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A survey of models of degradation for control applications

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ABSTRACT

The analysis of equipment degradation has traditionally developed in two main directions. One approach, of great interest for control system design, has been to consider that degradation causes fundamental changes to the behaviour of a system. Another approach, used in optimal maintenance planning and production scheduling, considers degradation as a separate process that affects performance but does not necessarily change the behaviour. This article provides a review of mathematical models of degradation that will facilitate the integration of degradation modelling into control and optimisation schemes. To this end, a new unified classification is proposed. It takes into account the influence of degradation on the behaviour of the system, as well as the factors influencing degradation. Understanding these mutual influences will enable improved optimization, design and operation of control systems. The flexibility of the proposed classification is demonstrated in an industrial application to a multi-product batch scheduling process.

1. Introduction

The modelling of degradation is well established for maintenance planning (Chen & Patton, 1999) with the resulting models being used to aid decisions related to restoring the performance of a system. In this context, *system* refers to a "combination of interacting elements organised to achieve one or more stated purposes" (BSI, 2015c), while *degradation* is a "detrimental change in physical condition, with time, use, or external cause" (BSI, 2017). However, models of degradation for use in control and optimisation applications must also capture the relationship between the way in which a system is operated and how its component parts degrade. A model for degradation therefore should be embedded within a model for the behaviour of the system. *Behaviour* refers to the dynamic relationships between variables of the system together with characteristic quantities such as efficiency of a machine or length of a batch. Frank, Garcia, and Koppen-Seliger (2000) indicates that models of behaviour used for control which do not consider degradation can be oversimplified and give only a partial description of a system.

Modelling of degradation within a control system requires both a description of how degradation affects the ability of the system to perform its function, and how degradation is influenced by the way the system is operated. *Influencing factors* include physical variables such as temperature and humidity, and also modes of operation such as the order of recipes in a batch process. Degradation might ultimately lead to a *fault* "characterised by the inability to perform a required function" (BSI, 2010). Previous work has focused on model-based fault-detection and diagnosis, and degradation modelling for reliability analysis and prognostics (Gorjian, Ma, Mittinty, Yarlagadda, & Sun, 2010; Isermann, 2005; Shahraki, Yadav, & Liao, 2017). Isermann (1984) provided a survey of methods for fault detection classified according to the system variables which are affected by degradation. However, modelling of the degradation itself was not discussed.

Degradation is often influenced by how the system is operated, with certain operating points likely to accelerate degradation. Hence it may be desirable to manipulate the operating set points in order to manage degradation and to reduce the risk of an unplanned stoppage in advance of a scheduled maintenance overhaul. The system would thus benefit from analysis of the impact of degradation.

The purpose of this paper is to show how models of degradation may be integrated into control systems. A summary of existing models of degradation, which have primarily been used in diagnostics and

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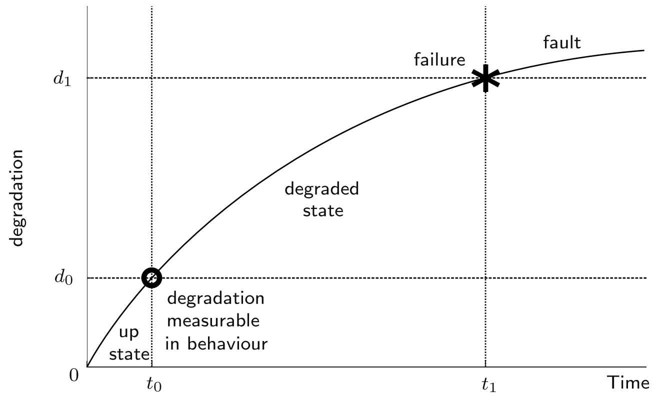

Fig. 1. Evolution of degradation in relation to the behaviour of a system

prognostics applications, is given. We provide a survey showing how models of degradation can be used in control and optimization. In particular, we propose a new classification according to the impact of degradation on the system, and the dependence of degradation on influencing factors.

This paper expands on the existing state of the art in degradation modelling with the following contributions:

- A new review of models of degradation in control and optimisation is provided;
- The models of degradation are classified anew from the perspective of how degradation is modelled in relation to the model of a system;
- Control systems taking account of degradation are classified from the perspective of how degradation is considered in a system;
- Recommendations regarding the use of models of degradation to improve control and optimisation systems are provided.

The rest of the paper is structured as follows. Section 2 defines and explains concepts related to degradation and to control systems. Subsequently, the new classification is introduced in Section 3 and described in Section 4. Section 5 presents models of degradation from the literature according to the new classification. Section 6 discusses how control systems can operate effectively in the presence of degradation, and how degradation models can help with this. An example of an industrial control application for a system with degradation is described in Section 7. The paper ends with a discussion and suggestions for further research.

2. Background and context

Section 2 provides explanations and definitions for the concepts to be discussed in the paper. The first sub-section defines terms and concepts related to degradation, including the concept of a degradation path model that underpins many degradation models. This section also classifies and summarizes existing models of degradation. The second sub-section defines terms and concepts relevant to the behaviour of a control system and gives an overview of the models that are commonly used to describe such behaviour. The terminology used in this section is gathered in the Glossary of Terms in Appendix A.

2.1. *Definitions and concepts related to degradation*

2.1.1. *Introduction to degradation*

Figure 1 shows an illustration of how degradation may progress over time. Throughout the paper, t refers to time and d refers to degradation. During the first stage, for time $t < t_0$, the value of degradation is too small to significantly influence the system. The system is therefore considered to be in *up state*. The black circle denotes the moment when the system enters a *degraded state*. When the degradation, d, is higher than a predefined threshold d_1, a *failure* occurs, marked with an asterisk. The last stage, when time $t > t_1$ and degradation $d > d_1$, represents faulty operation where the system is no longer able to perform one or more required functions.

BSI (2017) introduces the term *failure mechanism*, describing “physical, chemical or other processes which may lead or have led to failure”. These failure mechanisms belong to a more general group of *influencing factors*, where an influencing factor is an “observable qualitative or measurable quantitative item that affects a system property”. BSI (2016) categorises influencing factors according to their sources, such as the environment or operating personnel. The relationship between the influencing factors and the detrimental changes in the system properties is not explicitly described in the standards. For such relationships, the scientific literature suggests a variety of models depending on the type of influencing factor, the degradation processes and also on the application. This article presents a review and classification of those models of degradation that are useful for applications in control and optimisation.

2.1.2. *Degradation path model*

Meeker and Escobar (1998) describe the concept of a *degradation path model*. They analyzed degradation d as a function of time and discerned three functional forms of degradation path (Hong, Meeker, & Escobar, 2011; Meeker & Escobar, 1998). The degradation path in Figure 1 has a concave form characterized with parameter C and an upper boundary value d_f:

- Concave: $d(t) = d_f(1 - \exp(-Ct))$.

However degradation may take other functional forms characterized with parameter C and an initial value d_i:

- Linear: $d(t) = d_i + Ct$,
- Convex: $d(t) = d_i\exp(Ct)$,

In the linear and convex models, degradation starts at time $t = 0$ with a value d_i. This allows situations to be modelled where the system is initially already in a degraded state. Such situations may be caused by deficiencies in the manufacturing, storage or installation of an element in the system or may occur after maintenance activities where only partial performance has been restored

Degradation path models have been widely used to represent various types of degradation. Reviews of these approaches were conducted by Haghighi, Nooraee, and Rad (2010) and Xu, Hong, and Jin (2016). Hong, Meeker, and Escobar (2011) summarised a number of methods of modelling degradation primarily for reliability assessment and maintenance planning purposes. Shahraki et al. (2017) indicated that degradation path models may be insufficient because of the rigidity of the functional form.

The characterisation from Meeker and Escobar (1998) assumes that degradation is a strictly increasing function of time. However, Gertsbakh and Kordonskiy (1969) suggested that it is not mandatory to model degradation as a monotone function of time, because some systems might undergo a ‘burn-in’ period which improves the initial properties of a system.

2.1.3. *Existing models of degradation*

The standard BSI (2015) divides models of degradation into five groups:

- Physics-based models,
- Statistical models,
- Heuristic models,
- Data-driven models,
- Hybrid models.

These are often aggregated into three groups:

Table 1
Existing reviews of models of degradation

Authors	Classification	Applications
Isermann (1984)	Based on measurable signals Based on nonmeasurable state variables Based on nonmeasurable parameters Based on nonmeasurable characteristic quantities	Fault diagnosis
Jardine et al. (2006)	Time-domain Frequency domain Time-frequency domain Value type Data analysis combining event data and condition monitoring data	Diagnostics and prognostics
van Noortwijk (2009)	Gamma process based	Maintenance
Heng et al. (2009)	Physics-based Data-driven Integrated	Rotating machinery prognostics
Peng et al. (2010)	Physical Knowledge-based Data-driven Combination	Condition-based maintenance
Gorjian et al. (2010)	General degradation path Random process models Mixture model Time series Stress strength inference Cumulative damage Markov models Wiener models Gamma models	Reliability analysis
Sikorska et al. (2011)	Knowledge-based models Life expectancy models Artificial neural networks Physical models	Diagnostics and prognostics
Si et al. (2011)	Statistical data-driven	Prognostics
Qin (2012)	Physical Data-driven Based on deviations from the expected behaviour	Condition monitoring
Liao and Köttig (2014)	Experience-based Data-driven Physical Hybrid	Prognostics
Le (2015)	Experience-based Evolutionary and trending Physical Stochastic	Prognostics
BSI (2015)	Physical Data driven Knowledge based	Condition monitoring
Shahraki et al. (2017)	Data-driven Physics-based	Reliability analysis, maintenance planning, prognostics
Alaswad and Xiang (2017)	Discrete Proportional hazard models Continuous	Maintenance
Zhang et al. (2018)	Wiener process based	Prognostics
Lei et al. (2018)	Depending on a single health indicator Depending on a health indicator and time Depending on a health indicator and a stage sequence Depending on multiple health indicators Hybrid	Prognostics
Li et al. (2020)	Physical Data-driven	Reliability analysis
Kang et al. (2020)	Single mechanism Multi-mechanism Multi-performance	Maintenance

Table 2
Variables for describing the behaviour of a system (following Isermann (1984))

Input and output variables u and y in Eq. (1)
State variables x in Eq. (1)
Parameters, such a matrices **A, B, C, D** in Eq. (2)
Characteristic quantities that are functions of x and u

- Physical models,
- Data-driven models,
- Knowledge-based models.

Physical, data-driven, and knowledge-based models of degradation are widely used for prognostic applications, including condition monitoring and maintenance planning as indicated by Jardine, Lin, and Banjevic (2006), Heng, Zhang, Tan, and Mathew (2009), Peng, Dong, and Zuo (2010), Gorjian et al. (2010), Sikorska, Hodkiewicz, and Ma (2011), Le (2015), Shahraki et al. (2017), and Lei et al. (2018). Similarly, van Noortwijk (2009), Si, Wang, Hu, and Zhou (2011), Si, Wang, Chen, Hu, and Zhou (2013), and Zhang, Si, Hu, and Lei (2018) all presented reviews of applications of selected types of models of degradation for prognostic purposes, whereas Nguyen, Fouladirad, and Grall (2018) conducted a survey on selection of models of degradation using condition monitoring data. Furthermore, Zhang, Si, Hu, and Kong (2015) presented a review of data-driven methods used for estimation of degradation for prognostics.

A summary of existing reviews of models of degradation is in Table 1.

2.2. Definitions and concepts related to control systems

2.2.1. Introduction to control systems

A control system "responds to input signals from the process, its associated equipment, other programmable systems and/or an operator and generates output signals causing the process and its associated equipment to operate in the desired manner" (BSI, 2016). Sontag (1990) defines the effects of the inputs on the outputs of a system as its *input-output behaviour*. To analyse the behaviour in terms of the relationships between the inputs and the outputs, *mathematical models* are used, defined as "a set of equations that represents the system" (Ogata, 1997). Such equations include dynamic state-space equations and algebraic relationships. Other characteristic quantities such as duration of a batch reaction may also be included. Mathematical models that capture the behaviour of a system are called *behavioural models* (Willems, 2007).

The definitions related to behaviour of a system and mathematical models of the behaviour used in this paper are gathered below:

- *Input-output behaviour of a system* is a response of a system "to input signals from the process, its associated equipment, other programmable systems and/or an operator" (BSI, 2016), i.e. "the effect that inputs have on the outputs" (Sontag, 1990),
- *Inputs* are "signals that can be manipulated" (Ljung, 1999),
- *Outputs* are "observable signals that are of interest" (Ljung, 1999),
- *Behavioural models* are mathematical models of the input-output behaviour of a system (Willems, 2007).

The behaviour of a system can be described using the system variables listed in Table 2. This approach mirrors Isermann (1984) who first used this classification for process fault detection.

2.2.2. Models for behaviour of control systems

The dynamic behaviour of a system in up-state can be described as a set of nonlinear time-variant equations:

$$\dot{x}(t) = f(t, x(t), u(t)) \tag{1a}$$

Table 3
Mathematical models for systems with degradation

Models of behaviour	
Degradation-dependent	Degradation-independent
$\dot{x}_D(t) = f(t, x_D(t), u_D(t), h(d))$	$\dot{x}(t) = f(t, x(t), u(t))$
$y_D(t) = g(t, x_D(t), u_D(t), h(d))$	$y(t) = g(t, x(t), u(t))$
Models of degradation	
Factor-free	Factor-based
$h(d) = h(d(t))$	$h(d) = h(d(t, v, x(t), u(t), y(t)))$

$$y(t) = g(x(t), u(t)) \tag{1b}$$

with boundary conditions $x(t_0) = x_0$ where $t \in [t_0, \infty]$ is time, $x \in \mathbb{R}^n$ is a vector of n state variables, $u \in \mathbb{R}^m$ is a vector of m control variables. The outputs of the system are denoted with $y \in \mathbb{R}^k$. The functions $f : \mathbb{R}_+ \times \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$ and $g : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^k$ are nonlinear functions describing the dynamics of the system (Khalil, 2014).

Equations (1) include linear systems of form:

$$\dot{x}(t) = \mathbf{A}(t)x(t) + \mathbf{B}(t)u(t) \tag{2a}$$

$$y(t) = \mathbf{C}(t)x(t) + \mathbf{D}(t)u(t) \tag{2b}$$

where $\mathbf{A}(t) : \mathbb{R}_+ \rightarrow \mathbb{R}^{n\times n}$, $\mathbf{B}(t) : \mathbb{R}_+ \rightarrow \mathbb{R}^{n\times m}$, $\mathbf{C}(t) : \mathbb{R}_+ \rightarrow \mathbb{R}^{p\times n}$, $\mathbf{D}(t) : \mathbb{R}_+ \rightarrow \mathbb{R}^{p\times m}$ are matrices with functions of time as coefficients (Khalil, 2014).

2.2.3. Characteristic quantities

Characteristic quantities are related to items of equipment within a system. For instance, a compressor map describes the relationships between pressure ratio, mass flow rate and speed of a compressor, while a valve characteristic relates valve position to the flow rate through the valve.

With appropriate assignment of u, x, and y, characteristic quantities are modelled by a time-invariant version of Eq. (1b):

$$y = g(x, u) \tag{3}$$

For instance, a compressor map can be modelled as $P_2 = P_1\Psi(m, \omega)$, where P_2 and P_1 are the discharge and suction pressures, and Ψ is a nonlinear function of mass flow rate m and speed ω. Here, P_2 would be an output y, m would be a state variable x, and ω an input u. P_1 might be a state variable or an input depending on how the system is operated.

Characteristic quantities do not have to be system variables and may instead be performance indicators. An example is compressor efficiency $\eta = \eta(m, \omega)$, where η is an output y, and is a nonlinear function of the state and input variables on the right hand side. As a further example, the performance of a multi-purpose batch production can be defined as the processing time of all of the batches (an output, y) as a function of the sequence of recipes (an input, u).

3. Classification of models of degradation based on behaviour of a system and the influencing factors

In addition to introducing the various terms and concepts used in modelling of degradation, Section 2 also defined the behaviour of a system from a control perspective. The focus of this article is on models which combine both the influence of degradation on a system, and the influencing factors that affect the degradation of that system. This section now presents a new classification of models of behaviour of systems where degradation is present. It also characterizes the models of degradation taking influencing factors into account.

3.1. Classification based on detectability of degradation

We propose a classification of models of behaviour based on the following criteria:

- Degradation-dependent models of behaviour if degradation may be detected from the behaviour of a system,
- Degradation-independent models of behaviour if degradation does not affect the behaviour of a system.

The mathematical formulation of such models is presented in the upper section of Table 3.

A model of behaviour is said to be *degradation-dependent* when it is possible to monitor and quantify the degradation (usually by means of measurements of the input and output of the system). An example of a degradation-dependent model would be fouling of a heat exchanger, which is detectable from deviations in exit temperature. A degradation-dependent model augments Eqs. (1a) and (1b) by including the degradation explicitly in a model for degraded system variables x_D, u_D and y_D.

Conversely, a model of behaviour is considered to be *degradation-independent*, when the degradation does not influence the relationships between the model inputs and outputs. For example, the development of a leak in a heat exchanger may be modelled using a degradation independent model of behaviour. This is because it is not possible to detect or quantify the severity of developing cracks leading up to the leak other than by specialist equipment, typically not considered part of a control system. The formulation of a degradation-independent model is identical to Eq. (1). The behaviour of the system is indistinguishable from the system in up state, and the effect of degradation is not detectable in the system variables. Degradation-independent models of behaviour will be analysed in Sections 5.3 and 5.4 and their impact on control discussed in Section 6.

3.2. Classification based on influencing factors

Factors that influence degradation may be considered as inputs to the model of degradation:

- Factor-based models of degradation depend on influencing factors,
- Factor-free models of degradation are independent of any factors.

Influencing factors include the way in which the system is operated described with the variables in Table 2, and external factors v such as ambient temperature or humidity. Factor-free models of degradation typically depend only on time. These formulations are presented in the lower half of Table 3.

A model of degradation gives an expression for a value of a degradation function $h(d)$ for use in Eqs. (1b) and (2b) as shown in the lower row of Table 3. In the table, d is the degradation, and $h(d)$ is a function of the degradation that reflects the effect of degradation on a system variable.

3.2.1. Factor-free models of degradation

In a factor-free model of degradation, the degradation d is assumed independent of any influencing factors. The degradation does not take into account either factors from outside the system, or the system variables x, u and y. Degradation can however evolve with time, i.e. $d = d(t)$, as time itself is not considered an influencing factor. McPherson (2013) presented an overview of general time-dependent models of degradation.

In a system described by a factor-free model of degradation with a degradation-dependent model of behaviour, the factor-free degradation can affect the parameters and variables, as shown in Table 3. However, the structure of the model for behaviour remains the same. For instance, the linear system described by Eq. (2) will remain linear with respect to x, u, and y. If d varies with time, the parameters of the system will also

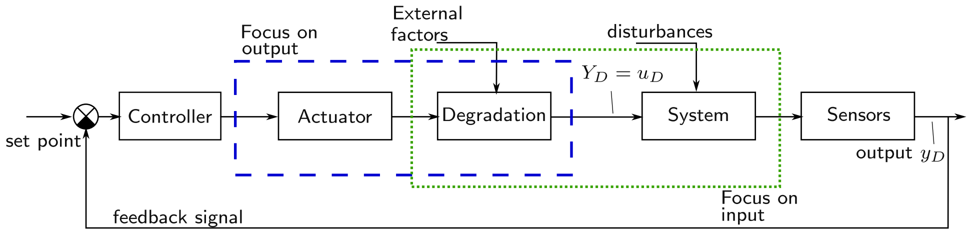

Fig. 2. Degradation-dependent control system showing input and output degradation

vary with time.

3.2.2. Factor-based models of degradation

Factor-based models of degradation provide a description of degradation in the form $h(d) = h(d(t, v(t), x(t), u(t), y(t)))$, where $v(t)$ represents variables that influence the degradation but which are not included as system variables, for instance environmental humidity or temperature.

Factor-based degradation might affect not only the values of the parameters and system variables, but also the structure of a degradation-dependent model of behaviour. For instance, it might introduce nonlinearity to a linear model or change the structure of Eq. (1).

3.3. Summary

Degradation affecting the system, and which affects the inputs or the outputs of the system, requires a degradation-dependent model of behaviour of the form shown in the upper left side of Table 3. A degradation-independent model is appropriate when the degradation does not affect the system.

Both the degradation-dependent and degradation-independent models of behaviour must be linked with a description of the degradation. This description can be factor-free or factor based, as shown in the lower row of Table 3. Either of the models of behaviour can be combined with either of the models for the influencing factors, thus there are four possible combinations of model structure. In particular, a degradation-dependent model of behaviour with a factor-based model of degradation has the potential to describe the effect of degradation on the system, and also the effect of the system on the degradation.

4. Models of degradation

Section 3.2 introduced a classification of models of degradation according to whether or not a model of degradation includes influencing factors in its formulation. Additionally, models of degradation may be further grouped according to:

- How the variables in a system can be influenced:
  - Additive models of degradation,
  - Multiplicative models of degradation.
- Which parts of a control system can be influenced:
  - Models of input degradation,
  - Models of output degradation.

4.1. Additive and multiplicative models of degradation

The effects of degradation on the system variables listed in Table 3 can be considered as additive or multiplicative (Isermann, 2006).

4.1.1. Additive models of degradation

In an additive model of degradation, the degraded value of a generic system variable V from Table 3 is offset relative to the equivalent value in up state. If the degradation of V is additive, it is modelled as

$$V_D = V + h(d) \tag{4}$$

where V_D denotes the degraded value, V is the value in up state without degradation, d is from the model of degradation and $h(d)$ is a function of the degradation that reflects the effect of degradation on V. Therefore, the degradation function would represent a deviation between the degraded value of a variable, V_D, and its counterpart in up state, $h(d) = V_D - V$.

A data-driven estimate of degradation would attempt to fit a model for degradation to measurements of V_D. Conversely, if V_D is not measurable, it would be possible to use a model of d to estimate V_D.

4.1.2. Multiplicative models of degradation

In a multiplicative model of degradation, the degraded value of a system variable is scaled according to a degradation function $h(d)$ as $V_D = h(d)V$. In particular, $h(d) = (1 - d)$ yields:

$$V_D = (1 - d)V \tag{5}$$

which can be rearranged to a form called the relative model of degradation

$$d = \frac{V - V_D}{V} \tag{6}$$

Equation (6) is widely used for degradation monitoring (Hameed, Hong, Cho, Ahn, & Song, 2009; Loboda, Yepifanov, & Feldshteyn, 2007). As with the additive case, Eq. (5) allows V_D to be estimated on the basis of a model for d, or conversely Eq. (6) allows estimation of d from measurements V_D if they are available.

Additive and multiplicative models can be also used together:

$$V_D = h_1(d)V + h_2(d) \tag{7}$$

with $h_1(d)$ representing a multiplicative degradation function, and $h_2(d)$ representing additive degradation function.

4.1.3. Uses of additive and multiplicative models

Additive and multiplicative models of degradation are used in fault-tolerant control systems that can accommodate failures in a component. In particular, they are used to describe the behaviour of a degraded actuator (Isermann, 2006; Noura, Theilliol, Ponsart, & Chamseddine, 2009). In that case, variable V is typically a characteristic quantity of a system, for instance, the flow through a valve calculated from valve position. Polycarpou and Helmicki (1995) indicated also that $h(d)$ might have various functional forms, such as polynomial or rational.

4.2. Input and output models of degradation

Gertsbakh and Kordonskiy (1969), Isermann (2006), Nikulin, Limnios, Balakrishnan, Kahle, & Huber-Carol (2010), and Patton, Frank, and Clark (2013) indicated that the effects of degradation can cause changes in the output of a system. At the same time, a control system usually comprises multiple subsystems which interact with each other. Typically, the output of the actuator is considered input to a system. From the perspective of the system, degradation of an actuator is perceived as

Table 4
Interpretation of additive and multiplicative faults on behaviour of an actuator (Noura et al., 2009)

	No additive faults	Additive faults
No multiplicative faults $h(d) = 1$	Healthy actuator	Bias
Multiplicative faults $h(d) \in (0, 1)$	Partial loss of effectiveness	
Multiplicative faults $h(d) = 0$	Failure	Blockage

Table 5
Applications of factor-free models of output degradation

Model of degradation	Application
Fixed value model	Gas turbine (Kurz & Brun, 2001; Meher-Homji, Chaker, & Motiwalla, 2001; Tsoutsanis, Meskin, Benammar, & Khorasani, 2015; Goebel, Subbu, & Frederick), compressor fouling (Aker & Saravanamuttoo, 1989), (Milosavljevic et al., 2016), pneumatic actuator (Beganovic & Söffker, 2017; Graves, Turcio, & Yoneyama, 2018)
Time-dependent - deterministic	Compressor fouling (Cicciotti, 2015; Tarabrin et al., 1996), CSTR (Lao et al., 2013), micro gas turbine (Zaccaria, Ferrari, & Kyprianidis, 2019)
Time-dependent - stochastic	Gas turbine (Li & Nilkitsaranont, 2009), control valve (McGhee, Galloway, Catterson, Brown, & Harrison, 2014)

degradation affecting the input of a system. Noura et al. (2009), Chen and Patton (1999) and Blanke, Kinnaert, Lunze, and Staroswiecki (2015) also indicated that degradation in a control system can be classified according to which element is affected by degradation. A classification of models of degradation using the inputs and outputs of a control aims to facilitate the integration of degradation modelling in control applications.

Figure 2 presents a block diagram representing a control system. The dashed blue box shows the parts of the system that would be described by a model of output degradation. The dotted green box represents a situation with input degradation.

Degradation that influences the outputs of the degradation-dependent model of behaviour will be considered separately from degradation influencing the inputs.

4.2.1. Output degradation

Degradation may be modelled as a change in the output such that the output in degraded state y_D is a function of degradation:

$$\dot{x}(t) = f(t, x(t), u(t)) \tag{8a}$$

$$y_D(t) = g(x(t), u(t), h(d)) \tag{8b}$$

In the static case when $\dot{x} = 0$, the output Y is an algebraic function of the inputs U, where U and Y are static values of the input and output variables.

Models of output degradation are useful for subsystems that describe actuators. For instance, they can model compressor fouling that affects compressor efficiency or heat exchanger fouling that affects the heat transfer coefficient.

4.2.2. Input degradation

Degradation may alternatively be modelled as a change in the input. For multiplicative degradation the degraded input is $u_D = h(d)u(t)$, where $u(t)$ is the input in up state without significant degradation. Hence:

$$\dot{x}_D(t) = f(t, x_D(t), h(d)u(t)) \tag{9a}$$

$$y_D(t) = g(x_D(t), h(d)u(t)) \tag{9b}$$

where x_D and y_D are the degraded state and input variables.

As an example, an input degradation approach is useful when considering the effect of a degraded actuator in a control loop. Noura et al. (2009) provided an interpretation of additive and multiplicative faults of an actuator, assuming $u_D = h(d)u$ (Table 4).

Table 6
Applications of factor-free models of input degradation

Model of degradation	Application examples
Fixed value model - two cases: up state or fully degraded	A fourth order dynamic system (Veillette, 1995), aircraft (Maki et al., 2004; Zhao & Jiang, 1998)
Fixed value model - several cases	A second order system (González-Contreras, Theilliol, & Sauter, 2007), three tank system (Theilliol et al., 2008; Theilliol et al., 2002), space vehicle (Gao et al., 2011), aircraft (Chamseddine, Theilliol, Zhang, Join, & Rabbath, 2015; Chen, Liu, & Fu, 2016; Jiang & Zhang, 2006; Li, Shi, & Yao, 2017; Shi, Wang, Wang, Wang, & Tomovic, 2017; Yang, Zhang, Jiang, & Liu, 2014; Ye & Yang, 2006; Yu, Fu, & Zhang, 2018; Y. Zhang, Jiang, & Theilliol, 2008; Y.M. Zhang & Jiang, 2001), a third order system (Chen, Niu, & Zou, 2013; Liu, Niu, Zou, & Karimi, 2015; Wang & Yao, 2010), heat exchanger (Ballé et al., 1998), TE benchmark (Yin et al., 2014), pulp mill (Zumoffen & Basualdo, 2008), CSTR (Mhaskar et al., 2006; Prakash et al., 2005), (Mhaskar, Liu, & Christofides, 2012), hydrothermal process (Boussaid et al., 2011), a wheeled robot (Ji et al., 2003)
Time-dependent model - fixed time and value	A third order system (Tao, Joshi, & Ma, 2001), aircraft (Wu, Zhang, & Zhou, 2000), tank level control (Li et al., 2019; Zhang & Qin, 2009), hydrogen production (Du, Mhaskar, Zhu, & Flores-Cerrillo, 2014), Shell control problem (Kettunen, Zhang, & Jämsä-Jounela, 2008)
Time-dependent model - fixed time	A third order system (Tao, Joshi, & Ma, 2001), ball-beam system (Zhang et al., 2010), valve leakages (Arıcı & Kara, 2018), electrical systems (Kaviarasan et al., 2016), aircraft (Jiang & Chowdhury, 2005; Liu & Crespo, 2012), CSTR (Wang et al., 2007; Yu et al., 2005), burner (Baldi et al., 2017), planetary lander (Boskovic, Jackson, Mehra, & Nguyen, 2009), robotic arm (Jiang et al., 2006)
Time-dependent - stochastic time	Aircraft (Tian, Yue, & Peng, 2010; Zhang & Jiang, 1999), second oder system (Gu et al., 2012), DC motor (Langeron, Grall, Barros, 2013), control valve (Mo & Xie, 2016)
Stochastic - Markov process	A first order system (Mahmoud et al., 2002), inverted pendulum (Wei et al., 2017), vehicle suspension system (Shen et al., 2014), landing vehicle (Huang et al., 2014)

Table 7
Applications of factor-based models of input degradation

Model of degradation	Factors	Application
Performance loss - heuristic	Control effort $u(k)$	Second order system (Vieira et al., 2015)
Performance loss - Wiener process	Changes of control effort $u(k)$ - discrete	Tank level control (Nguyen, Dieulle, & Grall, 2014a, 2014b, 2014c, 2015)
Performance loss - gamma process	Changes of control effort $u(k)$ - continuous	DC motor (Langeron, Grall, Barros, 2013), maintenance (Langeron et al., 2016), drilling unit (Langeron et al., 2015; 2017)
Performance loss - physical	Discharge current, state-of-charge (SOC), and operating temperature	Battery charging (Allam, Onori, Marelli, & Taborelli, 2015; Zou, Hu, Wei, Wik, & Egardt, 2018)

4.2.3. Uses of models of input and output degradation

The input to the controlled system is the output of an actuator such as a valve, compressor or heat exchanger. Hence $u_D = Y_D$. The degraded output of the actuator, Y_D, is typically modelled by a polynomial function of the input U with parameters k_i:

$$Y_D = h_1(d) \sum_{i=0}^{n} k_i \nu_i(U) + h_2(d) \tag{10}$$

where h_1 is a multiplicative degradation function, and h_2 is an additive degradation function (Isermann, 2006). The behaviour of the actuator is usually described with the algebraic Eq. (8b) because the dynamics of the states x of the actuator are usually much faster than the dynamics of the states of the controlled system (Aldhaheri & Khalil, 1996).

5. Models with degradation in control systems

This section of the paper discusses the approaches to degradation modelling from Table 3 and highlights prior work in each area that is related to their application in control systems. Figure 3 expands the classification indicated in Table 3 in the form of a hierarchical tree. The first level of the tree captures the four categories from Table 3. Subsequent layers present internal classifications within each category.

5.1. Degradation-dependent models of behaviour with factor-free models of degradation

As discussed by Chen and Patton (1999), factor-free models of degradation do not attempt to describe the mechanism of degradation. Rather, they assume the degradation is fixed, time-dependent or stochastic. Factor-free models of degradation have been combined with degradation-dependent models of behaviour to understand the behaviour of a control system in the presence of degradation of components within it. The approaches can be classified as models of output degradation and models of input degradation, as defined in Section 4.2.

5.1.1. Factor-free output degradation

Degradation-dependent models of behaviour with factor-free models of output degradation describe how the outputs or characteristic quantities of a system or sub-system change with degradation (i.e. y in Eq. (2a) or Eq. (4)). These models are primarily used in complex processes where the output of a degradation-dependent system constitutes an input to another system. Table 5 presents selected applications of such models.

5.1.1.1. Fixed values of output degradation. Models with fixed values of degradation treat the degradation function $h(d)$ as constant with n possible values, i.e. $h(d) \in \{h_1, h_2, \cdots, h_n\}$ Using models of output degradation with n fixed values effectively yields n outputs y_i, $i = 1, \ldots, n$, corresponding to separate values of h_i. Each output can be considered separately, as the transitions from h_i to h_j, $i, j = 1 \ldots, n$, $i \neq j$ are not defined. Examples can be found in works by Tsoutsanis, Meskin, Benammar, and Khorasani (2015), Meher-Homji, Chaker, and Motiwalla (2001), Aker and Saravanamuttoo (1989), and Kurz and Brun (2001) in which the performance of gas turbines was calculated for several values of fouling-induced degradation. They detected fouling from the behaviour by analysing changes of compressor characteristics when the degradation was constant. Furthermore, Kurz and Brun (2001) used the results to demonstrate the impact of an optimal cleaning schedule on the overall performance.

Behaviour and degradation cannot be analysed independently in a system described by a degradation-dependent model of behaviour. The controlled system has a different behaviour in the degraded state than in up state. As such, the control algorithm or the optimisation function must be adapted. Such an integrated analysis was done by Milosavljevic et al. (2016), who incorporated a factor-free model of degradation of a static compressor map with a degradation-dependent model of behaviour of a compressor to simulate optimal load-sharing among three compressors.

5.1.1.2. Time dependent and stochastic models of output degradation. Time-dependent models of degradation $h(d)$ take into account transitional behaviour as degradation moves between several values. Time-dependent models of $h(d)$ were used by Tarabrin, Schurovsky, Bodrov, and Stalder (1996) and Cicciotti (2015) for analysis of compressor efficiency and pressure ratio in degraded state. The degradation $h(d)$ was modelled as an exponential function of time with constant parameters. In particular, the time-dependent approach to modelling of fouling has been applied by Escher (1995), who modelled $h(d)$ as a nonlinear time trend to capture turbomachinery degradation. Li and Nilkitsaranont (2009), Loboda et al. (2007), and Loboda, Yepifanov, and Feldshteyn (2009) modelled degradation in turbomachinery using time trends. Lao, Ellis, and Christofides (2013) used a logistic function to approximate a degraded behaviour of a heater in continuous stirred tank reactors (CSTRs).

The $h(d)$ term may also be modelled as stochastic, with degradation moving between random values at random times. McGhee et al. (2014) modelled degradation of a valve using a stochastic model to capture sticking valve behaviour:

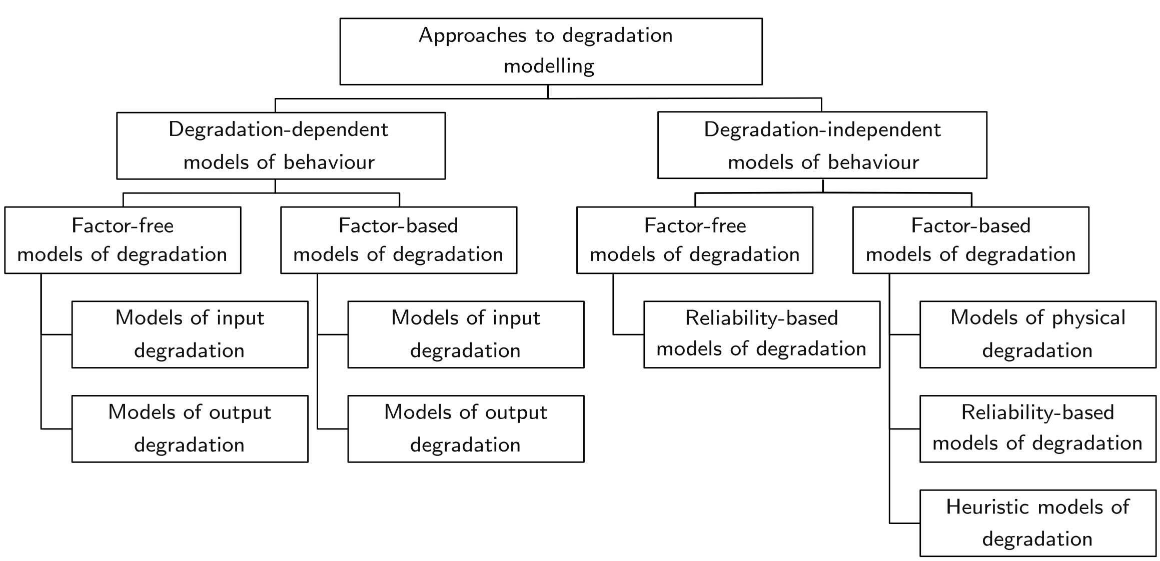

Fig. 3. A hierarchical tree with classification of models of degradation relative to the control systems

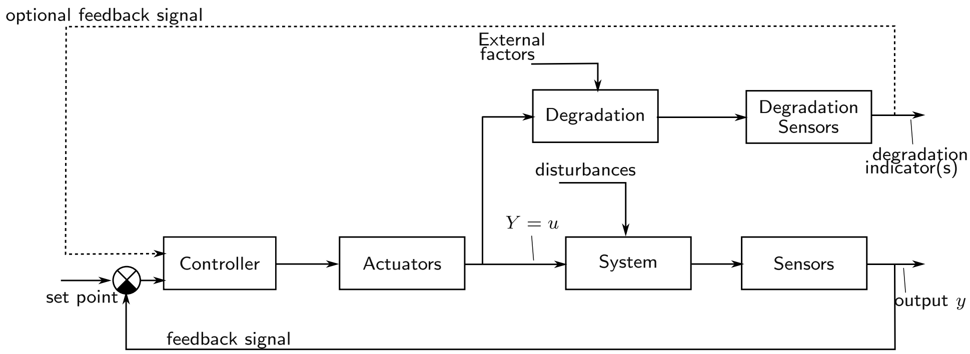

Fig. 4. Feedback control loop with a degradation-independent system

$$y_D(t+1) = y(0) - \delta y(t) \tag{11}$$

where y_D denotes a decreasing area of the pipe inside the valve in relation to the initial area $y(0)$ and the random variable δ comes from a uniform distribution.

Time-dependent and stochastic output degradation implies that the output changes during the operation of the system. Therefore the control algorithm has to handle the transitions. Recent reviews of stochastic models that can be used for degradation modelling were presented by Si et al. (2011) and Zhang et al. (2015).

5.1.2. Factor-free input degradation. Degradation-dependent models of behaviour with factor-free models of input degradation assume that the degradation may be detected from the behaviour of a system. The system can be typically identified as being in up state, degraded state, or fault state. Table 6 presents selected applications of factor-free models of input degradation.

Input degradation means that the inputs to a system change due to degradation. In models of behaviour of form Eq. (1), input degradation may be detected from the value of u which becomes u_D. Typically, u_D captures the multiplicative nature of input degradation, where $u_D = h(d)u$. In particular, the input degradation represents how an output of a degraded actuator enters the system after leaving the dashed blue box in Fig. 2.

5.1.2.1. Fixed values of input degradation. As mentioned in Section 5.1.1.1, in the simplest models, the degradation function $h(d)$ takes fixed values, $h(d) \in \{h_1, h_2, \ldots, h_n\}$. In consequence, there are n different input cases $u_D \in \{u_1, u_2, \ldots, u_n\}$ where typically $u_i = h_i u$. Fan, Liu, and Kwong (2017) observed that fixed values of $h(d)$ could emulate degradation processes which result in stuck actuators. Veillette (1995), Maki, Jiang, and Hagino (2004), and Zhao and Jiang (1998) considered an input to a system from an actuator that was either:

- In up state with $h(d) = 1$, and thus $u_D = u$,
- Failed with $h(d) = 0$ and $u_D = 0$.

González-Contreras, Theilliol, and Sauter (2007) assumed that the performance of a degraded actuator changed from 100% to 90%, from $h(d) = 1$ to $h(d) = 0.9$. Ballé, Fischer, Füssel, Nelles, and Isermann (1998), Theilliol, Noura, and Ponsart (2002), Gao, Jiang, Qi, and Xu (2011), Chamseddine, Theilliol, Zhang, Join, and Rabbath (2015), Graves, Turcio, and Yoneyama (2018), Chen, Liu, and Fu (2016), Li, Shi, and Yao (2017), and Theilliol, Join, and Zhang (2008) have modelled several values of degradation function, between 100% and 0% of performance. Liu, Niu, Zou, and Karimi (2015) used a fixed value model of degradation to design a controller for a third-order dynamic system with uncertain parameters. In all cases, degradation-dependent models of behaviour with $u_D = h(d)u$ were considered.

Wang and Yao (2010) considered multi-actuator systems. Some actuators could only be in up state $h(d) = 1$ or faulty with $h(d) = 0$, whereas other actuators could operate with partial performance $0 < h(d) < 1$. Similarly, Ji, Zhang, Biswas, and Sarkar (2003) designed a controller for a wheeled robot with several degraded actuators. Yin, Luo, and Ding (2014) showed that fixed values of input degradation extend to a more general class of inputs than stuck actuators by considering two levels of feed ratio as degradation of the Tennessee Eastman benchmark process.

In linear models of the form of Eq. (2), modifying the input u is equivalent to modifying the matrix $\mathbf{B}$ (Mahmoud, Jiang, & Zhang, 2002). Zhang and Jiang (2001), Jiang and Zhang (2006), Zhang, Jiang, and Theilliol (2008), and Shi, Wang, Wang, Wang, and Tomovic (2017) defined values for the matrices $\mathbf{B}$ of the linear system (2a) in degraded states. Additive models of degradation with fixed matrices from Eq. (2a) were used by Prakash, Narasimhan, and Patwardhan (2005).

A degradation-dependent model of behaviour is required when the presence of degradation can be detected from the behaviour of the system. In some cases, degradation may be detectable and also quantifiable. Yang, Zhang, Jiang, and Liu (2014) and Ye and Yang (2006) have used an adaptive identification procedure to estimate the value of $h(d)$ in aircraft applications. Boussaid, Aubrun, Abdelkrim, and Ben Gayed (2011) and Yu, Fu, and Zhang (2018) also assumed constant values of degradation, and estimated the values using online observers.

Similarly to the models of output degradation described in Section 5.1.1, if input degradation is modelled with fixed values h_i, it is possible to analyse the inputs separately for each i.

5.1.2.2. Time-dependent models of input degradation. Tao, Joshi, and Ma (2001) proposed a model of an actuator subsystem that degrades after a predefined time t_0. The degradation function $h(d)$ is therefore piecewise constant

$$h(d(t)) = \begin{cases} h_0, & t < t_0 \\ h_1, & t \geq t_0 \end{cases} \tag{12}$$

In consequence, if multiplicative degradation is considered

$$u_D = \begin{cases} h_0 u, & t < t_0 \\ h_1 u, & t \geq t_0 \end{cases} \tag{13}$$

Time-dependent models of form Eqs. (12) are an extension of the models described in Section 5.1.2.1. If degradation of an actuator can be described with such a model of degradation, then the system must be able to handle a stepwise change in the input signal u_D. Wu, Zhang, and Zhou (2000) used such an approach to model the degraded control surfaces of an aircraft system, whereas Zhang and Qin (2009) and Li, Ding, Luo, Peng, and Yang (2019) approximated degradation of pumps in a three tank system using this approach.

Other approaches proposed by Tao et al. (2001) modelled the degradation of the actuator as additive changes of the actuator output u:

$$u_D(t) = u(t) - h(d(t)) \tag{14a}$$

$$h(d(t)) = \tilde{u} + \tilde{d}(t) + \tilde{\delta}(t) \tag{14b}$$

where $\tilde{u}$ is an unknown constant, and $\tilde{\delta}(t)$ is bounded, but unknown. Furthermore, $\tilde{d}(t) = \sum_j \tilde{d}_j f_j(t)$, where $\tilde{d}_j$ are constant parameters and $f_j(t)$ are predefined functions. For instance, if $u(t)$ is the flow through a valve as in Arıcı and Kara (2018), then Eq. (14) provides a model such that the degraded flow rate u_D can vary according to $\tilde{d}(t)$, and can also be influenced by an unknown but bounded function $\tilde{\delta}(t)$. Additive time-dependent models of form Eq. (14) also represent continuous degradation that would influence the behaviour regardless of the input u.

The model (14) is not application specific. Such models were used for degradation of hydraulic actuators (Tao et al., 2001; Zhang, Xu, Guo, & Chu, 2010), continuous stirred tank reactor (CSTR) degradation (Wang, Zhou, & Gao, 2007), valve leakages (Arıcı & Kara, 2018), electrical systems degradation (Kaviarasan, Sakthivel, & Kwon, 2016), degraded aircraft system (Jiang & Chowdhury, 2005; Liu & Crespo, 2012), and burner degradation (Baldi, Le Quang, Holub, & Endel, 2017). Yu, Chang, and Yu (2005) simulated two kinds of degradation in a CSTR system: a fixed value model of degradation of a pump, and a time-dependent model of degradation representing a loss of inlet temperature. In all cases the degradation influenced the input signal $u_D = h(d)u$. Jiang, Staroswiecki, and Cocquempot (2006) used additive models of degradation for design of a control system for a robotic arm.

5.1.2.3 Stochastic models of input degradation Stochastic models assume that the value of the degradation function $h(d)$ changes only at certain time instants and is constant in between. The timings of the changes are not known in advance. Such an approach was applied by Zhang and Jiang (1999) and Tian, Yue, and Peng (2010) who assumed the constant value between the instants of change was:

$$h(d) = 1 - \theta \tag{15}$$

where θ had a normal distribution with positive mean and fixed variance. Gu, Liu, Peng, and Tian (2012) proposed a model that merged the random loss of performance of an actuator with its saturation, effectively combining the simple approach based on constant values with stochastic estimation and a nonlinear degradation function. A stochastic approach was also used by Mahmoud et al. (2002), Wei, Qiu, and Karimi (2017), and Shen, Park, and Wu (2014) who defined degradation as a Markov process such that the degradation at time t depended on the value at $t-1$. A Markovian model of degradation was also used by Huang, Shi, and Zhang (2014) who included time-dependency in the stochastic model, i.e. the random changes of $h(d)$ depended on time, as well as on the previous value of $h(d)$. Mo and Xie (2016) modelled degradation d as a stochastic loss of effectiveness of a control valve and included it in the dynamic behaviour using $u_D = (1-d)u$.

Stochastic models of degradation introduce both the transitional elements of time-dependent models of degradation and the uncertainty. Therefore, despite their relative simplicity, if the degradation is described by such a model, the controller must take the stochastic nature of degradation into account (Gu et al., 2012).

5.2. Degradation-dependent models of behaviour with factor-based models of degradation

Factor-based models of degradation of the form $h(d) = h(d(t, v(t), x(t), u(t), y(t)))$ take into account that control actions may have a direct impact on the degradation of the system (Singpurwalla & Wilson, 1998). Degradation-dependent models of behaviour with factor-based models of degradation consider further that such degradation is detectable from the behaviour of the system as shown in the Eq. (1) for $\dot{x}_D(t)$ and $y_D(t)$, and hence that the behaviour is itself influenced by use and operation.

5.2.1. Factor-based models of output degradation

Factor-based models of output degradation are often analysed using a physics-of-failure approach (Modarres, Amiri, & Jackson, 2017) and are case-specific. The main focus is on the degradation processes, such as:

- Erosion (Li, Wang, Tomovic, & Zhang, 2018),
- Wear (Cao & Dai, 2015),
- Corrosion and pitting (Chookah, Nuhi, & Modarres, 2011),
- Fouling (Brahim, Augustin, & Bohnet, 2003).

Suri and Onori (2016) described battery ageing with a physical model relating influencing factors such as state-of-charge, battery temperature, and power level to degradation. They analysed the influence of degradation of the battery in a vehicle simulation. Ahmad, Kano, Hasebe, Kitada, and Murata (2014) described degradation of a ladle in a steel making process as a function of repeated usage. They used the model of degradation for feedforward control of temperature during the process.

5.2.2. Factor-based models of input degradation

In the simplest case of a factor-based model of input degradation, the degradation function $h(d)$ depends directly on an input, u:

$$h(d) = h(d(u)) \tag{16}$$

For instance u might be the control effort. Such a model was proposed by Vieira, Galvão, and Yoneyama (2015) who described the degradation function as a first order discrete-time dynamic relationship

$$h(d(k+1)) = h(d(k)) + \alpha|u(k)| \tag{17}$$

in which $\alpha > 0$. They observed that the relationship assumes the degradation will remain constant if there is no change in $u(t)$. This is not the always the case, however. As an example, Meher-Homji, Chaker, and Motiwalla (2001) demonstrated that the degradation processes in turbomachinery would continue even after shut down of the piece of equipment.

5.2.2.1 Control effort as an influencing factor Vieira et al. (2015) included the degradation function with influencing factors in the model of behaviour of the form of Eqs. (2). They proposed to switch between the matrices of a model of a system with an actuator in up state and in degraded state:

$$\mathbf{B}(h(d)) = \begin{cases} \mathbf{B}^{\mathrm{nom}} & \text{if } h(d) < h^{\mathrm{lim}} \\ h(d)\mathbf{B}^{\mathrm{nom}} & \text{if } h(d) \geq h^{\mathrm{lim}} \end{cases} \tag{18}$$

where $\mathbf{B}^{\mathrm{nom}}$ is the nominal value in up state, $h(d)$ is the solution of Eq. (17), and h^{lim} is a predefined limit.

A similar approach to designing control systems taking account of degradation was considered by Langeron, Grall, Barros, 2013 who used stochastic processes to model the degradation function $h(d)$ and relate it with the behaviour of a system. They divided the behaviour into three phases, depending on the value of degradation d as in Fig. 1, i.e. $d \leq d_0$, $d \in (d_0, d_1)$, and $d \geq d_1$. Langeron, Fouladirad, and Grall (2016); Langeron, Grall, and Barros (2015, 2017) used shock models to find the values of the degradation function $h(d)$ related to degradation of a pump, and devised a predictive controller that took degradation into account. The shocks were defined as changes of the input u, i.e. the control action was considered a factor influencing degradation.

Both Vieira et al. (2015) and Langeron et al. (2016) used optimisation-based control to compensate for degradation. Therefore the feedback control problem became an optimisation problem with the degradation function included in the objective function (Langeron et al., 2016; Langeron et al., 2015; 2017) or in the constraints (Vieira et al., 2015).

5.2.2.2 External influencing factors

Singpurwalla and Wilson (1998) considered both usage and external factors as influencing factors in a model of input degradation. Using this approach, Nguyen (2015) modelled $h(d)$ as

$$h(d) = h_0 - W^{\mathrm{nd}} - W^{\mathrm{om}} \tag{19}$$

where W^{nd} and W^{om} denote a loss of effectiveness due to natural degradation and operating condition, called operating mode, respectively. W^{nd} and W^{om} are modelled as shock deterioration models

$$W^{\mathrm{nd}}(t) = \sum_{j=0}^{N(t)} \Delta W_j^{\mathrm{nd}} \tag{20}$$

and

$$W^{\mathrm{om}}(t) = \sum_{j=0}^{M(t)} \Delta W_j^{\mathrm{om}} \tag{21}$$

where $N(t)$ is the number of shocks due to external factors and $M(t)$ refers to the number of changes of the control action that happened during a certain time period t. The values ΔW_j^{nd} and ΔW_j^{on} denote the change in degradation after the j-th shock (change) and "are independently and identically distributed" (Nguyen, Dieulle, & Grall, 2015). Nguyen, Dieulle, and Grall (2014a, 2014b, 2014c) applied the model from Eq. (19) to a tank system to describe degraded performance of a pump subject to random shocks. Every time a shock occurred, i.e. with every change of $h(d)$ according to Eq. (19), the performance of an actuator decreased by a quantity $w(t)$ following a uniform distribution on a fixed interval $[0, \delta]$. Nguyen et al. (2015) modelled the performance of an actuator as changes of the matrix $\mathbf{B}$ from Eq. (2a):

$$\mathbf{B}(t) = \mathbf{B}^{\mathrm{nom}} - w(t) \tag{22}$$

Thus

$$u_D = (\mathbf{B}^{\mathrm{nom}} - w)u \tag{23}$$

In contrast to Langeron et al. (2016); Langeron et al. (2015, 2017) and Vieira et al. (2015), Nguyen, Dieulle, and Grall (2014a, 2014b, 2014c) analysed the influence of degradation of a pump on a system with a PID controller, without explicitly including the degradation function in the controller design.

Table 7 presents selected applications with factor-based input degradation. An overview of models of degradation that can be used to approximate the degradation function depending on the influencing factors was provided by Singpurwalla (1995) and Bagdonavičius and Nikulin (2001). A more recent review of such approaches was done by van Noortwijk (2009) and Bagdonavičius and Nikulin (2009).

5.3. Degradation-independent models of behaviour with factor-free models of degradation

Models of degradation that are independent from influencing factors and where degradation is not detectable in the behaviour have been of little use for control purposes. However, they are widely used in reliability engineering for prognostics and maintenance planning (Mann, Singpurwalla, & Schafer, 1974; Rausand & Høyland, 2004). ***Reliability*** is defined as an "ability of an item to perform a required function under given conditions for a given time interval" (BSI, 2010). It is described with a reliability function that captures the probability that the item will not fail in the time interval $[0, \ t]$ (Mann, Singpurwalla, & Schafer, 1974). The moment when an item fails at t_2 shows when degradation has reached a failure threshold in Fig. 1. Therefore the reliability function $R(t)$ measures the probability that the degradation will not reach a failure threshold in the given interval $[0, \ t]$. As such, it provides another way of describing the degradation function $h(d)$, i.e. $h(d) = R(t)$. Alternatively, a failure (hazard) rate is used instead of $R(t)$

$$z(t) = -\dot{R}(t) \tag{24}$$

which represents the probability that the item will fail in the interval $[t, \ t + \Delta t]$ if it has survived until the time t (Mann, Singpurwalla, & Schafer, 1974).

Factor-free reliability-based models of degradation can be found in industrial databases, such as 'OREDA Offshore & Onshore Reliability Data' (SINTEF, 2002) for oil and gas applications, and 'Military Handbook: Reliability Prediction of Electronic Equipment: MIL-HDBK-217F' (United States of America: Department of Defense, 1986) for electronics. As an example, Kopnov (1999) modelled crack growth as a set of fixed values, stochastically changing at random times. The probability of transitions was predefined (hence factor-free) and the cost of failure due to crack growth was included in the cost of operation. The behaviour of the system was not affected, because typically the effects of a crack are not observable in the behaviour until a component breaks.

Figure 4 shows an interpretation of a controller with a degradation-independent system. Degradation is assumed to be measured separately from the output y, and the input u does not depend on the degradation. The optional feedback loop sends the information about the degradation back to the controller. The controller adapts its output taking into account both the error between the setpoint and the feedback signal, and the current degradation. The adaptation might consist of changing the parameters of the controller as in a gain-scheduling controller, or might require a recalculation of the control output if model predictive control is used. The degradation and the system in Fig. 4 are considered separately from the controller point of view.

5.4. Degradation-independent models of behaviour with factor-based models of degradation

A factor-based model of degradation is useful when degradation is not detectable from the behaviour of the system. Degradation-independent models of behaviour with factor-based models of degradation can be divided into three groups:

- Physical models of degradation that is measurable before its influence is visible in the behaviour of the system. This could for example be during the early stages of Fig. 1 where $t < t_0$,
- Reliability-based models of degradation that are focused on the end of the degradation period i.e. when the system has failed ($t > t_1$ in Fig. 1),
- Heuristic models of degradation that are based on knowledge and assumptions about the degradation and the system, applicable for $t > 0$.

5.4.1. Factor-based physical models of degradation

Factor-based physical models are used to describe degradation that either is not advanced enough to be detectable in the behaviour of the system, or else actually does not change the behaviour. The degradation may be measurable or diagnosable in itself, perhaps with specialist equipment. An example would be development of a crack in a turbine blade that does not change the behaviour of the turbine until the blade fails.

According to Modarres et al. (2017) a physics-of-failure approach uses knowledge of physical and chemical properties of materials, load profile, environmental conditions, failure mechanisms and accelerated test data to build models of degradation and time to failure. The physical nature of the models indicates that the models of degradation will be case-specific.

Some physical phenomena are common enough to justify the use of a set of predefined models. Xu et al. (2016) presented an overview of general degradation path models, which are application independent. Application-specific models were described by Martin, Strutt, and Kinkead (1983), who focused on mechanical degradation, whereas Collins, Potirniche, and Daniewicz (2015) presented material-specific models of metal degradation, with the underlying influencing factors explained by Fisher (2015). Comprehensive reviews of the physical models of degradation with influencing factors were given by Escobar and Meeker

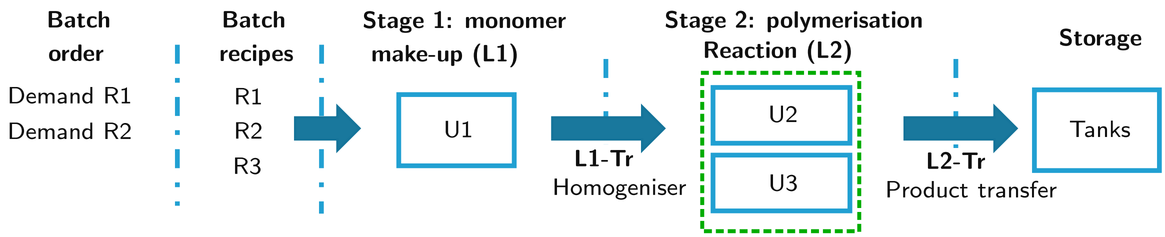

Fig. 5. The topology of the multi-product batch process (adapted from Wu et al. (2019)). The dashed green box indicates the two reactors used in this work

(2006), Nelson (2009), and recently by Pang, Si, Hu, Zhang, and Pei (2020). A brief summary is presented in Table 8. The models given in Table 8 show how the degradation d depends on the influencing factors. The value of d represents the degradation itself, whereas $h(d)$ is used if degradation d is not measurable.

The degradation d in the physical relationships from Table 8 assumes the influencing factors are constant. The evolution of the influencing factors over time is also of importance and should be taken into account. For that purpose, cumulative damage indicators (or exposure functions) are considered (Xu et al., 2016) and the degradation function has the form:

$$h(d(t)) = f(D(v(t), \beta), b) + \varepsilon \tag{25}$$

where $v(t)$ are influencing factors, β, b are constant parameters of the model, and ε represents measurement noise. The function $D(v(t), \beta)$ denotes the cumulative degradation up to time t (Nelson, 2009), sometimes called the *additive accumulation of damages* (Bagdonavičius & Nikulin, 2001), i.e.

$$D(v(t), \beta) = \int_0^t d(v(\tau), \beta) \mathrm{d}\tau \tag{26}$$

Palmgren-Miner's rule is an example of such an indicator, used for metal fatigue modelling and applied by Ray, Wu, Carpino, and Lorenzo (1994b). Palmgren-Miner's rule assumes that $D(v(t), \beta)$ is a linear function of influencing factors (Nelson, 2009). Table 9 summarises the physical models used for control purposes.

A variant of model predictive control can be used with the objective function including the degradation function. Ray, Dai, Wu, Carpino, and Lorenzo (1994); Ray, Wu, Carpino, and Lorenzo (1994a); Ray, Wu, Carpino, and Lorenzo (1994b) introduced the term *damage mitigating control* to emphasise that a degradation function is explicitly included in the objective function. This concept will be further described in Section 6.2.2. Another example is control of pasteurisation temperature (Pour, Puig, & Ocampo-Martinez, 2017, 2018). By including the degradation of the pump in the objective function, Pour, Puig, & Ocampo-Martinez (2017, 2018) were able to mitigate the degradation, at the same time satisfying constraints on energy consumption.

5.4.2. *Factor-based reliability-oriented models of degradation*

The two main approaches to factor-based models of degradation based on reliability analysis are:

- Parametric models, where the reliability function is often based on one of the physical relationships gathered in Table 8,
- Non-parametric models (or semi-parametric), usually in form of proportional hazard models.

Reliability-oriented models of degradation have not been widely used in control frameworks. Escobet, Quevedo, Puig, and Nejjari (2002) suggested a generic approach to control taking degradation into account called *health-aware control* that will be described in more detail in Section 6.2.2. Since then, several authors have used proportional hazard models in control applications, as listed in Table 10. In most cases, the control effort $u(t)$ was considered to be a factor influencing degradation. This approach was analysed in aircraft applications to allocate the control effort among several actuators with varying reliability functions (Khelassi, Theilliol, & Weber, 2010; Theilliol, Weber, Chamseddine, & Zhang, 2015; Weber, Boussaid, Khelassi, Theilliol, & Aubrun, 2012). Similarly, Guenab, Weber, Theilliol, and Zhang (2011) applied reliability-based control to a heating system with degrading pumps. Salazar, Weber, Nejjari, Sarrate, and Theilliol (2017) and Pour, Puig,

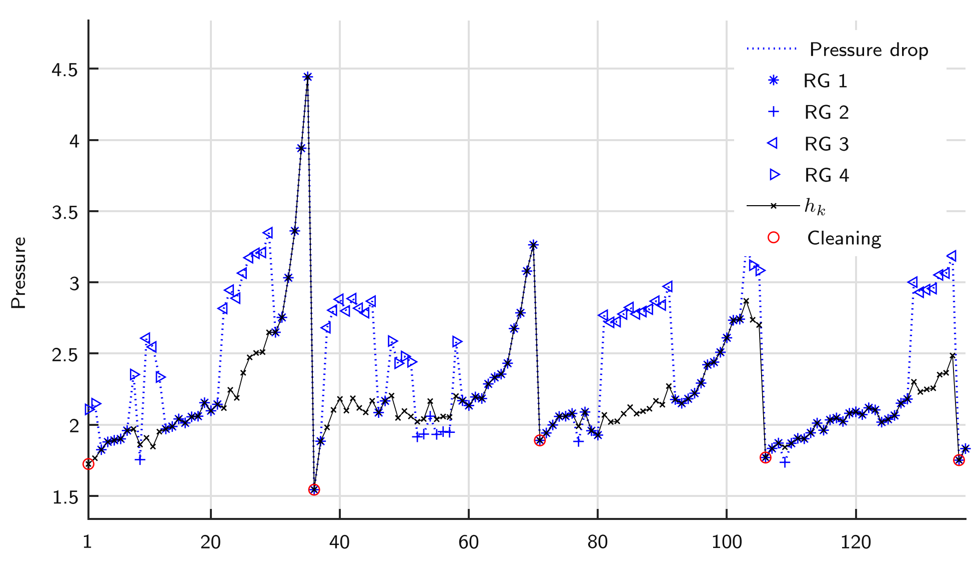

Fig. 6. Batch-to-batch evolution of fouling-related measurement. RG stands for recipe group consisting of several recipes which have similar physical properties

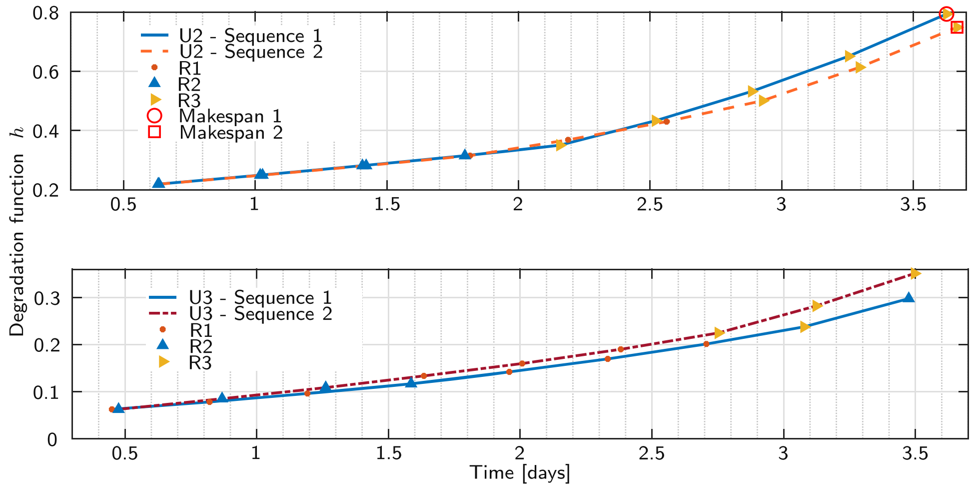

Fig. 7. Fouling evolution for two sequences of recipes (R1, R2, R3): reactor U2 (top) and reactor U3 (bottom)

and Cembrano (2019) controlled a drinking water network based on the reliability of the pumps to improve the reliability of the whole system.

Table 10 summarises the applications of reliability-oriented models of degradation for control purposes. All entries in this table used a degradation-independent model of behaviour, as the reliability does not influence the behaviour of a system. The controllers are designed as model predictive control or adaptive optimal control (Chamseddine, Theilliol, Sadeghzadeh, Zhang, & Weber, 2014).

5.4.3. Factor-based heuristic models

Physical and reliability-based models of degradation are not always available. As indicated by Meeker and Escobar (1998), the unavailability of a model of degradation might be due to lack of information about the degradation itself. However, available knowledge about the process and the influencing factors can be applied to build heuristic models of degradation. Even though the heuristic models do not have any physical interpretation, they provide a knowledge-based description of degradation. Therefore the models are application-specific.

Heuristic approaches can be used for control purposes. Thus, optimisation-oriented approaches are of use as they combine objective functions and constraints related to the behaviour and the degradation. For instance, Verheyleweghen, Gjøby, and Jäschke (2018) presented a hierarchical framework for model-based control of a subsea compressor station including degradation as a constraint and ensuring stable operation of the station. Pereira, Harrop Galvao, and Yoneyama (2010) designed a predictive controller that took into account limits on the degradation of pumps. Table 11 presents further control applications of heuristic models of degradation that do not have any underlying physical or reliability-oriented interpretation.

5.5. Summarising comment

The models of degradation presented in Section 5 are summarised in Table 12. The structure of the table reflects the hierarchical tree of the new classification, introduced in Fig. 3 in Section 3. Table 12 presents the differences between various combinations of the models of behaviour and the models of degradation in terms of their advantages and disadvantages. For instance, it is indicated in the table that factor-free models of degradation are usually easy to use, at the expense of the limited information that they provide about degradation. Conversely, factor-based models, whilst complex, provide more information about degradation.

Similarly, degradation-dependent models of behaviour enable analysis of the system subject to degradation. Nevertheless, the control algorithms must take into account that models of degradation can affect the functional form of degradation-dependent models. For instance, a factor-based model of degradation can introduce nonlinearity to a linear degradation-dependent system.

Table 8
Factor-based models of degradation as presented by Nelson (2009) and Escobar and Meeker (2006)

Name	Formula	Factors	Applications
Arrhenius life relationship	$d = A\exp(-BT)$ with constants A, B	Temperature T	Electrical insulation, semiconductor devices, batteries, plastics, lubricants
Inverse power relationship	$d = \frac{A}{V^{\gamma}}$ with constants A, γ	V - voltage, temperature range (Coffin-Manson r-ship), load (Palmgren), velocity (Taylor)	Electrical insulation, bearings, lamps, metal fatigue
Exponential relationship	$d = \exp(\gamma_0 - \gamma_1 V)$ with constants γ_0, γ_1	V	Dielectrics
Exponential-power relationship	$d = \exp(\gamma_0 - \gamma_1 x^{\gamma_2})$ with constants γ_0, γ_1, γ_2	x - voltage, temperature	Electrical components
Polynomial relationship	$d = \sum_{i=0}^{K} \gamma_i x^i$ with constants K, γ_i	x	Metal fatigue
Elastic-plastic relationship	$d = AN^{-a} + BN^{-b}$ with constants A, B, a, b	N - number of cycles	Metal fatigue
Eyring relationship	$d = \frac{A}{T}\exp(-BT)$ with constants A, B	T - temperature	Chemical degradation
Log-linear relationship	$\log d = \sum_{i=0}^{K} \gamma_i x_i$ with constants K, γ_i	x_i	Insulating tape, batteries
Generalised Eyring relationship	$d = \frac{A}{T}\exp(-BT)\exp(V(C - DT))$ with constants A, B, C, D	T - temperature, V - voltage	Capacitors

Table 9
Applications of degradation-independent models with factor-based physical models of degradation

Degradation type	Model	Applications
Fatigue (crack propagation)	Differential equations - Palmgren-Miner's relationship (Inverse power relationship (Nelson, 2009)), Difference equations (Patankar & Ray, 2000)	Aircraft (Caplin, Ray, & Joshi, 2001; Ray & Caplin, 2000), rocket engine (Ray, Dai, Wu, Carpino, & Lorenzo, 1994; Ray, Wu, Carpino, & Lorenzo, 1994a, 1994b), power plant (Ferrari-Trecate et al., 2002; Gallestey, Stothert, Antoine, & Morton, 2002; Kallappa et al., 1997; Kallappa & Ray, 2000), utility boiler (Li, Chen, Marquez, & Gooden, 2005; Li, Marquez, Chen, & Gooden, 2006), gas turbine engine (Tangirala et al., 1998), mass-beam system (Tangirala, Caplin, Keller, & Ray, 1999; Zhang, Ray, & Patankar, 2000; Zhang, Ray, & Phoha, 2000), actuator cylinder (Chen, Chen, & Yang, 2014), wind turbines (Beganovic & Söffker, 2016; Sanchez, Escobet, Puig, & Odgaard, 2017), bearing lifetime (Gökdere, Bogdanov, Chiu, Keller, & Vian, 2006), pasteurisation plant (Pour, Puig, & Ocampo-Martinez, 2017, 2018)
Thinning of a wall	Geometric damage indicator	Rocket engine (Dai & Ray, 1996)
Thermal degradation	Arrhenius relationship	Winding insulation (Gökdere, Bogdanov, Chiu, Keller, & Vian, 2006; Gökdere, Chiu, Keller, & Vian, 2005), electromechanic actuator (Brown et al., 2009), batteries (Hatzell, Sharma, & Fathy, 2012)
Thermal degradation	Polynomial relationship	Synchronous motor Samaranayake and Longo (2018)
Wear model	Stochastic differential equations	General machine wear (Rishel, 1991), (Lefebvre & Gaspo, 1996), metallic structures in mechanical systems (Ray, 1999), race car tire degradation (Heilmeier, Graf, & Lienkamp 2018)
Surface film forming	Partial differential equations	Electric cars battery charging (Moura, Stein, & Fathy, 2013; Yin & Choe, 2020)
Electrochemical losses	Partial differential equations	Systems of batteries (Cao, Lee, Subramanian, & Zavala, 2020)
Wear model	Stochastic differential equations	Cutting tool degradation (Hao, Liu, Gebraeel, & Shi, 2017)

6. Control applications taking account of degradation

Section 2 introduced the definitions of degradation-related terms from BSI (2017). This section reviews how models of degradation have been used in control schemes in order to tolerate or mitigate degradation and prevent failures.

6.1. The layers of industrial control automation

According to ANSI/ISA-95 standard (ANSI/ISA, 2010), industrial automation systems are structured in four layers:

- Regulatory control, maintaining a variable at a set point,
- Supervisory control, providing set-points to the regulatory control taking limitations of the variables into account,
- Optimisation, recalculating the operating point of the system taking economic objectives into account,
- Scheduling, focusing on the operation on the highest level, e.g. on the entire process plant.

The term *control* is interpreted broadly in this section to include any of these layers.

Table 13 summarises published work concerning control of degrading systems categorised according to the ANSI/ISA-95 layers. The column headings reflect the models of behaviour introduced in Fig. 3, either a degradation-dependent model of behaviour, or degradation-independent. The rows indicate whether the model of degradation was factor-based or factor-free.

The examples listed in the table show that degradation-dependent models of behaviour dominate in regulatory control applications and to some extent in supervisory control applications. This is because the regulatory and supervisory control operate at similar timescales as the system and thus the knowledge about the behaviour is necessary to ensure correct operation of the system.

Degradation-independent models of behaviour find many uses in the scheduling and optimisation layers for improving the performance of a system given the correct operation is already ensured by regulatory and supervisor control layers. A degradation-independent model of behaviour can be sufficient at these higher levels even if the real system does have degradation-dependent behaviour. This is because scheduling and optimisation operate at different timescales than the behaviour of a system. From their perspective, the degraded state of a system is masked by regulatory and supervisory control.

Table 13 shows that factor-based models of degradation have tended to be used mainly with degradation-independent models of behaviour, and mainly at the higher levels of automation. Factor-based models of degradation are useful for these levels of automation because their timescales are close to the timescale of factor-based degradation. Moreover, if the factors influencing degradation are known, the scheduling and optimisation layers can improve the performance of the system by explicitly attempting to mitigate degradation. For instance, Wiebe, Cecílio, and Misener (2018) proposed a data-driven optimisation framework that mitigates degradation of equipment by planning maintenance activities in chemical processes.

6.2. Control approaches for degrading systems

A question arises how the degradation should be taken into account within a control system to preserve the overall performance. The relationship between the influencing factors and degradation also raises a possibility of mitigating the detrimental changes by adjusting the operating conditions. Thus, there are two main groups of control approaches for degrading systems:

- Control systems aware of the degradation,
- Control systems mitigating the degradation.

6.2.1. Control systems aware of degradation

According to BSI (2017), a *fault* means that a system is unable to perform the required function. Ensuring the correct operation of a system in the presence of faults is a task of fault-tolerant control (Isermann, 2006). However, the literature on fault-tolerant control usually assumes a relaxed definition of a fault. Isermann and Ballé (1997) defined a fault as "an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable/usual/standard condition". Moreover, a fault "may develop abruptly (stepwise) or incipiently (driftwise)" (Isermann, 2006). This relaxed definition of a fault is similar to the definition of a degraded state from BSI (2017) provided in Table A.14. Therefore, the term *fault-tolerant control* includes the control of systems in a degraded state as well as when the system is unable to

Table 10
Applications of factor-based reliability-oriented models of degradation

Model of degradation	Factors	Application
PHM with exponential distribution and failure rate $z_i = d_i(t, l_i)$	Actuator loads l_i	Reconfigurable control (Guenab, Theilliol, Weber, Zhang, & Sauter, 2006) of a heating system (Guenab et al., 2011), aircraft applications ($i = 1$) (Khelassi, Theilliol, & Weber, 2010; Weber, Boussaid, Khelassi, Theilliol, & Aubrun, 2012)
PHM with exponential distribution and failure rate $z_i = d_i(t, u_i)$	Actuator loads u_i	Drinking water network (Pour et al., 2019; Salazar et al., 2017)
PHM with exponential distribution and failure rate $z_i = d_i(f(u_i))$ with $f(u_i) = \|u_i\|$ or $f(u_i) = u_i^2$	Actuator loads u_i	Control allocation for Unmanned Aerial Vehicle (UAV) (Chamseddine, Theilliol, Sadeghzadeh, Zhang, & Weber, 2014; Theilliol, Weber, Chamseddine, & Zhang, 2015), Drinking water network (Salazar et al., 2017)
PHM with exponential distribution and failure rate $z_i = d_i(\beta_i, u_i^2)$ with constant β_i	Actuator loads u_i	Control allocation for F-16 aircraft (Khelassi, Theilliol, Weber, & Ponsart, 2011)
PHM with Weibull distribution and scale parameter $z_i = \frac{z_i^0}{\exp(U_i)}$ with U_i the root-mean-square of u_i and constant zi^0	Actuator loads u_i	Control allocation for aircraft application (Khelassi, Jiang, Theilliol, Weber, & Zhang, 2011)
PHM with Weibull distribution and failure rate $z_i = d(y_i(t))$	Aggregated performance indicators y_i	Load allocation in an export compressor station (Nystad, 2008)

function.

The field of fault-tolerant control has been extensively researched by Blanke, Izadi-Zamanabadi, Bøgh, and Lunau (1997), Isermann (2006), Zhang and Jiang (2008), Muenchhof, Beck, and Isermann (2009), Hwang, Kim, Kim, and Seah (2010), and Jiang and Yu (2012). The text book by Mhaskar, Liu, and Christofides (2012) presents methods and applications of fault-tolerant control.

Control systems aware of degradation should compensate for the degraded behaviour of the controlled system. They therefore require knowledge about the degradation process and its influence on the system. For instance, Milosavljevic et al. (2016) and Cortinovis et al. (2016) designed model-based optimising control for a compressor station, taking into account that the behaviour of a compressor might be different than expected. Milosavljevic et al. (2016) simulated a load-sharing problem assuming that the characteristics of each compressor differed from the model. This is equivalent to considering multiple cases of output degradation, as discussed in Section 5.1.1.1. Cortinovis et al. (2016), on the other hand, assumed that the characteristics of a compressor change with time. For optimisation, they approximated the characteristics with a polynomial and identified the parameters of the polynomial online. As the characteristics were constant in a given time period, and there was no interaction from period to period, their approach is also equivalent to considering multiple cases of output degradation in each time period.

Factor-based models may also be included in degradation-aware control. For instance, Ahmad et al. (2014) used a degradation-dependent model of behaviour with a factor-based model of degradation in a control system of the temperature in a steel-making process. They did not mitigate the degradation, but were able to improve the performance of a feed forward controller due to improved accuracy of the model of behaviour.

6.2.2. *Control systems mitigating degradation*

Mitigation of degradation is usually considered a part of maintenance engineering. On the other hand, some control frameworks attempt to mitigate degradation. They make use of a factor-based model of degradation in the controller, or use the model to predict degradation for decision support in the optimisation layer of the automation hierarchy.

Usually, a form of optimal control is used for degradation mitigation, typically a linear-quadratic controller or a model-predictive controller. These approaches allow straightforward addition of models of degradation, either as constraints or directly in the objective function.

Such control approaches were explicitly proposed by Ray, Wu, Carpino, and Lorenzo (1994a) and Ray, Wu, Carpino, and Lorenzo (1994b) as *life-extending control* or *damage mitigating control*. Using a factor-based model of degradation, they designed a control algorithm to keep degradation below a threshold. Later, a patent by Fuller, 2005 gave a generic approach to life-extending control using model-predictive control with constraints on degradation, with estimates of degradation obtained from a factor-based model of degradation.

Applications of life-extending control can be found in Kallappa, Holmes, and Ray (1997), who designed a control system for a power plant with a structural degradation model as a state variable. They used a model predictive controller and included the degradation both in the objective function and in the constraints. Tangirala, Caplin, Keller, and Ray (1999) also used model predictive control to limit degradation in a gas turbine by including degradation in the constraints.

Degradation mitigation has also been applied in aircraft applications by Dai and Ray (1996), Ray and Caplin (2000), Ray, Caplin, and Joshi (2000), and Ray et al. (1994). They all used factor-based models of crack propagation with degradation-independent models of the behaviour of an aircraft to design a model-based controller which would ensure correct operation of the degraded system. Tangirala, Holmes, Ray, and Carpino (1998) demonstrated a control system aimed at mitigation of crack development in aircraft, and demonstrated its effectiveness on a laboratory test structure.

Other applications listed in Table 13 include Pereira, Harrop Galvao, and Yoneyama (2010), Vieira et al. (2015), Grosso, Ocampo-Martinez, and Puig (2016) who each used a degradation-independent model of behaviour and included a factor-based model of degradation in the constraints for a model predictive controller. Salazar, Sarrate, Nejjari, Weber, and Theilliol (2017), Sanchez, Escobet, Puig, and Odgaard (2017), and Pour et al. (2019) also used model predictive control, and included models of degradation in the objective function. Rosewater, Copp, Nguyen, Byrne, and Santoso (2019) provided a review on how factor-based models of degradation might be included in the objective of optimal control of batteries.

Escobet, Quevedo, Puig, and Nejjari (2002) investigated a concept similar to life-extending control, with the main focus shifted towards predictive health monitoring and decision making. They used models of degradation to predict the health of the system. The predicted value was then used to choose between either reconfiguration of a controller, or performing maintenance. This example shows how degradation modelling contributes to decision support for the optimisation and scheduling layers of the automation hierarchy.

Langeron, Grall, and Barros (2012) developed an extended fault-tolerant control framework for a DC motor including a model of degradation in the design of a PID controller. The developed controller was tested in simulation using a degradation-dependent model of

Table 11
Applications of factor-based heuristic models of degradation

Model of degradation	Factors	Application
$d(k+1) = d(k) + \Gamma\lvert u(k)\rvert + \Psi\lvert\Delta u(k)\rvert$ with constant parameters Γ, Ψ	Flow through a pump $u(k)$	Tank level control (Pereira, Harrop Galvao, & Yoneyama, 2010), Drinking water network (Grosso, Ocampo-Martinez, & Puig, 2012)
$d(k+1) = d(k) + \gamma\lvert u(k)\rvert + \eta_k$ with constant parameter γ, and η_k from a known normal distribution	Flow through an actuator: a pump or a valve $u(k)$	Drinking water network (Grosso et al., 2016)
$\Delta d = -(p_N N^3 + p_\Delta\lvert\Delta N\rvert^3)\exp(1 - GVF)$ with p_N and p_Δ from a known normal distribution	Speed N, Gas Volume Fraction GVF	Subsea compression system (Verheyleweghen & Jäschke, 2017)
$\dot{d} = \mathrm{E}(p_1\phi_0 + \int_0^\infty (p_2\lvert\phi(\tau)\rvert + p_3\lvert\dot{\phi}(\tau)\rvert)\mathrm{d}\tau)$ with constant weights p_1, p_2, p_3	Compressor dimensionless mass flow ϕ	Subsea compression system (Verheyleweghen, Gjøby, & Jäschke, 2018)
$d = V_s - V_b$	Voltages corresponding to the electrode surface V_s and the inner part of the electrode V_b	Battery in electronic vehicles (Fang, Wang, & Chen, 2017)

behaviour. Langeron, Grall, Barros, 2013 used a probabilistic description of health of a system and included a factor-based model of degradation in the objective function of a linear-quadratic controller. This approach was applied by Langeron et al. (2016) to a generic control system, and by Langeron (2015) and Langeron, Grall, and Barros (2017) who designed an LQR control system for a drilling system. The application included a model of actuator degradation in an LQR objective function.

Further applications presented by Pour, Puig, and Ocampo-Martinez (2018) and Verheyleweghen, Gjøby, and Jäschke (2018) described hierarchical control systems that mitigated degradation. Both applications were based on model-predictive control and used factor-based models of degradation of a pump and a compressor, respectively. Pour et al. (2018) included a model of degradation directly in the objective function, whereas Verheyleweghen, Gjøby, and Jäschke (2018) added a constraint on the value obtained from the model of degradation. The model of degradation used by Pour et al. (2018) was derived from Palmgren--Miner's relationship, and thus represents a physical model of degradation. The model of degradation from Verheyleweghen, Gjøby, and Jäschke (2018) was for accumulated damage based on a heuristic analysis.

Controllers that mitigate degradation make use of factor-based models of degradation, particularly degradation of actuators. The purpose of the controllers is to adjust the influencing factors in order to manage degradation. The adjustment might be done by feedback control in the lower layers of the automation hierarchy, and can be done manually if the design is for a decision support system.

7. Illustrative example

This section gives an industrial example showing how a factor-based model of degradation and an understanding of degradation-dependent behaviour can be used operationally to influence degradation through scheduling formulations.

The topology of the batch process has been described by Wu et al. (2019) and is shown in Fig. 5. Multi-product polymer batch production uses two parallel reactors for a variety of recipes. Such reactors are equipped with recirculation loops, in which pumps and heat exchangers are employed to cool the reactors during the polymerization (Stage 2, denoted with a dashed green box in Fig. 5). In this example, degradation is related to fouling as polymer residues are accumulated in the inner surface of the equipment such as reactors, pipes, and heat exchangers. Some recipes cause worse fouling than others.

Fouling has an impact on the pressure drop over the heat exchangers and on the duration of a batch. However, the recipe also affects both pressure and duration, so degradation due to fouling has to be inferred. Wu et al. (2019) proposed a model of degradation that can be used for scheduling taking degradation into account. In the following, their approach is put into the context of the new classifications proposed in this article.

7.1. Degradation-dependent model of behaviour for batch production

An important variable describing the behaviour of batch operations is the duration of a batch. In Wu et al. (2019) this has been modelled as a degradation-dependent model using a static model of behaviour:

$$T_{B_k} = f(h_k, r_k) \tag{27}$$

where T_B is the duration of a batch, $h_k = h_k(d_k)$ is a degradation function related to fouling, r is the recipe and k is the batch number.

7.2. Factor-based models of degradation for batch production

It is not possible to directly measure the degradation function h_k. Its value has to be inferred from measurements of the pressure drop over

Table 12
Synopsis of advantages and disadvatages of the combinations of models of degradation and models of behaviour from Fig. 3

Models of behaviour	Models of degradation	Advantages	Disadvantages
Degradation-dependent	Factor-free - input degradation	Enables analysis of behaviour of a system if degradation of only the input is known Does not change the functional form of the model of behaviour, although can introduce time-dependency	Does not consider that degradation can be affected by influencing factors Can be oversimplified
	Factor-free - output degradation	Enables analysis of systems with multiple subsystems Does not change the functional form of the model of behaviour Does not require knowledge about the underlying dynamics, only the output	Does not consider that degradation can be affected by influencing factors
	Factor-based - input degradation	Provides information about degradation and the behaviour of a system Takes into account that degradation is affected by influencing factors	Can change the functional form of the model of behaviour Requires knowledge about influencing factors
	Factor-based - output degradation	Enables analysis of systems with multiple subsystems Provides information about degradation and the behaviour of a system Requires only knowledge about outputs, not the underlying dynamic behaviour	Can change the functional form of the model of behaviour Requires knowledge about influencing factors
Degradation-independent	Factor-free - reliability-oriented	Is general and well-understood in reliability and maintenance engineering	Requires knowledge about past degradation Does not provide information about behaviour of a system
	Factor-based - physical	Provides accurate models of degradation Provides information about degradation as a function of influencing factors	Is complex Requires detailed knowledge about degradationAssumes that the behaviour of a system is not affected by degradation
	Factor-based - reliability-oriented	Captures uncertain nature of degradation Provides information about degradation as a function of influencing factors Is well-understood in reliability and maintenance engineering	Requires knowledge about past degradation Assumes that the behaviour of a system is not affected by degradation
	Factor-based - heuristic	Is tailored to the application Provides information about degradation as a function of influencing factors	Requires knowledge about degradation Does not have any interpretation Is application-specific Assumes that the behaviour of a system is not affected by degradation

the heat exchangers giving an estimate $\widehat{h}_k$ of the underlying degradation:

$$\widehat{h}_k = \frac{y_k - D_{r_k}}{C_{r_k}} \tag{28}$$

The pressure drop measurement y_k is influenced by the recipe because some polymers are more viscous than others. The model parameters C_{r_k} and D_{r_k} therefore depend on the recipe r_k used at the k-th batch. They were estimated from historical data from a BASF production facility from calibration campaigns (Wu et al., 2019) and then used for new campaigns. Figure 6 shows four campaigns in which $\widehat{h}_k$ has been inferred from the pressure measurements using Eq. (28).

The evolution of the underlying degradation may vary according to the sequencing of the recipes. A factor-based degradation model was used to reflect this dependence:

$$\widehat{h}_{k+1} = A_{r_k}\widehat{h}_k + B_{r_k} \tag{29}$$

The parameters A_{r_k} and B_{r_k} in the model (each having one value per recipe) were determined over several campaigns from historical measurements of the pressure drop via the estimates $\widehat{h}_k$ from Eq. (28) shown in Fig. 6.

7.3. Degradation-aware operation

Wu et al. (2019) integrated the models from Section 7.2 in mathematical formulations of a scheduling application. The static model of behaviour (27) was linear:

$$T_{B_{r_k}} = D_{r_k}\widehat{h}_k + E_{r_k} \tag{30}$$

with values for recipe-dependent parameters D_{r_k} and E_{r_k} determined from historical data within BASF. In Wu et al. (2019), the overall aim was an optimized schedule of recipes and batches assigned to the various available reactors with respect to minimization of makespan taking the degradation into account. Wu et al. (2019) defined the makespan as $MS = \max_{i\in I}(Te_i)$, and Te_i is the end time of Batch i conducted in one of the reactors. Makespan is a measure of short-term production capacity. The recipes and the degradation affect the end times of all batches through the model of behaviour from Eqs. (29) and (30), and therefore make a difference to the makespan. The details of the formulation were described by Wu et al. (2019). The interest for the current article is that the sequencing of recipes affects the degradation due to fouling in two reactors U2 and U3 in Stage 2 in Fig. 5 and finally affects the overall production capacity.

Figure 7 shows the timing and sequencing of batches in two reactors as well as the degradation function of all batches, in which the results are generated according to the process models. The symbols of a circle, up arrow, and right arrow in Fig. 7 denote the end time Te_i of each batch on horizontal axis, the degradation function of each batch on vertical axis and the recipe type using different shapes. Two curves connect the batch symbols and indicate the sequences of recipes in both reactors U2 (dashed orange and solid blue) and U3 (dash-dotted brown and dotted blue).

Figure 7 compares the underlying degradation due to fouling and the timing resulting from alternative sequences. Sequence 1 is the optimal solution generated from the proposed optimization and results in a shorter makespan, which is illustrated by the end times of the last batches highlighted by the symbol of a red cycle. Hence the optimal sequence gives better equipment utilization by considering degradation

Table 13
Uses of models of degradation and their influence on the models of behaviour, grouped according to the automation hierarchy from ANSI/ISA (2010)

	Degradation-dependent models of behaviour	Degradation-independent models of behaviour
Scheduling - factor-based models of degradation	Battery Energy Storage Systems (Cao et al., 2020)	Wind turbines (Beganovic & Söffker, 2016; Sanchez, Escobet, Puig, & Odgaard, 2017; Verheyleweghen, Gjøby, & Jäschke, 2018; Verheyleweghen & Jäschke, 2017), compressor station (Nystad, 2008), benchmark problem with three units (Hao et al., 2017; Hao, Yang, Ma, & Zhao, 2017), chemical plants (Wiebe et al., 2018)
Scheduling - factor-free models of degradation	Crack propagation (Beganovic & Söffker, 2017; Zhou, Serban, & Gebraeel, 2011)	Oil and gas (SINTEF, 2002), electronics (United States of America: Department of Defense, 1986)
Optimisation - factor-based models of degradation	Drilling unit (Langeron et al., 2015), (Langeron et al., 2017)	Turbomachinery (Dai & Ray, 1996; Ray, Dai, Wu, Carpino, & Lorenzo, 1994; Ray, Wu, Carpino, & Lorenzo, 1994a, 1994b), windings, bearings and cylinders (Chen et al., 2014; Ray, 1999), mass-beam system (Zhang, Ray, & Patankar, 2000; Zhang, Ray, & Phoha, 2000), pasteurisation plant (Pour, Puig, & Ocampo-Martinez, 2017, 2018), tank level (Pereira, Harrop Galvao, & Yoneyama, 2010), water network (Grosso, Ocampo-Martinez, & Puig, 2012, 2016; Salazar, Sarrate, Nejjari, Weber, & Theilliol, 2017; Salazar, Weber, Nejjari, Sarrate, & Theilliol, 2017), batteries (Fang et al., 2017)
Optimisation - factor-free models of degradation	Control valve (McGhee, Galloway, Catterson, Brown, & Harrison, 2014), turbomachinery (Aker & Saravanamuttoo, 1989; Cicciotti, 2015; Kurz & Brun, 2001; Li & Nilkitsaranont, 2009; Meher-Homji, Chaker, & Motiwalla, 2001; Tarabrin, Schurovsky, Bodrov, & Stalder, 1996; Tsoutsanis, Meskin, Benammar, & Khorasani, 2015), TE benchmark (Yin et al., 2014), pulp mill (Zumoffen & Basualdo, 2008)	Power plant (Ferrari-Trecate et al., 2002; Gallestey et al., 2002; Kallappa et al., 1997; Kallappa & Ray, 2000)
Supervisory control - factor-based models of degradation	General dynamic system (Vieira et al., 2015), tank system (Nguyen, Dieulle, & Grall, 2014a, 2014b, 2014c, 2015), battery charging (Allam, Onori, Marelli, & Taborelli, 2015; Rosewater, Copp, Nguyen, Byrne, & Santoso, 2019; Suri & Onori, 2016; Yin & Choe, 2020)	Turbomachinery (Tangirala, Caplin, Keller, & Ray, 1999), batteries (Hatzell, Sharma, & Fathy, 2012; Moura, Stein, & Fathy, 2013; Rosewater, Copp, Nguyen, Byrne, & Santoso, 2019), mass-beam system (Tangirala et al., 1998), electromechanical system (Gökdere, Bogdanov, Chiu, Keller, & Vian, 2006; Gökdere, Chiu, Keller, & Vian, 2005), aircraft (Brown et al., 2009; Caplin, Ray, & Joshi, 2001; Ray & Caplin, 2000), general machine wear (Lefebvre & Gaspo, 1996; Rishel, 1991), heating system (Guenab et al., 2006; Guenab et al., 2011)
Supervisory control - factor-free models of degradation	CSTR (Mhaskar, 2006; Mhaskar, Liu, & Christofides, 2012; Prakash, Narasimhan, & Patwardhan, 2005), vehicles (Boskovic et al., 2009), hydrothermal process (Boussaid et al., 2011), electrical systems (Langeron, Grall, & Barros, 2013; Samaranayake & Longo, 2015, 2018), burner (Baldi et al., 2017), Shell control problem (Kettunen et al., 2008), hydrogen production (Du et al., 2014), heat exchanger (Ballé et al., 1998)	Utility boiler (Baldi et al., 2017; Li et al., 2005; Li et al., 2006)
Regulatory control - factor-based models of degradation	Steel making process (Ahmad et al., 2014)	Aircraft (Khelassi, Jiang, Theilliol, Weber, & Zhang, 2011; Khelassi, Theilliol, & Weber, 2010; Khelassi, Theilliol, Weber, & Ponsart, 2011; Weber, Boussaid, Khelassi, Theilliol, & Aubrun, 2012)
Regulatory control - factor-free models of degradation	General dynamic system (Chen, Niu, & Zou, 2013; González-Contreras, Theilliol, & Sauter, 2007; Gu, Liu, Peng, & Tian, 2012; Mahmoud, Jiang, & Zhang, 2002; Tao, Joshi, & Ma, 2001; Veillette, 1995; Wang & Yao, 2010), aircraft (Chamseddine, Theilliol, Zhang, Join, & Rabbath, 2015; Chen, Liu, & Fu, 2016; Graves, Turcio, & Yoneyama, 2018; B. Jiang & Chowdhury, 2005; J. Jiang & Zhang, 2006; Li, Shi, & Yao, 2017; Maki, Jiang, & Hagino, 2004; Shi, Wang, Wang, Wang, & Tomovic, 2017; Tian, Yue, & Peng, 2010; Wu, Zhang, & Zhou, 2000; Yang, Zhang, Jiang, & Liu, 2014; Ye & Yang, 2006; Yu, Fu, & Zhang, 2018; Y. Zhang & Jiang, 1999; Y. Zhang, Jiang, & Theilliol, 2008; Y.M. Zhang & Jiang, 2001; Zhao & Jiang, 1998), three tank system (Li et al., 2019; Theilliol et al., 2008; Theilliol et al., 2002; Zhang & Qin, 2009), vehicles (Gao et al., 2011; Huang et al., 2014; Shen et al., 2014), ball-beam system (Zhang et al., 2010), control valve (Arıcı & Kara, 2018; Mo & Xie, 2016), electrical systems (Kaviarasan et al., 2016), inverted pendulum (Wei et al., 2017), CSTR (Wang et al., 2007)	

in the scheduling.

This industrial example shows how modelling of factor-based degradation and degradation-dependent behaviour can be used operationally to influence degradation and to improve batch production potentially through degradation-aware scheduling.

8. Discussion and conclusions

8.1. Synopsis

This paper has presented a perspective on degradation modelling for control applications with an emphasis on the links between degradation of components and the behaviour of a system. To this end, it gives an in-depth discussion of models of behaviour of the system and models of degradation. The models of behaviour have been classified as degradation-dependent or degradation-independent, to reflect whether the degradation affects the behaviour. The models of degradation have been classified as factor-free or factor-based, to capture how influencing factors affect degradation (Fig. 3).

The survey examines control applications where degradation modelling has been used. Table 13 groups the findings according to the proposed classification. Section 6 of the paper highlighted the following points:

- Degradation-dependent models of behaviour dominate in regulatory and supervisory control because such control needs accurate

knowledge of the behaviour over short timescales. However, the models of degradation are often factor-free, for instance degradation is assumed constant.
- Factor-based models of degradation are used in scheduling and optimisation, because the scheduling and optimisation layers make adjustments to the factors to mitigate degradation.
- Degradation-independent models of behaviour are the most widely used in scheduling and optimisation. The assumption is that degradation does not change behaviour because any degradation that does appear is compensated for by the regulatory and supervisory control.

Section 6 also discussed and gave examples of two main approaches to control of degrading systems:

- Control systems aware of degradation that compensate for the degraded behaviour of the controlled system. These systems include fault-tolerant control.
- Control systems mitigating the degradation that manage the degradation, also known as life-extending control.

8.2. Gaps and open questions

8.2.1. Regulatory control

A notable gap in the literature concerns the use of factor-based models of degradation at the regulatory control layer. A regulatory control system needs accurate knowledge of the behaviour of a system over short timescales, and this is why there is a preference for degradation-dependent models of behaviour. However, the level of degradation is mainly being estimated from factor-free models of degradation, whereas in practice degradation may depend on the way in which the system is operated, and also on external factors. An observation arising from the survey in this paper is that factor-based models of degradation have potential for developing a new class of regulatory control algorithms.

It is interesting to speculate why factor-based models of degradation have not been much used in the design or testing of control algorithms at the regulatory layer despite their obvious potential. Possible blocks to progress may be that factor-based models of degradation are case-specific, and that the models are formulated in such a way that they do not link easily into a control theory framework. Ideally a model of a degraded component would drop easily into the mathematical representation of a control system, much as Hammerstein or Wiener models can be used for representing generic nonlinearity in actuators. The input and output modelling approach in Section 4.2 is relevant to this. There may be a promising research direction in specifying some generic functional forms for Eqns. (8) and (9) whose parameters can be identified from data.

8.2.2. Optimisation and scheduling

It seems necessary to examine the assumption that a degradation-independent model of behaviour is sufficient in the scheduling and optimisation layers. Such schemes are often verified using simulations as a proxy for the real system. The work surveyed in this paper highlighted examples of scheduling and optimisation schemes being validated in a simulation that used a degradation-independent model of behaviour, even when the real system is known to have degradation-dependent behaviour. There seems to be scope for improved simulation environments that would be based on more realistic degradation-dependent models of behaviour. Using degradation-dependent models would therefore lead to an improved integration of control and scheduling, in a partial fulfilment of the gaps indicated by Baldea and Harjunkoski (2014).

8.2.3. Model validation

A control scheme in any layer of the automation hierarchy may incorporate models of degradation and models of behaviour. Also, simulations are often used by researchers to test and demonstrate their ideas. The simulation has to use an accurate representation of the real system. Validation of the models involves real data, ideally recorded during field operation. Validation is certainly present in some of the surveyed literature, and the models in Section 7 were validated against plant data. However, there remains an open research question about a systematic way to validate models of degradation and degradation-dependent models of behaviour.

There is a challenge in obtaining representative data that may be used to generate degradation models. Degradation typically happens slowly in relation to the dynamics of the system. Collection of data in a systematic and consistent way over many periods of operation can be a significant issue, especially for academic researchers as highlighted by Jardine et al. (2006). A potential way forward, given the current interest in industrial data analytics, would be for organisations to share relevant data, perhaps even making it public in the form of benchmark data sets.

8.3. Future research directions and conclusion

This survey paper has given a new perspective on degradation modelling for control applications. It has grouped the literature according to the proposed classification and also has reviewed control applications where degradation modelling has been used.

The paper has the aim to facilitate the choice of models of degradation and models of behaviour for integration in control systems at all layers from regulatory control to scheduling. The structured analysis emerging from the survey may be useful for integration of degradation modelling into applications where degradation has not yet been of a main focus. Furthermore, the findings of the survey may be used for improving existing approaches to control of degraded equipment, for instance by encouraging the use of factor-based models of degradation in the regulatory control layer.

In particular, the fields of degradation-aware control and degradation-mitigating control can benefit from the current survey. These approaches have the potential to explore the mutual influences between degradation and the behaviour of the system by including the models of degradation in design of an optimal control structure. The inclusion of models of degradation in control systems would improve the overall performance of a system, as has been demonstrated in the illustrative example.

More broadly, the survey provides a step in the direction of fusion of industrial condition monitoring and automatic control systems. Information obtained from the condition monitoring system can be used to improve and validate models of degradation. Then the models of degradation can be integrated into the next generation of control and optimisation systems.

Declaration of Competing Interest

Declarations of interest: none.

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Appendix A. Glossary of terms

A glossary of terms relevant to this review is presented in Table A1

Table A1
Glossary of terms related to industrial control systems and their degradation

Term	Explanation
Actuator	Functional unit that generates the manipulated variable, required to drive the final controlling element, from the output variable of the controlling element (BSI, 2016c)
Advanced process control (APC) and optimisation (APC-O)	APC: control strategy to cope with processes characterised by large time delays, non-minimum phase, non-linearity, loop instability and multi-variable coupling. APC enhances basic process control by addressing particular performance or economic opportunities in the process. Optimisation: decision-making strategy to meet the business objective under a weighted set of conditions and concerns. APC-O: Collection of advanced process control and optimisation strategies (BSI, 2015)
Ageing failure	Failure whose probability of occurrence increases with the passage of calendar time (BSI, 2012)
Basic Process Control System	System which responds to input signals from the process, its associated equipment, other programmable systems and or operators and generates output signals causing the process and its associated equipment to operate in the desired manner BSI (2016)
Behaviour of a system	Response of a system to input signals from the process, its associated equipment, other programmable systems and/or operator (following BSI (2016))
Behavioural model of a system	Mathematical models of the input/output behaviour of a system (Willems, 2007), including differential and algebraic equations, as well as other characteristic quantities (see: Characteristics)
Characteristics (of equipment)	Distinguishing attributes, qualities and properties of equipment and its subsystems which, by their presence and the relative magnitudes of their effects, define the configuration, performance, behaviour and capabilities of the equipment (BSI, 2016)
Condition(s)	Characteristics and parameters of the actual state of an item (BSI, 2010)
Condition monitoring	Activity, performed either manually or automatically, intended to measure at predetermined intervals the characteristics and parameters of the actual state of an item (BSI, 2010)
Degradation	Detrimental change in physical condition, with time, use, or external cause (BSI, 2017)
Degradation (of performance)	Undesired departure in the operational performance of any device, equipment or system from its intended performance (BSI, 2012)
Degraded state	State of reduced ability to perform as required, but with acceptable reduced performance BSI (2017)
Dependability	Ability to perform as and when required (BSI, 2012)
Diagnostics	Examination of symptoms and syndromes
Environment	All external conditions influencing a system at any given moment (BSI, 2018)
Equipment	Machine or group of machines including all machine or process control components (BSI, 2012)
Failure	Termination of the ability of an item to perform a required function (BSI, 2010)
Failure criteria	Pre-defined conditions to be accepted as conclusive evidence of failure (BSI, 2010)
Failure mechanism	Physical, chemical or other processes which may lead or have led to failure (BSI, 2010)
Fault	State of an item characterised by inability to perform a required function, excluding the inability during preventive maintenance or other planned actions, or due to lack of external resources (BSI, 2010)
Functionality	Extent to which the system provides functions to perform tasks required by the system mission (BSI, 2016)
Induced environment	Conditions external to a system generated as a result of the operation of the system (BSI, 2018)
Influencing factor	Observable qualitative or measurable quantitative item that affects a system property (BSI, 2016)
Item	Part, component, device, subsystem, functional unit, equipment or system that can be individually described and considered (BSI, 2010)
Loss (of function or performance)	Temporary degradation (BSI, 2016)
Maintenance	Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function (BSI, 2017)
Measurement	Process of experimentally obtaining one or more quantity values that can reasonably be attributed to a quantity (BSI, 2016)
Model	Mathematical or physical representation of a system or a process, based with sufficient precision upon known laws, identification or specified suppositions (BSI, 2016)
Natural environment	Conditions generated by the forces of nature and the effects of which are experienced by a system when it is at rest as well as when it is in operation (BSI, 2018)
Operating conditions	Physical loads and environmental conditions experienced by the item during a given period (BSI, 2017)
Parameter	Variable representing some significant measurable system characteristic (BSI, 2012)
Performance	Precision and speed with which the system executes its tasks under defined conditions (BSI, 2016); behaviour, characteristics and efficiency of a technological process, running in a machine derived by measurement and calculation of one or more parameters, for example, power, flow, efficiency or speed, which singly or together provide the necessary information (BSI, 2012)
Physical properties	See Characteristics
Prognostic	Analysis of the symptoms of faults to predict future condition and residual life within design parameters (BSI, 2012)
Reliability	Ability of an item to perform a required function under given conditions for a given time interval
State (actual)	A circumstance or condition of an ITEM at a time (BSI, 2014), Characteristics of an item at a specific point in time (BSI, 2001) (obsolete)
System	In condition monitoring and diagnostics: set of interrelated elements that achieve a given objective through the performance of a specified function (BSI, 2012); in process control: a subsystem of Basic Control System (BCS); Basic Process Control System (BPSC), system which responds to input signals from the process, its associated equipment, other programmable systems and (or) an operator and generates output signals causing the process and its associated equipment to operate in the desired manner (BSI, 2016)
System property	Defined parameter suitable for the description and differentiation of BPCS(s) (BSI, 2016)
Up state	State of an item characterised by the fact that it can perform a required function, assuming that the external resources, if required, are provided (BSI, 2017)
Wear-out-failure	Failure whose probability of occurrence increases with the operating time or the number of operations of the item and the associated applied stresses (BSI, 2017)

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