{60}\text{Hz}; \frac{1}{120}\text{Hz}\right\}$.

For $f = \frac{1}{30}$Hz, the proposed controller Prediction ON is able to keep the level within constraints while keeping the outflow nearly constant. This stops the propagation of the disturbance. Disturbances with a high frequency tend to have a low impact on controlled variables and require small corrections of the manipulated variables. However, the Prediction OFF and the FTMPC strategy do not work properly.

While the MPC with the Prediction ON strategy makes hardly any adjustments, the one with Prediction OFF strategy does not intervene when the level is within the constraints. The controller intervenes vehemently only when the constraints are violated. Borghesan et al. (2018b) explains that this creates non-linearities and lead to a limit cycle. The inflow is a sinusoid while the trend of outflow valve is not.

The FTMPC over reacts because the assumption in its model is that the change of the inflow is permanent. Under this wrong assumption, the controller changes the valve position of the outflow to compensate the inflow variations.

Table 6.4: Values of the metrics for the evaluation of the MPC performance

	Tag 33		Tag 34		Tag 30	
	σ_u [%]	Θ_v^{Area} [%]	σ_u [%]	Θ_v^{Area} [%]	σ_u [%]	Θ_v^{Area} [%]
Prediction ON	13.5	2.4	12.89	0.4	0.54	0
Prediction OFF	14.93	21.6	17.4	48.8	0.23	5.2 E-3
FTMPC	19.47	6.4	21.58	8.2	1.69	4.9E-2

As the frequency of the disturbance decreases, the approximation made in the FTMPC strategy is more reasonable. Indeed, a slow varying sinusoid resembles a permanent constant change. Therefore the control action improves. Also, as the frequency of the disturbance decreases, the Prediction OFF strategy reacts less frequently because there are less violations of the constraints when the feed changes more slowly. Since the controller is less aggressive, the control action improves. Therefore, the differences between the three strategies reduce.

6.3.3 Real disturbances

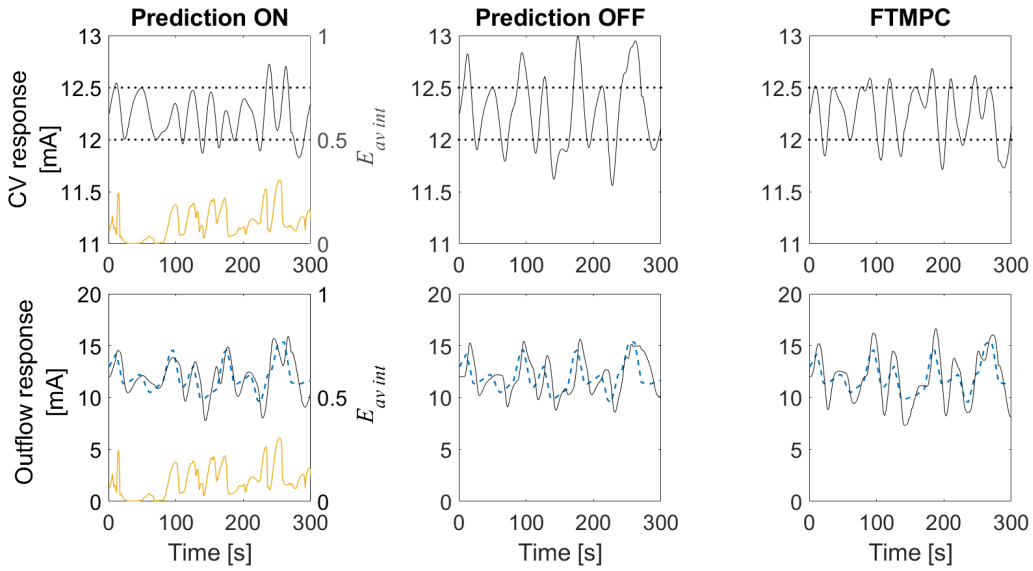
Fig. 6.3 shows the results of MPCs with representative sections of the real time series. The panels on the left hand side, corresponding to the strategy 'Predicton ON', show also the values of E_{av} over time, which is the metric evaluating the quality of the prediction made by the predictor at each instant (Section 4.3.1). To obtain comparable results, all signals have been scaled so that their range is within ±2 mA either side of the mean value.

Tables 6.4 shows for each considered time series the values of the metrics σ_u and Θ_v^{Area}, which assess respectively the violations of constraints of the controlled variable and the propagation of the disturbance through the manipulated variable (5.4). The implementation of the prediction improves the performance of the MPC in case of persistent oscillating disturbances as well as in case of abrupt spiky disturbances.

The benefits are higher for Tag 34 compared to the other signal affected by persistent disturbance, Tag 33. The reason is that the predictions that are obtainable for Tag 34 are more accurate. Indeed, the values of E_{av}, plotted on the panels on the left hand side, are higher for Tag 33 than for Tag 34. This is because of Tag 33 has a lower predictability than Tag 34.

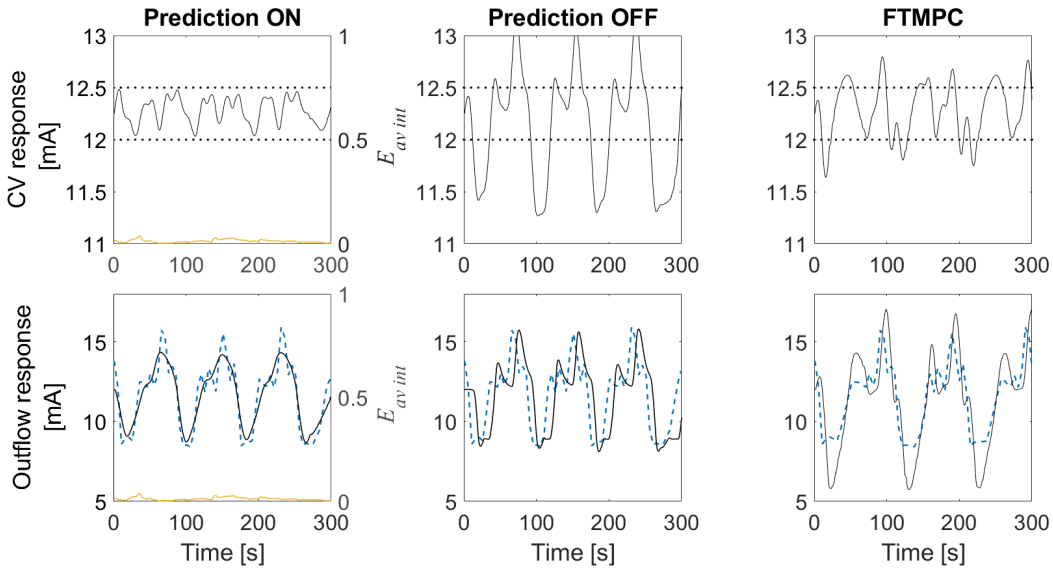
Finally, comparing the two solutions used normally in industrial MPCs shows that the MPC with Prediction OFF strategy violates the given constraints with both persistent disturbances (Tag 33 and Tag 34), whereas the FTMPC has fewer violations of the constraints but its control action is aggressive. This is very similar to what happened when the disturbance was sinusoidal.

Instead, when abrupt spiky disturbances appear, the FTMPC worsens the metric of the controlled variable as well as the ones of the manipulated variable. A spiky disturbance does not upset the controlled variable as a permanent change of the disturbance. The FTMPC overreacts and the large change in the outflow caused by the controller leads the level to violate its constraints.

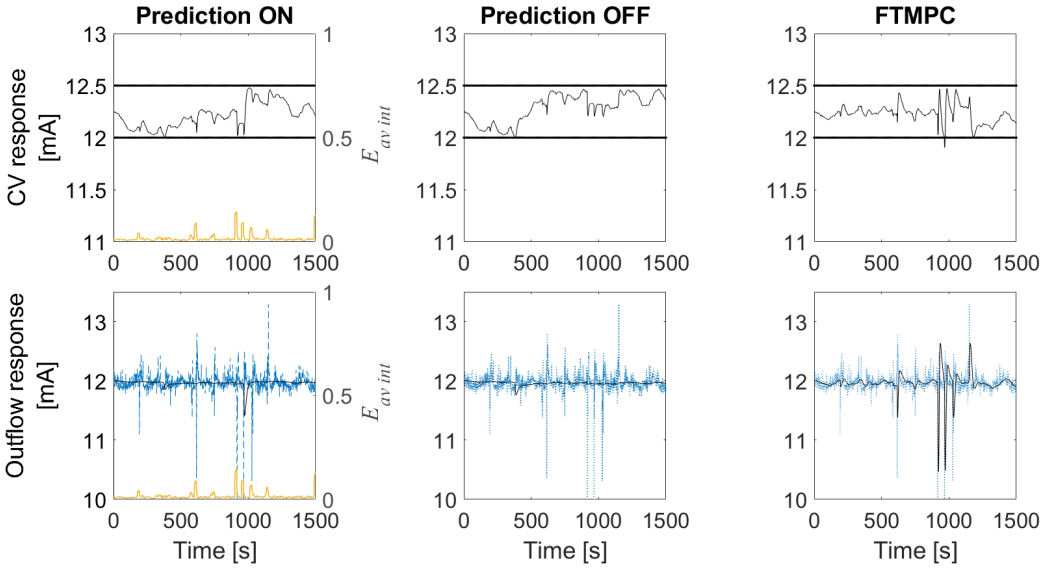


(a) Tag 33 SE Asian refinery

Figure 6.3: Results of the response of the level (CV) and of the outflow using real disturbances from a SE Asian refinery and from Eastman Chemical company plant. The inflow of the tank is dashed in blue. The value of the metrics $E_{av\ \mathrm{int}}$ is in yellow.



(b) Tag 34 SE Asian refinery



(c) Tag 30 Eastman Chemical company

Figure 6.3: *(continued)*Results of the response of the level (CV) and of the outflow using real disturbances from a SE Asian refinery and from Eastman Chemical company plant. The inflow of the tank is dashed in blue. The value of the metrics $E_{av\ \mathrm{int}}$ is in yellow.

Table 6.5: Questions for the case study of the CSTH and answers.

Question	Answer
Impact of disturbance frequency on performance of controllers	• The faster the frequency of the disturbance is, the larger are the benefits of using a multi-step prediction in an MPC controller. • The Prediction ON strategy allows a thoughtful use of the manipulated variable and avoidance of the violation of constraints, and it is able to stop the disturbance propagation. • The control action of FTMPC is overly aggressive when the frequency of the disturbance is high. • When the frequency decreases, the approximation made by the FTMPC resembles more the reality. • The controller can add non-linearities to the propagating disturbance
Impact of prediction algorithm on control performance	• The performance of the MPC controller with disturbance forecasting is better when the time series of disturbance is more predictable.

6.3.4 Conclusions for the CSTH

This case study tested the idea of exploiting a limited buffer capability with an MPC controller to counteract a propagating disturbance.

The aim of the controller is to reduce the variations of the manipulated outflow, keeping the level of the water within two tight constraints. The considered disturbances are purpose made sinusoidal disturbances and three real time series, characterized by persistent or by abrupt patterns, which have been analysed in Chapter 4.

The aims of this section were to show the impact of the frequency of the disturbance and the impact of the prediction algorithm on the MPC controller proposed in comparison to two other MPC strategies. Table 6.5 summarize the answers to such questions.

For faster frequencies, the strategies called Prediction OFF and FTMPC, often used in industrial settings, propagate downstream a disturbance affecting the feed of the considered buffer tank. Additionally, these strategies add non-linearities while propagating the disturbance. On the contrary, the proposed framework is able to minimize disturbance propagation or even stopping it. Nonethe-

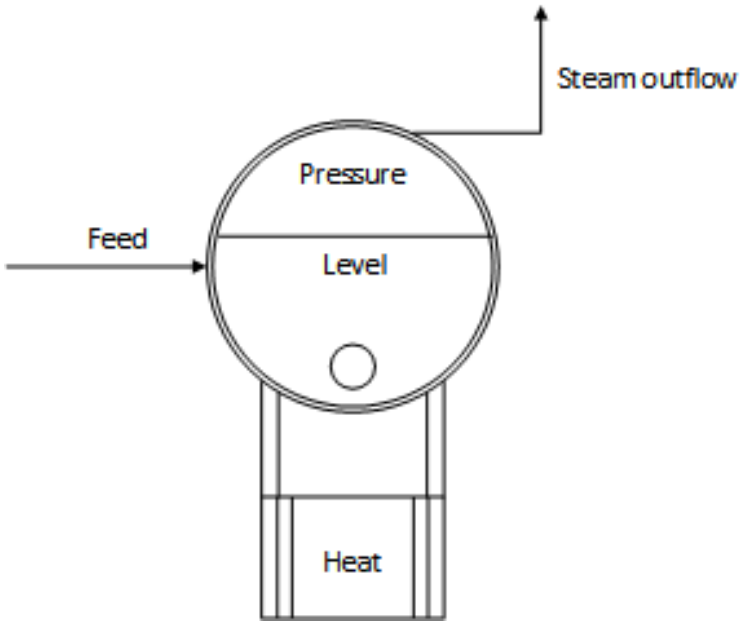


Figure 6.4: Case study of the steam boiler. Duplicated from Fig. 5.3.

less, the difference between the three strategies considered diminishes when the frequency of the sinusoidal disturbance reduces.

Using industrial disturbances, this section shows that combining an MPC controller tuned to not propagate disturbances with the weighted k-NN prediction algorithm presented in Chapter 4 improves performance of the controller. Performance is assessed using the metrics proposed in Chapter 5. However, the quality of the prediction of a disturbance has an impact on performance of the controller.

6.4 RESULTS: THE STEAM BOILER

6.4.1 Introduction

This section compares the three forms of MPC considered in Section 6.1 on the model of a steam boiler by Åström and Bell (1998), which was described in Section 5.7 and it is depicted in Fig. 6.4.

A purpose of this section is to examine the effects of changing controller parameters. This section tests variations of the sampling time of the controller, of the control horizon and of disturbance horizon, while the prediction horizon remains constant. For the purpose of testing, the future values of the disturbance are initially assumed to be known exactly to the MPC controller with

Table 6.6: Parameters of the tested disturbances for the case study of the steam boiler

Signal type	Pattern / Cycle length	Amplitude
Tag 34 Tag 33	1020 s	10% u^{Nom}
Tag 30	180 -300 s	20% u^{Nom}

the Prediction ON strategy. This assumption make it possible to exclude the impact of prediction errors on the analysis. The effects of the tested control parameters are analysed on both scenarios created for this model and described in Section 5.7.4.

Another task of this section is to show the applicability of proposed MPC framework on industrial case studies. Section 6.4.3 is going to show the results of the scenario where the disturbance is from the steam outflow, that is the load of the boiler. This case study shows whether there are benefits in using a multistep prediction when all variables must follow a set-point.

Section 6.4.4 considers the case where the disturbance comes from the heat provided to the boiler. This case study shows that the concept of buffer can be extended to variables different from levels. The controller has to avoid the propagation of the disturbance to loads by keeping the pressure and level within limits, using the tuning for buffer variables proposed in this thesis with time-varying weights (Section 5.3.3). Additionally a comparison is made for this scenario between using the perfect knowledge of the future disturbance values and the prediction algorithm. This highlights the impact of the sampling of the predictor on the performance of the controller proposed.

6.4.2 The parameters of the disturbances

Table 6.6 lists the disturbances and their parameters used for this section. Tag 33 and Tag 34 are persistent, Tag 30 is instead characterized by abrupt spiky patterns. Section 5.7.3 discussed when these two types of disturbances can occur in a boiler.

The amplitude of the disturbances has been set to 10% of the nominal value for Tag 33 and Tag 34 for both configurations considered. Åström and Bell (1998) and Elguindy (2013) changed the amplitude of the inputs of the system by roughly 10% of the nominal value when doing tests on the real power plants they modelled.

Table 6.7: Indication of ideal values of metrics for the case study of boiler where disturbances come from the steam outflow.

Ideal values of metrics	Description
$\Theta^{\text{Area}}_{\text{Pressure}} = 0$ and $\Theta^{\text{Area}}_{\text{Level}} = 0$	No constraints violations of pressure and level
$\Gamma^{y}_{\text{Pressure}} \rightarrow 0$ and $\Gamma^{y}_{\text{Level}} \rightarrow 0$	Good set-point tracking of controlled variables, in particular for the pressure.
$\sigma^{u}_{\text{Heat}} < k$ and $\sigma^{u}_{\text{Feed}} < k$	Manipulated variables are free to move. However excessive movements signify poor control.
$\sigma^{u}_{\text{Power Delivered}} \rightarrow 0$	Variations of the power delivered to the load should be small.

Tag 30 has been rescaled so that amplitude of its largest spikes is 20% of the nominal value. The purpose is to test the behaviour of the controllers to really severe disturbances.

6.4.3 Disturbance from the load

6.4.3.1 Introduction

The disturbance is from the steam outflow used by the loads in this case study. The controller has to use heat and feed of fresh water to keep pressure strictly at its set-point. Also the level has to follow its set-point although with a lower priority. In view of this controller strategy, described in Section 5.7.4, Table 6.7 shows the values that the metrics for this case should ideally have.

The power delivered to the load in form of steam should be constant to avoid a disturbance propagation back to the loads. To measure the variability of the power delivered, the metric $\sigma^{u}_{\text{Power Delivered}}$ is created. The metric sigma is the standard deviation of a variable normalised over its range, as Table 6.2 reminded. Section 5.7.4.2 showed that the power delivered depends mainly on the mass flow rate of steam and to a lesser degree on the pressure. However, the mass flow rate of steam leaving the boiler is the disturbance and does not depend on the controller, while the pressure is a controlled variable. This section shows whether the proposed MPC framework with disturbance forecasting can provide considerable benefits by keeping the pressure more constant to reduce further variations of the power delivered to the loads.

6.4.3.2 Analysis of the metrics - Tag 34

Fig. 6.5 shows the values of metrics when the disturbance is Tag 34. The bar graphs are distributed over several rows and columns. Each row shows a different metric and each column represent a different controller tuning in terms of controller sampling CS, control horizon CH and - if used - disturbance horizon DH. The number next to the label CS represents the value of the controller sampling in seconds. The number next to the labels CH and DH represent the values of control horizon and disturbance horizon in controller samples.

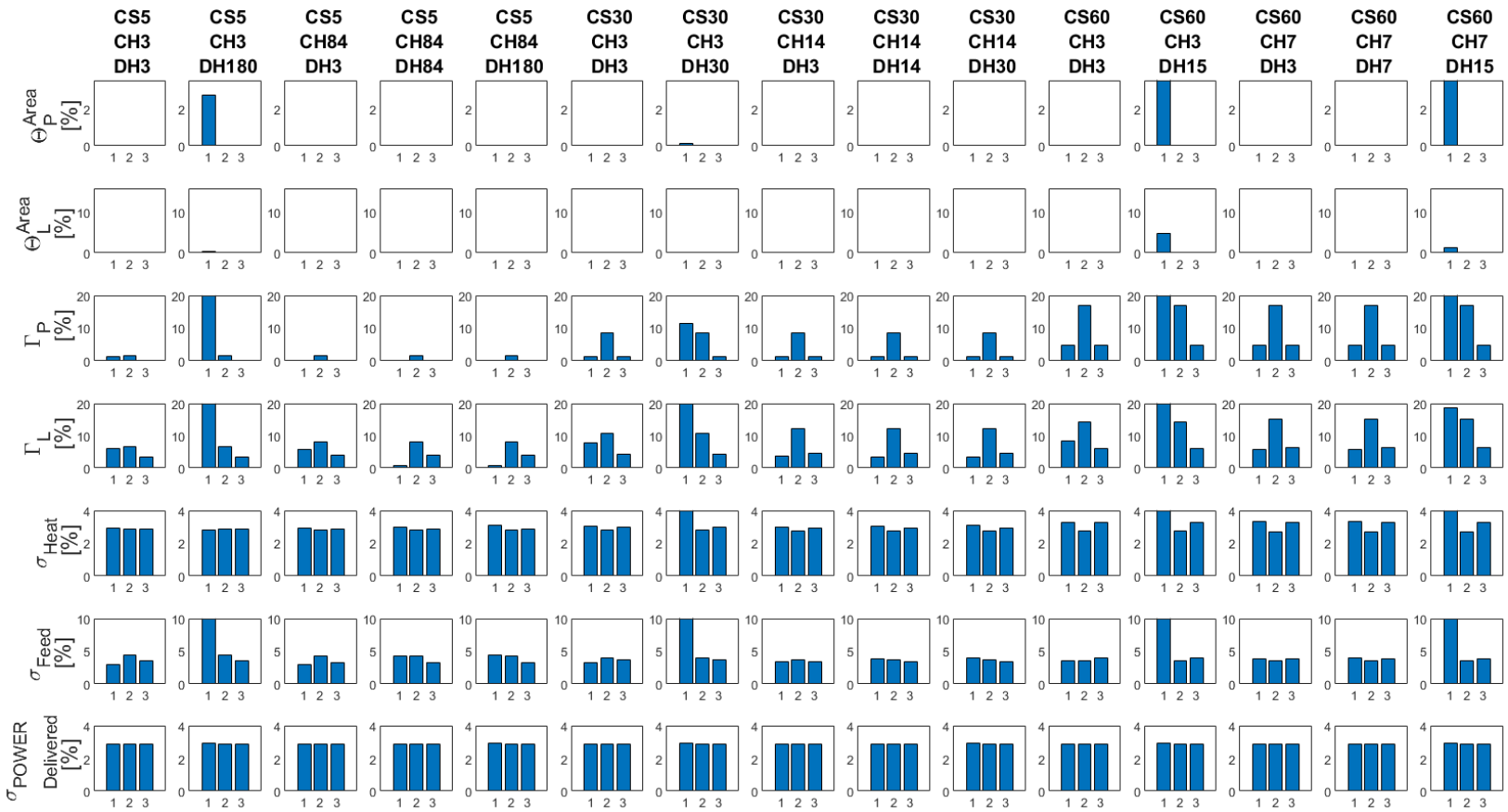


Figure 6.5: Performance matrices with Tag 34 as disturbance acting on the steam outflow
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC

Table 6.8: Description of the metrics in Fig. 6.5, when the disturbance comes from the steam outflow requested by the loads using the Tag 34

Topic	Observations
Disturbance horizon	• When the disturbance horizon is larger than the control horizon (for example, in cases CS 5 - CH 3 - DH 180, CS 60 - CH 3 - DH 15 and CS 5 - CH 3 - DH 90), there can be: – Violations of constraints visible in Θ^{Area} – Degradation of set-point tracking of pressure and level visible in Γ_P and Γ_L – Large variations of the feed of fresh water visible in σ^{u}_{Feed}
Set-point tracking	• As the controller sampling increases, all strategies worsen their performance in set-point tracking. For example, the values of Γ_P becomes higher. • The Prediction OFF strategy is often the worst for set-point tracking. • The Prediction ON strategy has better set-point tracking than the FTMPC when the control horizon is longer than three steps. • The faster the sampling rate is, the higher is the advantage of the Prediction ON strategy over the FTMPC. When the controller sampling is 60s (CS60), the advantage is negligible.
Disturbance propagation	• The power delivered to the load in form of enthalpy of the steam flow is pretty constant. • The variations of pressure do not cause a considerable variation of enthalpy of the steam delivered.

Table 6.8 describes the results. The focus is on the metrics that assess the set-point tracking and the propagation of the disturbance with three MPC strategies, on the impact of the tuning of the disturbance horizon for the Prediction ON strategy.

The metrics Γ and σ are high when the disturbance horizon is longer than the control horizon, and the control horizon is the short. This is the case shown in the 2^{nd}, 7^{th}, 12^{th} and 15^{th} column of bar graphs in Fig. 6.5. The high values of the metrics Γ indicate that the set-point of controlled variables is not tracked, and the high values of the metrics σ indicate that the manipulated variable have large variations. The metrics suggest that the controller is overly aggressive. A controller with a control horizon shorter than the disturbance horizon does not have enough degrees of freedom, intended as

Table 6.9: Comparison of the values of the metric Γ_{Pressure} and Γ_{Level} for the best tunings of the strategies Prediction ON and FTMPC when the disturbance comes from the loads.

		Prediction ON with perfect knowledge	FTMPC	Improvement over FTMPC
Tag 34	Optimal tuning	CS 5 - CH 84 - DH 84	CS 5 - CH 84	
	Γ_{Pressure}	0.063	0.076	16.75%
	Optimal tuning	CS 5 - CH 84 - DH 84	CS 5 - CH 3	
	Γ_{Level}	0.76	3.24	76.56%

number of times it can change the values of the manipulated variables over the prediction horizon, to compensate the foreseen variations of the disturbance. Finding an optimal control action can be difficult or unfeasible, and it can lead to aggressive control actions (Dughman and Rossiter, 2020; Valencia-Palomo, Rossiter, and López-Estrada, 2014). Section 6.4.3.5 will show the trends over time of the controlled and manipulated variables in one of these cases, and it will explain this phenomenon more in detail.

Excluding these cases from further analysis, the observation of the metrics Γ_{Pressure} and Γ_{Level} (third and fourth row of graphs in Fig. 6.5) shows that the set-point tracking is worst when the Prediction OFF strategy is used. These metrics assess the variation of the controlled variables, and are higher for this strategy.

When using the same tuning, the FTMPC provides better performance than the one of the Prediction ON only in few cases, when the control horizon is short (three steps in this experiment). The reason why long control horizon might improve performance is related to the problem seen when the disturbance horizon is longer than the control horizon. Long control horizon can give more freedom to the controller to find an optimal control action, as Section 6.4.3.5 will discuss further.

Table 6.9 compares the best tuning for the Prediction ON strategy with the best tuning for the FTMPC. The table shows there is a 16.75% improvement of the metric Γ_{Pressure} and a 76.5% improvement of the metrics Γ_{Level}.

Despite the differences, the metrics Γ are small in absolute terms for the Prediction ON and FTMPC. For example, the metric Γ_{Pressure} ranges between 0.063% and 4.75% depending on the tuning and strategy. This means that the standard deviation of the pressure is between 0.063% and 4.75% of its

Table 6.10: Comparison of the values of the metric Γ_{Pressure} and Γ_{Level} for the best tunings of the strategies Prediction ON and FTMPC when the disturbance comes from the loads.

		Prediction ON with perfect knowledge	FTMPC	Improvement over FTMPC
Tag 33	Optimal tuning	CS 5 - CH 84 - DH 84	CS 5 - CH 84	
	Γ_{Pressure}	0.068	0.070	2.92%
	Optimal tuning	CS 5 - CH 84 - DH 84	CS 5 - CH 3	
	Γ_{Level}	0.58	2.23	73.63%

admissible range. Interestingly, the FTMPC is not overly aggressive when the aim of the controller is tracking a set-point rather than controlling a variable acting as buffer, as in the previous case study. Forcing the controller to follow a set-point rather than to intervene strongly only when the constraints might be violated avoids limit cycles.

The metric $\sigma_{\text{Power delivered}}$ assesses the variations of the power delivered to the loads. This metrics, represented in the last row of the graphs in Fig. 6.5, is almost constant for the Prediction ON, Prediction OFF and FTMPC. The power delivered to the loads depends in minimal part to pressure of the steam, as explained earlier. Although there are visible differences in the set-point tracking of the pressure among the three MPC strategies, these differences do not reflect in variations of the power delivered in a visible way. A disturbance coming from a load cannot be considerably dampened by using one MPC strategy over the others.

6.4.3.3 Analysis of the metrics - Tag 33

Fig. 6.6 shows the values of metrics in case the disturbance has the trend of Tag 33. The observations done for Tag 34 are mostly valid also for Tag 33. However, when the disturbance horizon is larger than the control horizon, the peaks in the bar graphs of the strategy Prediction ON that manifest a deterioration of the performances are smaller and less severe than for the case of Tag 34. Remembering that for these tests the controller uses an exact information of the disturbance evolution, the difference can be attributed only to the different characteristic of the time series of the disturbance.

Section 6.4.3.5 will explain that setting long disturbance horizons together with short control horizon

Table 6.11: Comparison of the values of the metric Γ_{Pressure} and Γ_{Level} for the best tunings of the strategies Prediction ON and FTMPC when the disturbance comes from the loads.

		Prediction ON with perfect knowledge	FTMPC	Improvement over FTMPC
Tag 30	Optimal tuning	CS 5 - CH 84 - DH 60	CS 5 - CH 84	
	Γ_{Pressure}	0.079	0.083	4.5%
	Optimal tuning	CS 5 - CH 84 - DH 60	CS 5 - CH 84	
	Γ_{Level}	0.75	1.41	46.56%

can lead to large and fast changes of the manipulated variables, resulting in a too aggressive control action. The reason is that the controller cannot find an adequate optimal solution to compensate the foreseen disturbance. Tag 34 has faster variations within its repeating pattern than Tag 33, and the controller might have problems in finding a solution.

Table 6.10 provides the values of the metrics Γ obtained using the best tunings for the Prediction ON with perfect knowledge and for the FTMPC. The improvement of the metric Γ_{Pressure} is lower than for Tag 34 because the performance of the MPC is better when Tag 33 is used. In absolute terms, the values of the metrics is low for both strategies.

6.4.3.4 Analysis of the metrics - Tag 30

Fig. 6.7 shows the values of the metrics when the disturbance coming from the load is Tag 30. Most of the observations done before are still valid. It is noticeable that that the proposed MPC improves slightly the set-point tracking, providing lower values of the metrics Γ_{Pressure} and Γ_{Level}, only when the sampling is five seconds and the control horizon longer than three steps. In these cases, the improvement of Γ_{Pressure} is about 4%, as Table 6.11 shows.

In the other cases, the metric Γ_{Pressure} for the FTMPC is between 0% and 4% better. The sampling of the Tag 30 was 20s. A controller sampling of 30s or 60s is too large for the controller to benefit from a multi-step prediction of the disturbance.

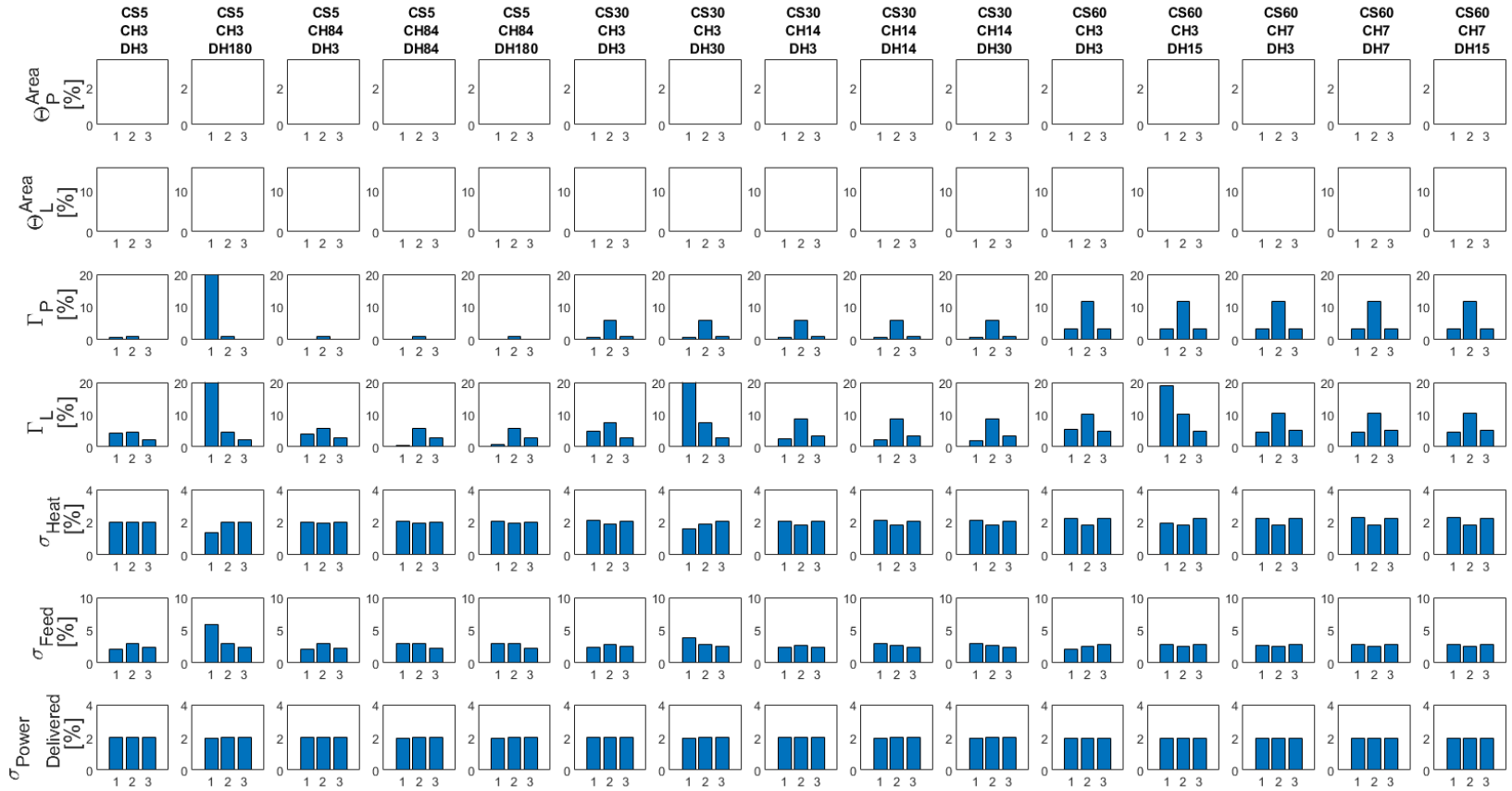


Figure 6.6: Performance matrices with Tag 33 as disturbance acting on the steam outflow.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC

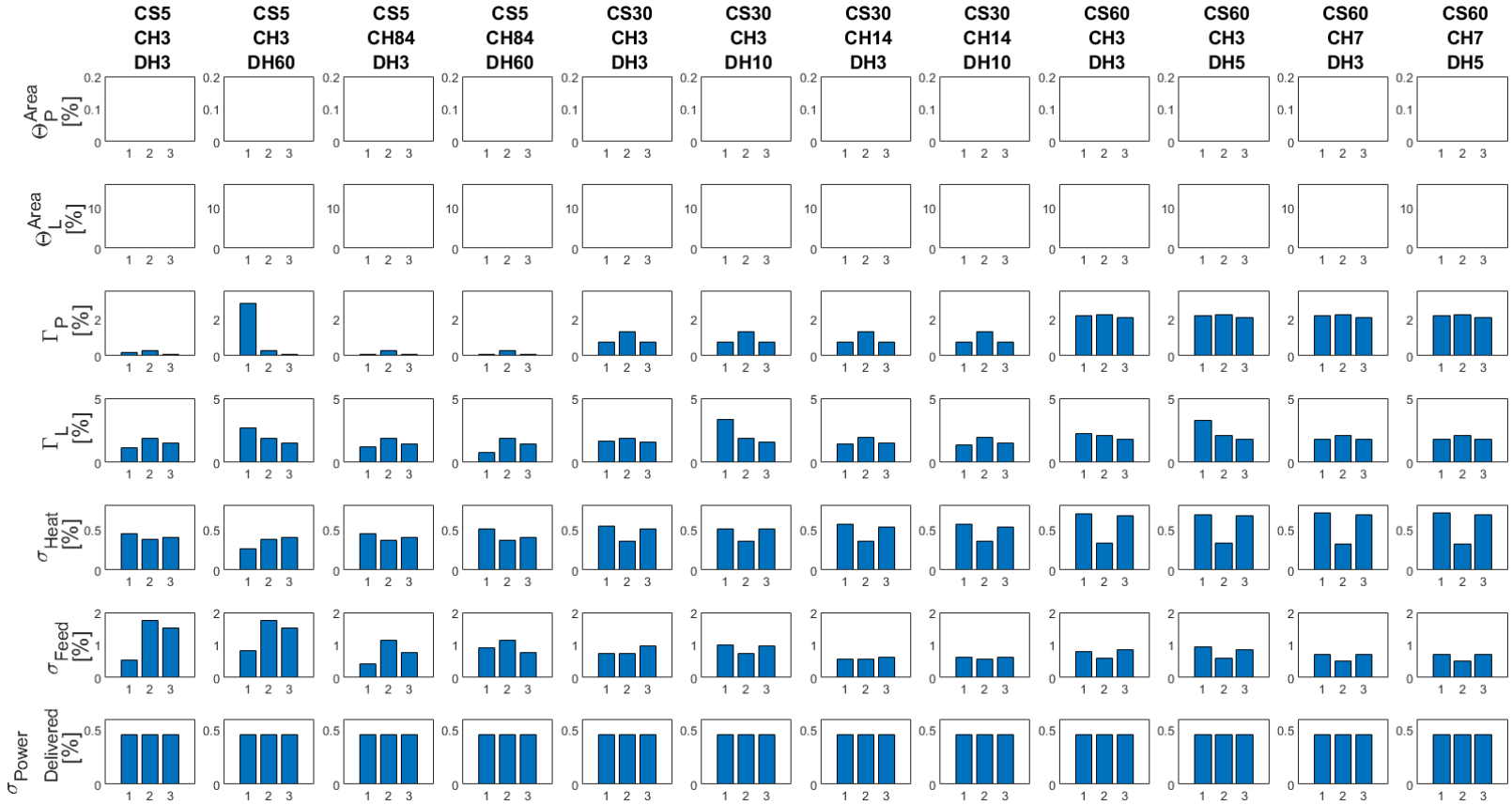


Figure 6.7: Performance matrices with Tag 30 as disturbance acting on the steam outflow.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC

6.4.3.5 Cause of poor performance when the disturbance horizon is longer than the control horizon

The previous sections highlighted that some metrics deteriorate for short control horizons and long disturbance horizons. This section provides examples of both situations.

Fig. 6.8 shows the trend of the controlled and manipulated variables relative to the three strategies for a set of tuning parameters when Tag 34 is used. The graphs in the first and second columns use the Prediction ON strategy with perfect knowledge about the future values of the disturbance. The difference is that the graphs in the first column are associated to a controller where the value of the disturbance horizon is equal to the value of the controller horizon. The graphs in the second column from the left show the trends obtained using a disturbance horizon longer than the control horizon. The graphs on the third column are associated to the the Prediction OFF, and those in the fourth column to the FTMPC.

Clearly, the graphs in the second column of Fig. 6.8 shows that using a long disturbance horizon causes the controller to be extremely aggressive and unable to track the set-points. Similar behaviours were found also for the other disturbance signals. This behaviour is similar to the one described by Rossiter and his co-authors (Dughman and Rossiter, 2020; Valencia-Palomo, Rossiter, and López-Estrada, 2014). The authors considered the case where a controller previews the h future values of the set-points. If the control horizon is c, they state that the controller has c degrees of freedom because it can change c times the control action over that control horizon. If $c < h$, the controller might not have enough degrees of freedom to compensate variations of the set-point seen in the preview. The solution can be unfeasible or too aggressive.

Section 5.2.2.3 reported that Rossiters and his co-authors provided this explanation for the case where there is a preview of set-points rather than of a disturbance. The present section suggests that this occurs also in the case of the preview of a disturbance.

The graphs on the fifth row show the 'Optimization status', which counts the number of iterations needed to find a solution to the objective function of the MPC. While all other strategies need only one iteration in this case, this number increases when a disturbance horizon longer than the control horizon is used. Sometimes the controller reaches the maximal number of iterations (which is equal

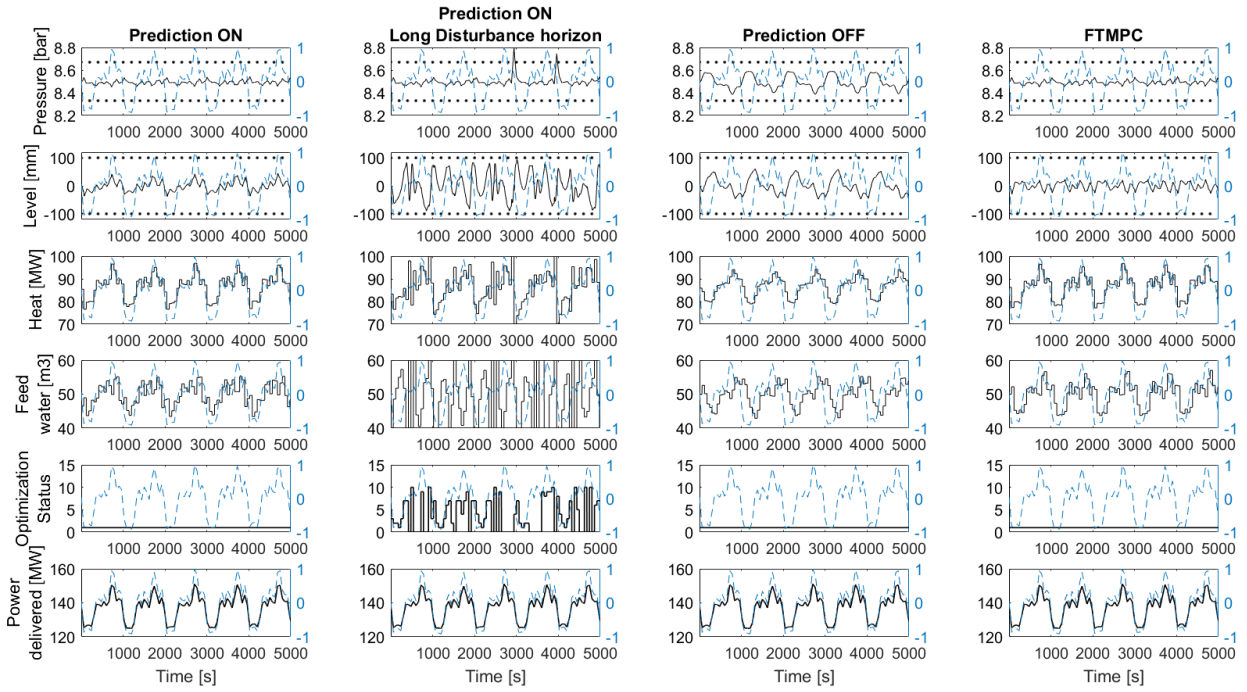


Figure 6.8: Disturbances from the steam outflow. The trend of the disturbance is dashed in blue.
Tag 34 CS 60 - CH 3 - DH 3 and DH 15 for case of long disturbance horizon.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples.

to 10 iterations) allowed by the optimizer. There is a limit to avoid that optimization process enters in a loop when a solution is unfeasible. Once the limit is reached, the suboptimal solution found so far is applied. Consequently, the optimization process is more complex when the disturbance horizon is longer than the control horizon. This might lead to solution which are suboptimal and aggressive.

6.4.3.6 Examples of control responses

This section compares the trends in Fig. 6.8 of the Prediction ON with perfect knowledge of the future values of the disturbance with the trends of the strategies Prediction OFF and FTMPC.

Fig. 6.8 shows that the set-point tracking capability of the Prediction OFF strategy is much poorer than the other two strategies because there is no information about the future values of the disturbance. Still, there is not a significant difference between Prediction ON and FTMPC (as long as the disturbance horizon is correct).

Table 6.12: Values Γ_{Pressure} and $\sigma_{\text{Power Delivered}}$ for the tuning parameters CS 60 - CH 3 - DH 3.

	Prediction ON	Prediction OFF	FTMPC
Γ_{Pressure}	4.65%	16.9%	4.74%
$\sigma_{\text{Power Delivered}}$	2.8437%	2.8584%	2.8438%

Table 6.12 shows the values of the metric Γ_{Pressure}, which assesses the variations of the pressure, and of $\sigma_{\text{Power Delivered}}$, which assesses the variations of the power delivered to the loads. While the metric Γ_{Pressure} is slightly smaller with the Prediction ON strategy, showing that the pressure is slightly more constant with this strategy, the metric $\sigma_{\text{Power Delivered}}$ is nearly equal for the three strategies. Therefore, an improvement of the pressure does not reduces too much the variations of the power delivered to the loads. The reason is that power delivered through steam depends mainly on the steam outflow, which is not controlled. The pressure has a limited impact if it stays within strict constraints.

6.4.3.7 Conclusions when the disturbance comes from the load

This section analysed the possible benefits of using a feed-forward action and particularly a detailed prediction of the disturbance when a problem of only set-point tracking is given.

The impact of disturbance horizon on the performance of the controller has been discussed, highlighting that the disturbance horizon should be smaller than the control horizon. In this way the the optimizer of an MPC controller has enough degrees of freedom, intended as number of times the controller can change its control action over the prediction horizon, to counteract the foreseen variations of the disturbance. Otherwise, an aggressive control action can result. The group of Rossiter provided this explanation in the case an MPC controller previews the set-points of controlled variables. Here, it has been observed that the number of iterations needed by the optimizer to find a feasible solution is far higher when the disturbance horizon is longer than the control horizon. This observation suggests that this explanation applies also for the case where the controller knows in advance the future values of a disturbance.

Another conclusion is that using a multistep prediction of a disturbance provides most of times similar performance to the one of the classical feed-forward strategy used in MPC, which is the

FTMPC. For large control horizon and fast sampling, the Prediction ON strategy tends to provide better performance compared to the FTMPC. However, the practical advantages of having a better tracking of the set-point are not relevant for this case study. The impact that an improvement of the set-point tracking of the pressure has on the power delivered to the loads is very small. The rate of the mass flow of steam requested to the boiler has a more important impact on the power delivered. Once one or more loads disturb a boiler, requesting a varying mass flow rate of steam, there are small variations of the pressure of steam with all three MPC strategies. These small variations of pressure do not change the power delivered to other loads considerably.

Because there is a limited advantage with the proposed MPC framework for this case study and for the sake of brevity, this section does not compare the performance obtainable doing the prediction with the k-NN algorithm developed in Chapter 4. However, this comparison will be done for the next two case studies.

6.4.4 Disturbance from the heat provided to the boiler

6.4.4.1 Introduction

This section considers the case where the disturbance comes from the heat provided to the boiler. Fig. 6.9 represents the case study. The aim is to stop the propagation of the disturbance to the loads. To do it, the variations of power delivered to the loads have to be minimised by reducing the variations of steam flow rate. Pressure and level act as buffer variables, and feed of water and steam outflow are the manipulated variables. Table 6.13 shows the values that the metrics should ideally have for this case study.

The section starts analysing the results assuming that the Prediction ON strategy has a perfect knowledge of the future evolution of the disturbance. As mentioned previously, this assumption makes it possible to exclude the impact of prediction errors on the analysis. Section 6.4.4.6 compares later such results with the ones achieved using the predictions obtained with the k-NN algorithm.

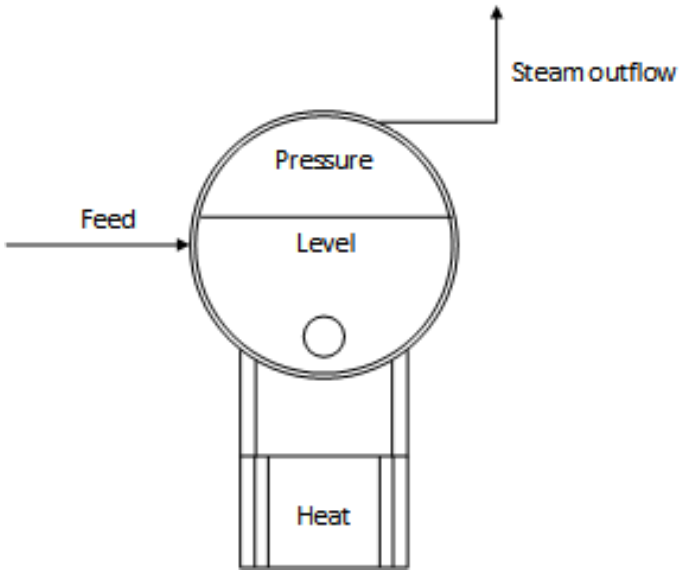


Figure 6.9: Case study of the boiler. Duplicated from Fig. 5.3.

Table 6.13: Indication of ideal values of metrics for the case study of boiler where disturbances come from the heat provided.

Ideal values of metrics	Description
$\Theta^{\text{Area}}_{\text{Pressure}} = 0$ and $\Theta^{\text{Area}}_{\text{Level}} = 0$	No constraints violations of pressure and level
$\Gamma^{y}_{\text{Pressure}} \gg 0$ and $\Gamma^{y}_{\text{Level}} \gg 0$	Large deviations of the controlled variables acting as buffer show that their buffer capability is exploited (which is good as longs as there is no constraints violations).
$\sigma^{u}_{\text{Steam Outflow}} \rightarrow 0$	Propagation of disturbances through variations of steam outflows are minimised.
$\sigma^{u}_{\text{Power Delivered}} \rightarrow 0$	Variations of the power delivered to the load should be small.

6.4.4.2 Analysis of the metrics - Tag 34

Fig. 6.10 lists the values of the metrics when the disturbance comes from the heat provided to the boiler and Tag 34 is used to represent the disturbance. A perfect knowledge of the future evolution of the disturbance is assumed for the Prediction ON strategy.

Table 6.14 summarises the description of the results. The table focuses on three aspects which are length of the disturbance horizon, constraints violation and ability to reduce the disturbance propagation. As in the previous case, where all controlled variables must follow a set-point, a disturbance horizon longer than the control horizon causes extremely aggressive behaviours of the controllers with Prediction ON (Section 6.4.3.5).

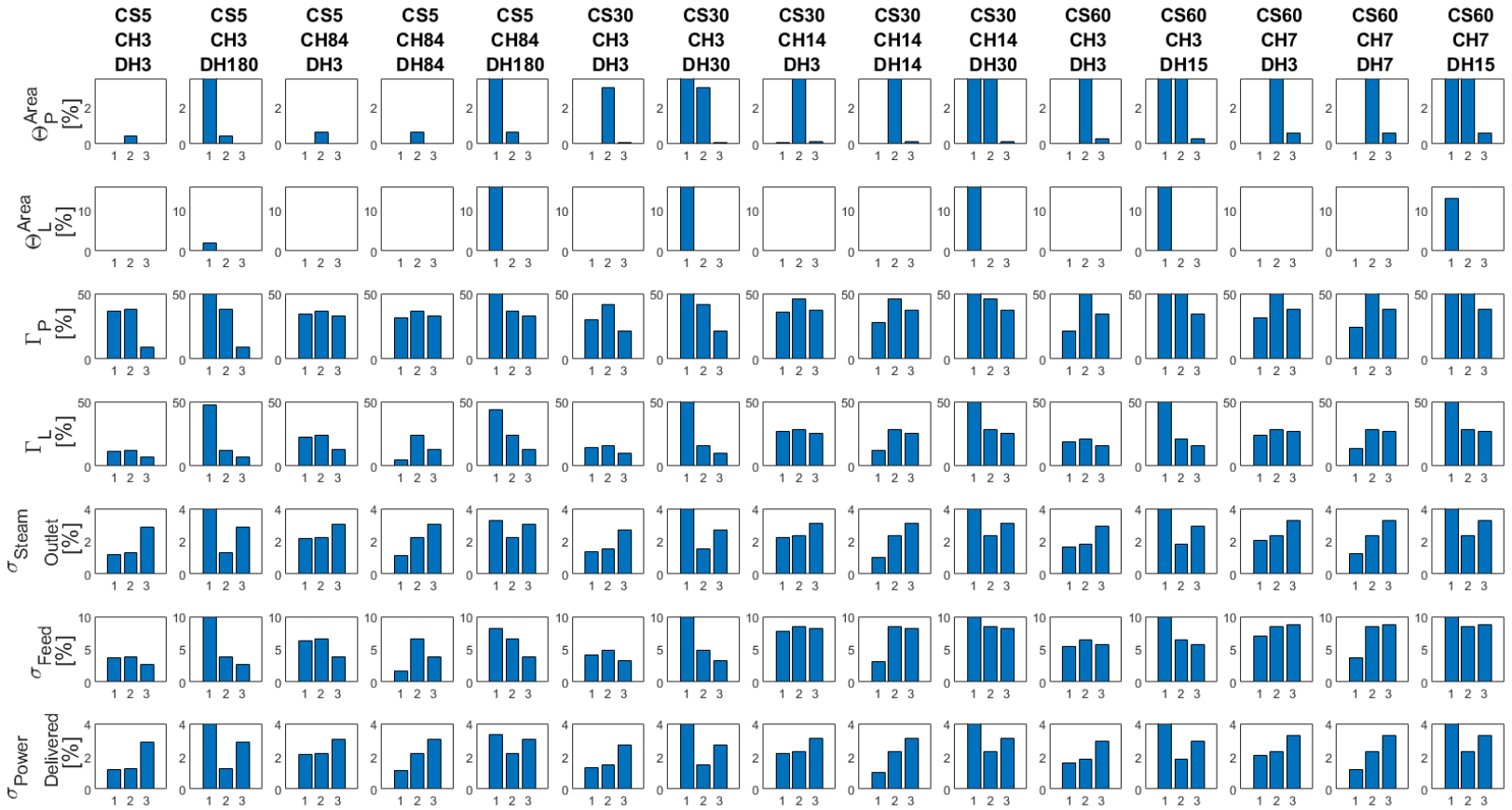


Figure 6.10: Performance metrics with Tag 34 as disturbance acting on the heat provided to the steam boiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC

Table 6.14: Description of the metrics in Fig. 6.10, when the disturbance comes from the heat provided to the boiler using Tag 34

Topic	Observations
Disturbance horizon	• When the disturbance horizon is longer than the control horizon, violations of constraints of controlled variables (shown by Θ) and higher movement of manipulated variables (shown by σ) occurs. • When the disturbance horizon is equal to the control horizon, the metrics $\sigma_{\text{Power Delivered}}$ and $\sigma_{\text{Steam Outflow}}$ are the smallest.
Constraints violation	• The strategy Prediction ON has no constraints violations (except when the disturbance horizon is longer than the control horizon). • The Prediction OFF violates always the constraints. • The FTMPC strategy violates the constraints of for some tunings. The extent of the violation increases with the controller sampling.
Disturbance propagation	• The values of $\sigma_{\text{Power Delivered}}$ are considerably smaller for the Prediction ON and Prediction OFF strategies compared to the FTMPC. • Although the values of $\sigma_{\text{Power Delivered}}$ can be similar for the Prediction ON and Prediction OFF strategies, the latter violates more the constraints.

In case the disturbance comes from the heat, there is the possibility of using controlled variables as buffer. By exploiting such buffers and avoiding manipulating the steam outflow, the variation of the power delivered to to load are greatly reduced. The power delivered depends mainly on the steam outflow, which is a manipulated variable, than on the pressure, which is a controlled variable that acts as buffer. Fig. 6.10 shows that the metric $\sigma_{\text{Power Delivered}}$ follows qualitatively the values of the metric $\sigma_{\text{Steam Outflow}}$ for various tuning parameters and strategies.

For Tag 34, the metric $\sigma_{\text{Power Delivered}}$ is reduced by 29% to 67% when using the strategy Prediction ON compared to the metrics obtained with the FTMPC.

The minimal values of $\sigma_{\text{Power Delivered}}$ are achieved in this case when the control horizon is equal to the prediction horizon. In this case, the metric $\sigma_{\text{Power Delivered}}$ improves by at least 44%.

6.4.4.3 Analysis of the metrics - Tag 33

The observations for Tag 34 are mostly valid also for Tag 33. The reduction of the metric $\sigma_{\text{Power Delivered}}$ while using the Prediction ON compared to the FTMPC are between 27% and 78%.

When the control horizon is equal to the disturbance horizon, the improvement is at least 52%.

What changes is that a disturbance horizon longer than the control horizon does not always lead to large variations of the manipulated variables. It can actually slightly improve the metric $\sigma_{\text{Power Delivered}}$ compared to the case where the disturbance horizon is equal to the control horizon. In these cases, the controller has more information about the future values of the disturbance and the degrees of freedom given by the control horizon are probably enough to find a good optimal solution.

However, a disturbance horizon longer than the control horizon causes large variations of manipulated and controlled variables for one tuning. This tuning has a short control horizon of three steps. So there are relatively few degrees of freedom for the optimization, which do not allow the controller to find always an optimal solution. This happens, as Fig. 6.11 shows, when the controller sampling CS is equal to 30s, the control horizon CH is 3 steps, and the disturbance horizon DH is 30 steps. Although it happens only for one tuning with this disturbance, it can be stated that setting the disturbance horizon longer than the control horizon increases the risk of having a very aggressive controller.

Setting the disturbance horizon and control horizon equal provides good performance and avoids risks. It is therefore recommended.

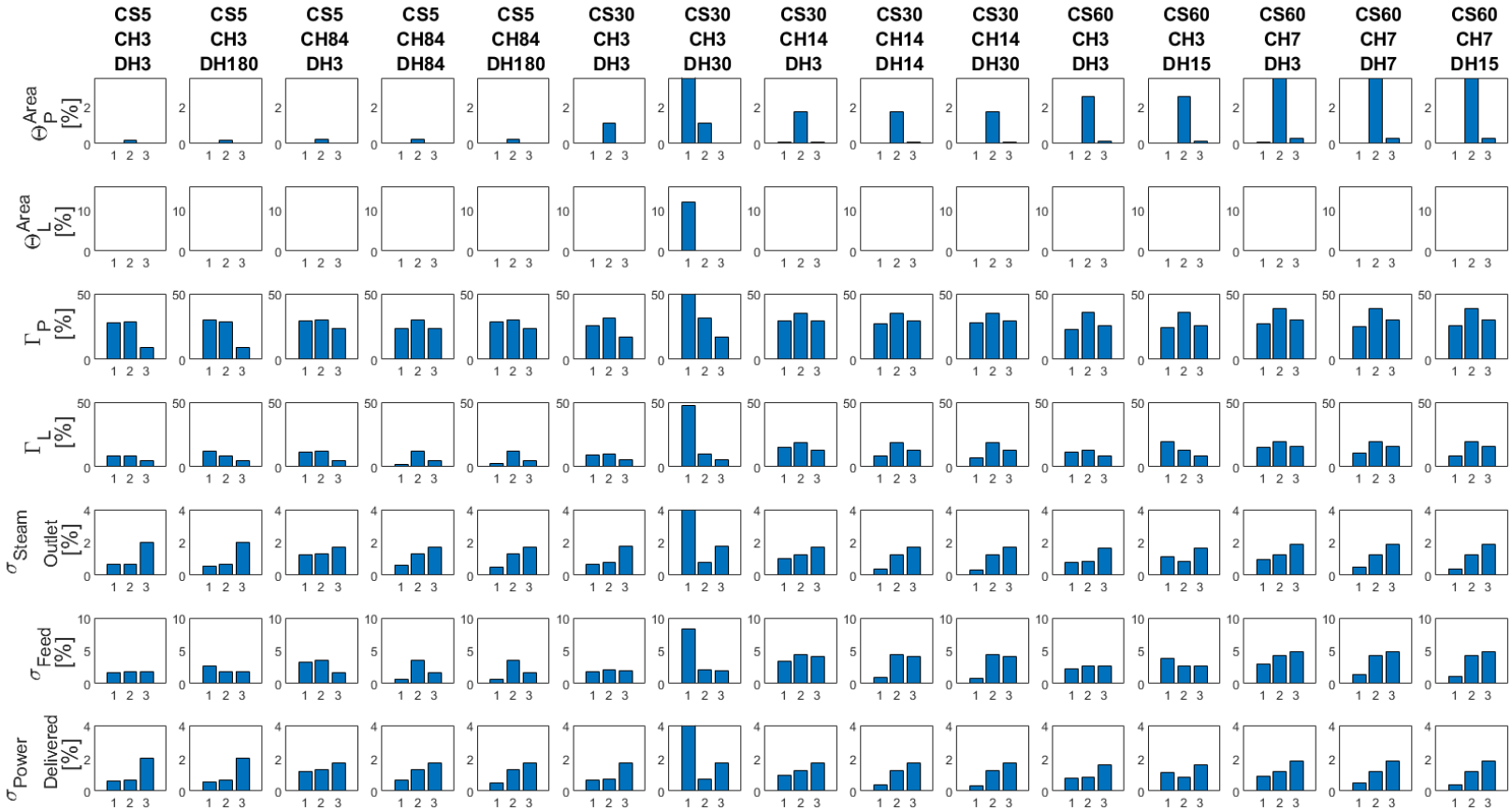


Figure 6.11: Performance metrics with Tag 33 as disturbance acting on the heat provided to the steam boiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC

6.4.4.4 Analysis of the metrics - Tag 30

Fig. 6.12 shows the results of the metrics for Tag 30, characterized by abrupt disturbances. The Prediction ON and Prediction OFF strategies reduce considerably the propagation of the disturbance downstream compared to the FTMPC strategy by maintaining the steam outflow constant when possible. The metric $\sigma_{\text{Power Delivered}}$ shows reductions by 45% to 75% when using the Prediction ON strategy in comparison to the FTMPC. As explained earlier in Section 6.3.2 regarding the CSTH, a controller with the FTMPC strategy overreacts to fast patterns of a disturbance. The reason is that the FTMPC has built in a wrong assumption about the future evolution of a disturbance, assuming that the future values of a disturbance are equal to the current one. The assumption is especially fallacious in case of fast disturbances. The controller with the FTMPC overreacts by manipulating the steam outflow to keep the pressure and level within constraints. This propagates the disturbance further to the loads.

The violations of the constraints for the Prediction ON strategy are higher than the ones for the FTMPC for this Tag. Still, such constraints violations are very small. The metric Θ_{Pressure} shows that the average violation of the constraints over time of the pressure is up to 0.07% of its admissible range. The metric Θ_{Pressure} is up to 0.02% for the FTMPC. Pragmatically, such violations do not constitute a relevant problem for both strategies. The value of this metric is two times larger for the Prediction OFF strategy compared to the the metric for the Prediction ON strategy. The reason is the Prediction OFF strategy lacks of any information about the future values of the disturbance and intervenes late. However, the violations are also small for the Prediction OFF strategy in absolute terms when Tag 30 is used. The average violations of the constraints over time of the pressure for the Prediction OFF strategy are up to 0.14% of the admissible range of this controlled variables.

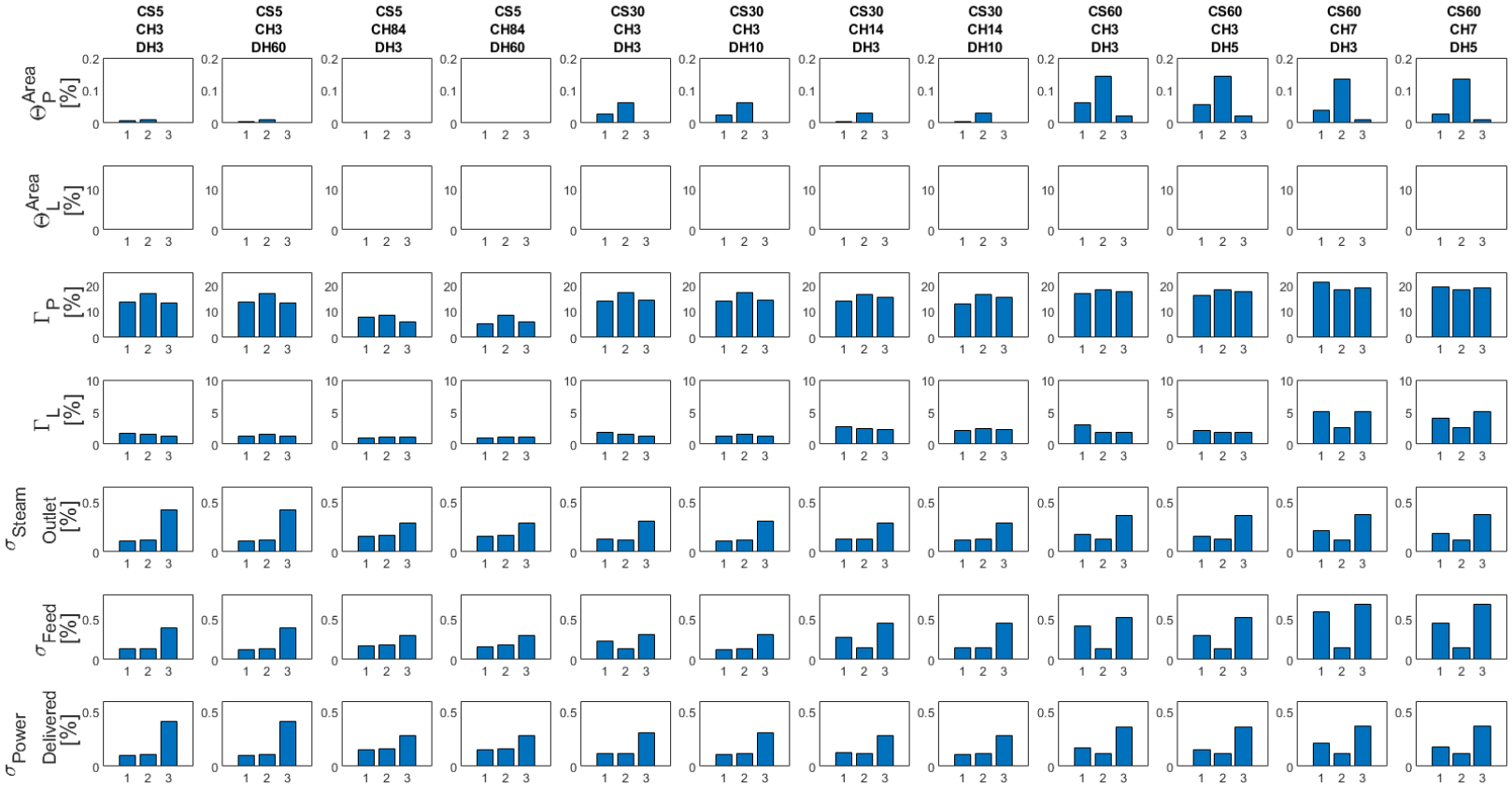


Figure 6.12: Performance metrics with Tag 30 as disturbance acting on the heat provided to the steam boiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with perfect knowledge, 2 - Strategy with prediction OFF, 3 - Strategy with FTMPC

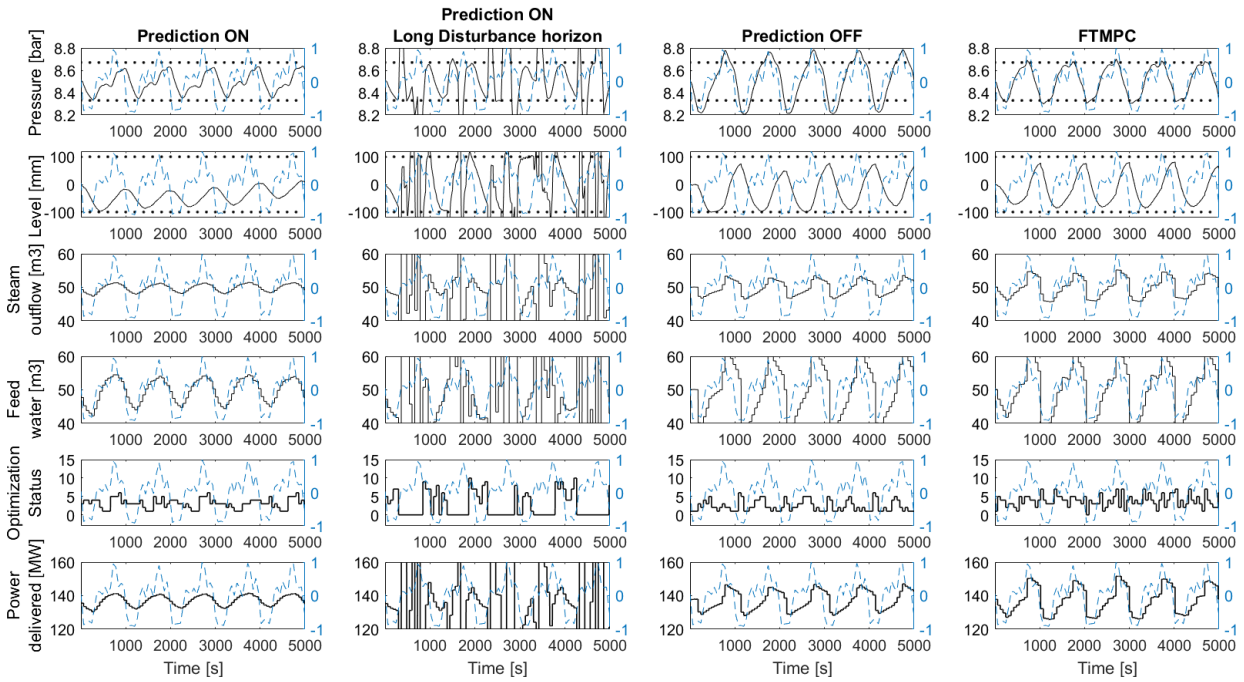


Figure 6.13: Disturbances from the heat provided to the boiler. The trend of the disturbance is dashed in blue.
Tag 34 CS 60 - CH 7 - DH 7/15. CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples.

6.4.4.5 Examples of control responses

This section shows the responses over time of the controllers with the three strategies. The results are shown for Tag 34 and Tag 30, the first one characterized by a persistent type of disturbance and the second one by an abrupt type of disturbance.

Fig. 6.13 shows the trends of the controlled and manipulated variables for the three strategies when the disturbance is Tag 34 for a set of tuning parameters. The trends in the first and second column of graphs from the left are obtained with a controller that uses the Prediction ON strategy with perfect knowledge about the future values of the disturbance. However, the trends in the first column have been obtained setting the disturbance horizon equal to the control horizon. The trends in the second column have been obtained setting the disturbance horizon longer than the control horizon. The strategies Prediction OFF and FTMPC have been used to obtain the trends in the third and fourth column of graphs.

The second column of graphs in Fig. 6.13 shows that using a long disturbance horizon can cause

the controller to be extremely aggressive. The findings reflects the results in Section 6.4.3.5. As explained there, the optimization process needs a control horizon longer or equal the disturbance horizon to have enough degrees of freedom, following the terminology of Rossiter, to counteract the foreseen variations of the disturbance over the prediction horizon. If not, the controller might not find a feasible solutions or finds a suboptimal one and the control action is aggressive. The graphs on the fifth row show the 'Optimization status', which counts the number of iterations needed to find a solution to the objective function of the MPC. This number is larger when a long disturbance horizon is used. For large parts of the simulations, the optimization status is equal to zero. This is a default value which means that the maximum number of iterations in optimization process has been reached (which is 10). This highlights that the optimizer does not find easily a feasible solution.

As seen previously when analysing the metrics, tuning the pressure and level as buffer variables reduces the use of steam outflow as manipulated variable with the Prediction ON strategy, and the constraints are observed. This results in a much more constant delivery of power to the load.

Fig. 6.14 shows the trend over time of the response for Tag 30. Here, the FTMPC reacts whenever a disturbance occurs. The FTMPC finds a control action that would have been optimal if the change of the disturbance had been permanent. However, in case of a spike, there is a large but temporary variation of the disturbance. The impact of a spike is much smaller than a step change of same amplitude. Therefore, a large variation of the manipulated variables is not needed.

On the contrary, the Prediction ON and Prediction OFF strategies do not overreact when abrupt disturbances occur. In this case of an abrupt disturbance, the Prediction OFF strategy behaves better than the FTMPC, unlike when the disturbance is persistent. The proposed Prediction ON strategy reacts well in both situations because predicting the disturbance allows finding the optimal control action in response to the specific disturbance occurring at that moment. This would be an advantage in a real production environment because there would be no need to change the structure of the controller depending on the type of disturbance occurring. Indeed, Chapter 1 explained that solving the cause of a disturbance might be time consuming. In the personal experience of the author, production engineers might be asked to find temporary solutions, such as retuning a controller, to compensate the effects of the disturbance.

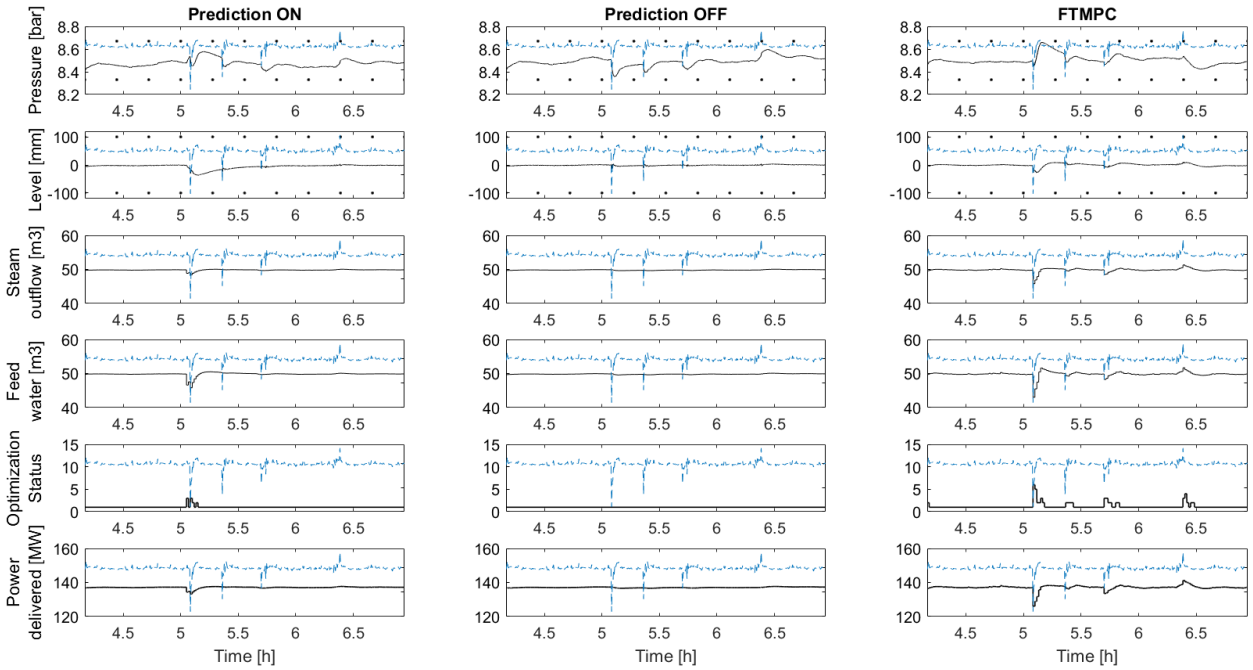


Figure 6.14: Disturbances from the heat provided to the boiler. The trend of the disturbance is dashed in blue.
Tag 30, CS 60 - CH 7 - DH 3. CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples.

6.4.4.6 Comparison between performance achievable with k-NN predictions versus perfect knowledge of disturbance

A perfect knowledge of the future values of the disturbances has been assumed in this case study so far for the Prediction ON strategy. This section shows the impact of the prediction algorithm on the performance of the controller with Prediction ON strategy.

Table 6.16 for Tag 34, Table 6.17 for Tag 33 and Table 6.18 for Tag 30 list the values of the three most important metrics for this case study, which are $\Theta^{\text{Area}}_{\text{Pressure}}$, $\Theta^{\text{Area}}_{\text{Level}}$ and $\sigma^{\text{Area}}_{\text{Power delivered}}$. As reminder, the metric $\Theta^{\text{Area}}_{\text{Pressure}}$ and $\Theta^{\text{Area}}_{\text{Level}}$ assess the average violation of the constraints of pressure of steam and level of water. The metric is normalized over the range between the constraints of the variable. The metric $\sigma^{\text{Area}}_{\text{Power delivered}}$ assesses the standard deviation of the power delivered to the loads. This metric is normalized over the possible range of power.

The tables are divided in sections related to one of the metrics. Each row represent a tuning of the controller. The values of the tuning parameters are listed in the first three columns from the

left. The first parameter is the controller sampling in seconds with the label CS. As Section 5.3.2 described, this value is equal to the sampling time of the measurement of the disturbance used by the prediction algorithm. The second and third column state the values of the control horizon with the label CH, and of the disturbance horizon with the label DH. Both the control horizon and the disturbance horizon are defined in steps.

The remaining columns correspond to the four strategies considered. The fourth column from the left correspond to the strategy called Prediction ON k-NN, where the Prediction is obtained using the weighted k-NN method of Chapter 4. The fifth column corresponds to the strategy Prediction On with a perfect knowledge about the future values of the disturbance, called in the table Prediction ON Perfect. The last columns correspond to the Prediction OFF and FTMPC strategies.

Analysis of the results The sampling of the controller and of the measurement of the disturbance for the prediction algorithm is the parameter that explains mostly the difference between Prediction ON with perfect knowledge and Prediction ON with k-NN. Specifically:

- When a signal is highly predictable, like Tag 34, the performance achievable with the k-NN are very close, if not identical, to the one obtainable with the perfect knowledge of the prediction for all the sampling considered. This can be seen comparing the fourth and fifth columns of Table 6.16 and seeing how similar the values for the various metrics are
- When the signal is not really predictable, like Tag 33 or Tag 30, fast sampling even nullifies the difference between perfect knowledge and use of the k-NN predictions. The values of the metrics in the fourth and fifth columns of Table 6.17 and Table Table 6.18 are similar when the controller sampling CS is equal to five seconds.
- Larger sampling amplifies the differences instead. An example is the metric $\sigma^{\text{Area}}_{\text{Power delivered}}$ for Tag 30 with the parameters CS 60, CH 7, DH 5. The difference between the strategies Prediction ON with k-NN and Prediction ON with perfect knowledge is large.

Table 6.15 compares the best values of the metric $\sigma^{\text{Area}}_{\text{Power delivered}}$ obtained with the strategy Prediction ON with k-NN with the best values obtained with the FTMPC. The Prediction ON strategy improves the metric by 62% to 64% for the three tags.

Table 6.15: Comparison of the values of the metric $\sigma_{\text{Power Delivered}}$ for the best tunings of the strategies Prediction ON and FTMPC when the disturbance comes from the heat provided.

		Prediction ON with k-NN	FTMPC	Improvement over FTMPC
Tag 34	Optimal tuning	CS 30 - CH 14 - DH 14	CS 30 - CH 3	
	$\sigma_{\text{Power Delivered}}$	1.02	2.69	62.08%
Tag 33	Optimal tuning	CS 5 - CH 3 - DH 3	CS 5 - CH 84	
	$\sigma_{\text{Power Delivered}}$	0.63	1.69	62.72%
Tag 30	Optimal tuning	CS 5 - CH 3 - DH 3	CS 5 - CH 84	
	$\sigma_{\text{Power Delivered}}$	0.1	0.28	64.29%

Explanation of the results The sampling rate of the measurement of the disturbance is equal to the sampling rate of the controller in this case study. Both have an impact on the difference between the performance of the controller with the strategy Prediction ON with perfect knowledge and the strategy Prediction ON with k-NN.

The sampling used for the measurements of the disturbance can have an impact on the quality of the prediction, and the quality of the prediction of the disturbance has an impact on the performance of the controller, as shown in Section 6.4.3.6 about the case study of CSTH.

For example, the original sampling of Tag 30 is 20s. Measuring this disturbance every 30s or 60s implies an interpolation of the original time series and a downsampling. For a such fast disturbance, downsampling might mean removing some peaks from the time series. Therefore, the algorithm might not find the right nearest neighbours, the quality of the prediction decreases, and the controller does not calculate an optimal control action.

Also, a high sampling rate of the controller makes the feedback of the controller stronger. This helps compensating the mismatch caused by the error of the prediction. This helps with Tag 33 and Tag 30.

Regarding the Tag 30, which is characterised by abrupt disturbances, it must also be noted that the controller with the strategy Prediction ON with perfect knowledge has information about an upcoming disturbance event before this occurs. This allows the controller to do adjustments before the disturbance enters the system. On the contrary, the k-NN algorithm can predict the future trend

of an abrupt disturbance only when the abrupt event has already started. The strategy Prediction ON with k-NN reduces the gap with the strategy Prediction ON with perfect knowledge when the controller has a fast sampling rate. In this way, the controller can re-evaluate the control action as soon as a disturbance occurrence is detected and predicted with the k-NN.

Table 6.16: Values of the the metrics for the steam boiler when the disturbance acts on the heat provided - Tag 34.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples.

			$\Theta^{\text{Area}}_{\text{Pressure}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	2.30×10^{-3}	2.35×10^{-3}	4.40×10^{-1}	0.00
5	3	180	6.58	6.04		
5	84	3	2.51×10^{-2}	2.50×10^{-2}		
5	84	84	2.08×10^{-3}	2.45×10^{-3}	6.13×10^{-1}	4.25×10^{-3}
5	84	180	1.41	3.09×10^{2}		
30	3	3	0.00	0.00	2.99	8.40×10^{-2}
30	3	30	2.12×10^{2}	1.05×10^{2}		
30	14	3	6.02×10^{-2}	5.38×10^{-2}		
30	14	14	0.00	1.43×10^{-5}	4.87	1.28×10^{-1}
30	14	30	6.98×10^{2}	6.21×10^{2}		
60	3	3	0.00	0.00	7.85	2.83×10^{-1}
60	3	15	1.55×10^{2}	8.55×10^{1}		
60	7	3	5.59×10^{-3}	3.13×10^{-3}		
60	7	7	0.00	0.00	1.01×10^{1}	6.01×10^{-1}
60	7	15	4.58×10^{1}	3.18×10^{1}		

			$\Theta^{\text{Area}}_{\text{Level}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	0.00	0.00	0.00	0.00
5	3	180	3.20	2.04		
5	84	3	0.00	0.00		
5	84	84	0.00	0.00	0.00	0.00
5	84	180	5.96×10^{-1}	6.03×10^{1}		
30	3	3	0.00	0.00	0.00	0.00
30	3	30	4.31×10^{1}	2.19×10^{1}		

30	14	3	3.61×10^{-4}	4.39×10^{-4}	7.99×10^{-4}	0.00
30	14	14	0.00	0.00		
30	14	30	1.39×10^{2}	1.25×10^{2}		
60	3	3	1.12×10^{-2}	1.14×10^{-2}	1.60×10^{-3}	0.00
60	3	15	3.51×10^{1}	1.91×10^{1}		
60	7	3	5.18×10^{-3}	5.05×10^{-3}	8.38×10^{-4}	0.00
60	7	7	0.00	0.00		
60	7	15	1.45×10^{1}	1.31×10^{1}		

			$\sigma^{u}_{\text{Power Delivered}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	1.18	1.18	1.26	2.88
5	3	180	8.79	7.05		
5	84	3	2.12	2.12	2.18	3.03
5	84	84	1.14	1.15		
5	84	180	4.12	3.31		
30	3	3	1.32	1.33	1.47	2.69
30	3	30	9.44	8.50		
30	14	3	2.20	2.20	2.28	3.10
30	14	14	1.02	1.03		
30	14	30	8.95	8.25		
60	3	3	1.63	1.62	1.79	2.91
60	3	15	2.83×10^{1}	2.28×10^{1}		
60	7	3	2.02	2.03	2.30	3.24
60	7	7	1.20	1.21		
60	7	15	1.88×10^{1}	2.11×10^{1}		

Table 6.17: Values of the the metrics for the steam boiler when the disturbance acts on the heat provided - Tag 33.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon in samples, DH - Disturbance horizon in samples.

			$\Theta^{\text{Area}}_{\text{Pressure}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	5.79×10^{-3}	5.79×10^{-3}	1.73×10^{-1}	0.00
5	3	180	7.27×10^{-3}	2.48×10^{-2}		
5	84	3	1.15×10^{-2}	1.15×10^{-2}		
5	84	84	3.79×10^{-3}	2.46×10^{-3}	2.06×10^{-1}	0.00
5	84	180	4.35×10^{-3}	4.29×10^{-3}		
30	3	3	1.37×10^{-2}	1.39×10^{-2}	1.06	3.50×10^{-2}
30	3	30	9.51×10^{-3}	5.87×10^{1}		
30	14	3	1.09×10^{-1}	5.19×10^{-2}		
30	14	14	3.94×10^{-2}	2.33×10^{-2}	1.80	9.12×10^{-2}
30	14	30	2.62×10^{-2}	1.85×10^{-2}		
60	3	3	2.94×10^{-2}	2.22×10^{-2}	2.45	1.12×10^{-1}
60	3	15	6.39×10^{-3}	4.41×10^{-3}		
60	7	3	1.92×10^{-1}	5.16×10^{-2}		
60	7	7	4.78×10^{-2}	1.84×10^{-2}	3.60	2.82×10^{-1}
60	7	15	3.42×10^{-2}	1.91×10^{-2}		

			$\Theta^{\text{Area}}_{\text{Level}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	0.00	0.00	0.00	0.00
5	3	180	1.36×10^{-1}	0.00		
5	84	3	0.00	0.00		
5	84	84	0.00	0.00	0.00	0.00
5	84	180	0.00	0.00		
30	3	3	0.00	0.00	0.00	0.00
30	3	30	0.00	1.20×10^{1}		

30	14	3	0.00	0.00		
30	14	14	0.00	0.00	0.00	0.00
30	14	30	0.00	0.00		
60	3	3	0.00	0.00	0.00	0.00
60	3	15	0.00	1.70×10^{-2}		
60	7	3	0.00	0.00		
60	7	7	0.00	0.00	0.00	0.00
60	7	15	0.00	0.00		

			$\sigma^u_{\text{Power Delivered}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	6.28×10^{-1}	6.28×10^{-1}	6.66×10^{-1}	2.01
5	3	180	3.11	5.76×10^{-1}		
5	84	3	1.22	1.22		
5	84	84	7.03×10^{-1}	6.48×10^{-1}	1.29	1.69
5	84	180	5.67×10^{-1}	5.07×10^{-1}		
30	3	3	8.14×10^{-1}	6.66×10^{-1}	7.32×10^{-1}	1.75
30	3	30	9.91×10^{-1}	5.71		
30	14	3	1.21	9.82×10^{-1}		
30	14	14	7.71×10^{-1}	3.62×10^{-1}	1.23	1.72
30	14	30	6.24×10^{-1}	3.14×10^{-1}		
60	3	3	1.12	7.59×10^{-1}	8.33×10^{-1}	1.61
60	3	15	7.40×10^{-1}	1.11		
60	7	3	1.23	9.08×10^{-1}		
60	7	7	9.14×10^{-1}	4.99×10^{-1}	1.19	1.85
60	7	15	6.42×10^{-1}	3.96×10^{-1}		

Table 6.18: Values of the the metrics for the steam boiler when the disturbance acts on the heat provided - Tag 30.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon

			$\Theta^{\text{Area}}_{\text{Pressure}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	7.06×10^{-3}	7.06×10^{-3}	9.10×10^{-3}	0.00
5	3	60	5.83×10^{-3}	4.53×10^{-3}		
5	84	3	0.00	0.00	0.00	0.00
5	84	60	0.00	0.00		
30	3	3	2.99×10^{-2}	2.87×10^{-2}	6.09×10^{-2}	0.00
30	3	10	2.33×10^{-2}	2.42×10^{-2}		
30	14	3	3.86×10^{-3}	3.11×10^{-3}	3.01×10^{-2}	0.00
30	14	10	9.61×10^{-3}	5.63×10^{-3}		
60	3	3	7.16×10^{-2}	6.27×10^{-2}	1.42×10^{-1}	2.12×10^{-2}
60	3	5	7.65×10^{-2}	5.78×10^{-2}		
60	7	3	6.54×10^{-2}	3.99×10^{-2}	1.34×10^{-1}	8.79×10^{-3}
60	7	5	5.66×10^{-2}	2.85×10^{-2}		

			$\Theta^{\text{Area}}_{\text{Level}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	0.00	0.00	0.00	0.00
5	3	60	0.00	0.00		
5	84	3	0.00	0.00	0.00	0.00
5	84	60	0.00	0.00		
30	3	3	0.00	0.00	0.00	0.00
30	3	10	0.00	0.00		
30	14	3	0.00	0.00	0.00	0.00
30	14	10	0.00	0.00		
60	3	3	0.00	0.00	0.00	0.00
60	3	5	0.00	0.00		

60	7	3	0.00	0.00	0.00	0.00
60	7	5	0.00	0.00		

			$\sigma^{u}_{\text{Power Delivered}}$			
CS	CH	DH	Prediction ON k-NN	Prediction ON Perfect	Prediction OFF	FTMPC
5	3	3	1.04×10^{-1}	1.04×10^{-1}	1.13×10^{-1}	4.14×10^{-1}
5	3	60	1.06×10^{-1}	1.02×10^{-1}		
5	84	3	1.54×10^{-1}	1.54×10^{-1}	1.63×10^{-1}	2.82×10^{-1}
5	84	60	1.57×10^{-1}	1.50×10^{-1}		
30	3	3	1.06×10^{-1}	1.22×10^{-1}	1.14×10^{-1}	3.06×10^{-1}
30	3	10	1.07×10^{-1}	1.07×10^{-1}		
30	14	3	1.09×10^{-1}	1.26×10^{-1}	1.19×10^{-1}	2.82×10^{-1}
30	14	10	1.10×10^{-1}	1.09×10^{-1}		
60	3	3	2.56×10^{-1}	1.72×10^{-1}	1.14×10^{-1}	3.62×10^{-1}
60	3	5	2.80×10^{-1}	1.52×10^{-1}		
60	7	3	2.71×10^{-1}	2.10×10^{-1}	1.14×10^{-1}	3.66×10^{-1}
60	7	5	2.83×10^{-1}	1.81×10^{-1}		

6.4.4.7 Conclusions when the disturbance comes from the heat provided to the boiler

The tests in Section 6.4.4 examined the configuration in which the disturbance comes from the heat provided to the boilers. Such tests showed how a multivariable system can be controlled exploiting its buffer capabilities.

When the future prediction of the disturbance is assumed exact, the control system with the Prediction ON strategy was able to attenuate significantly the deviations of power delivered to the loads in form of steam. Compared to the FTMPC, the strategy Prediction ON with k-NN reduced the metric $\sigma_{\text{Power Delivered}}$ by 44% to 75% for the same tuning parameters, when the disturbance horizon is set equal to the control horizon and the sampling time is faster than every 30s. Compared

to the Prediction OFF, the Prediction ON strategy reduced the metric $\sigma_{\text{Power Delivered}}$ by a smaller amount. However, the Prediction ON strategy did not show large violations of constraints.

When the disturbance prediction is calculated with the weighted k-NN algorithm, the results change depending on the sampling rate of the measurement of the disturbance for the prediction algorithm and depending on the sampling rate of the controller. A sampling rate of the measurement which is too large removes dynamics of the pattern of a disturbance which are needed for a correct search of the nearest neighbours and a correct prediction.

Also a fast sampling rate of the controller increases the feedback of the MPC and compensates for the error caused by a poorer prediction, as for Tag 33 and Tag 30.

The MPC with disturbance forecasting seems to bring advantages to the control of a steam boiler when the disturbance comes from the heat provided. However, it must be reminded that these disturbances are not always predictable. An example is when the calorific value of the fuel is not constant, as Section 5.7.3.3 discussed. This is a relatively common type of disturbance but the proposed MPC with disturbance forecasting cannot be used in this case.

6.4.5 Conclusions for the steam boiler

The model of the steam boiler provided two case studies to test the proposed MPC framework. In one case study the problem is of pure set-point tracking and the controller must compensate the disturbances coming from the load. In the second case study, the aim is keeping the controlled variables within constraints rather then letting them track strictly a set-point. The controller has to reduces the disturbance propagation from the heat provided to the boiler to the power delivered to the load in form of the steam outflow.

Using several combinations of the tuning parameters and time series of disturbances, the steam boiler has served within the chapter to compare the Prediction ON strategy with the Prediction OFF and FTMPC strategies when the controlled variables must follow a set-point, when variables act as buffer, and to analyse the impact of the disturbance horizon and of the controller sampling on performance. Table 6.19 summarizes the answers to such questions.

Table 6.19: Questions for the two case studies of the steam boiler and answers.

Question	Answer
Performance with variables that must follow a set-point	• The Prediction ON strategy does not always improve the tracking of the set-points compared to a FTMPC solution. It needs a long control horizon and fast sampling. • Improving the set-point tracking might have limited effects on the system. For example. pressure does not affect the power delivered to loads too much. • When the disturbance is from the steam outflow, the proposed MPC framework with a multi-step prediction of the disturbance does not bring advantages over the FTMPC because the differences in the tracking of the set-points impact minimally on the power delivered to the other loads.
Performance with variables that act as buffer	• A buffer variable need not necessarily be a level but any variable that implies storage of mass of liquid and gas, or energy. • The use of a detailed prediction of the disturbance reduces the propagation of a disturbance downstream and permits to observe the constraints of a system. • For the same tuning, the strategy Prediction ON with k-NN reduces the metric $\sigma_{\text{Power Delivered}}$ by 45% to 75% compared to the value with the FTMPC, when the disturbance horizon is set equal to the control horizon and a sampling rate faster than every 30s is used.
Length of the disturbance horizon	• A disturbance horizon longer than the control horizon might cause aggressive control actions and large deviations of the controlled systems from their nominal operating points for certain tunings. • To avoid these aggressive behaviours, the optimizer of the MPC needs to be allowed to change the control action over the prediction horizon for a number of times that is higher then the number of times the foreseen disturbance changes. This is like providing the optimizer of enough degrees of freedom to a find a feasible solution. • Setting the disturbance horizon equal to the control horizon is recommended.
Impact of disturbance sampling rate on performance	• The sampling rate does not have an impact when a disturbance is highly predictable, like Tag 34. • When the signal is not well predictable, like Tag 33, or has a very fast dynamic, like Tag 30, a larger sampling rate of the measurement of the disturbance and of the controller deteriorates the performance of the controller. • With large sampling rate, the Prediction ON strategy used with the k-NN might not be advantageous for disturbances not highly predictable and/or with with very fast dynamics.

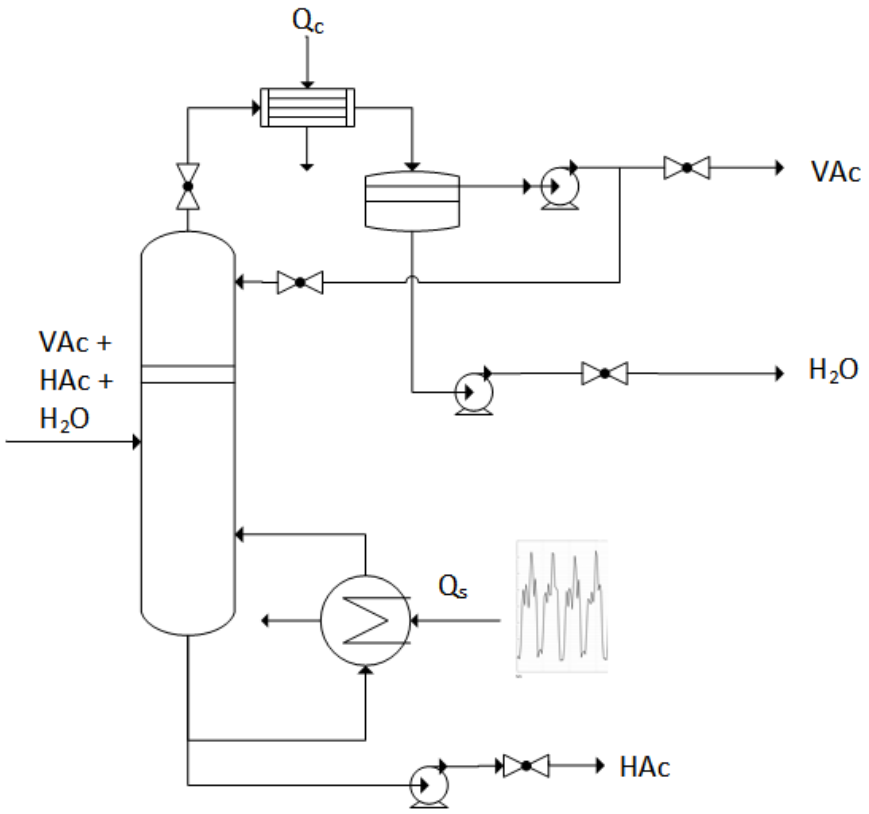


Figure 6.15: Case study of the VAc distillation column. Copied from Fig. 5.5.

6.5 RESULTS: THE VAC COLUMN

6.5.1 Introduction

This section compares the three forms of MPC discussed in Section 6.1 on the model of an azeotropic distillation column from Chen et al. (2003), Luyben and Tyréus (1998), Luyben et al. (1998), and Luyben (2002). The case study is represented in Fig. 6.15 and described in Section 5.8.1.

This is a case study where certain variables have to follow their set-points, and others have to act as buffer variables. Different control and disturbance horizons are tested. The interest is assessing whether certain tunings of the controller can be beneficial for the buffer variables but not for the controlled variables that must track a set-point. It will be also checked whether the prediction method proposed provides good performance in practice with a distillation column.

Table 6.20 lists the disturbances and their parameters used for this section. The amplitudes of the disturbances are arbitrary, however the length of the disturbance pattern reflects the real signals.

Table 6.20: Parameters of the tested disturbances for the case study of the VAc Column

Signal type	Pattern / Cycle length	Amplitude
Tag 34 Tag 33	1020 s	5% u^{Nom}
Tag 30	180 -300 s	20% u^{Nom}

Table 6.21: Indication of ideal values of metrics for the case study of the VAc column.

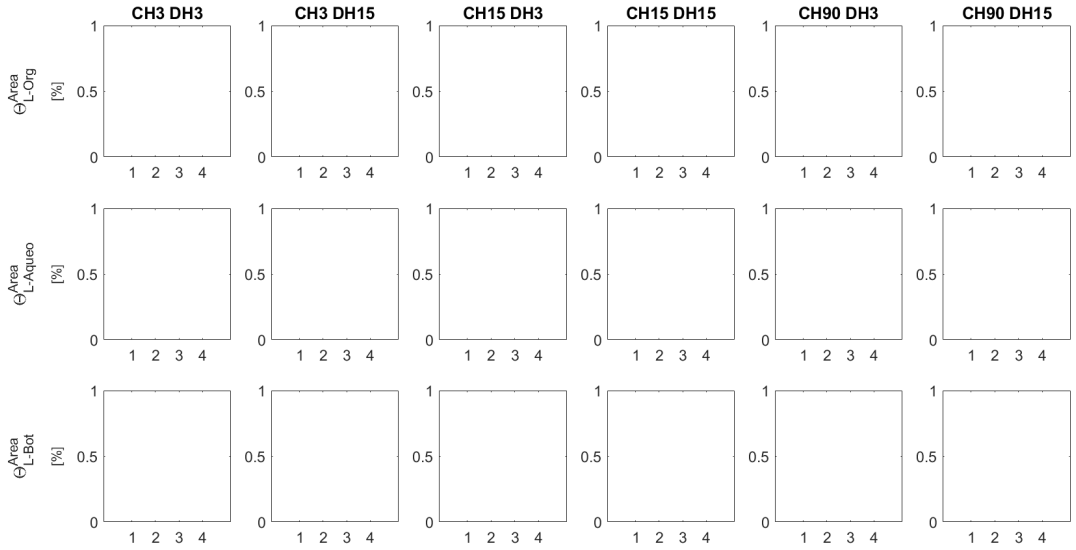
Ideal values of metrics	Description
$\Gamma^{y}_{\text{Temp St. 16}} \rightarrow 0$ $\Gamma^{y}_{\text{HAc-Top}}, \Gamma^{y}_{\text{VAc-Bot}}, \Gamma^{y}_{\text{H2O-Bot}} \rightarrow 0$	The quality of the product should be constant. Therefore, the temperatures of controlled tray and of the organic phase, together with all measured concentrations should not deviate from their set-points.
$\Theta^{\text{Area}}_{\text{L-Aqueo}}, \Theta^{\text{Area}}_{\text{L-Org}}, \Theta^{\text{Area}}_{\text{L-Bot}} = 0$	No constraints violations of all levels.
$\sigma^{u}_{\text{F-Org}}, \sigma^{u}_{\text{F-Bot}} \rightarrow 0$	Propagation of disturbances through variations of the outflow from the bottom and from the organic phase of the decanter should be minimized.
$\Gamma^{y}_{\text{Temp -Dec}} \rightarrow 0$	Propagation of disturbance through varitions of the temperature of organic outflow should be minimized.

Also, it can be reminded that Tag 30 was originally the signal of a disturbed steam flow into the base of a distillation column.

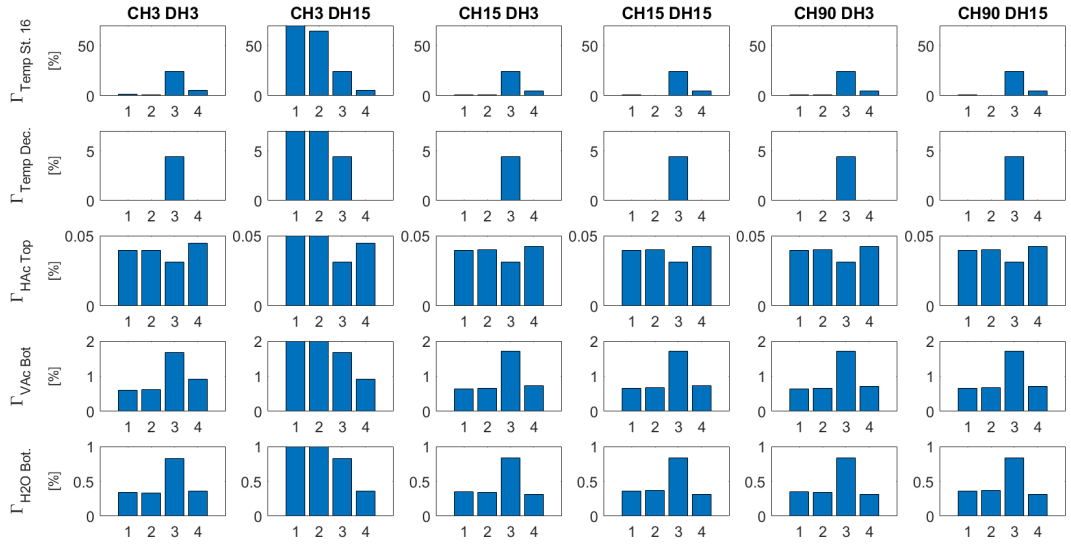
The disturbance affects the duty of the reboiler and Section 5.8.4 defined the priorities of the controller. The controller has to keep the compositions of the outflows and the controlled temperature at their set-point. These are the controlled variables that must stay constant. The controller keeps the level of the bottom of the column and the level of the organic phase in the reflux drum within constraints. These are the controlled variables that act as buffer. The corresponding outflows from the bottom of the column and from the organic phase of the decanter should stay constant to avoid propagation of disturbances downstream. The temperature of the organic phase should stay constant to not change the enthalpy of the organic outflow and propagate the disturbance. The level of the aqueous phase should track its set-point although with a low priority. Table 6.21 shows the values that the metrics should have for this case.

6.5.2 Analysis of the metrics

Fig. 6.16, Fig. 6.17 and Fig. 6.18 show the metrics associated to respectively Tag 34, Tag 33 and Tag 30. The bar graphs are distributed over several rows and columns. Each row shows a metric and each column represent a various controller tuning in terms of controller sampling, control horizon and, if used, disturbance horizon. Each graph shows four bars, corresponding respectively to the

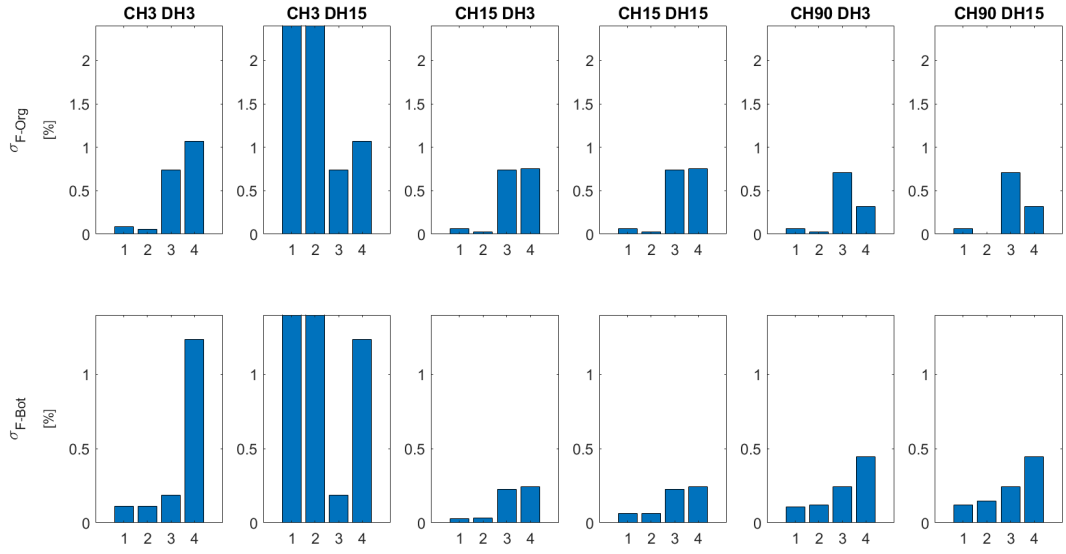


(a) Θ for buffer variables. No violations of constraints.



(b) Γ for the variables who must track a set-point

Figure 6.16



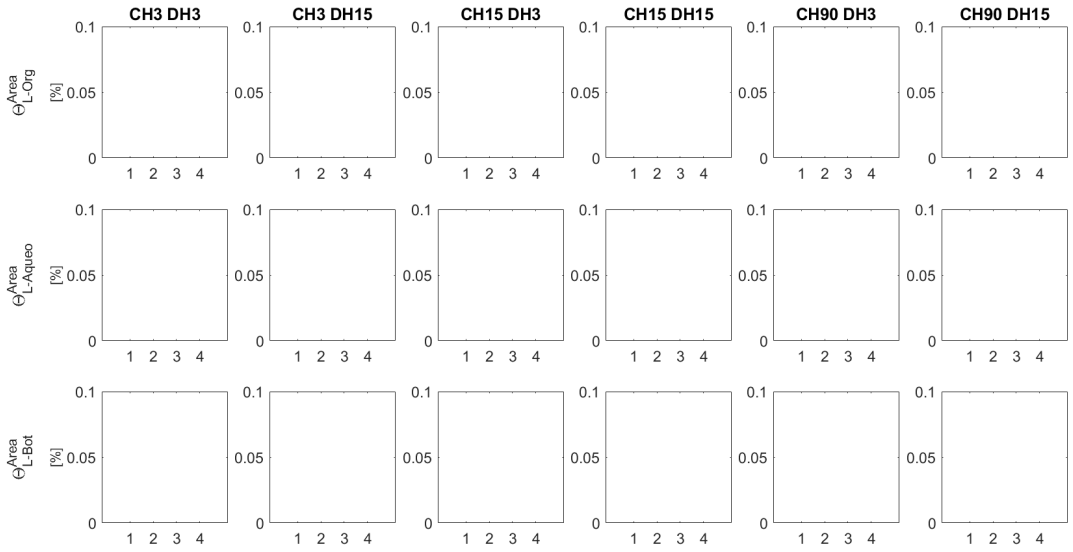
(c) σ for the MV associated to flows

Figure 6.16: Performance metrics with Tag 34 as disturbance acting on the heat provided to the column through the steam in reboiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN, 2 - Strategy with Prediction ON with perfect knowledge, 3 - Strategy with prediction OFF, 4 - Strategy with FTMPC

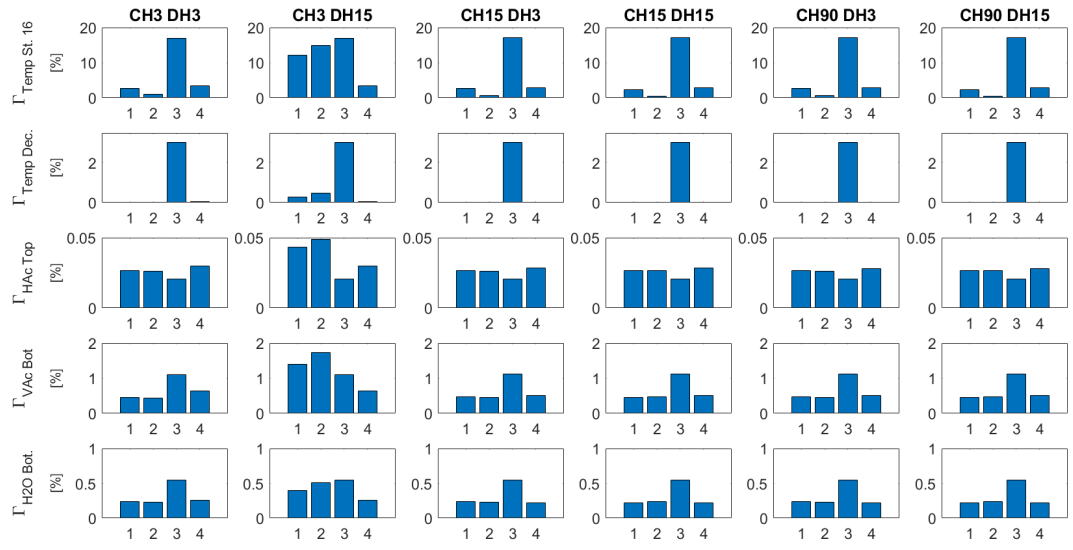
metric of the strategy Prediction ON using the k-NN algorithm, Prediction ON using the exact information about the future evolution of the disturbance, Prediction OFF and FTMPC. This allows to compare the potential benefits of the Prediction ON with perfect knowledge with the benefits really obtainable using the $k-$nearest neighbours algorithm.

THE IMPACT OF DISTURBANCE HORIZON Also in this case study, a disturbance horizon longer than the control horizon deteriorates the performance. The second column of graphs in each Fig. 6.16, Fig. 6.17 and Fig. 6.18 shows a case of controller tuning where this occurs. The metrics Γ and σ are far larger than in the other cases, especially for Tag 34, represented in Fig. 6.16b and Fig. 6.16c. Tag 34 was causing more severe issues when the disturbance horizon is longer than the control horizon also in the two case studies of the steam boiler. As in the case of the steam boiler, the explanation might be that Tag 34 has variations within its repeating pattern that are faster than those of Tag 33. If the control horizon is shorter than the disturbance horizon, the controller might not have enough degrees of freedom to counteract these fast foreseen changes in the disturbance. This might cause inappropriate reactions of controller.

Set-point tracking The set-point tracking of the Prediction ON with exact disturbance forecasting and of the FTMPC is better than the Prediction OFF looking at the metrics Γ. However, the values of the metrics $\Gamma_{\text{HAc -Top}}$, which assess the concentration of the HAc in the outflow from the organic phase from the decanter, are an exception. The reason is that there are fewer manipulated variables than controlled variables, and the controller prioritises some controller variables over the

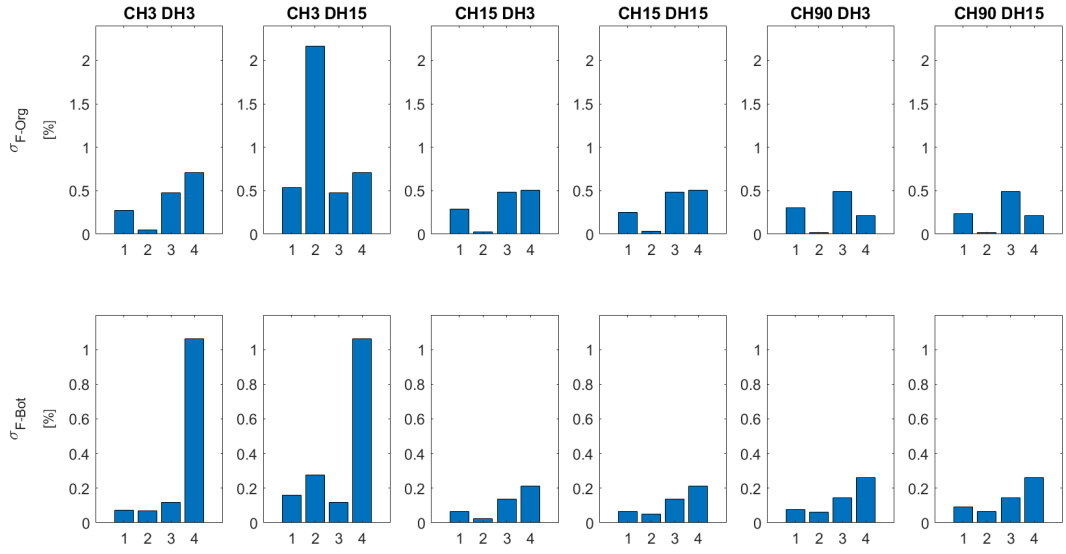


(a) Θ for buffer variables. No violations of constraints.



(b) Γ for the variables who must track a set-point

Figure 6.17



(c) σ for the MV associated to flows

Figure 6.17: Performance metrics with Tag 33 as disturbance acting on the heat provided to the column through the steam in reboiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN, 2 - Strategy with Prediction ON with perfect knowledge, 3 - Strategy with prediction OFF, 4 - Strategy with FTMPC

others to minimise its objective function. The metric Γ for the HAc composition on the top of the column is in the range of 0.05%, while the metric Γ for the other two compositions are instead in the range of 1-2%. Therefore, the controllers with Prediction ON and FTMPC strategy tend to minimize their objective function by strongly reducing the deviation from the set-point of the concentration of the water and VAc in the bottom of the column, rather than the concentration of HAc in the top of the column.

There is a slight improvement of about 5% to 10% of the metrics Γ for the concentrations when the strategy Prediction ON is used in place of the strategy FTMPC. However, the values of the metrics are low in absolute terms for both strategies. In future works, it would be beneficial to assess economically the advantages of reducing the variations of the concentrations of these amounts, and to see the advantages in a plant scale.

The handling of buffer variables The metrics Θ represented in Fig. 6.16a, Fig. 6.17a, and Fig. 6.18a shows that none of the control strategies violates the constraints of buffer variables for all Tag 34, Tag 33, and Tag 30. The difference between the control strategies lies in the use of

the outflows as manipulated variables. The Prediction ON strategy can potentially greatly reduce the metrics $\sigma_{\text{F-Bot}}$ and $\sigma_{\text{F-Org}}$ related to the outflows from the bottom of the column and the organic phase of the decanter. However, using the Prediction ON strategy with the k-NN method reduces the advantages because of the degradation in the quality of the predictions.

Comparison between performance achievable with perfect knowledge of the future values of the disturbance and k-NN predictions When the k-NN method is used instead of assuming perfect knowledge of the future values of the disturbances, the performance of the controller deteriorates. When the disturbance is Tag 34, there is a deterioration but performances are still better than with the other two strategies.

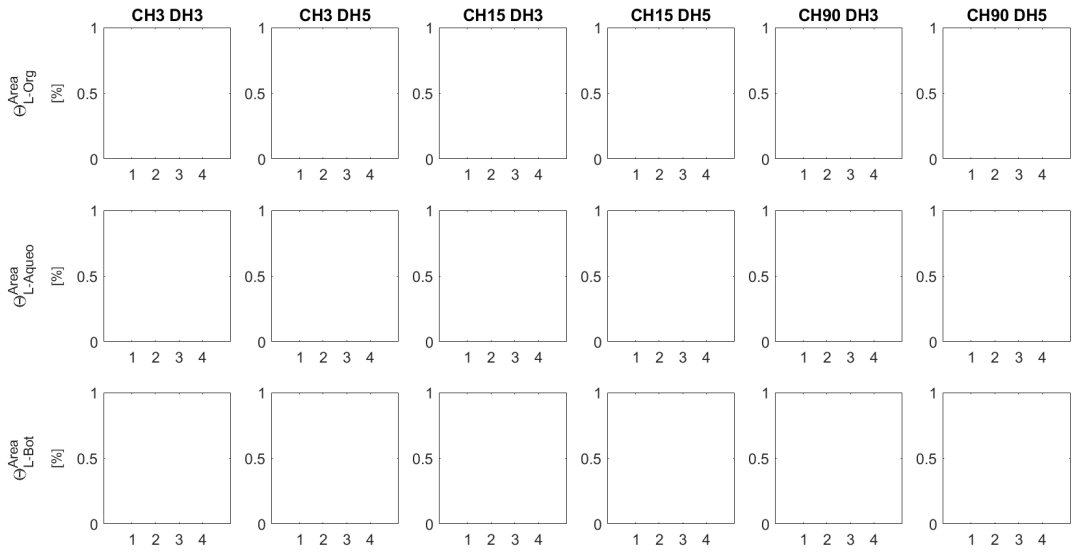
With Tag 33 there is a particular deterioration of the tracking capability of the metric $\Gamma_{\text{Temp. St 16}}$, assessing the set-point tracking of the temperature of the 16^{th} stage of the column. Although the tracking of the setpoint of controlled temperature worsens, the metrics Γ for the concentrations are not worse compared to the Prediction ON with perfect knowledge. Also the metrics $\sigma_{\text{F-Org}}$, assessing the propagation of a disturbance through the flow of organic material from the decanter, worsens when the Prediction ON strategy with k-NN is used in place of the Prediction ON strategy with perfect knowledge. The lower quality of the prediction obtainable with Tag 33 is the reason behind the degradation of the performance.

With Tag 30, the degradation is much more visible, as Fig. 6.18 shows. This figure shows for the Tag 30 the values of the various metrics Γ and σ, which represent respectively the ability of the controller to track the setpoints and the ability to stop the propagation of disturbances. The first bars from the left of each graph in Fig. 6.18 represent the values of the metrics when the k-NN method is used. Such values are higher than the values represented in the second bars of each graph, which represent the values of the metrics when perfect knowledge of the future values of the disturbances is assumed. The discrepancy highlights the degradation of performance.

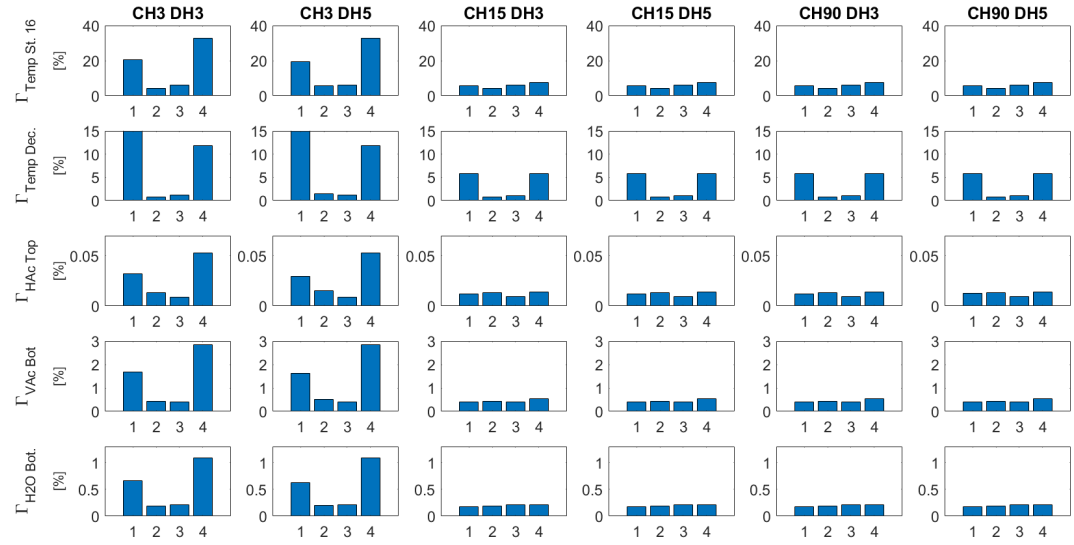
There are two reasons behind this degradation. A reason is that using a large sampling rate of 60s downsamples the time series of the disturbance and removes the characteristics peaks of Tag 30. The quality of the prediction deteriorates because the prediction algorithm might miss nearest neighbours. A solution might be sampling the disturbance for prediction purposes at higher

frequency than the sampling of the controller. The resulting prediction is then downsampled to match the sampling of the controller.

The other reason for the strong deterioration of the performance is that the Prediction ON strategy with perfect knowledge predicts a spike of Tag 30 before it occurs. The controller can adjust the manipulated variables before they enter the system. On the contrary, the strategy using the k-NN method for predicting the disturbances can predict the future values of the disturbance event only when this has already started, as Section 4.10 showed. This explains why the difference between these two strategies of the controller is large. To overcome this problem the sampling rate of the controller should be increased, so that the controller can change its control action as soon as an abrupt event of the disturbance starts and is detected. Section 6.5.5 analyses this solution.

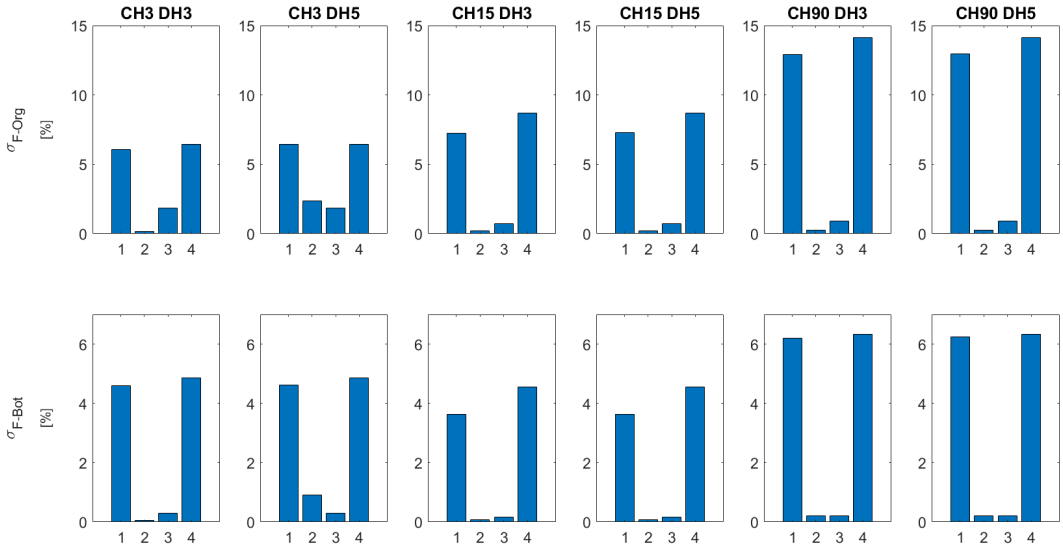


(a) Θ for buffer variables. No violations of constraints.



(b) Γ for the variables who must track a set-point

Figure 6.18



(c) σ for the MV associated to flows

Figure 6.18: Performance metrics with Tag 30 as disturbance acting on the heat provided to the column through the steam in reboiler.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN, 2 - Strategy with Prediction ON with perfect knowledge, 3 - Strategy with prediction OFF, 4 - Strategy with FTMPC

6.5.3 Examples of control responses

6.5.3.1 The behaviour with persistent disturbances

This section discusses the responses over time of the controllers with the four strategies in this case study, including the Prediction ON with k-NN and with perfect knowledge. Fig. 6.19 and Fig. 6.20 show the show the trends over time when the disturbances are Tag 34 and Tag 33.

Fig. 6.19a and Fig. 6.20a shows that the Prediction OFF strategy exhibits far larger oscillations of the controlled variables than the other strategies.

The FTMPC and the two Prediction ON strategies show similar set-point tracking capability for the temperatures and concentrations, shown in Fig. 6.19a and Fig. 6.20a. The difference is the handling of the buffers. The outflows from the organic phase of the decanter oscillates with FTMPC, which is represented in top-left corner of Fig. 6.19a and Fig. 6.20a. With the Prediction ON strategy with exact predictions, the propagation of disturbance from the decanter is completely stopped because the flow is constant. The flow from the bottom of the distillation column moves slightly but the movement is still dampened compared to the other strategies.

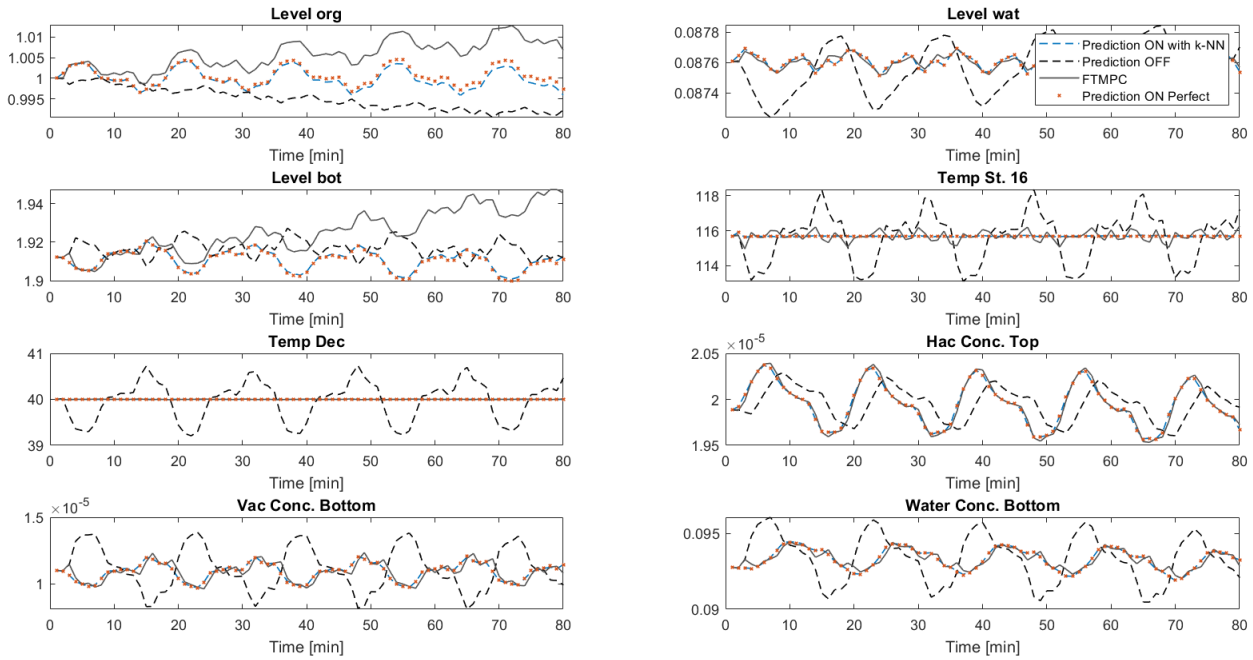
Comparing the two versions of Prediction ON shows that using the k-NN impacts the performances only when Tag 33 is used. In this case, the handling of the buffer variables is worse because the flow of organic phase from the decanter is not strictly constant as when the exact predictions are used. Still, such flow oscillates less than in the case of FTMPC.

6.5.3.2 The behaviour with abrupt disturbances

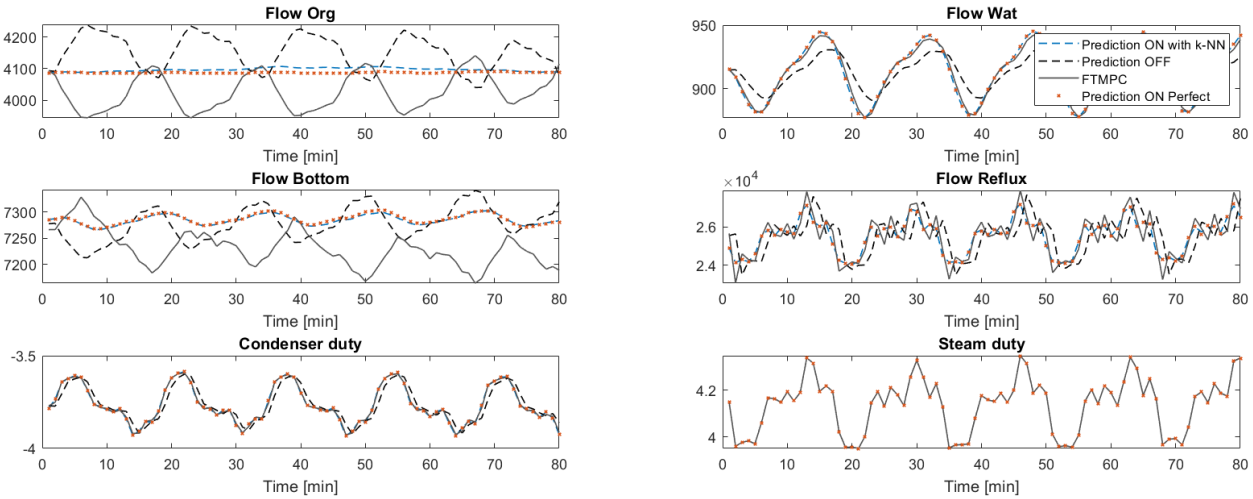
Fig. 6.21 shows the trends over time of controlled and manipulated variables when the disturbance is Tag 30 that has abrupt disturbances.

The best strategy for an abrupt disturbance is is the one of the Prediction OFF and of the Prediction ON with exact disturbance prediction because they do not overreact when a spike of the disturbance occurs. On the contrary, the FTMPC is continuously misled by the fast spikes characterizing Tag 30. The FTMPC supposes that these are permanent changes of the disturbance while they are not, resulting in large variations of the outflows related to the organic phase and bottom of the column.

Looking at the organic outflow from the decanter in Fig. 6.21b, the flow of the organic flow changes from 5000 $kg \cdot hr^{-1}$ to circa 0 $kg \cdot hr^{-1}$ twice within an interval of only 100 minutes because



(a) Trend over time of the controlled variables

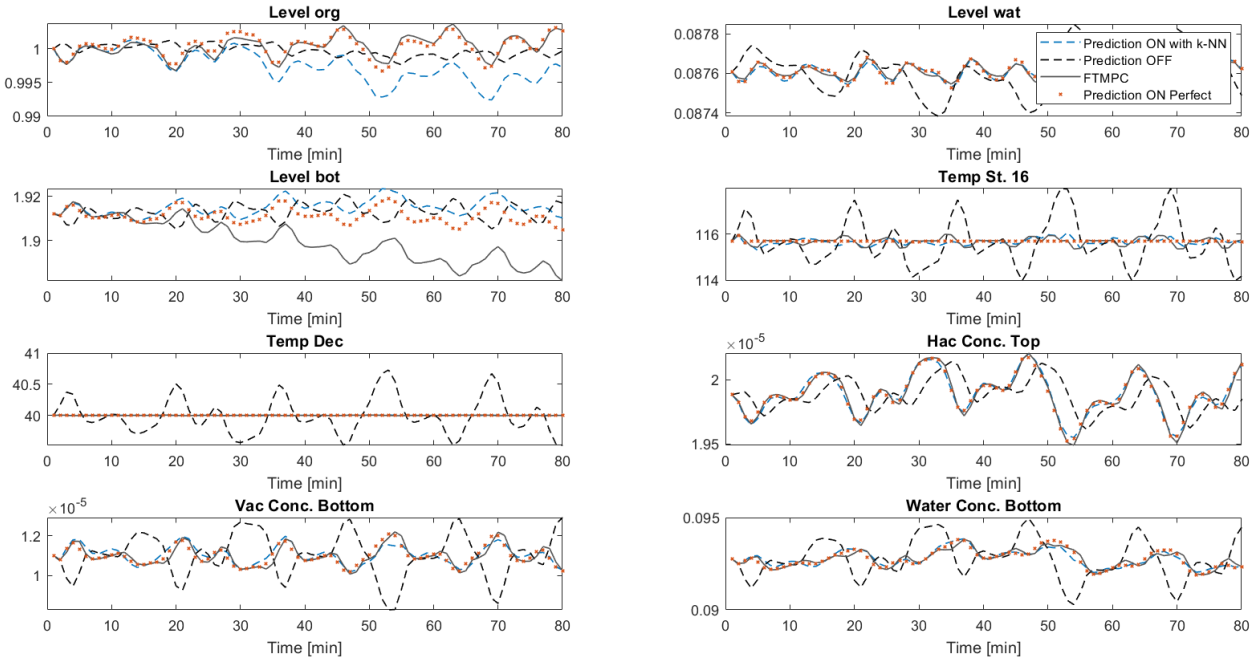


(b) Trend over time of the manipulated variables

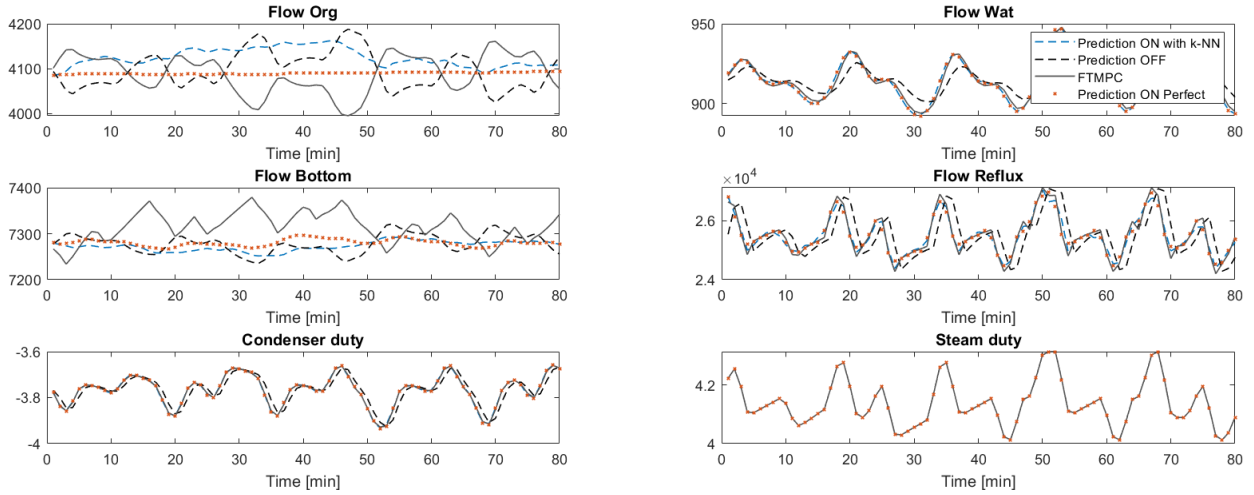
Figure 6.19: Trends over time of variables related to the VAc column with a disturbance acting on the heat provided to the boiler - Tag 34 - CS 60 - CH 90 - DH 15

the controller with the FTMPC assumes that the associated level would otherwise violate the constraints. Similarly, it moves the outflow associated to the bottom level of the column.

In real industrial systems, the flows would not change so much. The controller would normally be programmed to automatically switch off in case the control actions to be applied are too large. When it switches off, the controller would also give an alarm. The alarm and the switching off of



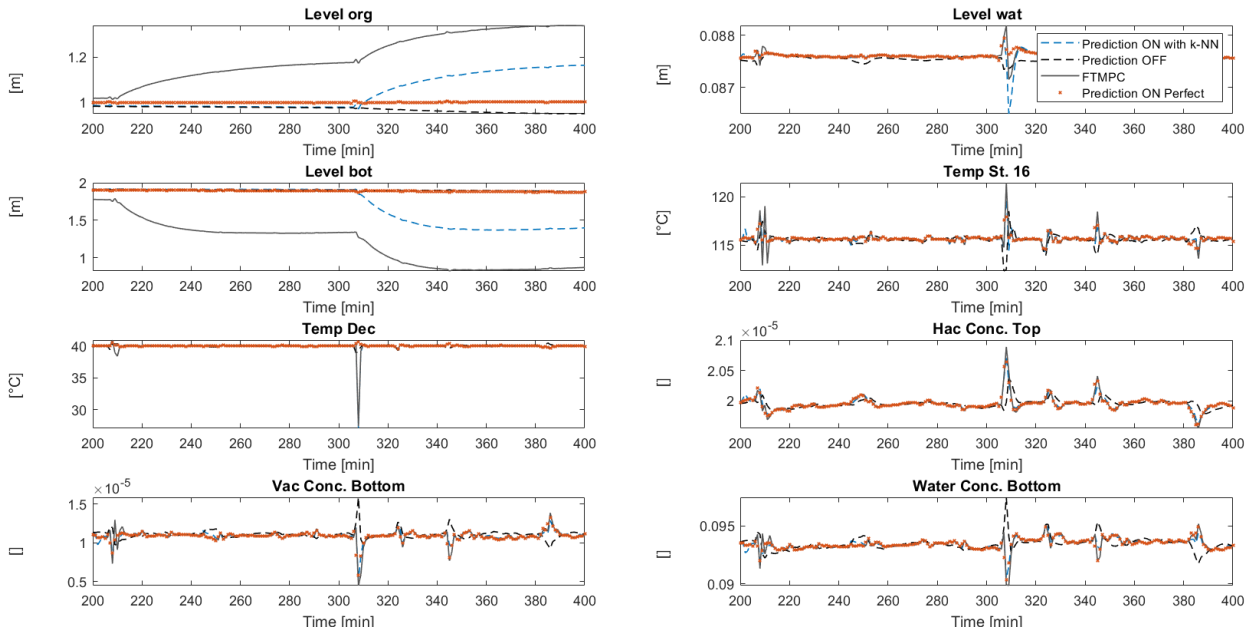
(a) Trend over time of the controlled variables



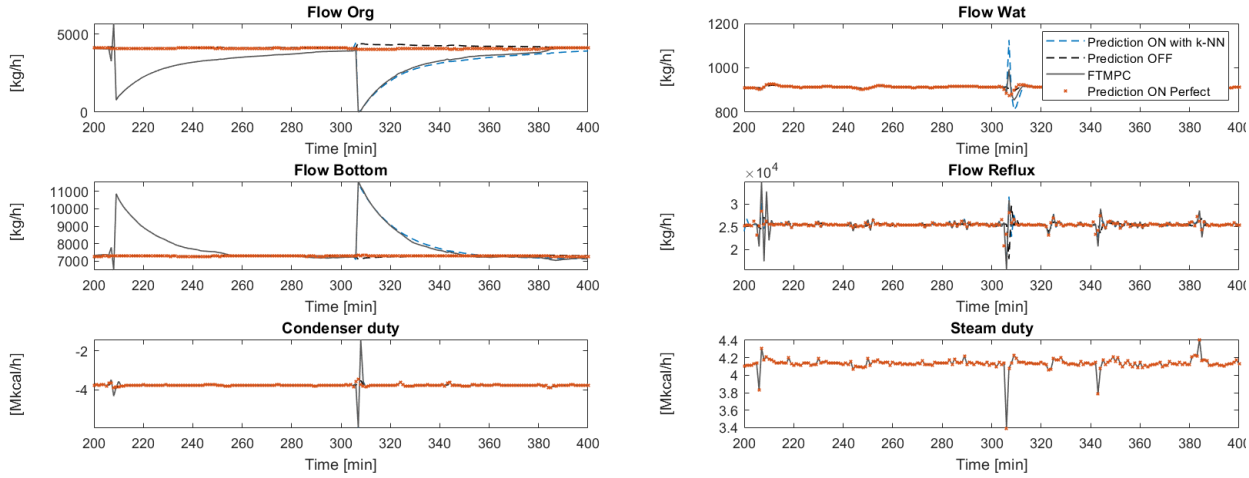
(b) Trend over time of the manipulated variables

Figure 6.20: Trends over time of variables related to the VAc column with a disturbance acting on the heat provided to the boiler - Tag 33 - CS 60 - CH 90 - DH 15

the controller might seem incomprehensible to the operators. The controller with FTMPC switches off because of its wrong assumption about the future values of the disturbance. These behaviours can cause a problem for the acceptance of the system, in the working experience of the present author.



(a) Trend over time of the controlled variables



(b) Trend over time of the manipulated variables

Figure 6.21: Trends over time of variables related to the VAc column with a disturbance acting on the heat provided to the boiler - Tag 30 - CS 60 - CH 90 - DH 5

The FTMPC causes problems with abrupt disturbances but it works better in set-point tracking than the Prediction OFF. Ideally, as the Prediction ON strategy with ideal forecasts of the disturbance shows, the Prediction ON strategy offers a calm but prompt response both in this case with spiky and persistent disturbances.

However, the Prediction ON using the k-NN method can partially fail. Fig. 6.21 shows that while the FTMPC causes two unnecessary disturbances, the Prediction ON strategy with k-NN causes

only one spike in the trends of the manipulated variable. This is partially a success but it shows also the limits of the implementations used. The algorithm failed in providing a good prediction in one case because the sampling of 60 s is too large to capture properly that abrupt event, which was sampled originally every 20 seconds.

6.5.4 Comments on the impact of tuning weights on the controller response in presence of abrupt disturbances

Fig. 6.21 shows that the controllers Prediction ON with k-NN and FTMPC initially change largely the values of the manipulated variables. After some sampling instants, the controller realizes that the disturbance values are back to their previous stationary values u_0, so it starts changing the values of the manipulated values but it does it slowly. The reason lays in the controller tuning because a weight has been set on the 'Move suppression' and not on the 'Manipulated variable tracking' parameter, as Table 5.10 has shown. Therefore, the controller knows it has to limit the variations of the manipulated variables $u(t) - u(t-1)$, rather than the deviations of manipulated variable from the $u(t) - u_0$.

Probably, this behaviour is not the best for a downstream unit which sees a slow disturbance coming instead of a fast one which might be maybe more easily dampened (because process units are often low pass filters). Setting a weight in 'Manipulated variable tracking' parameter and not weight on 'Controlled variable tracking' has been also tested. In this case, once the controller understands it has been misled, it brings back the manipulated variable to its set-point, without amplifying the effect of such mistake for the downstream units. However this solution means also that the buffer controlled variables, acting as integrators like the levels, are not centered back in the middle of buffer range. This limits the buffer capability of such controller at the following disturbance occurances, as Section 5.3.3 discussed.

The present author believes that if the controller would control not just one process unit but also an hypothetical downstream unit, the trend of the outflows considered here would be more friendly for the downstream unit. However, increasing the size of MPC controllers has its drawbacks.

So improving the behaviour of controller in presence of misleading feedforward actions needs further investigation that should go probably in these directions:

- Reducing the failure in predicting abrupt short disturbances
- Developing algorithms for the mutual collaboration between controllers that work on adjacent plant sections

6.5.5 Analysis of the metrics when the sampling rate of the measurement of the disturbance is faster than the controller sampling

This section tests separately the impact of the sampling of the measurement of the disturbance and the impact of the sampling of the controller on the performance of the proposed MPC framework. Tag 30 is used for this test because this tag caused the largest discrepancy between the results with the strategy Prediction ON with k-NN and the strategy Prediction ON with perfect knowledge about the future values of the disturbance.

Fig. 6.22 shows the metric E_{av}, which has been used in Chapter 4 to assess the quality of the prediction of a disturbance at a specific instant, for three cases. In one case the disturbance is downsampled every 60s, in one case it is sampled at the original sampling of 20s, and in the third case it is oversampled every 5 seconds. In all cases the prediction algorithm run every 60s, which is the sampling rate of the MPC controller. The metric E_{av} is lower, and the quality of the prediction is therefore better, when the the time series is not downsampled. The figure shows there are not certain peaks of E_{av} when the sampling rate is 20s or 5s. The oversampling at 5s provides a marginal advantage in a couple of situations. For example, in correspondence of the peak at sample 380, the red dot corresponding to a sampling of 20s is above the blue line correpoding to a sampling of 5s. Oversampling provides more sampling for the k-NN to distinguish two or more nearest neighbours. This might help distinguish real nearest neighbours from false nearest neighbours.

The question is whether this improvement of the quality of the prediction is enough to nullify the difference in performance between the strategy Prediction ON with k-NN and the Prediction ON

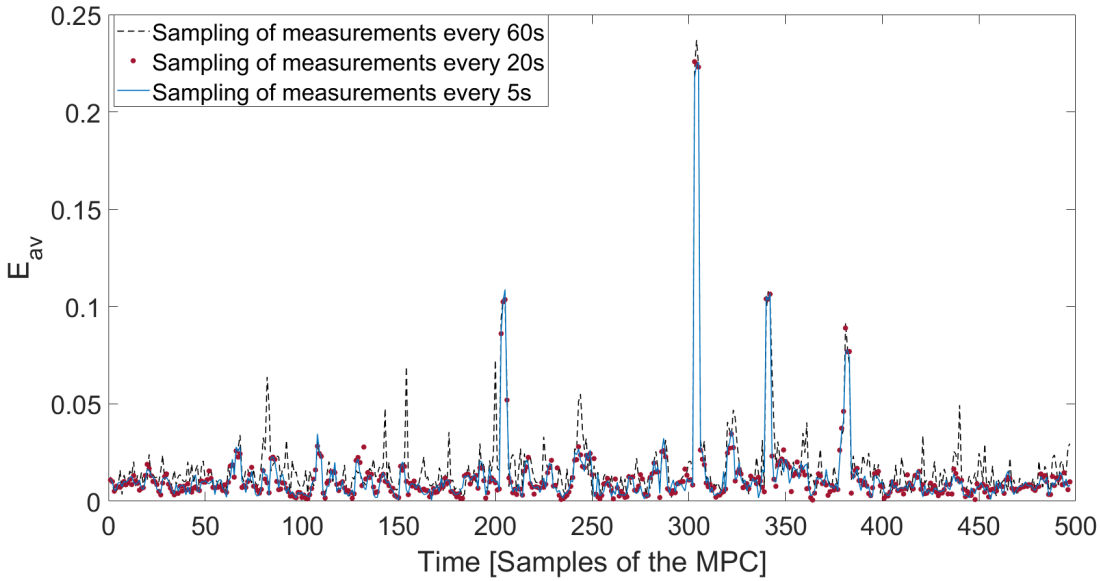


Figure 6.22: Values of the metrics E_{av} using three sampling rates for the measurement of the disturbance in case of Tag 30.

strategy with perfect knowledge about the future evolution of the future values of the disturbance.

Fig. 6.23 shows bar graphs with the values of the metrics Γ, and σ for Tag 30 (the metrics Θ are all equal to zero and therefore they are not shown). The bar graphs are distributed over several rows and columns. Each row shows a metric and each column represent a various controller tuning in terms of controller sampling, control horizon and, if used, disturbance horizon. Each graph shows five bars. The first bar from the left corresponds to the metric of the strategy Prediction ON using the k-NN algorithm where the disturbance is recorded with the same sampling rate of the MPC controller, which is 60s. The second bar corresponds to strategy Prediction ON using the k-NN algorithm where the disturbance is recorded every 5s for the prediction algorithm. The third bar corresponds to the Prediction ON using the perfect knowledge about the future evolution of the disturbance. The remaining bars correspond respectively to the Prediction OFF and FTMPC strategies.

Using a faster sampling of 5s for the measurement of the disturbance improves the metrics of the controller. The second bar of each graph, corresponding to the approach where the disturbance is sampled at a faster sampling rate than the one of the controller, is generally lower than the first bar, where the sampling rate is the same. However, there is still a large difference with the

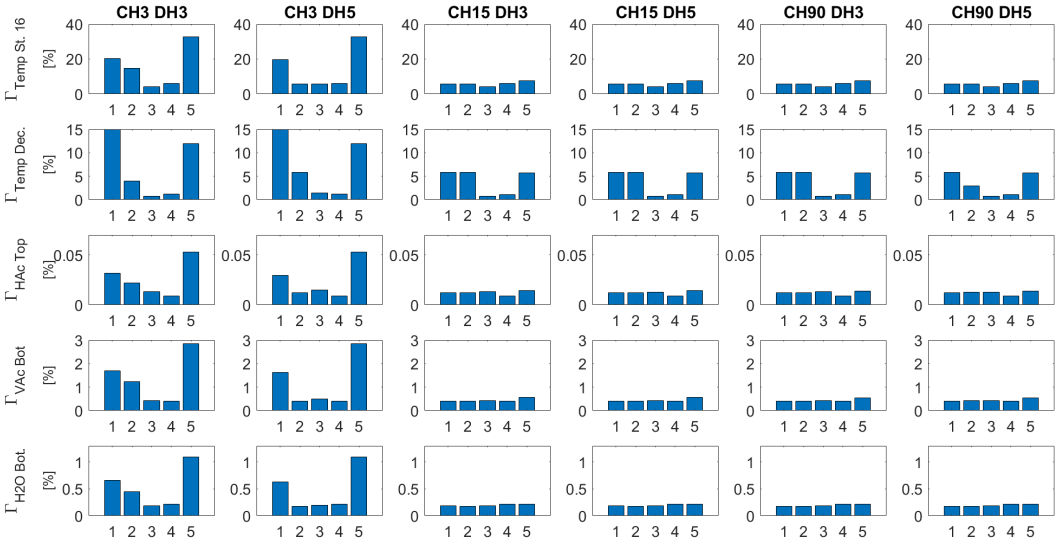
strategy Prediction ON with perfect knowledge about the future values of the disturbance, which is represented by the third bar of each graph.

The reason is that the controller with the Prediction ON with perfect knowledge has information about future abrupt events before they occur. Therefore, this controller can do certain small corrections to the manipulated variables before the abrupt events of the disturbance occur. A prediction based on k-NN cannot instead predict an abrupt event before it occurs.

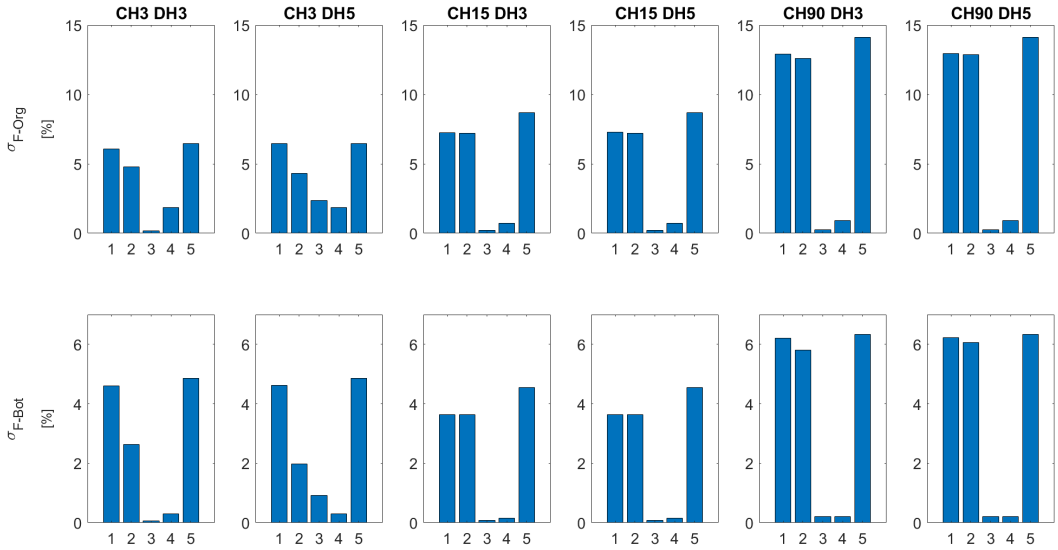
The solution is increasing the sampling rate of the MPC controller, so that the controller detects and predicts the future evolution of the abrupt disturbance sooner. Fig. 6.24 shows the values of the metrics when the sampling of the controller is 20s. This values is equal to the original sampling of the measurement of the disturbance. There are four bars for each graph. The first bar from the left corresponds to the Prediction ON strategy with k-NN, the second bar corresponds to the strategy Prediction ON with perfect knowledge, the third bar corresponds to the MPC with the strategy Prediction OFF, and the last to the FTMPC.

The figure shows that the values of the metrics for the Prediction ON with k-NN and Prediction ON with perfect knowledge are more similar than when the sampling rate of the controller was 60s. The figure shows also that the values of the metrics are lower for the Prediction ON with k-NN than for Prediction OFF and FTMPC. The metric $\sigma_{\text{F-Org}}$ decreases here by 95% using the Prediction ON strategy. The outflow from the organic phase is simply kept constant despite the disturbance. This is the highest improvement registered. Also the metric $\Gamma_{\text{VAc-Bot}}$ improves greatly by 62.5%. However, the improvement is small in absolute terms. Further investigations should probably assess the economical impact of such disturbances on a plant scale.

The drawback of increasing the sampling rate of the controller is the computational time that might increase above acceptable levels.

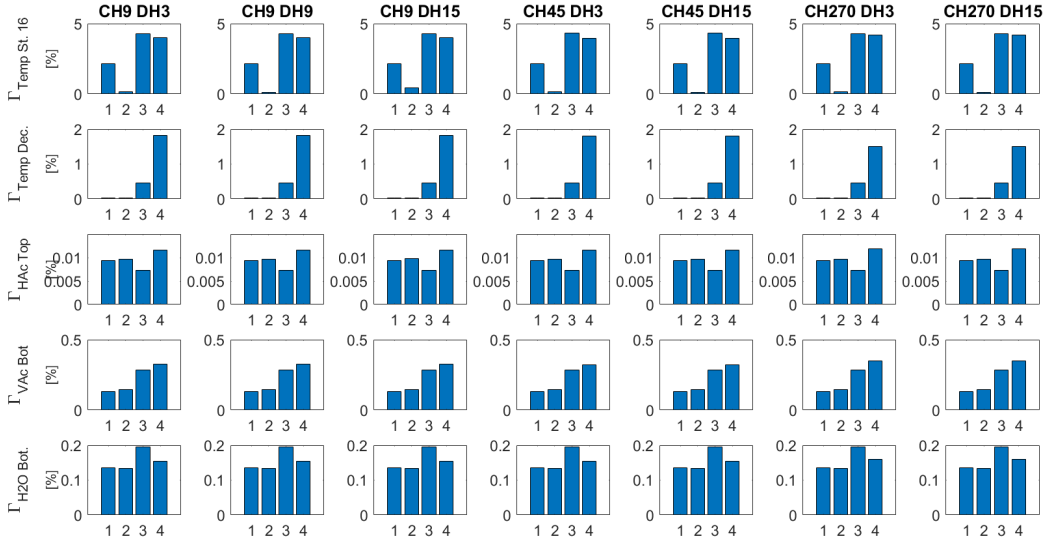


(a) Γ for the variables who must track a set-point

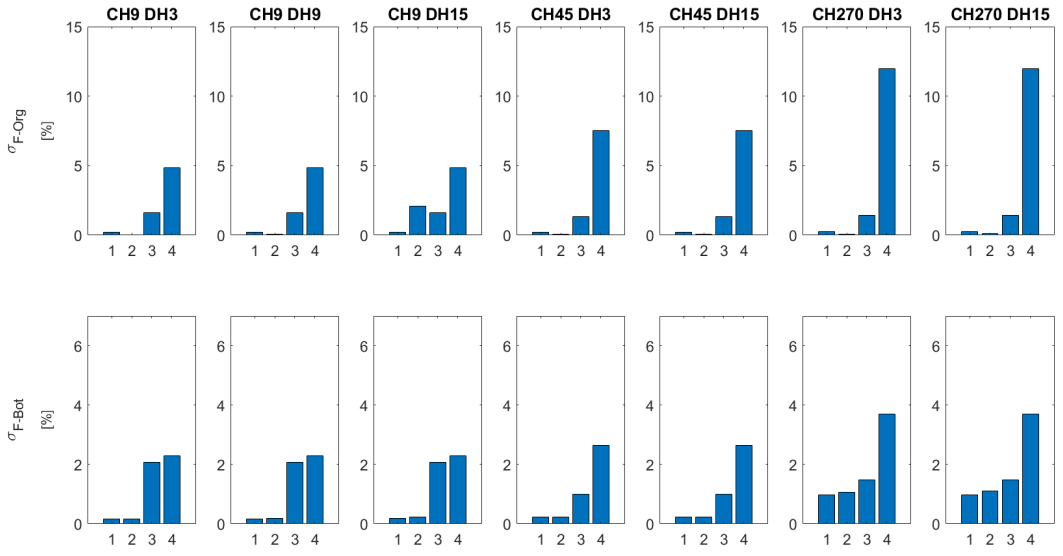


(b) σ for the MV associated to flows

Figure 6.23: Performance metrics with Tag 30 as disturbance acting on the heat provided to the column through the steam in reboiler. Controller sampling equal to 60s.
LEGEND: CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN with sampling of the disturbance measurement equal to 60s, 2 - Strategy with Prediction ON with k-NN with sampling of the disturbance measurement equal to 5s, 3 - Strategy with Prediction ON with perfect knowledge, 4 - Strategy with prediction OFF, 5 - Strategy with FTMPC



(a) Γ for the variables who must track a set-point



(b) σ for the MV associated to flows

Figure 6.24: Performance metrics with Tag 30 as disturbance acting on the heat provided to the column through the steam in reboiler. Controller sampling equal to 20s.
LEGEND: CS - Controller sampling in seconds, CH - Control horizon, DH - Disturbance horizon, 1 - Strategy with Prediction ON with k-NN, 2 - Strategy with Prediction ON with perfect knowledge, 3 - Strategy with prediction OFF, 4 - Strategy with FTMPC

Table 6.22: Questions and answers solved by the case study of the VAc distillation column.

Question	Answer
Performance with variables that must follow a set-point	• The Prediction ON strategy can improve only marginally (5% to 10% of the metrics Γ) the tracking of the set-points of concentrations compared to a FTMPC solution. Further analysis are required to assess the benefits of these improvements.
Performance with variables that act as buffer	• The Prediction ON strategy can even stop completely the disturbance propagation as seen for the CSTH tank.
Trade-offs when a system has CV acting as buffer and CV which must follow a set-point	• There is no trade-off when a system has controlled acting as buffer and CV which must follow a set-point
Length of the disturbance horizon	• A disturbance horizon longer than the control horizon might cause aggressive control actions and large deviations of the controlled systems from their nominal operating points.
Impact of disturbance sampling on performance	• The same considerations done for the steam boiler are valid for this case study. • The sampling does not have an impact when a disturbance is highly predictable, like Tag 34. • When the signal is not well predictable, like Tag 33, or has a very fast dynamic, like Tag 30, a larger sampling deteriorates the controller performance. • With large sampling, the Prediction ON strategy using the k-NN might not be advantageous for disturbances not highly predictable and/or with with very fast dynamics. • The disturbance forecasting should run at a higher sampling rate than the controller.

6.5.6 Conclusions for the VAc

The case study of the VAc column is chosen to test whether a compromise in terms of tuning of a controller is needed when there is the simultaneous presence of controlled variables that can act as buffer and controlled variables that must strictly follow their set-points. Furthermore, it is used to demonstrate whether a disturbance horizon longer than the control horizon can cause problems also in another case study in addition to the ones of the steam boilers. Table 6.22 summarises the findings.

The impact of the disturbance horizon confirms findings from previous sections. It has been observed also in this case study, that the disturbance in Tag 34 can make the controller particularly aggressive when the disturbance horizon is set longer than the control horizon. This might be caused by the larger variations present in Tag 34 that the controller tries to compensate. If the control horizon is shorter than the disturbance horizon, the controller does not not have enough degrees of freedom to compensate for these variations.

It has been shown that the two types of controlled variables are not posing conflicts. Providing a detailed prediction of the disturbance can provide good tracking of the set-points and, at the same time, block the disturbance propagation of a disturbance downstream.

However, testing the prediction technique developed in Chapter 4 shows some limits seen with the steam boiler. While the predictions provided by k-NN works very well with the regular signal of Tag 34, the performance decreases from the ideal case where the exact prediction is provided to the controller when predicting Tag 33 and Tag 30.

In the case of Tag 33 the problem is the forecastability of such signal. Predicting the signal with $k-$nearest neighbours provides still some advantages over the FTMPC strategy.

In the case of Tag 30 the problem is due to the sampling of the disturbance used for the prediction, which is too slow, and especially the sampling of the controller that must be fast to counteract fast disturbances. Nonetheless, increasing the sampling rate of the measurement of the disturbance and of the controller is computationally expensive.

6.6 SUMMARY

This chapter presents the results of the implementation of the MPC with disturbance forecasting proposed in this thesis. Table 6.23 answers schematically the answers that this chapter wanted to solve.

It tests whether and how providing a disturbance prediction can be beneficial in the case studies described in the former Chapter 5. The case studies are the CSTH tank, the steam boiler (in its two configurations) and the VAc column. The chapter discusses different control objectives, tuning choices, and compared the case with an ideal disturbance prediction with the one with a disturbance

prediction obtained using the weighted version of the algorithm presented in Chapter 4.

The proposed MPC provides advantages when the disturbances, be they persistent or abrupt, are characterised by fast dynamics and when the controlled system has controlled variables that can act as buffer. In this case, the proposed MPC can reduce or even stops the propagation of the disturbance through the manipulated variables.

The proposed MPC can provide slightly better performance in set-point tracking than the FTMPC, and both the proposed MPC and the FTMPC are far better than the Prediction OFF strategy. This means that if a system is characterised by controlled variables that act as buffer and by variables that have to follow a set-point, no compromise is required. However, if the system has only variables that must follow a set-point, there might no real advantage over the FTMPC strategy, like in the case presented of the steam boiler with the disturbance coming from the request of steam outflow from the loads.

Regarding the tuning of the controller, the chapter shows that disturbance horizon should be shorter or equal to the control horizon. Otherwise, the controller can be extremely aggressive. Furthermore, a large sampling time of the disturbance and of the controller can strongly deteriorate the performance of the controller, depending on the disturbance. Providing a fast sampling of disturbance algorithm and of the controller can be however computationally expensive for applications which need long prediction horizons.

Table 6.23: List of questions for this chapter and answers.

Question	Answer
Conditions for the improvement of performance with the Prediction ON strategy	The Prediction ON strategy provides advantages towards the FTMPC and Prediction OFF strategies when buffer variables are presents, or when the speed of the disturbances patterns are fast. The quality of predictions provided is the limit in certain situations.
Impact of the speed of the pattern of a disturbance on the performances achievable by the three different MPC strategies.	The slower the speed of the disturbance pattern, the better is the approximation done in the FTMPC and so the FTMPC performance is better. However, the slower the speed of such pattern is and the greater is the impact of the disturbance on the controlled variables. Therefore, the Prediction OFF controllers suffer in tracking set-points or constraints handling without feedforward action. For a fast abrupt disturbance, the behaviour of the FTMPC is too aggressive and the Prediction OFF strategy is fine because it does not react to negligible disturbance. The Prediction ON strategy is potentially able to properly work for all patterns speeds, as long as the sampling of the controller is fast enough and quality of the prediction good.
Tuning of the disturbance horizon	Setting the disturbance horizon longer than the control horizon might lead to way too aggressive controller, especially for a short control horizon. The optimizer of the controller needs enough degrees of freedom to compensate the foreseen variations of the disturbance. The control horizon gives degrees of freedom. Often a control horizon equal to the disturbance horizon leads to the best performance.
Impact of the sampling rate of the measurement and of the controller sampling.	A slow sampling of the measurement of the disturbance downsamples fast disturbances. This removes dynamics from the time series and deteriorates the quality of the prediction. A fast controller sampling is needed for fast and especially abrupt disturbances. A fast controller sampling increases the feedback of the controller and can compensate errors of the prediction algorithm.
Extension of the concept of buffer to variables different from levels.	A controlled variable that implies storage of mass or energy can act as buffer. Here, the pressure of a steam boiler was an indicator of mass of steam, and of energy that steam can deliver.

Table 6.23 continued from previous page

Question	Answer
Advantages of using the Prediction ON strategy when all CV should track a set point.	Most of cases, the advantages of using a Prediction ON strategy are limited compared to a more simple FTMPC when dealing with variables that must track a set-point. The system might not benefit from an extra improvement of the set-point tracking.
Trade-offs in terms of disturbance horizon, control horizon and sampling when there are both CV working as buffer and CV that have to follow their set points.	The are apparently no trade-offs in these situations.
Quality of predictions using the weighted k-NN method from Chapter 4 for control purposes.	The quality of the predictions are good as long the signal is highly predictable. When the signal is not highly predictable, like for Tag 33 and Tag 30, the performances are not adequate for all case studies. Still, increasing the sampling rate of the measurement of the disturbance, and especially of the controller, improves the prediction and nullify the difference between the results obtainable with the k-NN and those ideally obtainable using a perfectly known disturbance prediction. Nonetheless, using a high sampling rate is computationally expensive.

Chapter 7

CRITICAL EVALUATION OF THE THESIS AND FUTURE WORK

This chapter recalls the aim and the achievements of this thesis, and compares them with the initial research questions. The aim is to show how they have been fulfilled, which merits the methods have but also which limitation they pose.

7.1 SUMMARY AND DISCUSSION OF CONTRIBUTION OF THE THESIS

The stated aim of the thesis has been '*Increasing the level of automation in various areas of a process site by optimizing, given the constraints applied to the process, the response to fast complex disturbances, examining the trade off between rejection of the disturbance on controlled variables and avoidance of disturbance propagation*'.

To serve this, the following technical objectives have been specifically defined.

1. Review the most important persistent and abrupt disturbances, and their causes, propagating in a chemical and oil process site with a focus on propagation in steam and electrical utilities
2. Show whether a multistep prediction of persistent or abrupt disturbances is possible using an amount of industrial data smaller than a few hours, and provide a term for the forecastability of the time series
3. Propose an MPC with a data-driven multi-step forecasting and test whether the disturbance forecasts obtained in point 2 are good enough in conjunction with MPC for realistic case studies with industrial disturbances.

4. Analyse with new metrics the controller action of MPC controllers used in industrial settings in terms of disturbance handling and set-point tracking for persistent and spiky abrupt disturbances (fast complex disturbances)

The technical objectives define the areas of research, which the following sections analyse.

7.2 REVIEW OF PERSISTENT AND ABRUPT DISTURBANCES IN A PROCESS SITE

7.2.1 Merits of the method proposed

So far site-wide disturbances have not received much attention. The published literature lacks a clear overview of the disturbances that can propagate site-wide.

Chapter 3 reviews the disturbances occurring in a process production site, considering their nature, whether persistent or abrupt, and their causes. The review examined disturbances propagating within a production plant and also disturbances propagating to and from site utilities. The utilities considered are the steam utilities and electric utility.

The review might help future researchers working on the topic because it indicated which are the interactions between process and utilities that are more important.

7.2.2 Limits of the method proposed

The review has been conducted reading the academic and professional literature, interviewing engineers from ABB and visiting the site for gas treatment in Kollsnes, Norway, run by Equinor.

It was particularly hard to find case studies regarding the interaction between electromechanical systems and process, and the discussion with industrial professionals has been particularly useful to understand what problems might arise.

Academic literature often focuses on design of electro-mechanical systems rather than the problems that can arise once the system is running. Understanding the problems that can arise in operations requires experience and extensive but also deep inter-disciplinary knowledge, possibly not only with one particular plant but with a multitude of them. Industrial practitioners do not interact often

with academics. Even when this occurs, it is hard to find people with this broad experience. These are limiting factors for academic research.

A problem faced not only with electromechanical systems but also with steam utility is analysing quantitatively the impact of site-wide disturbance. The reason is that there are not, to the best of the current author's knowledge, benchmark models for site-wide disturbance as there are for plant-wide disturbances, such as those of Luyben and Tyréus (1998) and Downs and Vogel (1993). Creating simulators of such systems is hard because few data are publicly available. Estimating parameters requires engineering judgement often based on know-how and experience, and parameters impact the results of an analysis. It is not a coincidence that both Luyben and Tyréus (1998) and Downs and Vogel (1993) were working in industry when they published their benchmark models for plant-wide disturbances, working respectively for Du Pont and Eastman Chemical Company.

7.2.3 Future work

Future work should envisage the creation of a detailed benchmark model comprehensive of one or more steam generation units, steam distribution network and sections of one or more production plants, possibly heat integrated. This model would allow researchers to assess the impact of the disturbances between steam utility and production plants considered in Chapter 3.

Electrical disturbances do not have a large impact on site-wide disturbances according to the review in this thesis. For this reason, an electrical utility would have a lower priority in such a benchmark model. However, that conclusion was based also on the current regulations that electric utility have to satisfy. Although it is a speculation, future power systems might request more flexibility to industrial loads in the future because of the upcoming stronger presence of sources of renewable energy, which are known to be less constant in delivering power to the system. In this case, the electrical utility might have to be simulated.

7.3 PREDICTION OF PERSISTENT AND ABRUPT INDUSTRIAL DISTURBANCES, AND ASSESSMENT OF THEIR FORECASTABILITY

7.3.1 Merits of the methods proposed

The technical objective was to understand whether it is possible to use to training data shorter than few hours to provide a multi-step prediction of persistent as well as abrupt process disturbances. Furthermore, there was also the need to understand whether a signal is first of all forecastable.

The k-NN method has the merit of working even when only a few occurrences of disturbance pattern have been collected. The method is also robust to the choice of the parameters, which do not need to be retrained continuously. Furthermore, the k-NN has the considerable advantage of working for persistent but also for abrupt disturbances without need of structural changes.

The key improvement over the standard k-NN algorithm presented in this thesis has been the use of weights to base the prediction more on those neighbours which are more similar to the last evolving pattern of the time series. Using such weights improves the prediction quality, especially when the disturbance pattern is not very regular.

The work in this thesis also proposed two ways to analyse the forecastability of a time series. The first method is based on a qualitatively analysis based on a phase plot. It is easy to implement and easy to interpret with a bit of experience. A quantitative method is also proposed which derives from the Harris index and it is based on a prediction error achievable by an AR process. The advantage of such method is that allows to compare different signals in terms of forecastability in a somehow objective way. A feature which is not available by inspecting qualitatively the phase plots.

The work presented in this thesis about the prediction of process disturbances has been published as an invited paper in a special issue of Computers and Chemical Engineering dedicated to the the conference PSE2018.

7.3.2 Limits of the methods proposed

A drawback of the k-NN method is that the computational power requested to find the nearest neighbours increases with the length of the time series from which the past neighbours should be found. There might be a maximal number of samples of the past time series above which the system cannot run in real time any more. This implies that the system has to rely on recent measurements. This is a limitation when predicting abrupt disturbances because these disturbance events might not occur frequently. If the old measurements are discarded, the algorithm cannot find nearest neighbours of these infrequent disturbances.

A further issue is that the sampling rate for recording the time series of disturbances must be adjusted depending on the disturbance. Disturbances with fast dynamics need a faster sampling. On the contrary, setting a fast sampling rate might be unnecessary for slow disturbance but it would increase the computational power requested to find nearest neighbours.

Next to the computational issues, there is a problem of quality of the prediction. The k-nearest neighbours method works very well with regular time series. However, performance decrease when noise is present or when the time series of the disturbance is irregular. Some disturbances are inherently less forecastable than others. Still, there might be other methods that can improve the performance of the forecasting of process disturbances.

Also, the metric $E_{av\,\mathrm{int}}$, which was proposed for the assessment of the performance of the prediction, shows limits in its applicability to abrupt disturbances. This metric averages the quality of the prediction for all instants of time over an interval of time. However, the evaluation should be probably made only for the interval of times corresponding to abrupt patterns and should neglect the intervals of time between two abrupt occurrences. Otherwise, the metric is influenced by the prediction quality obtained in these intervals between abrupt events. The problem is defining rigorously the start and the end of an abrupt event without removing relevant segments of a time series.

Another issue is that the use of a forecastability index is related to the quality of prediction. The forecastability index proposed in this thesis is based on the principle of how well an autoregressive process can predict that disturbance. Nonetheless, the fact that an autoregressive process cannot properly predict a time series does not imply that a different prediction method cannot predict

the disturbance. For this reason it has been stated that the proposed index can work as term of comparison between different time series rather than an absolute metric.

The issue is defining which prediction method is used for reference. As example, there exist different structures of networks within the family of artificial neural networks. The structure is often chosen based on the experience of the developer and not based on analytical methodologies. Defining a reference model is hard and a subtle topic. Maybe, using a simple method, like the autoregressive process, provides a more robust and standard choice that is more selective in defining whether a time series is forecastable.

7.3.3 Future work

One area of research for the future is optimizing the search of nearest neighbours and the sampling rate for the measurement of the disturbance. An idea might be memorizing the patterns that repeat over time. The search would not be over past nearest neighbours found in the time series rather over averaged models of the persistent or abrupt patterns that have occurred. It remains the problem of defining how the patterns should be learnt and stored in the system.

Another area of research is testing other prediction methods for the time series forecasting to improve the quality of the predictions and assessing the forecastability of time-series. Artificial Neural Network (ANN) and support vector regression were tested at a very late stage of this PhD and provided initial results where the metrics which assess the quality of the prediction were five to ten times worse than those of proposed k-NN method. Further tests are needed but the reason is probably the limited amount of data for training. Transfer learning with ANN might be a solution to be investigated. Transfer learning is a technique where an ANN is trained on an initial dataset which has similar characteristics to the final dataset and is long enough to obtain good initial parameters of the parameters. This can be considered a pre-training. After the ANN is trained on the short dataset which is of specific interest. This last training acts as fine tuning for the parameters of the ANN. Bauer et al. (2018) provide a large data repository of plant-wide disturbances on which the ANN might be pre-trained. Alternatively, the dataset for the pre-training might be created with simulators.

Another area for future work might be trying to investigate the possibility to separate the determ-

inistic components of time series from its unpredictable part. This would permit the assessment of the predictability of a time series, but also enable the implementation of a stochastic MPC, which will be discussed in Section 7.4.3. This might be possible through a wavelet decomposition of the time series (Guntu et al., 2020; Masuda and Aihara, 2001).

7.4 MPC WITH A DATA DRIVEN MULTI-STEP PREDICTION, TESTED ON INDUSTRIAL CASE STUDIES

7.4.1 Merits of the method

This thesis has presented a novel MPC controller using a multi-step prediction of a disturbance that can provide better performance in managing propagating fast process disturbances compared to industrial MPC controllers. The main advantage is stopping or strongly attenuating the propagation of a disturbance, while the tracking of the set-points is similar and in some cases better than another industrial strategy called Frozen Time MPC. By comparison, the FTMPC is very good in tracking a set-point but it is also noticeably the worst in attenuating the propagation of a disturbance.

A merit is also that the new controller replicates the strategies that the present author saw used by operators to handle propagating disturbances. The operators control some flows manually to keep them constant and prevent a disturbance from propagating. However, some manual adjustment might be required over time. Here, this strategy is used by a controller which does small adjustments automatically.

7.4.2 Limits of the method

A limit is that the performance of the controller depends on the quality of the prediction. This depends also on the predictability of the time series. A time series of a process disturbance tends to lose predictability, the further the point of measurement is from the cause of the disturbance.

Another limit of the proposed MPC framework is that the sampling of the controller has to be fast enough to obtain good performance with very fast and abrupt disturbances. Unfortunately, setting a fast sampling rate can be unfeasible in real-time applications because of the computational power requested.

It has also to be considered that the proposed MPC controller might have limited advantages if the control problem is only of set-point tracking and there is no buffer in the system that must be controlled.

7.4.3 Future work

Future work can focus on improving the quality of the disturbance prediction to improve the controller performance. Another area of work is using stochastic MPC to take the uncertainty of the disturbance prediction into account. The problem is defining a probabilistic distribution of the prediction. It might be possible to decompose the time series as the sum of components which are deterministic and of components which are noise. The probabilistic distribution should model the noise.

The proposed MPC framework should also be tested on a whole simulated production plant or on a whole utility, rather than on a single unit process unit, such as a boiler or a distillation column. This might lead to the development of distributed MPCs, where multiple controllers have to exchange information to coordinate and stop the propagation of disturbances. Furthermore, assessing a whole plant or a whole utility would permit to assess the economical benefits of stopping the disturbance, and also to assess to which extents it is economically beneficial to improve the set-point tracking of the controlled variables. Formulating the tuning of MPC in terms of an economic MPC might be another future research area.

It might be worth considering using the proposed MPC in conjunction with algorithms for root cause analysis of plant-wide and site-wide disturbances. The control system might help identifying the source of a disturbance by stopping the propagation of the disturbance.

Finally, an optimization of the control strategies to handle a process disturbance might reduce the need of buffers in process plants. The reduction in Capital Expenditure (CapEx) can assessed taking various scenarios into account.

7.5 ANALYSIS WITH NEW METRICS TO ASSESS A CONTROLLER WHEN HANDLING PROPAGATING DISTURBANCE

7.5.1 Merits of the method

This thesis presented metrics that describe in a concise way the performance of a controller in presence of propagating disturbance. The metrics are Θ, Γ and σ, which assess respectively the violations of constraints of a controlled variable, the set-point tracking of a controlled variable, and the propagation of a disturbance through a manipulated variable. A merit of the metrics is that they are very detailed in analysing specific behaviours of the controller. This makes it possible to understand which aspects of the controller should be improved. Another merit is that it is possible to compare the values of a metric when used for different variables, because the metrics are normalised over the range of the corresponding controlled and manipulated variables.

7.5.2 Limits of the method

While these metrics are concise and have a good level of detail to analyse the performance of a controller for a process unit, such as a boiler or a distillation column, they are too detailed to analyse the performance of the control system of a whole production plant or utility.

The metrics Θ, Γ are applied to controlled variables, and the metric σ to manipulated variables. When a whole plant is considered, there would be too many values of these metrics that have to be analysed, one for each variable considered.

7.5.3 Future work

In the future the metrics proposed in this thesis might be combined to obtain possible a single metric that judges the performance of the control system for a process unit. As further step, a single metric might be created for a single plant or utility by combining the metrics related to the single process units. The aim is to have also a top-down system of metrics that allows the personnel in production to assess briefly the performance of their production site.

7.6 SUMMARY

The present chapter reminded the aim of the thesis and technical objectives. For each technical objectives, the chapter explained the merits and the limits of the solutions found, and proposed possible topics for future research.

Chapter 8

SUMMARY AND CONCLUSIONS

This thesis proposes a control framework to improve the response of control systems to propagating process disturbances. Disturbances are undesired deviations of process variables from their set-points. A common feature of many disturbances is that their time series show repetitions of fast and complex patterns. These patterns can repeat at regular intervals, in which case the disturbance is defined as persistent. Alternatively, if the intervals between two events of a disturbances is not regular, the disturbance is defined as abrupt. Another feature is that such disturbances can propagate and manifest in several measurements. If they propagate within a plant they are defined as plant-wide disturbances. If they propagate also to utilities of a process site, they are defined as site-wide disturbances. Previous literature has focused on plant-wide disturbances. By contrast, site-wide disturbances have received little attention so far.

Chapter 1 provided an introduction to the problem, described the impact of the plant-wide and site-wide disturbances on the operations of a process site, and explained the role of a controller in the propagation of the disturbance. A controller has to reject a disturbance from the controlled variables using the manipulated variables. However, when manipulated variables change their values to reject a disturbance, the disturbance might propagate downstream. The chapter explained there is a trade off between rejecting a disturbance and avoiding further propagation of the disturbance into other sections of a production site.

Chapter 1 states also the research aim of the thesis which is '*Increasing the level of automation in various areas of a process site by optimizing, given the constraints applied to the process, the response to fast complex disturbances, examining the trade off between rejection of the disturbance on controlled variables and avoidance of disturbance propagation*'. The thesis proposes to integrate an algorithm for the forecasting of a disturbance in a Model Predictive Control (MPC). This MPC framework should optimally manage propagating disturbances.

The following technical objectives have been specified to achieve the research aim.

1. Review the most important persistent and abrupt disturbances, and their causes, propagating in a chemical and oil process site with a focus on propagation in steam and electrical utilities
2. Show whether a multistep forecast of persistent or abrupt disturbances is possible using an amount of industrial data smaller than a few hours and provide a term for the forecastability of the time series
3. Analyse with new metrics the controller action of MPC controllers used in industrial settings in terms of disturbance propagation and set-point tracking for persistent and spiky abrupt disturbances (fast complex disturbances)
4. Propose an MPC with a data-driven multistep forecasting and test whether the disturbance forecasts obtained in point 2 are good enough in conjunction with a such MPC for realistic case studies with industrial disturbances

Chapter 2 provided a literature review of MPC and time series forecasting. Chapter 3 to Chapter 6 focused on solving the technical objectives.

Chapter 3 achieved the first technical objective. The work in the chapter provided a review of the possible causes and propagation mechanisms of site-wide disturbances that affect process plants, steam utility and electrical utility. It was also defined which are the types of disturbance that the proposed MPC framework might handle.

Chapter 4 focused on the second technical objective. The chapter successfully showed that a multistep forecast of persistent or abrupt industrial disturbances is possible with a dataset smaller than few hours. Indeed, the proposed method, based on k-nearest neighbours, needs only a few occurrences of the pattern characterising the disturbance to provide good forecasts.

Chapter 5 and Chapter 6 fulfilled the third and the fourth technical objectives. The chapters showed the implementation of the MPC with disturbance forecasting on three simulated case studies. It also showed how certain metrics can be used to assess the behaviour of a controller when handling process disturbances. Two of these case studies were industrial, a steam boiler and a distillation

column. Implemented on these industrial case studies,the MPC with disturbance forecasting was able to dampen the propagating disturbance by up to 65% in the case study of the steam boiler, and up 95% in the case study of the distillation column when compared to an other MPC strategy used in industrial settings, which is called Frozen Time MPC. The set-point tracking showed smaller advantages up to 10% in most cases.

Importantly, the proposed MPC with disturbance forecasting replicates the way plant operators handle manually process disturbances. The difference is that the operators have to do manual adjustments over time, while the proposed MPC does these adjustments automatically. This goes towards the research aim of this thesis, which is increasing the level of automation in process plants in response to fast and complex disturbances.

Chapter 7 critically evaluated the achievements of the thesis, showing the merits and the limits of the solutions found, and providing directions for future researchers. The present author thinks that most important areas of future research are improving the quality of the disturbance prediction, testing the MPC with disturbance forecasting on larger systems and assessing its economical benefits, implementing a system that can adapt the sampling to be used for controller and disturbance algorithm, and integrating control strategies with root cause analysis of plant-wide and site-wide disturbances. These can be interesting topics that have great potential for increasing the level of automation in process plants.

BIBLIOGRAPHY

G. Adams, B. Burke, G. Goodwin, J. Gravdahl, R. Peirce, and A. Rojas. Managing steam and concentration disturbances in multi-effect evaporators via nonlinear modelling and control. In *IFAC Proceedings Volumes*, volume 41, pages 13919–13924. IFAC, 2008. ISBN 9783902661005.

A. Afram and F. Janabi-Sharifi. Theory and applications of HVAC control systems - a review of model predictive control (MPC). *Building and Environment*, 72:343–355, 2014. ISSN 03601323.

S. Aghabozorgi, A. Seyed Shirkhorshidi, and T. Ying Wah. Time-series clustering - a decade review. *Information Systems*, 53:16–38, 2015. ISSN 03064379.

E. O. Agunlejika, P. Langston, B. J. Azzopardi, and B. N. Hewakandamby. Flow instabilities in a horizontal thermosyphon reboiler loop. *Experimental Thermal and Fluid Science*, 78:90–99, 2016.

A. Alane and P. J. Heggs. Experimental study of complex two-phase instabilities during the start-up of a vertical thermosyphon reboiler operating under vacuum. *Chemical Engineering Research and Design*, 89(10):2012–2023, 2011. ISSN 02638762.

M. Alhajeri and M. Soroush. Tuning guidelines for model-predictive control. *Industrial and Engineering Chemistry Research*, 59(10):4177–4191, 2020. ISSN 0888-5885.

J. J. Alves and G. P. Towler. Analysis of refinery hydrogen distribution systems. *Industrial and Engineering Chemistry Research*, 41:5759–5769, 2002. ISSN 0888-5885.

ARC Advisory Group. Improving agility, performance, and profitability with MPC – a decade of success, 2006. `https://www.controlglobal.com/assets/Media/MediaManager/wp{_}07{_}007{_}arc{_}pavilion{_}mpc.pdf` [accessed on 24 December 2017].

K. Åström and R. Bell. Drum-boiler dynamics. (technical reports tfrt-7577). Technical report, Department of Automatic Control, Lund Institute of Technology, 1998.

K. Åström and R. Bell. Drum-boiler dynamics. *Automatica*, 36(3):363–378, 2000. ISSN 00051098.

K. J. Åström and R. Bell. Dynamic models for boiler-turbine alternator units: Data logs and parameter estimation for a 160 MW unit. Technical report, Lund, 1987.

A. Aswani, H. Gonzalez, S. S. Sastry, and C. Tomlin. Provably safe and robust learning-based model predictive control. *Automatica*, 49(5):1216–1226, 2013. ISSN 00051098.

A. Baggini. In *Handbook of Power Quality*. John Wiley & Sons, 2008. ISBN 978-0-470-06561-7.

S. S. Bahakim and L. A. Ricardez-Sandoval. Simultaneous design and MPC-based control for dynamic systems under uncertainty: A stochastic approach. *Computers and Chemical Engineering*, 63:66–81, 2014. ISSN 00981354.

L. E. Bakken, E. Lunde, and M. Løes. Power dip impact on compressor system stability. *Proceedings of the ASME Turbo Expo*, 9:1–9, 2016. doi: 10.1115/GT2016-56950.

S. Basu and D. A. Kumar. *Power Plant Instrumentation and Control Handbook - A Guide to Thermal Power Plants*. Academic Press - Elsevier, Second edition, 2019. ISBN 978-0-1281-9504-8.

M. Bauer. *Data-driven Methods for Process Analysis*. Phd thesis, University of London, 2005.

M. Bauer, A. Horch, L. Xie, M. Jelali, and N. Thornhill. The current state of control loop performance monitoring - a survey of application in industry. *Journal of Process Control*, 38: 1–10, 2016. ISSN 09591524.

M. Bauer, L. Auret, D. le Roux, and V. Aharonson. An industrial PID data repository for control loop performance monitoring (cpm). *IFAC-PapersOnLine*, 51(4):823–828, 2018. ISSN 2405-8963.

A. Bemporad, F. Borrelli, and M. Morari. Model predictive control based on linear programming - the explicit solution. *IEEE Transactions on Automatic Control*, 47(12):1974–1985, 2002a. ISSN 0018-9286.

A. Bemporad, M. Morari, V. Dua, and E. N. Pistikopoulos. The explicit linear quadratic regulator for constrained systems. *Automatica*, 38(1):3–20, 2002b. ISSN 00051098.

D. Bernardini and A. Bemporad. Stabilizing model predictive control of stochastic constrained linear systems. *IEEE Transactions on Automatic Control*, 57(6):1468–1480, 2012. ISSN 00189286.

T. Besselmann, E. Lunde, P. Jörg, T. O. Stava, K. Knutsen, and S. Van de moortel. Partial torque ride through with model predictive control. In *2016 Petroleum and Chemical Industry Conference Europe (PCIC Europe)*, Berlin, 2016.

B. J. Binder, T. A. Johansen, and L. Imsland. Improved predictions from measured disturbances in linear model predictive control. *Journal of Process Control*, 75:86–106, 2019. ISSN 09591524.

N. Birla and A. Swarup. Optimal preview control: A review. *Optimal Control Applications and Methods*, 36(2):241–268, 2015. ISSN 01432087.

M. H. J. Bollen. The influence of motor reacceleration on voltage sags. *IEEE Transactions on Industry Applications*, 31(4):667–674, 1995. ISSN 19399367.

G. Bontempi, S. B. Taieb, Y.-A. L. Borgne, and L. Borgne. Machine learning strategies for time series forecasting. *Second European Summer School, eBISS 2012, Brussels, Belgium, July 15-21, 2012, Tutorial Lectures*, pages 62–77, 2013. ISSN 18651348.

C. Bordons and J. R. Cueli. Predictive controller with estimation of measurable disturbances. Application to an olive oil mill. *Journal of Process Control*, 14(3):305–315, 2004. ISSN 09591524.

F. Borghesan, M. Chioua, and N. F. Thornhill. Forecast of persistent disturbances using k -nearest neighbour methods. In *Computer Aided Chemical Engineering, Volume 44*, pages 631–636, 2018a.

F. Borghesan, M. Chioua, and N. F. Thornhill. An MPC with disturbance forecasting for the control of the level of a tank with limited buffer capacity. In *2018 26th Mediterranean Conference on Control and Automation (MED)*, pages 1–9, 2018b.

F. Borghesan, M. Chioua, and N. F. Thornhill. Forecasting of process disturbances using k-nearest neighbours, with an application in process control. *Computers and Chemical Engineering*, 128: 188 – 200, 2019a. ISSN 00981354.

F. Borghesan, N. F. Thornhill, and T. Haugen. Cycle of three interviews within ABB Norway. Personal Communications, 2019b.

C. L. Bottasso, P. Pizzinelli, C. E. Riboldi, and L. Tasca. Lidar-enabled model predictive control of wind turbines with real-time capabilities. *Renewable Energy*, 71:442–452, 2014. ISSN 09601481.

S. D. Cairano, D. Bernardini, A. Bemporad, and I. V. Kolmanovsky. Stochastic MPC with learning for driver-predictive vehicle control and its application to HEV energy management. *IEEE Transactions on Control Systems Technology*, 22:1018–1031, 2014.

E. Camacho and C. Bordons. *Model Predicitve Control*. Springer Verlag, 2008. ISBN 978-1852336943.

D. S. Carrasco and G. C. Goodwin. Feedforward model predictive control. *Annual Reviews in Control*, 35(2):199–206, 2011. ISSN 13675788.

R. C. Cavalcante, R. C. Brasileiro, V. L. Souza, J. P. Nobrega, and A. L. Oliveira. Computational intelligence and financial markets: A survey and future directions. *Expert Systems with Applications*, 55:194–211, 2016. ISSN 09574174.

I. Cecilio, S. Chen, and N. Thornhill. Importance of auxiliary systems for process fault detection and diagnosis. *19th Mediterranean Conference on Control and Automation*, pages 952–957, 2011.

I. M. Cecilio. *On extending process monitoring and diagnosis to the electrical and mechanical utilities : an advanced signal analysis approach*. Phd thesis, Imperial College London, 2014.

B.-J. Chen, M.-W. M.-W. Chang, and C.-J. C.-J. Lin. Load forecasting using support vector machines: a study on EUNITE competition 2001. *IEEE Transactions on Power Systems*, 19(4): 1821–1830, 2004. ISSN 0885-8950.

P.-C. Chen and J. S. Shamma. Gain-scheduled ℓ^1-optimal control for boiler-turbine dynamics with actuator saturation. *Journal of Process Control*, 14(3):263–277, 2004. ISSN 09591524.

R. Chen, K. Dave, T. J. McAvoy, and M. Luyben. A nonlinear dynamic model of a vinyl acetate process. *Industrial and Engineering Chemistry Research*, 42(20):4478–4487, 2003. ISSN 08885885.

L. Cheng and M. A. Duran. Logistics for world-wide crude oil transportation using discrete event simulation and optimal control. *Computers and Chemical Engineering*, 28(6-7):897–911, 2004. ISSN 00981354.

M. Chioua, M. Bauer, S. L. Chen, J. C. Schlake, G. Sand, W. Schmidt, and N. F. Thornhill. Plant-wide root cause identification using plant key performance indicators (kpis) with application to a paper machine. *Control Engineering Practice*, 49:149–158, 2016. ISSN 09670661.

M. A. A. S. Choudhury, S. L. Shah, and N. F. Thornhill. *Diagnosis of Process Nonlinearities and Valve Stiction: Data Driven Approaches*. Springer Verlag, Berlin/Heidelberg, 2008. ISBN 978-3540792239.

A. Cortinovis, H. J. Ferreau, D. Lewandowski, and M. Mercangoz. Safe and efficient operation of centrifugal compressors using linearized MPC. *Proceedings of the IEEE Conference on Decision and Control*, 2015-February(February):3982–3987, 2014. ISSN 07431546.

A. Cortinovis, H. J. Ferreau, D. Lewandowski, and M. Mercangöz. Experimental evaluation of mpc-based anti-surge and process control for electric driven centrifugal gas compressors. *Journal of Process Control*, 34:13–25, 2015.

A. Cortinovis, M. Mercangöz, T. O. Stava, S. Van de Moortel, and E. Lunde. Dynamic time to surge computation for electric driven gas compressors during voltage dips. *IFAC-PapersOnLine*, 49(7):949–954, 2016. ISSN 24058963.

A. Cortinovis, M. Mercangöz, T. Besselmann, A.-M. Ditlefsen, T. O. Stava, Van de Moortel, Sture, and E. Lunde. Enabling voltage dip ride-throughs of large electric driven gas compressors. *Journal of Process Control*, 74:76 – 87, 2019. ISSN 0959-1524.

M. L. Darby and M. Nikolaou. MPC: Current practice and challenges. *Control Engineering Practice*, 20(4):328–342, 2012. ISSN 09670661.

J. G. De Gooijer and R. J. Hyndman. 25 years of time series forecasting. *International Journal of Forecasting*, 22(3):443–473, 2006. ISSN 01692070.

M. Debert, G. Colin, Y. Chamaillard, L. Guzzella, A. Ketfi-Cherif, and B. Bellicaud. Predictive energy management for hybrid electric vehicles - prediction horizon and battery capacity sensitivity. *IFAC Proceedings Volumes (IFAC-PapersOnline)*, 43(7):270–275, 2010. ISSN 14746670.

L. Desborough and T. Harris. Performance assessment measures for univariate feedback control. *The Canadian Journal of Chemical Engineering*, 70(6):1186–1197, 1992.

D. Dougherty and D. J. Cooper. Tuning guidelines of a dynamic matrix controller for integrating (non-self-regulating) processes. *Industrial and Engineering Chemistry Research*, 42(8):1739–1752, 2003. ISSN 0888-5885.

J. J. Downs and M. H. Caveness. Influence of process variability propagation in plantwide control. In G. P. Rangaiah and V. Kariwala, editors, *Plantwide Control : Recent Developments and Applications*, chapter 8. John Wiley & Sons, Incorporated, 2012. ISBN 9781119968979.

J. J. Downs and S. Skogestad. An industrial and academic perspective on plantwide control. *Annual Reviews in Control*, 35(1):99–110, 2011. ISSN 13675788.

J. J. Downs and E. F. Vogel. A plant-wide industrial process control problem. *Computers and Chemical Engineering*, 17(3):245–255, 1993. ISSN 00981354.

S. S. Dughman and J. A. Rossiter. Systematic and effective embedding of feedforward of target information into mpc. *International Journal of Control*, 93(1):98–112, 2020. ISSN 13665820.

S. G. Dukelow, B. G. Liptak, X. Cheng, and R. H. J. Meeker. Boiler control and optimization. In B. G. Liptak, editor, *Process Control and Optimization : Process Control and Optimization*, chapter 8. CRC Press LLC, 2005.

G. V. Durga Prasad, M. Pandey, and M. S. Kalra. Review of research on flow instabilities in natural circulation boiling systems. *Progress in Nuclear Energy*, 49(6):429–451, 2007. ISSN 01491970.

R. Dzedzemane, J. D. le Roux, C. J. Muller, and I. K. Craig. Steam header state-space model development and validation. *IFAC-PapersOnLine*, 51(21):207–212, 2018. ISSN 24058963.

A. Elguindy. *Drum-boiler Control Performance Optimization using an Observer-based State-feedback Controller within MATLAB / Simulink Environment*. Msc thesis, Universität Bremen, 2013.

Emerson Automation Solutions. *Control Valve Handbook*. Fisher Controls International, Fifth edition, 2019.

M. Farina, L. Giulioni, and R. Scattolini. Stochastic linear model predictive control with chance constraints – a review. *Journal of Process Control*, 44:53–67, 2016. ISSN 0959-1524.

T. C. Fu. A review on time series data mining. *Engineering Applications of Artificial Intelligence*, 24(1):164–181, 2011. ISSN 09521976.

X. Gao, F. Yang, C. Shang, and D. Huang. A review of control loop monitoring and diagnosis: Prospects of controller maintenance in big data era. *Chinese Journal of Chemical Engineering*, 24(8):952–962, 2016. ISSN 10049541.

S. Ghabraei, H. Moradi, and G. Vossoughi. Design & application of adaptive variable structure & h-∞ robust optimal schemes in nonlinear control of boiler-turbine unit in the presence of various uncertainties. *Energy*, 142:1040–1056, 2018. ISSN 03605442.

J. C. Gomez, M. M. Morcos, C. A. Reineri, and G. N. Campetelli. Behavior of induction motor due to voltage sags and short interruptions. *IEEE Transactions on Power Delivery*, 17(2):434–440, 2002. ISSN 08858977.

R. L. Gruel, P. W. Huber, and W. M. Hurwitz. Piping response to steam-generated water hammer. *Journal of Pressure Vessel Technology, Transactions of the ASME*, 103(3):219–225, 1981.

E. W. Gunther and H. Mebta. A survey of distribution system power quality-preliminary results. *IEEE Transactions on Power Delivery*, 10(1):322–329, 1995. ISSN 0885-8977.

R. K. Guntu, P. K. Yeditha, M. Rathinasamy, M. Perc, N. Marwan, J. Kurths, and A. Agarwal. Wavelet entropy-based evaluation of intrinsic predictability of time series. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 30(3):033117, 2020. ISSN 1054-1500.

Q. Guo, Q. Liang, J. Ni, S. Xu, G. Yu, and Z. Yu. Markov chain model of residence time distribution in a new type entrained-flow gasifier. *Chemical Engineering and Processing: Process Intensification*, 47(12):2061–2065, 2008. ISSN 02552701.

G. S. S. Hahn. Boiler efficiency and steam quality: The challenge of creating quality steam using existing boiler efficiencies. *Bullettin of the National Board of Boiler and Pressure Vessel Inspector*, 1998. https://www.nationalboard.org/Index.aspx?pageID=164{&}ID=235.

T. J. Harris. Assessment of control loop performance. *The Canadian Journal of Chemical Engineering*, 67(5):856–861, 1989.

V. Havlena. System and method for predicting future disturbances in model predictive control application, Patent number US9760067B2, 2011.

R. Henrion and A. Möller. Optimization of a continuous distillation process under random inflow rate. *Computers and Mathematics with Applications*, 45(1-3):247–262, 2003. ISSN 08981221.

H. Hippert, C. Pedreira, and R. Souza. Neural networks for short-term load forecasting: a review and evaluation. *IEEE Transactions on Power Systems*, 16(1):44–55, 2001. ISSN 08858950.

T. Hong and S. Fan. Probabilistic electric load forecasting: a tutorial review. *International Journal of Forecasting*, 32(3):914–938, 2016. ISSN 01692070.

A. Horch, J. Cox, and N. Bonavita. Root cause analysis of plant-wide disturbances. *ABB Review*, pages 24–29, 2007.

E. C. Horton, M. W. Foley, and K. E. Kwok. Performance assessment of level controllers. *International Journal of Adaptive Control and Signal Processing*, 17(7-9):663–684, 2003. ISSN 08906327.

Q. Hu, R. Zhang, and Y. Zhou. Transfer learning for short-term wind speed prediction with deep neural networks. *Renewable Energy*, 85:83–95, 2016. ISSN 18790682.

B. Huang, S. Shah, and R. Miller. Feedforward plus feedback controller performance assessment of MIMO systems. *IEEE Transactions on Control Systems Technology*, 8(3):580–587, 2000. ISSN 10636536.

W. Huang, Y. Nakamoria, and S.-Y. Wang. Forecasting stock market movement direction with support vector machine. *Computers and Operations Research*, 32(10):2513–2522, 2005. ISSN 03050548.

M. Hultgren, E. Ikonen, and J. Kovács. Integrated control and process design for improved load changes in fluidized bed boiler steam path. *Chemical Engineering Science*, 199:164–178, 2019. ISSN 00092509.

V. Hütten, T. Krause, C. Beer, S. Demmig, and V. A. Ganesan. VSDS motor inverter design concept for compression trains avoiding interharmonics in operating speed range and verification. In *Proceedings of the Forty-Second Turbomachinery Symposium*, Houston, Texas, 2013.

R. J. Hyndman. Cyclic and seasonal time series, 2011. Personal Blog, https://robjhyndman.com/hyndsight/cyclicts/.

R. J. Hyndman, A. B. Koehler, K. J. Ord, and R. D. Snyder. Prediction intervals for exponential smoothing using two new classes of state space models. *Journal of Forecasting*, 24:17–35, 2005. ISSN 0277-6693.

IEC. Electromagnetic compatibility (EMC) - Part 2-2: Environment - Compatibility levels for low-frequency conducted disturbances and signalling in public low-voltage power supply systems, EN 61000-2-2:2002. Technical report, 2002a.

IEC. Electromagnetic compatibility (EMC) - Part 2-8: Environment - Voltage dips and short interruptions on public electric power supply systems with statistical measurement results, EN 61000-2-8:2002. Technical report, 2002b.

IEC. Disturbance variable - IEV ref 351-48-08, 2017. URL http://www.electropedia.org/iev/iev.nsf/display?openform&ievref=351-48-08.

IEEE Industry Applications Scoiety. *IEEE Recommended Practice for Electric Power Distribution for Industrial Plants (IEEE Red Book)*. 1999. ISBN 1559373334.

ISA. ISA-S75-01. Technical report, 2007.

S. Y. Jiang, M. S. Yao, J. H. Bo, and S. R. Wu. Experimental simulation study on start-up of the 5 MW nuclear heating reactor. *Nuclear Engineering and Design*, 158(1):111–123, 1995.

P. Jorg, A. Tresch, and M. Bruha. A model based approach to optimize controls of a large LCI VSD for minimal grid-side sub-synchronous torsional interaction. *Petroleum and Chemical Industry Conference Europe Conference Proceedings, PCIC EUROPE*, 2013. ISSN 2166949X.

R. H. Julien, M. W. Foley, and W. R. Cluett. Performance assessment using a model predictive control benchmark. *Journal of Process Control*, 14(4):441–456, 2004. ISSN 09591524.

J. Jung and R. P. Broadwater. Current status and future advances for wind speed and power forecasting. *Renewable and Sustainable Energy Reviews*, 31:762–777, 2014. ISSN 13640321.

S. Kakac and B. Bon. A review of two-phase flow dynamic instabilities in tube boiling systems. *International Journal of Heat and Mass Transfer*, 51(3-4):399–433, 2008. ISSN 00179310.

H. Kantz and T. Schreiber. *Nonlinear Time Series Analysis*. Cambridge University Press, Cambridge, Second edition, 2004. ISBN 978-0521529020.

H. B. S. Kapp. BASF cooperates with partners to introduce online control of complex batch processes, 2015. https://www.basf.com/en/company/news-and-media/news-releases/2015/03/p-15-172.html.

R. Kehlhofer, F. Hannemann, B. Rukes, and F. Stirnimann. *Combined-Cycle Gas & Steam Turbine Power Plants*. PennWell, 2009. ISBN 9781593701680.

M. Kessler. Flow instabilities in a vertical tube reboiler. In *WIT Transactions on Engineering Sciences*, volume 83, pages 325–335, 2014. ISBN 9781845647940.

S. Khan. System planning. In *Industrial Power Systems*. 2008. ISBN 978-0-8247-2443-6.

A. Khotanzad, R. Afkhami-Rohani, and D. Maratukulam. ANNSTLF - artificial neural network short-term load forecaster - generation three. *IEEE Transactions on Power Systems*, 13(4): 1413–1422, 1998. ISSN 08858950.

H. Kister. *Distillation Operation*. McGraw-Hill's AccessEngineering. McGraw-Hill Education, 1990. ISBN 9780070349100. https://books.google.co.uk/books?id=XG4MCrEBEB8C.

M. Kita, T. Hataya, and Y. Tokimasa. Study of a rotordynamic analysis method that considers torsional and lateral coupled vibrations in compressor trains with a gearbox. In *The Thirty-sixth Turbomachinery Symposium*, 2007.

E. D. Klenske, M. N. Zeilinger, B. Schoelkopf, and P. Hennig. Gaussian process based predictive control for periodic error correction. *IEEE Transactions on Control Systems Technology*, 24(1): 110–121, 2016. ISSN 1063-6536.

A. Koerber and R. King. Combined feedback-feedforward control of wind turbines using state-constrained model predictive control. *IEEE Transactions on Control Systems Technology*, 21(4): 1117–1128, 2013.

U. Kortela and P. Lautala. Computer aided control of power plants in the pulp and paper industries. *IFAC Proceedings Series*, 16(21):463–470, 1984.

P. Kundur and N. Balu. *Power System Stability and Control*. EPRI power system engineering series. McGraw-Hill, 1994. ISBN 9780780334632.

J. Laks, L. Pao, E. Simley, A. Wright, N. Kelley, and B. Jonkman. Model predictive control using preview measurements from lidar. In *49th AIAA Aerospace Sciences Meeting including the New Horizons Forum and Aerospace Exposition*, number January. American Institute of Aeronautics and Astronautics, 2011. ISBN 978-1-60086-950-1.

M. Längkvist, L. Karlsson, and A. Loutfi. A review of unsupervised feature learning and deep learning for time-series modeling. *Pattern Recognition Letters*, 42(1):11–24, 2014. ISSN 01678655.

M. Ławryńczuk. Nonlinear predictive control of a boiler-turbine unit: A state-space approach with successive on-line model linearisation and quadratic optimisation. *ISA Transactions*, 67: 476–495, 2017. ISSN 00190578.

Y. LeCun, Y. Bengio, and G. Hinton. Deep learning. *Nature*, 521(7553):436–444, 2015. ISSN 0028-0836.

E. Lerch. Full electrical LNG plants : highest availability and energy efficiency through overall system design. In *LNG 17*, pages 1–12, Houston, Texas, 16-19 April, 2013, 2013. ISBN 9781629935331.

E. Lerch. Operational , economic and environmental benefits of electrically driven LNG with a combined cycle power plant. In *LNG 18*, 2016.

G. Li and J. Shi. On comparing three artificial neural networks for wind speed forecasting. *Applied Energy*, 87(7):2313–2320, 2010. ISSN 03062619.

P. Li, H. Arellano-Garcia, and G. Wozny. Chance constrained programming approach to process optimization under uncertainty. *Computers and Chemical Engineering, year = 2008, volume = 32, number = 1-2, pages = 25–45, issn = 00981354, __markedentry = [fborghe1:6], isbn = 1570-7946, keywords = chance constraints,control,linear,nonlinear,optimization,uncertainty,*.

P. Li, M. Wendt, H. Arellano-Garcia, and G. Wozny. Optimal operation of distillation processes under uncertain inflows accumulated in a feed tank. *AIChE Journal*, 48(6):1198–1211, 2002. ISSN 00011541.

W. H. Lio, B. L. Jones, and J. A. Rossiter. Preview predictive control layer design based upon known wind turbine blade-pitch controllers. *Wind Energy*, 20(7):1207–1226, 2017. ISSN 10991824.

B. G. Liptak. Feedback and feedforward control. In *Instrument Engineers' Handbook Volume Two : Process Control and Optimization*, chapter 2. CRC Press, Fourth edition, 2005.

T. Loscha, V. Hütten, E. Lerch, and C. Beer. Safe , reliable , efficient rotating & electrical solutions for 2 – 7 MTPA LNG applications. In *LNG18*, Perth, Australia, 2016.

M. L. Luyben and B. D. Tyréus. An industrial design/control study for the vinyl acetate monomer process. *Computers and Chemical Engineering*, 22(7-8):867–877, 1998. ISSN 00981354.

W. L. Luyben. Heterogeneous azeotropic distillation. In *Plantwide Dynamic Simulators in Chemical Processing and Control*, chapter 9. CRC Press, First edition, 2002. ISBN 9781482275803.

W. L. Luyben. Mathematical modeling and control of a multiboiler steam generation system. *Industrial and Engineering Chemistry Research*, 43(8):1839–1852, 2004. ISSN 0888-5885.

W. L. Luyben. Evaluation of criteria for selecting temperature control trays in distillation columns. *Journal of Process Control*, 16:115–134, 2006. ISSN 09591524.

W. L. Luyben. Design and control of a modified vinyl acetate monomer process. *Industrial and Engineering Chemistry Research*, 50(17):10136–10147, 2011. ISSN 08885885.

W. L. Luyben, M. L. Luyben, and B. D. Tyreus. *Process Control*. McGraw-Hill Professional Publishing, 1998. ISBN 978-0070067790.

J. Machowski, J. Bialek, and J. Bumby. *Power System Dynamics: Stability and Control*. John Wiley & Sons, 2011. ISBN 9781119965053.

M. Madsen, J. Filso, and M. Soltani. Preview-based asymmetric load reduction of wind turbines. *Proceedings of the IEEE International Conference on Control Applications*, pages 1424–1429, 2012.

Y. Majanne. Model predictive pressure control of steam networks. *Control Engineering Practice*, 13(12):1499–1505, 2005. ISSN 09670661.

H. Markiewicz and A. Klajn. Voltage Disturbances - Standard EN 50160 - Voltage Characteristics in Public Distribution Systems. Technical Report July 2004, Leonardo Da Vinci Programme / International Copper Association, 2004.

N. Masuda and K. Aihara. Prediction of chaotic time series with wavelet coefficients. *Electronics and Communications in Japan, Part III: Fundamental Electronic Science (English translation of Denshi Tsushin Gakkai Ronbunshi)*, 84(6):50–59, 2001. ISSN 10420967.

A. K. Mathur and S. G. Ravi. Neural net based disturbance predictor for model predictive control, Patent number US5408406A, 1995.

Mathworks. Optimization problem - documentation Matlab 2017b. `www.de.mathworks.com/help/mpc/ug/optimization-problem.html` [accessed on 21st January 2018].

Mathworks. Choose sample time and horizons - documentation Matlab 2017b, 2018. `www.de.mathworks.com/help/mpc/ug/choosing-sample-time-and-horizons.html` [accessed on 21st January 2018].

Mathworks. Design and cosimulate control of high-fidelity distillation tower with aspen plus dynamics, 2020a. `https://www.mathworks.com/help/mpc/ug/design-and-cosimulate-control-of-high-fidelity-distillation-tower-with-aspen-plus-dynamics.html` [22nd August 2020].

Mathworks. Tune weights, 2020b. `https://uk.mathworks.com/help/mpc/ug/tuning-weights.html` [accessed on 29th August 2020].

Mathworks. Specify constraints, 2020c. `https://uk.mathworks.com/help/mpc/ug/specifying-constraints.html` [accessed on 17th August 2020].

D. Mayne. Robust and stochastic model predictive control: Are we going in the right direction? *Annual Reviews in Control*, 41:184–192, 2016.

D. Q. Mayne. Model predictive control: Recent developments and future promise. *Automatica*, 50 (12):2967–2986, 2014. ISSN 00051098.

D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. Scokaert. Constrained model predictive control: Stability and optimality. *Automatica*, 36(6):789–814, 2000. ISSN 00051098.

N. J. McDonald. *Optical measurement of pressure transient induced flow in hydraulic system*. PhD thesis, Loughborough University, 2000.

R. Mehra, J. Amin, K. Hedrick, C. Osorio, and S. Gopalasamy. Active suspension using preview information and model predictive control. *Proceedings of the 1997 IEEE International Conference on Control Applications*, pages 860–865, 1997. ISSN 1085-1992.

G. Mesfin and M. Shuhaimi. A chance constrained approach for a gas processing plant with uncertain feed conditions. *Computers and Chemical Engineering*, 34(8):1256–1267, 2010. ISSN 00981354.

N. A. I. B. Mohd Noor. *Flexible Operation of Industrial Plants for Power Management and Demand-Side Response*. PhD thesis, Imperial College London, 2018.

K. R. Muske and T. A. Badgwell. Disturbance modeling for offset-free linear model predictive control. *Journal of Process Control*, 12:617–632, 2002.

National Grid. Frequency response obligations statutory, code and operational standards. pages 1–8, 2006. https://www.nationalgrid.com/uk/Electricity/Codes/gridcode/gridcodedocs/.

S. Nunokawa, T. Itoh, O. Suenaga, and T. Katayama. Design of temperature control system with preview action for coke oven plant. In *IFAC Proceedings Volumes*, volume 30, pages 97–102, 1997.

F. Oldewurtel, A. Parisio, C. N. Jones, D. Gyalistras, M. Gwerder, V. Stauch, B. Lehmann, and M. Morari. Use of model predictive control and weather forecasts for energy efficient building climate control. *Energy and Buildings*, 45:15–27, 2012. ISSN 03787788.

D. G. Olsen, W. Y. Svrcek, and B. R. Young. Plantwide control study of a vinyl acetate monomer process design. *Chemical Engineering Communications*, 192(10-12):1243–1257, 2005. ISSN 00986445.

P. Oram and F. Borghesan. Interview within BP. Personal Communications, 2019.

J. Patel, S. Shah, P. Thakkar, and K. Kotecha. Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert Systems with Applications*, 42(1):259–268, 2015. ISSN 09574174.

G. Prasad, G. W. Irwin, E. Swidenbank, and B. W. Hogg. A hierarchical physical model-based approach to predictive control of a thermal power plant for effcient plant-wide disturbance rejection. *Transactions of the Institute of Measurement and Control*, 24:523–560, 2002.

Process Engineering. Evonik chalks up APC gains. *Process Engineering*, 2009. URL http://processengineering.co.uk/article/1313848/evonik-chalks-up-apc-gains.

J. Rossiter. Model predictive control 3_8 summary of horizon choice, 2014. https://youtu.be/uv5tDPgm_24.

P. Rotondo, G. Maragioglio, G. Boccadamo, and V. Depau. Gearbox sub-synchronous radial vibration at the train 1 TNF, induced by process phenomena. In *44 th Turbomachinery & 31st Pump Symposia*, Houston, Texas, 2015.

S. Z. Rouhani and M. S. Sohal. Two-phase flow patterns: A review of research results. *Progress in Nuclear Energy*, 11(3):219–259, 1983.

G. Sabia, C. Heinze, F. Alobaid, E. Martelli, and B. Epple. Aspen dynamics simulation for combined cycle power plant – validation with hot start-up measurement. *Energy*, 187:115897, 2019. ISSN 03605442.

S. Santoso, E. Powers, and W. Grady. Electric power quality disturbance detection using wavelet transform analysis. In *Proceedings of IEEE-SP International Symposium on Time- Frequency and Time-Scale Analysis*, pages 166–169. IEEE, 1994. ISBN 0-7803-2127-8.

N. Sapankevych and R. Sankar. Time series prediction using support vector machines: A survey. *IEEE Computational Intelligence Magazine*, 4(2):24–38, 2009. ISSN 1556603X.

D. Schlipf, L. Y. Pao, and P. W. Cheng. Comparison of feedforward and model predictive control of wind turbines using LIDAR. In *2012 IEEE 51st IEEE Conference on Decision and Control (CDC)*, pages 3050–3055. IEEE, 2012. ISBN 978-1-4673-2066-5.

D. E. Seborg, T. F. Edgar, and D. A. Mellichamp. *Process Dynamics and Control*. John Wiley & Sons, Second edition, 2004. ISBN 0-471-00077-9.

A. Shamshad, M. A. Bawadi, W. M. A. Wan Hussin, T. A. Majid, and S. A. M. Sanusi. First and second order markov chain models for synthetic generation of wind speed time series. *Energy*, 30(5):693–708, 2005. ISSN 03605442.

W. Shen, X. Chen, M. Pons, and J. Corriou. Model predictive control for wastewater treatment process with feedforward compensation. *Chemical Engineering Journal*, 155(1-2):161–174, 2009. ISSN 13858947.

M. N. Sinner and L. Y. Pao. A study on horizon length for preview-enabled model predictive control of wind turbines. *Proceedings of the American Control Conference*, 2019-July:3488–3493, 2019. ISSN 07431619.

S. Skogestad. The dos and don'ts of distillation column control. *Chemical Engineering Research and Design*, 85:13–23, 2007. ISSN 02638762.

S. Spinelli, M. Farina, and A. Ballarino. An optimal hierarchical control scheme for smart generation units: An application to combined steam and electricity generation. *Journal of Process Control*, 94:58–74, 2020. ISSN 09591524.

Spirax Sarco. Steam boilers - the inside story (Youtube series), 2014. `https://youtu.be/azDyYDGWxb0` [accessed on 06 November 2019].

Spirax Sarco. Condensate removal, 2019. `https://beta.spiraxsarco.com/learn-about-steam/condensate-removal` [accessed on 06 November 2019].

P. A. S. Steimer, G. A. S. Scheuer, and C. A. S. Stulz. *ETH Lecture Notes: Electrical Drives 2*. ETH, Zurich, 2010.

G. N. G. Stein and F. N. G. Ghassemi. Grid code review panel – issue assessment proforma voltage fluctuations PP 11/51. a panel paper., 2019. `https://www.nationalgrideso.com/document/13916/download` [accessed on 14 September 2019].

L. Suganthi and A. A. Samuel. Energy models for demand forecasting - a review. *Renewable and Sustainable Energy Reviews*, 16(2):1223–1240, 2012. ISSN 13640321. URL http://dx.doi.org/10.1016/j.rser.2011.08.014.

Swagelok Energy Advisors. Steam quality-plant operations require a high steam quality, 2009. https://bit.ly/2Htm0Oe.

Swagelok Energy Advisors. The number one problem in a steam system: Water hammer, 2019. https://bit.ly/3fjwEcA.

K. Takaba. A tutorial on preview control systems. In *SICE 2003 Annual Conference*, pages 1388–1393.

S. J. Taylor and B. Letham. Forecasting at scale. *The American Statistician*, 72(1):37–45, 2018.

N. F. Thornhill. *Detection and Diagnosis of Distributed Disturbances in Chemical Processes*. PhD thesis, 2005a.

N. F. Thornhill. Finding the source of nonlinearity in a process with plant-wide oscillation. *IEEE Transactions on Control Systems Technology*, 13(3):434–443, 2005b. ISSN 10636536.

N. F. Thornhill and A. Horch. Advances and new directions in plant-wide disturbance detection and diagnosis. *Control Engineering Practice*, 15:1196–1206, 2007.

N. F. Thornhill, M. Oettinger, and P. Fedenczuk. Refinery-wide control loop performance assessment. *Journal of Process Control*, 9(2):109–124, 1999. ISSN 09591524.

N. F. Thornhill, J. W. Cox, and M. A. Paulonis. Diagnosis of plant-wide oscillation through data-driven analysis and process understanding. *Control Engineering Practice*, 11:1481–1490, 2003.

N. F. Thornhill, S. C. Patwardhan, and S. L. Shah. A continuous stirred tank heater simulation model with applications. *Journal of Process Control*, 18(3-4):347–360, 2008.

TLV. What is stall? https://www.tlv.com/global/ME/steam-theory/stall-phenomenon-pt1.html [accessed on 06 November 2019].

TLV. What is water hammer/ steam hammer?, 2019. https://www.tlv.com/global/ME/steam-theory/what-is-waterhammer.html [accessed on 06 November 2019].

TMEIC. Industrial motors overview. Introduction to TMEIC motors. Technical report, 2019.

G. Towler and R. Sinnott. Utilities and energy efficient design. In *Chemical Engineering Design: Principles, Practice and Economics of Plant and Process Design*, chapter 3rd. Elsevier Ltd, Second edition, 2013. ISBN 9780080966595.

G. Valencia-Palomo, J. A. Rossiter, and F. R. López-Estrada. Improving the feed-forward compensator in predictive control for setpoint tracking. *ISA Transactions*, 53(3):755–766, 2014. ISSN 00190578.

S. Vasudevan and G. P. Rangaiah. Performance assessment of plantwide control systems. In G. P. Rangaiah and V. Kariwala, editors, *Plantwide Control : Recent Developments and Applications*, chapter 12. John Wiley & Sons, Incorporated, 2012. ISBN 9781119968979.

V. Venkatasubramanian, R. Rengaswamy, K. Yin, and S. N. Kavuri. *Computers and Chemical Engineering, keywords = diagnosis,fault detection,process safety, number = 3, pages = 293–311, title = A review of process fault detection and diagnosis. Part I: Quantitative model-based methods, volume = 27, year = 2003*. ISSN 00981354.

E. I. Vlahogianni, M. G. Karlaftis, and J. C. Golias. Short-term traffic forecasting: Where we are and where we're going. *Transportation Research Part C: Emerging Technologies*, 43:3–19, 2014. ISSN 0968090X.

J. C. Wachel and F. R. Szenasi. Field verification of lateral-torsional coupling effects on rotor instabilities in centrifugal compressors. In *NASA Lewis Research Center. Rotordynamic Instability Problems in High-Performance Turbomachinery*, pages 15–34, 1980.

J. C. Wachel and F. R. Szenasi. Analysis of torsional vibrations in rotating machinery. *Proceedings of the twenty-second Turbomachinery Symposium*, pages 127–151, 1993.

Z. Wang, X. Wang, and C. Y. Chung. An analytical method for calculating critical voltage sag clearance time of induction motors. *IEEE Transactions on Power Delivery*, 27(4):2412–2414, 2012. ISSN 08858977. doi: 10.1109/TPWRD.2012.2202204.

R. Weron. Electricity price forecasting: a review of the state-of-the-art with a look into the future. *International Journal of Forecasting*, 30(4):1030–1081, 2014. ISSN 01692070.

F. Woodward. *Industrial waste treatment handbook*. Elsevier/Butterworth-Heinemann, Amsterdam; Boston, Second edition, 2006. ISBN 978-0-0805-5986-8.

Working Group CIGRE. Modeling of gas turbines and steam turbines in combined-cylce power plants. Technical report, 2003.

X. Wu, J. Shen, Y. Li, and K. Y. Lee. Steam power plant configuration, design, and control. *Wiley Interdisciplinary Reviews: Energy and Environment*, 4(6):537–563, 2015. ISSN 20418396.

T. Wymann and P. Jorg. Power loss ride-through in a variable speed drive system. *11th Petroleum and Chemical Industry Conference Europe Electrical and Instrumentation Applications, PCIC 2014*, 2014.

S. Xie, X. Hu, T. Liu, S. Qi, K. Lang, and H. Li. Predictive vehicle-following power management for plug-in hybrid electric vehicles. *Energy*, 166:701–714, 2019. ISSN 03605442.

M. Yesilbudak, S. Sagiroglu, and I. Colak. A new approach to very short term wind speed prediction using k-nearest neighbor classification. *Energy Conversion and Management*, 69:77–86, 2013. ISSN 01968904.

N. Yoshitani and A. Hasegawa. Model-based control of strip temperature for the heating furnace in continuous annealing. *IEEE Transactions on Control Systems Technology*, 6(2):146–156, 1998. ISSN 10636536.

T. Zhang, Z. J. Ooi, M. Skrzypek, and C. S. Brooks. A multi-dimensional dataset for two-phase instability in low pressure natural circulation based on direct transient local measurement. *International Journal of Heat and Mass Transfer*, 151:119447, 2020. ISSN 00179310.

B. Zhou, M. Chioua, M. Bauer, J. C. Schlake, and N. F. Thornhill. Improving root cause analysis by detecting and removing transient changes in oscillatory time series with application to a 1,3-butadiene process. *Industrial and Engineering Chemistry Research*, 58(26):11234–11250, 2019. ISSN 15205045.