

THE ROLE OF FLEXIBILITY IN GENERATION EXPANSION
PLANNING OF POWER SYSTEMS WITH A HIGH DEGREE OF
RENEWABLES & VEHICLE ELECTRIFICATION



A thesis submitted to
Imperial College London
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by

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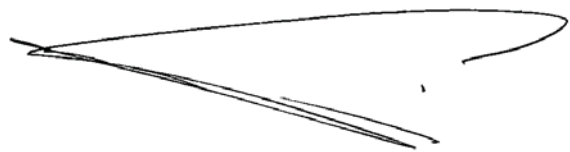
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A handwritten signature in black ink, consisting of a series of loops and strokes that form the name Pedro Javier Ramírez Torrealba.

Pedro Javier Ramírez Torrealba

London, United Kingdom, October 2014

*Dedicated to my wife Pilar, and my son Pedro,
for supporting me all the way,
and to my parents for making me be who I am.*

ABSTRACT

Renewable energy is beginning to play a major role in the production of clean and inexhaustible energy to supply electricity demand and to hedge against the price volatility of natural gas and oil. However, renewables are expected to increase existing net-demand variability and unpredictability. This will mean that in order to maintain the balance between demand and supply, flexible generation or demand will have to modify their production or consumption at higher rates and frequencies for larger shares of renewables in order to accommodate such extensive and rapid changes as effectively and economically as possible.

This thesis addresses the relevance of generation and demand flexibility for the future expansion of power systems that expect large contributions from renewable resources and high levels of vehicle electrification. A novel fully integrated large-scale mixed-integer linear generation expansion planning model was developed, which incorporates detailed modelling of generation and demand (specifically electric vehicles) flexibility characteristics. Computational tractability and efficiency of the model are achieved by clustering generation and flexible demand resources, which allows using integer instead of binary decision variables. The use of integer variables allows reducing the model size in terms of both decision variables and constraints, and also avoids non-linearities in the model formulation.

Case studies on conventional generation flexibility show that total system costs are underestimated by up to 24% with a traditional generation expansion planning model when compared to the results obtained with the proposed model. In addition, the optimal generation mix calculated by the traditional model is not only infeasible in terms of security, but also inefficient for absorbing available renewable energy and much more expensive of operating. The case studies also show that reductions in the minimum stable generation, and improvements in ramping capability, reduce the curtailment of renewable energy by up to 73%, as well as the total system costs by up to 20%. The case studies on Electric Vehicle (EV) flexibility and its impact on generation expansion planning, on the other hand, show that if the flexibility potential of flexible EV is not utilized, the installed capacity can increase by up to 50%, the total system costs can rise in by to 18%, the level of renewables curtailment can become up to 69x bigger, and the average energy prices can climb by up to 18%, with respect to the case in which EV flexibility is fully utilized.

Finally, the developed model is able to produce useful indicative energy planning results that can help regulators, system planners and analysts to design and assess the proper market conditions, energy policies, and incentives required to deliver secure, affordable, sustainable and less polluting power systems in the future.

PUBLICATIONS

Some ideas and/or figures have appeared previously in the following publications:

JOURNAL PAPERS

Pedro J. Ramírez, Dimitrios Papadaskalopoulos, and Goran Strbac. Generation Expansion Planning and Demand Flexibility Investment Co-optimization. *Submitted to IEEE Transactions on Smart Grid*, 2014.

CONFERENCE PAPERS

Pedro Ramírez, Dimitrios Papadaskalopoulos, and Goran Strbac. Impact of Electric Vehicles Flexibility on Generation Expansion Planning. In *2013 4th IEEE PES Innovation Smart Grid Technologies Europe (ISGT Europe)*, pages 1–5, Lyngby, Denmark, 2013.

RESPONSES TO PUBLIC CONSULTATIONS

Goran Strbac, Manuel Castro, and **Pedro Ramírez**. Response to OFGEM capacity assessment consultation: measuring and modelling the risk of supply shortfalls. Reference: 132/11, Imperial College London, London, UK, 2012.

*Your time is limited, so don't waste it living someone else's life.
Don't be trapped by dogma - which is living with the results of other people's thinking.
Don't let the noise of other's opinions drown out your own inner voice.
And most important, have the courage to follow your heart and intuition.
They somehow already know what you truly want to become.
Everything else is secondary.*

— Steve Jobs

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ACRONYMS & ABBREVIATIONS

AR	Auto-Regressive
BRA	Base Residual Auction
CAPEX	Capital Expenditure
CCGT	Combined-Cycle Generating Turbine
CCS	Carbon Capture and Storage
CM	Capacity Markets
CO ₂	carbon dioxide
CONE	Cost Of New Entry
DECC	Department of Energy & Climate Change
DSM	Demand Side Management
DSR	Demand Side Response
EDF	Électricité de France
EFOR	Effective Forced Outage Rate
EGEAS	Electric Generation Expansion Analysis System
EIA	US Energy Information Administration
EMR	Electricity Market Reform
EoM	Energy-only-Market
EPEC	Equilibrium Problem with Equilibrium Constraints
EPIA	European Photovoltaic Industry Association
EPRI	Electric Power Research Institute
EPS	Emissions Performance Standard
ETSAP	Energy Technology Systems Analysis Programme
EU	European Union
EV	Electric Vehicle
FERC	Federal Energy Regulatory Commission
FRR	Frequency Regulation Reserve
GB	Great Britain
GEP	Generation Expansion Planning
GHG	Greenhouse Gas
IAs	Incremental Auctions
ICAP	Installed Capacity
ICAP-P	Installed Capacity – Payment

ACRONYMS & ABBREVIATIONS

ICE	Internal Combustion Engine
IEA	International Energy Agency
IRP	Integrated Resources Planning
ISO	Independent System Operator
IT	Information Technologies
KDS	Kernel Density Estimation
LDA	Locational Deliverability Area
LDC	Load Duration Curve
LOLE	Loss Of Load Expectation
LOLP	Loss Of Load Probability
LP	Linear Programming
MARKAL	MARKet ALlocation
MCP	Mixed Complementarity Problem
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MIT	Massachusetts Institute of Technology
MM	Missing-Money
NE	New England
NECA	National Electricity Code Administrator
NGET	National Grid Electricity Transmission
NGOs	Non-Governmental Organizations
NLP	Non-Linear Programming
NREL	National Renewable Energy Laboratory
NY	New York
NYISO	New York Independent System Operator, Inc.
OCGT	Open-Cycle Generating Turbine
OECD	Organisation for Economic Co-operation and Development
O&M	Operation & Maintenance
PER	Peak Energy Revenue
PJM	Pennsylvania – New Jersey – Maryland Interconnection L.L.C.
PPA	Purchased Power Agreement
PV	Photovoltaic
QSR	Quick-Start Reserve
RAM	Random Access Memory
RM	Reserve Margin
ROM	Reliability and Operation Model
RPM	Reliability Pricing Model

RR	Reserve Requirement
ScR	Scarcity Rent
SEM	Single Electricity Market
SMP	System Marginal Price
SPR	Spinning Reserve
SRP	Short-Run Profit
TOC	Total Operational Cost
TSC	Total System Cost
UC	Unit Commitment
UCAP	Unforced Capacity
UK	United Kingdom
US	United States
V ₂ G	Vehicle-to-Grid
VOLL	Value Of Lost Load
VRE	Variable Renewable Energy
VRR	Variable Resource Requirement
WACC	Weighted Average Cost of Capital
WASP	Wein Automatic System Planning package
WILMAR	Wind Power Integration in Liberalised Electricity Markets
WNA	World Nuclear Association

Part I

RESEARCH MOTIVATION & THESIS STRUCTURE

INTRODUCTION

During the last four decades, the electricity industry has experienced and continues to experience profound transformations in many countries around the world. The first major change was restructuring and deregulation which resulted in the dismemberment of the monopoly structure of the large vertically integrated utilities into a more diverse, competitive and dynamic framework. Nowadays the major drivers for changes are large-scale penetration of renewable generation, carbon emissions reduction targets and the multiple changes in the market structures and regulations implemented to achieve those objectives. All these changes are to consolidate the increasing demand for electricity with the aim of creating more secure, affordable, sustainable and less polluting power systems.

The aggressive carbon emissions reduction targets imposed by many countries, in combination with their associated renewable generation agendas, are changing the way in which electricity is being produced and distributed. The inherent intermittency and stochastic nature of most renewable generation is heavily modifying the time dynamics of net-demand, increasing its variability and unpredictability. Such changes in net-demand are translated into the need for more system flexibility, which will play a key role in the evolution of modern power system, as it is crucial for the effective and efficient integration of renewables and the reduction of carbon emissions.

This chapter gives a preamble to the research topic of this thesis, presenting the motivation and questions that guided this research, its objectives and key contributions.

1.1 GENERATION BUSINESS: PAST, PRESENT & FUTURE

During the 1980's and 1990's, the electricity industry initiated a very complex and deep structural transformation in many countries around the world. This led to deregulation and liberalization of the electricity market and its opening to competition [5, 6, 7, 8, 9]. Vertically integrated monopolistic structure of the large state companies was transformed to a diverse, competitive and dynamic framework that allowed private investors to enter the business. This was especially true for generation and supply, because the transmission and distribution segments remained as monopolistic activities due to the nature of their businesses [10, 1, 11].

Electricity generation in most of current power systems has not changed much since the beginning of the electricity industry [12]. The bulk of electricity demand is still being supplied by generation capacity fuelled by fossil fuels in most of the countries around the world. However, worldwide environmental and economic concerns, and the envisaged electrification of

transport and heat are changing this scenario, modifying present power system configurations towards modern and advanced power systems that are increasingly characterized by the penetration of renewables, distributed generation, flexible and efficient demand side resources, storage technologies and interconnection to other countries [13, 14, 15].

The climate change concerns have forced governments around the world to commit themselves to substantial reductions in greenhouse gas emissions over the next decades. Electricity generation from fossil fuel is the biggest single source of carbon emissions, which is responsible for more than a third of the total carbon emissions in countries like United Kingdom (UK) and United States (US) [16, 17, 18]. The decarbonisation of electricity generation will require deep and multilevel changes in current power systems if the ambitious greenhouse gas emissions reduction targets for 2050 are to be achieved [19, 20, 21].¹ Such changes will involve the integration of large amounts of renewable generation, and the construction of more low-carbon conventional generation (nuclear generation and power plants equipped with carbon capture and storage technology), electrification of large segments of the transport and heat demand, improvements in energy efficiency and the integration of flexible demand side technologies, among others. All of these will require not only important technological changes and developments, but also significant changes in the worldwide economy.

The multiple changes required to de-carbonise electricity generation are modifying, and will modify even further, the way in which electricity is produced and distributed [15]. In the operational timescale, all these changes will impact the time dynamics of net-demand, greatly increasing its variability and unpredictability, and will require changes to the operation of dispatchable generation [22]. For example, it has already been seen that in power systems with considerable amount of intermittent generation, the traditional operational regime of conventional generation is changing towards one where there a significant increase in the cycling frequency and more prominent power variability of power plants [23]. This is due to the need to compensate for fluctuations in intermittent renewable generation. New electricity demand from the envisaged electrification of transportation and heating will also contribute to increase variability and uncertainty of net-demand, requiring further changes in the operation of conventional generation. In the long-term, on the other hand, the change in the operation of power systems, and the integration of new generation and demand side technologies, will impact on their evolution, and thus, their planning [21].

The design of future power systems and of the market structures and regulations required to support their evolution require updating the planning methodologies and tools that are being used by governments, regulators, system planners, and analysts, among others, as they commonly rely on very simplified representations of electricity demand and power system operation [24]. This is a challenging task because it requires deciding on how much detail of the power system operation should be incorporated into generation expansion planning in order to produce adequate, realistic, more accurate and meaningful results when assessing the long-term expansion of future low-carbon power systems [25].

¹ The Energy Roadmap document [20] suggests that Greenhouse Gas (GHG) emissions in the European Union (EU) should be reduced by at least 80% with respect to 1990 levels. The document sets out milestones which form a cost-effective pathway to this goal (reductions of the order of 40% by 2030 and 60% by 2040) and also shows how the main sectors responsible for Europe's emissions, i.e. power generation, industry, transport, buildings and construction, as well as agriculture, can make the transition to a low-carbon economy most cost-effectively.

The improvement in the operational component of generation expansion planning models and tools necessitates the inclusion of the technical and operational characteristics that determine the unit commitment and power production scheduling for conventional generation. It also means modelling the dynamics of flexible demand side technologies. In other words, new generation expansion planning models need to consider the flexibility characteristics of their generation and demand resources. Flexibility refers to the extent to which a power system, or a component of it, can modify its electricity production or consumption in response to expected or unexpected variations in electricity demand or supply [26, 27, 28, 29].

It is widely recognised that large-scale penetration of renewables will boost the need for flexibility in order to cope with the uncertainty and variability introduced by such intermittent generation into net-demand [13, 30, 15]. The need for more and also new sources of flexibility highlights the role that flexibility will play in the generation expansion of future power systems [14]. Understanding the role of flexibility, and identifying the benefits of investing and using flexibility, is of crucial importance not only from a security and adequacy perspective, but also for the effective and efficient integration of renewables, carbon emissions reductions, and the development of sustainable and efficient future low-carbon power systems .

This thesis develops a comprehensive and exhaustive investigation about the value of generation and demand flexibility, and their economic and environmental impacts. In the demand side, this thesis focuses its attention on the electric vehicles, because they are today considered as one of the most important flexible demand technologies in the near term. This is not only due to their penetration, technological developments and compatibility, but also because they can contribute to improve the energy security by not consuming fossil fuels, and most importantly due to they are a potential mitigation option for carbon emissions. This is especially relevant because the transport sector is the second largest source, after the electricity generation, of energy-related greenhouse gas emissions worldwide [31, 32, 33].

1.2 RESEARCH MOTIVATION, OBJECTIVES & QUESTIONS

1.2.1 *Motivation*

Power systems flexibility, or operational flexibility,² is receiving increasing attention due to a number of reasons, such as:

1. The large-scale penetration of renewables will radically modify net-demand time dynamics, which will translate into the need for additional flexibility that will be required to handle the increased variability and uncertainty introduced by those renewables [13, 15].
2. Increased variability of net-demand will change the operational regime of conventional generation, making low-carbon baseload inflexible generation less efficient for the absorption of renewable energy, reducing its economic viability. Improved flexibility of conventional generation, and flexibility from the demand side, can help stabilize net-

² System flexibility refers to the capability of a power system to respond to expected or unexpected variations in electricity demand or supply.

demand levels, restoring the cost-effectiveness of baseload generation, and also reduce system costs [34, 35].

3. The greenhouse gas emissions reduction targets will require aggressive lowering of carbon emission levels in many countries worldwide [19, 20, 21]. This can be achieved by either increasing the amount of renewable generation constructed or by building baseload low-carbon generation which is frequently inflexible.³

Variability and uncertainty are not new challenges for power systems, as they have existed since the first customer was connected to the first power plant [12]. For this reason, power systems have a range of flexible resources that are used to manage fluctuations in electricity demand and supply [30]. Flexibility has been traditionally associated with quick dispatchable conventional generation. However, balancing demand and supply can also be achieved through the use of other resources, such as storage, demand side management and response, and interconnections to other power systems, among others [14]. The electrification of other energy sectors, such as transport and heating, can also contribute to provide flexibility [34]. Fleets of electric vehicles and space heating devices equipped with thermal storage, can help manage surpluses of renewable energy by using their storage capability if they are smartly controlled, i.e. if their electricity consumption is optimally scheduled.

A large number of studies have shown the operational challenges that large variability and uncertainty in net-demand can cause to the operation of power systems, concluding also that operational flexibility will impact the optimal generation mix that will be required to accommodate large deployments of intermittent generation [13, 30, 15]. However, the vast majority of those studies have limited their extent only to the analysis of power systems operation to show evidence of such conclusion. Generation side flexibility is determined by the technical and operational characteristics that rule the operation of individual generation units. These are minimum stable operation, maximum power output, minimum up and down times, upward and downward ramping capability, among others [36, 37]. On the other hand, demand side flexibility is more complex, as it is not only given by the technical and operational characteristics of the electricity consuming devices, but also influenced by the consumers' preferences and requirements, and the willingness to make modifications in their electricity demand patterns [34]. Those parameters define the flexibility of generation and demand side resources, and traditionally they have been ignored or highly simplified in generation expansion planning [38].

Only when modelling the generation commitment, and the technical and operational constraints that determine the power output and reserve scheduling of a power system, can the flexibility of conventional generation be modelled with sufficient detail [39]. However, power system operation modelling is preceded by a planning phase, so a poor and deficient generation expansion planning phase can potentially lead to suboptimal investment decisions. These decisions are then used as input for detailed operation models, resulting in a vicious circle as the results of those complex operation models are used later to feedback generation expansion planning models. This translates generally into the need for manually adjusting generation investment plans when the generation capacity is not able to handle all expected

³ This can also be achieved using carbon capture and storage technology in gas-fired power plants.

operational scenarios. Generation operation modelling is normally highly simplified or even omitted when analysing and designing energy policies. This means that the role of flexibility is neglected and can affect the decision making process of regulators, system planners, analysts, and other regulatory bodies, resulting in the design of poor, unstable, short-term and suboptimal market structures and regulations.

The practice of separating generation expansion planning and power system operation modelling into two somehow independent phases have been motivated by the complexity of merging both into a single problem. Modelling only the operation of conventional generation requires complex and large size models, which solution is generally time consuming and computationally demanding [40]. For these reasons, the inclusion of the technical and operational characteristics of conventional generation and flexible demand into generation expansion planning leads to computational tractability issues.

Most of the developed generation expansion planning models have ignored so far technology-specific inter-temporal constraints of flexible generation and demand side resources. This thesis aims to contribute to filling this gap by proposing a novel fully integrated generation expansion planning model, which not only explicitly incorporates the operational flexibility of conventional generation and flexible demand (specifically electric vehicles due to their significant penetration and flexibility potential), but that also includes the costs of enabling such flexibility.

1.2.2 Objectives

This research is framed into the Power System Economics area [41, 1, 42], with a specific emphasis on the analysis of the role of flexibility in the generation expansion process from an economic and environmental perspective, for power systems that expect a large-scale deployment of renewables and a wide transport electrification.

The main objective of this thesis and research is to explore the role that generation and demand flexibility will play in the future expansion of power systems, in order to understand its impacts on generation investment and operation, renewables integration, and carbon emissions. It also investigates the value that investing in flexibility can deliver to improve the affordability and sustainability of power systems. These objectives were achieved in the following ways:

1. through an extensive and detailed review of the literature related to the generation expansion planning and flexibility modelling, that surveyed the state-of-the-art techniques, tools and methods used, and which allowed the identification of knowledge gaps;
2. through a rigorous analysis of the economics involved in the generation investment problem, in order to understand why traditional generation expansion planning is becoming less reliable, and how generation and demand operational flexibility can heavily impact the decision making process of regulators, system planners and analysts;
3. through the development of optimization models to represent this economic process, together with generation technical and operational characteristics and the dynamics of flexible demand;

4. through the use of the developed optimization models to simulate, analyse and understand the role of flexibility in the generation investment process and its links with the integration of renewable resources, carbon emissions, and enabling costs;
5. and finally, through the comparison and analysis of theoretical and practical results obtained from the developed models.

1.2.3 Questions

The research conducted and summarized in this thesis, will address the following three research questions:

Q₁: What are the impacts of omitting generation and demand side flexibility modelling in the generation expansion of future power systems with a large volume of intermittent renewable resources?

To understand how power systems operation and expansion are being affected by the large-scale penetration of renewables and the electrification of the transport sector, it is necessary to develop a generation expansion model that incorporates an accurate representation of the real operation of conventional generation and flexible demand in modern power systems. Such model will enable an understanding not only of the impacts of the large-scale deployment of renewables and vehicle electrification, but also the role that flexibility plays in this new scenario. The objectives that arise from this research question are:

- Develop the modelling methodology, and implement a computationally efficient algorithm, that allows considering the technical and operational characteristics, i.e. the operational flexibility, of conventional generation and flexible demand.
- Compare the results that traditional generation expansion planning models produce against those obtained with the developed model.
- Evaluate the long-term economic and environmental consequences of ignoring flexibility.
- Estimate the renewable energy curtailment levels that can be expected if the technical and operational limitations of conventional generation are considered.
- Calculate the additional costs of including flexibility in generation expansion planning.

Q₂: What are the operational, economic and environmental benefits of investing in conventional generation flexibility, and how do those benefits change for different levels of renewable generation?

Investing in the improvement of conventional generation flexibility characteristics of the different conventional generation technologies can generate a wide range of economic and environmental benefits at multiple timescales. In order to assess the magnitude of those benefits, it is required to run a series of suitably designed case studies that integrate the improved operational flexibility of conventional generation. By comparing the system performance with

and without the flexibility improvements, it is then possible to estimate the benefits created by such investment. The objectives that arise from this research question are:

- Design and implement case studies to quantify the system benefits of investing in improving the different flexibility parameters of available conventional generation technologies.
- Quantify the system benefits of the different flexibility enhancements by estimating the improvements in the system performance compared to the cases where the flexibility characteristics were not modified.

Q3: What are the society benefits of promoting and using flexible electric vehicles?, How can those benefits change for different penetration levels of electric vehicles and renewable generation?, How much should customers be willing to pay for it?

To understand how power systems operation and expansion can benefit from using demand side flexibility, specifically that from electric vehicles in this thesis, the generation expansion model must incorporate a detailed modelling of the temporal dynamics and technical characteristics of their electricity demand. Additionally, if the optimal deployment of flexible electric vehicles needs to be estimated, the model must account for the cost of enabling such flexibility. Such an improved generation expansion model will enable the understanding of firstly the benefits that using electric vehicles flexibility may generate at different timescales and sectors of future power systems, secondly, how such flexibility can help integrate renewables and reduce carbon emissions, and thirdly, how electric vehicles users may react to the cost of the technology required to convert an inflexible electric vehicle into a flexible one. The objectives that arise from this research question are:

- Develop the modelling methodology for efficiently incorporating flexible and inflexible electric vehicles into the developed generation expansion planning model.
- Design and implement case studies to quantify the long-term economic and environmental benefits (or consequences) of using (or ignoring) electric vehicles flexibility, and to estimate the optimal deployment of such flexibility depending on its enabling cost.
- Estimate the renewable energy curtailment levels that can be expected if electric vehicles are operated as flexible loads, or considered as inflexible loads.
- Calculate the additional costs of including electric vehicles flexibility in generation expansion planning.

1.3 SCOPE & METHODOLOGY

1.3.1 Scope of the research

The developed model and the analysis and results presented in this thesis will be useful for the different stakeholders involved in the generation and consumption of electricity, as well for

those who are in charge of overseeing and controlling this industry. The analysis and results presented are expected to create awareness within regulators, system planners, energy and environmental analysts, among others, about the short and long-term impacts that flexibility has on the integration of renewables, reduction of carbon emissions, security of supply and resource adequacy, and also the value that investing in flexibility can create for society. They also provide clear evidence that ignoring flexibility in the generation expansion planning of power systems can potentially lead to suboptimal generation investment decisions, and also to the design of the inadequate market structures, regulations and incentives, which will inhibit the market conditions required to deliver secure, affordable and sustainable low-carbon power systems. The model, on the other hand, is expected to be useful for regulators, system planners, policy analysts, governmental and non-governmental agencies, smart-grid technology developers, and researchers, among others, as it could help to assist their individual decision-making processes.

1.3.2 *Research methodologies*

Different methodologies have been used to analyse the generation expansion planning problem. Those methodologies were used to study and understand the relationships and impacts of flexibility on generation expansion from an economic and environmental perspective. The methodologies used during this research were:

- Screening Curves Analysis.
- Linear Programming.
- Mixed-Integer Linear Programming.

The Screening Curves Analysis was used to analyse the economic foundations of the optimal generation investment problem from a theoretical point of view. On the other hand, Linear Programming was used to make the bridge between the economic analysis developed using the Screening Curves technique and the traditional optimization formulation of the generation expansion planning problem. The purposes of these analyses were: a) understand and identify the weaknesses of the traditional methods used for generation expansion planning; and b) explain why not considering net-demand dynamics and generation and demand side flexibility are limiting their applicability in modern power systems. Finally, Mixed-Integer Linear Programming was used to develop and formulate the large-scale mixed-integer linear optimization model proposed in this thesis to model the generation expansion planning problem considering the flexibility characteristics of conventional generation and flexible electric vehicles.

1.4 RESEARCH CONTRIBUTIONS

In addressing the research questions formulated in Section 1.2.3, the following original contributions are made by this thesis:

- Development of a computationally efficient generation expansion planning model that allows the assessment of the short and long-term economic and environmental performance of power systems with large volumes of renewables and high degrees of transport electrification.
- Development of a methodology for capturing, modelling and incorporating a detailed representation of the technical and operational characteristics of flexible demand, in the form of large fleets of smart charging electric vehicles, in generation expansion planning. Electric vehicles are grouped into different types using the concept of clustering, which allows avoiding non-linearities in the model formulation.
- The developed generation expansion model, apart from including the full set of different conventional generation technologies flexibility characteristics, allows to optimally scheduling the electricity demand of flexible electric vehicles according to a detailed model of their users' travelling requirements and batteries/grid connections' technical properties.
- In contrast to previous works, the enabling costs for introducing and coordinating electric vehicles flexibility are explicitly incorporated in the proposed model. This allows determining the optimal number of flexible electric vehicles along with the optimal portfolio of generation assets.
- Compare and quantify the economic and environmental implications of considering conventional generation flexibility characteristics in generation expansion planning, with respect to traditional expansion planning that neglects them.
- Analyse and quantify the economic and environmental impacts of carbon emissions regulations and their potential interaction with power system flexibility.
- Estimate and quantify the economic and environmental benefits that can be achieved by investing in the improvement of conventional generation flexibility characteristics and how those benefits change depending on the enabling costs, under different scenarios of renewable generation and vehicle electrification.
- Comprehensive assessment of the economic and environmental implications of inflexible electric vehicles operation, and the benefits that can be obtained by smartly controlling their electricity consumption.
- Analyse the relationship between the value delivered by electric vehicles flexibility, the cost of the technology required to enable such flexibility, and the users' travelling patterns. This allows identifying and informing industry stakeholders regarding the types of electric vehicles that create more value when becoming flexible.

1.5 THESIS STRUCTURE

In order to achieve the objectives of this research, address its research questions and deliver the proposed original contributions, this thesis is divided into seven chapters as follows:

CHAPTER 2 starts by providing an overview of electricity markets, briefly analysing current market structures and their main characteristics, the market failures and regulations, and the sources of uncertainty in the generation business. Then, it briefly analyses the market reform started in Great Britain in 2010 to show a concrete example of the reaction of a government because its concern about the security and adequacy of its power system due to the challenges to which the electricity industry is and will be exposed. Finally, it analyses the generation business and expansion planning history over the last seventy years, describing its evolution, the current state, and the state-of-the-art methodologies and tools used for generation expansion planning, and concludes with a discussion about why flexibility must be considered in the design of future low-carbon power systems.

CHAPTER 3 analyses the traditional generation expansion planning, in order to understand why traditional planning methods nowadays lack of validity. From a centralized perspective and by using the Screening Curves technique, the optimal generation investment economics are analysed in depth, dissecting the market failures, regulations and market structures, and their influence in this economic activity. Optimization theory is then used to establish the bridge between the previous pure economic analysis and the traditional Linear Programming formulation of the generation expansion planning problem. Finally, the last portion of this chapter analyses why generation and demand flexibility matters today and in the future of power systems, and also why the vast majority of generation expansion planning methodologies and tools used by regulators, system planners, and analysts, needs to be updated in order to consider flexibility.

CHAPTER 4 describes the methodologies developed for capturing and modelling the flexibility characteristics of conventional generation and flexible demand, which are then used to build a novel and fully integrated large-scale mixed-integer program which is designed to model in one stage the generation expansion and operation of power systems with a high penetration of renewables and electric vehicles. This chapter starts by analysing the meaning of flexibility in generation and demand, and how these are modelled. In parallel, it also develops the different building blocks of the proposed model and ends by presenting the full model formulation.

CHAPTER 5 assesses the economic and environmental impacts of conventional generation flexibility through three case studies. The first case study compares the results obtained by using a traditional expansion planning model formulation, and those obtained when the flexibility characteristics of conventional generation are included in generation expansion planning. The second case study analyses the impacts that carbon emissions regulations can have in the future expansion of power systems and how these regulations can affect power systems flexibility. The third and last case study explores the economic and environmental benefits that can be obtained by investing in improving different flexibility characteristics of conventional generation technologies, specifically minimum stable generation, minimum up and down times, and ramping capability. Finally, some general conclusions are outlined at the end of this chapter.

CHAPTER 6 assesses the economic and environmental impacts of demand flexibility in the form of smart charging electric vehicles through two case studies. The first case study analyses the consequences of not using the potential flexibility from electric vehicles and the benefits that using such flexibility can have at different timescales and sectors of power systems. The second case study analyse how the value created by flexible electric vehicles depends on the flexibility enabling cost and users' travelling patterns.

CHAPTER 7 outlines the key conclusions and messages of the research summarized in this thesis, and identifies the areas for further research.

Part II

ELECTRICITY MARKET & TRADITIONAL GENERATION EXPANSION PLANNING

A REVIEW OF ELECTRICITY MARKET FUNDAMENTALS & ISSUES

The continuous growth of electricity demand since its first commercial uses in the late nineteenth century, resulted in its historical development and expansion. The fast evolution and technological development of the electricity industry showed the economical inefficiency of the monopolistic structure under which this industry operated since then, and it was not until the last third of the twentieth century when this structure underwent radical changes in many countries around the world due to the growing demand for this commodity.

The breakdown of the monopolistic business of the large vertically integrated state companies, and its shifting to a competitive structure, was the first step in the electricity industry restructuring process. Although the restructuring, privatization and deregulation of the electricity industry brought competition and improved market efficiency, leading to reductions in electricity prices, regulation was and is still required. This regulation, plus the uncertainty naturally linked to the generation business, have led to the weakening of incentives for new investments, and because of this, to create concern in governments about resource adequacy and security of supply in the short and long-term.

A brief introductory literature review is presented in this chapter, in which the evolution and characteristics of the electricity market are analysed, especially over the last three decades, with the focus on the generation business and expansion planning.

2.1 RESTRUCTURED ELECTRICITY MARKETS

The demand for electricity, which started with the Second Industrial Revolution that happened between 1870 and 1914 [43], and its continuous growth since then, resulted in the historical development and expansion of the electricity industry. The fast evolution and technological development of this industry [44], promptly showed the economical inefficiency of the monopolistic market structure under which the electricity industry operated since then, and it was not until the last third of the twentieth century, when this framework underwent radical changes in many countries around the world, which sought meeting that rising demand for electricity in quantity, quality and price.

The first step in the electricity industry restructuring was the breakup of the monopolistic business of the large vertically integrated state companies, which led to the liberalization of the generation business and its opening to competition [8, 45]. However, freeing the generation business did not lead to perfect competition, nor the desired resource adequacy behaviour, and new regulations and market arrangements were implemented in reaction to those problems

[46, 11]. This resulted in a highly dynamic adjustment process that has not stopped since then, because of the new challenges that the electricity industry faces every day.

2.1.1 *Market structure*

The restructuring and deregulation process that took place during the eighties in many countries around the world [5, 7, 9] led a deep change in the electricity market structure, as well as in the organization of the electricity companies.

The restructuring, privatization and deregulation of the electricity industry shifted the monopolistic business of the large vertically integrated state companies by a competitive activity in the generation arena [47]. However, the transmission and distribution segments of the electricity industry, due to the nature of their businesses, in general remained as monopolistic activities and are under strict regulation [46, 10].

Competition meant that the electricity prices were not fixed by the large state companies anymore. However, the size of the generation market and the number of participants are, in most cases, not very large and do not create the required conditions for competition [48], and thus, complete deregulation was and is still not possible. Market power abuses, exercised by dominant generation companies, plus the size of the electricity markets in many countries, forced governments to keep in place strict monitoring and regulation of the market [11].

2.1.2 *Market pricing issues*

The freeing of the electricity industry and, in particular, the opening of the generation business to competition did not result, in most cases, as was expected. Perfect competition conditions have not been reached because poor market structures and different types of market failures (short-term inelasticity of demand, market power abuse, market intervention, unpriced products, entry barriers, etc.) [49, 11, 50].

One of the market failures that was of particular interest for this research is the price responsiveness of the demand for electricity [51]. The short-term demand for electricity is today almost perfectly inelastic due to several reasons, such as, the fact that most consumers are not exposed to real time energy prices (this is related to the current lack of real-time metering and billing [52, 53]), and because in general there is no substitution for this commodity.

The inelasticity of electricity demand creates a market failure when demand is larger than supply, because there will not exist a market clearing price due to the fact that demand and supply curves fail to intersect, as shown in figure 2.1.

2.1.3 *Regulation*

The market failures and imperfections, and the market designs created to try to repair them, have required the constant intervention of the electricity market through different types of regulatory measures such as new market frameworks, tariff regulations, revenues and price caps, among others [1, 46, 11, 10].

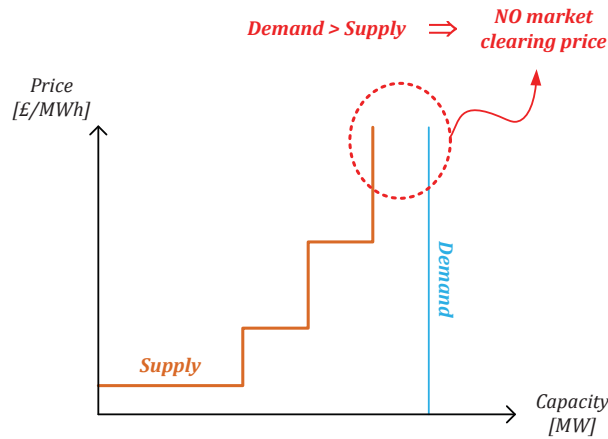


Figure 2.1: Conceptual representation of market failure created by the inelasticity of electric demand when there is lack of generation capacity.

The failure of the market in providing the required price signals to ensure resource adequacy and security of supply in the most cost-effective way, is today the main issue that governments must overcome. This objective must be accomplished through new regulations, which allow the regeneration of the necessary incentives for generation investment [54].

2.1.4 Market uncertainties

The efficiency of the market, which was improved by the transition of the generation business to competition and led to lower costs for consumers, brought a host of other problems related to the investment process for investors. One of the most significant effects of the electricity market restructuring was that the old and inefficient central planning of the generation expansion, evolved into a dynamic and competitive process that attracted private investors to the generation market [55].

The expansion of this area of the electricity industry is driven today by the inherent economic aspects related to this business, such as demand, fuel prices, new regulations, and electricity prices, among others, all of which are considered by private investors when they assess their investment projects. Notwithstanding the growth rate of electricity demand seems to be increasing in most countries around the world, in the medium and long-term there is a generalized concern about the generation market expansion and its adaptation to the penetration of larger amounts of intermittent renewable resources, as it is the case of Great Britain (GB).

2.2 ELECTRICITY MARKET: ENERGY, CAPACITY & SECURITY OF SUPPLY

The market structure¹ widely adopted once the industry restructuring took place, with the aim of making the market efficient, was the competitive Energy-only-Market (EoM) design [56]. In simple terms, under this market framework generators and consumers compete in the wholesale market submitting their offers and bids respectively, and the market equilibrium is

¹ The market structures are analysed from a high level point of view in Chapter 3, not entering into details about how the electricity products and services are traded.

reached when supply and demand are matched.² Then, only the energy and ancillary services delivered by suppliers are the resources that are paid in this type of market structure.

Several defects have been identified and argued against this market framework. The primary argument is that it does not provide the correct and necessary price signals to ensure enough and stable generation investment, and in this way resource adequacy [50, 57]. Although, many improvements and modifications have been proposed, some of which have been implemented into this market design in countries around the world, the problems persist, which may suggest that the main issue is not related to the market structure, but with the level of market intervention exercised by governments [58].

Looking to induce the market to create the appropriate type and level of price signals, Capacity Markets (CM)³ (in addition to energy markets) were introduced in order to provide the right incentives to support investments at the appropriate levels, in the correct locations and of the right types [59]. Supporters of capacity markets claim that this market structure ensures resource adequacy [60] and improves the operational incentives for generating companies. Detractors on the other side, have shown evidence that this is not necessarily true and even more, that they did not lead to the least cost solution [61].

Capacity markets rely on capacity payments as the main driver to ensure the proper levels of generation investment [59, 62]. Under this market structure, generators should compete to supply the capacity required to meet the reserve margins established to ensure reliability of the system.⁴ Different kinds of results have emerged from the distinct implementations of this market structure, and in most of the cases, this framework has required further modifications to comply with the expected results [63, 64, 65].

The debate on which market structure will prevail as the most suitable one to “keep the lights on” is an active area of discussion [66, 67, 68, 69, 70], in which there is no consensus. Further research on this topic is needed, as their results will play a key role in the future development of the electricity generation business worldwide.

2.3 GREAT BRITAIN & THE ELECTRIC MARKET REFORM

The challenges that today arise in the electricity market, such as CO₂ emission regulations, high fuel prices, inefficient price signals, market power, intermittent renewable generation incorporation requirements and obligations, international importation and exportation energy agreements, Demand Side Response (DSR), and depletion of fossil fuel reserves, among others, suggest that a major restructuring of the industry is going to be necessary in the coming years.

A recent example is the industry restructuring process that started in 2010, which was motivated by the UK’s government concerns with the capacity generation expansion in GB and the inevitable compromise in security of supply and resource adequacy as a product of the renewables agenda and the lack of investment incentives. New regulations and changes to the

² The function of clear and settle the market is typically made by the market operator or a special-purpose independent entity.

³ In Chapter 3, the concept of Capacity Markets is used to refer to Capacity Mechanisms sometimes, but they are not the same, and when needed, a proper distinction will be made. Capacity markets are a type of capacity mechanism.

⁴ This corresponds to a CM where capacity resources are traded in the market.

GB's electric market framework were proposed in Electricity Market Reform (EMR) document released by UK's government in late 2010 [71], which aimed to create long-term incentives to attract investors in conventional low-carbon and renewable generation technologies. These market reforms look to provide greater certainty to generation investors through four key elements:

- Provide a clearer long-term price for carbon, by putting in place a carbon price floor.
- Set out long-term contracts for low carbon generation that will make more attractive the investment in clean energy generation technologies.
- Introduce additional payments to encourage the construction of reserve plants or demand reduction measures for security of supply.
- Introduce a back-stop to limit how much carbon the dirtiest power stations (coal) can emit through the use of an Emissions Performance Standard (EPS).

The UK's government proposed new reforms look to establish the basis for a sustainable economy, and in that way, they aim to ensure the development of the electricity market, through providing greater certainty for investors. This effort is their first step towards maintaining secure and affordable electricity supply to customers, and to achieve cost-effectively the UK's 2030 and 2050 decarbonisation targets.

Similar restructuring of electricity markets in many other countries have also been initiated, and four essential objectives can be identified:

1. solve market failures and imperfections;
2. replace high-emission and ageing generation fleets;
3. achieve cost-effectively decarbonisation targets and renewables integration;
4. and, maintain electric supply security and affordability to customers.

These objectives highlight the relevance of advanced generation expansion planning models, as they will assist governments in their decision-making processes when deciding on the modifications required to their electricity market structures and regulations, so as to achieve those targets in an effective and efficient way. This translates into the need for new models that are not only able of handling different market structures and regulations, but also able of incorporating a detailed representation of power system components and operation.

2.4 THE GENERATION BUSINESS IN RESTRUCTURED ELECTRICITY MARKETS

Since the 1950's, the modelling of the operation and expansion of power systems has been under continuous development [72]. The research in this field has been motivated by two factors: technical and economic. From the technical point of view, aspects such as security of supply and quality of the service were the most important when deciding the planning of both, the operation and expansion of the system when the industry was vertically integrated. However, although such aspects are of great interest to electricity owners and consumers, since

it occurred the restructuring of the electricity industry, its market and regulatory framework, economical aspects are of far greater importance due to the associated risks as result of this transition [73].

The breakdown of the vertically integrated world of the electricity industry during the 1980's, where countries such as Chile [74, 5], UK [7, 75, 76] and US [9, 77] were pioneers, brought competition into the energy wholesale market, and as result, electricity prices were not established any longer by the large state electric companies. The separation of the generation segment, as a competitive activity, shifted the inefficient central planning generation expansion of the monopoly by a competitive activity, where the inherent economical aspects related to the generation business define today the expansion of this area of the electricity industry.

2.4.1 *Generation expansion planning*

General overview

Electricity demand supply is a problem that involves many aspects of power systems, and that needs to consider a series of technical, operational, temporal and economic factors. The Generation Expansion Planning (GEP) problem is basically the exercise of calculating the optimal generation capacity mix that is required to satisfy electricity demand over a period of time. Since providing electricity requires having the generation resources to do so, this exercise must to be done in advance and over a long-term horizon, as the construction of those assets may involve many years before they are effectively able of providing electricity.

Before the breakdown of the electricity industry during the 1980's, electricity was mainly provided by the large vertically integrated state companies. Those companies used GEP to determine the required mix of generation capacity, i.e. type and size of the generation plants, to build in order to provide electricity to customers. This process was generally not efficient, as there was no incentive for those companies in finding the minimum cost generation mix, and instead the planning was performed mainly over the basis of system security measures, leading to oversized and costly power systems.

The deregulation of the electricity sector changed this panorama, as the introduction of competition in the generation business meant that some or all the generation, and also the planning process, was not controlled anymore by the state companies. However, full deregulation has not been possible, and the relevance of centralized planning is still a key role of regulators when designing the market structures and regulations required to achieve their targets in terms of capacity expansion, security of supply, resource adequacy, and CO₂ emissions reduction, among many others.

Competition in the generation arena however has made planning of power systems a complex, dynamic and diverse process, as it is not any longer conducted by a single entity, but instead by many at the same time, each of them with specific and different objectives. The objective of private generation owners and investors are most of the time antagonistic to those of regulators, as the former look to maximize their profits, and the latter look to maximize the benefit of all market participants. These interests conflict has derived in the need for a

strict regulation of the electricity market, which has introduced distortion in the market price signals [78], and therefore, impacted the socially optimal capacity expansion of power systems [79].

Electricity market interventions, and the distortions that these have introduced into price signals today highlight the relevance of indicative generation planning tools to assist regulators in their decision-making process [25]. Indicative planning refers to the centralized planning process that allows regulators to assess the design of market structures, regulations, incentives, etc. Traditionally such process has relied on very strong assumptions and simplified representations of power systems technical and economical characteristics, which has translated into the design of deficient and unstable energy policies, and as a result, into weak long-term price signals for generation investment.

Generation expansion planning involves two main components, i.e. the investment and the operation of power systems. The first component corresponds to the investment decisions that need to be taken in order to decide on what type of generation capacity should be built and when. The second component, on the other hand, corresponds to the decisions on how the available generation capacity must to be operated, so it is conditioned by the investment decisions that have been taken. This sequence of decisions that need to be taken defines a very complex and interrelated problem that traditionally has been simplified by partitioning the planning process into two types of problems. The first type focuses on the investment decisions, assuming a highly simplified modelling of the power systems operation [80, 81, 82, 83]. The second type, concentrates on a detailed modelling of the operational aspects of power systems by assuming a given generation portfolio [84, 85, 86].

The complexity of modelling capacity planning in full detail has been for long time one of the reason why the decoupling of generation expansion planning and operational modelling practice is still in use. However, the fundamental issue with this partitioning of the planning process is that it breaks the natural sequence of the problem, underestimating the undeniable and non-trivial interactions that exist between investment and operational decisions, which ultimately leads to suboptimal solutions for the generation expansion planning process.

Another argument traditionally used to support these practices is that chronology of demand is not relevant, as historically electricity demand varies smoothly and with a rate slower than the response time of conventional generation. However, the large-scale penetration of renewables is modifying the way in which power systems are operated, as their energy contribution is changing the time dynamics of net-demand, making it less predictable and much more volatile. This has been exacerbated even further by the electrification of other energy sectors, such as transport and heating. This new scenario makes the former assumption not valid anymore, due to the required changes in the operation of conventional generation also impacts its investment.

New generation expansion planning tools are required to improve the planning role of regulators, system planners and analysts, so they can create stable and long-term market structures and regulations. This requires the development of fully integrated generation expansion models that are able to combine both, the short-time dimension of generation operation, and the long-term dimension of the investment process.

In this thesis, a fully integrated GEP model is presented, which successfully combines the long-term dimension of the generation investment process, with the short-time scale of power systems operation. The model incorporates not only a detailed modelling of the operation of conventional generation, but also those of flexible demand. This model is used to explore not only the interaction between generation investment and operation, but also the impacts of flexible demand on those decisions. Additionally, the value of investing in generation and demand flexibility is analysed in depth.

Generation expansion planning history

The GEP looks to optimize the generation capacity expansion of a power system, in order to assist regulators and other market stakeholders in their individual decision-making processes [25]. This is a complex and challenging problem because the multiple dimensions that involves. The GEP problem is non-linear, non-convex, combinatorial, dynamic, stochastic, multiperiod and by nature discrete [87]. Due to the large magnitude of the problem, typically only some of those dimensions are included depending on the specific application, which has given place to a wide variety of models since the middle of the last century.

Since the 1950's, the modelling of the operation and expansion of power systems has been under continuous development. First attempts of optimizing GEP used graphical approaches [88, 89], and it is in 1957 when the GEP problem was formulated by Massé and Gibrat as a LP model by first time [90]. In [91], Anderson reviews, develops and tests quantitative methods of appraising investment in electricity supply,⁵ and Bessière in [93] describes the optimization methods utilized by Électricité de France (EDF) when choosing electrical production equipment during the 1950's and 1960's. Sasson and Merrill in [94], present a wide review of mathematical optimization applications to power system problems.

Bessière in [95] presents a detailed description of the "Investment '85" model used by EDF for their investment decision problems. This model is an expanded version of the model developed by Massé and Gibrat [90], which was modified in order to consider time varying demand and was solved using computers. Despite the limited capability of computing equipment on those years, this first computational implementation of the GEP problem constitutes a milestone in the development of capacity expansion models. Since then, the progress in the computing area and the development of new algorithms and solvers, has translated into a rapid progress in the GEP modelling, which has allowed developing and solving more complex representations of this problem.

The use of Load Duration Curve (LDC) was the most popular approach used by the early GEP graphical methods, and their use has persisted until today as they provide valuable intuition about the economics involved in the electricity market, and are useful to understand its behaviour. In [88], Kirchmayer, et al. use LDC to analyse and determine the optimum economic size of steam-electric generating units, and Galloway, et al. use them to develop a method for evaluating the economics of low-cost peaking generation, which was solved using a digital computer procedure [96]. Many others works using LDC can be found in the literature, within which stand out the works of Marsh and Wright [97], Jacoby [98], Booth [99], and Caramais

⁵ This work was later summarized by Anderson in [92].

[100]. Marsh and Wright introduce angled availability in the LDC in order to account for generation maintenance occurring during non-peak hours, and Jacoby develops a method to include hydro generation in the LDC method. Booth, on the other hand, proposed a method based on probability distributions and dynamic-programming in order to account for generator outages, and Caramanis, et al. extended Booth's work in order to include non-dispatchable generation.

Recent works using LDC include those of Ramos, et al. [101], and Batlle and Rodilla [102]. Ramos, et al. present a non-linear static optimal generation model based on the use of LDC, in which they include a detail representation of hydro resources costs and technical characteristics. Batlle and Rodilla, on the other hand, develop the traditional screening curves technique, which is based on the use of the LDC, in order to incorporate cycling operation of thermal units.

The computing developments between the mid 1970's and 1980's allowed improving GEP models by modelling the LDC in greater detail. Including non-sequential representations of LDC became popular, as it allowed the capture of demand variations in different time scales (daily, weekly, seasonally, etc.). This was complemented by further developments in the optimization area, which resulted in improved and new optimization methods. Those were used to create some very famous models that are still in use today, such as MARKET ALlocation (MARKAL) [80],⁶ Wein Automatic System Planning package (WASP) [81],⁷ and Electric Generation Expansion Analysis System (EGEAS) [104].⁸

Since the late 1980's and until today GEP models have been under continuous and rapid development, which is characterized by models of increased complexity and wider extension, such as the inclusion of Demand Side Management (DSM) [105, 106], Integrated Resources Planning (IRP) [38], price-elastic demand [107, 108], markets and competition [68, 109, 83], transmission expansion [110, 111], multiple objectives [112, 113], and uncertainty [114, 115, 116, 117, 118], among others.⁹ All new extensions of the GEP problem have been possible due to the development of new optimization algorithms and techniques, that allow handling the large-scale of the problem. Within those is possible to mention expert systems, neural networks, fuzzy logic, genetic algorithms, and cross-entropy, among others. However, those techniques are complex and require a good amount of calibration, which restricts their use and applicability. Nevertheless, improvements in commercial solvers for LP, Mixed Integer Programming (MIP) and Non-Linear Programming (NLP) models are enabling quick and rich

⁶ MARKAL is an integrated long-term multi-sector energy model used to carry out economic analyses of different energy related systems at global, national and municipal level over a time frame of up to several decades. The model was developed in the late 1970's by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA) [103].

⁷ WASP is a generation expansion planning model that takes into consideration fuel availability and environmental constraints, that was originally developed in 1982 by the Tennessee Valley Authority and the Oak Ridge National Laboratory in US. The model was develop to analyse the economic competitiveness of nuclear power generation in comparison to other generation expansion alternatives for supplying the future electricity requirements of a country or region.

⁸ EGEAS is a modular generation expansion model that can by used to produce integrated resource plans, evaluate independent power producers, develop avoided costs and environmental compliance plans, and analyse life extension alternatives. The model was developed in the early 1980's by Massachusetts Institute of Technology (MIT) and Stone and Webster Engineering Corporation, under the sponsorship of Electric Power Research Institute (EPRI).

⁹ Interested readers are referred to [91, 119, 87, 79, 120], for further details on the generation expansion modelling at different stages of history.

implementations of GEP models, as they allow decoupling the model from the solution procedure, and is attracting the attention of researchers, system planners and analysts [121, 122, 123].

Despite all the progress on optimization techniques and solvers, in most of the cases GEP modelling still relies on very strong simplifications of the operational characteristics of power systems, which underestimates their impact in the long-term investment decisions. Large-scale renewables integration is heavily affecting the operational regime of conventional generation, as their contribution to electricity supply is changing the time dynamics of net-demand. This is translating into increased system flexibility requirements in order to make an efficient and effective use of those resources, revealing the need for considering generation and demand flexibility in generation expansion planning. This thesis aims to contribute to filling this gap by conducting a deep analysis of the role that flexibility will have in the future expansion of low-carbon power systems.

2.4.2 *The role of flexibility in future expansion of power systems*

There is a generalized agreement that large-scale penetration of renewables will demand large amounts of system operational flexibility in order to achieve an efficient and effective integration of those generation resources. Such a fact has been recognized by several recent reports and publications, which highlight that current GEP models fail in modelling the flexibility characteristics of power systems, and thus, in properly assessing the impact of such simplification in generation expansion planning [13, 30, 15, 124, 27]. While the issue is recognized, no further efforts are made in order to update available models and tools in order to incorporate flexibility, and instead flexibility metrics are proposed [26, 28, 29, 15].

Flexibility assessment today is primarily performed using highly detailed generation operation models (software packages), that are capable of modelling the complex technical and operational characteristics of generation resources, transmission constraints and power flows, generation outages, and maintenance, balancing mechanisms, market structures and regulations, etc.¹⁰ However, those proprietary models are expensive, require big input databases, and in general operate as black-boxes, and does not make them flexible for incorporating new and future technologies (renewables, storage, electric vehicles and heating, etc.).

In response to the lack of modelling flexibility and restricted access to commercial generation operation software packages, researchers have recently developed models that fill this gap, keeping data requirements at an accessible level, being open source, and allowing the incorporation of new features and technologies.¹¹ However, those models only address the operational part of the generation expansion process, require the inputting of the generation expansion plans data, and generally have a simple representation of system operational flexibility characteristics. This is due to the computational burden and time that including those characteristics in the generation expansion planning modelling demands. Additionally, regulators, system planners and analysts typically do not consider operational models when

¹⁰ Interested readers are referred to [125, 122, 120, 126] for extensive and up-to-date reviews on electricity systems models.

¹¹ Examples of those models are Wind Power Integration in Liberalised Electricity Markets (WILMAR) [127], Reliability and Operation Model (ROM) [128], StartNet and StarGen [129], among others.

assessing new market regulations and energy policies, which means that power system flexibility is either not considered or highly simplified.

Notwithstanding the global awareness of the interactions between system operational flexibility and the large-scale renewables integration, a reduced number of works have explored rigorously this in the context of generation expansion planning. Rosekrans, et al. in [130] present and compare the generation planning results obtained using the Elfin¹² and WASP models, and they highlight the dramatic differences obtained when the model's features include or not a detailed characterization of the thermal power plants' operation. However, their work does not consider the impact of renewables, CO₂ emissions, nuclear generation and hydro plants. In [131], Deng and Oren analyse the implications that generation operational constraints may have on the valuation of generation assets, finding that such valuation depends on the model specification and the nature of the operating characteristics. Nonetheless the interesting results obtained in this work, the model developed is not for generation planning but for valuation of generation capacity, and due to the stochastic formulation limited to short time assessment horizons.

Shortt and O'Malley develop two algorithms for including operational technical characteristics into LP GEP models in [132], concluding that traditional methods for generation expansion planning have to be changed when considering intermittent generation, as the conventional generation associated cycling costs have great impact on investment decisions. Despite that Shortt and O'Malley have developed interesting heuristics for including production costs into capacity planning, the iterative updating of the generation capacity makes the methods unreliable for properly evaluating the capacity expansion process.

Better approaches for evaluating operational flexibility impact into capacity planning are those developed by Kirschen, et. al [40], Sisternes [133], Palmintier and Webster [134], and Ramírez, et. al [34]. which are the first known efforts of including the modelling of the technical and operational constraints of conventional generation into a long-term GEP model. Kirschen, et. al, and Sisternes, both develop binary generation expansion models that include unit commitment decisions and constraints, and analyse their impact when considering renewable resources. However, Kirschen, et. al analyse a small generation system, and Sisternes only considers minimum stable generation and ramping constraints. The binary GEP formulation presented on those works also limits their applicability for large and more detailed power systems, due to the exponential explosion of the solution space created by the investment and unit commitment decision variables, that leads to tractability issues with those models. Palmintier and Webster, and Ramírez, et. al, on the other hand, overcome this tractability issue by using a clustering approach in their GEP models formulation, thereby being able to model large power systems with detailed conventional generation operational constraints. Nonetheless, Palmintier and Webster only focus on analysing the impact of the conventional generation operational constraints on the optimal generation matrix, and do not include any type of flexible demand resources, thereby underestimating the undeniable value that demand flexibility will have in future power systems development. Ramírez, et. al go a step further by including

¹² Elfin is a production costing and capacity expansion planning model developed in the 1980's by the Californian part of the Environmental Defense Fund in US, and that is used today by the Californian Pacific Gas & Electricity, large utilities and Non-Governmental Organizations (NGOs) in several countries.

flexible EV in their GEP model, which they use for analysing the impact that this demand-side flexibility may have in capacity planning. All these works show clear evidence of the impact that flexibility modelling has on generation expansion planning, but none of these works analyse the value that investing in flexibility may have in future expansion of power systems.

The need for new and fully integrated GEP models is clear [24], as they will assist regulators in the design and implementation of market structures and long-term energy policies, that will induce stability in the energy markets and long-term price signals that will lead to the development of sustainable and efficient future power systems. This thesis develops a GEP model that incorporates a detail modelling of the flexibility characteristics of conventional generation and demand-side technologies, specifically electric vehicles, in order to explore the role that flexibility will have in the development of power systems with large contribution of renewables and transport electrification.

GENERATION INVESTMENT ECONOMICS & ITS LP FORMULATION

The generation expansion optimization problem is non-linear, non-convex, combinatorial, dynamic, multiperiod, discrete, and innately stochastic. Nevertheless, several acceptable assumptions and simplifications can be made in order to create a feasible problem, manageable with the computational tools that are currently available. However, a compromise in the accuracy of the results is inevitable when the model's degrees of freedom (uncertain elements) increase.

As analysed in Section 2.4.1 of the previous chapter, a considerable number of modern GEP models still use LDC in their formulations, and those are actively used by regulators, system planners, energy analysts, utilities, NGOs, etc. Although the applicability of LDC analysis in modern power system is being restricted due to the validity of the strong assumptions on which it is based, they still provide a rich and good insight into the economics involved in the generation investment process.

In this chapter the optimal generation investment problem is analysed using a graphical approach. Starting from a pure economic perspective, and using the LDC and the Screening Curves, this problem is analysed and dissected in order to understand the economic implications that different market structures and energy regulations have in this process. Then, using mathematical programming, an equivalent LP model is formulated. Finally, the last section of this chapter analyses why modelling flexibility is important in power systems with large-scale integration of renewables and high penetration of flexible demand technologies.

3.1 OPTIMAL GENERATION INVESTMENT ECONOMICS

The multiple challenges that the electricity industry face today are associated with a significant element of financial risk for generation investment. On the other hand, governments begin to fear an imminent compromise of the resource adequacy and security of supply in their power systems as result of the incorporation of large amounts of renewables.

For this reason, enormous interest¹ is presently being shown in the economic modelling of the generation investment process, looking for models that can reliably evaluate possible outcomes of this economic activity. Investors on one side, seek to minimize the risk of their investments, and governments on the other, seek the proper energy policy designs that will crucially define the generators and consumers' behaviour, as well as the market framework

¹ For a complete survey of the critical research areas in the energy segment of restructured electric power markets refer to [135].

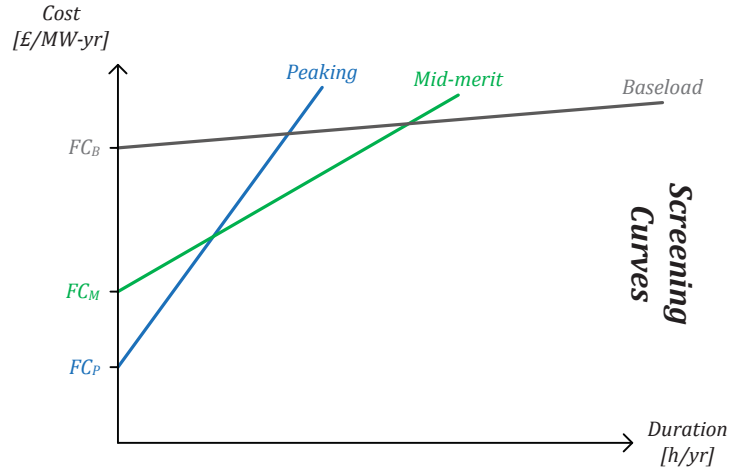


Figure 3.1: Screening Curves (AC_i^K) considering three generation technologies: Baseload, Mid-merit and Peaking (B , M and P respectively) (figure adapted from [1]).

required to ensure that enough generation capacity is available to securely and sustainably satisfy demand at competitive prices.

3.1.1 What are the drivers for this economic activity?

Since the restructuring and the opening of the industry to competition, the generation investment business and its expansion are driven by the price signals that emerge from the electricity market. Those signals are the result of the economic interaction between market participants, i.e. consumers and producers of electricity, and regulators.

The margin between generation and demand translates into high or low electricity prices, signalling that more or less generation is required respectively. However, due to the nature of this commodity, its consumption and production, regulation has been inevitably required in order to ensure as much as possible the conditions for perfect competition.

The regulation of the electricity market is today a key driver that coordinates the investment in generation, because of its impact on market price signals. Additionally, the uncertainty created by the economic factors that influence this business activity, such as new emission requirements, fuel prices, resource availability, DSR, weather conditions, and renewable generation incorporation/requirements, among others, constitute additional drivers that must be taken into account at the moment of planning power systems and deciding on generation investment.

3.1.2 Screening curves & the long-run equilibrium

The Screening Curves are useful to compare generation costs between different generation technologies [1, 66, 58, 55]. These curves plot the average cost of capacity (AC_i^K) as a function of three factors: fixed costs (FC_i), incremental costs (π_i^{inc}), and capacity factor (cf_i).

$$AC_i^K = FC_i + cf_i \times \pi_i^{\text{inc}}. \quad (3.1)$$

The fixed costs² in equation (3.1), correspond to the overnight construction costs amortized over the expected lifetime of a generation plant. On the other hand, the incremental costs³ are those related to the power output of a generation plant, such is the case of the fuel costs associated with each type of generation technology. Fixed and incremental costs could also include additional fixed and variable components respectively, such as administration costs, O&M costs, CO₂ emission costs, etc. In this chapter it is assumed that these costs are already included on the value of those parameters, or that they are zero.

The Screening Curves show the total cost per unit of capacity per year for different types of capacity (generation technologies) as a function of their capacity factor [1, 2]. When these curves are used in combination with the LDC, they are useful to calculate the optimal generation investment portfolio (mix of generation technologies) in the long-run equilibrium.⁴ This technique was developed for regulated power systems and assume that the LDC is fixed, which in a competitive environment is not true, because electricity prices affect the shape of this curve, and vice versa [1]. Nevertheless, it is very useful to partially confirm a long-run market equilibrium and to understand the basis of the generation investment process in a competitive environment.

The intersections between the screening curves (see figure 3.1) determine the capacity factors⁵ that limit the optimal region for each generation technology, i.e. the region where demand is supplied in the cheapest and most secure way by each generation technology. If those capacity factors are mapped now into durations (horizontal axis of figure 3.1) and then, if those durations are projected into the LDC, it is possible to read the optimal capacity levels of each type of generation technology from the vertical axis of this last curve, as it is shown in figure 3.2.⁶

As discussed before, the screening curves technique was developed when the electricity industry was vertically integrated, which meant that the generation portfolio was not the result of the electricity markets forces, but the outcome of a central planned exercise driven by the security standard defined for the power system.

Although this method is old, it can be used for investment decisions in competitive electricity markets if uncertainty is not considered and the electricity price is not centrally established, but the result of the economic interaction between demand and supply. This basically means that the market clearing price must be equal to the marginal cost of the energy. When there is enough generation capacity available in the system, the market clearing price is equal to the marginal cost of generation of the most expensive generation unit running in the sys-

2 Fixed costs also include any other costs that do not depend on the level of production, but on the generation capacity installed. For example, the fixed operational and maintenance costs, which must be paid independently if a plant is generating or not. However, the main component of this type of costs is the one related to the construction cost.

3 The fuel costs are the main component of this type of costs. There are other costs that are also related to the production of energy, for example, the variable Operation & Maintenance (O&M) costs.

4 A long-run equilibrium is a situation in which entry and exit from an industry is complete and the economic profits for all firms are zero, with prices such that quantities demanded and supplied are equal.

5 On these capacity factors is where two generation technologies have the same average cost of capacity, and where the switching between generation technologies happen.

6 K_i is the optimal amount of capacity of each generation technology i .

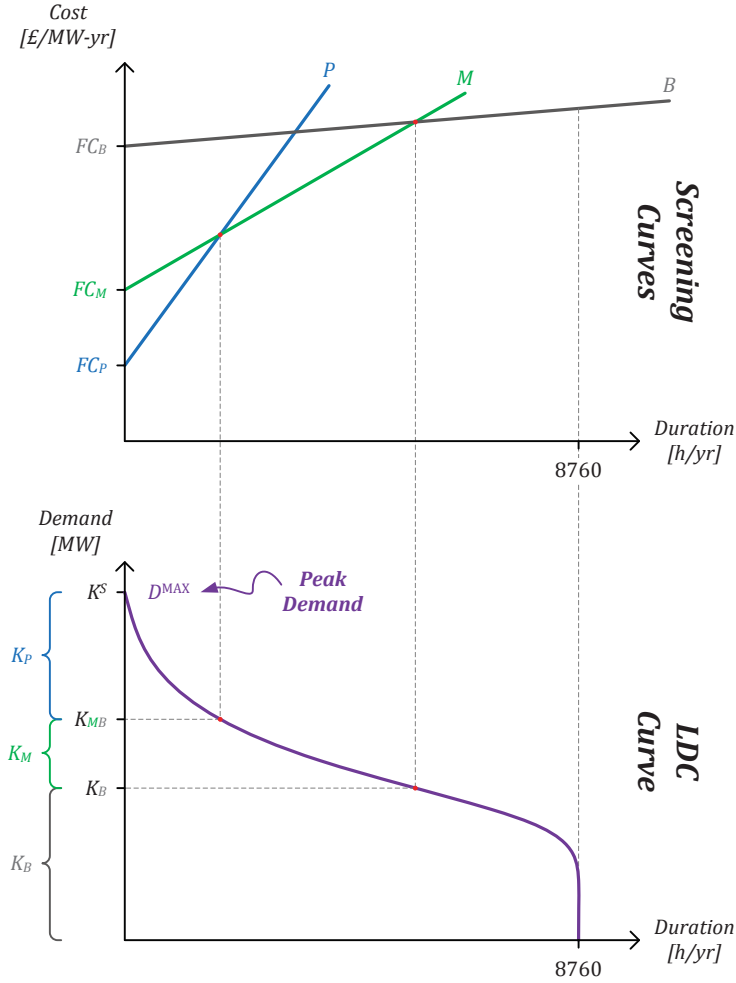


Figure 3.2: Optimal generation portfolio derivation using the screening curves technique (figure adapted from [1]).

tem, and when not, equal to the value that an average consumers puts on an unsupplied unit of energy, or equal to some centrally defined limit value.⁷

In a liberalized and competitive market, the electricity prices that emerge from the market are the source of fixed and variable costs recovery for generators. These market price signals drive the costs recovery process and the adjustment of the generation portfolio in every power system around the world that does not have a monopolistic structure [78].

From figure 3.2 it must be noted that, if enough capacity is built in order to satisfy peak demand, and no generation outages are considered, then the electricity price will never rise above the marginal cost of production of the most expensive generation technology. This means that all generation technologies, and especially peaking generation in an EoM, will fail to recover their fixed costs,⁸ and unless electricity prices can rise above this level, or additional incentives are put in place, some generation capacity will be decommissioned up to the point where all are at their break-even point.

⁷ In the case of an inelastic demand.

⁸ The fixed costs, in an EoM are recovered by a generation plant only when the energy price is above its marginal cost of generation.

3.1.3 Energy-only-market & spike-pricing

An EoM [56, 58], as briefly described in Section 2.2, corresponds to a market where energy and ancillary services are the only resources that are paid by electricity consumers. Before proceeding further with the analysis, the following general assumptions need to be made:

- Perfectly competitive market.
- Inelastic demand.⁹
- Energy is traded through a wholesale market.
- Single node and aggregated demand.
- There are three types of generation technologies: B , M and P .¹⁰
- No uncertainty.
- Non-chronological demand (LDC).¹¹
- Target capacity (K^T) for the power system is equal to peak demand.¹²
- Price spikes level equal to $VOLL$,¹³ which is centrally specified by the regulator.
- Long-run equilibrium.
- All generation technologies are 100% available.

Demand for electricity is, in the short-run, almost perfectly inelastic due to several reasons such as the nature of the production and consumption of this commodity, the fact that consumers are in general not exposed to real time electricity prices, and there is limited substitution for this commodity in almost all the cases, amongst others.

The insensitivity of electricity demand to prices creates a market failure when demand (D_t) is larger than the total capacity of the system (K^S),¹⁴ i.e. when $D_t > K^S$, because there will not exist a market clearing price due to the fact that demand and supply curves do not intersect under such circumstances.

During peak hours, i.e. during hours on which demand is larger than the total capacity of the system, the situation shown on the left of figure 3.3 arises.

From an economic point of view, this means that the price for this commodity will be infinite, which is absurd from the consumer point of view, because this would imply that the marginal consumer will not react at all to this price, and from the government's point of view, it will be politically unacceptable and irresponsible to expose their citizens to this situation, considering that the electricity is a basic commodity in the developed world.

⁹ Inflexible demand.

¹⁰ Only three generation technologies are considered for the economic analysis presented in this chapter. Nevertheless, the analysis can be easily extended to consider more technologies.

¹¹ Generic LDC, that can be net-of-wind. This assumption disregards the importance of the chronology of demand.

¹² $K^T = D^{\text{MAX}} = \max_{t \in T} \{LDC_t\}$.

¹³ $VOLL$ is the value that an average consumer puts on an unsupplied megawatt-hour of energy [1].

¹⁴ $K^S = \sum_{i \in I} K_i$.

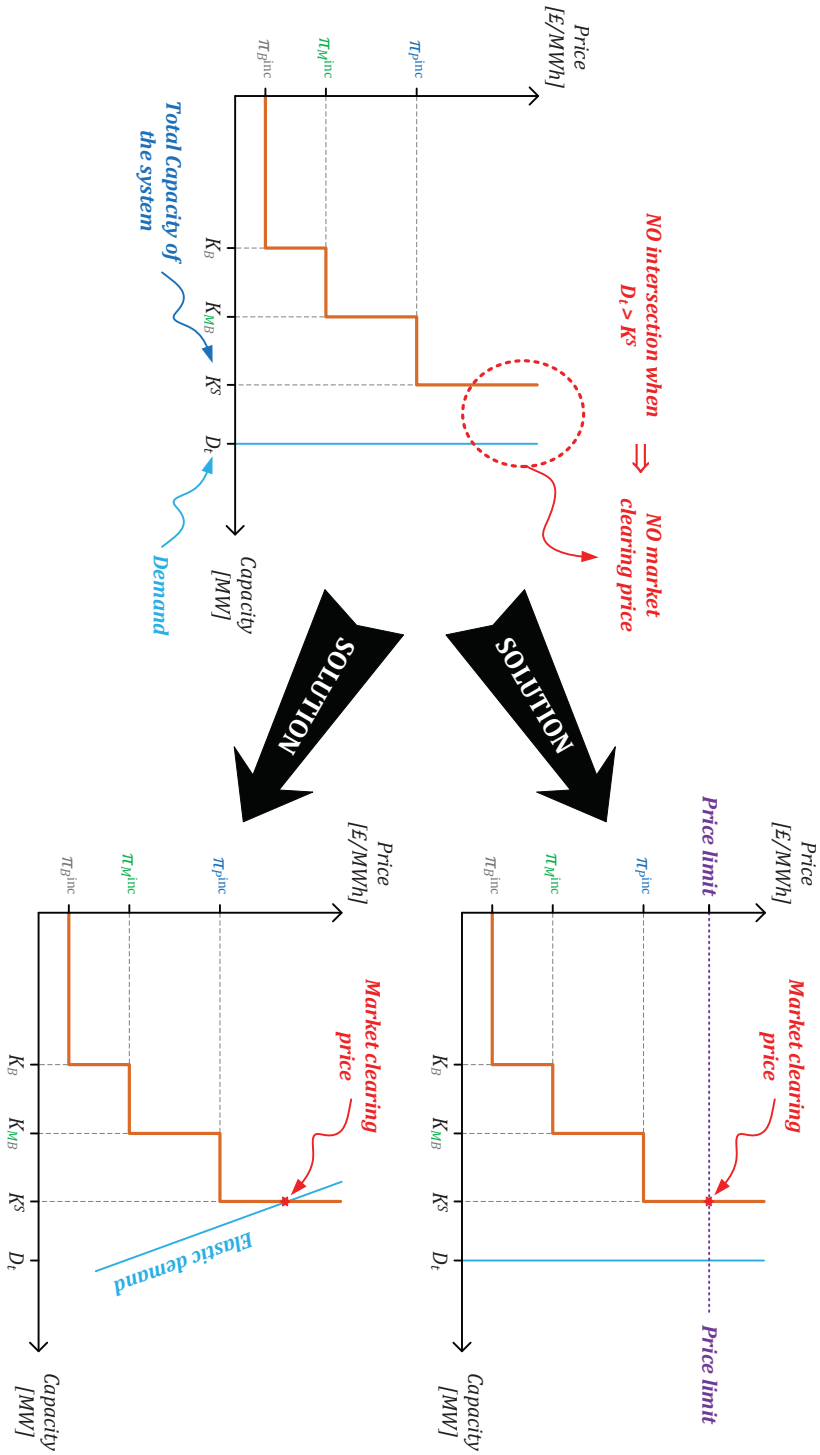


Figure 3.3: *Left:* Market failure in the short-run due to the inelasticity of electricity demand. *Right-top:* Price-limiting regulation. *Right-bottom:* Elastic demand.

In order to repair this market failure, it is necessary to limit the electricity price through a price-limiting regulation, or assume a price elasticity for the electricity demand as conceptually shown in the top and bottom parts of the right-side of figure 3.3 respectively. Two common types of price-limiting policies are: **VOLL** and price-cap (π^{Cap}). These regulations have in common that in both cases the highest level of the electricity price is centrally defined, but they differ in what they try to economically represent.

The **VOLL** regulation, or **VOLL**-pricing policy,¹⁵ tries to represent the willingness to pay of a marginal consumer for an additional megawatt-hour of energy when the system is short of generation resources. This value is estimated by the regulator, or other central body [138]. On the other hand, the price-cap regulation puts a cap value to the electricity price, which is fixed by the regulator based on internal calculations, and that aims to protect the citizens against high energy prices, keeping those prices within a politically acceptable range.¹⁶

A spike-pricing regulation,¹⁷ such is the case of the **VOLL**-pricing policy, allows electricity prices to rise well above the marginal cost of generation of the most expensive generation technology. This allow generation technologies, and especially peaking generation, to recover their fixed costs during hours in which the system is short of resources, as illustrated in figure 3.4. The amount of price spikes hours, and also their height, will drive the generation investment, and as result of this process, the market will deliver the optimal generation mix. This implies that, it is the market and not the regulator, who will define the level of security (reserve margin) of the system. The only action that the regulator can take in order to achieve the security standard defined for their system, if other types of incentives or measures are not implemented, is to adjust the price spikes level.

As established at the beginning of this section, it is assumed that the level of the price spikes is equal to **VOLL**. Then, the market will deliver an optimal generation portfolio, that is one where there is enough hours of price spikes to allow peaking generation, as well as the other generation technologies, to recover their fixed costs. The Scarcity Rent (**ScR**),¹⁸ as shown in figures 3.5 and 3.6, is the profit collected by generation technologies when the System Marginal Price (**SMP**) is above their marginal (incremental) cost of generation (π_i^{inc}). As it can be seen from figure 3.6,¹⁹ unlike non-peaking generation, the scarcity rent for peaking generation is only different than zero during peak hours, i.e. when price spikes occur.

¹⁵ This regulation has been studied and implemented by Australia's National Electricity Code Administrator (**NECA**) [136, 137].

¹⁶ The price-cap value currently used in Pennsylvania – New Jersey – Maryland Interconnection L.L.C. (**PJM**) (Mid-Atlantic region power pool), and also in New York Independent System Operator, Inc. (**NYISO**), is \$1,000/MWh [139]. It must be noted that the Federal Energy Regulatory Commission (**FERC**) in late January and early February 2014 issued a series of orders waiving the \$1,000/MWh price-cap in **PJM** and **NYISO** in order to ensure that electricity suppliers will be able to recover their costs in light of gas prices that soared in **US** due to extreme cold weather conditions on the region on those months. In the **FERC**'s orders, they explained that the measure of allowing electricity suppliers to submit offers above the \$1,000/MWh cap was preferable that the prior approach, which allowed costs recovery through out-of-market uplift payments, which induces the market to produce artificially suppressed prices and inefficient resource selection. The waivers remained in effect until the end of the winter period in **US** [140].

¹⁷ Also known as scarcity-pricing policy.

¹⁸ Scarcity Rent, as defined in [1], is revenue minus variable operation costs (which does not include start-up and non-load costs).

¹⁹ Slice of figure 3.5 for any demand segment t such that $\{t \in T \mid t \in [0, t^{PS}]\}$.

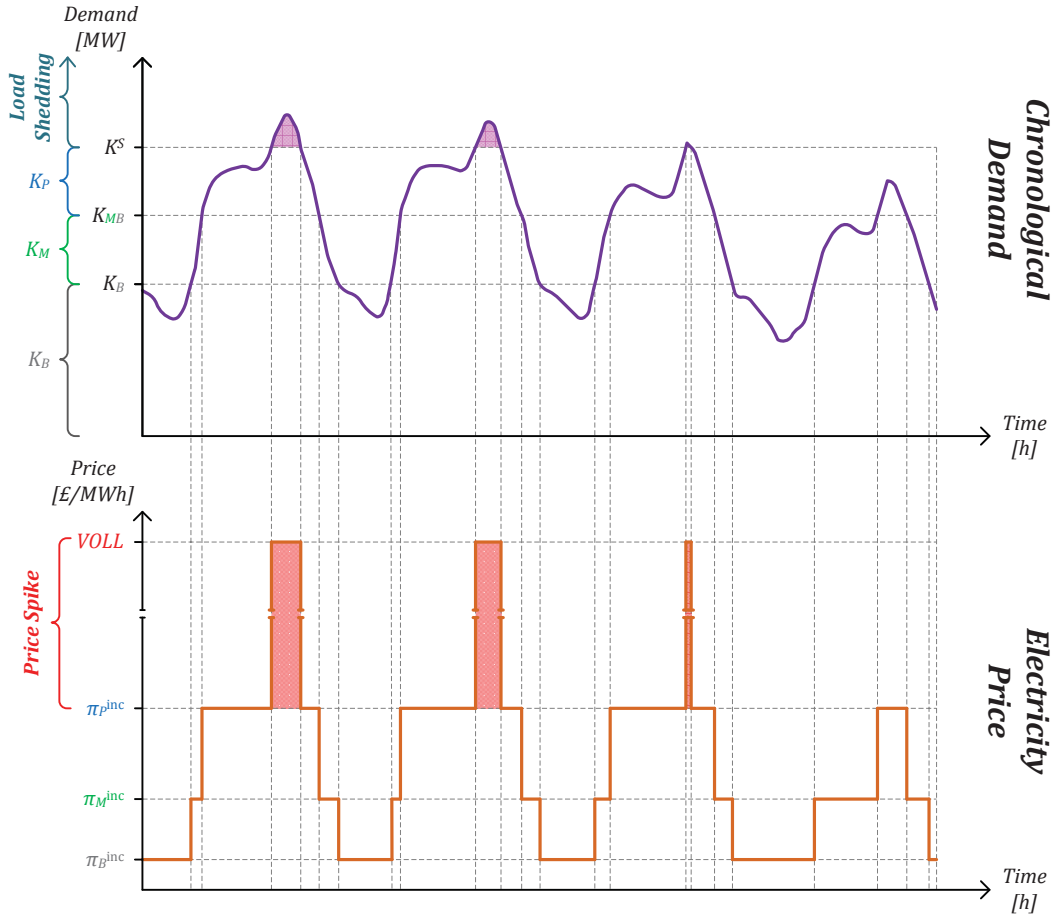


Figure 3.4: Chronological demand and electricity price with a **VOLL**-pricing policy and inflexible demand.

To find the optimal generation portfolio, the points ①, ② and ③ in figure 3.7 need to be derived.²⁰

In an **EoM** with a **VOLL**-pricing policy, where there are no any additional incentives, peaking generation recover their fixed costs only during peak hours, i.e. when they are fully utilized and the electricity price rises above their marginal cost of generation up to **VOLL**.²¹ In the long-run equilibrium, peaking generation must be able to recover exactly their fixed costs (FC_P) and no more, with the revenues collected during price spikes hours.

From figures 3.5 to 3.8, for peaking generation technology it is required that:

$$\text{Annual Investment Peaking Generation} = \underbrace{\text{Annual ScR}_P^{\text{peak hours}}}_{t \in [0, t^{PS}]}, \quad (3.2)$$

$$K_P \times FC_P = t^{PS} \times [VOLL - \pi_P^{\text{inc}}] \times K_P, \quad (3.3)$$

$$\frac{FC_P}{t^{PS}} + \pi_P^{\text{inc}} = VOLL. \quad (3.4)$$

²⁰ In other words, calculate the optimal values of t^{PS} , t^P and t^M .

²¹ Only during those hours, i.e. during any demand segment t such that $\{t \in T \mid t \in [0, t^{PS}]\}$, **SMP** = **VOLL** $\Rightarrow$ $\text{ScR}_P > 0$.

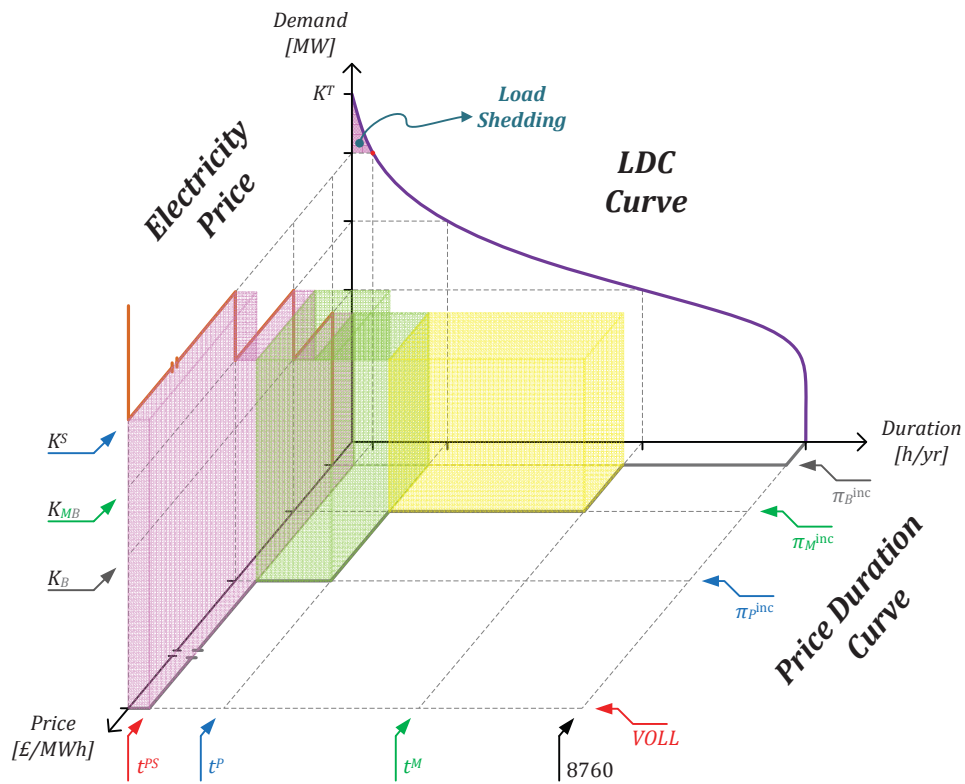


Figure 3.5: Scarcity rent of all generation technologies during the year.

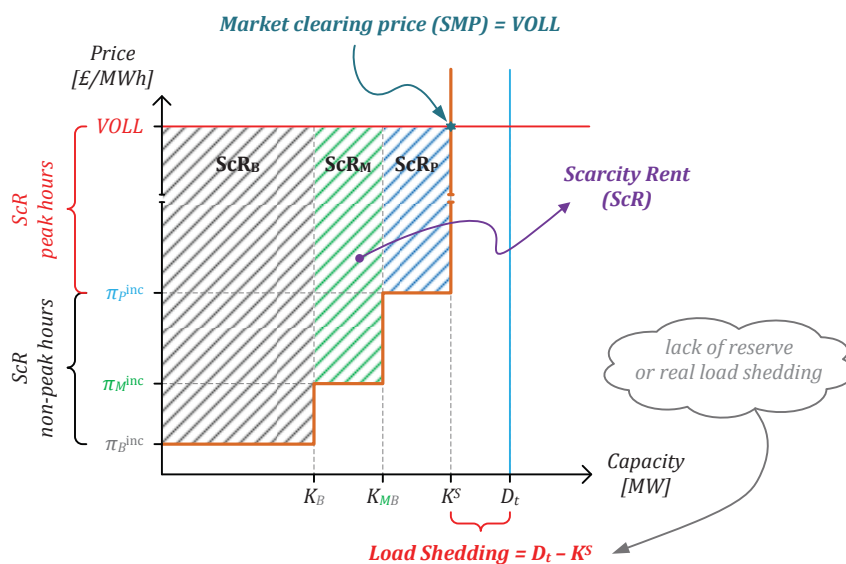


Figure 3.6: Scarcity rent during peak hours, i.e. during any demand segment t such that $\{t \in T \mid t \in [0, t^{PS}]\}$.

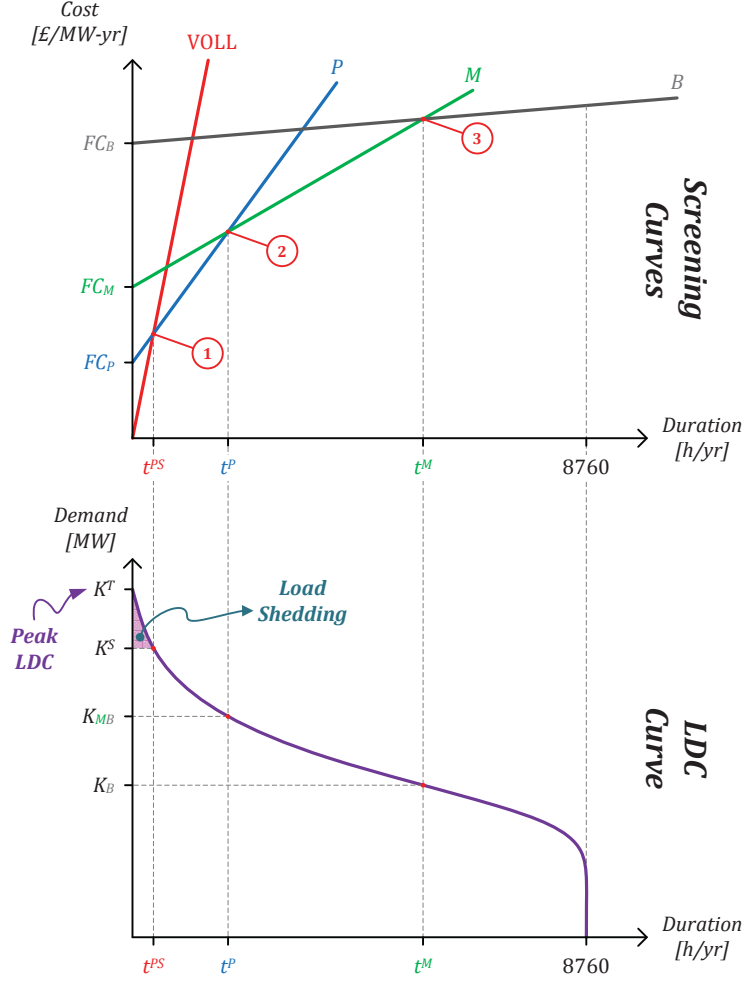


Figure 3.7: Optimal capacity factors and generation capacities in an EoM with VOLL-pricing policy.

Equation (3.4) establishes that, if the average value of the energy during peak hours is equal to VOLL, then peaking generation will be able to recover exactly their fixed costs. From equation (3.4) it is possible to derive the following expression for the optimal value of t^{PS} :

$$t^{PS} = \frac{FC_P}{VOLL - \pi_p^{inc}}. \quad (3.5)$$

Mid-merit generation has positive profit ($ScR_M > 0$), when the electricity price rises above their marginal cost of generation, i.e. when the SMP $> \pi_M^{inc}$. This happens during peak hours, and also during the non-peak hours in which peaking generation is not running at full capacity.²² The annual ScR of mid-merit generation is given then by:

$$\text{Annual } ScR_M = \underbrace{\text{Annual } ScR_M^{peak \text{ hours}}}_{t \in [0, t^{PS}]} + \underbrace{\text{Annual } ScR_M^{non-peak \text{ hours peak. gen.}}}_{t \in (t^{PS}, t^P)}, \quad (3.6)$$

$$\text{Annual } ScR_M = t^{PS} \times [VOLL - \pi_M^{inc}] \times K_M + (t^P - t^{PS}) \times [\pi_p^{inc} - \pi_M^{inc}] \times K_M. \quad (3.7)$$

²² Peak hours and non-peak hours for peaking generation are all those demand segment t such that: $\{t \in T \mid t \in [0, t^{PS}]\}$ and $\{t \in T \mid t \in (t^{PS}, t^P)\}$, respectively.

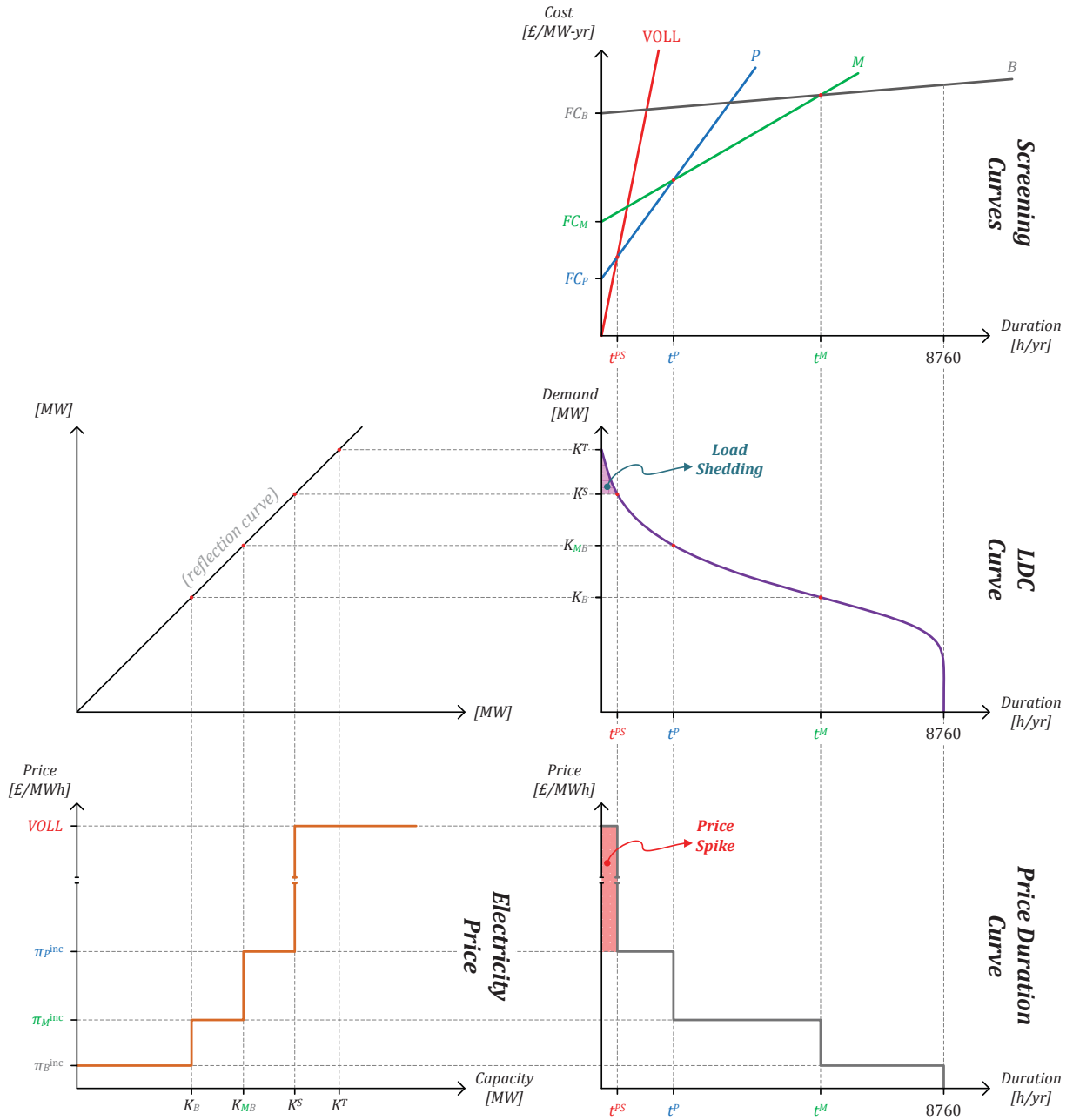


Figure 3.8: Derivation of the optimal generation portfolio in an EoM with a VOLL-pricing policy using the screening curves technique (figure adapted from [2]).

The minimum amount of hours that mid-merit generation must run at full capacity is related with the optimal capacity factor of the peaking generation (t^P),²³ i.e. when all mid-merit capacity has been deployed and an additional megawatt-hour of energy will come from peaking generation. It must be noted that at t^P , the average cost of capacity is the same for peaking and mid-merit generation technologies. Then:

$$\text{Annual Investment Mid-merit} = \text{Annual ScR}_M. \quad (3.8)$$

Substituting equation (3.7) in the previous equation:

$$\begin{aligned} K_M \times \text{FC}_M &= t^{PS} \times [\text{VOLL} - \pi_M^{\text{inc}}] \times K_M + (t^P - t^{PS}) \times [\pi_P^{\text{inc}} - \pi_M^{\text{inc}}] \times K_M, \\ \text{FC}_M &= t^{PS} \times [\text{VOLL} - \pi_P^{\text{inc}}] + t^P \times \pi_P^{\text{inc}} - t^P \times \pi_M^{\text{inc}}. \end{aligned} \quad (3.9)$$

Then, substituting equation (3.5) in the previous equation:

$$\begin{aligned} \text{FC}_M &= \text{FC}_P + t^P \times \pi_P^{\text{inc}} - t^P \times \pi_M^{\text{inc}}, \\ \text{FC}_M + t^P \times \pi_M^{\text{inc}} &= \text{FC}_P + t^P \times \pi_P^{\text{inc}}, \\ \frac{\text{FC}_M}{t^P} + \pi_M^{\text{inc}} &= \frac{\text{FC}_P}{t^P} + \pi_P^{\text{inc}}. \end{aligned} \quad (3.10)$$

Equation (3.10) establishes that, the average cost of energy for peaking and mid-merit generation is equal at t^P , and thus, an additional megawatt-hour of energy will come from peaking generation. From this equation is possible to derive the following expression for the optimal value of t^P :

$$t^P = \frac{\text{FC}_M - \text{FC}_P}{\pi_P^{\text{inc}} - \pi_M^{\text{inc}}}. \quad (3.11)$$

Finally, baseload generation has a positive profit ($\text{ScR}_B > 0$), when the electricity price rises above their marginal cost of generation, i.e. when $\text{SMP} > \pi_B^{\text{inc}}$. This happens during peak hours, and also during the non-peak hours in which peaking and mid-merit generation are not running at full capacity.²⁴ The annual ScR of baseload generation is given then by:

$$\begin{aligned} \text{Annual ScR}_B &= \underbrace{\text{Annual ScR}_B^{\text{peak hours}}}_{t \in [0, t^{PS}]} + \underbrace{\text{Annual ScR}_B^{\text{non-peak hours peaking generation}}}_{t \in (t^{PS}, t^P]} \\ &\quad + \underbrace{\text{Annual ScR}_B^{\text{non-peak hours mid-merit generation}}}_{t \in (t^P, t^M]}, \end{aligned} \quad (3.12)$$

²³ This optimal capacity factor of peaking generation is at the same time the lowest capacity factor of mid-merit generation.

²⁴ Peak hours and non-peak hours for peaking and mid-merit generation are all those demand segment t such that: $\{t \in T \mid t \in [0, t^{PS}]\}$, $\{t \in T \mid t \in (t^{PS}, t^P]\}$ and $\{t \in T \mid t \in (t^P, t^M]\}$, respectively.

$$\begin{aligned} \text{Annual ScR}_B = t^{PS} \times [\text{VOLL} - \pi_B^{\text{inc}}] \times K_B + (t^P - t^{PS}) \times [\pi_P^{\text{inc}} - \pi_B^{\text{inc}}] \times K_B \\ + (t^M - t^P) \times [\pi_M^{\text{inc}} - \pi_B^{\text{inc}}] \times K_B. \end{aligned} \quad (3.13)$$

The minimum amount of hours that baseload generation must run at full capacity is related to the optimal capacity factor of the mid-merit generation (t^M),²⁵ i.e. when all baseload capacity has been deployed and an additional megawatt-hour of energy will come from mid-merit generation. It must be noted that at t^M , the average cost of capacity is the same for mid-merit and baseload generation technologies. Then:

$$\text{Annual Investment Baseload} = \text{Annual ScR}_B. \quad (3.14)$$

Substituting equation (3.13) in the previous equation:

$$\begin{aligned} K_B \times \text{FC}_B = t^{PS} \times [\text{VOLL} - \pi_B^{\text{inc}}] \times K_B + (t^P - t^{PS}) \times [\pi_P^{\text{inc}} - \pi_B^{\text{inc}}] \times K_B \\ + (t^M - t^P) \times [\pi_M^{\text{inc}} - \pi_B^{\text{inc}}] \times K_B, \\ \text{FC}_B = t^{PS} \times [\text{VOLL} - \pi_B^{\text{inc}}] + t^P \times [\pi_P^{\text{inc}} - \pi_B^{\text{inc}}] + t^M \times \pi_M^{\text{inc}} - t^M \times \pi_B^{\text{inc}}. \end{aligned} \quad (3.15)$$

Then, substituting equations (3.5) and (3.11) in the previous equation:

$$\begin{aligned} \text{FC}_B &= \text{FC}_M + t^M \times \pi_M^{\text{inc}} - t^M \times \pi_B^{\text{inc}}, \\ \text{FC}_B + t^M \times \pi_B^{\text{inc}} &= \text{FC}_M + t^M \times \pi_M^{\text{inc}}, \\ \frac{\text{FC}_B}{t^M} + \pi_B^{\text{inc}} &= \frac{\text{FC}_M}{t^M} + \pi_M^{\text{inc}}. \end{aligned} \quad (3.16)$$

Equation (3.16) establishes that, the average cost of energy for mid-merit and baseload generation is equal at t^M , and thus, an additional megawatt-hour of energy will come from mid-merit generation. From this equation is possible to derive the following expression for the optimal value of t^M :

$$t^M = \frac{\text{FC}_B - \text{FC}_M}{\pi_M^{\text{inc}} - \pi_B^{\text{inc}}}. \quad (3.17)$$

Using the values calculated for t^{PS} , t^P and t^M , in combination with the LDC, it is possible to calculate the optimal capacity level of each of the generation technologies, their optimal capacity factors, and also the maximum load shedding that will occur, as conceptually shown in figures 3.7 and 3.8.

Finally it must be noted that, in the long-run equilibrium, an EoM with a VOLL-pricing policy will deliver an optimal generation portfolio, in which capacity will be built up to the point

²⁵ This optimal capacity factor of mid-merit generation is at the same time the lowest capacity factor of baseload generation.

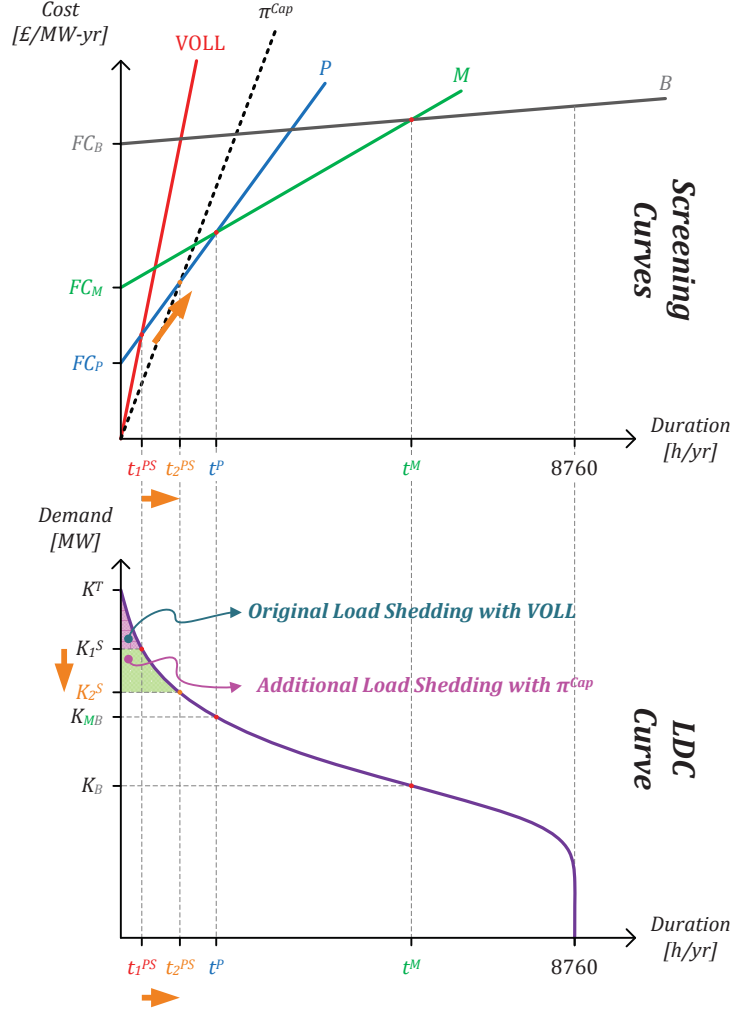


Figure 3.9: Change in the optimal generation portfolio due to the implementation of a price-cap regulation.

where the required hours of price spikes will allow all generation technologies to recover their fixed costs. This implies that less generation than the targeted level will be built ($K^S < K^T$) and that level of capacity will depend on the calculation of the **VOLL** made by the regulator. In other words, the market will deliver the optimal generation portfolio and it is the regulator who must adjust the level of the **VOLL** in order to satisfy the security standard established beforehand for their power system. If the value of **VOLL** is set too low, then more hours of price spikes will be required and the regulator will fail to reach the required level of security of supply, unless some additional incentives or measures are implemented.

3.1.4 Price-cap regulation in an energy-only-market

A price-cap regulation, as well as the **VOLL**-pricing policy, is a price-limiting policy in which the electricity prices are capped, when the system is short of generation resources, at a centrally defined level π^{Cap} . The intended effect of the price-cap is to protect consumers from very high electricity prices, keeping the prices within a politically acceptable range.

Assuming that the price-cap value is set at a level much lower than $VOLL$,²⁶ then as explained in the previous section, more hours of high prices will be needed to allow generation technologies to recover their fixed costs, and this will mean that, the total capacity of the system will be lower than the one reached with the $VOLL$ -pricing policy.²⁷ This effect is conceptually shown in figure 3.9.²⁸

In figure 3.9 it is possible to see that, a low π^{Cap} compared to the $VOLL$, increases inevitably the amount of hours that peaking generation, and also the other generation technologies, require to recover their fixed costs, and increases in the long-run equilibrium, the amount of load shedding both in duration and peak value. Needless to say that, the total generation capacity of the system also decreases and, if no additional incentives or measures to maintain the required levels of investment are implemented, the electricity prices will not allow the security of supply to be maintained at the same level as before, leading to a less secure power system.

The derivation of the optimal values of t_2^{PS} , t^P and t^M , and the optimal generation portfolio for a price-cap regulation, is analogous to the derivation made in the Section 3.1.3 for the $VOLL$ -pricing policy, but the only difference is that in this case the price spikes level is equal to π^{Cap} .

The reduction in the ScR levels for all the generation technologies generates the so-called missing-money problem, which basically refers to the lost profit that was required to keep an adequate level of generation, which is due to the reduction of the electricity prices cap when the system is short of resources.

3.1.5 The missing-money problem

The Missing-Money (MM) problem [56, 141] refers to the lost ScR (figure 3.10), which is required to maintain the appropriate level of generation capacity in the system, due to a price-cap policy that keeps energy prices too low.

In order to understand the missing-money problem, let us suppose that for a very long time the power system had a $VOLL$ -pricing regulation, which delivered the expected level of security. Under this scenario, in the long-run, the optimal generation portfolio is the one that was derived in Section 3.1.3.²⁹

Now let us assume that, the regulator announces a new price regulation which establishes that from now on and in order to protect consumers, the electricity price will be capped at π^{Cap} during times in which the power system is short of generation resources. To simplify the analysis, it is assumed that the new regulation only affects peaking generation.³⁰

Given the scenario described in the previous paragraph, what begins to happen instantaneously is what it is depicted in figure 3.10, i.e. peaking generation lose MM_P and their ScR is

²⁶ $\pi^{Cap} \ll VOLL$.

²⁷ $K_2^S < K_1^S \Rightarrow K_{\pi^{Cap}}^S < K_{VOLL}^S$.

²⁸ t_1^{PS} and t_2^{PS} are the optimal time durations of the price spikes for the $VOLL$ -pricing policy and the price-cap regulation, respectively.

²⁹ Optimal generation portfolio defined by the capacity factors: t_1^{PS} , t^P and t^M in figure 3.9.

³⁰ Basically it is assumed that mid-merit and baseload generation will not react at all to this regulatory change.

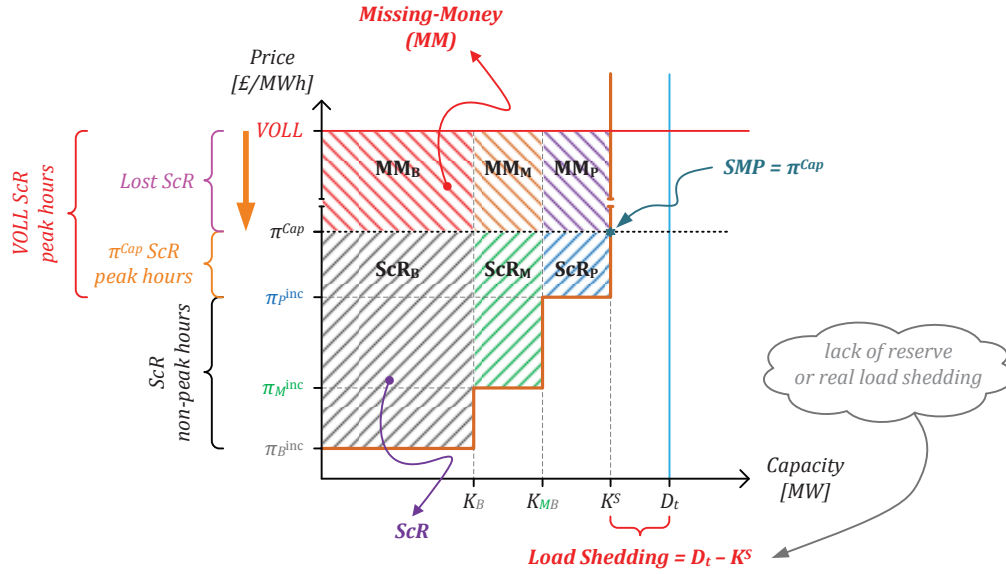


Figure 3.10: Missing-money problem due to a price-cap regulation during peak hours, i.e. during any demand segments t such that $\{t \in T \mid t \in [0, t^{PS}]\}$.

drastically reduced.³¹ Peaking generation now begins to make losses, because the level of electricity prices during peak hours does not allow them to recover the fixed costs of their installed capacity K_P ,³² and the reaction to this loss will be the decommission of some plants, up to the point where they are again able to break-even. After a few months, if they are able to quickly react to the new market price signals, the system will reach a new long-run equilibrium,³³ in which there is less peaking generation capacity.³⁴

The total capacity of the system decreases and the number of peak prices hours increase as conceptually shown in figure 3.9.³⁵ This means that the level of security of the power system also decrease and does not satisfy the security standard established by the regulator, which has been assumed was t_1^{PS} . Thereby and as was outlined earlier, the new level of electricity prices during peak hours is too low, and does not allow the required level of generation capacity to be maintained.

Price-cap regulations protect consumers and reduce the volatility of the electricity prices. However, they also create a series of undesirable effects, such as:

- Drastically reduce the scarcity rent levels perceived by the generation technologies during peak hours, and thus, the recovery of their fixed costs.
- Limit the energy prices at a level much lower than the **VOLL**.
- Produce a clear distortion in the market price signals.
- Artificially suppress high energy prices that are fundamental to incentivize new investments.

³¹ Because π^{Cap} is much lower than the **VOLL** level.

³² $(K_1^S - K_{MB})$ in figure 3.9.

³³ Optimal generation portfolio defined by the capacity factors: t_2^{PS} , t^P and t^M in figure 3.9.

³⁴ $(K_2^S - K_{MB})$ in figure 3.9.

³⁵ The peak value and the number of hours of load shedding increase.

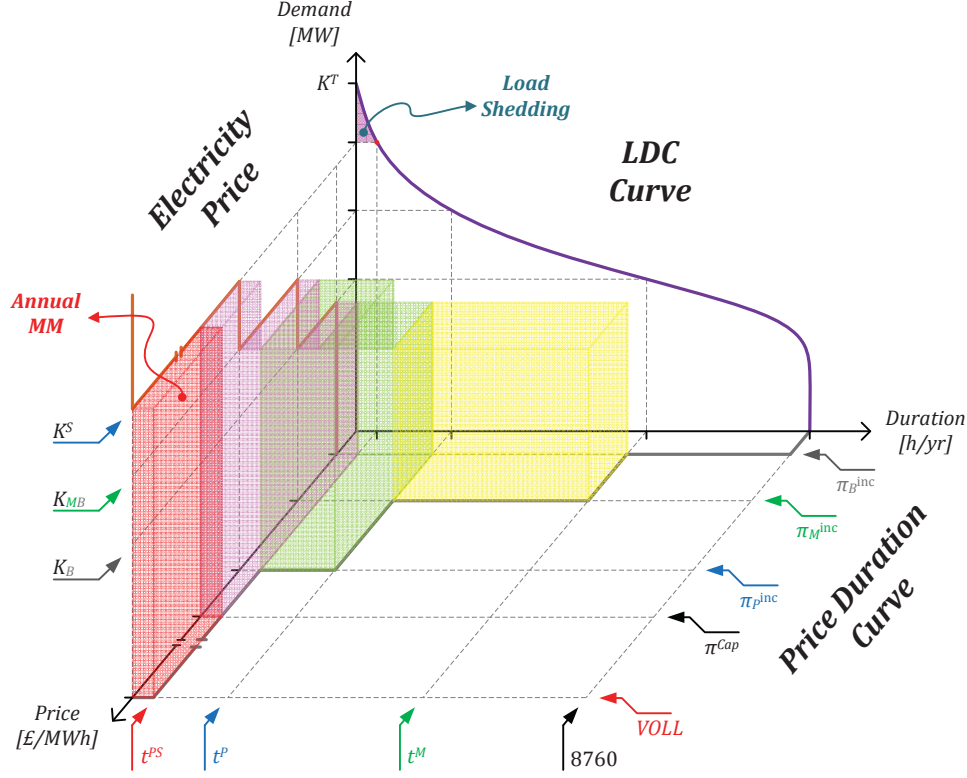


Figure 3.11: Annual missing-money problem.

- Failure by generators to recover their fix costs.³⁶
- Security of supply is compromised and cannot be maintained at the adequate level.
- Incentives for resource adequacy and security are virtually eliminated.

The market price distortion is the most important side effect of a price-cap regulation, and which gives origin to the others. As can be seen from figures 3.10 and 3.11, the distortion is generated in the price signals when the SMP rises above the marginal cost of generation of the peaking technology, keeping the prices at a level much lower compared to the VOLL-pricing policy. Under the assumptions made at the beginning of this section,³⁷ the annual MM will be given by:

$$\begin{aligned}
 \text{Annual MM} &= \text{Lost ScR during } t_1^{PS}, \\
 &= t_1^{PS} \times \underbrace{\left[\text{VOLL} - \pi^{Cap} \right]}_{\text{MM per hour}} \times K^S.
 \end{aligned} \tag{3.18}$$

In order to maintain the investment in the levels required to ensure the resource adequacy and the security of supply, the market price signals must be restored. One of the approaches widely adopted for this purpose are the capacity mechanisms, which basically consist in the creation of an additional stream of revenue for generators, which looks to secure the recovery of fixed costs.

³⁶ This happens until a new long-run equilibrium is reached.

³⁷ The system is exposed to the new regulation instantaneously, i.e. t^{PS} does not change.

3.1.6 Why capacity mechanisms may be needed?

If high electricity prices are not allowed due to political reasons, a price-cap regulation generates the missing-money issue, discouraging the expected levels of investment required to comply with the generation capacity target, and thus, with the security standard specified for the power system, i.e. t_1^{PS} , if it is assumed that the system was optimally designed based on a **VOLL**-pricing policy.³⁸

Aiming to restore the market price signals that have been distorted by excessive market regulations, and at the same time, deal with the electricity market failures and its imperfections, capacity mechanisms have been introduced and evolved over the last almost two decades. Such mechanisms seek to induce new generation investments, and also delay the retirement of old generations plants, by providing an additional stream of revenue to complement the revenue collected in the energy market. Capacity revenue is the name given to this additional revenue stream, which has various forms and is used as a name for several different concepts.

Conceptually speaking, there are two types of capacity payments, and the essential difference between them is given by who receives the benefit of the power plant's gross margin.³⁹ In one case, the capacity payment gives the buyer the right to the energy produced by the power plant at the energy's marginal cost of production.⁴⁰ This type of payment is analogous to a call option on the energy price, and sometimes is called a physical option.

The opposite approach to defining capacity is a form in which the buyer has the right to the energy output of the power plant, but does not control the price at which it receives this energy.⁴¹ Depending on the specific terms of the transaction, the buyer will typically have the right to call on the capacity of the plant at any time, but will pay the higher of marginal production cost or the energy spot price, so the positive difference between marginal cost and the market price is retained by the power plant owner.⁴²

Some people argue that the call option is more natural, implies less intervention and regulation, and provides intrinsic value to customers [61], and others claim that they require a very complex infrastructure for both generators and consumers [54]. However, although more complex in terms of intervention, regulation and implementation, the second type of capacity payments has been adopted in many countries around the world [63, 70, 3, 49], and is the type of capacity mechanism that is being implemented in the **GB**'s electricity market [71, 142, 143, 144]. Under this approach, the capacity is treated as a product traded in a capacity market, and it is valued through a auctioning mechanism that is centrally specified.

Capacity mechanisms can be classified into two groups depending on who can provide capacity resources: market-based and targeted mechanisms, as shown in figure 3.12. Under a market-based mechanism, commonly known as capacity payments, a market for capacity is introduced in addition to the energy market, and suppliers are allowed to operate in both

³⁸ $t_1^{PS} = t^{PS} = \frac{FC_p}{VOLL - \pi_p^{inc}}$, as shown in equation (3.5).

³⁹ Gross margin is the difference between the **SMP** and the power plant's incremental costs.

⁴⁰ Capacity and energy that is purchased as a bundle like this is sometimes called a power purchase, as evidenced in the commonly used industry term Purchased Power Agreement (**PPA**).

⁴¹ This type of capacity payment is sometimes called the reliability or regulatory value of capacity.

⁴² Examples of this type of payment are the administratively managed capacity markets in **PJM**, New York (**NY**) and New England (**NE**) power systems [3].

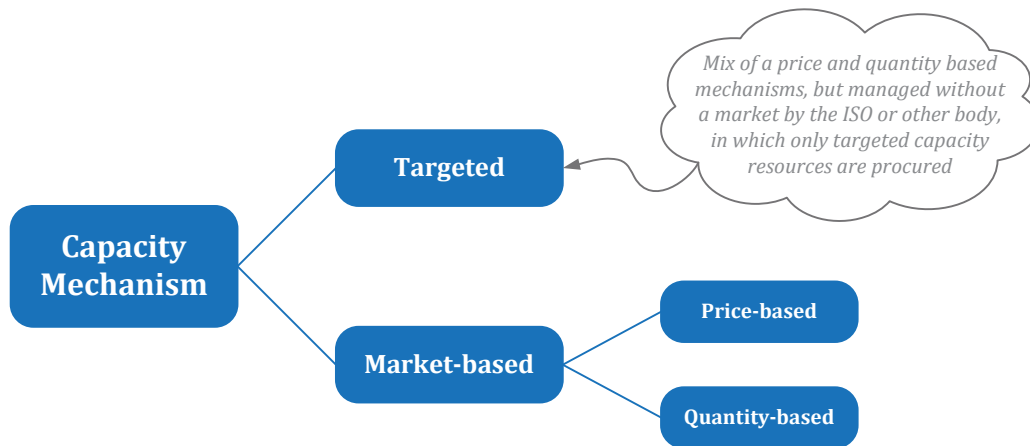


Figure 3.12: Capacity mechanisms.

of those markets. In this capacity market, all providers willing to offer their capacity⁴³ can sell it, and the total volume of capacity required to satisfy a predefined security standard is purchased.⁴⁴ On the other hand, in a targeted capacity mechanism the Independent System Operator (ISO), or other central body, is responsible for procuring a volume of specific reliable back-up capacity that is required to meet the security standard. Targeted mechanism differs from a market-based mechanism in that it only covers a small subset of capacity resources.⁴⁵

An alternative distinction between capacity mechanisms can be made depending on how the capacity is priced, which leads to two groups: price-based and quantity-based (see figure 3.12). In a price-based capacity mechanisms, the capacity price is administratively established and designed in such way that it aims to deliver the security standard specified for the system.⁴⁶ On the other hand, under quantity-based mechanisms, is not the capacity price what is centrally established, but the level of capacity required to comply with the security standard.⁴⁷ The price of capacity in this case, is defined by the economic interaction of capacity demand and supply, i.e. the price at which demand and supply for capacity are equal.

A capacity mechanism seeks to restore the market price signals up to the level required to ensure security of supply and resource adequacy through an additional revenue stream. In the case of a market-based capacity mechanism, this revenue stream comes from a capacity market, in which capacity resources are traded through an auction process, and is supplementary to the energy revenues. Such market operates in parallel to the energy market, but it has a different time frame (see figure 3.13).⁴⁸

⁴³ Whether in the form of generation or non-generation technologies and approaches such as storage or DSR.

⁴⁴ There are several forms of capacity market, depending on the nature of the capacity and how it is bought and sold. In particular, there are a number of ways to purchase capacity, including through a central auction or a suppliers' obligation.

⁴⁵ The mix of capacity resources procured by the central body will depend on the ISO's requirements for flexibility and responsiveness. In other words, not all existing generating and non-generating resources will necessarily be able to meet these requirements.

⁴⁶ This type of mechanism was implemented in the former England and Wales Pool, which was based on the VOLL, and in the Single Electricity Market (SEM) in Ireland, where the price mechanism is based on the cost of providing peaking capacity.

⁴⁷ The capacity mechanisms implemented in PJM, NY and NE power systems are examples of this type of mechanism.

⁴⁸ For example, in the case of PJM Reliability Pricing Model (RPM), a capacity auction is performed three years in advance to the delivery year. This auction corresponds to the Base Residual Auction (BRA), but three additional Incremental Auctions (IAs) are conducted in order to compensate any possible changes that can happen between

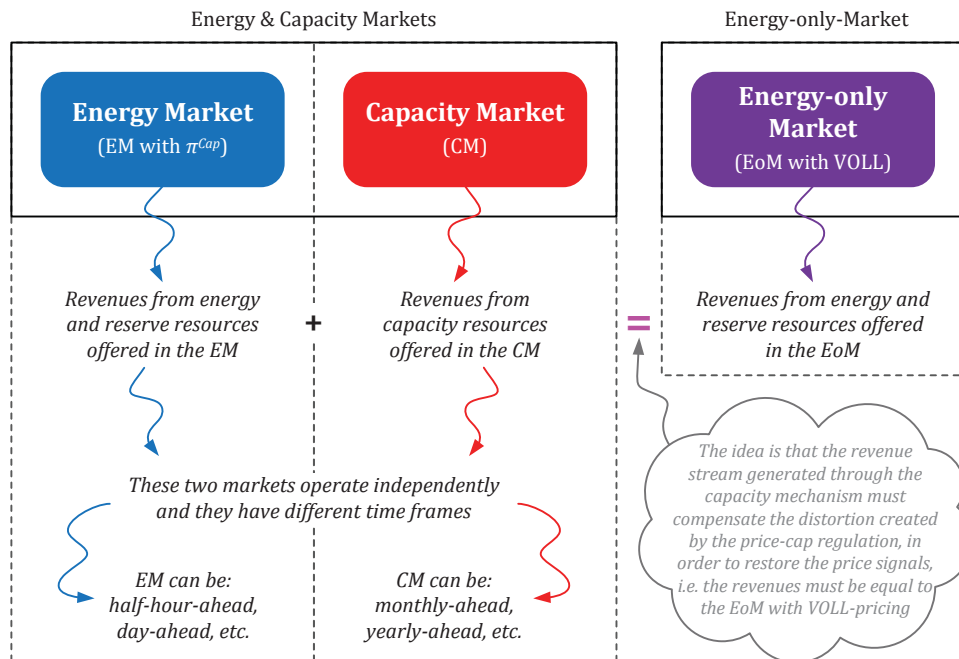


Figure 3.13: Conceptual comparison between Energy and Capacity markets versus an Energy-only-Market with VOLL-pricing policy.

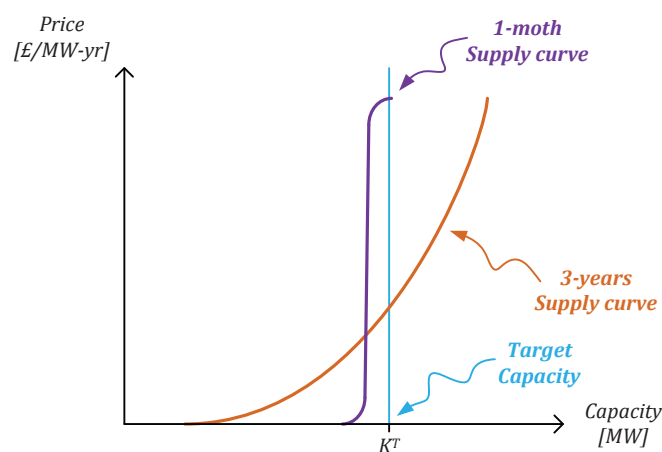


Figure 3.14: Conceptual comparison of the capacity supply curves for capacity auction considering different time horizons (figure adapted from [3]).

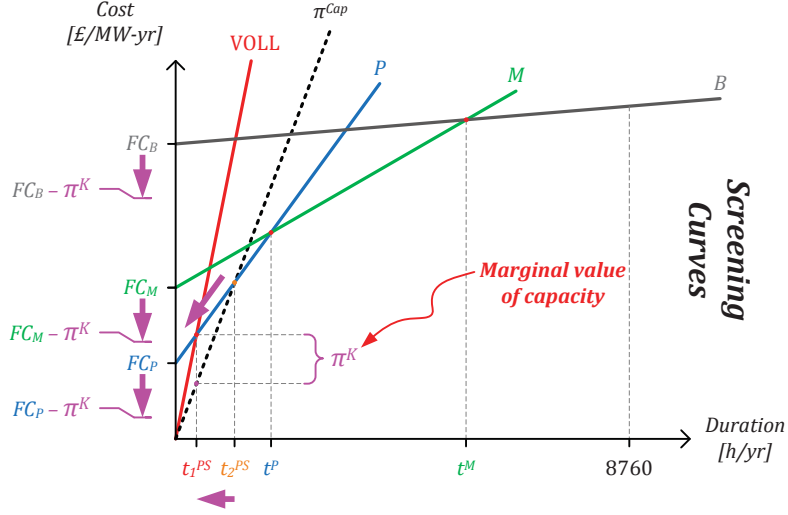


Figure 3.15: Marginal value of capacity.

Price-cap regulation does not ensure an adequate level of generation capacity as result of the electricity prices cap reduction during peak hours (see figures 3.9 and 3.10). In order to keep this level of capacity as required by the security standard, the market-based capacity mechanism must restore the annual MM (equation (3.18)). Before proceeding further with the analysis, the following general assumptions, which are additional to the assumptions outlined in Section 3.1.3, are made:

- The capacity market is open to all generation capacity available in the system.⁴⁹
- The capacity resources are auctioned one-year ahead.
- All the generation capacity resources are offered in the capacity market.
- The capacity payments are proportional only to the installed capacity of each generation technology.⁵⁰
- The electricity price-cap is equal to π^{Cap} .
- The system designed with the VOLL-pricing policy is optimal in terms of reliability, i.e. t_1^{PS} is the amount of hours specified by the security standard for the power system.⁵¹

As it was analysed in Sections 3.1.4 and 3.1.5, and also shown in figures 3.9 and 3.10, the missing-money problem will lead the system to reach an equilibrium in the long-term defined by the values: t_2^{PS} , t^P and t^M . The idea now is induce the market to go back to the long-run

the BRA and the delivery year, such as changes in the demand forecast or in the ability to meet capacity obligations [145, 146]. Capacity auctions performed three or four years in advance allow new suppliers or potential ones to participate, and also DSR to be offered in the capacity market, all of which makes the capacity supply curve less steep (see figure 3.14) and helps to mitigate market power attitudes. The capacity market that is being implemented in GB's electricity market is analogous to the one that is in use in PJM [144].

⁴⁹ All generation technologies, i.e. B , M and P , satisfy ISO's requirements of flexibility and responsiveness.

⁵⁰ In other words, it is assumed that the availability of generation capacity resources is not considered for the calculation of the capacity payments.

⁵¹ In other words this means that price spike hours will occur during t_1^{PS} hours a year, but this satisfy the security standard. This imply that $K^S < K^T$, and then during those peak hours the situation depicted in figure 3.10 happens.

equilibrium reached with the [VOLL](#)-pricing policy,⁵² using the capacity payments mechanism described before. This means that for each unit of capacity, each generation technology must receive an amount of money such that, they will break-even again with t_1^{PS} hours of price spikes, although the electricity prices are capped at π^{Cap} . This amount of money is the marginal value of capacity, i.e. π^K .⁵³

As previously assumed, the capacity payments are paid proportionally to the installed capacity. Then, the peaking generation technology, in order to break-even, must collect enough revenue from the energy and capacity markets such that is able to recover exactly their fixed costs. This means that:

$$\text{Annual Investment Peaking Generation} = \underbrace{\text{Annual ScR}_P^{\text{peak hours}}}_{t \in [0, t_1^{PS}]} + \text{Capacity Payment}, \quad (3.19)$$

$$K_P \times FC_P = t_1^{PS} \times [\pi^{Cap} - \pi_P^{\text{inc}}] \times K_P + \pi^K \times K_P, \quad (3.20)$$

$$\pi^K = FC_P - t_1^{PS} \times [\pi^{Cap} - \pi_P^{\text{inc}}]. \quad (3.21)$$

Substituting equation (3.5) in the previous equation:

$$\begin{aligned} \pi^K &= FC_P - \frac{FC_P}{\text{VOLL} - \pi_P^{\text{inc}}} \times [\pi^{Cap} - \pi_P^{\text{inc}}], \\ \pi^K &= \underbrace{\frac{FC_P}{\text{VOLL} - \pi_P^{\text{inc}}}}_{t_1^{PS}} \times [\text{VOLL} - \pi^{Cap}], \\ \pi^K &= t_1^{PS} \times [\text{VOLL} - \pi^{Cap}]. \end{aligned} \quad (3.22)$$

If the capacity is priced at π^K , the question now is: Is the mid-merit generation technology able to break-even?, which requires proving that the equality between left and right hand sides of the following equation holds:

$$\text{Annual Investment Mid-merit} \stackrel{?}{=} \text{Annual ScR}_M + \text{Capacity Payment}. \quad (3.23)$$

Substituting equation (3.6) in the previous equation:

⁵² For an [EoM](#) with a [VOLL](#)-pricing policy the long-run equilibrium is defined by the values: t_1^{PS} , t^P and t^M .

⁵³ π^K is the marginal value of capacity or the marginal value of capacity in the forward market, or simply capacity price.

$$K_M \times FC_M \stackrel{?}{=} \underbrace{\text{Annual ScR}_M^{\text{peak hours}}}_{t \in [0, t_1^{PS}]} + \underbrace{\text{Annual ScR}_M^{\text{non-peak hours peaking generation}}}_{t \in (t_1^{PS}, t^P]} + \text{Capacity Payment},$$

$$K_M \times FC_M \stackrel{?}{=} t_1^{PS} \times [\pi^{Cap} - \pi_M^{\text{inc}}] \times K_M + (t^P - t_1^{PS}) \times [\pi_P^{\text{inc}} - \pi_M^{\text{inc}}] \times K_M + \pi^K \times K_M. \quad (3.24)$$

Substituting now equation (3.22) in the previous equation:

$$FC_M \stackrel{?}{=} t_1^{PS} \times [\pi^{Cap} - \pi_M^{\text{inc}}] + (t^P - t_1^{PS}) \times [\pi_P^{\text{inc}} - \pi_M^{\text{inc}}] + t_1^{PS} \times [\text{VOLL} - \pi^{Cap}],$$

$$FC_M \stackrel{?}{=} t_1^{PS} \times [\text{VOLL} - \pi_P^{\text{inc}}] + t^P \times [\pi_P^{\text{inc}} - \pi_M^{\text{inc}}]. \quad (3.25)$$

Substituting now equations (3.5) and (3.11) in the previous equation:

$$FC_M \stackrel{?}{=} \frac{FC_P}{\text{VOLL} - \pi_P^{\text{inc}}} \times [\text{VOLL} - \pi_P^{\text{inc}}] + \frac{FC_M - FC_P}{\pi_P^{\text{inc}} - \pi_M^{\text{inc}}} \times [\pi_P^{\text{inc}} - \pi_M^{\text{inc}}],$$

$$FC_M \stackrel{?}{=} FC_P + FC_M - FC_P,$$

$$FC_M \stackrel{\checkmark}{=} FC_M. \quad (3.26)$$

From equation (3.26) it can be seen that, if the capacity price is set at π^K and capacity payments proportional to the installed capacity are paid at this rate, then the mid-merit generation technology will break-even. Applying the same procedure it is easy to prove that the baseload generation technology will also break-even for this capacity price, and thus, that the implemented capacity mechanism allows to reach the same long-run equilibrium as in the **VOLL**-pricing policy case (see figure 3.16).⁵⁴

The marginal value of capacity, as it can be seen from equations (3.21) and (3.22), can be expressed as function of t_1^{PS} (or as function of t_1^{PS} and **VOLL**), which makes the calculation of this value complex in real life, as well as its payment. This is because t_1^{PS} cannot be predicted accurately,⁵⁵ and also the estimation of the **VOLL** is very complex, for not to say impossible as argued in [1, 59], due to the subjectivity of this parameter.

The composition of the capacity price needs to be analysed in order to understand why it is not exactly equal to the fixed costs of the peaking technology, if some peak hours are expected

⁵⁴ Making: $(FC_P - \pi^K) + \pi_P^{\text{inc}} \times t^{PS-new} = \pi^{Cap} \times t^{PS-new}$, it is easy to probe that: $t^{PS-new} = t_1^{PS}$, as it is shown in figure 3.16.

⁵⁵ t_1^{PS} depends on the load forecast and also on the availability and outages of generation plants. This issue also leads to a second problem: how to pay the capacity payments: *ex-ante* or *ex-post*? [54, 59].

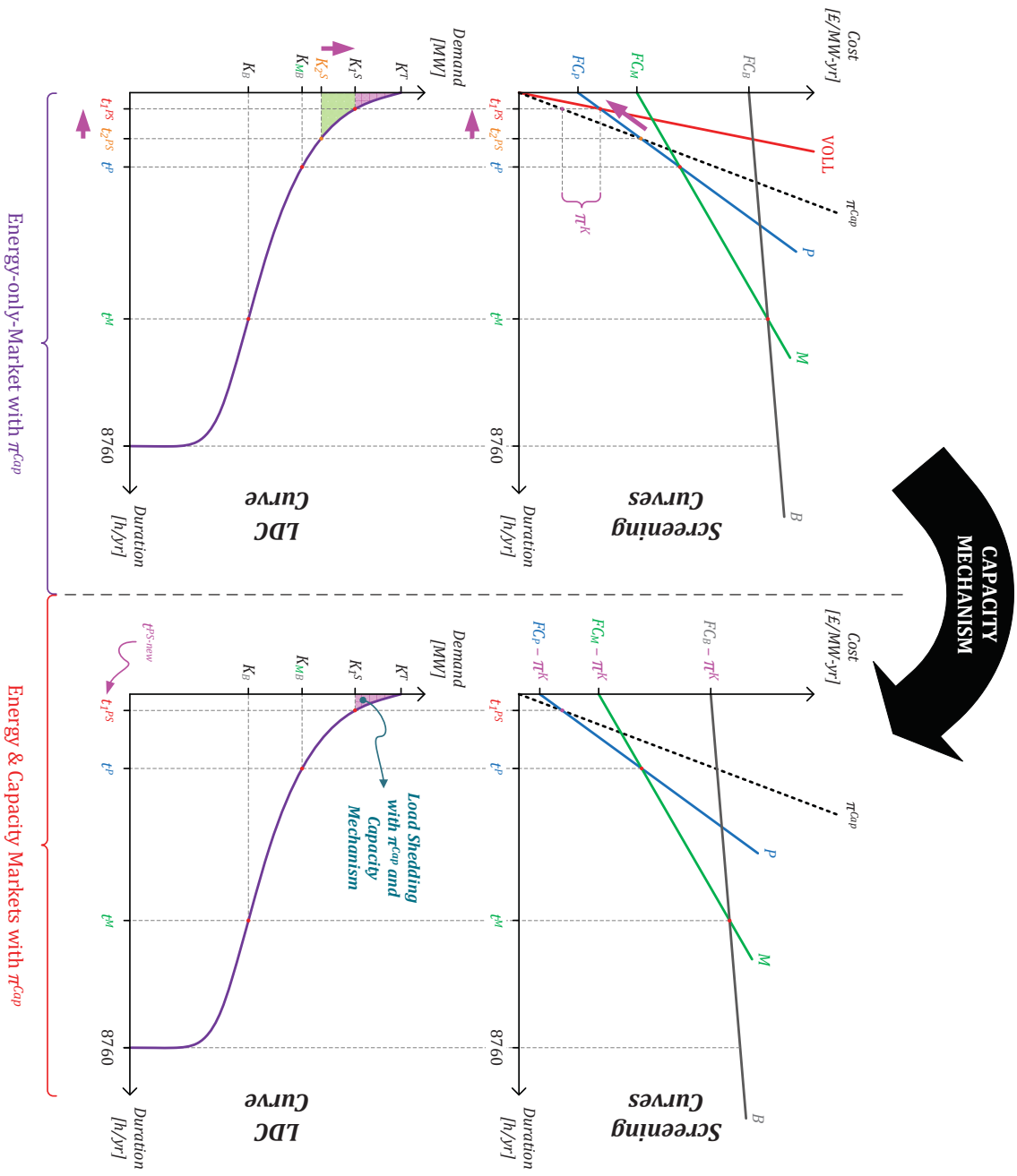


Figure 3.16: Optimal generation portfolio in the long-run equilibrium for an EoM with price-cap regulation and capacity payments for all.

to happen during the year. For such purpose, let us analyse what happens if the capacity price is set equal to the fixed costs of the peaking generation, i.e. $\pi^K = FC_P$, instead of as defined by equation (3.21).

The Short-Run Profit (SRP)⁵⁶ of peaking generation, is formed by two components: Peak Energy Revenue (PER) and Installed Capacity – Payment (ICAP-P). The PER corresponds to the revenues collected during peak hours because the provision of energy and reserve services,⁵⁷ and the ICAP-P, to the revenues collected because the capacity mechanism.

$$SRP_P = PER_P + ICAP-P_P. \quad (3.27)$$

Using the right hand side of equation (3.20), the previous equation can be rewritten as:

$$\begin{aligned} SRP_P &= t_1^{PS} \times [\pi^{Cap} - \pi_P^{inc}] \times K_P + \pi^K \times K_P, \\ SRP_P &= \left(t_1^{PS} \times [\pi^{Cap} - \pi_P^{inc}] + \pi^K \right) \times K_P. \end{aligned} \quad (3.28)$$

Making now $\pi^K = FC_P$ in the previous equation:

$$SRP_P = \left(\underbrace{t_1^{PS} \times [\pi^{Cap} - \pi_P^{inc}]}_{\text{double-payments issue}} + FC_P \right) \times K_P. \quad (3.29)$$

From the previous equation it is possible to see that, if the capacity price is set equal to the fixed costs of the peaking generation technology, there will be more profit (extra-revenue) than what is required by peaking generation to break-even, generating the so-called double-payments issue [147, 148].⁵⁸ Now, if instead of making π^K equal to the fixed costs of the peaking generation, equation (3.22) is used in equation (3.28):

$$\begin{aligned} SRP_P &= \left(t_1^{PS} \times [\pi^{Cap} - \pi_P^{inc}] + t_1^{PS} \times [VOLL - \pi^{Cap}] \right) \times K_P, \\ SRP_P &= t_1^{PS} \times (VOLL - \pi_P^{inc}) \times K_P. \end{aligned} \quad (3.30)$$

Substituting now equation (3.5) in the previous equation:

$$\begin{aligned} SRP_P &= \frac{FC_P}{VOLL - \pi_P^{inc}} \times (VOLL - \pi_P^{inc}) \times K_P, \\ SRP_P &= FC_P \times K_P. \end{aligned} \quad (3.31)$$

⁵⁶ Yearly revenue stream that allow generation technologies to recover their fixed costs.

⁵⁷ The production of each generation technology can include a reserve component, which is not differentiated from the production in this analysis. This means that: $PER_i = ScR_i$. PER revenues are larger than zero when the SMP is above the marginal cost of generation of a generation technology i .

⁵⁸ This can also be verified for the other generation technologies, applying the same procedure.

As shown before, if the capacity price level is set according to equation (3.22) (or equation (3.21)), all the generation technologies will earn economic profits⁵⁹ to cover just their annual (annuitized) fixed costs, and thus, they will break-even.⁶⁰ The capacity price as established by equation (3.21) has two components:

$$\pi^K = \underbrace{FC_P}_{(A)} - \underbrace{t_1^{PS} \times [\pi^{Cap} - \pi_P^{inc}]}_{(B)}, \quad (3.32)$$

where:

(A) Cost Of New Entry (CONE) of a benchmark peaking generation unit.⁶¹

(B) Expected PER over the year.⁶²

The capacity price π^K , as defined by equation (3.32), is also called Net-CONE [59], and corresponds to the cost of entry of a new benchmark generation unit, net of the earnings that this new entrant is expected to collect from the energy market during peak hours, and is the parameter used to define the capacity demand curve used in the capacity market. In the case of PJM RPM, the former capacity demand curve was called Installed Capacity (ICAP) demand curve. The ICAP demand curve was replaced by the Unforced Capacity (UCAP) demand curve [145], due to the ICAP curve did not consider the availability of generation units. The main idea behind the UCAP demand curve, was modify the capacity payments in order to encourage generation plants to improve their availability.⁶³

The construction of the capacity demand curve considering the Net-CONE prevents the double-payments issue, because the capacity price level, and thus the capacity payments, are net of revenues collected in the energy market, providing only the economic profit required to recover the fixed costs. The shape of the capacity demand curve is defined centrally by the regulator, and there is no standardize procedures to construct it. That is why, different capacity demand curves can be found in systems such as PJM, NY and NE.

Finally, the capacity payments allow the restoration of the exact amount of missing-money generated by the price-cap regulation, restoring the market price signals up the level required to ensure that enough generation is built to satisfy the security standard established for the power system.

3.2 A LP FORMULATION OF THE OPTIMAL GEP

At present, the expansion of the generation portfolio in countries around the world is conditioned and influenced by several aspects such as the market framework and regulations,

⁵⁹ Economic Profit = Revenues – Costs.

⁶⁰ $SRP_i = FC_i \times K_i, \forall i \in I$.

⁶¹ This value represents the annuitized capital costs of building a new generation unit, and it is estimated by the regulator, or other central body, through a market research.

⁶² This is an expected value due to t_1^{PS} is the expected number of hours of load curtailment.

⁶³ PJM's capacity demand curve is called today Variable Resource Requirement (VRR) curve. The VRR curve corresponds to the downward sloping demand curve utilized in PJM for the BRA. This curve is defined to provide auction participants with a clear understanding of the level of capacity demand prior to the BRA. In PJM, VRR curves are specified for all Locational Deliverability Area (LDA), in order to provide locational price signals for capacity investment [149, 150].

demand growth, fuel prices, environmental regulations, renewables incorporation, etc. The analysis of the generation investment process is a challenging task, which is of special interest for investors, as well as for governments. Investors on one side want to take proper investment decisions in order to minimize their risk exposure and, at the same time, maximize the profitability of their investments. On the other hand, governments want to ensure that the electric supply is secure and affordable, both in the short and long-term, through the creation of the required market conditions to attract new generation investors and projects.

The GEP is a long-term optimization problem which looks to find the optimal generation capacity mix investment strategy that allows supplying future demand in a particular power system. From a centralized perspective, such type of models allow regulators in planning the generation capacity required to securely and efficiently supply future electricity demand in a cost-effective manner, while from a decentralized and liberalized market one, they are indicative energy planning tools used in the decisions-making process of the different market players [25].

Over the last sixty years, the modelling of the capacity expansion process has become an active area of research as discussed in Section 2.4, especially after the restructuring of the electricity industry and the opening of the generation business to competition. The Screening Curves techniques, used in Section 3.1 to analyse the optimal generation investment economics, allows to derive the optimal generation portfolio required to satisfy demand at minimum cost. Using mathematical programming theory, the same objective can be achieved formulating this problem as a LP optimization problem if some assumptions are made. In this section the GEP problem is formulated as a cost minimization LP program, in order to make the link with the economic analysis of the previous section. A generic formulation is developed, which allows representing the different market structures and regulations analysed in previous sections.

3.2.1 Modelling assumptions

A deterministic formulation of the generation investment problem needs to be established. For that purpose, the following set of general assumptions are made:⁶⁴

- Perfectly competitive market.
- Inelastic demand.
- There is an energy price regulation that caps the electricity prices at a centrally defined value, when demand is larger than the total available capacity.⁶⁵
- Energy is traded through a wholesale market.
- There are only two markets (when applicable): Energy and Capacity.⁶⁶

⁶⁴ This set of assumptions is similar to the one established in Section 3.1.3, but with some modifications and additional assumptions.

⁶⁵ This value can be $VOLL$ or π^{Cap} , depending on the price regulation implemented in the power system by the regulator.

⁶⁶ A capacity market will exist only when a market based capacity mechanism is implemented.

- No ancillary services.
- Single node and aggregated demand.
- There are N^I types of generation technologies.
- No uncertainty.
- Long-run equilibrium.
- Total system cost minimization.
- Traditional economic dispatch.
- Time resolution of one hour⁶⁷ and hourly LDC.⁶⁸

3.2.2 Energy-only-market

From a centralized perspective, the GEP problem looks to find the optimal generation portfolio that minimizes the Total System Cost (TSC), i.e. investment and operation costs. This problem can be understood as a two stages problem:

$$\text{TSC} = \underbrace{\text{Investment Cost}}_{1^{\text{st-stage}}} + \underbrace{\text{Operation Costs}}_{2^{\text{nd-stage}}}, \quad (3.33)$$

where in the 1st-stage generation investment decisions must be taken regarding what types of generation technologies must installed and how much of each of them ($\hat{K}_i$). Then, in the 2nd-stage, the power system must be operated, which implies the economic dispatch of the available generation ($\hat{P}_{ti}$), and the curtailment of the load (L_t^{curt}) that cannot be supplied, in order to satisfy demand in the most cost-effective way.⁶⁹

The capacities to be installed of each generation technology type, are related to the costs incurred due to their construction, and those that needs to be paid although the capacity is not being utilized, i.e. fixed O&M. These costs are represented by the fixed costs (FC_i), and corresponds to the amortized Capital Expenditure (CAPEX) and the fixed O&M costs per unit of capacity of each technology.

Related to the operation of the power system are all those costs involved in the production of electricity, i.e. the incremental cost of generation (π_i^{inc}), and also those related to the curtailment of load, i.e. the load curtailment value (π^{LC}).⁷⁰ Such costs depend on the level of power production, i.e. $\hat{P}_{ti}$, and on the level of load curtailment, i.e. L_t^{curt} , respectively. Then, the TSC is given by:

⁶⁷ $\tau_i = 1$ [h].

⁶⁸ In other words, this assumption implies that the time dynamics of demand are negligible, and also that demand is not affected by electricity prices.

⁶⁹ The caret symbol, i.e. “^”, is used in this section to distinguish the variables used in the LP formulation, from those used in the integer formulation presented in Chapter 4.

⁷⁰ The value given to the load curtailment depends on the regulation established for the system. So far, two price regulations have been analysed: Value Of Lost Load and price-cap, in which π^{LC} is equal to VOLL and π^{Cap} , respectively.

$$\text{TSC} = \underbrace{\sum_{i \in I} \hat{K}_i \text{FC}_i}_{\text{Investment Cost}} + \underbrace{\sum_{t \in T} \sum_{i \in I} \tau_t \hat{P}_{ti} \pi_i^{\text{inc}}}_{\text{Operational Cost}} + \underbrace{\sum_{t \in T} \tau_t L_t^{\text{curt}} \pi^{\text{LC}}}_{\text{Load Curt. Cost}}. \quad (3.34)$$

Operation Costs

The GEP problem, for an EoM with a electricity price limiting policy, can be written in an optimization form as follows:

$$\mathcal{P}) \min_{\hat{K}_i, \hat{P}_{ti}, L_t^{\text{curt}}} \left\{ \sum_{i \in I} \hat{K}_i \text{FC}_i + \sum_{t \in T} \tau_t \left[\sum_{i \in I} \hat{P}_{ti} \pi_i^{\text{inc}} + L_t^{\text{curt}} \pi^{\text{LC}} \right] \right\}, \quad (3.35)$$

subject to:

$$\hat{P}_{ti} \leq K_i, \quad \tau_t \mu_{ti} \geq 0, \quad \forall t \in T, \forall i \in I, \quad (3.36)$$

$$\sum_{i \in I} \hat{P}_{ti} + L_t^{\text{curt}} = D_t, \quad \tau_t \pi_t \text{ free}, \quad \forall t \in T, \quad (3.37)$$

$$\{\hat{K}_i, \hat{P}_{ti}, L_t^{\text{curt}}\} \in \mathbb{R}_{\geq 0}, \quad \forall t \in T, \forall i \in I. \quad (3.38)$$

The objective function to be minimized (equation (3.35)), as explained at the beginning of this section, is the TSC. The first set of constraints, or capacity constraints (equation (3.36)), establish that the electricity production of any technology i during any demand segment t can never exceed the installed capacity of that technology. The second set of constraints, or demand balance equations (equation (3.37)), establish that the total production of all generation technologies, plus the load curtailment (shedding), must be equal to the demand level for all demand segments t . Finally, equation (3.38) corresponds to the decision variables type and sign constraints. At the right of each set of the constraints, the Lagrange multipliers associated to each of them are included. The description of each of those multipliers, sets, decision variables and parameter used in the previous formulation can be found in the nomenclature.

The GEP formulation given by equations (3.35) to (3.38) allows representing the GEP for an EoM with VOLL-pricing or price-cap policies. In an EoM with a VOLL-pricing policy, as analysed in Section 3.1.3, energy and reserve are the only resources traded in the electricity market. In order to prevent the market failure created by the inelasticity of demand when the system is short of generation resources,⁷¹ the energy not served⁷² is penalized at VOLL,⁷³ which is a regulated and a centrally established value. On the other hand, if a price-cap regulation is considered, then instead of valuing an unsupplied megawatt-hour of energy at the willingness to pay for it by an average consumer, i.e. VOLL, the energy not served is penalized at π^{Cap} .⁷⁴

3.2.3 Energy & capacity markets

Scarcity rent is the main driver for investment in an EoM structure, which is conditioned as stated in Sections 3.1.3 to 3.1.5, by the price regulation established by the regulator to

⁷¹ When $D_t > \sum_{i \in I} K_i$, as shown in figure 3.3 [1].

⁷² The energy not served is equal to $\sum_{t \in T} \tau_t L_t^{\text{curt}}$.

⁷³ $\pi^{\text{LC}} = \text{VOLL}$.

⁷⁴ $\pi^{\text{LC}} = \pi^{\text{Cap}} \ll \text{VOLL}$.

control high electricity prices. Inefficient price regulations create distortions in the market price signals, which discourage investment, compromising the security of supply and resource adequacy of the power system in the long-term.

In order to introduce a capacity mechanism, which as stated in Section 3.1.6 is assumed to be market-based mechanism with a centrally specified capacity requirement, only a long-run constraint must be added. This constraint must ensure that enough capacity is built in order to satisfy the security standard established before hand for the power system. Before proceeding, the following additional assumptions are made:⁷⁵

- The capacity market is open to all generation capacity available in the system.
- The capacity resources are auctioned one-year ahead.
- All the generation capacity resources are offered in the capacity market.
- The capacity payments are proportional only to the installed capacity of each generation technology.
- All capacity resources are paid at the same rate.⁷⁶

The long-term capacity constraint that must be added to the GEP optimization formulation presented in the previous section (equations (3.35) to (3.38)), in order to extend it to consider a CM, is the following one:

$$\sum_{i \in I} \bar{A}_i K_i \geq (1 + RR^K) \times D^{\text{MAX}}, \quad \pi^K \geq 0. \quad (3.39)$$

The long-run capacity constraint, or capacity target constraint, requires that the total available installed capacity must be at least equal to the peak demand⁷⁷ plus the Reserve Margin (RM), which is specified through a Reserve Requirement (RR) factor, i.e. RR^K .⁷⁸ The Lagrange multiplier associated with this constraint, i.e. π^K , represents the marginal value of capacity, or capacity price, in the forward capacity market, i.e. in the capacity auction that is held one-year in advance as assumed before.

Constraint (3.39) will enforce to build more generation capacity than peak demand if the RR factor is positive, which means that there will not be price-spikes as the installed generation capacity will always be able to satisfy demand.⁷⁹ This implies that the capacity price will be equal to the fixed cost of the peaking generation technology, as there will not be ScR for them to recover fixed costs.⁸⁰

⁷⁵ This set of assumptions is similar to the one established in Section 3.1.6, but with some modifications and additional assumptions.

⁷⁶ There is only one capacity price, i.e. π^K .

⁷⁷ $D^{\text{MAX}} = \max_{t \in T} \{D_t\}$.

⁷⁸ $RM = RR^K \times D^{\text{MAX}}$.

⁷⁹ $RM > 0 \Rightarrow \sum_{i \in I} \bar{A}_i K_i > D_t, \forall t \in T$.

⁸⁰ If instead the factor $(1 + RR^K)$ is changed by another factor, which value can be smaller than 1, then it is easy to see that there will be prices-spikes that will generate ScR for peaking generation, which will complement the capacity payment, and therefore, the capacity price will be smaller than their fixed costs, as demonstrated in Section 3.1.6.

3.3 WHY FLEXIBILITY OF GENERATION & DEMAND MATTERS?

Variability and uncertainty are inherent characteristics of modern power systems. Penetration of electricity in human's daily life is making electricity demand a very dynamic and complex process, characterized by constant changes, increased variability and growing demand [151, 15]. The large-scale penetration of intermittent renewables is one of the key factors in the increased variability and unpredictability of net-demand,⁸¹ product of their inherent intermittency and stochastic nature.⁸²

It is in this context where flexibility begins to play a more important role. Generally speaking, flexibility refers to the extent to which a power system, or a component of it, can modify the electricity production or consumption in response to expected or unexpected variations in electricity demand or supply. To understand why flexibility is needed and what is its importance for the development of power systems, it is useful understanding which are the features introduced by renewable generation in the time dynamics of net-demand, when the share of such renewables in the power system is not negligible.

Large shares of renewables are expected to boost existing net-demand variability in amplitude, frequency and rate of change, as it can be seen in figure 3.17, where the variability of demand and net-demand is depicted in a simulation of a challenging week in 2030, considering the Gone Green UK future energy scenario [152].⁸³ The blue line corresponds to the demand, while the red one corresponds to the demand net of wind and solar PV power output, i.e. the net-demand, assuming that all the energy provided by those renewables is utilized, and a perfect forecast of demand and renewables power generation.⁸⁴ Additionally, renewables forecasting will largely increase the net-demand forecast uncertainty as shown in figure 3.18, where the forecast errors of demand and net-demand are shown for the same week simulated in figure 3.17.⁸⁵

Demand shapes follows a regular and smooth pattern characterized by an increasing demand during working hours, with a peak at around 7:00PM that is when people arrives home

81 The net-demand is defined as the total system electricity demand minus the power contribution of Variable Renewable Energy (VRE) resources at each demand segment t . This residual power demand must be supplied by conventional generation and other controllable generation resources in the power system.

82 The variability of demand is not a new phenomenon, and exists since electricity was commercially supplied by first time to customers in 1879 by the California Electric Light Company [12].

83 The simulation presented in figure 3.17 was created using UK historical demand data obtained from the UK National Grid Electricity Transmission (NGET) website, a normalized wind power output profile simulated using the model developed by Sturt and Strbac [153, 154], and a normalized solar PV profile obtained from The Centre for Sustainable Electricity and Distributed Generation (Annex A). The UK historical demand data was used to produce a normalized demand profile which was then escalated by the peak demand expected in year 2030 of the Gone Green UK future energy scenario [152] (blue line). The wind and solar PV power output profiles (yellow and green areas) were created using normalized profiles, as described before, which were escalated by the expected levels of wind and solar PV generation capacity expected in year 2030 of the Gone Green UK future energy scenario [152]. The net-demand (red line) was obtained subtracting the wind and solar PV power output from the demand profile. Finally, in figure 3.17 a challenging week is plotted, i.e. a week with high variability of wind and solar PV generation.

84 Only wind and solar PV are the VRE technologies considered in this simulation.

85 The simulation presented in figure 3.18 was created using the demand, wind and solar PV profiles simulated in figure 3.17, and shows the forecast uncertainty of demand and net-demand, i.e. demand and net-demand profiles plus/minus 1, 2 and 3 forecast error standard deviations (Annex A). This simulation assumes a 4-hours lead time forecast error, where the standard deviation of the demand is 1% of the demand level at each demand segment t , while those of wind and solar PV generation are 7.8% and 3.9% of the respective power available levels at each demand segment t (table A.3).

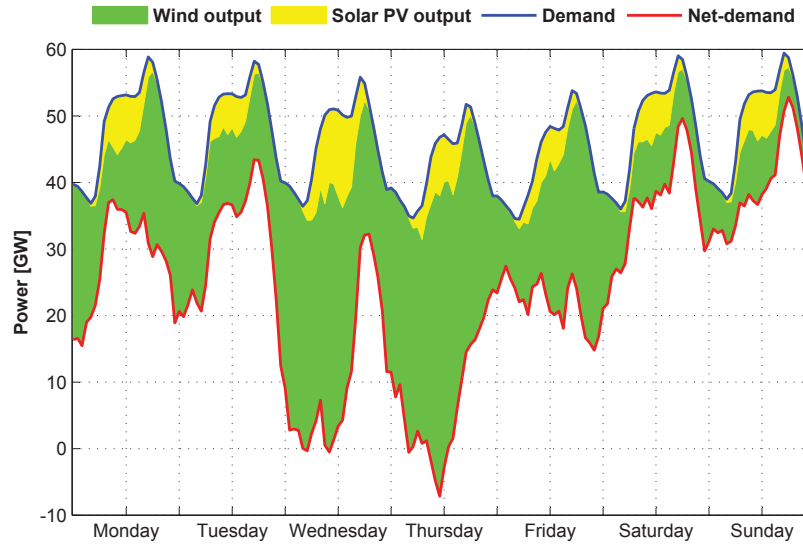


Figure 3.17: Simulation of the variability of demand (*blue line*) and net-demand (*red line*) for a challenging week in 2030, considering the Gone Green UK future energy scenario, where wind and solar PV generation accounts for the 47% and 13% share of the total power system generation capacity respectively.

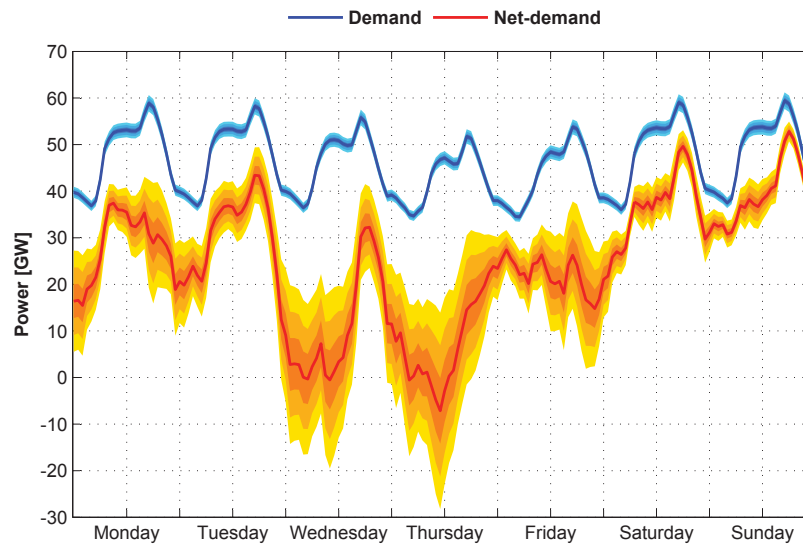


Figure 3.18: Simulation of the forecast uncertainty of demand (*blue line*) and net-demand (*red line*) for a challenging week in 2030, considering the Gone Green UK future energy scenario and 50% share of renewable generation.

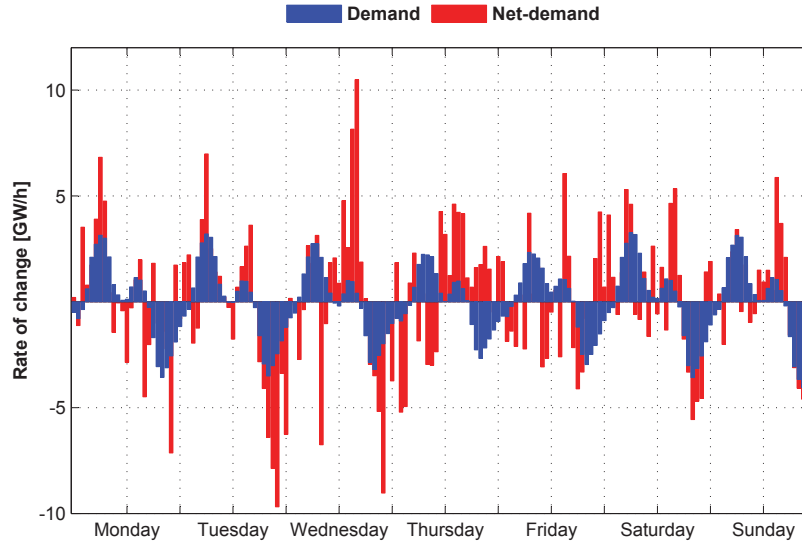


Figure 3.19: Simulation of the rate of change, between consecutive demand segments t (hours), of demand (*blue bars*) and net-demand (*red bars*) for a challenging week in 2030, considering the Gone Green UK future energy scenario and 50% share of renewable generation.

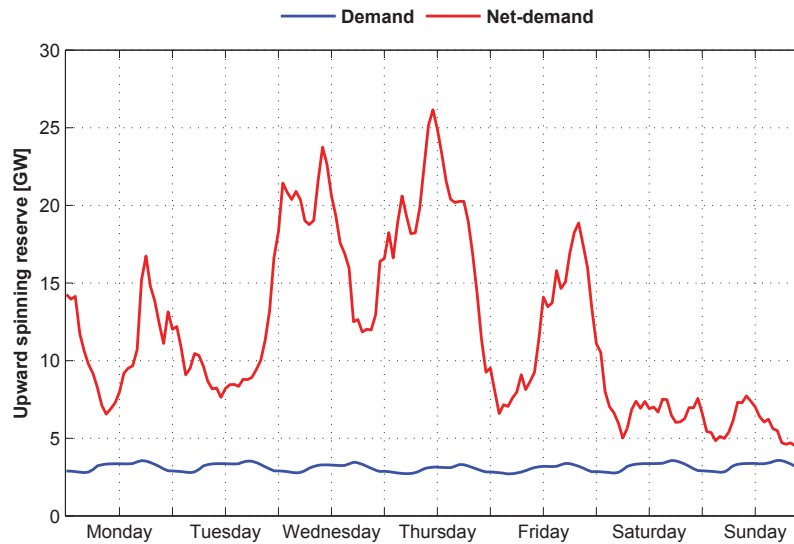


Figure 3.20: Simulation of the required level of upward spinning reserve in the case of demand (*blue line*) and net-demand (*red line*) for a challenging week in 2030, considering the Gone Green UK future energy scenario and 50% share of renewable generation.

from work, after which gradually decreases during night time.⁸⁶ Net-demand on the contrary exhibits an irregular and non-smooth pattern, which highlights the boosted variability caused by the 50% VRE capacity share. Larger shares of renewables will translate into a larger variability and uncertainty in net-demand, which will need to be supplied by existing and new controllable generation capacity. Current power systems, as analysed by Milligan, et al. in [156], have the flexibility resources to accommodate moderate amounts of renewables. However, increasing renewables penetration levels, will put under stress those power systems, revealing the need for additional system flexibility. This is illustrated in figures 3.17 and 3.18, where a number of interesting features in the net-demand, which will be more frequent for larger shares of renewables, can be highlighted:

1. Net-demand falls below zero during four periods, which means that there is an excess of energy in the system which will need to be stored or exported, or otherwise curtailed, which will not be economically beneficial for electricity consumers, as it will basically mean throw away cheap energy.
2. The rate of change of net-demand is much more larger than that of demand, as illustrated in figure 3.19 that shows the demand and net-demand rate of change between consecutive hours.⁸⁷ This will translate into that available generation will need to increase and decrease its production at higher rates.
3. The uncertainty of net-demand is much bigger than that of demand. This will increase the level of the reserve services required to handle unexpected deviations from the original forecasts. For example, figure 3.20 shows a simulation that compares the required level of upward spinning reserve.⁸⁸

Each of the net-demand features described before will create challenging operational conditions for the existing controllable generation. Large renewables production, as explained in point (1), will contribute with enough power to fully satisfy demand, reducing production of baseload generation and forcing it to reach their minimum stable operational levels. Below those levels, baseload generation units need to be shut-down, requiring keeping them offline at least by their minimum down time,⁸⁹ before being able of bringing them online again. On the other hand, once baseload generation units are brought online, they need to stay turned on for at least their minimum up time, which is of the same order of magnitude that the minimum down time, which will mean that frequent and successive excesses of energy in the system will be lost, due to these timing operational restrictions. Additionally, start-up and shut-down manoeuvres of this type of generation are costly, which will justify the renewables

⁸⁶ Customers electricity demand still can be predicted with low levels of forecasting error [155], but this is expected to change due to the envisaged electrification of other energy sectors.

⁸⁷ The simulation presented in figure 3.19 was created using the demand and net-demand profiles simulated in figure 3.17, and shows the rate of change of those profiles, i.e. the variability of demand (blue bars) and net-demand (red bars), between consecutive demand segments: $[\text{Rate of change of Profile}]_t = [\text{Profile}]_t - [\text{Profile}]_{(t-1)}$.

⁸⁸ The simulation presented in figure 3.20 was created using the demand and net-demand profiles simulated in figure 3.17, and shows the level of upward spinning reserve required in the case of demand (blue line) and net-demand (red line), which is calculated as the size of the largest generation unit in the power system, i.e. nuclear generation unit (table A.2), plus 3 forecast error standard deviations (Annex A, table A.3).

⁸⁹ For baseload generation technologies, i.e. nuclear and coal power plants, the minimum down time can vary from several tens of hours for coal generation, up to weeks for nuclear power plants.

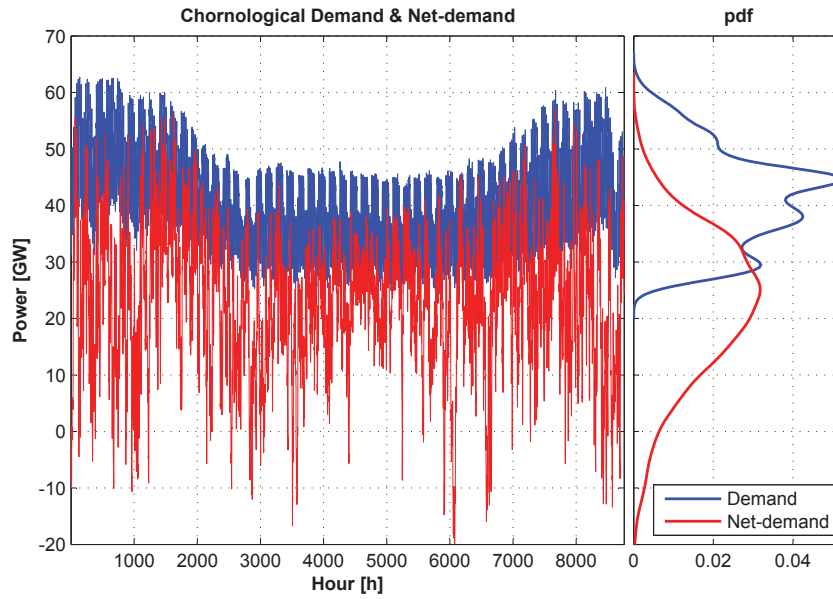


Figure 3.21: *Left*: Simulation of the variability of demand (*blue line*) and net-demand (*red line*) in 2030 considering the Gone Green UK future scenario. *Right*: Probability density functions estimated from the simulated demand and net-demand using a Normal KDS procedure.

energy spillage. These type of situations can be handled only by low minimum operational level and quick start-up/shut-down generation units. This will mean that in the long-term and for large renewables penetration levels, the share of this type of generation units is expected to increase, making baseload generation investment and operation economically inefficient, which will also translate into the decommissioning of existing baseload generation units.

The increased net-demand rate of change product of the large-scale penetration of renewables, as described in point (2) and exemplified in figure 3.19, will force existing generation units to change their power output at higher and more frequent rates. These type of situations are not only costly, but also will expose thermal generation to increased stresses and wear, reducing the lifetime of generation units. Curtailment of renewables, or faster ramping capability generation units, will be then required, and given the emissions reduction targets, the second option will translate in the demand for larger shares of fast ramping generation in future power systems, as well as in the decommissioning of slow existing generation units.⁹⁰ On the other hand, the increased uncertainty of net-demand, as described in point (3) and shown in figure 3.18, and the increased cycling of conventional generation analysed in previous paragraphs, will demand larger amounts of long and short-term reserve services in order to make front to the imbalances created by unexpected deviations from the forecasted values, generation outages, and sudden changes in electricity demand. In the short-term, primary and secondary reserve levels will increase due to the reduced forecast accuracy of renewables for larger penetration levels of renewables, and also due to the increased probability of generation outages, product of the additional wear and stress to which generation units will be exposed. In the long-term, on the other hand, increased generation outages will diminish their availability levels, resulting in the need of more and smaller thermal generation units.

⁹⁰ This also highlights the potential value that investing in improving the technical and operational characteristics of conventional generation may have for future power systems, as studied in this thesis.

The situation previously depicted will be exacerbated and complicated even further due to the CO₂ emissions reduction targets and CO₂ emissions policies implemented or under implementation in many countries around the world to promote renewables integration and low-carbon generation investment. CO₂ emissions caps and/or CO₂ prices will promote the use of low-emissions generation in the short-term. This will increase system flexibility, but may have the adverse effect of leave the existing more pollutant and slow generation as last resort during peak hours. This can create operational issues, as the timing constraints of this type of generation, i.e. ramping capability and minimum up/down times, will not allow absorbing the additional net-demand variability. In the long-term, on the other hand, the CO₂ emissions limits and/or CO₂ prices will promote investment in low emissions generation capacity, i.e. nuclear, Carbon Capture and Storage (CCS) equipped generation, etc. However, large-scale penetration of renewables will discourage the investment in clean and cheap baseload generation, i.e. nuclear, due to its lack of flexibility, which will translate into power systems with larger operational costs, and higher electricity prices for consumers.

The power output of renewables fluctuates according to the available resource. Such fluctuations in the generation side will mean that in order to maintain the balance between demand and supply, conventional generation or demand will have to modify their production or consumption at higher rates and frequencies for larger shares of VRE, in order to accommodate such extensive and rapid changes as effectively and economically possible (see figure 3.21 that expands the simulation horizon presented in figure 3.17 to a full year). This increased responsiveness required for the power system will translate in larger demands for flexibility resources, which traditionally have been associated with quickly dispatchable conventional generation, but that today product of the large penetration of smart (flexible) grid technologies, opens the window for new sources of flexibility such as non-thermal generation, DSR, and storage, among others, in the electricity sector, and also to others outside of it product of the electrification of other energy sectors such as transportation and heating. In the demand side and of particular interest for this research are the EV, whose power demand can be smartly and optimally controlled when they are equipped with smart-grid technologies. Additionally, the concept of Vehicle-to-Grid (V2G) will allow EV injecting power into the grid when required. However, this operational mode of EV is not analysed in this thesis and will be topic for further research, as well as the use of the electric heating flexibility.

Traditional resource adequacy planning, as analysed in this chapter, have largely rely on very strong assumptions such as using LDC and not considering the non-convex costs of conventional generation operation, to calculate the overall adequate level of generation capacity, neglecting the undeniable importance of the different generation technologies technical and operational characteristics when chronological demand is considered.

Traditional generation expansion planning models, in general, only consider the costs of the fuel consumed and the CO₂ generated (incremental costs) when supplying demand,⁹¹ omitting considering the non-convex costs associated with the generation of electricity. The non-convex power generation costs are those related to the cycling of conventional generation units, i.e. the costs incurred due to start-up and shut-down events, and also those related

⁹¹ These type of costs are called incremental costs due to they are proportional to the power output produced by generation units.

to the unit commitment status of generation units. The costs associated with changes in the commitment status of generation units, i.e. when generation units are turned on or off, include fuel, CO₂ emissions, and fixed O&M costs which are incurred due to start-up and shut-down manoeuvres. On the other hand, the no-load costs, which include fuel and CO₂ emissions costs, are non-convex costs that have to be paid if a generation unit is online. The non-convex power generation costs have to be paid independently if a generation unit is or not producing electricity, and thus they do not depend on the power output of generation units. These costs have been traditionally omitted under the assumption that chronology of demand is irrelevant, and thus, that those costs are negligible compared to the incremental costs. As analysed before, such an assumption lacks of validity due to the large-scale penetration of renewables and their impact on net-demand will increase the number of start-up and shut-down events, and also will require having more generation units online.

Today, planners must ensure that power systems contain the required amount of flexible resources that will allow accommodating increasing penetrations of VRE resources, and for this reason generation flexibility needs to be considered in GEP, as well as the flexibility characteristics of alternative sources of flexibility. The challenge to keep the lights on demands complex and integrated GEP models that are able to incorporate a detailed characterization of supply and demand sides, in order to produce meaningful indicative energy planning results that can guide regulators to create the proper market conditions and incentives that will deliver the required future power systems configuration.

In Chapter 4 a novel and fully integrated large-scale mixed-integer linear GEP model is presented, which incorporates a detailed modelling of flexible demand, as well as of the generation side unit commitment, and that allows investing not only in generation capacity, but also in flexible demand in systems with a high degree of renewables and electrification of the transport sector. This model is used later to show evidence of how investing in flexibility of conventional generation and demand can reduce total systems costs, help to the efficient integration of renewables, and also to decrease the demand for peaking flexible generation.

Part III

STRATEGIC-GEP MODEL & CASE STUDIES

INCLUDING FLEXIBILITY MODELLING IN GEP

The effective integration of increasing levels of renewables will involve using the energy coming from those variable renewable energy (VRE) resources when it is available, trying always to make the most use of it as economically possible. For such purpose there must exist sufficient physical flexibility in the power system, i.e. in the generation fleet and demand side, in order to effectively balance the system at all times.

Integrating higher penetrations of renewables impose the need for more flexibility and so flexibility must be considered in resource adequacy planning so that it properly evaluates the required levels of system flexibility needed to meet electricity demand. The physical attributes, or flexibility characteristics, of generation resources refer to their technical and operational limitations, which are considered when modelling the unit commitment (UC) problem. On the other hand, those of demand resources depends on the type of demand, but mainly refers to the dynamics of their electricity consumption.

In this chapter the developed Strategic-GEP model is presented. For such purpose, the building blocks of this model are analysed first, starting by the conventional generation UC, then passing by flexible electric vehicles, hydro pumped-storage and renewables modelling, to end up with the full formulation of the proposed optimization model.

4.1 WHAT IS MEANT BY FLEXIBILITY CHARACTERISTICS?

Flexibility refers to, as described in Section 3.3, the extent to which a power system, or a component of it, can modify the electricity production or consumption in response to expected or unexpected variations in electricity demand or supply [15]. From a system perspective, the flexibility of the system describes the capability of the power system to reliably manage rapid and large imbalances between supply and demand, whatever the cause.

Power system flexibility depends on the resources that are capable of providing flexibility. Traditionally, flexibility has been associated with generation resources that can be quickly dispatched. Although this type of flexible resources are of the greatest importance, flexibility provision is not only restricted to power plants. Due to the fast development and penetration of smart-grid technologies, other sources of flexibility such as demand-side management or response, and storage, among others, may potentially be used to balance the system.

Flexibility may also come from resources outside of the electricity sector. The envisaged electrification of other energy sectors, such as transportation and heating, combined with the rapid development and penetration of smart-grid technologies may drive potential synergies with

the energy sector as result of the growing importance of flexibility. The smart charging/dis-charging of EV fleets in the transportation sector, and space heating using electric thermal storage systems in the heating sector, may be used to manage surpluses and variations of VRE outputs, helping to lowering the demand for flexibility from conventional generation.

The physical attributes¹ of conventional generation in the supply side, and flexible EV in the demand side, are analysed in this section.

4.1.1 Generation

Quick start and dispatchable generation is today the main source of flexibility. However, the extent of this flexibility is governed by the technical and operational limitations of those generation resources, i.e. minimum stable and maximum power outputs, ramping capability, minimum up and down times, start-up and shut-down times, and must-run operation, among others [36, 157].

MINIMUM STABLE POWER OUTPUT refers to minimum power output level at which a generation unit can stably produce electricity.

MAXIMUM POWER OUTPUT refers to the maximum power output level of a generation unit.

RAMPING CAPABILITY refers to the maximum rate at which a generation unit can increase (ramp-up) or decrease (ramp-down) its power output.

MINIMUM UP & DOWN TIMES refers to the minimum time during which a generation unit cannot be turned off or on respectively.

START-UP TIME refers to the time required to bring online a generation unit, i.e. the time required to reach the minimum stable generation level.

SHUT-DOWN TIME refers to the time required to turn off a generation unit, i.e. the time required to reach zero output.

MUST-RUN OPERATION refers to the operational condition of generation units that must be always online, due to either technical and/or economic reasons.

4.1.2 Flexible demand of electric vehicles

The flexibility that can be provided by the demand side not only depends on the type of demand, but also on the temporal dynamics and technical characteristics of their electricity demand. In the case of EV this refers to the travelling and energy demand patterns of EV users, their willingness to modify them, and the EV battery and grid connection power electronics, respectively.

The EV users travelling and energy demand patterns characterize the time and amplitude domains of the flexibility that they can provide, and include the travelling and parking times, and also the travelling energy requirements. On the other hand, the EV power electronics govern

¹ Flexibility characteristics.

the physical extent of their flexibility and include EV battery capacity, charging/discharging efficiencies, minimum and maximum energy levels, and maximum charging/discharging rate, among others.

Flexible EV operation can be understood as a storage facility, with the difference that they are not always connected to the grid, i.e. when they are travelling or parked at a location where there is no connection point to the grid. Because of this, flexibility can only be provided during a reduced set of demand segments (hours) in the day, during which the EV are parked and plugged to the grid.

In this thesis, as described in Chapter 1 and later in this chapter, EV are considered as smart loads,² which means that the flexibility of EV is given by the possibility of optimally scheduling their power consumption during the day.³

4.2 THE UNIT COMMITMENT PROBLEM

4.2.1 Unit commitment problem: meaning, modelling & solution

What UC means?

In power systems operation, one of the most important problems is computing the generation scheduling required to reliably balance electricity demand and supply at all times, while satisfying the technical and operational constraints of available generation units. Generation scheduling involves planning both the commitment and the production output of a set of generation units for a specific horizon of time. The commitment of a generation unit refers to the actions of starting the unit, bringing it to synchronous speed,⁴ and connecting it to the grid so it can generate the scheduled power production.

The unit commitment of a generator is conditioned by its specific technical and operational characteristics, and for this reason, solving the commitment of a set of generation units is not a trivial task and given that some of those technical and operational constraints are very complex, it needs to be solved well in advance of real time. This is what is commonly referred as the unit commitment (UC) problem, and its increasing relevance for the operation and planning of modern power system is proven by the prolific literature on this topic, especially during the last decade, which is due to the combination of at least four independent factors. The first is the explosive progress of the Information Technologies (IT), which have allowed tackling to some extent the computational burden required to solve this problem. The second is the development of new optimization techniques and methods, which have allowed improvements in the efficiency of the existing models, and also increases in their complexity, being able to model technical and operational limitations that were not possible before. The

² Flexible loads.

³ The capability of discharging energy into the grid, also known as V2G [158, 159, 160] is not analysed in this thesis and will be matter for further research. This EV operation mode is not analysed due the skepticism among experts about the feasibility of V2G, and also to the fact that the infrastructure required to enabling V2G at large-scale is far from being implemented, and will require more research [161, 162, 163].

⁴ Synchronizing a generation unit is the process of matching the speed and frequency of a generator (voltage, frequency and phase angle) so that it can be disconnected from the starting bus and connected to the grid [164, 165, 166].

third is the need to adapt UC models according to the specific characteristic of each power system, which have demanded the development of a wide spectrum of models. Finally, the rapid and large penetration of renewables worldwide is undoubtedly the key driver for the research in this area nowadays, as discussed in Sections 2.4.2 and 3.3.

The large-scale penetration of renewables, as analysed in Section 3.3, is changing the way in which power systems are operated in order to reliably produce electricity. Large and unexpected variations in the output of VRE resources will introduce uncertainty and variability in net-demand, which amplitude, frequency and rate of change will keep power systems under constant stress. This needs to be incorporated in the UC modelling to schedule robust and reliable generation to maintain security of supply in the short-term. On the other hand, power systems in the long-term need to have the adequate amount of flexible resources to allow the effective and efficient accommodation of new renewable resources. This means that system planners must ensure that proper system flexibility modelling is included in generation expansion planning in order to account for the expected future levels of renewable generation.

Generally speaking, the UC problem involves deciding on the on/off status, and the production output, of a set of generation units. The production output implies making continuous decisions for each generating unit about how much power needs to produce at each point in time on the assessment horizon. On the other hand, turning on or off generating units imply making discrete decisions, for each point in time on the assessment horizon, whether each generating unit must or not be online.

The discrete nature of the UC problem, the inherent combinatorial characteristic of its solution, and the complexity of its constraints, makes solving it a difficult and non-trivial task, even for short assessment horizons. This is why UC problems have been traditionally confined to short time horizons, which normally extend from 24 to a few hundred hours. Extending this problem to longer time horizons, using traditional formulations, makes the problem computationally intractable for real power systems. This is the reason why resource adequacy planning has historically avoided including detailed generation technical and operational characteristics in this long-term planning exercise thereby accepting suboptimal solutions for the long-term investment decisions.

How the UC problem can be modelled and solved?

During the past five decades, algorithms of many types have been developed to solve the UC problem as optimally as possible. The main motivation for the extensive research in this area has been the fact that better solutions can translate into significant cost savings. The variability that VRE resources introduce in net-demand, and the expected increase in the system operational costs, have boosted even further research on this topic.

The first approaches used to solve the UC problem were based on power system operators' practical experience and heuristic techniques, i.e. non-rigorous computer aided empirical methods, such as priority lists [167, 168, 169, 170, 171]. This was followed by the use of computing machines to optimize UC in the late 1960's [172, 173, 174]. The computer revolution and the growing access to computers during the 1970's, in combination with the significant progress

in the linear⁵ and integer⁶ optimization fields since the late 1940's and mid 1950's respectively, boosted the development of UC models of increasing detail and complexity [94, 177].

Since the first use of optimization theory to optimize power systems operation, many methods and techniques have been developed and applied to solve the UC problem. These methods and techniques can be roughly categorized into four groups:

1. Dynamic Programming, e.g. [178, 177];
2. Integer and Mixed Integer Programming, e.g. [179, 180, 37];
3. Decomposition techniques: Lagrangian Relaxation, Benders Decomposition, Augmented Lagrangian Relaxation, e.g. [181, 182, 183, 184, 185];
4. Heuristic and meta-heuristic approaches: Priority Listing, Taboo Search, Simulated Annealing, Evolutionary Programming, Neural Networks, Expert Systems, Fuzzy Systems, Genetic Algorithms, Ant Colony Search Algorithms, and Particle Swarm Optimization, among others, e.g. [186, 187, 188, 189].

The performance, and the advantages and disadvantages of each of those methods, underpins the scope of this thesis. Interested readers are referred to [85, 86, 190, 191, 192, 193, 194, 195], for extensive information and reviews of the UC problem.

Decomposition techniques, and predominantly Lagrangian Relaxation [196], have prevailed as the most used approaches to solve the generation scheduling problem [197, 198]. Nevertheless, the progress and increased efficiency of integer programming algorithms and solvers, plus the simplicity in the implementation of complex constraints that they offered, are shifting the UC modelling to Mixed Integer Linear Programming (MILP) formulations, e.g. [37, 199, 200, 201, 202, 203].

Exhaustive enumeration was an early use of concepts from MILP theory, and as suggested by its named, implied the full enumeration of the solution space in order to select the minimum cost one [172, 173]. The main drawback of this approach is that it is not scalable for large power systems. A recent application of exhaustive enumeration can be found in [198], where this technique is used to solve some of the sub-problems of the hybrid decomposition approach based on Lagrangian Relaxation and sequential quadratic programming proposed to solve the UC problem of hydro-power plants.

In 1962, Garver [180] formulates for the first time the power generation scheduling problem as an integer program, and proposes an algorithm based on the Gomoroy's [204] and Euclid's algorithms to solve it. Later, Muckstadt & Wilson [181] present a decomposable MILP formulation for the dispatch of thermal power generating equipment for which solution they use a modification of the Bender's partitioning procedure [205], and Dillon & Egan [206] solve their UC model using an algorithm based on the Branch-and-Bound technique [179].

⁵ With the pioneer works of George B. Dantzig, who published the Simplex Algorithm in 1947 [175], and the Theory of Duality developed by John von Neumann.

⁶ For a list of the mixed-integer programming milestones between 1954 and 1973 please refer to pages 4 to 6 of the book "50 Years of Integer Programming 1958-2008: From the Early Years to the State-of-the-Art" [176]. Interested readers may find in this book an extensive and detailed coverage of the history of the research on integer programming.

New and very efficient [MILP](#) solvers are making [UC MILP](#) formulations more and more common. However, the effectiveness and efficiency of such solvers in solving the [UC](#) problem depends on many factors, such as the number of generation units to be scheduled, how much detail is incorporated into the modelling, and how well and tightly defined is the solution space, among others. This scalability drawback of the [UC](#) problem has been partially overcome by means of combining [MILP](#) with other methods such as dynamic programming [207], logic programming [208], quadratic programming and decomposition procedures, e.g. [183, 184, 209, 210, 211, 212].

The attention on [MIP](#) and particularly in [MILP](#) models has been lately renewed due to a number of factors, among which stand out the notable increase in [MILP](#) solvers efficiency [213] and the chance of integrating non-linear features. This has allowed extending the use of [MILP](#) to solve more [UC](#) problems with acceptable accuracy and in running times that are compatible with real power system operation [37]. The previous, added to fact that [MILP UC](#) models are much simpler of formulate and modify, makes them a useful tool for decision-makers that require highly customized models for their specific needs. However, such customization according to the users' needs must to be made carefully due to new constraints and additional features in the models may lead to tractability, or even solvability, issues.

The latest trends on the [MILP](#) research applied to the [UC](#) problem are focused on two somehow antagonistic targets which are the searching for tighter formulations in one side, and on the other, the searching for more precise and accurate representations of real-world power system operation. Tighter and compacter [UC](#) formulations look for effective continuous relaxations of the models that allow solving them more efficiently and providing better lower bounds. On the other hand, a more accurate representation of generation and demand side resources, together with their specific flexibility characteristics, allow taking better operational decisions.

Ross Baldick in [214] proposes a solution algorithm to the [UC](#) problem based on Lagrangian Decomposition, in which he adds surrogate constraints in order to tightening the dual problem. Rajan & Takriti [215] develop a strong relaxation of the minimum up/down time constraints polytopes that completely describes its convex hull and leads to large improvements in computational time. This constraint tightening, and others proposed for the minimum up/down time are analysed and compared by Hedman, et al. in [216], providing also an overview of other [UC](#) valid inequalities. In [37], Carrion & Arroyo propose a [MILP](#) formulation for the thermal [UC](#) problem that compared to previously reported models requires fewer binary variables and constraints, which allows decreasing the computational burden and improving computing time. Frangioni, et al. [217], Wu [218] and Jabr [219], propose tighter piecewise linear approximations of the non-linear (quadratic) power cost curves of thermal units. A better representations of the polyhedra ramping constraints is developed by Ostrowski, et al. in [220], and Morales-España, et al. [221] develop a [MILP](#) formulation for start-up and shut-down power trajectories that they claim to be tighter and more compact than other formulations found in the literature. The same claim is done by the latter authors for the [MILP](#) formulation of the thermal unit commitment problem presented in [201]. A review and comparison of [MILP UC](#) models reported in the literature is presented in [222], in which some extensions that allow addressing all the generator initial conditions are also provided.

In the line of improving the accuracy of the representation of real-world generation units, several works propose better representations of the technical and operational characteristics of hydro units. Nilsson & Sjelvgren [223] study the impact of start-ups in the operational costs and scheduling of hydro power units, showing evidence of their relevance for resource adequacy planning and highlighting the need of further research and modelling. Gollmer, et al. [210] study the solution of the UC problem of hydro-thermal systems using primal and dual algorithms, analysing their pros and cons, and proposing ad-hoc model extensions that include staggered fuel prices, and reverse policies involving hydro units, among others. A new methodology for addressing the long-term hydrothermal coordination planning based on the Mixed Complementarity Problem (MCP) [224, 225] and in the context of deregulated electricity markets is developed by Ventosa, et al. in [226]. Chang, et al. [227] describes their experiences modelling the short-term hydro scheduling in a hydro-dominant power system using MILP, focusing in a detail modelling of the discrete and dynamic constraints of hydro units. In [200], Borghetti, et al. present an UC formulation for the short-term scheduling of a single reservoir pump-storage hydro power plant built from the model developed in [228], and where they develop a sophisticated linear approximation of the water head effect. Khodayar, et al. [229] proposes a model for the wind and pumped-storage hydro units coordination, which is incorporated in a transmission-constrained UC and used to study how such coordination could be used to reduce intra-hour wind energy imbalances. The hydro-power dispatch is modelled as an Equilibrium Problem with Equilibrium Constraints (EPEC) by Almeida & Conejo [230], which they use to show that in a market environment the equilibrium solutions may significantly differ from the optimal solution obtained using a centralized UC model. A literature survey of the short-term hydrothermal coordination optimization modelling can be found in [193]. On the other hand, for thermal generation units recent works focused on improvements of power trajectories modelling, and also in making a clearer distinction between those and the energy produced. Arroyo & Conejo [231] develop a rigorous mixed-integer linear formulation of the ramping limitations that affect thermal generators operation, i.e. start-up and shut-down power trajectories, and ramping constraints, and that allows for the correct evaluation of their power contribution. In [221], Morales-España, et al. improve previously reported start-up and shut-down power trajectories constraints, by means of tighter and more compact formulations of those constraints. García-González, et al. [232] and Morales-España, et al. [203] present UC formulations that make a clear distinction between power and energy.

Other research tendency that is gaining increasing attention and worth to mention is the inclusion of uncertainty in the UC problem modelling. For an extensive and very comprehensive review on this topic, interested reader are referred to [233].

Finally, a common denominator in almost all UC problem formulations reported in the literature is that they are limited to either a small number of generation units, or to a short assessment horizon, given that the combinatorial nature of the UC problem for larger power systems, or longer time horizons, lead to tractability issues. To overcome this problem, a clustering approach is used in 4.2.4 to reformulate the traditional binary UC formulation presented in 4.2.2. The clustering approach is then used for modelling flexible EV and hydro pumped-storage units in Sections 4.3 and 4.4 respectively, and then in the Strategic-GEP model formulation reported in this thesis. The clustering approach used for generation and flexible demand side

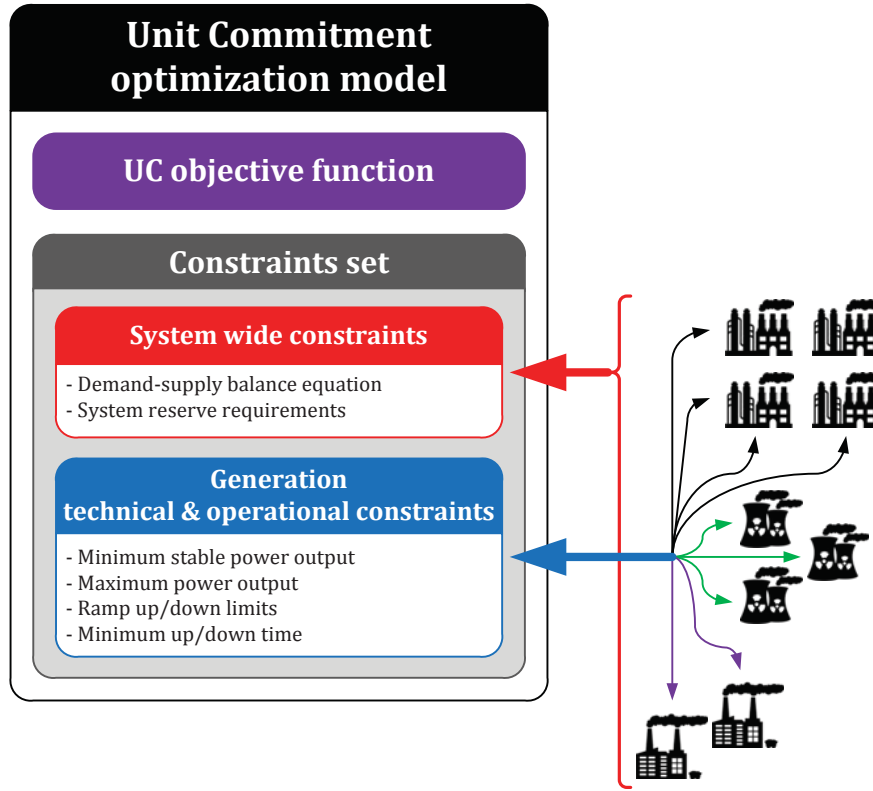


Figure 4.1: Conceptual representation of the UC model basic structure.

resources is also combined with tight constraints formulation for reducing the problem size and improving the computation performance of the model.

4.2.2 Traditional UC binary formulation

The unit commitment is an optimization problem used to determine when generation units need to be turned on or off, and how online generation units must be dispatched in order to supply electricity demand and meet reserve requirements at minimum cost,⁷ while satisfying a series of technical and operational constraints related to the generation side, i.e. minimum/maximum power production limits, ramping limitations and minimum up/down time in the case of a basic UC formulation [36, 157]. In the traditional approach, the commitment status of each generation unit is modelled using a binary variable that takes the value “1” when the unit is online, and “0” when the unit is offline.

The basic components of an UC optimization model, as shown in figure 4.1, are the objective function and the constraints set. The constraints set can be divided into two blocks: system-wide constraints, and the generation technical and operational constraints.⁸ In terms of decision variables, the UC problem involve two decision variables per each generation unit in the system, i.e. the unit commitment status, and the production output, of each of those

⁷ This is the case of a centralized minimum cost generation scheduling problem.

⁸ The constraints set also includes the decision variables constraints, i.e. integrality, sign and bounds.

units⁹ for each demand segment t .¹⁰ Before proceeding with the mathematical formulation of the UC problem, the following general assumptions are made:

- Perfectly competitive market.
- Inelastic demand.
- No ancillary services.
- Single node and aggregated demand.
- There are N^G conventional generation units in the system.
- No uncertainty.
- Centralized minimum cost UC scheduling.
- Hourly time resolution.¹¹

Objective function

From a centralized perspective, the UC problem looks to find the optimal generation scheduling that minimizes the Total Operational Cost (TOC), which is given by the sum of the variable (fuel and O&M), start-up and shut-down costs of all generation units g , over all demand segments t . The TOC is then given by:

$$\text{TOC} = \sum_{t \in T} \sum_{g \in G} \left\{ C_{tg}^{\text{variable}} + C_{tg}^{\text{start-up}} + C_{tg}^{\text{shut-down}} \right\}. \quad (4.1)$$

The variable costs of each generation unit g are those related to the production of electricity in each demand segment t , i.e. the fuel cost, CO₂ emissions costs,¹² and the variable O&M costs. The variable costs are then given by:

$$C_{tg}^{\text{variable}} = C_{tg}^{\text{fuel}} + C_{tg}^{\text{variable-O\&M}}, \quad \forall t \in T, \forall g \in G. \quad (4.2)$$

The fuel cost corresponds to the cost of the fuel that needs to be burned to produce the heat that is then used to generate electricity. The fuel cost is typically modelled as a non-linear convex quadratic function of the power output [36, 214, 157, 234], but for practical purposes this function can be approximated by a piecewise linear function [37, 218] as shown in figure 4.2,¹³ which allows linearising the UC problem and use the powerful commercially available solvers for MILP.

The piecewise linear fuel cost is then given by:

$$C_{tg}^{\text{fuel}} = \tau_t \pi_g^{\text{NL}} u_{tg} + \sum_{l \in L} \tau_t \pi_{gl}^{\text{inc}} p_{tgl}^{\text{seg}}, \quad \forall t \in T, \forall g \in G, \quad (4.3)$$

⁹ Lower case letters are used for the decision variables corresponding to individual generation units, in order to differentiate from those used in the UC clustered formulation in which upper case letters are used instead.

¹⁰ Reserve services are not considered in the basic UC formulation presented in this section.

¹¹ This means that each demand segment has a duration of one hour, i.e. $\tau_t = 1$ [h].

¹² When a price for CO₂ emissions is considered.

¹³ If enough segments are used to construct this piecewise linear cost function, the results obtained are similar to those obtained using the non-linear quadratic cost function.

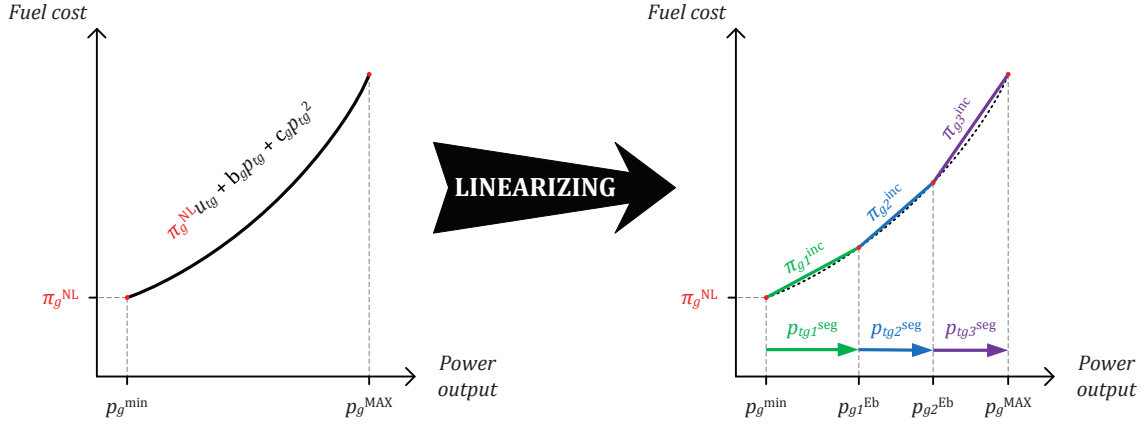


Figure 4.2: Piecewise linear approximation of non-linear convex quadratic fuel cost function.

where the first term corresponds to the no-load cost at the minimum stable generation level ($p_g^{\min}$), and the second to the incremental cost incurred when the power output is above $p_g^{\min}$.¹⁴ The variable O&M costs, on the other hand, corresponds to the operation and maintenance costs incurred when generating electricity and are given by:

$$C_{tg}^{\text{variable-O\&M}} = \tau_t \pi_g^{\text{O\&M}} p_{tg}, \quad \forall t \in T, \forall g \in G. \quad (4.4)$$

The start-up and shut-down costs correspond, as their names suggest, to the costs associated with starting or shutting down a generation unit respectively, and are given by:

$$C_{tg}^{\text{start-up}} = \left[\pi_g^{\text{Sup-fuel}} + \pi_g^{\text{Sup-O\&M}} \right] s_{tg}^{\text{Up}}, \quad \forall t \in T, \forall g \in G, \quad (4.5)$$

$$C_{tg}^{\text{shut-down}} = \left[\pi_g^{\text{SDwn-fuel}} + \pi_g^{\text{SDwn-O\&M}} \right] s_{tg}^{\text{Dwn}}, \quad \forall t \in T, \forall g \in G, \quad (4.6)$$

where it is assumed that these costs include two constant terms, one corresponding to the fuel required to change the commitment status of a generation unit, and the other corresponding to the O&M costs required to perform such manoeuvre. It must be noted that this formulation is a simplification commonly used for long-term UC models [40, 202], and does not differentiate between cold, warm or hot start-up costs [37].

Decision variables type & sign constraints

A UC problem formulation includes two types of decision variables, i.e. binary and continuous. As mentioned earlier, the commitment status of a generation unit g during each demand segment t , i.e. u_{tg} , is modelled using binary variables, while its scheduled production output, i.e. p_{tg} and p_{tg}^{seg} , are modelled using continuous variables.

Additional decision variables are used to model the start-up and shut-down events, i.e. s_{tg}^{Up} and s_{tg}^{Dwn} respectively, which can be modelled either as binary or continuous decision variables. In the latter case, the integrality constraint of those variables is relaxed, but in exchange additional constraints to ensure the non-negativity of those variables when there is a change

¹⁴ The incremental cost corresponds to the cost of the fuel required to generate the incremental power above the minimum stable generation level, i.e. $(p_{tg} - p_g^{\min})$.

in the commitment status of a generation unit are required.¹⁵ This relaxation allows reducing the number of binary variables in the model, which may translate into reduced computational times. However, modern solvers can handle large number of discrete decision variables very efficiently, and enforcing the integrality constraints on those variables can improve the computational time with respect to the previous case in practice, as shown by Ostrowski, et al. in [220]. The start-up and shut-down decision variables are non-zero and equal to “1”, only when there is a change in the unit commitment status of a generation unit, i.e. when a generation unit is started or shut down.

The decision variables type and sign constraints are given by:

$$\left\{ u_{tg}, s_{tg}^{\text{Up}}, s_{tg}^{\text{Dwn}} \right\} \in \{0, 1\}, \quad \forall t \in T, \forall g \in G, \quad (4.7)$$

$$\left\{ p_{tg}, p_{tg}^{\text{seg}} \right\} \in \mathbb{R}_{\geq 0}, \quad \forall t \in T, \forall g \in G, \forall l \in L. \quad (4.8)$$

System-wide constraints

The system-wide constraints corresponds to those that involves all generation units available in the system. One of those constraints is the demand balance equation, which ensures that total instantaneous power generation of all online units must be equal to the electricity demand at all demand segments t , and is formulated as follows:

$$\sum_{g \in G} p_{tg} = D_t, \quad \forall t \in T. \quad (4.9)$$

Only the demand balance equation is included in the basic UC formulation presented in this section. In Section 4.2.3 additional constraints to include ancillary services in the UC problem are developed, which allows a better representation of the real operation of power generation units.

Generation technical & operational constraints

The generation technical and operational constraints are specific to each generation units, and enforce that during the operation of those, they never go behind their physical and operational limitations.

MINIMUM STABLE & MAXIMUM POWER OUTPUT CONSTRAINTS enforce that each generation unit g , when online ($u_{tg} = 1$), never goes below its minimum stable generation level, i.e. p_g^{min} , or above its maximum power output level, i.e. p_g^{MAX} , respectively. On the other hand, these constraints ensure that when a generation unit is offline ($u_{tg} = 0$), its power output is zero. These constraints are formulated as follows:

$$u_{tg} p_g^{\text{min}} \leq p_{tg} \leq u_{tg} p_g^{\text{MAX}}, \quad \forall t \in T, \forall g \in G, \quad (4.10)$$

¹⁵ Due to the unit commitment status of a generation unit is a binary variable, the start-up and shut-down events can only take binary values as well [37].

where p_{tg} is the total instantaneous power output of generator g during demand segment t . p_{tgl}^{seg} is the power generated in segment l of the piecewise linear production function of generator g during demand segment t . These variable are related and constrained by the following set of equations:

$$p_{tg} = u_{tg} p_g^{\min} + \sum_{l \in L} p_{tgl}^{\text{seg}}, \quad \forall t \in T, \forall g \in G, \quad (4.11)$$

$$p_{tgl}^{\text{seg}} \leq u_{tg} \begin{cases} p_{gl}^{\text{Eb}} - p_g^{\min}, & l = 1 \\ p_{gl}^{\text{Eb}} - p_{g(l-1)}^{\text{Eb}}, & 1 < l < N^L \\ p_g^{\text{MAX}} - p_{g(N^L-1)}^{\text{Eb}}, & l = N^L \end{cases}, \quad \forall t \in T, \forall g \in G, \forall l \in L. \quad (4.12)$$

UPWARD & DOWNWARD RAMPING LIMIT CONSTRAINTS enforce that each generation unit g , when increasing or decreasing its power output, it does not go above the maximum rate of change (ramping) up, i.e. Δ_g^{Up} , or down, i.e. Δ_g^{Dwn} , respectively. These constraints are formulated as follows:

$$p_{tg} - p_{(t-1)g} \leq u_{tg} \tau_t \Delta_g^{\text{Up}} + s_{tg}^{\text{Up}} \max \{ p_g^{\min}, \tau_t \Delta_g^{\text{Up}} \}, \quad \forall t \in T, \forall g \in G, \quad (4.13)$$

$$p_{(t-1)g} - p_{tg} \leq u_{tg} \tau_t \Delta_g^{\text{Dwn}} + s_{tg}^{\text{Dwn}} \max \{ p_g^{\min}, \tau_t \Delta_g^{\text{Dwn}} \}, \quad \forall t \in T, \forall g \in G, \quad (4.14)$$

where it must be noted that the right hand side of the previous constraints enforce not only normal ramping limitations during online operation (first term), but also higher ramping rates during start-up and shut-down events (second term). If the second term is not included, and the ramping capability is lower than the minimum stable generation level, these constraints will prevent a generation unit from turning on or off respectively.

MINIMUM UP & DOWN TIME CONSTRAINTS enforce that each generation unit g cannot be turned off or on, if it has not been by at least the minimum up time, i.e. MT_g^{Up} , or the minimum down time, i.e. MT_g^{Dwn} , respectively. These constraints are formulated using the most compact formulation found in literature [215, 220] as follows:

$$u_{tg} \geq \sum_{\hat{t}=t-(\text{MT}_g^{\text{Up}}/\tau_t)+1}^t s_{\hat{t}g}^{\text{Up}}, \quad \forall t \in \left[\left(\text{MT}_g^{\text{Up}}/\tau_t \right) + 1, N^T \right], \forall g \in G, \quad (4.15)$$

$$1 - u_{tg} \geq \sum_{\hat{t}=t-(\text{MT}_g^{\text{Dwn}}/\tau_t)+1}^t s_{\hat{t}g}^{\text{Dwn}}, \quad \forall t \in \left[\left(\text{MT}_g^{\text{Dwn}}/\tau_t \right) + 1, N^T \right], \forall g \in G. \quad (4.16)$$

START-UP & SHUT-DOWN EVENTS STATE EQUATIONS relate the start-up and shut-down events with the unit commitment status of a generation unit g during consecutive demand segments, and are formulated as follows:

$$u_{tg} = u_{(t-1)g} + s_{tg}^{\text{Up}} - s_{tg}^{\text{Dwn}}, \quad \forall t \in T, \forall g \in G. \quad (4.17)$$

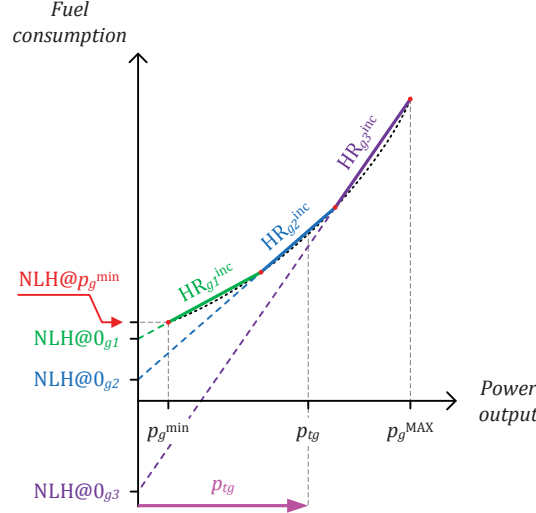


Figure 4.3: Convex piecewise linear fuel consumption function for generation unit g .

4.2.3 UC formulation improvements & additional constraints

The basic UC formulation presented in Section 4.2.2 can be improved by means of reducing the number of decision variables and constraints, and also by adding additional constraints to achieve a better representation of the real operation of power generation units.

A formulation of the production function that does not require modelling the power production in each demand segment l of the piecewise linear production function is presented first, and then, a set of constraints is introduced to model the provision of the different types of reserve services, i.e. primary, secondary and tertiary reserves.

Fuel consumption function

The convex piecewise linear fuel cost function presented in Section 4.2.2 can be reformulated in order to avoid defining decision variables for the power produced in each segment l of this function, i.e. p_{tgl}^{seg} , and instead only use the total instantaneous power output, i.e. p_{tg} . For this purpose, let us define a new decision variables $f_{tg}^{\text{fuel-use}} \in \mathbb{R}_{\geq 0}$,¹⁶ which represent the instantaneous fuel consumption of each generator g during demand segment t . The equation (4.3) can be then rewritten as follows:

$$C_{tg}^{\text{fuel}} = \tau_t \pi_g^{\text{fuel}} f_{tg}^{\text{fuel-use}}, \quad \forall t \in T, \forall g \in G, \quad (4.18)$$

where π_g^{fuel} corresponds to the cost of the fuel used by generator g .

The non-linear relationship between fuel usage and power output, which is approximated by a convex piecewise linear function with N^L segments, as shown in figure 4.3, can be formulated as follows:

$$f_{tg}^{\text{fuel-use}} \geq \text{NLH@0}_{gl} u_{tg} + \text{HR}_{gl}^{\text{inc}} p_{tg}, \quad \forall t \in T, \forall g \in G, \forall l \in L, \quad (4.19)$$

¹⁶ Please noted that $f_{tg}^{\text{fuel-use}}$ does not include the fuel used during start-up and shut-down events, which need to be treated separately as they only depend on the changes in the unit commitment status.

where $NLH@0_{gl}$ and HR_{gl}^{inc} represent the hypothetical no-load fuel usage at zero power output, and the incremental heat rate of the segment l of the piecewise linear fuel consumption function for generation unit g respectively. When a generator unit g is operating, this constraint is always satisfied in equality to the highest segment of the piecewise linear function, given that the fuel cost is positive and the optimizer will minimize the fuel usage. When the unit is offline instead, the commitment status variable forces the fuel usage to be zero.

This reformulation of the fuel consumption cost allows reducing the number of decision variables by $(N^T \times N^G \times [N^L - 1])$, and the number of constraints by $(N^T \times N^G)$. Constraints (4.11) and (4.12) are then not required anymore.

Operating reserves: system-wide constraints

Electricity demand, as analysed in Section 3.3, is a dynamic and complex process characterized by constant and unexpected changes, all of which are rapidly increasing due to large-scale penetration of VRE resources. Consequence of this is that in order to maintain the balance between generation and demand, or in other words a reliable operation of the power system, different types of reserve services are required to manage electricity demand variability and uncertainty, unexpected outages of generation units, failures of transmission lines, renewables forecast errors, etc.

The reserve services can be classified according to the grid operation time-frames into two main groups, i.e. regulation and load following services, and subdivided depending on the direction of the response, i.e. upward and downward reserves [235, 22]. The primary reserve, or Frequency Regulation Reserve (FRR), belongs to the first group, while the secondary reserve, or Spinning Reserve (SPR), and the tertiary reserve, or Quick-Start Reserve (QSR), corresponds to load following reserves.¹⁷

FREQUENCY REGULATION RESERVE typically ranges from several seconds to 5 minutes and is used to compensate the variability happening between consecutive demand segments.¹⁸ It is for this reason that the FRR can only be provided by online generation units, and the sum of all the FRR provided by all capable generation units needs to be at least equal to an externally calculated system-wide level for both upward and downward frequency regulation. Two system-wide constraints are needed then to ensure that the required amounts of upward and downward FRR are scheduled:

$$\sum_{g \in G^{\text{FRR-Up}}} r_{tg}^{\text{FRR-Up}} \geq RR_t^{\text{FRR-Up}}(\Xi), \quad \forall t \in T, \quad (4.20)$$

$$\sum_{g \in G^{\text{FRR-Dwn}}} r_{tg}^{\text{FRR-Dwn}} \geq RR_t^{\text{FRR-Dwn}}(\Xi), \quad \forall t \in T, \quad (4.21)$$

where $r_{tg}^{\text{FRR-Up}}$ and $r_{tg}^{\text{FRR-Dwn}}$ correspond to the upward and downward FRR provided by generation unit g during demand segment t respectively. $RR_t^{\text{FRR-Up}}$ and $RR_t^{\text{FRR-Dwn}}$ are

¹⁷ There are other names and/or types of reserve services, some of them specially created to handle specific power system characteristics, which are not analysed in this thesis [236, 235, 22].

¹⁸ Rapid changes occurring between consecutive economic dispatches of the system.

the externally determined system-wide demand level for upward and downward **FRR** during demand segment t .¹⁹

SPINNING RESERVE typically ranges from 5–15 minutes to a few hours and is used to compensate for contingencies, and also for load following purposes. This type of reserve (up and down) can be provided by generation units that are online, or that can be quickly started (up), and as in the case of **FRR**, the sum of all **SPR** provided by all capable generation units must be at least equal to an externally calculated system-wide level for both upward and downward spinning reserve. Two system-wide constraints are needed then to ensure that the required amounts of upward and downward **SPR** are scheduled:

$$\sum_{g \in G^{\text{SPR-Up}}} r_{tg}^{\text{SPR-Up}} + \sum_{g \in G^{\text{QSR}}} r_{tg}^{\text{QSR}} \geq \text{RR}_t^{\text{SPR-Up}}(\Xi), \quad \forall t \in T, \quad (4.22)$$

$$\sum_{g \in G^{\text{SPR-Dwn}}} r_{tg}^{\text{SPR-Dwn}} \geq \text{RR}_t^{\text{SPR-Dwn}}(\Xi), \quad \forall t \in T, \quad (4.23)$$

where $r_{tg}^{\text{SPR-Up}}$ and $r_{tg}^{\text{SPR-Dwn}}$ correspond to the upward and downward **SPR** provided by generation unit g during demand segment t respectively. $\text{RR}_t^{\text{SPR-Up}}$ and $\text{RR}_t^{\text{SPR-Dwn}}$ are the externally determined system-wide demand level for upward and downward **SPR** during demand segment t . It must be noted that in equation (4.22) quick-start generation units are allowed to provide tertiary reserve, i.e. r_{tg}^{QSR} , which can complement the **SPR** provided by online generation to satisfy the demand for upward spinning reserve during each demand segment t .

QUICK-START RESERVE are off-line generation units that are available and can be quickly started to provide tertiary reserve services when needed. As shown in the left-hand side of constraint (4.22), quick-start units can only provide tertiary reserve services for the fulfilment of the demand for upward spinning reserve at each demand segment t . The total contribution of **QSR** to the upward **SPR** demand is limited to be only a fraction of this level through the following constraint:

$$\sum_{g \in G^{\text{QSR}}} r_{tg}^{\text{QSR}} \leq \alpha_{\text{QSR-SPR}}^{\text{MAX-contrib}} \text{RR}_t^{\text{SPR-Up}}(\Xi), \quad \forall t \in T. \quad (4.24)$$

In other words, this constraint ensures that at most $\alpha_{\text{QSR-SPR}}^{\text{MAX-contrib}}$ of the total demand level for upward **SPR** at demand segment t is provided by tertiary reserve.

Operating reserves: generation constraints

Primary and secondary reserve services can only be provided by online generation units, therefore, the level of reserve services that each unit can provide is limited by their technical and operational characteristics.²⁰ On the other hand, tertiary reserve can only be provided by offline quick-start units, and as in the case of primary and secondary reserves, is also limited

¹⁹ $\Xi = \{D_t, K^{\text{wind}}, p_t^{\text{wind-pwr-av}}, K^{\text{solar}}, p_t^{\text{solar-pwr-av}}, \text{etc.}\}$

²⁰ Minimum and maximum power output levels, instantaneous power output, maximum deployment, etc.

by the technical and operational characteristics of those units.²¹ Additional constraints must be added then in order to ensure that such limitations on the reserve services provision are respected.

ONLINE RESERVE SERVICES are limited by the gap between the instantaneous power output and the maximum power output level in the case of upward reserve services, and the minimum stable generation level in the case of downward reserve services. These limitations are enforced by the following constraints:

$$r_{tg}^{\text{FRR-Up}} + r_{tg}^{\text{SPR-Up}} \leq u_{tg} p_g^{\text{MAX}} - p_{tg}, \quad \forall t \in T, g \in \{G^{\text{FRR-Up}}, G^{\text{SPR-Up}}\}, \quad (4.25)$$

$$r_{tg}^{\text{FRR-Dwn}} + r_{tg}^{\text{SPR-Dwn}} \leq p_{tg} - u_{tg} p_g^{\text{min}}, \quad \forall t \in T, g \in \{G^{\text{FRR-Dwn}}, G^{\text{SPR-Dwn}}\}. \quad (4.26)$$

FRR MAXIMUM DEPLOYMENT is limited by the maximum upward and downward ramping capability that a generation unit g is able to sustain during a limited period of time, generally during a few seconds to 5 minutes, after which reaches a maximum FRR deployment level, when there is spare capacity,²² which depends on the instantaneous power output and the level of SPR provided, as described by Erinmez et al. in [4] and shown in figure 4.4. These restrictions are enforced by the following constraints:

$$r_{tg}^{\text{FRR-Up}} \leq \min \left\{ u_{tg} \text{FRR}_g^{\text{MAX-Up}}, \sigma_g^{\text{FRR-Up}} \left[u_{tg} p_g^{\text{MAX}} - (p_{tg} + r_{tg}^{\text{SPR-Up}}) \right] \right\}, \quad \forall t \in T, \forall g \in G^{\text{FRR-Up}}, \quad (4.27)$$

$$r_{tg}^{\text{FRR-Dwn}} \leq \min \left\{ u_{tg} \text{FRR}_g^{\text{MAX-Dwn}}, \sigma_g^{\text{FRR-Dwn}} \left[(p_{tg} - r_{tg}^{\text{SPR-Dwn}}) - u_{tg} p_g^{\text{min}} \right] \right\}, \quad \forall t \in T, \forall g \in G^{\text{FRR-Dwn}}. \quad (4.28)$$

SPR MAXIMUM DEPLOYMENT is limited by the maximum upward and downward ramping capability that a generation unit g is able to sustain during a limited period of time, generally during 10 to 20 minutes, after which reaches a maximum SPR deployment level. These restrictions are enforced by the following constraints:

$$r_{tg}^{\text{SPR-Up}} \leq u_{tg} \text{SPR}_g^{\text{MAX-Up}}, \quad \forall t \in T, \forall g \in G^{\text{SPR-Up}}, \quad (4.29)$$

$$r_{tg}^{\text{SPR-Dwn}} \leq u_{tg} \text{SPR}_g^{\text{MAX-Dwn}}, \quad \forall t \in T, \forall g \in G^{\text{SPR-Dwn}}. \quad (4.30)$$

QSR MAXIMUM DEPLOYMENT is limited by the maximum upward ramping capability that an offline generation unit g is able to sustain during a limited period of time, after which

²¹ Quick-start units, when online, can provide both FRR and SPR.

²² When $(p_{tg} + r_{tg}^{\text{SPR-Up}}) \in [p_g^{\text{min}}, p_g^{\text{MAX}})$, or when $(p_{tg} - r_{tg}^{\text{SPR-Dwn}}) \in [p_g^{\text{min}}, p_g^{\text{MAX}})$, for upward and downward FRR respectively.

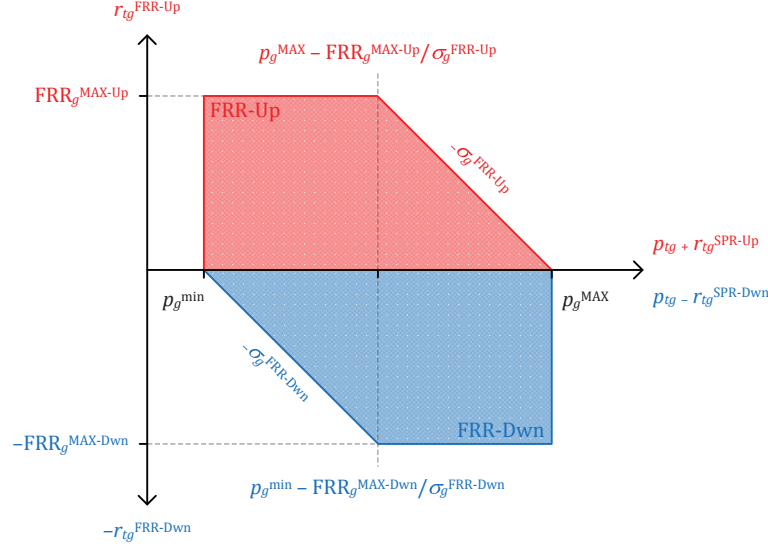


Figure 4.4: Feasibility region for upward and downward FRR provision level as a function of the sum between the instantaneous power output level and the level of SPR provision (figure adapted from [4]).

reaches a maximum QSR deployment level. This restriction is enforced by the following constraint:

$$r_{tg}^{\text{QSR}} \leq [1 - u_{tg}] \text{QSR}_g^{\text{MAX}}, \quad \forall t \in T, \forall g \in G^{\text{QSR}}. \quad (4.31)$$

Finally, constraint (4.8) needs to be updated as follows:

$$\{p_{tg}, f_{tg}^{\text{fuel-use}}, r_{tg}^{\text{FRR-Up}}, r_{tg}^{\text{FRR-Dwn}}, r_{tg}^{\text{SPR-Up}}, r_{tg}^{\text{SPR-Dwn}}, r_{tg}^{\text{QSR}}\} \in \mathbb{R}_{\geq 0}, \quad \forall t \in T, \forall g \in G. \quad (4.32)$$

4.2.4 Clustering & UC integer formulation

The UC problem is by nature hard to solve due to the complexity of the generation technical and operational constraints, but most importantly, due to the high dimensionality of the problem's solution space created by the binary on/off decision variables [36, 37], which has confined this type of problems to assessment horizons of no more than a few hundred hours.

Several approaches haven been proposed in the literature to make front the curse of dimensionality of this problem, in order to increase their complexity to achieve a better representation of the real operation of power systems, and also to extend the assessment horizons to longer time periods. Within those approached it worth to mention the use of representative periods, heuristic constraints, relaxation of operational constraints and clustering of identical units.

Representative periods allows expanding the assessment horizon under the assumption that such horizon can be represented by a reduced set of representative periods (days, weeks, etc.). Heuristics constraints, on the other hand, look to shrink the solution space by means of introducing additional restrictions to the original problem. Operational constraints relaxation is another method to reduce the size of the UC problem and improving its solution time,

and consist in relaxing some of the operational constraints for generation units that due to their size or technical characteristics does not create a significant difference compared to the original problem.²³

The clustering of similar or identical generation units allows drastically reducing the solution space,²⁴ as the binary on/off decision variables can be replaced by integer variables that allow eliminating a large number of identical or similar permutations of the binary unit commitment decision variables. This is a very powerful concept that can be used not only for generation units, but also for demand side appliances, and is one of the key features of the model presented in this thesis.

In this section, using the concept of clustering, a new integer formulation is proposed to model the UC of large fleets of conventional generation units. The essential difference between the developed methodology and the traditional UC modelling approach [37] is that integer variables are used to model the commitment status of clusters of generation units. The use of integer variables allows not only to massively reducing the number of discrete decision variables required to model the UC problem, but also critically reduce the number of constraints required to model the technical and operational limitations of conventional generation operation, as explored in Section 4.6.11.

Clustering in power systems modelling

In power system the concept of generation clustering, i.e. aggregation of generation units of similar or identical characteristics, was used by first time by Hara, et al. in [172], where it is used to first classify a thermal power system into groups of identical generation units, and then calculate the optimal economic unit commitment and maintenance of that system.

It is not until the last decade and a half that several publications using the clustering concept can be found in the literature. Gollmer, et al. use this concept in [210] for aggregating the commitment boolean variables associated with a group of thermal units of identical design into integer variables that are then used in the UC of an hydro-thermal power system. In [238], García-González, et al. use an integer variable to model the number of units in a pumped-storage facility that are running in pumping mode, when analysing the benefits of the combined optimization of a wind farm and a pumped-storage facility from the point of view of a generation company in a market environment. Sen and Kothari in [239] perform a cardinality reduction by the generator equivalencing concept, when solving the UC scheduling of a large power system. This concept consist in clustering the power system and representing it by an equivalent smaller system with a reduced number of representative generation units, which allows formulating a UC problem that is easier to handle and solve than the original large system. In [240], Cerisola utilizes homogeneous aggregation of generation units, which commitment is represented by integer decision variables, when formulating a modified Benders decomposition for MIP problems that is used to solve the medium-term UC of an hydro-thermal system. Generation units are also aggregated in the midterm offer demand

²³ For example, for small peaking generation units that are able to stably operate at very low power output levels is possible to relax the integrality constraint of their unit commitment status variables.

²⁴ Interested readers are referred to [237], where Sherali, et al. explore the computational benefits of improving discrete programming models via symmetry considerations, such as the aggregation of binary into integer variables.

equilibrium model proposed by Langrené, et al. [241], which they used to examine the impact that generation dynamic constraints have on electricity prices. Integer decision variables are also used by Palmintier and Webster [134] to decide on the unit commitment and investment in different generation technologies when analysing the impact that UC constraints have on those decisions. The same authors use this model in [242] to benchmark different types of heterogeneous generation clustering based on a set of performance metrics. The results presented in the last two papers are derived from [243], where Palmintier develops a single year generation expansion model that incorporates UC constraints. Aunedi also uses integer decision variables in his thesis [244], and subsequent publications [245, 246], to formulate a multi-unit scheduling model that he uses to study the value of flexible demand-side technologies in the operation of power systems with a high penetration of intermittent renewable generation. Finally, Ramírez, et al. in [34] present a fully integrated generation expansion model, in which the operational dynamics of flexible EV and generation UC scheduling constraints are explicitly incorporated using an integer formulation, which is then used to study the impacts that EV flexibility may have on power generation system development.

Clustering concept applied to power generation aggregation

The binary on/off unit commitment decision used in the traditional UC formulation presented in previous sections can be replaced, as discussed before and shown in the conceptual diagram presented in figure 4.5, by integer commitment decision variables that instead represent the commitment status of a cluster of generation units. This approach allows massively reducing the problem size in terms of decision variables and constraints, as they are now formulated for each generation cluster instead of individual generation units, which translates into reduced computational requirements and times that allows expanding the modelling to longer assessment horizons without sacrificing the accuracy of the results.

In an unclustered power system, the number of possible combinations of the binary unit commitment status variables grows exponentially with the number of generation units in the system, i.e. 2^{N^G} combinations for each demand segment t . On the other hand, using a clustering approach allows reducing the number of possible combinations to the product of the cardinalities of the domains of all integer unit commitment status variables, i.e. $\prod_{i \in I} (N_i^I + 1)$ combinations for each demand segment t . For example, in the case of the power system shown in figure 4.5, the clustering approach allows reducing the number of discrete combinations of unit commitment status variables in each demand segment t from 512 to 60.²⁵

When aggregating individual generation units of similar (or equal) technical and operational characteristics into a cluster, the binary UC status variables associated to all generation units g in that cluster during each demand segment t , i.e. u_{tg} ,²⁶ are changed by a single integer UC status variable, i.e. U_{ti} . This integer commitment status variable represents the number of

²⁵ For a realistic size power systems, let us say with 150 generation units, which are of four types: nuclear (15 units), coal (25 units), CCGT (60 units) and OCGT (50 units), the clustering approach allows reducing the number of discrete combinations in each demand segment t from about 1.43×10^{45} to approximately 1.29×10^6 .

²⁶ $\{u_{tg} \in \{0, 1\} \mid g \in i, i \in I, \forall t \in T\}$.

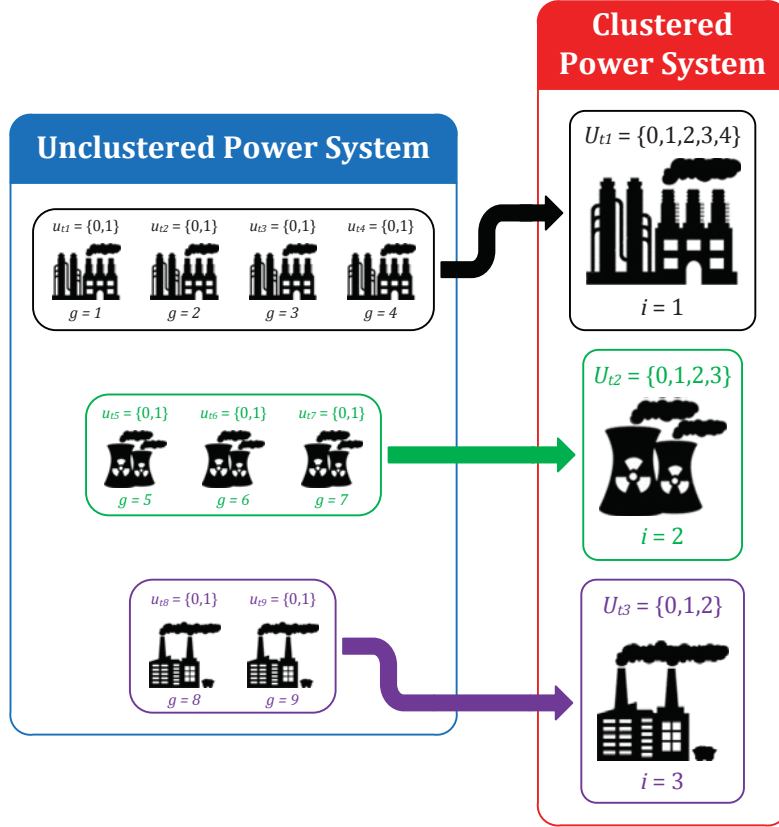


Figure 4.5: Conceptual diagram of the clustering concept applied to the power system showed in figure 4.1 for a single demand segment t . In a traditional binary UC model formulation there is a single binary unit commitment decision variable, i.e. u_{tg} , associated with each generation unit g in the power system (*unclustered power system*). In a clustered UC model formulation instead, there is a single integer unit commitment decision variable, i.e. U_{ti} , associated to each generation cluster i in the power system (*clustered power system*).

generation units of type i that are online during demand segment t , and its domain goes from zero up to the number of generation units contained in each cluster, i.e. N_i^I .²⁷

UC integer formulation: nomenclature conventions & basic assumptions

An integer formulation of the UC problem does not deviate much from the traditional binary formulation as shown in figure 4.6, and only simple changes are required to reformulate the latter using the clustering approach. In this formulation upper case letters are used for the decision variables (integer and continuous), in order to differentiate from those used in the binary UC formulation, and instead of indexing those variable by generation unit g , they are now indexed by cluster i .²⁸

The basic assumption made for the integer UC formulation, apart from the homogeneity of the generation units within each cluster,²⁹ is that the instantaneous power output of a

²⁷ $\{U_{ti} \in \mathbb{Z}_{\geq 0}^I \mid \mathbb{Z}_{\geq 0}^I \subset \mathbb{Z}_{\geq 0}, |\mathbb{Z}_{\geq 0}^I| = (N_i^I + 1), U_{ti} = \{0, 1, \dots, N_i^I\}, \forall t \in T, \forall i \in I\}$.

²⁸ Generation clusters in this thesis are defined by generation technology types, i.e. groups of generation units with identical technical and operational characteristics.

²⁹ Within each cluster, all individual units are assumed to have exactly the same technical and operational characteristics, i.e. fuel consumption function, minimum and maximum power output levels, ramping capability, minimum up/down time, etc.

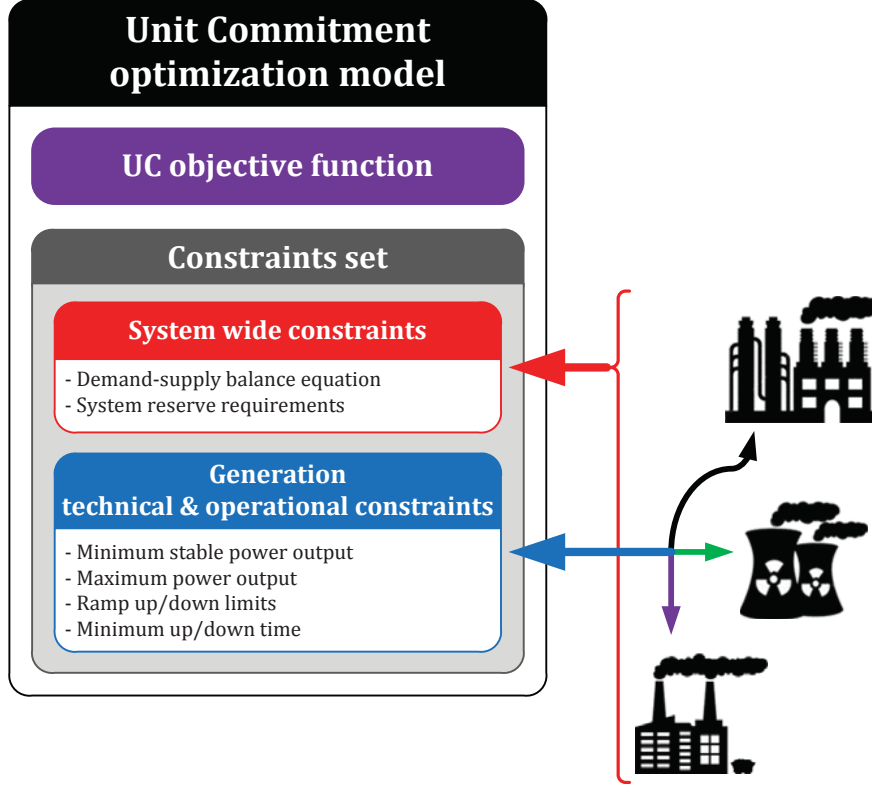


Figure 4.6: Conceptual diagram of the UC integer model basic structure.

generation cluster i is evenly distributed within the units that are online in that cluster at each demand segment t . This assumption ensures that the instantaneous power output of all online generation units in a cluster i lie on the same piecewise linear segment l of the fuel consumption function (equation (4.19)) at each demand segment t .³⁰

UC integer formulation: decision variables type & sign constraints

The continuous decision variables used in the integer UC model are analogous to those defined for the binary formulation, but now they represent the power output and reserve services provided by each cluster i of generation units. On the other hand, the meaning of the discrete decision variables change, as they do not represent the unit commitment, or commitment status changes, of a single generation unit anymore, but those of a group of generation units. The domain of the UC commitment variables as discussed before also changes, moving from the binary to the positive integer numbers. This change requires to modify constraint (4.7), which is replaced by the following one:

$$\{U_{ti}, S_{ti}^{\text{Up}}, S_{ti}^{\text{Dwn}}\} \in \mathbb{Z}_{\geq 0}^i, \quad \forall t \in T, \forall i \in I. \quad (4.33)$$

³⁰ Another way of ensure this holds, is assuming a simplified 1-segment fuel consumption function, i.e. constant incremental heat rate for each cluster i .

UC integer formulation: objective function & constraints

Apart from the nomenclature and variables indexing modifications, no further changes are required to equations (4.1) to (4.6), (4.8) to (4.12), (4.15), (4.17) to (4.30), and (4.32). The upward and downward ramping limit (equations (4.13) and (4.14)), minimum down time (equation (4.16)), and tertiary reserve maximum deployment (equation (4.31)) constraints, on the other hand, need to be updated, and two additional constraints to bound the UC status variables, i.e. for must-run and non-must run generation technologies, needs to be added as described below.

UPWARD & DOWNWARD RAMPING LIMIT CONSTRAINTS need to be updated to account for start-up and shut-down events, as well as the ramping capability of the online generation of each technology i , which is proportional to the number of online generation units in that cluster. Constraints (4.13) and (4.14) need to be replaced then by the following ones:

$$P_{ti} - P_{(t-1)i} \leq \left[U_{ti} - S_{ti}^{\text{Up}} \right] \tau_t \Delta_i^{\text{Up}} + S_{ti}^{\text{Up}} \max \left\{ p_i^{\min}, \tau_t \Delta_i^{\text{Up}} \right\} - S_{ti}^{\text{Dwn}} p_i^{\min}, \quad \forall t \in T, \forall i \in I, \quad (4.34)$$

$$P_{(t-1)i} - P_{ti} \leq \left[U_{ti} - S_{ti}^{\text{Up}} \right] \tau_t \Delta_i^{\text{Dwn}} + S_{ti}^{\text{Dwn}} \max \left\{ p_i^{\min}, \tau_t \Delta_i^{\text{Dwn}} \right\} - S_{ti}^{\text{Up}} p_i^{\min}, \quad \forall t \in T, \forall i \in I. \quad (4.35)$$

MINIMUM DOWN TIME CONSTRAINT needs to be updated in order to ensure that the number of offline generation units of technology i at demand segment t is at least equal to the number of generation units turned off $\left[\left(\text{MT}_i^{\text{Dwn}} / \tau_t \right) - 1 \right]$ demand segments before t . Constraint (4.16) needs to be replaced then by the following one:

$$N_i^I - U_{ti} \geq \sum_{\hat{t}=t-(\text{MT}_i^{\text{Dwn}}/\tau_t)+1}^t S_{\hat{t}i}^{\text{Dwn}}, \quad \forall t \in \left[\left(\text{MT}_i^{\text{Dwn}} / \tau_t \right) + 1, N^T \right], \forall i \in I. \quad (4.36)$$

QSR MAXIMUM DEPLOYMENT needs to be limited now by the number of generation units of technology i that are offline at demand segment t . Constraint (4.31) needs to be replaced then by the following one:

$$R_{ti}^{\text{QSR}} \leq \left[N_i^I - U_{ti} \right] \text{QSR}_i^{\text{MAX}}, \quad \forall t \in T, \forall i \in I^{\text{QSR}}. \quad (4.37)$$

UC UPPER BOUNDS need to limit the UC status of generation technology i at each demand segment t . For must-run generation, i.e. technologies with generation units that due to their technical and/or operational characteristics cannot be turned off, it is required to ensure that the number of online generation units is always equal to number of units contained in each generation technology clusters. On the other hand, for non-must-run generation, it is required to ensure that the number of online generation units is smaller

or equal to the number of generation units contained in each generation technology clusters. This is enforced by the following constraints:

$$U_{ti} = N_i^I, \quad \forall t \in T, \forall i \in I^{\text{mr}}, \quad (4.38)$$

$$U_{ti} \leq N_i^I, \quad \forall t \in T, \forall i \in I \setminus I^{\text{mr}}. \quad (4.39)$$

4.3 FLEXIBLE EV MODELLING

4.3.1 *Relevance of flexible EV for GEP*

Electricity demand is a potential passive source of flexibility which has gain increasing interest due its role in the power system setting and the rapid progress of smart-grid technologies. Economic, environmental and energy security concerns have paved the way for the wide decarbonisation of energy systems through the large-scale integration of renewable generation and the electrification of transport and heat sectors. This electrification phenomenon however introduces significant challenges to the operation and development of present and future power systems.

The limited controllability and predictability of [VRE](#) resources are expected to require large volumes of flexible generation to compensate them, implying adverse economic effects. Furthermore, the electrification of transport and heat sectors will lead to disproportionately larger demand peaks, and subsequently higher generation and network costs compared to the increase in the total electrical energy consumption, due to the temporal patterns of users' driving and heating requirements [247]. In this context, flexible demand technologies attract great interest due to their ability of modulating electricity consumption, i.e. redistribute or reschedule users' power consumption requirements in time through the employment of different types of energy storage technologies [248, 249, 14].

The smart coordination of flexible electricity demand,³¹ could yield significant economic, environmental and technical benefits across different timescales and all different sectors of the power system. In the short-term demand flexibility can help efficiently balancing supply and demand during peak hours and help handling unpredictable variations in renewables energy supply. On the other hand, in the long-term it can help reducing the requirements for flexible generation capacity, with the efficient and effective integration of renewables, and also limiting peak demand levels, which can improve significantly the economic efficiency of future low-carbon power systems.

Technological developments and economies of scale are allowing the wide penetration of flexible demand technologies. Amongst those, [EV](#) exhibit a particularly significant flexibility potential due to their inherent ability to store electrical energy in their batteries,³² their station-

³¹ These are loads equipped with smart-grid technologies that allow controlling the timing of their electricity consumption.

³² The electric energy storing capability allows the temporal decoupling between the time during which electricity is consumed for charging [EV](#) batteries, and the time when the stored energy is used for travelling purposes.

any character (parked for more than 90% to 95% of the time in average [158, 159, 250]),³³ and their low energy consumption requirements with respect to the significant capacity of their batteries [159, 251, 252].³⁴ The possibility of using the electric energy stored in EV batteries to feed the grid, which is known as vehicle-to-Grid (V2G) capability [160, 161, 251, 253, 254], enhances even further the potential benefits that can be achieved if EV are smartly controlled as either flexible loads or flexible power sources when they are plugged into the grid.³⁵

Electric vehicles are today considered as one of the most important flexible demand technologies in the near term, not only due to their penetration, technological developments³⁶ and compatibility [255, 256], but also because they are a potential mitigation option for CO₂ emissions [257],³⁷ and can contribute to improve the energy security by not consuming fossil fuels.

All the potential benefits achievable through the smart use of EV have resulted in a very fruitful literature, specially over approximately the last two decades and a half.³⁸ All those works compare the different types of benefits that using EV flexibility can have with respect to the inflexible operation of them, in terms of different objectives, such as fossil fuels consumption and CO₂ emissions reduction [256, 257], generation costs changes and reduction [161, 260, 261, 262, 263, 264, 265], generation matrix change and expansion [34, 266], EV users benefits [253], distribution networks investment and losses reduction [254, 267], power and ancillary service provision [159, 160, 268], effective renewables integration [162, 30], distributed energy resource investment and scheduling [269], and demand peak reduction [247, 250], among many others. However, the role of EV flexibility in generation expansion planning of power systems with high degree of renewables penetration has not been analysed in deep.

Finally, EV are not the only potential flexible demand technologies, and many others such as electric heating, domestic appliances, and many industrial loads, among others, can also be smartly operated in order to provide additional flexibility. In this thesis only EV are analysed, and other types of flexible demand technologies will be topic of future research.

4.3.2 Unclustered flexible EV modelling

The operation of flexible EV, i.e. EV equipped with flexible (smart) demand technologies that allow to control their power demand in time, depends on many technical and operational

³³ The large number of hours during which EV are parked and idle means that there is a wide time period during which EV batteries charging can be spread, if the charging process is available and smartly controlled.

³⁴ Such properties allows to modulate EV flexible demand using a wide range of charging patterns.

³⁵ As it was mentioned earlier in this chapter, the V2G capability of discharging energy into the grid is not analysed in this thesis and will be matter for further research.

³⁶ IBM is working on a very promising project since 2009 called “The Battery 500 Project”, in which they are developing state-of-the-art battery technology in order to extend the average 100 miles travelling capability of current lithium-ion battery technology. The target is to develop a new type of lithium-air battery technology that is expected to improve the energy density in approximately ten times, which will allow travelling 500 miles. Such a technological development is expected to boost EV penetration, which has been detracted by the low travelling range offered by current batteries. Interested readers are referred to the following link for further details on this topic: www.ibm.com/smarterplanet/us/en/smart_grid/article/battery500.html.

³⁷ In the UK approximately between 21% and 22% of the greenhouse gases emissions are associated to the operation of Internal Combustion Engine (ICE) vehicles [258, 259, 19].

³⁸ A complete review of the current literature on EV, the electric grid, and renewable energy integration can be found in [163].



Figure 4.7: Single flexible EV operation modelling of the highlighted vehicle. Different types of EV are shown using different colours, but only the one that is highlighted is assumed to be flexible.

characteristics, as well as on other non-technical ones, such as users' travelling patterns and energy requirements, all of which can make their modelling quite complex. However, a simplified model can capture the main features of their flexible operation, which are given by the battery charging capability and charging timing. Nevertheless, the modelling presented in this thesis can be complexified in order to achieve a better representation of the real operation of this type of flexible demand technology.

Before proceeding with the flexible EV operation modelling of a single vehicle (such as the one highlighted in figure 4.7), the following set of assumptions are made:

- Pure EV, which means that it is fully powered (moved) by the electric energy stored in the battery.³⁹
- EV battery linear charging.⁴⁰
- Single EV battery charging mode.⁴¹
- No V2G capability.
- EV user's driving requirements and patterns are characterized by the energy demand for travelling purposes, and the travelling times.
- No uncertainty in the EV user's driving patterns.

Under the assumptions described before, the operation of a single flexible EV of type v , can be modelled through a set of three equations as follows:

BATTERY BALANCE EQUATION expresses the electrical energy balance in the battery of an EV of type v when considering the charging losses of the battery and the grid connection's

³⁹ Hybrid EV vehicles, i.e. vehicles that can be moved by burning fuel or using their batteries, are not considered in this thesis.

⁴⁰ Non-linear characteristics of EV battery charging are not considered in this thesis.

⁴¹ The model does not include the possibility of different types of charging speeds, i.e. fast and slow charging.

power electronics, the self-discharging energy losses of the battery, and the EV user's travelling energy requirements. This equation is formulated as follows:

$$e_{tv}^{\text{EV}} = \eta_v^{\text{chg}} p_{tv}^{\text{EV}} \tau_t + \eta_v^{\text{elec}} e_{(t-1)v}^{\text{EV}} - e_{tv}^{\text{tr}}, \quad \forall t \in T, \forall v \in V, \quad (4.40)$$

where e_{tv}^{EV} and p_{tv}^{EV} are the energy level in the battery and the electric power demand of an EV of type v at demand segment t respectively. η_v^{chg} and η_v^{elec} are the charging and self-discharging energy efficiencies of the EV type v battery respectively. Finally, e_{tv}^{tr} corresponds to the EV type v user's electric energy requirements for travelling purposes.⁴²

BATTERY ENERGY LIMITS ensure that the energy level in the battery of an EV of type v is bounded by the minimum and maximum states of charge of the battery at each demand segment t , i.e. $e_v^{\text{bat-min}}$ and $e_v^{\text{bat-MAX}}$ respectively. This is ensured by the following constraint:

$$e_v^{\text{bat-min}} \leq e_{tv}^{\text{EV}} \leq e_v^{\text{bat-MAX}}, \quad \forall t \in T, \forall v \in V. \quad (4.41)$$

POWER CHARGING LIMITS establish the maximum charging power rate of the battery of an EV of type v and the grid connection's power electronics at each demand segment t , and also ensure that the EV cannot charge the battery when it is not plugged into the grid. These conditions are ensured by the following constraint:

$$p_{tv}^{\text{EV}} \leq \begin{cases} p_v^{\text{chg-MAX}}, & \forall t \in T_v^{\text{gc}} \\ 0, & \forall t \in T \setminus T_v^{\text{gc}} \end{cases}, \quad \forall v \in V, \quad (4.42)$$

where $p_v^{\text{chg-MAX}}$ is the maximum charging power rate of the battery of an EV of type v , and T_v^{gc} is the sub-set of demand segments t of a time period T during which the EV type v is plugged into the grid.⁴³

Finally, the type and sign constraints of the decision variables used for the unclustered EV modelling are given by:

$$\{p_{tv}^{\text{EV}}, e_{tv}^{\text{EV}}\} \in \mathbb{R}_{\geq 0}, \quad \forall t \in T, \forall v \in V. \quad (4.43)$$

In the following section, using the concept of clustering, a new integer formulation is proposed to model the operation of large fleets of EV. The essential difference between the developed methodology and other methods proposed in literature is that the integer formulation allows modelling the operation of an entire EV cluster v instead of the operation of single EV units. Additionally, the formulation allows splitting the operation of flexible and inflexible EV, which are interrelated by the number of flexible EV contained in each EV cluster v . Finally,

⁴² This parameter is derived from the combination of the EV user's travelling requirements that are expressed in terms of the travelling times and distances, and the electrical energy consumption of the EV per unit of distance travelled (this includes the energy consumption of the electric motor and remaining on-board electric equipment). The explanation of the methodology used to estimate this parameter is behind the scopes of this thesis, but interested readers are referred to [244] for further details regarding this methodology.

⁴³ A period of time T must be understood as a sequentially ordered set of demand segments t , i.e. $T = \{1, 2, 3, \dots, N^T\}$.

the clustering methodology developed allows keeping the model linear when the number of flexible EV in each EV cluster v is defined as a decision variable for the model.

4.3.3 Clustered flexible EV modelling

The clustering concept can also be used to cluster EV by EV type as shown in figure 4.8, and instead of modelling the operation of single EV separately as described in Section 4.3.2, model the operation of an entire EV cluster. The key assumption in this case, apart from the EV homogeneity within each EV cluster, and that is analogous to the one made for clustering generation units in Section 4.2.4, is the even distribution of the power consumption and battery energy level of each EV cluster v within the EV contained in each of those clusters.⁴⁴ The previous is supported by the assumption of linear charging of EV batteries.⁴⁵

The new integer clustering methodology proposed in this section for modelling the operation of large fleets of EV differs from previous formulations in the following aspects:

1. it models the operation of clusters of EV instead of the operation of individual EV;
2. flexible and inflexible EV operation are modelled independently;
3. the number of flexible EV in each EV cluster v is a decision variable for the model;⁴⁶
4. all the constraints used to model the operation of flexible EV are adjusted so as to represent the operation of the flexible EV contained in each EV cluster v , i.e. $N_v^{\text{EV-Flex}}$;
5. the inflexible EV operation is modelled through their contribution towards electricity demand, which is built using the individual inflexible demand patterns of the different types of EV and the number of inflexible EV in each EV cluster v , i.e. $N_v^{\text{EV-Inflex}}$. Given that the number of flexible EV in each EV cluster v is a decision variable for the model, the power demand of inflexible EV is adjusted according to these decision variables;
6. and, due to the power consumption of all flexible EV of each EV cluster v is modelled through a single decision variable, i.e. P_{tv}^{EV} , the total power demand of all flexible EV constitutes a linear term for the demand balance equations. When the power demand of flexible EV is individually modelled and if the number of flexible EV in each EV cluster v is a decision variable, the power contribution of all flexible EV of type v towards electricity demand is given by the product of decision variables, i.e. $N_v^{\text{EV-Flex}} p_{tv}^{\text{EV}}$, what creates non-linearities in the model formulation.

The clustered EV modelling does not deviate much from that presented in the previous section, and only simple changes are required to reformulate it using the clustering approach. In this formulation upper case letters are used for the decision variables, in order to differentiate

⁴⁴ It must be noted that it is assumed that it is not possible distinguishing between individual EV within each cluster and their respective power consumption and battery energy level, and instead it is assumed that all flexible EV inside of each EV cluster v have the same power consumption and battery energy level at each demand segment t . The same applies to inflexible EV.

⁴⁵ All assumptions made for the unclustered EV modelling are valid for the clustered formulation.

⁴⁶ It can also be an input parameter for the model in the case that the number of flexible EV in each EV cluster v is known.

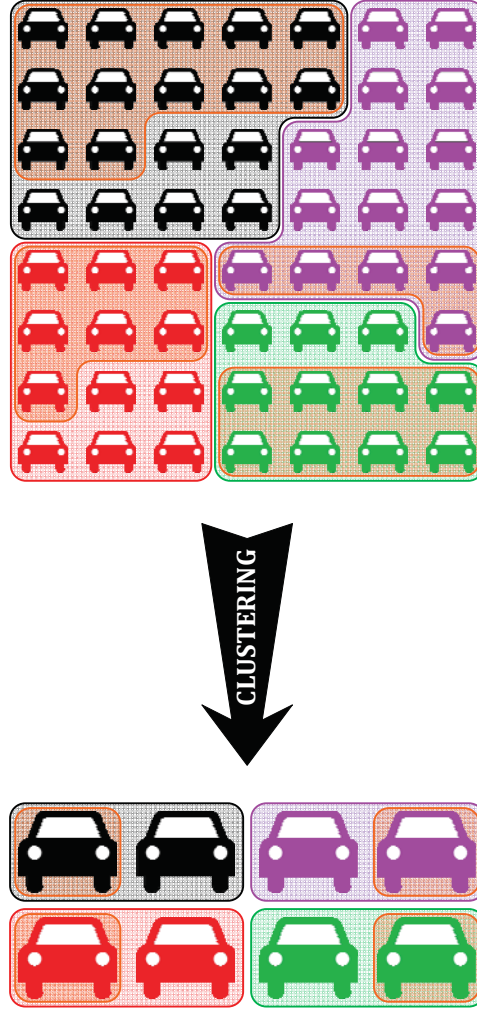


Figure 4.8: Conceptual diagram of the EV clustering per EV type v . Inside of each EV cluster there are flexible and inflexible vehicles. The flexible EV in each cluster are those highlighted.

from those used in the single EV modelling. The indexing of those variables does not change and depends on the EV type.⁴⁷

The decision variables used in the clustered EV modelling are analogous to those defined for the unclustered case, but now they represent the power consumption and battery energy level of each EV cluster v . Apart from the obvious nomenclature update, all the equations except equation (4.43), need to be updated in order to account for the number of flexible EV in each EV cluster v , i.e. $N_v^{\text{EV-Flex}}$.⁴⁸

BATTERY BALANCE EQUATION constraint (4.40) needs to be replaced then by the following one:

$$E_{tv}^{\text{EV}} = \eta_v^{\text{chg}} P_{tv}^{\text{EV}} \tau_t + \eta_v^{\text{elec}} E_{(t-1)v}^{\text{EV}} - N_v^{\text{EV-Flex}} e_{tv}^{\text{tr}}, \quad \forall t \in T, \forall v \in V, \quad (4.44)$$

where E_{tv}^{EV} and P_{tv}^{EV} are the total battery energy level and the total electric power demand of EV cluster v at demand segment t respectively.

⁴⁷ The EV clusters in this thesis are defined according to the different types of EV.

⁴⁸ The total number of EV in each EV cluster v is N_v^{EV} , which is the sum of flexible and inflexible EV, i.e. $N_v^{\text{EV}} = N_v^{\text{EV-Flex}} + N_v^{\text{EV-Inflex}}$.

BATTERY ENERGY LIMITS constraint (4.41) needs to be replaced then by the following one:

$$N_v^{\text{EV-Flex}} e_v^{\text{bat-min}} \leq E_{tv}^{\text{EV}} \leq N_v^{\text{EV-Flex}} e_v^{\text{bat-MAX}}, \quad \forall t \in T, \forall v \in V. \quad (4.45)$$

POWER CHARGING LIMITS constraint (4.42) needs to be replaced then by the following one:

$$P_{tv}^{\text{EV}} \leq \begin{cases} N_v^{\text{EV-Flex}} p_v^{\text{chg-MAX}}, & \forall t \in T_v^{\text{gc}} \\ 0, & \forall t \in T \setminus T_v^{\text{gc}} \end{cases}, \quad \forall v \in V. \quad (4.46)$$

4.4 STORAGE MODELLING

4.4.1 Why storage?

Energy storage refers to all devices or physical media that are capable of storing energy which can be used at a later time to perform useful processes. Due to widespread introduction of electric energy as an essential commodity in modern life, energy storage became a key factor for economic development. However, a critical drawback of this commodity is the fact that it must be consumed when is being generated, or otherwise immediately converted into another form of energy such as potential, kinetic or chemical.

The storage of electric energy is essential for balancing demand and supply. For low penetration levels of renewables, net-demand can be forecasted with low error and existing conventional generation can provide the required load following capability to balance the system [156]. However, the large-scale deployment of renewables will make this task much more complex, due to those generation resources will greatly increase the variability and uncertainty of net-demand. Larger amounts of system flexibility will be required then to balance the system at all times and under the different range of expected system operation conditions. In this scenario is that energy storage will play a key role, as it will be useful for storing excess of renewable energy, generate electricity when net-demand peaks, or also when net-demand rate of change is high and cannot be absorbed by available system flexibility [270, 249].

A traditional way of storing energy on a large-scale is through the use of hydrologic storage facilities, such as hydroelectric dams and pumped-storage power plants. Almost the 99% of worldwide large-scale electricity storage capacity is given by hydrologic storage systems [271].⁴⁹ The ambitious renewables agendas and the CO₂ emissions reduction targets of many countries around the world are highlighting the relevance that traditional, and new storage technologies, will have in future low-carbon power systems. Larger shares of wind and solar PV generation, will demand of higher amounts of flexible resources to cover the intermediate period between the falling off of renewable generation and the coming online of any type of back-up capacity, which can potentially be provided by energy storage resources.

⁴⁹ Other possible large-scale methods for storing electricity include: batteries, flywheel, compressed air energy storage, hydrogen storage, thermal energy storage, and power to gas. However, technological maturity and/or economic barriers for their large-scale deployment have limited the applicability of those technologies to power systems.

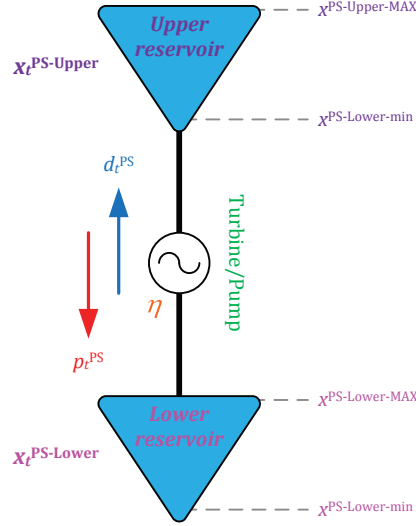


Figure 4.9: Conceptual diagram of a basic hydro pumped-storage power plant composed of an upper and a lower reservoir.

The need for more flexibility have attracted increasing attention into energy storage technologies, which have resulted in a rich research and development over the last two decades. A number of works have studied the key role and value of energy storage in power system with a high penetration level of renewable generation [272, 273, 274, 275, 276, 277, 278], concluding that storage allows reducing the system operation costs, and the integration of larger amounts of renewables. The flexibility potential that can be obtained from energy storage facilities highlights their importance for the operation and expansion of future power systems [279]. Include the modelling of energy storage in generation expansion planning is then very important.

Among all available energy storage technologies, hydroelectric storage is still, and will be, the most important one in modern power systems, at least until the multiple barriers that limit the applicability of other potential large-scale energy storage technologies has been overcome. Within the available hydroelectric technologies, hydro pumped-storage power plants can be used to provide the storage capability required to absorb the excess of renewables energy, and also to generate power and provide reserve services due to their high operational flexibility [238, 280, 281].

4.4.2 Unclustered hydro pumped-storage modelling

A hydro pumped-storage plant is a type of hydroelectric energy storage facility that is used to balance demand and supply. This type of power plants, in its most basic configuration, is composed by two water reservoirs between which water is pumped or discharged at hours of low or high electricity demand (prices) respectively, as shown in the conceptual diagram shown in figure 4.9. One of the reservoirs is located at a higher geographical location, so that energy can be stored in the form of gravitational potential energy of water.

When electricity demand is low and there is excess of generation in the system, an electrically-powered water pump is used to pump water into the upper reservoir. On the other hand, when electricity demand is high, the water is released back to the lower reservoir through a turbine

that generates electricity. Due to the losses in the pumping process, a hydro pumped-storage power plant is a net-consumer of electricity. However, due to they use cheap electricity to fill the upper reservoir, and then they sell electricity during peak-demand hours, when energy prices are high, the net-benefit is positive.

The modelling of hydro power can be quite complex due to the uncertainty linked to the hydrological cycle of water and its impact on natural inflows, and the non-linearities involved in the generation of electricity (net-head losses, etc.), among others. However, by assuming that the hydro pumped-storage power plant is isolated from the hydrologic chain, and also that the losses are negligible, a simplified model can be formulated to represent the operation of this type of facility. Before proceeding with the hydro pumped-storage operation modelling, the following set of assumptions are made:

- The hydro pumped-storage plant does not have any natural inflow, and there is no water evaporation from the reservoirs.
- The total energy stored in the hydro pumped-storage facility, i.e. the sum of the energy stored in the upper and lower reservoirs, is constant.
- There is only one turbine/pump assembly in the hydro pumped-storage power plant.
- All the variables associated with the operation of the hydro pumped-storage power plant, with the exception of unit commitment variables, are considered in terms of energy.
- Only one type of hydro pumped-storage power plant is considered.

Under the assumptions described before, the operation of a single hydro pumped-storage power plant can be modelled through the following set of equations:

RESERVOIRS ENERGY BALANCE EQUATIONS or water balance equations, express the electrical energy balance in each of the water reservoirs when considering the efficiency of the pump-turbine cycle, i.e. η^{ptc} . These equations are formulated as follows:

$$x_t^{\text{PS-Upper}} = x_{(t-1)}^{\text{PS-Upper}} + \eta^{\text{ptc}} d_t^{\text{PS}} \tau_t - p_t^{\text{PS}} \tau_t, \quad \forall t \in T, \quad (4.47)$$

$$x_t^{\text{PS-Lower}} = x_{(t-1)}^{\text{PS-Lower}} + p_t^{\text{PS}} \tau_t - \eta^{\text{ptc}} d_t^{\text{PS}} \tau_t, \quad \forall t \in T, \quad (4.48)$$

where $x_t^{\text{PS-Upper}}$ and $x_t^{\text{PS-Lower}}$ are the energies stored in the upper and lower reservoirs at demand segment t respectively. p_t^{PS} and d_t^{PS} are the power generated (turbine power) and the power consumed (pumping power) by the hydro pumped-storage plant at demand segment t .

RESERVOIRS ENERGY LIMITS ensure that the energy stored in the reservoirs is bounded by their minimum and maximum capacity limits at each demand segment t , i.e. $x^{\text{PS-Upper-min}}$ and $x^{\text{PS-Lower-min}}$, and $x^{\text{PS-Upper-MAX}}$ and $x^{\text{PS-Lower-MAX}}$, respectively. This is ensured by the following constraints:

$$x^{\text{PS-Upper-min}} \leq x_t^{\text{PS-Upper}} \leq x^{\text{PS-Upper-MAX}}, \quad \forall t \in T, \quad (4.49)$$

$$x^{\text{PS-Lower-min}} \leq x_t^{\text{PS-Lower}} \leq x^{\text{PS-Lower-MAX}}, \quad \forall t \in T. \quad (4.50)$$

PUMP/TURBINE POWER LIMITS ensure that the power consumed when the hydro pumped-storage plant is operating in pumping mode, and that the power generated when is operating in turbine mode, is within the capacity limits of the turbine/pump assembly, i.e. $p^{\text{PS-min}}$ and $p^{\text{PS-MAX}}$, and $d^{\text{PS-min}}$ and $d^{\text{PS-MAX}}$, respectively. This is ensured by the following constraints:

$$u_t^{\text{PS-p}} d^{\text{PS-min}} \leq d_t^{\text{PS}} \leq u_t^{\text{PS-p}} d^{\text{PS-MAX}}, \quad \forall t \in T, \quad (4.51)$$

$$u_t^{\text{PS-t}} p^{\text{PS-min}} \leq p_t^{\text{PS}} \leq u_t^{\text{PS-t}} p^{\text{PS-MAX}}, \quad \forall t \in T, \quad (4.52)$$

where $u_t^{\text{PS-p}}$ and $u_t^{\text{PS-t}}$ are unit commitment variables for the pumping and turbine operating modes at each demand segment t respectively.

START-UP & SHUT-DOWN EVENTS STATE EQUATIONS relate the start-up ($s_t^{\text{PS-Up-p}}$ and $s_t^{\text{PS-Up-t}}$) and shut-down ($s_t^{\text{PS-Dwn-p}}$ and $s_t^{\text{PS-Dwn-t}}$) events with the unit commitment statuses of the turbine/pump assembly during consecutive demand segments, and are formulated as follows:

$$u_t^{\text{PS-p}} = u_{(t-1)}^{\text{PS-p}} + s_t^{\text{PS-Up-p}} - s_t^{\text{PS-Dwn-p}}, \quad \forall t \in T, \quad (4.53)$$

$$u_t^{\text{PS-t}} = u_{(t-1)}^{\text{PS-t}} + s_t^{\text{PS-Up-t}} - s_t^{\text{PS-Dwn-t}}, \quad \forall t \in T. \quad (4.54)$$

OPERATING MODE STATE EQUATION ensures that the turbine/pump assembly is either operating in turbine or pumping mode, or is not operating at all. This is ensured by the following constraint:

$$u_t^{\text{PS-p}} + u_t^{\text{PS-t}} \leq 1, \quad \forall t \in T. \quad (4.55)$$

Finally, the type and sign constraints of the decision variables used for the single hydro pumped-storage modelling are given by:

$$\{u_t^{\text{PS-t}}, u_t^{\text{PS-p}}, s_t^{\text{PS-Up-t}}, s_t^{\text{PS-Dwn-t}}, s_t^{\text{PS-Up-p}}, s_t^{\text{PS-Dwn-p}}\} \in \{0, 1\}, \quad \forall t \in T, \quad (4.56)$$

$$\{x_t^{\text{PS-Upper}}, x_t^{\text{PS-Lower}}, p_t^{\text{PS}}, d_t^{\text{PS}}\} \in \mathbb{R}_{\geq 0}, \quad \forall t \in T. \quad (4.57)$$

In the following section, using the concept of clustering, a new integer formulation is proposed to model the operation of clusters of hydro pumped-storage power plants. The essential difference between the developed methodology and other methods proposed in literature is that the integer formulation allows modelling the joint operation of large fleets of hydro pumped-storage facilities instead of the individual operation of each of those facilities. The clustered formulation allows using integer decision variables for modelling the commitment status of the turbine/pump assemblies of the hydro pumped-storage clusters, which allows avoiding the use of binary decision variables, and thus, to massively reduce the number of discrete decision variables and constraints required to model their operation.⁵⁰

⁵⁰ A methodology for capturing, modelling and including the technical and operational characteristics of hydro pumped-storage technology clusters in the generation expansion planning problem is developed in Section 4.4.3, and also incorporated in the Strategic-GEp model formulation presented in Section 4.6. However, hydro pumped-

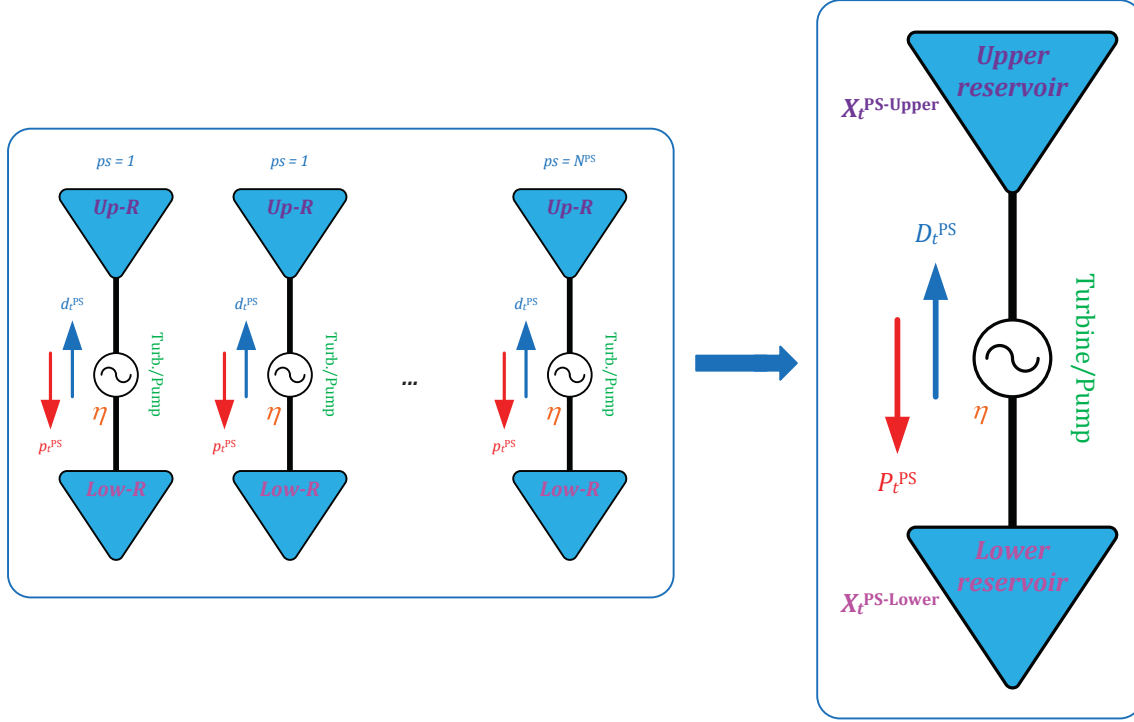


Figure 4.10: Conceptual diagram of the clustering of hydro pumped-storage power plants of the same type.

4.4.3 Clustered hydro pumped-storage modelling

The clustering concept can also be extended to cluster hydro pumped-storage resources of the same type as shown in figure 4.10.⁵¹ The key assumption in this case, apart from the hydro pumped-storage power plants homogeneity, and that is analogous to the ones made for clustering generation units and EV in Sections 4.2.4 and 4.3.3 respectively, is the even distribution of the instantaneous power consumption and generation between the units that are online and operating in pumping and turbine mode respectively at each demand segment t . The same assumption applies to the water reservoirs.

The clustered hydro pumped-storage modelling does not deviate much from the clustering methodology presented in the previous sections, and only simple changes are required to reformulate it using the clustering approach. In this formulation upper case letters are used for the decision variables, in order to differentiate from those used in the single hydro pumped-storage modelling. The indexing of those variables does not change due to there is only one cluster.

The decision variables used in the clustered hydro pumped-storage modelling are analogous to those defined for the unclustered case, but now they represent the power consumption and generation, and the reservoirs levels, of the whole cluster. Apart from the obvious nomenclature update, equations (4.49), (4.50), (4.55) and (4.56) need to be updated in order to account for the total number of hydro pumped-storage resources in the cluster, i.e. N^{PS} , and

storage technology was not included in the case studies due to lack of input data and time constraints, but it will be topic for further research.

⁵¹ Only one type of hydro pumped-storage power plant is considered in this formulation. Nevertheless, it can be easily extended to consider other types.

two additional constraints to bound the hydro pumped-storage UC status variables need to be added as described below.

RESERVOIRS ENERGY LIMITS constraints (4.49) and (4.50) need to be replaced then by the following ones:

$$N^{\text{PS}} x^{\text{PS-Upper-min}} \leq X_t^{\text{PS-Upper}} \leq N^{\text{PS}} x^{\text{PS-Upper-MAX}}, \quad \forall t \in T, \quad (4.58)$$

$$N^{\text{PS}} x^{\text{PS-Lower-min}} \leq X_t^{\text{PS-Lower}} \leq N^{\text{PS}} x^{\text{PS-Lower-MAX}}, \quad \forall t \in T. \quad (4.59)$$

OPERATING MODE STATE EQUATION constraint (4.55) needs to be replaced by the following one:

$$U_t^{\text{PS-p}} + U_t^{\text{PS-t}} \leq N^{\text{PS}}, \quad \forall t \in T. \quad (4.60)$$

UC UPPER BOUNDS needs to limit the UC status of the hydro pumped-storage cluster. This is enforced by the following constraints:

$$U_t^{\text{PS-p}} \leq N^{\text{PS}}, \quad \forall t \in T, \quad (4.61)$$

$$U_t^{\text{PS-t}} \leq N^{\text{PS}}, \quad \forall t \in T. \quad (4.62)$$

Finally, due to integer instead of binary decision variables are used for the UC status of the hydro pumped-storage cluster, equation (4.56) needs to be updated as follows:

$$\{U_t^{\text{PS-t}}, U_t^{\text{PS-p}}, S_t^{\text{PS-Up-t}}, S_t^{\text{PS-Dwn-t}}, S_t^{\text{PS-Up-p}}, S_t^{\text{PS-Dwn-p}}\} \in \mathbb{Z}_{\geq 0}, \quad \forall t \in T. \quad (4.63)$$

4.5 RENEWABLES MODELLING

Renewables power generation modelling can be a quite complex task due to need of first forecasting time-series for wind speed or solar radiation, which are then converted into power using wind turbine and solar PV power output curves (non-linear), and also because the dynamics of wind turbines and solar PV panels are rather complex [282, 283]. For wind-speed and solar radiation forecasting a wide range of techniques have been applied, being the most common one the use of Auto-Regressive (AR) models [284, 285, 286], which are calibrated using historical meteorological measurements. Other methods include artificial neural networks [287, 288], hybrid models, adaptive models [289], and fuzzy, among others [290, 291].⁵²

The large penetration of renewables in power systems requires including these power sources in the modelling of the operation and expansion of power systems, as their inherent intermittency is and will impact them in the short and long-term, as it has been discussed earlier in this thesis [299, 300]. A simplified approach is used for the modelling of wind and solar PV generation, assuming that those are continuous dispatchable sources of power.⁵³ The power

⁵² Interested readers are referred to [292, 293, 294, 295, 296, 297, 298] for additional information and surveys on this topic.

⁵³ A wind or solar PV farm is composed of many wind turbines or solar PV panels respectively. Each of those generation units can be operated continuously between zero and their maximum output (depending of course on

produced (dispatched) by each of those **VRE** resources depends on the available power from each resource at each point in time, which is given by an exogenous pattern.⁵⁴ Additionally, renewables curtailment is considered, as the power system may not be able of absorbing all available renewable power, due to lack of flexibility.

4.5.1 Wind power

The operation of the wind generation is modelled through two set of equations as follows:

WIND BALANCE EQUATION establishes that the wind power dispatched (produced) plus the wind power curtailed, i.e. P_t^{wind} and $P_t^{\text{wind-curt}}$ respectively, must always be equal to the wind power available, i.e. $P_t^{\text{wind-pwr-av}}$, at each demand segment t . This equation is formulated as follows:

$$P_t^{\text{wind}} + P_t^{\text{wind-curt}} = P_t^{\text{wind-pwr-av}}, \quad \forall t \in T. \quad (4.64)$$

WIND POWER DISPATCH establishes that the wind power dispatched cannot exceed the available wind power at each demand segment t . This is ensured by the following constraint:

$$P_t^{\text{wind}} \leq P_t^{\text{wind-pwr-av}}, \quad \forall t \in T. \quad (4.65)$$

4.5.2 Solar power

The operation of the solar **PV** generation is analogous to the wind generation, and modelled through the following equations:

SOLAR PV BALANCE EQUATION establishes that the solar **PV** power dispatched (produced) plus the solar **PV** power curtailed, i.e. P_t^{solar} and $P_t^{\text{solar-curt}}$ respectively, must always be equal to the solar **PV** power available, i.e. $P_t^{\text{solar-pwr-av}}$, at each demand segment t . This equation is formulated as follows:

$$P_t^{\text{solar}} + P_t^{\text{solar-curt}} = P_t^{\text{solar-pwr-av}}, \quad \forall t \in T. \quad (4.66)$$

SOLAR PV POWER DISPATCH establishes that the solar **PV** power dispatched cannot exceed the available solar **PV** power at each demand segment t . This is ensured by the following constraint:

$$P_t^{\text{solar}} \leq P_t^{\text{solar-pwr-av}}, \quad \forall t \in T. \quad (4.67)$$

Finally, the type and sign constraints of the decision variables used to model the operation of the **VRE** resources are given by:⁵⁵

the available power), so the clustering of wind turbines and solar **PV** panels located in the same geographical area is straight forward. The available power aggregation of **VRE** resources spread over a large geographical area, a country for example, is more complex and requires a series of adjustments [153, 154].

⁵⁴ Wind-speed and solar radiation forecasting is behind of the scopes of this thesis, and fixed available aggregated power patterns are used instead as inputs for the developed model.

⁵⁵ It must be noted that the wind and solar **PV** power dispatched corresponds to the power that can be dispatched from the total installed wind and solar **PV** capacity respectively.

$$\{p_t^{\text{wind}}, p_t^{\text{wind-curt}}, p_t^{\text{solar}}, p_t^{\text{solar-curt}}\} \in \mathbb{R}_{\geq 0}, \quad \forall t \in T. \quad (4.68)$$

4.6 STRATEGIC-GEP MODEL

During the 1980's, the restructuring, deregulation and privatization process of the electricity market started in many countries around the world, leading to profound changes in its structure as well as in the organization of the electricity industry [8, 45, 5, 7]. The monopolistic business of the large vertically integrated state companies changed by a competitive activity in the generation arena [9, 47].

Product of such profound structural changes in this sector of the electric industry, the non-stop increasing electricity demand and the rapid developments and accessibility to computer hardware, is that over the last three decades the GEP problem has gain increasing attention and complexity, which has been boosted even further by the large-scale penetration of renewable energies into power systems. Traditional GEP models have used discretized LDC [301], in combination with highly simplified generation operation models. One of those models are the Screening Curves, which was analysed in detail in Section 3.1 [49, 2].

Screening Curves in combination with the LDC can be used to calculate the optimal generation capacity investment portfolio. However, the use of LDC is based on a very strong assumption which, as clearly established in [302], is that the costs and availability of supply depend only upon the magnitude of the load and not on the time at which loads occurs. In other words, this means that chronology of demand can be ignored under the assumption that demand time dynamics are slow and thus negligible. Such assumption makes conventional generation scheduling constraints irrelevant for generation expansion planning and still seems to hold for power systems with small amounts of intermittent generation.

Nowadays, the previous assumption lacks of validity product of the increasing, large-scale and rapid penetration of renewables, which have radically changed the time dynamics of net-demand, making it less predictable and much more variable in time, amplitude and frequency. The increased unpredictability of net-demand directly impacts the operation of conventional generation, which is constrained by the flexibility characteristics of the different generation technologies, and what also has a direct influence in their electricity generation costs.

This new paradigm leads to the unavoidable requirement of including generation flexibility constraints, i.e. UC technical and operational characteristics, into GEP modelling [132]. This is not a simple task because, as analysed in Section 4.2, the UC problem is by nature hard to solve [37, 36]. Two GEP models, which consider a binary UC formulation for the operation of the conventional generation and analyse the impact of intermittent generation into the optimal generation mix, are presented in [40] and [133]. In both papers, the curse of dimensionality of the UC problem is handled using the concept of typical weeks, and in [40] additional heuristic constraints are used to reduce the solution space and improve the computational efficiency of the model. However, a simple representation of the conventional generation technical and operational constraints is considered in those works, underestimating the impact of generation flexibility.

Other very attractive way to make the UC problem computationally tractable for longer assessment horizons is, as analysed in Section 4.2.4, the use of the concept of clustering or aggregation of identical units [172, 210, 239], which provides identical solutions than the traditional binary formulation,⁵⁶ but in much faster times and with much lower computational requirements. This approach is used by Palmintier and Webster to analyse the impact of the commitment constraints into the GEP [134].

Flexible demand is not included in any of the previous GEP models [40, 133, 134], underestimating the value that demand flexibility will have for the expansion of future low-carbon power systems. Additionally, only the impact of including UC technical and operational constraint is analysed, and no attention is given to analyse what is the value of investing in improving conventional generation flexibility.

The large-scale penetration of wind and solar PV generation is on-going in many countries around the world, and is affecting the way in which their power systems are being operated and how they will need to evolve in order to effectively and efficiently face the variability and uncertainties of these sources of energy, as well as from other forms of renewable energy. In the short-term this has translated into changing the operational regime of conventional generation by one in which there is a significant increment in the plant's cycling frequency and more pronounced power output variability to compensate the fluctuations on the intermittent power injected into the grid. On the other hand, and due to the flexibility of conventional generation is limited by their technical and operational characteristics, in the long-term this will imply that the optimal generation mix will move towards larger proportions of flexible and more expensive capacity resources, making cheap and inflexible thermal generation not reliable from a security point of view, as well as not convenient from an economic perspective.

An alternative and very attractive passive source of flexibility, as analysed in Section 4.3.1, is electricity demand. The electrification of transport and heat sectors has been incentivized by economic, environmental and security concerns, and is expected that will introduce a significant amount of new demand. If such new demand is operated inflexibly, i.e. not controlling its schedule and leaving it follow the traditional pattern of demand (consumers' driving and heating requirements), it is expected that the costs required in new generation capacity and transmission network will be disproportionately larger compared to the total electric energy consumption [247]. Additionally, the foreseen incremental requirements of flexible generation to support the large-scale integration of renewables energies will not be economically sustainable either.

The wide penetration of flexible demand technologies, which have the ability of rescheduling in time their electric power demand [248], is today being incentivized by new technological developments, economies of scale, and also by the potential benefits that they potentially have for the operation and expansion of power systems. Due to all those potential benefits, apart from their undeniable broad penetration in future and their capability to facilitate the integration of renewables, is that today is imperative and required including also the modelling of flexible demand into the GEP problem. Flexible demand is incorporated in the GEP models presented in [303] and [106]. In the former paper, Rutz, et al. represent flexible demand by a price-sensitive linear demand function built based on initial demand/price projections and an

⁵⁶ If a single affine fuel consumption function is used.

assumed price elasticity of electric demand, while in the latter, Martins, et al. model flexible demand as a new peak generation group without any inter-temporal operational constraints.

Using the concept of self-price elasticity, the authors in [68] and [304] include demand response when analysing the capacity expansion problem for imperfectly competitive restructured and regulated monopoly markets respectively. However, the rescheduling capability of flexible demand is not captured in none of those papers. In [305] and [108] flexible demand is modelled through self and cross-price elasticities, allowing a better representation of the inter-temporal operational characteristics of flexible demand. Although the main properties of manually-facilitated flexible demand participation are captured in these representations, they fail in characterizing the inherent technology-specific operational complexity and dynamics of different loads, which are likely to be automatically controlled in future smart grids.

Within all available flexible demand technologies, EV are considered as one of the most important ones in the near future due to, as discussed in Section 4.3.1, their penetration and technological compatibility makes them a potential option for providing flexibility, mitigating CO₂ emissions and improving system's energy security. This is why, including EV in GEP modelling is also important, as they may help reducing the demand for conventional generation flexibility, and achieve a more effective and efficient integration of renewables.

The impact of EV on GEP is analysed in [306] and [260]. Both studies underestimate the value of EV demand flexibility due to in the former paper a set of pre-defined fixed EV charging profiles are used, disregarding the capability of optimally schedule EV demand, and in the latter, no inter-temporal UC constraints are considered, and EV scheduling is decoupled from the UC scheduling and generation investment. Authors of [262] and [266] analyse the impact of EV in the expansion of Northern European countries' power systems. The first paper uses the Balmorel model [82], while in the second paper the WILMAR model is used with the same objective [84]. Both models are enhanced to consider EV but, the Balmorel model does not include start-up costs which must be considered in power systems with large contributions of renewables, and the WILMAR model only analyses operational costs and does not include investment costs, reason why in [84] the authors feed their model with previous runs of the Balmorel model. In [34] a fully integrated GEP model is presented, in which the operational dynamics of flexible EV and generation UC scheduling constraints are explicitly incorporated. Notwithstanding the previous model allows a more accurate insight of the impact of EV flexibility on the generation system development, the penetration of flexible EV is an exogenous parameter in this paper, as well as in all the other aforementioned papers.

Although significant work has been done on analysing the impact that conventional generation technical and operational characteristics may have on the operation and expansion of power systems, and the effects of flexible demand on the operational aspects of those, the value of investing in flexibility and the impacts of flexible demand on generation expansion have not been analysed in depth and with sufficient detail.

In this thesis, as discussed in Chapters 1 and 7, a novel and integrated large-scale mixed-integer linear GEP model is presented, which incorporates a detailed modelling of the flexibility characteristics of conventional generation and flexible demand, in the form of smart-charging EV, and that allows investing not only in generation capacity, but also in flexible

demand, in systems with large penetration of renewable generation and vehicle electrification.

4.6.1 Strategic-GEP model general overview

The Strategic-GEP model is an integrated large-scale mixed-integer linear generation expansion planning model that allows assessing the role of generation and demand flexibility in future expansion of power systems with a high degree of renewables and vehicle electrification. This is achieved through a detailed modelling of the conventional generation technical and operational characteristics, and the modelling of flexible demand operation, in the form of smart-charging electric vehicles. Computational tractability is achieved using the concept of clustering for the aggregation of UC, generation investment, and flexible demand investment decision variables. A key contribution of this thesis is that the proposed model allows evaluating not only the impacts of generation and demand flexibility in the expansion of future power systems, but also the value that investing in flexibility may have for them.

4.6.2 Model structure, modifications, simplifications & assumptions

Model's structure

The Strategic-GEP model is composed of two main blocks as shown in figure 4.11, i.e. the objective function and the constraints set. The objective function, which is analysed in Section 4.6.3, includes all the investment (conventional generation and EV flexibility) and operation costs. The constraints sets, on the other hand, which are analysed in Sections 4.6.4 to 4.6.10, can be divided into seven main blocks: system-wide constraints, conventional generation technical and operational constraints, flexible EV operational constraints, hydro pumped-storage operational constraints, renewables operational constraints, generation and flexible EV investment constraints, and decision variables type and sign constraints (not shown in figure 4.11).

Modifications

The GEP as analysed in Section 3.2, involves deciding on the optimal generation capacity mix that allows supplying future electricity demand in a particular power system. The Screening Curves in combination with the LDC (Section 3.1.2) allow calculating the optimal total capacity required from each available generation technology as extensively analysed in Section 3.1, and this technique can be formulated as an equivalent LP problem as shown in Section 3.2. Those approaches although useful, rely on very strong assumptions and simplifications, which make them obsolete in modern power systems with high penetration of renewables as discussed in Section 3.3 and along this chapter.

The basic structure of the GEP LP problem developed in Section 3.2 however does not change, but it needs to be adapted in order to recognize the discrete nature of the conventional generation side, in both investment and operational terms. In other words, instead of calculating and operating the total capacity required from a pool of generation technologies ($\hat{K}_i$ and $\hat{P}_{ti}$ in the LP formulation), now it is required to calculate the total number of generation units of

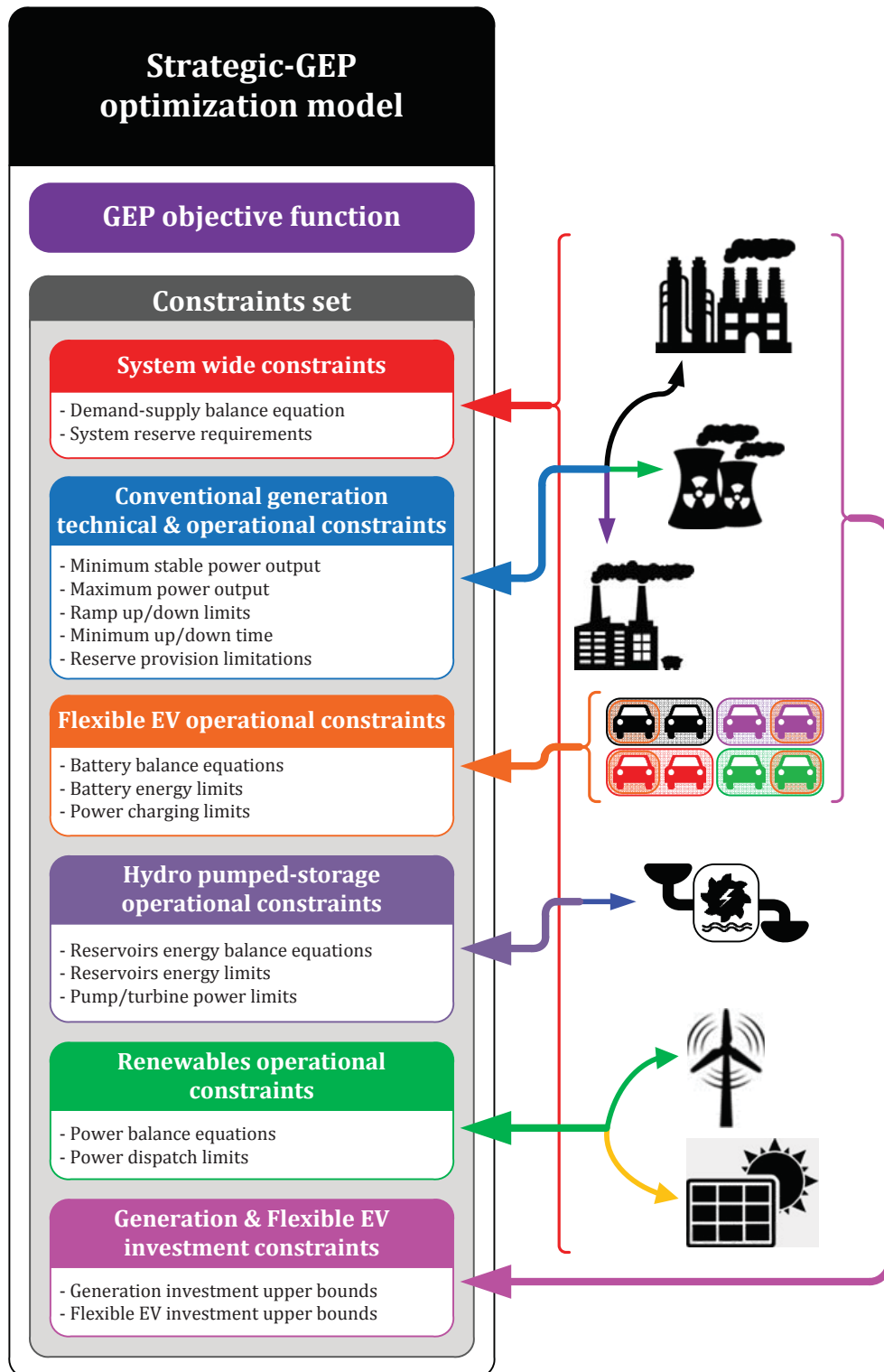


Figure 4.11: Conceptual diagram of the Strategic-GEP optimization model structure.

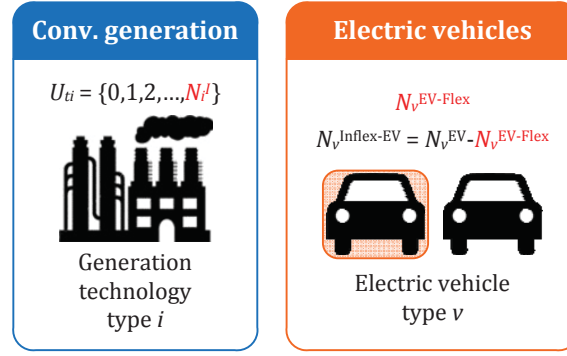


Figure 4.12: Conceptual diagram of clustered conventional generation and flexible EV investment for a single type of generation technology i , and a single EV type v .

each technology required to satisfy demand at minimum cost, in the case of a total system cost minimization formulation.

New integer variables needs to be introduced as outlined in the previous paragraph for the investment in conventional generation, i.e. N_i^I , which represents the number of generation units of technology type i to be built.⁵⁷ These variables establish an upper bounds for the UC of the generation units of each technology type i at each demand segment t . Additionally, the Strategic-GEP model allows also deciding on the investment on flexible demand, i.e. flexible EV, so additional integer variables must be added in order to decide on the optimal number of EV of each EV type v that are made flexible, i.e. $N_v^{EV-Flex}$. These variables establish upper bounds to the operation of each type of flexible EV at each demand segment t . The previous is graphically represented in figure 4.12.

Simplifications

In order to improve the computational efficiency of the Strategic-GEP model, the operational time is divided into a set of representative periods (weeks or months to characterize a year as conceptually shown in figure 4.13). Such a simplification allows reducing the number of operational decision variables for conventional generation, hydro pumped-storage, and flexible EV, without sacrificing the temporal resolution of the demand segments t .

This modification requires expanding the indexing of all time-dependant decision variables and parameters in order to account for not only the demand segments t , but also the representative periods, which requires introducing a new index n .⁵⁸ Each period must be weighted by a scaling factor, i.e. Φ_n , in both the objective function and system-wide constraints that involve all time periods at the same time. This scaling factor reflects the relative weight that each period has in the original assessment horizon.

The scheduling of the conventional generation units needs to be initialized in order to account for the status of those generation units at the beginning of each representative period. This status of each generation unit is influenced by its previous operation, i.e. unit commitment, power output, elapsed minimum up/down time, and if not properly initialized it may bias the optimal solution. In pure UC problems such initial status is part of the input data, but

⁵⁷ From now on generation technology types are used instead of referring to generation clusters.

⁵⁸ In the case of figure 4.13, the cardinality of the representative periods set N is equal to four, i.e. $\{n \in N \mid N = \{\text{Winter week, Spring week, Summer week, Autumn week}\}\}$.

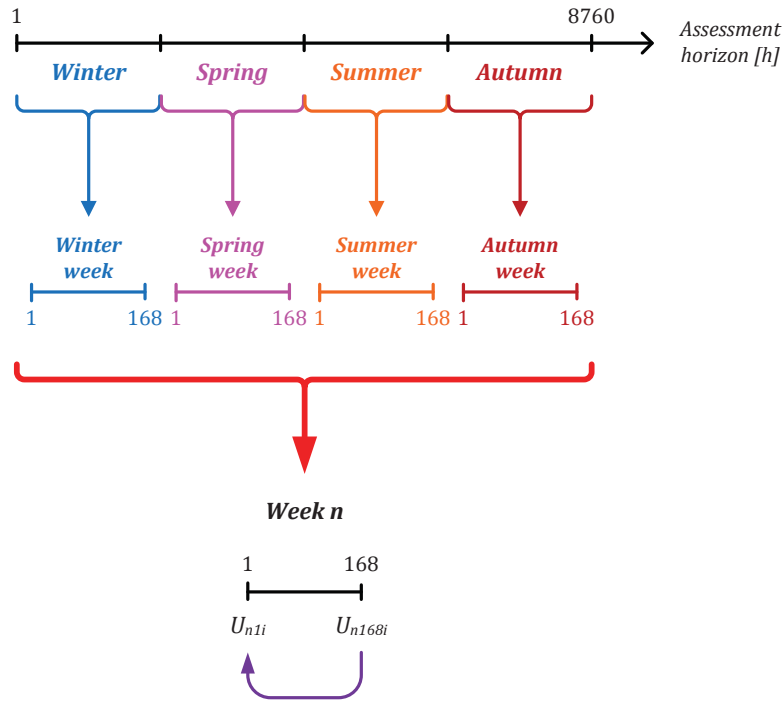


Figure 4.13: Conceptual diagram of assessment horizon reduction into four representative periods, weeks in this case, and the linkage that must be established between the end and the start of each period for the operation of the conventional generation and hydro pumped-storage technologies.

when considering representative periods this is not the case and a linkage between the final and initial demand segments of each of those periods must to be established.

When characterizing the original assessment horizon through a reduced set of shorter representative periods it can be assumed that each of those periods is followed by an identical one. In other words, this is equivalent to say that the final demand segment of each representative period is followed by the first one, as shown at the bottom of figure 4.13. The previous translates into that all generation technical and operational constraints of the Strategic-GEP model are adjusted in order to reflect such assumption. In terms of time-dependant input data for the model, it was selected so that there are no jumps between the last and first demand segments that can violate conventional generation ramping rates, and that the maximum absolute difference between those values is not larger than those observed in consecutive segments of the data.

Assumptions

The Strategic-GEP model is based on a deterministic long-run equilibrium approach, where the total system cost (TSC) is minimized assuming a perfectly competitive market.⁵⁹ The TSC includes the total generation and EV flexibility investment costs, plus the total conventional generation and hydro pumped-storage operational cost, and the costs associated with the curtailment of load, conventional generation and renewables (wind and solar PV). In terms of

⁵⁹ Cost minimization models can be used to represent competitive markets given that the marginal pricing economic theory demonstrates that the optimal solution obtained under this market structure, or if a cost-minimization central-planner is considered, are equal [8, 78, 307].

market structure, the model allows considering both energy and capacity markets, and also spike-pricing and price-cap energy pricing regulations [49].⁶⁰

The model formulation considers a single node in which there is inflexible and flexible demand,⁶¹ conventional generation, hydro pumped-storage, and renewable generation connected. Flexible demand involves EV with smart (controllable) charging capability,⁶² the realization and coordination of which requires certain enabling costs per EV.⁶³ Although the total EV penetration constitutes a fixed input of the model, the numbers of flexible EV in the system is a decision variable for the model. The inflexible EV demand of each individual vehicle is a fixed input for the model, and is derived by assuming that they start charging their batteries immediately after they are plugged into the grid and until they are fully charged [252].⁶⁴ It is assumed that only day-ahead information will be used for the coordination of flexible EV in the operational timescale and thus all flexible EV exhibit only intra-day flexibility. The total EV population has been categorized into different types according to the EV users' driving patterns and travelling requirements, and the operational properties of EV batteries and grid connections [244].

Using the concept of clustering [134, 244], conventional generation and EV clusters are defined according to the available generation technologies and EV types respectively, and integer instead of binary decision variables are used for generation investment, UC and flexible EV investment, as described in previous sections. The installed wind and solar PV generation capacities are fixed inputs of the model, determined by the national and international targets for renewable energy integration and CO₂ emissions reduction. CO₂ emissions of conventional generation are penalized through a CO₂ price, and limited by a system-wide cap.

In order to capture the diversity of system conditions in a computationally manageable fashion, the Strategic-GEP model employs an approach based on the definition of representative periods [29].⁶⁵ Nevertheless, the model is not restricted to representative periods and can be configured to handle any type of assessment horizon.⁶⁶

4.6.3 Objective function

The objective function of the Strategic-GEP model to be minimized is the TSC:

⁶⁰ The case studies presented in this thesis however consider only an energy-only-market, where energy prices can spike up to VOLL.

⁶¹ The inflexible demand is assumed to be composed of two components, i.e. load demand (non-EV system demand) and inflexible EV power consumption.

⁶² In other words, flexible EV can be optimally scheduled in the operational timescale by the model in order to differ their electricity demand towards low energy prices hours. EV V2G capability is not considered in the model formulation and will be topic for further research.

⁶³ Costs required to introduce and coordinate EV flexibility, i.e. installation and operation of suitable metering, control and communication infrastructure.

⁶⁴ The total EV inflexible demand is not an input for the model, and depends on the number of flexible EV of each type v in the system.

⁶⁵ Five typical weeks are used in the case studies developed in Chapters 5 and 6.

⁶⁶ A summary of the assumptions made for the Strategic-GEP model formulation can be found at the beginning of Appendix A.

$$\begin{aligned}
\text{TSC} = & \sum_{i \in I} C_i^{\text{Generation-Investment}} \\
& + \sum_{n \in N} \sum_{t \in T} \Phi_n \left\{ \sum_{i \in I} C_{nti}^{\text{Generation-Operation}} + C_{nt}^{\text{Hydro-PS-Operation}} + C_{nt}^{\text{System-Operation}} \right\} \\
& + \sum_{v \in V} C_v^{\text{EV-Flexibility-Investment}}, \quad (4.69)
\end{aligned}$$

which includes five terms:

1. the investment cost in each conventional generation technology type i (first line);
2. the operational cost of each generation technology type i at each period n and each demand segment t (second line, first term);
3. the operational cost of the hydro-pumped storage technology at each period n and each demand segment t (second line, second term);
4. the system operation costs at each period n and each demand segment t (second line, third term);
5. and, the flexibility investment cost in each EV type v (third line).

Generation investment cost

The generation investment cost in each generation technology i is given by the investment cost in new generation units, i.e. $N_i^{I\text{-new}}$, and is given by the following expression:

$$C_i^{\text{Generation-Investment}} = \text{FC}_i K_i N_i^{I\text{-new}}, \quad \forall i \in I, \quad (4.70)$$

where FC_i are the fixed costs of generation technology i ,⁶⁷ K_i the capacity size of each generation unit of technology i , and $N_i^{I\text{-new}}$ the number of new generation units of type i to be built.

Generation operational costs

The generation operational cost in each generation technology i at each period n and each demand segment t is given by:

$$C_{nti}^{\text{Generation-Operation}} = C_{nti}^{\text{start-up}} + C_{nti}^{\text{variable}} + C_{nti}^{\text{shut-down}}, \quad \forall n \in N, \forall t \in T, \forall i \in I. \quad (4.71)$$

⁶⁷ $\text{FC}_i = \{(\text{WACC}_i \times \text{CAPEX}_i) / [1 - \exp(-\text{WACC}_i \times \text{LT}_i)]\} + \pi_i^{\text{fix-O\&M}}$, where WACC_i is the Weighted Average Cost of Capital (WACC) for investment in generation technology i , CAPEX_i the capital expenditures of generation technology i , LT_i the expected lifetime of a generation unit of technology i , and $\pi_i^{\text{fix-O\&M}}$ the annual fix O&M costs of generation technology i .

START-UP COSTS correspond to the costs associated with the start-up of generation units of technology i , and are given by:

$$C_{nti}^{\text{start-up}} = \left[\pi_i^{\text{Sup-fuel}} + \pi_i^{\text{Sup-O\&M}} \right] S_{nti}^{\text{Up}}, \quad \forall n \in N, \forall t \in T, \forall i \in I, \quad (4.72)$$

where $\pi_i^{\text{Sup-fuel}}$ is the fuel cost of bringing online a generation unit of technology i ,⁶⁸ and $\pi_i^{\text{Sup-O\&M}}$ the fix O&M cost associated with such a manoeuvre.

VARIABLE COSTS correspond to the costs associated with the production of electricity by generation technology i , which are given by:

$$C_{nti}^{\text{variable}} = C_{nti}^{\text{variable-O\&M}} + C_{nti}^{\text{fuel}} + C_{nti}^{\text{CO}_2\text{-emissions}}, \quad \forall n \in N, \forall t \in T, \forall i \in I, \quad (4.73)$$

where the first term corresponds to the variable O&M costs, the second to the cost of the fuel consumed, and the third to the cost of the CO₂ emitted, when producing electricity. Each of those terms are given by the following expressions:

$$C_{nti}^{\text{variable-O\&M}} = \tau_t \pi_i^{\text{O\&M}} P_{nti}, \quad \forall n \in N, \forall t \in T, \forall i \in I, \quad (4.74)$$

$$C_{nti}^{\text{fuel}} = \tau_t \pi_i^{\text{fuel}} F_{nti}^{\text{fuel-use}}, \quad \forall n \in N, \forall t \in T, \forall i \in I, \quad (4.75)$$

$$C_{nti}^{\text{CO}_2\text{-emissions}} = \left[\pi_i^{\text{Sup-CO}_2} S_{nti}^{\text{Up}} + \tau_t \pi_i^{\text{CO}_2} F_{nti}^{\text{fuel-use}} + \pi_i^{\text{SDwn-CO}_2} S_{nti}^{\text{Dwn}} \right] \times \left(1 - \text{ER}_i^{\text{CCS-CO}_2} \right), \quad \forall n \in N, \forall t \in T, \forall i \in I, \quad (4.76)$$

where $\pi_i^{\text{O\&M}}$ is the variable O&M cost of generation technology i , $\pi_i^{\text{Sup-CO}_2}$ the CO₂ cost associated with the start-up event of technology i ,⁶⁹ $\pi_i^{\text{CO}_2}$ the CO₂ cost associated with the electricity production of generation technology i ,⁷⁰ $\pi_i^{\text{SDwn-CO}_2}$ the CO₂ cost associated with the shut-down event of a generation unit of technology i ,⁷¹ and $\text{ER}_i^{\text{CCS-CO}_2}$ the CO₂ emissions reduction factor due to a CCS system.

SHUT-DOWN COSTS correspond to the costs associated with the shut-down of generation units of a generation unit of technology i , and are given by:

$$C_{nti}^{\text{shut-down}} = \left[\pi_i^{\text{SDwn-fuel}} + \pi_i^{\text{SDwn-O\&M}} \right] S_{nti}^{\text{Dwn}}, \quad \forall n \in N, \forall t \in T, \forall i \in I, \quad (4.77)$$

⁶⁸ $\pi_i^{\text{Sup-fuel}} = H_i^{\text{Sup}} \pi_i^{\text{fuel}}$, where H_i^{Sup} is the heat consumed during an start-up event of a generation unit of technology i , and π_i^{fuel} the fuel cost of generation technology i . The fuel cost of generation technology i corresponds to the cost of the fuel used by that technology to produce electricity, i.e. $\pi_i^{\text{fuel}} = \pi_{\psi}^{\text{fuel}}$, where $\{\psi \in \Psi \mid \Psi = \{\text{uranium, coal, gas, oil}\}\}$.

⁶⁹ $\pi_i^{\text{Sup-CO}_2} = H_i^{\text{Sup}} \pi_i^{\text{CO}_2}$.

⁷⁰ $\pi_i^{\text{CO}_2} = \text{EF}_i^{\text{CO}_2} \pi^{\text{CO}_2}$, where $\text{EF}_i^{\text{CO}_2}$ is the CO₂ emissions factor of generation technology i , and π^{CO_2} the CO₂ price for the whole power system. The CO₂ emissions factor of a generation technology i corresponds to the CO₂ emission factor of the fuel used by that technology to produce electricity, i.e. $\text{EF}_i^{\text{CO}_2} = \text{EF}_{\psi}^{\text{fuel}}$, where $\{\psi \in \Psi \mid \Psi = \{\text{uranium, coal, gas, oil}\}\}$.

⁷¹ $\pi_i^{\text{SDwn-CO}_2} = H_i^{\text{SDwn}} \pi_i^{\text{CO}_2}$.

where $\pi_i^{\text{SDwn-fuel}}$ is the fuel cost of taking offline a generation unit of technology i ,⁷² and $\pi_i^{\text{SDwn-O\&M}}$ the fix **O\&M** cost associated with such a manoeuvre.

Hydro pumped-storage operational cost

The hydro pumped-storage operational cost at each period n and each demand segment t is given by:

$$C_{nt}^{\text{Hydro-PS-Operation}} = C_{nt}^{\text{PS-start-up}} + C_{nt}^{\text{PS-shut-down}}, \quad \forall n \in N, \forall t \in T. \quad (4.78)$$

START-UP COSTS correspond to the costs associated with the start-up of turbines and pumps, and are given by:

$$C_{nt}^{\text{PS-start-up}} = \pi^{\text{PS-SUp-p}} S_{nt}^{\text{PS-Up-p}} + \pi^{\text{PS-SUp-t}} S_{nt}^{\text{PS-Up-t}}, \quad \forall n \in N, \forall t \in T, \quad (4.79)$$

where $\pi^{\text{PS-SUp-p}}$ and $\pi^{\text{PS-SUp-t}}$ are the costs of the pumping and turbine modes start-up manoeuvres respectively.

SHUT-DOWN COSTS correspond to the costs associated with the shut-down of turbines and pumps, and are given by:

$$C_{nt}^{\text{PS-shut-down}} = \pi^{\text{PS-SDwn-p}} S_{nt}^{\text{PS-Dwn-p}} + \pi^{\text{PS-SDwn-t}} S_{nt}^{\text{PS-Dwn-t}}, \quad \forall n \in N, \forall t \in T, \quad (4.80)$$

where $\pi^{\text{PS-SDwn-p}}$ and $\pi^{\text{PS-SDwn-t}}$ are the costs of the pumping and turbine modes shut-down manoeuvres respectively.

System operation costs

The system operation costs at each period n and each demand segment t are given by:

$$\begin{aligned} C_{nt}^{\text{System-Operation}} = & C_{nt}^{\text{load-curtailment}} + C_{nt}^{\text{generation-curtailment}} \\ & + C_{nt}^{\text{wind-curtailment}} + C_{nt}^{\text{solar-curtailment}}, \end{aligned} \quad \forall n \in N, \forall t \in T, \quad (4.81)$$

where the right hand terms correspond to the costs associated with the curtailment of load, conventional generation,⁷³ wind generation and solar **PV** generation respectively. Each of those terms are given by the following expressions:

$$C_{nt}^{\text{load-curtailment}} = \tau_t L_{nt}^{\text{curt}} \pi^{\text{LC}}, \quad \forall n \in N, \forall t \in T, \quad (4.82)$$

⁷² $\pi_i^{\text{SDwn-fuel}} = H_i^{\text{SDwn}} \pi_i^{\text{fuel}}$, where H_i^{SDwn} is the heat consumed during an shut-down event of a generation unit of technology i .

⁷³ Conventional generation curtailment occurs when demand becomes very low, and due to technical and operational limits of conventional generation it is not possible reducing their power output fast enough so has to prevent such a situation, which is very rare in modern power systems. However, the large-scale penetration of renewables and their effects in net-demand can potentially create the conditions for this situation to happen. Generation curtailment is penalized at a very high cost (higher than **VOLL**) in order to avoid its occurrence, and in the Strategic-GEp model, these variables allows avoiding infeasibilities in its solution.

$$C_{nt}^{\text{generation-curtailment}} = \tau_t P_{nt}^{\text{curt}} \pi^{\text{GC}}, \quad \forall n \in N, \forall t \in T, \quad (4.83)$$

$$C_{nt}^{\text{wind-curtailment}} = \tau_t P_{nt}^{\text{wind-curt}} \pi^{\text{WC}}, \quad \forall n \in N, \forall t \in T, \quad (4.84)$$

$$C_{nt}^{\text{solar-curtailment}} = \tau_t P_{nt}^{\text{solar-curt}} \pi^{\text{PVC}}, \quad \forall n \in N, \forall t \in T, \quad (4.85)$$

where L_{nt}^{curt} , P_{nt}^{curt} , $P_{nt}^{\text{wind-curt}}$ and $P_{nt}^{\text{solar-curt}}$ are the load, generation, wind and solar PV curtailment at each period n and each demand segment t . π^{LC} , π^{GC} , π^{WC} and π^{PVC} , on the other hand, are the prices assigned (penalization value) to each of those types of curtailment.

Flexibility investment cost

The flexibility investment cost in each EV type v is proportional to the number of EV that are converted into flexible EV, i.e. $N_v^{\text{EV-Flex-new}}$, and is given by the following expression:

$$C_v^{\text{EV-Flexibility-Investment}} = \text{FC}_v^{\text{EV-Flexibility}} N_v^{\text{EV-Flex-new}}, \quad \forall v \in V, \quad (4.86)$$

where $\text{FC}_v^{\text{EV-Flexibility}}$ is the annuitized EV flexibility enabling cost per EV of type v .⁷⁴

4.6.4 System-wide constraints

The system-wide constraints are those that impose restrictions over several components of the power system at the same time, such as the demand balance equation, ancillary services demand, and total CO₂ emissions limit, among others. Some of these constraints have been previously analysed, so in those cases no further explanation will be given, but the respective equations will be rewritten in order to reflect the new changes introduced to nomenclature, and the simplifications outlined in Section 4.6.2.

Demand balance equation

The demand balance equation establishes that the total power supply provided by conventional generation, hydro pumped-storage, and renewables resources, plus load and minus generation curtailment, must satisfy the total electricity demand at each period n and each demand segment t , and is given by:

$$\sum_{i \in I} P_{nti} + P_{nt}^{\text{PS}} + P_{nt}^{\text{wind}} + P_{nt}^{\text{solar}} + L_{nt}^{\text{curt}} - P_{nt}^{\text{curt}} = D_{nt}^{\text{System}}, \quad \forall n \in N, \forall t \in T, \quad (4.87)$$

where D_{nt}^{System} is the total system electricity demand at each period n and each demand segment t , which includes the load, hydro pumped-storage, and flexible and inflexible EV demands. D_{nt}^{System} is given by the following expression:

$$D_{nt}^{\text{System}} = L_{nt} + D_{nt}^{\text{PS}} + D_{nt}^{\text{EV-Flexible}} + D_{nt}^{\text{EV-Inflexible}}, \quad \forall n \in N, \forall t \in T, \quad (4.88)$$

⁷⁴ Investment costs required to enable and coordinate EV flexibility.

where L_{nt} is the load demand at each period n and demand segment t ,⁷⁵ D_{nt}^{PS} the electricity consumed by the hydro pumped-storage power plants at each period n and demand segment t , and $D_{nt}^{\text{EV-Flexible}}$ and $D_{nt}^{\text{EV-Inflexible}}$ the electricity demand of the entire flexible and inflexible EV fleet respectively at each period n and each demand segment t . The EV demands are given by the following expressions:

$$D_{nt}^{\text{EV-Flexible}} = \sum_{v \in V} P_{ntv}^{\text{EV}}, \quad \forall n \in N, \forall t \in T, \quad (4.89)$$

$$D_{nt}^{\text{EV-Inflexible}} = \sum_{v \in V} \left[N_v^{\text{EV}} - N_v^{\text{EV-Flex}} \right] d_{ntv}^{\text{EV-Inflex}}, \quad \forall n \in N, \forall t \in T, \quad (4.90)$$

where $d_{ntv}^{\text{EV-Inflex}}$ is the EV inflexible demand level of an individual EV of type v at each period n and each demand segment t .

Frequency regulation reserve demands

$$\sum_{i \in I^{\text{FRR-Up}}} R_{nti}^{\text{FRR-Up}} \geq \text{RR}_{nt}^{\text{FRR-Up}}(\Xi), \quad \forall n \in N, \forall t \in T, \quad (4.91)$$

$$\sum_{i \in I^{\text{FRR-Dwn}}} R_{nti}^{\text{FRR-Dwn}} \geq \text{RR}_{nt}^{\text{FRR-Dwn}}(\Xi), \quad \forall n \in N, \forall t \in T. \quad (4.92)$$

The previous constraints are updated versions of constraints (4.20) and (4.21) respectively.⁷⁶

Spinning reserve demands

$$\sum_{i \in I^{\text{SPR-Up}}} R_{nti}^{\text{SPR-Up}} + \sum_{i \in I^{\text{QSR}}} R_{nti}^{\text{QSR}} \geq \text{RR}_{nt}^{\text{SPR-Up}}(\Xi), \quad \forall n \in N, \forall t \in T, \quad (4.93)$$

$$\sum_{i \in I^{\text{SPR-Dwn}}} R_{nti}^{\text{SPR-Dwn}} \geq \text{RR}_{nt}^{\text{SPR-Dwn}}(\Xi), \quad \forall n \in N, \forall t \in T. \quad (4.94)$$

The previous constraints are updated versions of constraints (4.22) and (4.23) respectively.

Quick-start reserve maximum contribution towards upward spinning reserve demand

$$\sum_{i \in I^{\text{QSR}}} R_{nti}^{\text{QSR}} \leq \alpha_{\text{QSR-SPR}}^{\text{MAX-contrib}} \text{RR}_{nt}^{\text{SPR-Up}}(\Xi), \quad \forall n \in N, \forall t \in T. \quad (4.95)$$

This constraint is the updated version of constraint (4.24).

System CO₂ emissions intensity limit

The system CO₂ emissions intensity limit constraint establishes an upper bound for the power system CO₂ intensity, and is given by:

⁷⁵ Non-EV system demand.

⁷⁶ $\Xi = \{L_{nt}, D_{nt}^{\text{PS}}, D_{nt}^{\text{EV-Flexible}}, D_{nt}^{\text{EV-Inflexible}}, p_i^{\text{MAX}}, K^{\text{wind}}, p_{nt}^{\text{wind-pwr-av}}, K^{\text{solar}}, p_{nt}^{\text{solar-pwr-av}}\}$.

$$\frac{\sum_{n \in N} \sum_{t \in T} \sum_{i \in I} \Phi_n \text{EMI}_{nti}^{\text{CO}_2}}{\sum_{n \in N} \sum_{t \in T} \Phi_n \tau_t \left\{ \sum_{i \in I} P_{nti} + P_{nt}^{\text{PS}} + P_{nt}^{\text{wind}} + P_{nt}^{\text{solar}} \right\}} \leq \text{SEI}, \quad (4.96)$$

where SEI is the system-wide CO_2 emissions intensity limit, and $\text{EMI}_{nti}^{\text{CO}_2}$ the CO_2 emissions of generation technology i at each period n and each demand segment t , which is given by the following expression:

$$\text{EMI}_{nti}^{\text{CO}_2} = \text{EF}_i^{\text{CO}_2} \left[H_i^{\text{SUP}} S_{nti}^{\text{UP}} + \tau_t F_{nti}^{\text{fuel-use}} + H_i^{\text{SDwn}} S_{nti}^{\text{Dwn}} \right] \times \left(1 - \text{ER}_i^{\text{CCS-CO}_2} \right), \quad \forall n \in N, \forall t \in T, \forall i \in I. \quad (4.97)$$

System target capacity

The system target capacity constraint, as analysed in Section 3.2.3, corresponds to a long-term capacity constraint that looks to enforce that enough conventional generation capacity is built in order to satisfy demand at all times, as is given by:

$$\sum_{i \in I} \bar{\mathcal{A}}_i K_i N_i^I \geq \left(1 + \text{RR}^K \right) \max_{\substack{n \in N \\ t \in T}} \left\{ D_{nt}^{\text{System}} \right\}, \quad (4.98)$$

where RR^K is the capacity planning reserve factor, and $\bar{\mathcal{A}}_i$ the capacity derating factor.⁷⁷ The capacity planning reserve, which in Section 3.2.3 is referred as reserve requirement factor, corresponds to the percentage of extra conventional generation that needs to be build above system's peak demand, and is meant to account for the operating reserve requirements during peak demand periods, and also for the electricity demand growth's uncertainty.⁷⁸

4.6.5 Conventional generation operational constraints

Fuel consumption

$$F_{nti}^{\text{fuel-use}} \geq \text{NLH@0}_{il} U_{nti} + \text{HR}_{il}^{\text{inc}} P_{nti}, \quad \forall n \in N, \forall t \in T, \forall i \in I. \quad (4.99)$$

The previous constraint is the updated version of constraint (4.19).

⁷⁷ This derating factor can represent either the firm capacity ratio, or the availability ratio, depending on the application and modelling approach. The firm capacity ratio is the fraction of the installed capacity of a generation unit that can reliably generate electricity during peak demand periods, and for thermal power plants is calculated based on the Effective Forced Outage Rate (EFOR). The availability ratio, on the other hand, is the same fraction of the installed capacity, but its calculation is based on the average availability of the generation unit through the year, which considers planned (maintenance) and unplanned outages, and reserve provisions [3]. Due to planned outages are not scheduled during peak times, firm capacity is typically higher than availability.

⁷⁸ This is a simple approach to ensure a total system capacity target level, but traditionally probabilistic methods are used in generation expansion planning, which use metrics that include the Loss Of Load Expectation (LOLE) and Loss Of Load Probability (LOLP) [308, 309]. It must be noted that in constraint (4.98) the capacity contribution of VRE resources is assumed to be zero [310, 311, 312].

Power output limits

$$U_{nti} p_i^{\min} \leq P_{nti} \leq U_{nti} p_i^{\text{MAX}}, \quad \forall n \in N, \forall t \in T, \forall i \in I. \quad (4.100)$$

The previous constraint is the updated version of constraint (4.10).

Power ramping limits

$$P_{nti} - P_{n(t\ominus 1)i} \leq \left[U_{nti} - S_{nti}^{\text{Up}} \right] \tau_t \Delta_i^{\text{Up}} + S_{nti}^{\text{Up}} \max \left\{ p_i^{\min}, \tau_t \Delta_i^{\text{Up}} \right\} - S_{nti}^{\text{Dwn}} p_i^{\min},$$

$$\forall n \in N, \forall t \in T, \forall i \in I, \quad (4.101)$$

$$P_{n(t\oplus 1)i} - P_{nti} \leq \left[U_{nti} - S_{nti}^{\text{Up}} \right] \tau_t \Delta_i^{\text{Dwn}} + S_{nti}^{\text{Dwn}} \max \left\{ p_i^{\min}, \tau_t \Delta_i^{\text{Dwn}} \right\} - S_{nti}^{\text{Up}} p_i^{\min},$$

$$\forall n \in N, \forall t \in T, \forall i \in I. \quad (4.102)$$

The previous constraints are the updated versions of constraints (4.34) and (4.35) respectively.⁷⁹

Minimum up & down times

$$U_{nti} \geq \sum_{\hat{t}=t-(\text{MT}_i^{\text{Up}}/\tau_t)+1}^t S_{n\hat{t}i}^{\text{Up}},$$

$$\forall n \in N, \forall t \in \left[\left(\text{MT}_i^{\text{Up}}/\tau_t \right) + 1, N^T \right], \forall i \in I \setminus I^{\text{mr}}, \quad (4.103)$$

$$U_{nti} \geq \sum_{\hat{t}=N^T-(\text{MT}_i^{\text{Up}}/\tau_t)+t+1}^{N^T} S_{n\hat{t}i}^{\text{Up}} + \sum_{\hat{t}=1}^t S_{n\hat{t}i}^{\text{Up}},$$

$$\forall n \in N, \forall t \in \left[1, \left(\text{MT}_i^{\text{Up}}/\tau_t \right) \right], \forall i \in I \setminus I^{\text{mr}}, \quad (4.104)$$

$$N_i^I - U_{nti} \geq \sum_{\hat{t}=t-(\text{MT}_i^{\text{Dwn}}/\tau_t)+1}^t S_{n\hat{t}i}^{\text{Dwn}},$$

$$\forall n \in N, \forall t \in \left[\left(\text{MT}_i^{\text{Dwn}}/\tau_t \right) + 1, N^T \right], \forall i \in I \setminus I^{\text{mr}}, \quad (4.105)$$

⁷⁹ It must be noted that constraints (4.101) and (4.102) are formulated using the mathematical operator “ $\ominus$ ”, which ensures the carry-over relationships that wraps the representative periods around in an equilibrium fashion.

$$N_i^I - U_{nti} \geq \sum_{\hat{t}=N^T - (\text{MT}_i^{\text{Dwn}}/\tau_t) + t + 1}^t S_{nti}^{\text{Dwn}} + \sum_{\hat{t}=1}^t S_{nti}^{\text{Dwn}},$$

$$\forall n \in N, \forall t \in \left[1, \left(\text{MT}_i^{\text{Dwn}}/\tau_t\right)\right], \forall i \in I \setminus I^{\text{mr}}. \quad (4.106)$$

Constraints (4.103) and (4.105) are the updated versions of constraints (4.15) and (4.36) respectively. Constraints (4.104) and (4.106), on the other hand, are new and complementary to (4.103) and (4.105) respectively, and they ensure that the minimum up/down time constraints respect the assumption that each representative period is followed by a similar one.

Online reserve services

$$R_{nti}^{\text{FRR-Up}} + R_{nti}^{\text{SPR-Up}} \leq U_{nti} p_i^{\text{MAX}} - P_{nti},$$

$$\forall n \in N, \forall t \in T, \forall i \in \left\{I^{\text{FRR-Up}}, I^{\text{SPR-Up}}\right\}, \quad (4.107)$$

$$R_{nti}^{\text{FRR-Dwn}} + R_{nti}^{\text{SPR-Dwn}} \leq P_{nti} - U_{nti} p_i^{\text{min}},$$

$$\forall n \in N, \forall t \in T, \forall i \in \left\{I^{\text{FRR-Dwn}}, I^{\text{SPR-Dwn}}\right\}. \quad (4.108)$$

The previous constraints are the updated versions of constraints (4.25) and (4.26) respectively.

FRR maximum deployment

$$R_{nti}^{\text{FRR-Up}} \leq \min \left\{ U_{nti} \text{FRR}_i^{\text{MAX-Up}}, \sigma_i^{\text{FRR-Up}} \left[U_{nti} p_i^{\text{MAX}} - \left(P_{nti} + R_{nti}^{\text{SPR-Up}} \right) \right] \right\},$$

$$\forall n \in N, \forall t \in T, \forall i \in I^{\text{FRR-Up}}, \quad (4.109)$$

$$R_{nti}^{\text{FRR-Dwn}} \leq \min \left\{ U_{nti} \text{FRR}_i^{\text{MAX-Dwn}}, \sigma_i^{\text{FRR-Dwn}} \left[\left(P_{nti} - R_{nti}^{\text{SPR-Dwn}} \right) - U_{nti} p_i^{\text{min}} \right] \right\},$$

$$\forall n \in N, \forall t \in T, \forall i \in I^{\text{FRR-Dwn}}. \quad (4.110)$$

The previous constraints are the updated versions of constraints (4.27) and (4.28) respectively.

SPR maximum deployment

$$R_{nti}^{\text{SPR-Up}} \leq U_{nti} \text{SPR}_i^{\text{MAX-Up}}, \quad \forall n \in N, \forall t \in T, \forall i \in I^{\text{SPR-Up}}, \quad (4.111)$$

$$R_{nti}^{\text{SPR-Dwn}} \leq U_{nti} \text{SPR}_i^{\text{MAX-Dwn}}, \quad \forall n \in N, \forall t \in T, \forall i \in I^{\text{SPR-Dwn}}. \quad (4.112)$$

The previous constraints are the updated versions of constraints (4.29) and (4.30) respectively.

QSR maximum deployment

$$R_{nti}^{\text{QSR}} \leq [N_i^I - U_{nti}] \text{QSR}_i^{\text{MAX}}, \quad \forall n \in N, \forall t \in T, \forall i \in I^{\text{QSR}}. \quad (4.113)$$

The previous constraint is the updated version of constraint (4.37).

Number of generation units

The total number of available generation units of technology i in the system is equal to the initial number of generation units of each technology type at the beginning of the assessment horizon, i.e. $N_i^{I-\text{old}}$, plus the new generation units added to the system. The previous is expressed as follows:

$$N_i^I = N_i^{I-\text{old}} + N_i^{I-\text{new}}, \quad \forall i \in I. \quad (4.114)$$

UC state equation

$$U_{nti} = U_{n(t \ominus 1)i} + S_{nti}^{\text{Up}} - S_{nti}^{\text{Dwn}}, \quad \forall n \in N, \forall t \in T, \forall i \in I. \quad (4.115)$$

The previous constraint is the updated version of constraint (4.17).

UC limits & restrictions

$$U_{nti} \leq N_i^I, \quad \forall n \in N, \forall t \in T, \forall i \in I \setminus I^{\text{mr}}, \quad (4.116)$$

$$U_{nti} = N_i^I, \quad \forall n \in N, \forall t \in T, \forall i \in I^{\text{mr}}, \quad (4.117)$$

$$S_{nti}^{\text{Up}} = 0, \quad \forall n \in N, t = 1, \forall i \in I \setminus I^{\text{mr}}, \quad (4.118)$$

$$S_{nti}^{\text{Dwn}} = 0, \quad \forall n \in N, t = 1, \forall i \in I \setminus I^{\text{mr}}. \quad (4.119)$$

Constraints (4.116) and (4.117) are the updated version of constraints (4.39) and (4.38) respectively. Constraints (4.118) and (4.119), on the other hand, are new and ensure that there are no start-up or shut-down events happening between the last and first demand segment of each period n , in order to respect the assumption that each representative period is followed by a similar one.

4.6.6 Flexible EV operational constraints

Number of flexible EV

The total number of flexible EV of each EV type v in the system is equal to the initial number of flexible EV of each EV type v at the beginning of the assessment horizon, i.e. $N_v^{\text{EV-Flex-old}}$, plus the new flexible EV. The previous is expressed as follows:

$$N_v^{\text{EV-Flex}} = N_v^{\text{EV-Flex-old}} + N_v^{\text{EV-Flex-new}}, \quad \forall v \in V. \quad (4.120)$$

Battery balance equation

$$E_{ntv}^{\text{EV}} = \eta_v^{\text{chg}} P_{ntv}^{\text{EV}} \tau_t + \eta_v^{\text{elec}} E_{n(t \ominus 1)v}^{\text{EV}} - N_v^{\text{EV-Flex}} e_{ntv}^{\text{tr}}, \quad \forall n \in N, \forall t \in T, \forall v \in V. \quad (4.121)$$

The previous constraint is the updated version of constraint (4.44).

Battery energy limits

$$N_v^{\text{EV-Flex}} e_v^{\text{bat-min}} \leq E_{ntv}^{\text{EV}} \leq N_v^{\text{EV-Flex}} e_v^{\text{bat-MAX}}, \quad \forall n \in N, \forall t \in T, \forall v \in V. \quad (4.122)$$

The previous constraint is the updated version of constraint (4.45).

Power charging limits

$$P_{ntv}^{\text{EV}} \leq \begin{cases} N_v^{\text{EV-Flex}} p_v^{\text{chg-MAX}}, & \forall t \in T_v^{\text{gc}} \\ 0, & \forall t \in T \setminus T_v^{\text{gc}} \end{cases}, \quad \forall n \in N, \forall v \in V. \quad (4.123)$$

The previous constraint is the updated version of constraint (4.46).

Energy neutrality constraint

The energy neutrality constraint establishes that the EV battery energy level at the end of each day must be equal to a pre-defined level. This constraint expresses the assumption that EV only have intra-day flexibility, and is given by the following expression:

$$E_{ntv}^{\text{EV}} = N_v^{\text{EV-Flex}} e_v^{\text{ed}}, \quad \forall n \in N, \forall t \in T^{\text{ed}}, \forall v \in V, \quad (4.124)$$

where e_v^{ed} is the required EV type v battery energy level at the end of the day.⁸⁰

4.6.7 Hydro pumped-storage operational constraints

Reservoirs energy balance equations

$$X_{nt}^{\text{PS-Upper}} = X_{n(t-1)}^{\text{PS-Upper}} + \eta^{\text{ptc}} D_{nt}^{\text{PS}} \tau_t - P_{nt}^{\text{PS}} \tau_t, \quad \forall n \in N, \forall t \in T, \quad (4.125)$$

$$X_{nt}^{\text{PS-Lower}} = X_{n(t-1)}^{\text{PS-Lower}} + P_{nt}^{\text{PS}} \tau_t - \eta^{\text{ptc}} D_{nt}^{\text{PS}} \tau_t, \quad \forall n \in N, \forall t \in T. \quad (4.126)$$

⁸⁰ If this constraint is not considered, then intra-period EV flexibility is allowed.

The previous constraints are the updated versions of constraints (4.47) and (4.48) respectively.

Reservoirs energy limits

$$N^{\text{PS}} x^{\text{PS-Upper-min}} \leq X_{nt}^{\text{PS-Upper}} \leq N^{\text{PS}} x^{\text{PS-Upper-MAX}}, \quad \forall n \in N, \forall t \in T, \quad (4.127)$$

$$N^{\text{PS}} x^{\text{PS-Lower-min}} \leq X_{nt}^{\text{PS-Lower}} \leq N^{\text{PS}} x^{\text{PS-Lower-MAX}}, \quad \forall n \in N, \forall t \in T. \quad (4.128)$$

The previous constraints are the updated versions of constraints (4.58) and (4.59) respectively.

Reservoirs final energy status

The reservoirs final energy status constraints establish that the energy level of the upper and lower reservoirs at the end of each day must be equal to a pre-defined levels. In other words, these constraints enforce that the energy that was discharged during the day into the lower reservoir must be restored in the upper reservoir before the end of the day. These constraints are given by the following expressions:

$$X_{nt}^{\text{PS-Upper}} = N^{\text{PS}} x^{\text{PS-Upper-ed}}, \quad \forall n \in N, \forall t \in T^{\text{ed}}, \quad (4.129)$$

$$X_{nt}^{\text{PS-Lower}} = N^{\text{PS}} x^{\text{PS-Lower-ed}}, \quad \forall n \in N, \forall t \in T^{\text{ed}}, \quad (4.130)$$

where $x^{\text{PS-Upper-ed}}$ and $x^{\text{PS-Lower-ed}}$ are the required energy levels in the upper and lower reservoirs at the end of the day respectively.

Pump/turbine power limits

$$U_{nt}^{\text{PS-p}} d^{\text{PS-min}} \leq D_{nt}^{\text{PS}} \leq U_{nt}^{\text{PS-p}} d^{\text{PS-MAX}}, \quad \forall n \in N, \forall t \in T, \quad (4.131)$$

$$U_{nt}^{\text{PS-t}} p^{\text{PS-min}} \leq P_{nt}^{\text{PS}} \leq U_{nt}^{\text{PS-t}} p^{\text{PS-MAX}}, \quad \forall n \in N, \forall t \in T, \quad (4.132)$$

The previous constraints are the updated versions of constraints (4.51) and (4.52) respectively.

Start-up & shut-down events state equations

$$U_{nt}^{\text{PS-p}} = U_{n(t \ominus 1)}^{\text{PS-p}} + S_{nt}^{\text{PS-Up-p}} - S_{nt}^{\text{PS-Dwn-p}}, \quad \forall n \in N, \forall t \in T, \quad (4.133)$$

$$U_{nt}^{\text{PS-t}} = U_{n(t \ominus 1)}^{\text{PS-t}} + S_{nt}^{\text{PS-Up-t}} - S_{nt}^{\text{PS-Dwn-t}}, \quad \forall n \in N, \forall t \in T. \quad (4.134)$$

The previous constraints are the updated versions of constraints (4.53) and (4.54) respectively.

Operating mode state equation

$$U_{nt}^{\text{PS-t}} + U_{nt}^{\text{PS-p}} \leq N^{\text{PS}}, \quad \forall n \in N, \forall t \in T. \quad (4.135)$$

The previous constraint is the updated version of constraint (4.60).

UC limits & restrictions

$$U_{nt}^{\text{PS-p}} \leq N^{\text{PS}}, \quad \forall n \in N, \forall t \in T, \quad (4.136)$$

$$U_{nt}^{\text{PS-t}} \leq N^{\text{PS}}, \quad \forall n \in N, \forall t \in T, \quad (4.137)$$

$$S_{nt}^{\text{PS-Up-p}} = 0, \quad \forall n \in N, t = 1, \quad (4.138)$$

$$S_{nt}^{\text{PS-Up-t}} = 0, \quad \forall n \in N, t = 1, \quad (4.139)$$

$$S_{nt}^{\text{PS-Dwn-p}} = 0, \quad \forall n \in N, t = 1, \quad (4.140)$$

$$S_{nt}^{\text{PS-Dwn-t}} = 0, \quad \forall n \in N, t = 1. \quad (4.141)$$

Constraints (4.136) and (4.137) are the updated version of constraints (4.61) and (4.62) respectively. Constraints (4.138) to (4.141), on the other hand, are new and ensure that there are no start-ups or shut-downs events happening between the last and first demand segment of each period n , in order to respect the assumption that each representative period is followed by a similar one.

4.6.8 Renewables operational constraints

Wind generation

$$P_{nt}^{\text{wind}} + P_{nt}^{\text{wind-curt}} = P_{nt}^{\text{wind-pwr-av}}, \quad \forall n \in N, \forall t \in T, \quad (4.142)$$

$$P_{nt}^{\text{wind}} \leq P_{nt}^{\text{wind-pwr-av}}, \quad \forall n \in N, \forall t \in T. \quad (4.143)$$

The previous constraints are updated versions of constraints (4.64) and (4.65) respectively.

Solar PV generation

$$P_{nt}^{\text{solar}} + P_{nt}^{\text{solar-curt}} = P_{nt}^{\text{solar-pwr-av}}, \quad \forall n \in N, \forall t \in T, \quad (4.144)$$

$$P_{nt}^{\text{solar}} \leq P_{nt}^{\text{solar-pwr-av}}, \quad \forall n \in N, \forall t \in T. \quad (4.145)$$

The previous constraints are updated versions of constraints (4.66) and (4.67) respectively.

4.6.9 Conventional generation & flexibility investment constraints

Generation investment upper bound

$$N_i^{I\text{-new}} \leq N_i^{I\text{-MAX}}, \quad \forall i \in I. \quad (4.146)$$

The previous constraint establishes an upper bound for the number of new generation units of each technology type i that can be added to the system.⁸¹

Flexible EV investment upper bound

$$N_v^{\text{EV-Flex-new}} \leq N_v^{\text{EV}} - N_v^{\text{EV-Flex-old}}, \quad \forall v \in V. \quad (4.147)$$

The previous constraint establishes that the number of new flexible EV is limited by the number of EV of each type v that are not flexible.

4.6.10 Decision variables type & sign constraints

System operation

$$\left\{ L_{nt}^{\text{curt}}, p_{nt}^{\text{curt}}, p_{nt}^{\text{wind-curt}}, p_{nt}^{\text{solar-curt}} \right\} \in \mathbb{R}_{\geq 0}, \quad \forall n \in N, \forall t \in T. \quad (4.148)$$

Conventional generation

$$\left\{ U_{nti}, S_{nti}^{\text{Up}}, S_{nti}^{\text{Dwn}}, N_i^{I\text{-new}}, N_i^I \right\} \in \mathbb{Z}_{\geq 0}, \quad \forall n \in N, \forall t \in T, \forall i \in I, \quad (4.149)$$

$$\left\{ P_{nti}, F_{nti}^{\text{fuel-use}}, R_{nti}^{\text{FRR-Up}}, R_{nti}^{\text{FRR-Dwn}}, R_{nti}^{\text{SPR-Up}}, R_{nti}^{\text{SPR-Dwn}}, R_{nti}^{\text{QSR}} \right\} \in \mathbb{R}_{\geq 0}, \quad \forall n \in N, \forall t \in T, \forall i \in I. \quad (4.150)$$

Flexible EV

$$\left\{ N_v^{\text{EV-Flex}}, N_v^{\text{EV-Flex-new}} \right\} \in \mathbb{Z}_{\geq 0}, \quad \forall v \in V, \quad (4.151)$$

$$\left\{ p_{ntv}^{\text{EV}}, E_{ntv}^{\text{EV}} \right\} \in \mathbb{R}_{\geq 0}, \quad \forall n \in N, \forall t \in T, \forall v \in V. \quad (4.152)$$

Hydro pumped-storage

$$\left\{ U_{nt}^{\text{PS-t}}, U_{nt}^{\text{PS-p}}, S_{nt}^{\text{PS-Up-t}}, S_{nt}^{\text{PS-Dwn-t}}, S_{nt}^{\text{PS-Up-p}}, S_{nt}^{\text{PS-Dwn-p}} \right\} \in \mathbb{Z}_{\geq 0}, \quad \forall n \in N, \forall t \in T, \quad (4.153)$$

$$\left\{ X_{nt}^{\text{PS-Upper}}, X_{nt}^{\text{PS-Lower}}, P_{nt}^{\text{PS}}, D_{nt}^{\text{PS}} \right\} \in \mathbb{R}_{\geq 0}, \quad \forall n \in N, \forall t \in T. \quad (4.154)$$

⁸¹ This constraint allows shrinking the solution space for the model, and also can be used to establish centrally defined limits for the investment levels allowed in each type of generation technology i .

Renewable generation

$$\{P_{nt}^{\text{wind}}, P_{nt}^{\text{solar}}\} \in \mathbb{R}_{\geq 0}, \quad \forall n \in N, \forall t \in T. \quad (4.155)$$

4.6.11 Model implementation, solution method & model validation

Model implementation & solution method

The Strategic-GEP model has been implemented using FICO® Xpress Optimization Suite,⁸² which is an optimization tool composed of two main components: Xpress-Mosel and Xpress-Optimizer. Xpress-Mosel is a high-level modelling and programming language that allows the user writing mathematical programming and optimization models in a form that is close to algebraic notation. Xpress-Optimizer, on the other hand, is a collection of integrated, sophisticated, and robust high-performance optimization solvers for solving large-scale linear problems, mixed integer problems, quadratic problems, mixed integer quadratic problems and quadratically constrained quadratic problems. All the simulations presented in this thesis have been carried out on a Windows-based desktop computer, with a 3.33GHz Intel(R) Xeon(R) processor and 12GB of Random Access Memory (RAM).⁸³

Figure 4.14 shows a flow diagram of the Strategic-GEP algorithm, as implemented in FICO® Xpress Optimization Suite. The model first reads all the simulation parameters from an Excel spreadsheet, and then proceeds to solve the Strategic-GEP model. The optimal solutions and other output data is finally exported to an Excel spreadsheet for post-processing, analysis and plotting. The input data for the model, and the output data from the model are:

1. Input data (Annex A):

- General parameters (table A.7):
 - Number of typical periods.
 - Number of demand segments.
 - Peak non-EV system demand.
 - Wind and solar PV installed capacity.
 - Maximum QSR contribution towards upward SPR.
 - Value of lost load (VOLL).
 - Cost of over generation.
 - Cost of wind and solar PV curtailment.
 - Number of EV types.
 - EV penetration level.
 - System CO₂ emissions intensity limit.
 - CO₂ price.

⁸² www.fico.com/en/products/fico-xpress-optimization-suite/.

⁸³ For details regarding the computational performance of the Strategic-GEP model, interested readers are referred to [34, 39].

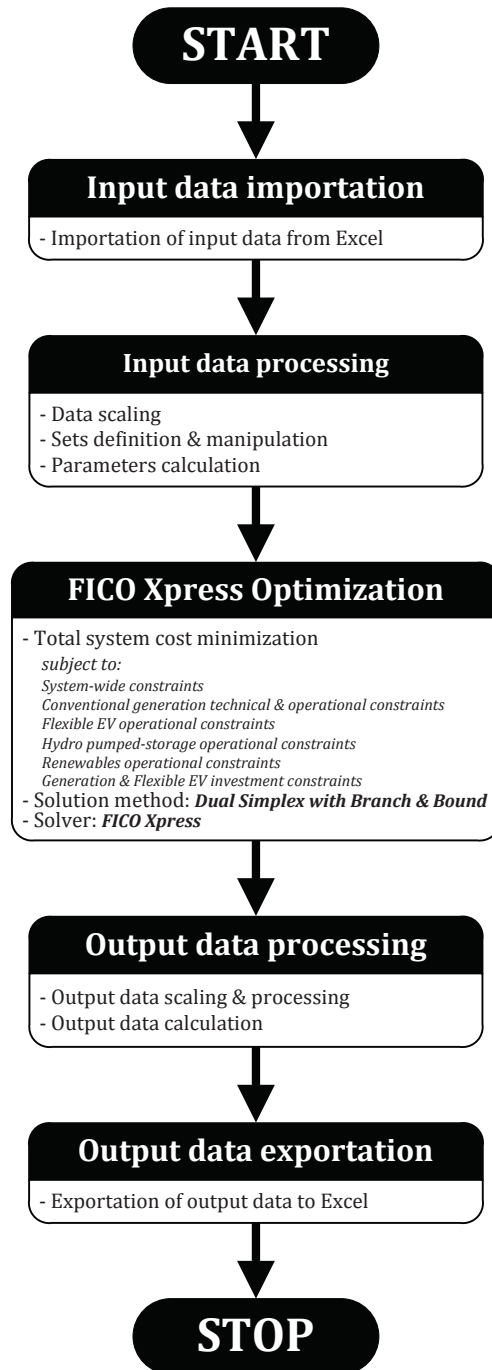


Figure 4.14: Flow diagram of the Strategic-GEP algorithm implemented in FICO® Xpress Optimization Suite.

- Fuel cost.
- CO₂ emissions factors.
- Typical periods weighting factor.
- Generation technical data (table A.2):
 - Conventional generation technology types.
 - Capacity of generation units of each generation technology type.
 - Power output limits (minimum stable generation and maximum power output).
 - Start-up heats and start-up fixed costs.
 - No-load heats.
 - Incremental heat rates.
 - CCS CO₂ emissions reduction factor.
 - Minimum up and down times.
 - Upward and downward ramping capability.
 - Must-run generation technologies.
 - FRR (up/down), SPR (up/down), and QSR reserve provision capability flags.
 - Maximum FRR (up/down), SPR (up/down), and QSR reserve deployment levels.
- Generation costs data (table A.1):
 - Fixed O&M costs.
 - Variable O&M costs.
 - Capital expenditures (CAPEX).
 - Lifetime.
 - Weighted average cost of capital (WACC).
 - Fixed costs.
- EV data (tables A.4, A.5 and A.6):
 - Battery technical characteristics (maximum charging power rate, battery energy capacity, energy level at the end of the day, maximum and minimum energy limits, charging efficiency, and energy efficiency).
 - EV types, travelling times and requirement, and quantity.
- System non-EV demand, wind and solar PV power profiles:
 - Normalized power profiles.
 - Forecast error standard deviations (table A.3).

2. Output data:

- Costs:
 - Conventional generation investment cost.

- Conventional generation start-up and shut-down costs.
- Conventional generation O&M cost.
- Conventional generation fuel cost.
- Conventional generation CO₂ emissions cost.
- Curtailment costs (conventional generation, load, wind and solar PV).
- Flexible EV investment cost.
- Total system cost.
- System operation:
 - Conventional generation curtailment level.
 - Load curtailment level.
 - System non-EV demand level.
 - Net-demand level.
 - System CO₂ intensity level.
 - Energy price level.
 - Load weighted energy price.
 - FRR (up/down), SPR (up/down), and QSR reserve price levels.
- Conventional generation:
 - Generation capacity.
 - Number of units (new and old).
 - Power output level.
 - Unit commitment status.
 - Start-up and shut-down events.
 - FRR (up/down), SPR (up/down), and QSR reserve provision level.
 - Fuel consumption level.
 - CO₂ emissions level.
 - Capacity factors.
- Renewables (wind and solar PV):
 - Curtailment levels.
 - Power available levels.
 - Power dispatch levels.
 - Utilization factors.
- EV:
 - Number of flexible (new and old) and inflexible EV.
 - Flexible and inflexible EV power consumption level.

- Flexible EV battery energy level.
- Model solution:
 - Solution time.
 - Solution GAP.
 - Solution status.
 - Objective function value.

For the sensitivity analyses developed in Chapters 5 and 6, automatized algorithms were created to perform sensitivity analysis on the following parameters: CO₂ price (Section 5.2), conventional generation flexibility characteristics (minimum stable generation, minimum up-/down time and ramping capability, Section 5.3), and EV flexibility enabling cost (Section 6.2). Figure 4.15 shows the flow diagram of the algorithm created to perform the sensitivity analysis on the minimum stable generation parameter, which combines the use of FICO® Xpress Optimization Suite and Matlab.⁸⁴

The Strategic-GEP model performs the optimization of conventional generation and flexible EV investments, and conventional generation and power system operation in a single level, i.e. the optimization model is not decomposed in multiple hierarchical stages. This approach allows ensuring that the investment decision are not decoupled from the modelling of the power system operation, and thus, allows capturing and accounting for the non-trivial interactions that exist between investment and operational decisions. The single level optimization formulation proposed in the Strategic-GEP model allows ultimately ensuring that the investment decision are feasible for the operation of the power system. The complexity of the Strategic-GEP model in terms of number of decision variables and constraints is shown in tables 4.1 and 4.2.

Table 4.1: Strategic-GEP computational complexity: number of decision variables.

<i>Variable category</i>	<i>Number of continuous variables</i>	<i>Number of discrete variables</i>
System operation	$4 \cdot N^N \cdot N^T$	
Conventional generation	$7 \cdot N^N \cdot N^T \cdot N^I$	$3 \cdot N^N \cdot N^T \cdot N^I + 2 \cdot N^I$
Flexible EV	$2 \cdot N^N \cdot N^T \cdot N^V$	$2 \cdot N^V$
Hydro pumped-storage	$4 \cdot N^N \cdot N^T$	$6 \cdot N^N \cdot N^T$
Renewable generation	$4 \cdot N^N \cdot N^T$	

The solution method selected to solve the Strategic-GEP model was Dual Simplex [175, 313] with Branch and Bound [179],⁸⁵ which are implemented in the FICO Xpress solver. Branch and bound is an improvement over brute force or complete enumeration, as it prunes away subsets of solutions which cannot have a better solution than the best solution already found

⁸⁴ www.mathworks.com.

⁸⁵ The Branch and Bound method was proposed in 1960 by Land and Doig [179] for solving discrete programming problems, and has become the most commonly used tool for solving discrete and combinatorial optimization problems [314, 315].

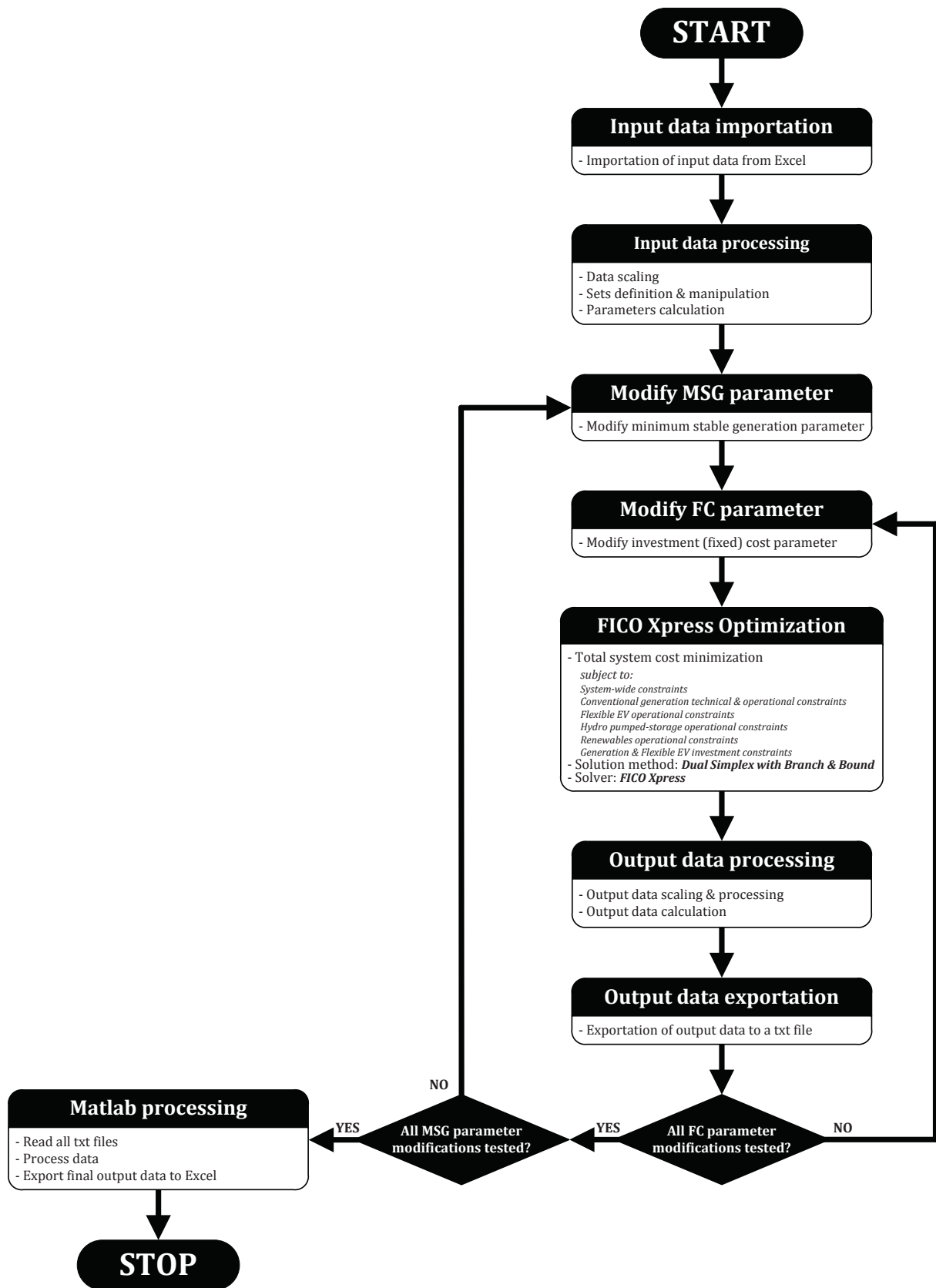


Figure 4.15: Flow diagram of the algorithm created to perform a sensitivity analysis on the minimum stable generation of Nuclear, CCGT and OCGT generation technologies.

Table 4.2: Strategic-GEP computational complexity: number of constraints.

<i>Constraint category</i>	<i>Number</i>
System-wide	$7 \cdot N^N \cdot N^T + 1$
Conventional generation operation	$7 \cdot N^N \cdot N^T \cdot N^I + 2 \cdot N^N \cdot N^T \cdot (N^I - I^{mr})$ $+ 2 \cdot N^N \cdot N^T \cdot (I^{FRR-Up} + I^{FRR-Dwn} $ $+ I^{SPR-Up} + I^{SPR-Dwn}) + N^N \cdot N^T \cdot I^{QSR} $ $+ 2 \cdot N^N \cdot (N^I - I^{mr}) + N^I$
Flexible EV operation	$4 \cdot N^N \cdot N^T \cdot N^V + N^N \cdot T^{ed} \cdot N^V + N^V$
Hydro pumped-storage operation	$12 \cdot N^N \cdot N^T + 2 \cdot N^N \cdot T^{ed} + 2 \cdot N^N$
Renewables operation	$4 \cdot N^N \cdot N^T$
Generation & Flexible EV investment	$N^I + N^V$

at that point. This method was selected due to is the standard tool used to solve mixed integer problems, and also because its advantages, which are: a) the method knows when it has found an optimal solution; b) in the case that there is more than one optimal solution, the method allows finding all optimal solutions if needed; and c) the method allows determining the bounds of the problem, which gives an indication of the quality of a solution. Finally, Dual Simplex is used because this method is generally more efficient for the complete optimization of the subproblems generated by the Branch and Bound method.

Model validation

The computational performance and validation of the Strategic-GEP model was tested against an equivalent formulation without clustering the conventional generation units, i.e. a formulation that uses binary variables for generation investment and unit commitment decisions variables. The conventional generation investment decision variables were initially bounded to 500 units per generation technology in the integer formulation, which translates into a full set of 4,500 candidate generation units for the binary model (Binary-4500 in table 4.3). The latter was not manageable by the desktop computer due to the RAM memory limitation, so in a new test, the size of the set of candidate generation units for the binary formulation was reduced to 536 units (Binary-536 in table 4.3), based on the optimal solution found with the Strategic-GEP integer model.

Table 4.3 shows a comparison between the binary (with and without the candidate units set reduction) and integer formulations of the Strategic-GEP model in terms of the number of generation-related discrete decision variables and constraints, the solution time, and the error of the Integer with respect to the Binary-536 model (in terms of the optimal value of the objective function), obtained after running the above models for 50% EV penetration, 30GW wind generation capacity and an EV flexibility enabling cost equal to £280/EV-yr. Even with a reduced set of candidate generation units, the binary model involves a very large number of decision variables and constraints, exhibiting a prohibitive computational requirement for practical applications. With the proposed integer formulation, the numbers of decision vari-

ables and constraints, as well as the required computational time, are dramatically reduced without compromising the model's results accuracy, as shown in table 4.3.

The integer model was also tested without the EV clustering technique, resulting in a non-linear MIP problem, which failed to converge after one week.

Table 4.3: Binary versus integer Strategic-GEP models comparison

<i>Model formulation</i>	<i>Number of discrete variables</i>		<i>Number of constraints</i>	<i>Solution time (ks)</i>	<i>Error (%)</i>
	<i>Investment</i>	<i>Operation</i>			
Binary-4500	4,500	11,344,500	60,949,000	–	–
Binary-536	536	1,351,256	7,647,662	346	0.08
Integer	9	22,689	121,898	6	

IMPACT OF GENERATION FLEXIBILITY ON GEP

Nowadays generation planning is focused on estimating the overall level of generation capacity, generally assuming simplified representations of demand and ignoring the different flexibility characteristics of generation and demand side resources. However, the key function of generation planning is to ensure that enough and adequate resources are available to reliably balance electricity demand and supply at all times, and under the expected range of system operating conditions.

GEP of power systems that expect large-scale deployments of renewable generation need to evaluate the required levels of system flexibility. For this purpose the flexibility characteristics of generation and demand side resources must be included in generation expansion planning.

In this chapter, the role of conventional generation flexibility in the expansion of future low-carbon power systems is analysed through a set of case studies. The developed case studies show evidence not only of the relevance of including the flexibility characteristics of generation capacity in GEP, but also the value that investing in such flexibility may generate in terms of costs savings, CO₂ emissions reduction and renewable generation integration.

5.1 STRATEGIC-GEP VERSUS TRADITIONAL GEP

Traditional expansion planning has for long time relied in the use of simplified representations of electricity demand (e.g. LDC) and generation operation, and even today many GEP models and commercial software packages still use them. Those tools are widely used by governments, regulators, system planners, and analysts, among others, when assessing the capacity expansion of their power systems, and the market structures and regulations implemented to guide this process according to their specific targets. Neglecting the relevance of net-demand chronology, and its impact into the operation of conventional generation, makes the results of their planning exercises and analyses to be biased toward power systems with lack of flexibility, and into the design of poor and unstable energy policies.

The results obtained using a traditional generation expansion planning model (GEP-LP),¹ and the Strategic-GEP model (STR-GEP) are compared in this case study in order to assess the economic and environmental implications of ignoring conventional generation flexibility characteristics. The following assumptions were made for this case study:

- Energy-only-market.

¹ Model described in Section 3.2.2.

- No ancillary services.
- Target year 2030 according to input data (table A.7).
- EV in the system are assumed inflexible, and the EV penetration level equal to 9.3%.
- Power system is built from scratch.
- The system CO₂ intensity limit is set at 50 [gCO₂/kWh], and the CO₂ price at £76/tonneCO₂.

If chronology of demand is assumed to be irrelevant, the technical and operational characteristics of conventional generation are meaningless for generation expansion planning. This simplification relies on a very strong assumption, which is to assume that the costs and availability of generation depend only on the magnitude of demand and not on the time when demand occurs [302]. As discussed in previous chapters, this assumption was valid for power systems with small amounts of renewables, as their contribution to power supply did not introduced a significant amount of variability and uncertainty in net-demand, and the available flexibility on those power systems was capable of handling the fluctuations introduced by VRE resources [156].

Large-scale renewables penetration has changed the previous panorama, demanding larger amounts of system flexibility to compensate the fluctuations and uncertainty created by renewable generation, and also to accommodate as effectively possible the power production of those generation resources. Lack of flexibility leads to the underutilization of available renewable energy. This translates into the need for burning larger amounts of fossil fuels to satisfy demand, and in the subsequent increase of CO₂ emissions.

Figures 5.1 and 5.2 graphically compare the optional generation mixes and total system costs obtained with the GEP-LP and Strategic-GEP models in the following three cases:^{2,3}

GEP-LP in this case the optimal generation mix is calculated using a LP GEP model, which does not account for the non-convex generation costs (no-load, start-up and shut-down costs), and does not consider any type of flexibility characteristics of the conventional generation technologies.

STR-GEP in this case the optimal generation mix is calculated using the Strategic-GEP model, which includes a full and detailed representation of the convex and non-convex generation costs, as well as the full set of technical and operational constraints that rule the operation and commitment of the conventional generation.

STR-GEP* in this case the optimal generation mix is calculated using the Strategic-GEP model, including an additional constraint to limit the level of renewable energy curtailment to be not larger than the one obtained in the GEP-LP case.

At first glance, the results obtained with both models (“GEP-LP” versus “STR-GEP”) look similar in terms of optimal generation capacity mix, however the GEP-LP system is much more

² Please refer to table B.1 for the numeric figures associated to each of the simulated scenarios.

³ The third bar in the plots shown in figure 5.1, which is labelled “STR-GEP*”, corresponds to a simulation of the Strategic-GEP model where the level of renewable energy curtailment is matched to the one obtained with the GEP-LP model.

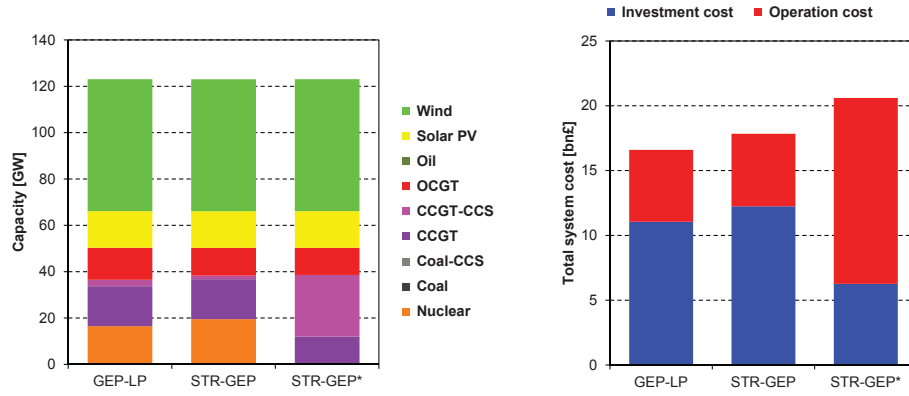


Figure 5.1: Comparison of the optimal generation mixes (*left plot*), and the total system costs (*right plot*), obtained with the GEP-LP and Strategic-GEP models.



Figure 5.2: Comparison of the generation matrix composition (*top pie charts*), and the costs structure composition (*bottom pie charts*), for the simulated scenarios.

flexible than the Strategic-GEP system, in which all technical and operational characteristics are included to limit the operation of conventional generation, while in the former none of those is included, which means that all available generation in that system is fully flexible.

The full flexibility of the GEP-LP system allows absorbing renewable energy at all times except when net-demand is negative. This translates into a very low level of renewable energy curtailment (0.5TWh approximately) as shown in figure 5.3. However, this is not a realistic situation as it assumes that all generation capacity can be turned on/off instantaneously, as many times as needed, at zero cost, and also that the power output can vary from zero up to the total installed capacity of each generation technology. Real conventional generation operation is limited by the technical and operational characteristics of each of those technologies.⁴ This can be visualized in the power system dispatch comparison shown in figure 5.4.

The minimum stable generation, ramping limitations and minimum up/down time of conventional generation are, as discussed in Section 3.3, crucial flexibility characteristics that limit

⁴ These are minimum stable generation and maximum power output, ramping limitations, minimum up/down time, and must-run operation, among others, plus the costs associated with the start-up and shut-down of generation units.

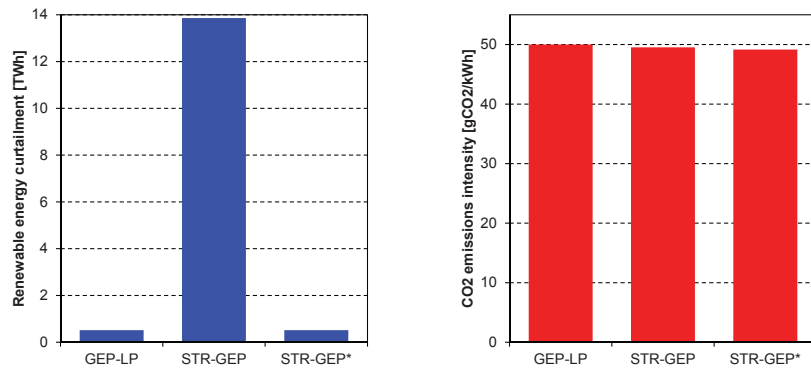


Figure 5.3: Comparison of the levels of renewable energy curtailment (*left plot*), and CO₂ emission intensities (*right plot*), obtained with the GEP-LP and Strategic-GEP models.

Table 5.1: Comparison of the renewable energy curtailment and the total operation cost reductions when the STR-GEP optimal generation mix is fixed and the technical and operational limitations of conventional generation are relaxed.

<i>Flexibility characteristic relaxed</i>	<i>Renewable energy curtailment reduction wrt STR-GEP</i>	<i>Total operation cost reduction wrt STR-GEP</i>
Minimum stable generation	46.10%	1.53%
Minimum up/down time	0.68%	2.12%
Ramping limitations	3.53%	0.03%
Start-up costs	0.44%	2.77%
All + start-up costs	96.28%	6.64%

the capability of a power system to absorb renewable energy. For example, in the case of the STR-GEP system, nuclear generation is a must-run technology, i.e. it cannot be turned off, and the minimum stable generation is 80% of the capacity of each generation unit (see table A.2). This means that the total nuclear generation output cannot be less than 15.6GW at each demand segment t . In other words, all renewable energy that makes net-demand level lower than 15.6GW needs to be curtailed, as it cannot be absorbed. The ramping capability, on the other hand, limits the rate at which conventional generation can modify its power output and thus, the capability of following net-demand. The minimum up and down times limitations also contribute to reduce the capability of absorbing renewable energy, as they limit the frequency with which generation units can be turned on-off and vice versa.

The available flexibility in the Strategic-GEP system allows absorbing approximately 92% of the available renewable energy. This translates into a renewable energy curtailment level of approximately 14TWh, as shown in the left plot of figure 5.3.⁵ A comparison that shows the impact of the different flexibility characteristics of conventional generation in terms of renewable energy curtailment and total system cost is presented in table 5.1. In this simulation, the different technical and operational characteristics of conventional generation are relaxed in the case of the STR-GEP when the power system is fixed. Minimum stable generation and ramping limitations are the most relevant factors that affect the utilization of available renewable energy, while the costs of operating the power system are mostly affected by the minimum stable generation, minimum up/down time and start-up costs.⁶ This highlights the

⁵ Numerical figures can be seen in table B.1.

⁶ For all case studies in Chapters 5 and 6 it is assumed that the shut-down costs are zero.

relevance that investing in flexibility can have for reducing costs, integrating renewables and achieving CO₂ emissions reduction targets.

In terms of total systems costs, the Strategic-GEP system is more expensive than the GEP-LP system, mainly due to the fact that the former system has 18% more nuclear generation, which increase the investment costs in approximately 11%. The operation costs, on the other hand, are only 1% higher than those of the GEP-LP system, due to the combined effect of a larger share of nuclear generation, and less gas-fired generation (9% lower compared to GEP-LP). However, the renewable energy spillage is not penalized, so renewables curtailment is cheaper than increasing the cycling regime of flexible generation or building new flexible generation, resulting in the effect that it is shown in the left plot of figure 5.3, where the renewable energy curtailment in the Strategic-GEP case is 27x bigger compared to the GEP-LP case.⁷ In order to satisfy the CO₂ emissions constraint, the Strategic-GEP model chooses building more nuclear⁸ and less gas-fired generation, which also increases the level of renewable energy spillage due to the reduced system flexibility.

The GEP-LP system only curtail renewables when the net-demand level is negative, i.e. when the available wind and solar PV power is larger than the electricity demand of the system. This is possible due to the generation capacity in this case is assumed fully flexible as explained earlier in this section, but does not reflect the real operation of conventional generation. If the level of renewable energy curtailment is enforced to be similar to the one obtained in the GEP-LP case (STR-GEP* case), the optimal generation mix calculated by the Strategic-GEP model is completely different to the one obtained without this additional restriction, as shown in the left plot of figure 5.1. In order to absorb the same amount of renewable energy, the optimal system needs to be composed only by flexible gas-fired generation. This reduces the investment costs by 46%, but increase the system operation costs by 159% compared to the GEP-LP case, as shown in the right plot of figure 5.1. Even more, if the GEP-LP system is converted into an equivalent power system, i.e. a power system with discrete generation units, and this system is fixed and operated respecting the technical and operational characteristics of those generation units, the power system is able to satisfy the CO₂ emissions restriction by means of curtailing approximately 8TWh of electricity demand and 10TWh of renewable energy. From an economical point of view this power system is very inefficient, due to the system operation costs are 6x bigger compared to the STR-GEP* system, part of the installed generation capacity is underutilized (OCGT generation capacity factor is zero), and available renewable energy is not effectively used (curtailment level is 19x bigger). On the other hand, from an operational point of view the system is highly unreliable, as it requires curtailing load in order to reduce CO₂ emissions.

Finally, the dramatic differences in the results obtained show clear evidence that generation planning of modern power systems using a traditional approach leads to solutions that are far from being optimal, and moreover, to power systems that are unreliable, inefficient and potentially very costly for consumers. This highlights the importance of including the conventional

⁷ The level of nuclear generation, plus the fact of being a must-run and inflexible generation technology, also greatly contributes to the large level of renewable energy curtailment observed in the Strategic-GEP case.

⁸ CO₂ emissions free generation technology.

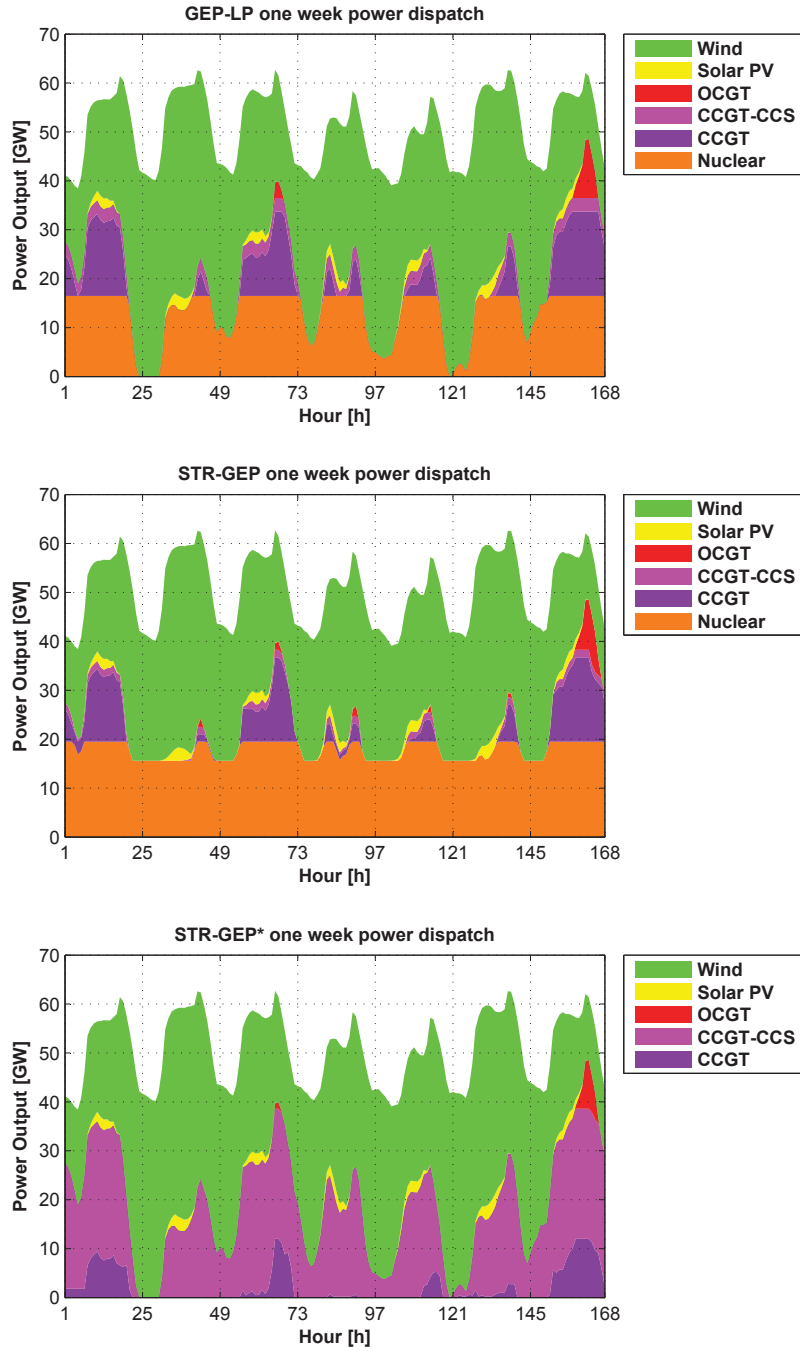


Figure 5.4: Comparison of one week power system dispatch of the power systems GEP-LP, STR-GEP and STR-GEP*. 5.1.

generation flexibility characteristics in the planning of future low-carbon power systems with large-scale penetration of renewables.

5.2 IMPACT OF CO₂ EMISSIONS LIMIT & PRICE INTO GEP

Carbon dioxide (CO₂) is the principal GHG pollutant that accounts for almost three-quarters of the global GHG emissions, and a major contributor to climate change. Electricity generation from fossil fuel-fired power plants use coal, oil, natural gas, or other forms of fuel derived from those, for generating electricity. In the case of UK for example, electricity generation is the biggest single source of CO₂ emissions, which is responsible for more than a third of the total CO₂ emissions [17].

Reduction of CO₂ emissions in the electricity sector is being achieved through a wide variety of efforts, such as increasing efficiency of power plants and fuel conversion, development of CCS technology, improvements of energy efficiency in the consumers side, nuclear energy, and the integration of renewable resources, among others. All those efforts have been incentivised by a series of market regulations and policies, such as CO₂ taxes and emissions limits, carbon price, long-term contracts, and subsidies, among others, which aim to create the market conditions required to incentivize investment in low-carbon generation technologies, achieve cost-effectively decarbonisation targets and renewables integration, and maintain electricity supply secure and affordable to customers.

The large-scale penetration of renewable resources is undoubtedly the key for achieving the ambitious CO₂ emissions reduction targets of many countries. However, this brings a lot of new challenges for both operation and planning of future power systems, as additional flexibility is required to effectively integrate renewables. From a regulatory perspective, the limitation of the CO₂ emissions, and the penalization of those emissions, are two very popular normative measures used by regulators to promote renewables integration and investment in low-carbon generation. Nonetheless, the excessive limitation and penalization of CO₂ emissions may have unwanted effects on this effort, such as increase renewables curtailment, and degrade utilization of generation assets, among others.

In the following case study, the effects of CO₂ emissions limits and CO₂ prices on GEP are studied using the Strategic-GEP model. The following assumptions were made for this case study:

- Energy-only-market.
- Target year 2030 according to input data (table A.7).
- EV in the system are inflexible, and EV penetration level equal to 9.3%.
- Power system is built from scratch.
- CO₂ intensity limits of 50 and 100 [gCO₂/kWh], and also a case without the CO₂ emissions constraint.
- The CO₂ price is changed from 0 up to £200/tonneCO₂, in steps of £10/tonneCO₂.

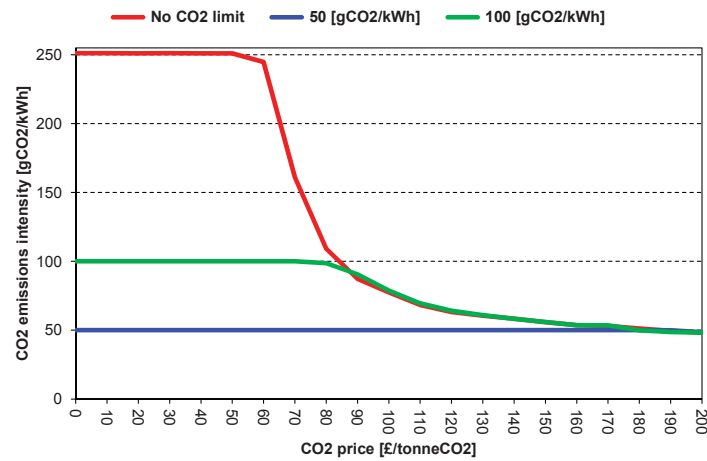


Figure 5.5: Comparison of CO_2 emissions intensity for different carbon emissions limits and prices.

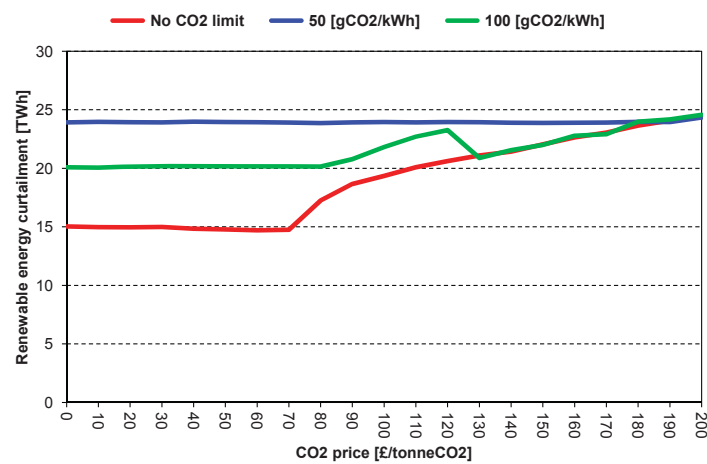


Figure 5.6: Comparison of the renewable energy curtailment level for different carbon emissions limits and prices.

Limiting total carbon emissions, and penalizing CO_2 emissions, allows drastically reducing the levels of CO_2 emissions intensity in a power system, as shown in figure 5.5, where the system CO_2 emissions intensity is compared for different carbon emissions limits and prices. For low CO_2 prices (below approximately £60/tonne CO_2), and if the carbon emissions are not constrained (“No CO_2 limit” case), the system carbon intensity rises up to approximately 251 [g CO_2 /kWh]. Low-carbon baseload generation is not installed due to the high penetration level of renewables (73GW approximately between wind and solar PV generation) demands large amounts of generation flexibility to cope with the variability and uncertainty introduced in net-demand by those power sources, and also because their investment and operational costs makes them too expensive for supplying electricity.⁹ This results in an optimal power system where there is only traditional gas-fired generation supplying electricity demand, i.e. CCGT and OCGT generation, which are responsible of the high level of CO_2 emissions as shown in figure 5.8.

⁹ An additional factor is that due to CO_2 emissions are not limited in this case, there is no incentive for installing nuclear generation. Net-demand variability also makes inflexible baseload generation operation challenging and costly, making gas-fired flexible generation a cost-effective option for supplying electricity.

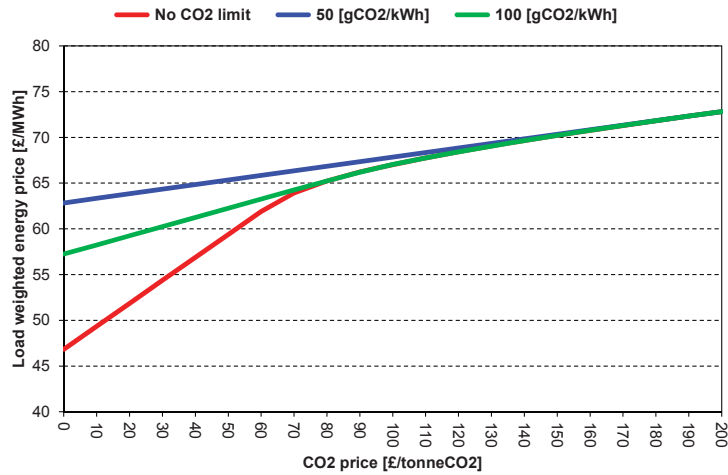


Figure 5.7: Comparison of the load weighted energy price level for different carbon emissions limits and prices.

When the CO₂ price is set in the range between 60 and £80/tonneCO₂ in the “No CO₂ limit” case, the carbon emissions intensity begins to rapidly decrease in reaction to this price. This change is due to the level of carbon price begins impacting the operation of CCGT and OCGT generation (smaller capacity factors), resulting in the installation of less generation capacity of those technologies, specially CCGT, which are replaced by CCGT-CCS generation.¹⁰ Although CCGT-CCS generation allows reducing the CO₂ emissions, it is less flexible than OCGT and more expensive than CCGT. This translates into higher levels of renewable energy curtailment, and higher system costs, as shown in figures 5.6 and 5.8 (first column), respectively. The same pattern, but at a smaller rate, can be observed in the “No CO₂ limit” and 100 [gCO₂/kWh] limit cases for carbon prices above £90/tonneCO₂. At approximately £170/tonneCO₂, the carbon price is high enough to induce the market to deliver a power system that is capable of satisfying the CO₂ emissions limit, without needing to enforce it.¹¹ However, this is achieved by the combined effect of larger shares of CCGT-CCS generation and higher levels of renewable energy curtailment.

The carbon emissions target can be achieved by either limiting the total amount of carbon that can be generated in a power system, or by penalizing CO₂ emissions at high prices, as shown in figure 5.5. However, both regulatory measures generate a series of side effects:

1. Reduction of the investment level in cheap gas-fired power generation that increase energy prices for consumers, as shown in figure 5.7 and in the second column of figure 5.8.
2. Reduction of the investment in highly flexible generation that reduces the flexibility of the power system, reducing its capability to follow net-demand, and can affect security of supply.
3. Degradation of the capacity factor of existent generation capacity, as shown in last column of figure 5.8.

¹⁰ CCS technology is assumed to reduce CO₂ emissions by 90% [316] (see table A.2).

¹¹ Also in the case of 100 [gCO₂/kWh], the high carbon price induce the market to deliver a power system of similar generation composition that in the other two cases.

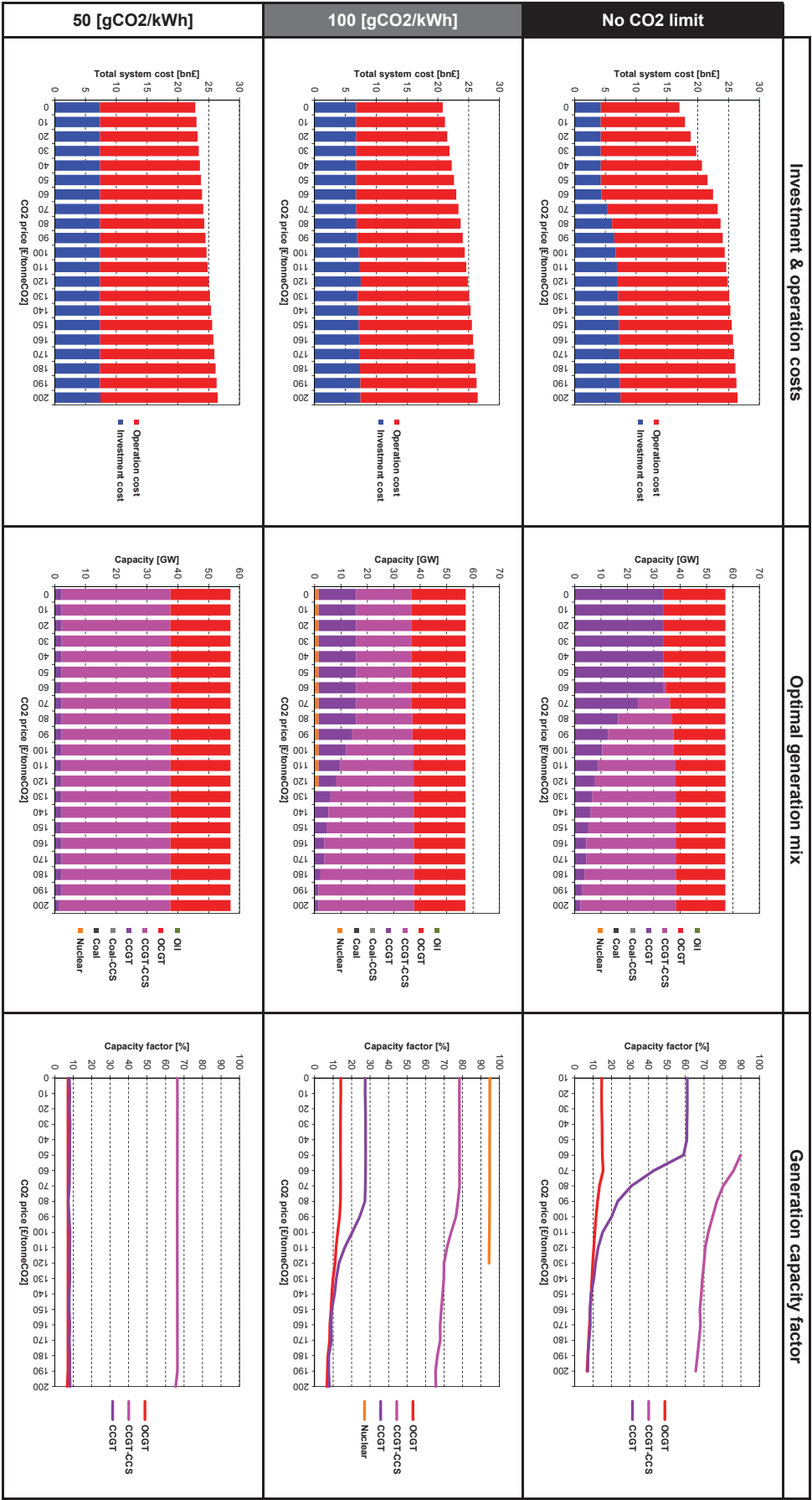


Figure 5.8: Comparison of the total system costs (*first column*), optimal conventional generation mixes (*second column*), and generation capacity factors (*third column*) for different carbon emissions limits and prices.

4. Increase of the renewable energy curtailment levels, as shown in figure 5.6.

Strong carbon emissions regulations, and the potential interaction between them, can have severe impacts on the integration of renewables, as well as on the operation and evolution of power systems. The large-scale penetration of renewables will demand larger levels of system flexibility, which will be mostly provided by conventional generation at least until flexibility from demand is properly understood and the infrastructure required to use it is in place. However low carbon emissions limits and high CO₂ prices give more value to carbon emissions than flexibility, which can affect the integration of renewable generation. This highlights not only the relevance of considering CO₂ emissions in generation expansion planning, but also the potential interaction between those and the system flexibility. The proper design of long-term and stable carbon emissions regulations needs to consider the flexibility characteristics of conventional generation, as their operation is conditioned by those regulations.

5.3 INVESTMENT IN CONVENTIONAL GENERATION FLEXIBILITY

Modelling and including the technical and operational characteristics of conventional generation into generation expansion planning results in richer and more realistic representation of the real operation of power systems, and thus into a better evaluation of the long-term generation investment decisions, as shown in Section 5.1. This is particularly important in power system with a high degree of renewables penetration due to their effect in demand that, as discussed throughout this thesis, translates into radical changes in the time dynamics of net-demand, and thus in the operation of available conventional generation.

The relevance of improving the system operation modelling part of GEP models is today widely recognized, however only a few recent works can be found in literature about this topic as discussed in Section 2.4.2. Those works are focused on studying how the inclusion of generation flexibility characteristics into GEP models can affect optimal generation mixes. However, investigating about the value that such flexibility has for the system, and the benefits that investing in generation flexibility can have for the development of future low-carbon power systems is not explored.

In this section, the investment in conventional generation flexibility is studied using the Strategic-GEP model, in order to analyse its impacts and benefits for the future expansion of power systems. For this purpose three case studies are developed, in which sensitivity analyses are performed on the minimum stable generation, minimum up/down time, and ramping capability of conventional generation technologies. The following assumptions were made for this case study:

- Energy-only-market.
- Target year 2030 according to input data (table A.7).
- EV in the system are inflexible, and the EV penetration level equal to 9.3%.
- Different levels of wind capacity: 10GW, 30GW and 50GW.
- Power system is built from scratch.

Table 5.2: Generation capacity, system costs, curtailment levels, CO₂ emissions and renewables utilization factors in the base case scenarios.

	Parameter	Units	Base Case Scenario		
			BC-10GW	BC-30GW	BC-50GW
Generation Capacity	Nuclear	GW	19.50	16.50	4.50
	Coal	GW	0.00	0.00	0.00
	Coal-CCS	GW	0.00	0.00	0.00
	CCGT	GW	11.25	8.25	4.50
	CCGT-CCS	GW	18.62	18.24	30.40
	OCGT	GW	13.05	17.10	18.45
	Oil	GW	0.00	0.00	0.00
	Solar PV	GW	15.81	15.81	15.81
	Wind	GW	10.00	20.00	30.00
	TOTAL	GW	88.23	95.90	103.66
Costs	Investment	bn£	14.72	13.12	8.92
	Operation	bn£	13.01	12.13	15.47
	TOTAL	bn£	27.72	25.25	24.39
Curtailment	Load	TWh	0.01	0.00	0.00
	Generation	TWh	0.00	0.00	0.00
	Wind	TWh	0.11	7.08	18.20
	Solar PV	TWh	0.09	0.20	0.29
	Renewable energy curtailment	TWh	0.20	7.28	18.48
CO ₂	Emissions	MtonneCO ₂	18.17	18.17	18.17
	Intensity	gCO ₂ /kWh	50.00	50.00	50.00
UF	Wind Utilization Factor	%	99.7	91.3	86.5
	Solar PV Utilization Factor	%	99.3	98.4	97.8

- The system CO₂ intensity limit is set at 50 [gCO₂/kWh], and the CO₂ price at £76/tonneCO₂.
- The base case scenarios are those where the flexibility parameters of the generation technologies have not been modified, and there is one base case scenario for each wind capacity level.¹²

Larger levels of renewable generation capacity lead to power systems with larger amounts of flexibility, which is required to compensate the increased variability and uncertainty created in net-demand by those intermittent power sources. For example, in the base case scenario BC-50GW there is 77% less baseload and 24% more gas-fired generation capacity compared to the BC-10GW, as shown in the left plot of figure 5.9 and in table 5.2. In terms of total system costs, larger amounts of flexibility increase the operation costs, while the reduction on the baseload inflexible generation reduces the investment costs of the power system. For example, the investment costs are reduced by 39%, while the operation costs increase by 19% in the BC-50GW with respect to the BC-10GW, as show in the right plot of figure 5.9 and in table 5.2. Additionally, figure 5.10 also presents a comparison of the generation matrix and costs structure compositions of the base case scenarios.¹³

¹² In the figures of this section, the base case scenarios are denoted as “BC-ZGW”, where $Z = \{10, 30, 50\}$.

¹³ In figures 5.9 and 5.10, the optimal generation mixes and total system costs, and the generation matrix and costs structure compositions are plotted for the base cases respectively. The base cases are defined according to the level of wind generation available in the system, i.e. BC-10GW, BC-30GW and BC-50GW for 10GW, 30GW and 50GW of wind generation capacity respectively. In each of the base cases, the optimal generation mixes are calculated without modifying any of the flexibility characteristics of the conventional generation and are used as base of

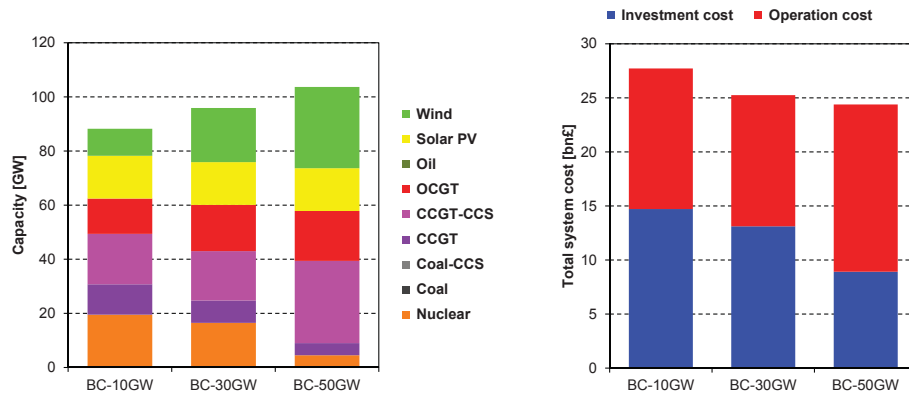


Figure 5.9: Comparison of the optimal generation mixes (*left plot*), and the total system costs (*right plot*), of the base case scenarios.

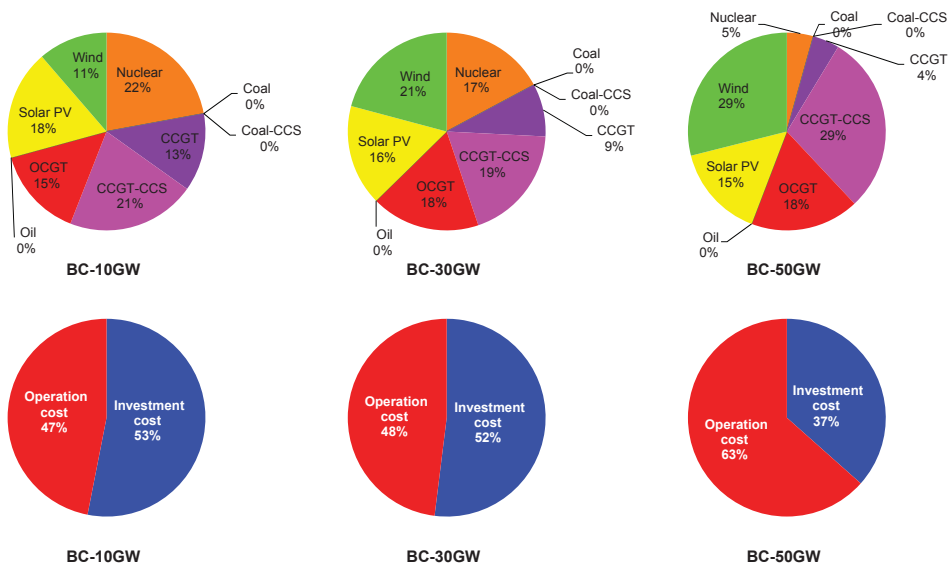


Figure 5.10: Comparison of the generation matrix composition (*top pie charts*), and the costs structure composition (*bottom pie charts*), of the base case scenarios.

Renewable energy curtailment increases for larger amounts of renewable generation capacity in the system as shown in table 5.2. This is due to combined effects of the carbon emissions limit, CO₂ price, generation capacity costs, and also due to at some point it is cheaper curtailing renewables than building new low-carbon generation capacity. The larger levels of renewables curtailment, and reduced levels of carbon-free baseload generation (nuclear) and mid-merit generation (traditional CCGT) are compensated by building more OCGT generation capacity to compensate for the loss of flexibility. Additional CCGT-CCS generation also helps compensating the loss of flexibility, but most importantly, compensates the reduction of the carbon-free emissions baseload generation capacity and allows satisfying the CO₂ emissions restriction. For example, in the BC-50GW the nuclear and CCGT generations get reduced by 77% and 60% respectively, while OCGT and CCGT-CCS generation increased by 41% and 63% respectively, with respect to the BC-10GW.

Finally, in the following sections the impact of investing in conventional generation flexibility is studied by means of sensitivity analyses on the minimum stable generation, minimum up/down time and ramping capability.

5.3.1 Minimum stable generation

The minimum stable generation or minimum stable power output, i.e. $p_i^{\min}$ in the Strategic-GEP model, refers to minimum power output level at which a generation unit can stably and reliably produce electricity. Different generation technologies have different minimum stable generation levels that depends on the technical and operational characteristics of each generation technology, such as fuel source, plant design and size, among others.

Large-scale integration of renewables is a key driver for the decarbonisation of many power systems around the world. The growing share of renewable generation capacity on those systems, and the bigger power injections of those VRE resources when wind is strongly blowing, or the sun is shining, is making net-demand negative¹⁴ more frequently. However, due to technical characteristics of conventional generation and also to system security and power quality reasons, a minimum amount of this generation needs to be online all the time. The minimum stable generation level of this minimum amount of required online generation limits the capability of a power systems to absorb renewables energy, the excess of which needs to be curtailed if there is no available storage or flexible demand resources. Renewables energy curtailment is undesired due to several reasons such as it reduces renewable generation economic viability, increases system costs, CO₂ emissions and energy prices, among others, all of which will become more severe for larger penetrations of renewables.

In this case study the impact of the minimum stable generation of different conventional generation technologies is studied using the Strategic-GEP model. For this purpose, a sensitivity analysis was performed on this parameter for each of those generation technologies as follows:

comparison for the sensitivity analyses developed in this section on the flexibility parameters of the conventional generation technologies.

¹⁴ Renewable generation exceeds system electricity demand.

1. The minimum stable generation was reduced to 90%, 70%, 50% and 10% of its original value.¹⁵
2. For each reduction of the minimum stable generation, the investment (fixed) cost was incremented from 0% up to 60%, in steps of 20%. Such increment reflects the hypothetical additional investment cost required to reduce the minimum stable generation level.¹⁶

The procedure previously described was applied for studying nuclear and gas-fired generation technologies (CCGT and OCGT).¹⁷ Coal and oil generation technologies were not studied because their costs, carbon emissions, and the total CO₂ emissions limit established for the system discards them for future installation.

Nuclear generation

The reduction of the minimum stable production of nuclear generation only generates benefits of up to approximately 3% of total system cost reduction for low levels of renewables, and investment cost increments lower than approximately 10%, as shown in last row of figure 5.11. This is due to the reduced ramping capability of this generation technology and also due to the fact that it cannot provide any type of reserve services, which are significantly increased for larger amounts of renewables in the system.

The cost benefits of investing in reducing $p_i^{\min}$ of nuclear generation are given by a larger investment in baseload generation and less investment in CCGT-CCS. This translates into increased investment costs (increase of up to 16%) and reduced operation costs (reduction of up to 25%) as shown in first and second rows of figure 5.11. The improved nuclear flexibility allows massively reducing the levels of renewable energy curtailment at all levels of wind penetration, with the highest benefits at 30GW of wind generation as shown in figure 5.14, with curtailment reductions of up to approximately 43%.¹⁸ This is due to at low levels of wind penetration, reductions of nuclear $p_i^{\min}$ above 50% do not generate further reductions as it is already low enough so as to absorb peak renewable generation.¹⁹ At high penetration levels of wind, on the other hand, the reduction of renewables curtailment level is lower because there is much less nuclear generation capacity compared to the other cases, which reduces the absorption capability of the power system. Nevertheless, although the small nuclear generation capacity (4.5GW) with respect to the other cases, nuclear $p_i^{\min}$ reduction allows lowering renewables curtailment in up to 2TWh (approximately 10%). Finally, the ramping capability of nuclear generation also limits the renewables absorption capability of the power system.

¹⁵ In the figures of this section, the reduction of the minimum stable generation level is denoted as “X%-Pmin”, where $X = \{90, 70, 50, 10\}$. The new minimum stable generation level is given by: $p_i^{\min-\text{new}} = X\% \times p_i^{\min}$.

¹⁶ In the figures of this section, the increment of the fixed cost is denoted as “Y%+FC”, where $Y = \{0, 20, 40, 60\}$. The new fixed cost is given by: $FC_i^{\text{new}} = (1 + Y\%) \times FC_i$.

¹⁷ CCGT generation includes traditional CCGT and CCGT-CCS, and they are analysed as a whole.

¹⁸ It must be noted that the generation capacity mixes of the different generation technologies under study change, so comparing the reduction of renewable energy curtailment with respect to the base case scenarios is meaningless, and that is why only absolute figures are shown in figure 5.14. In figure 5.19 a comparison of the reduction in the renewable energy curtailment levels when the flexibility characteristics of base case scenarios conventional generation mixes are improved is shown.

¹⁹ Assuming no ramping limitations.

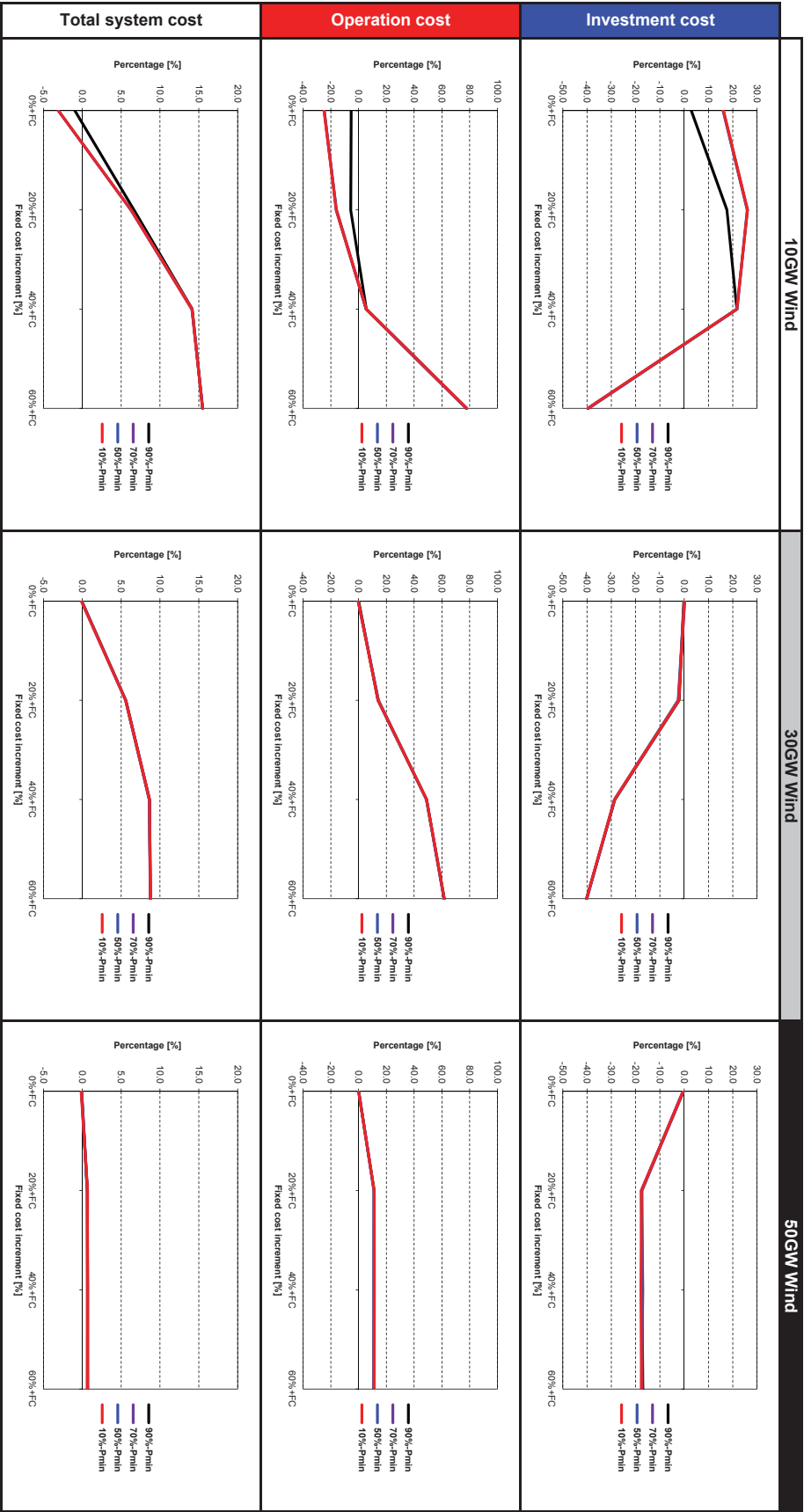


Figure 5.11: Comparison of the investment, operation and total system costs change with respect to the base case scenario of each wind generation level when the minimum stable generation level of nuclear generation technology is reduced to 90%, 70%, 50% and 10% of its original value.

CCGT generation

The reduction of the minimum stable production of CCGT generation²⁰ generates benefits of up to approximately 5% of total system cost reduction for high levels of renewables and investment cost increments lower than approximately 25%, as shown in last row of figure 5.12. Compared to nuclear generation technology, CCGT is much more flexible and can provide primary and secondary reserve services, which are influenced by the minimum stable generation level. Compared to OCGT generation, on the other hand, although not as flexible, the size of the generation units is between 2.3x and 5x bigger, making the reduction of their $p_i^{\min}$ much more significant and valuable, as it can be seen comparing figures 5.12 and 5.13.

The cost benefits of investing in reducing $p_i^{\min}$ of CCGT generation are given by a larger investment in baseload generation and less investment in CCGT-CCS. This translates into increased investment costs (increase of up to 42%) and reduced operation costs (reduction of up to 20%) as shown in first and second rows of figure 5.12. The larger shares of baseload generation are compensated by the improved flexibility of CCGT, and also by larger shares of OCGT generation. This allows reducing the levels of renewable energy curtailment by up to approximately 44% when the minimum stable generation is reduced by at least 10% for levels of wind generation equal or lower than 30GW, and by at least 30% when the wind generation is larger than 30GW. Despite the increased level of traditional gas-fired generation, the CO₂ emissions constraints can be satisfied due to the larger shares of nuclear generation and reduced levels of renewable energy curtailment.

Finally, the value of CCGT flexibility increases for larger shares of renewable generation, which highlights the potential that investing in this type of flexibility can have for the effective and efficient integration of VRE resources.

OCGT generation

The reduction of the minimum stable production of OCGT technology generates benefits of up to approximately 2.5% of total system cost reduction for high levels of renewables, and investment cost increments lower than approximately 80%, as shown in last row of figure 5.13. Compared to nuclear generation technology, OCGT is far more flexible and can provide all type of reserve services, which are influenced by the minimum stable generation level. Compared to CCGT generation, on the other hand, their size and lower minimum stable generation level do not generate as much benefits as those achieved by reducing $p_i^{\min}$ of CCGT generation, as it can be seen comparing figures 5.13 and 5.12.

The cost benefits of investing in reducing $p_i^{\min}$ of OCGT generation are given by, as in the case of CCGT but a lower scale, a larger investment in baseload generation and less investment in CCGT-CCS. This translates into increased investment costs (increase of up to 17%) and reduced operation costs (reduction of up to 12%) as shown in first and second rows of figure 5.13. As in the CCGT case, the larger shares of baseload generation are compensated by the improved flexibility of OCGT, and also by larger shares of CCGT generation.

Finally, and as in the CCGT case, the value of OCGT flexibility increases for larger shares of renewable generation, and the benefits achieved by reducing OCGT $p_i^{\min}$ in terms of renewable

²⁰ CCGT and CCGT-CCS.

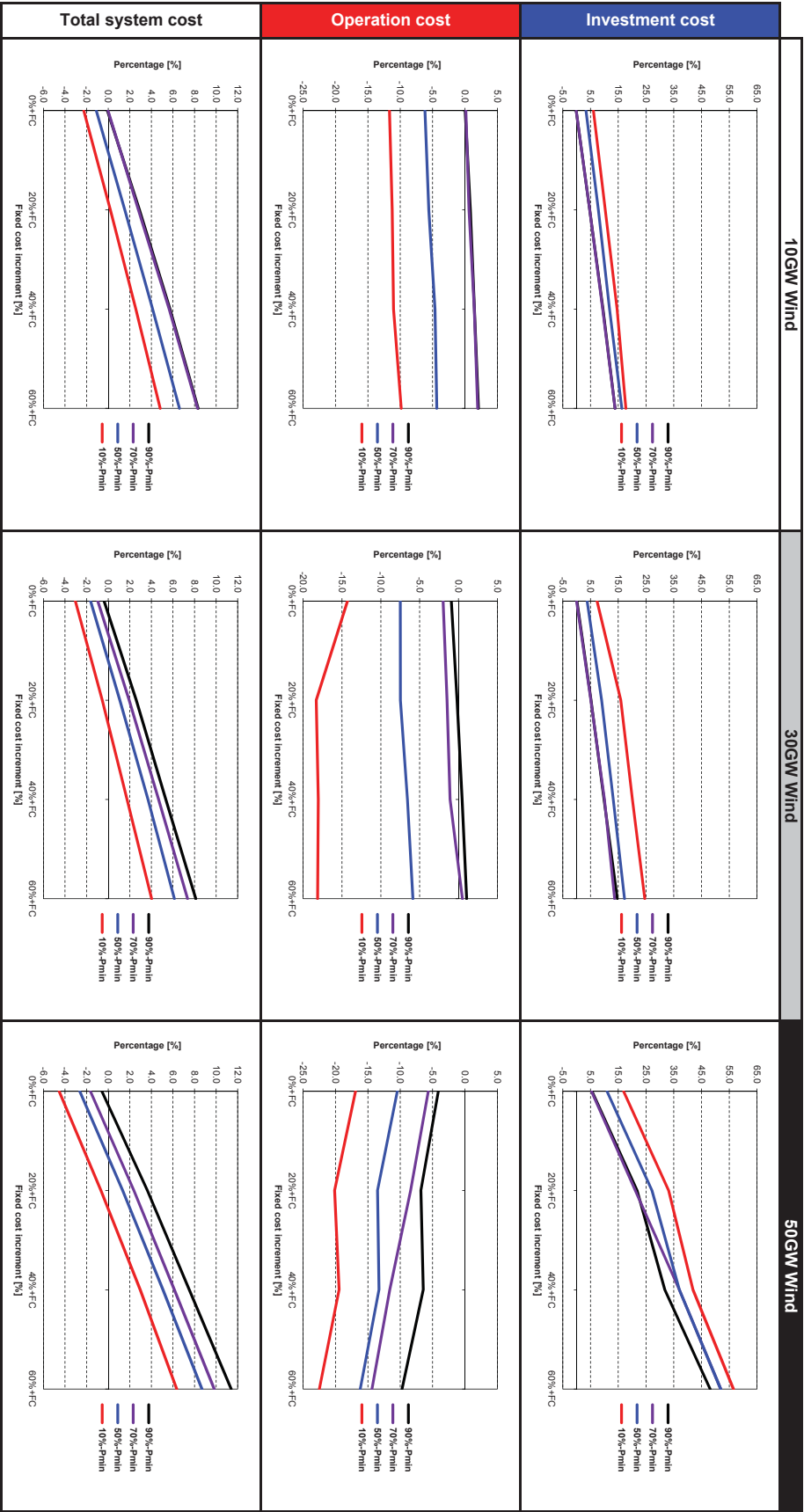


Figure 5-12: Comparison of the investment, operation and total system costs change with respect to the base case scenario of each wind generation level when the minimum stable generation level of CCGT generation technology is reduced to 90%, 70%, 50% and 10% of its original value.

energy curtailment are smaller than those of nuclear and CCGT, due to their size and small $p_i^{\min}$. Nevertheless, the simulations show that investing in reducing the minimum stable generation of gas-fired power plants cannot only generate cost saving benefits, but also help integrating renewables into power systems.

5.3.2 Minimum up/down time

The minimum up and down times, i.e. MT_i^{Up} and MT_i^{Dwn} in the Strategic-GEP model respectively, refers to the minimum amount of time during which a generation unit cannot be turned off or on respectively. Different generation technologies have different minimum up and down times, and as in the case of the minimum stable generation, they depends on the technical and operational characteristics of each generation technology, such as fuel source, plant design and size, and boilers cooling and warming speeds, among others.

The large-scale deployment of renewables will allow meeting most or all electricity demand. This will become more frequent for larger penetration levels of intermittent generation and will require operate baseload generation at their minimum stable generation levels, and also curtail renewable energy when its level will allow reducing electricity demand below the minimum stable operation of the system.

Operating a power system below its minimum stable generation level requires shutting down generation units, which can require hours (CCGT), days (coal), or even weeks (nuclear) of minimum down time before they can be restarted. On the other hand, once generation units are restarted, they are also restricted to be online by their minimum up time before they can be shut-down, which also limits the capability of absorbing renewable energy. Additionally, such cycling regime is costly not only due to fuel consumption, but also because of the additional O&M required, and the increased mechanical and thermal wear and tear. In the long-term this will translate into the need for more flexible generation units, that can be turned on and off faster, more often and with lower costs.

In this case study the impact of the minimum up and down times of CCGT generation technology is studied using the Strategic-GEP model. For this purpose, a sensitivity analysis was performed on these parameters as follows:

1. The minimum up and down times were reduced simultaneously in 2, 4, 6 and 12 hours.²¹
2. For each reduction of the minimum up/down time, the investment (fixed) cost was incremented from 0% up to 60%, in steps of 20%. Such increment reflects the hypothetical additional investment cost required to reduce the minimum up/down time.

The procedure previously described was applied for studying only CCGT generation. OCGT generation was not studied, due to the fact that it is already fast enough, and nuclear generation minimum up and down times are too high with respect to the time dynamics of renewable generation. Coal and oil generation technologies were not studied because their

²¹ In the figures of this section, the reduction of the minimum up/down time is denoted as “minus- H h”, where $H = \{2, 4, 6, 12\}$. The new minimum up/down time is given by: $MT_i^{\text{Up-new}} = MT_i^{\text{Up}} - H$, and $MT_i^{\text{Dwn-new}} = MT_i^{\text{Dwn}} - H$, respectively. It must be noted that in the case “minus-12h”, the minimum up time was reduced to 0 hour, as it cannot be negative for obvious reasons.

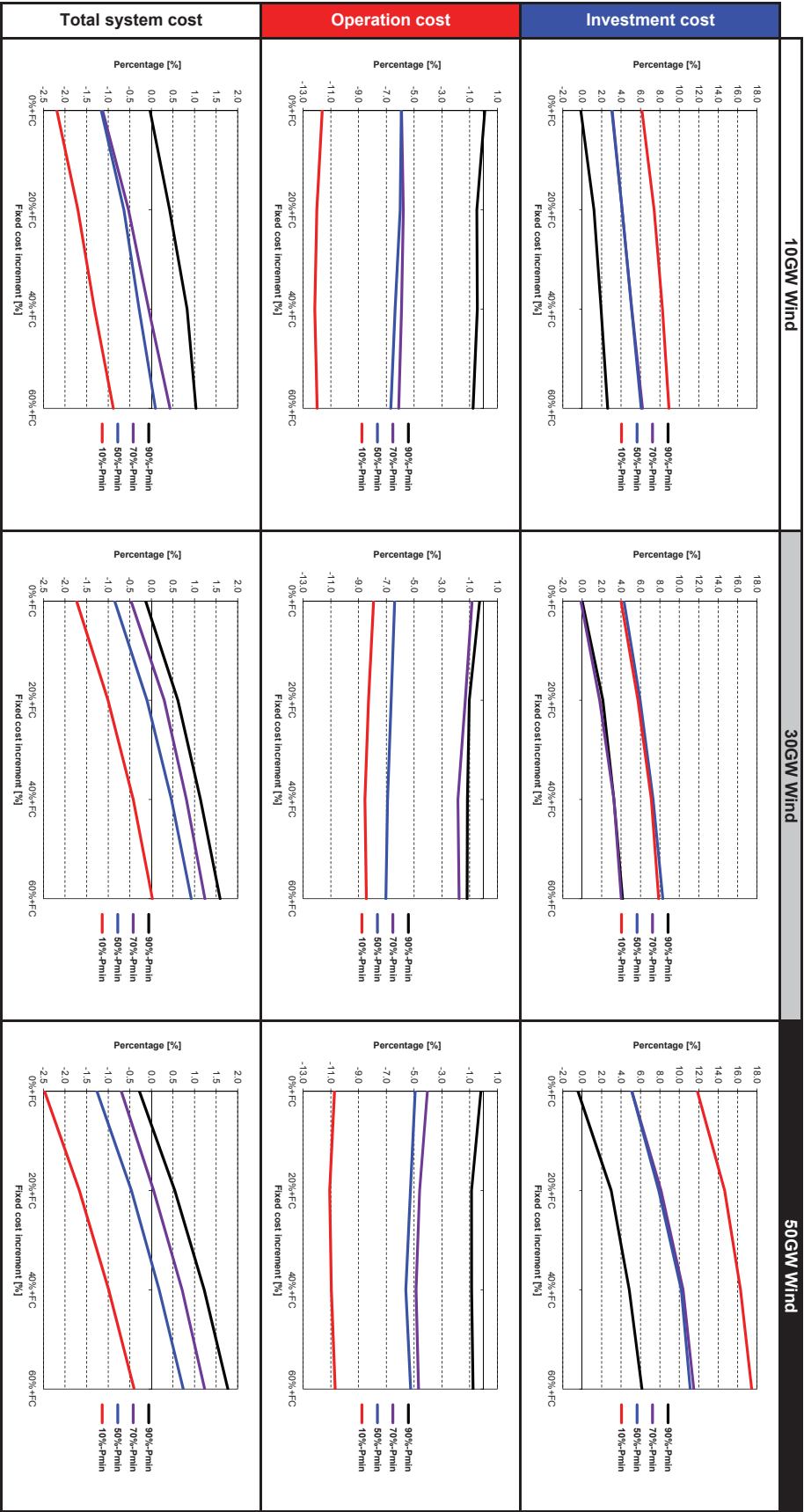


Figure 5-13: Comparison of the investment, operation and total system costs change with respect to the base case scenario of each wind generation level when the minimum stable generation level of OCGT generation technology is reduced to 90%, 70%, 50% and 10% of its original value.

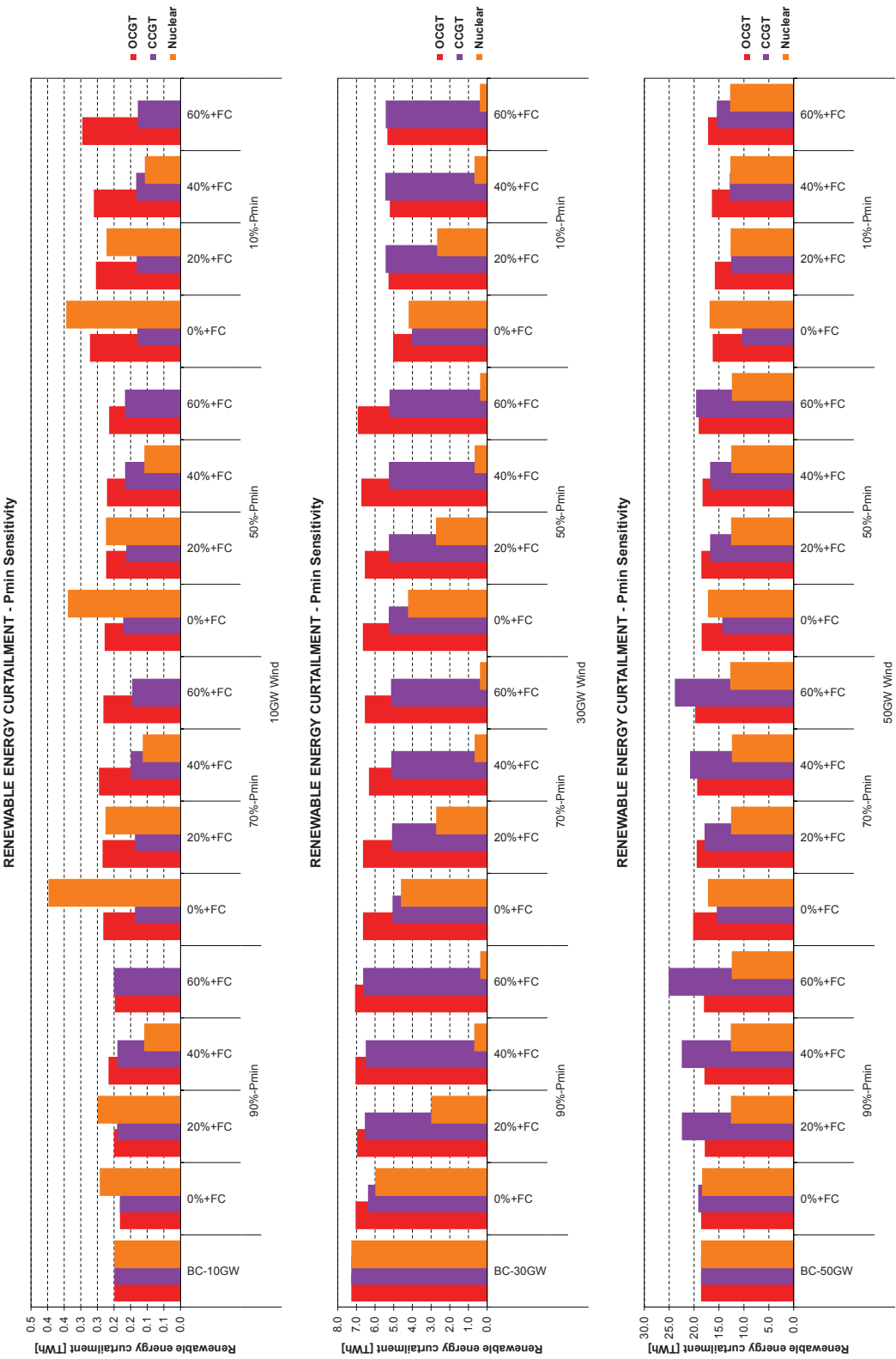


Figure 5.14: Comparison of the level of renewable energy curtailment in the case that the minimum stable generation level of Nuclear, CCGT and OCGT generation technologies is reduced.

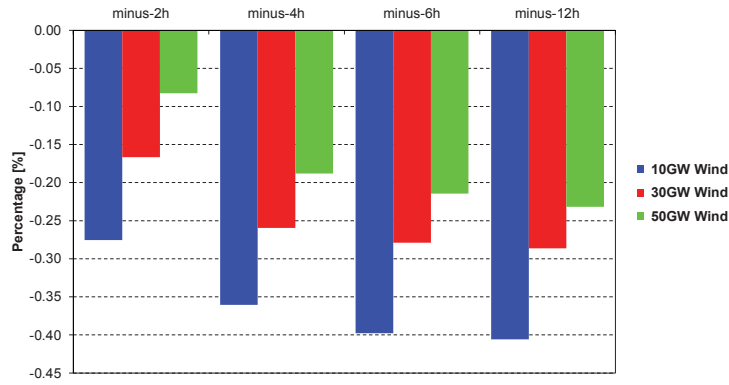


Figure 5.15: Comparison of the total system cost change with respect to the base case scenario of each wind generation level when the minimum up and down times of CCGT generation technology are reduced in 2, 4, 6 and 12 hours, and the additional investment cost required is zero.

costs, carbon emissions, and the total CO₂ emissions limit established for the system discards them for future installation.

CCGT generation

The reduction of the minimum up/down time of CCGT technology generates very small benefits of up to 0.4% of total system cost reduction for low levels of renewables, and if the investment cost increment is negligible, as shown in last row of figure 5.16 and also in figure 5.15, which compares the total system cost reduction for zero investment cost increment.

The simulations do not show clear and conclusive evidence of the cost benefits achieved by reducing the minimum up/down time of CCGT generation. This suggests that the benefits of improving this flexibility characteristic are marginal. Nevertheless, renewable energy curtailment levels are lowered by between 3.5% and 14%. Improving CCGT flexibility by reducing its minimum up/down time does not generate much benefit compared to those achieved by reducing their minimum stable generation level. Nevertheless, this highlights the potential benefits that improving multiple flexibility characteristics of conventional generation at the same time may have.

5.3.3 Ramping capability

The upward and downward ramping capability, i.e. Δ_i^{Up} and Δ_i^{Dwn} in the Strategic-GEP model respectively, refers to the maximum rate of change in which a generation unit can increase or decrease its power output level between consecutive demand segments respectively. Different generation technologies have different upward and downward ramping capabilities, and as in the case of the minimum stable generation and minimum up/down time, they depend on the technical and operational characteristics of each generation technology, such as fuel source, plant design and size, and boilers cooling and warming speeds, among others.

The power injection of VRE resources changes the rate of change of net-demand, increasing its magnitude between consecutive demand segments for larger penetration levels of renewables as analysed in Section 3.3. This translates into the need for changing more frequently

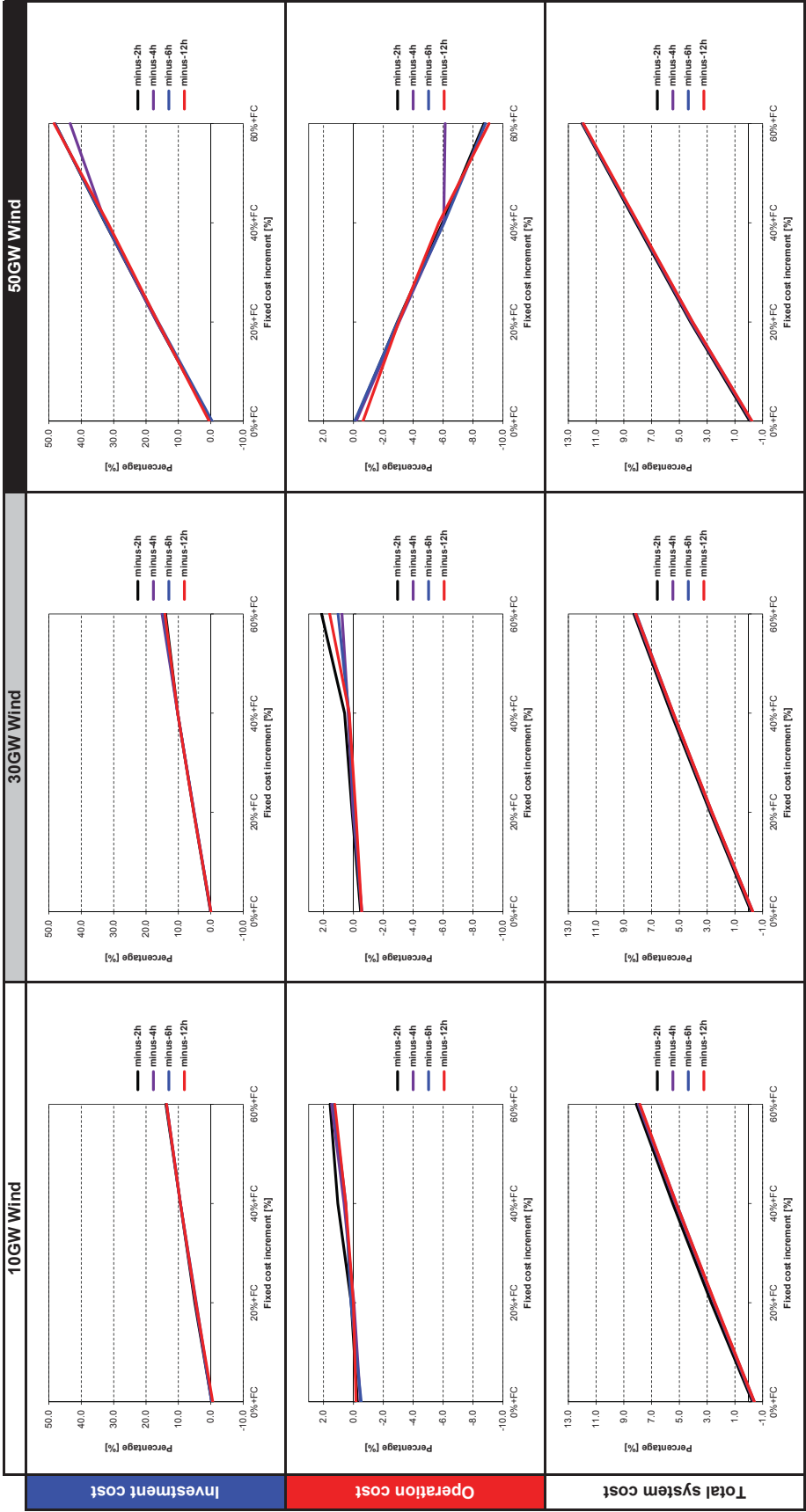


Figure 5.16: Comparison of the investment, operation and total system costs change with respect to the base case scenario of each wind generation level when the minimum up and down times of CCGT generation technology are reduced in 2, 4, 6 and 12 hours.

and at higher rates the power output of conventional generation. For high levels of renewables this will mean that baseload and mid-merit generation technologies will be frequently operated against their ramping limits, and more peaking generation units will be required to be online to provide the additional ramping needs of the power system.

Generation reserves are the additional generation capacity that is reserved, i.e. not used (online or offline) but ready to be deployed, in order to handle unexpected imbalances between supply and demand. Traditionally those imbalances have been given by unexpected increases in electricity demand, or by outages of generation units or transmission lines. Today, the uncertainty created by medium or large-scale deployment of renewables and the error in forecasting the production of those generation resources require of larger amounts of the different types of reserve services. Reserve services provision span over different timescales, going from seconds in the case of the frequency regulation, up to years in the case of the system capacity margin.

The reserves provision capability of the different types of conventional generation technologies are conditioned by their ramping capability over the different timescales of the power system operation. For example, frequency regulation reserves can only be provided by thermal generation units that are able of modifying their power output in a matter of few seconds or minutes, limiting the provision of this type of reserve to coal, gas and oil-fired generation units.²² In this case study the impact of the ramping capability of different conventional generation technologies is studied using the Strategic-GEP model. For this purpose, a sensitivity analysis was performed on this parameter for each of those generation technologies as follows:

1. The upward and downward ramping capability were increased simultaneously in 2x, 3x, 4x, ..., and up to 6x in the case of CCGT, and up to 10x in the case of nuclear generation, with respect to the original value.²³
2. For each reduction of the minimum stable generation, the investment (fixed) cost was incremented from 0% up to 60%, in steps of 20%. Such increment reflects the hypothetical additional investment cost required to increase the ramping capability.

The procedure previously described was applied for studying nuclear and CCGT generation technologies. OCGT generation was not studied due to the fact that it is already fast enough. Coal and oil generation technologies were not studied because their costs, carbon emissions, and the total CO₂ emissions limit established for the system discards them for future installation.

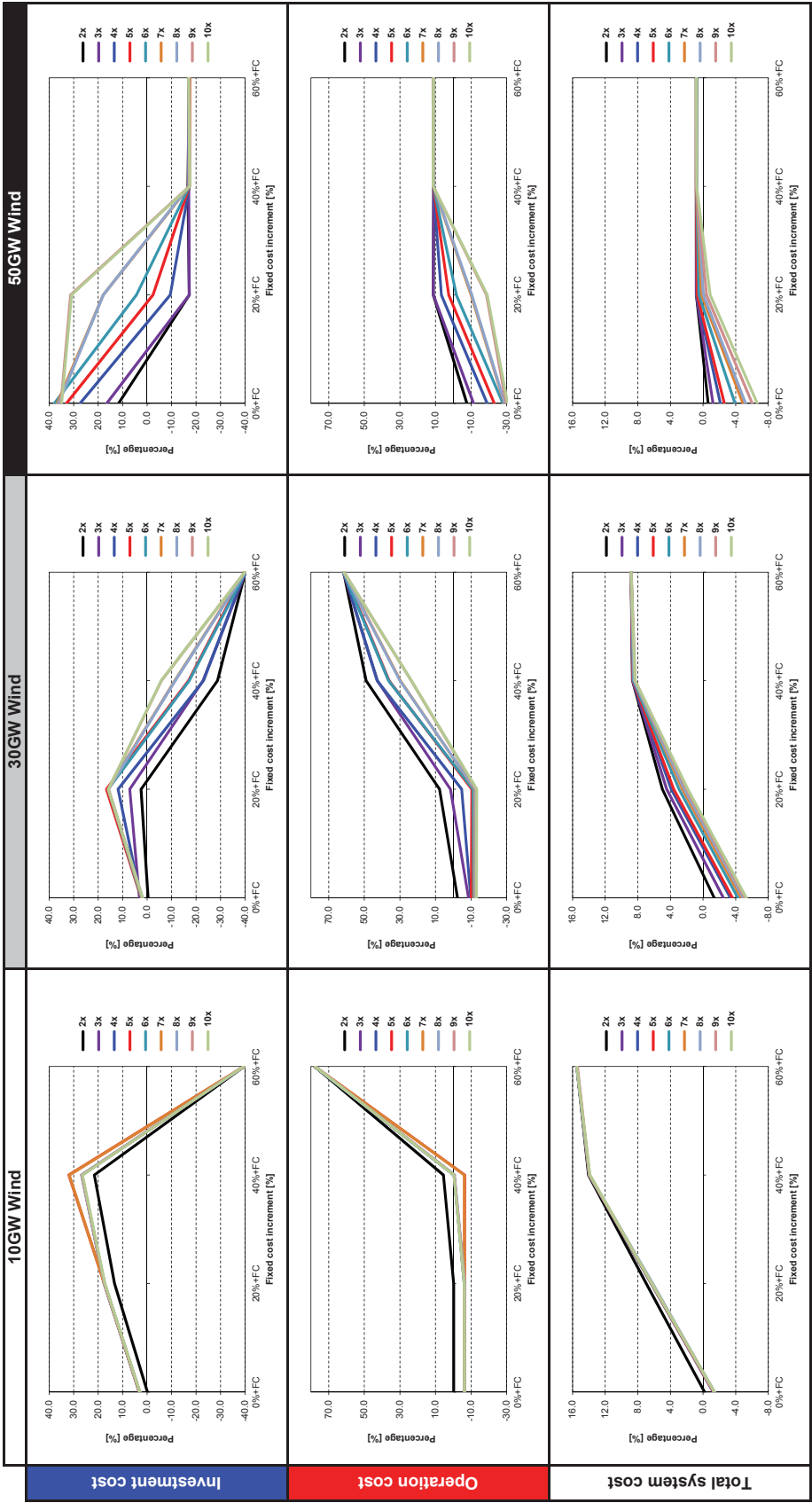


Figure 5-17: Comparison of the investment, operation and total system costs change with respect to the base case scenario of each wind generation level when the upward and downward ramping capability of nuclear generation technology are increased in 2x, 3x 4x, and up to 10x.

Nuclear generation

The improvement of the ramping capability of nuclear technology generates benefits of up to approximately 7% of total system cost reduction for high levels of renewables, and investment cost increments lower than approximately 30%, as shown in last row of figure 5.17. The benefits are due to the load following capability of nuclear generation is improved and also due to the improved flexibility allows this technology to provide primary and secondary reserves, with higher benefits for higher levels of renewables.

The cost benefits of investing in increasing the ramping capability of nuclear generation are given by a larger investment in baseload nuclear generation and less investment in CCGT-CCS. This translates into increased investment costs (increase of up to 38%) and reduced operation costs (reduction of up to 31%) as shown in first and second rows of figure 5.17. The improved nuclear flexibility allows reducing the levels of renewable energy curtailment at medium and low levels of wind penetration by up to approximately 40%. At high levels of wind generation, on the other hand, more nuclear generation is built for larger improvements of its ramping capability, because it is a cheap and clean source of energy, and also of primary and secondary reserves. This translates into higher levels of renewable energy curtailment, because the increased amount of nuclear generation rises the minimum stable operation level of the whole power system.

The combined effect of reducing the minimum stable operation level and improving the ramping capability of nuclear generation can undoubtedly generate multiple benefits such as drastically reduce the renewable energy curtailment and thus help with the integration of those VRE resources, and also reduce power system costs and energy prices by allowing the installation of more nuclear generation capacity that can supply larger portions of electricity demand and reserve services. Finally, improving the flexibility characteristics of nuclear generation can make this generation technology a competitive source of energy compared to other gas-fired generation technologies, but still the capital intensity of nuclear generation investment is still a barrier to achieve such goal. Nevertheless, current development of small modular nuclear reactors offers an attractive way for drastically reducing investment costs, and what can finally make nuclear generation a flexible and cost-effective energy alternative [317].

CCGT generation

The improvement of the ramping capability of CCGT technology generates benefits of up to approximately 7% of total system cost reduction for high levels of renewables, and investment cost increments lower than approximately 50%, as shown in last row of figure 5.18. The improved load following capability allows CCGT generation to provide larger amounts of primary

22 The reserves provision capability is also conditioned by the type of fuel and size of the different types of generation technologies.

23 In the figures of this section, the increase of the upward/downward ramping capability is denoted as “Qx”, where $Q = \{2, 3, 4, \dots, 10\}$. The new upward/downward ramping capability is given by: $\Delta_i^{\text{Up-new}} = Q \times \Delta_i^{\text{Up}}$, and $\Delta_i^{\text{Dwn-new}} = Q \times \Delta_i^{\text{Dwn}}$, respectively. It must be noted that upward/downward ramping capability are assumed to be equal, i.e. $\Delta_i^{\text{Up-new}} = \Delta_i^{\text{Dwn-new}}$. Additionally, it was assumed that nuclear generation is able to provide primary and secondary reserves starting from “2x”. The time bases used to calculate the primary and secondary reserve capabilities of conventional generation are 5 and 10 minutes respectively.

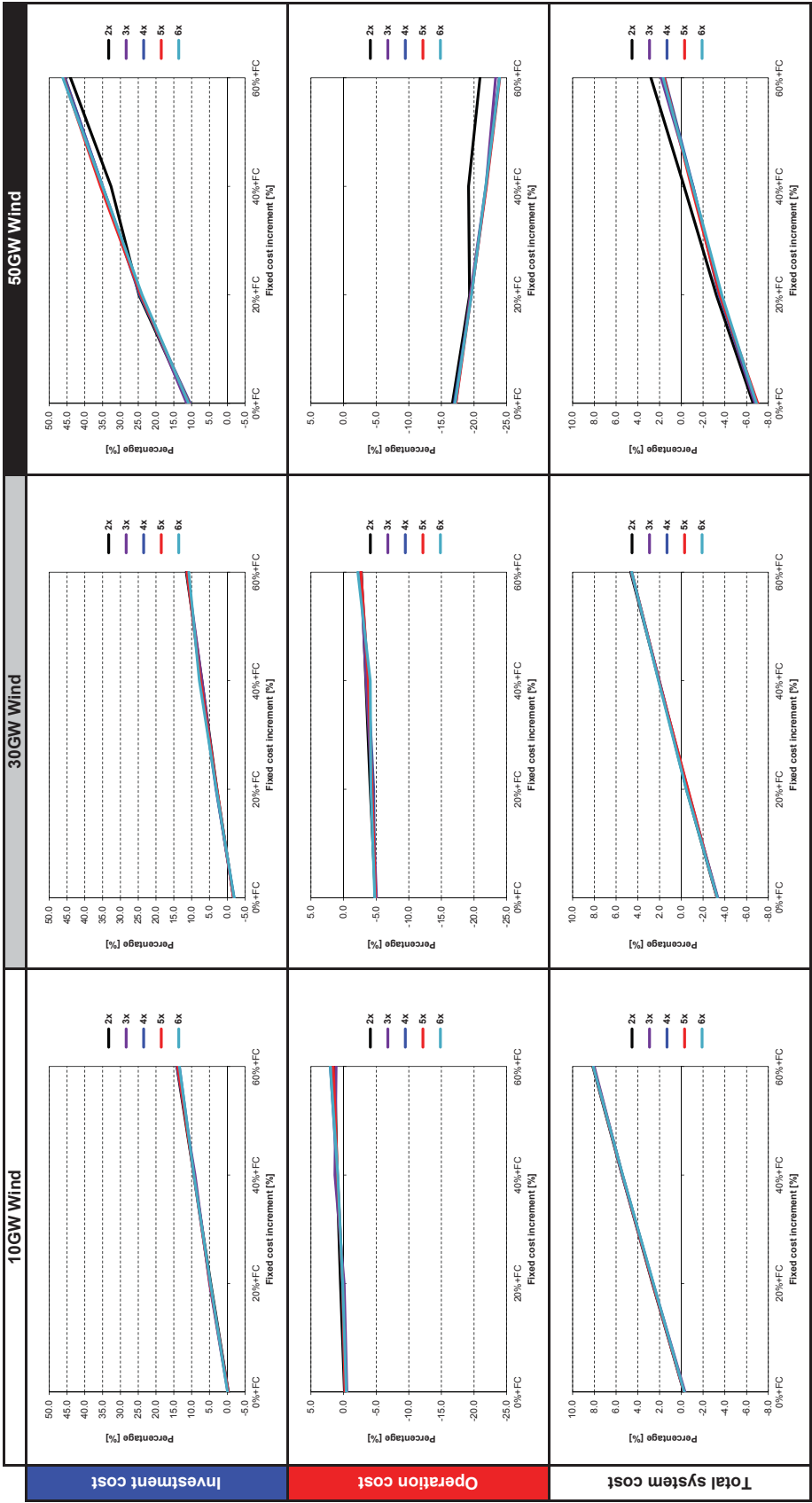


Figure 5.18: Comparison of the investment, operation and total system costs change with respect to the base case scenario of each wind generation level when the upward and downward ramping capability of CCGT generation technology are increased in 2x, 3x 4x, and up to 6x.

and secondary reserve services. This translates into smaller shares of OCGT generation, and thus, into reduced operation costs, with higher benefits for higher levels of renewables.

The cost benefits of investing in increasing the ramping capability of CCGT generation are given by larger investment in CCGT generation and less investment in CCGT-CCS²⁴ and OCGT at low and medium levels of renewables penetration. This translates into reduced investment costs (reduction of up to 2%) and reduced operation costs (reduction of up to 20%), as shown in first and second rows of figure 5.18. For large levels of renewables, on the other hand, the cost benefits are given by increased investment in baseload nuclear generation (between 2.3x and 2.7x more), CCGT generation (between 1.2x and 3.2x more) and OCGT generation (between 1% and 30% more),²⁵ and reduced shares of CCGT-CCS (between 35% and 45% less), which increases investment costs in up to 36%, but reduce operation costs in up to 22%.

The improved CCGT flexibility allows reducing the levels of renewable energy curtailment at medium and low levels of wind penetration, with reductions of up to approximately 30%. At high levels of renewable generation, on the other hand, the additional nuclear generation increases the curtailment level of renewables between 10% and 43%, because it rises the minimum stable operation level of the whole power system. Nevertheless, larger shares of nuclear generation allows satisfying the CO₂ emissions limit.

Comparing the benefits of improving conventional generation flexibility characteristics in terms of renewables energy curtailment reduction is, as noted at the beginning of this section, not straightforward due to for each modification of those characteristics the optimal conventional generation mix changes. This also changes the flexibility characteristics of the power system compared to the base case scenarios, and the other scenarios as well. For this reason an additional case study was conducted, in which the base case scenarios optimal conventional generation mixes are fixed, and the flexibility characteristics of the conventional generation of those are then modified. Figure 5.19 summarizes the results of this case study, which are in line with previous simulations, and show the benefits that improving conventional generation flexibility can have for the effective and efficient integration of renewables in future low-carbon power systems.

5.4 CONCLUSIONS

The large-scale penetration of renewables invalidates the assumption that costs and availability of generation depends only on the magnitude of demand and not on the time when demand occurs, which is widely used in generation expansion planning. Net-demand chronology has been drastically modified due to the contribution of intermittent generation, resulting in deep changes in the operation of conventional generation and into the need of operating it more frequently and at the limit of their flexibility characteristics. GEP of modern power system must consider the conventional generation flexibility characteristics in order to ensure that

²⁴ Renewable energy curtailment is reduced in average by 19% and 29% for low and medium levels of renewables respectively, which allows satisfying the CO₂ emissions constraint although there is no additional nuclear generation.

²⁵ The additional OCGT generation is required to compensate the reduced flexibility of the power system due to the additional nuclear capacity.

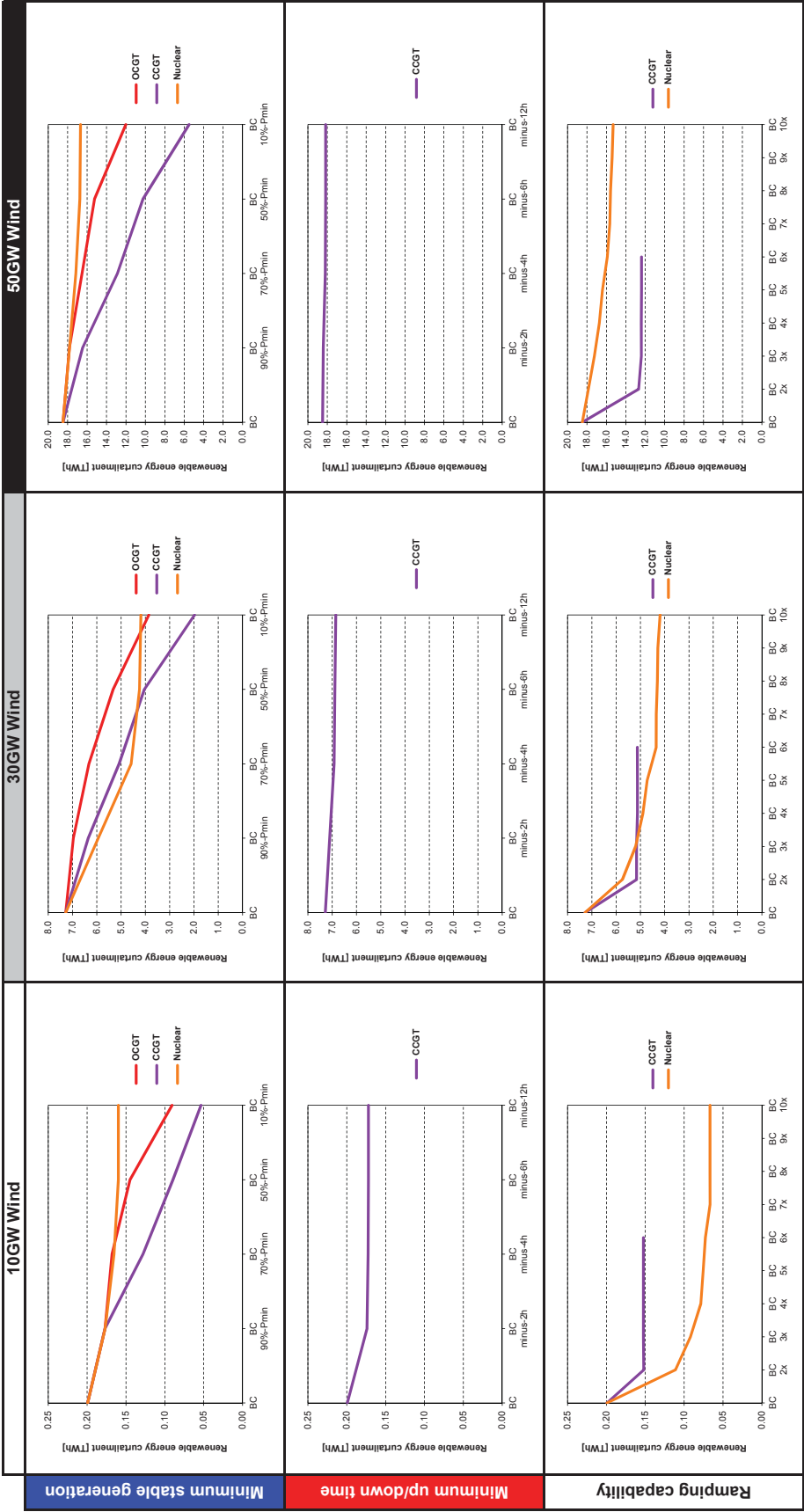


Figure 5.19: Comparison of the renewable energy curtailment reduction achieved by improving conventional generation flexibility characteristics (minimum stable generation, minimum up/down time and ramping capability) of the base case scenarios power systems.

the proper amount and the adequate type of generation resources are available to securely and affordably supply electricity demand.

Carbon emissions targets, and the regulatory measures created to achieve those targets, can have great impact not only in the operation of conventional generation, but also in the integration of [VRE](#) resources and evolution of future power systems. Regulators need to consider the potential interaction between new energy policies and the flexibility characteristics of conventional generation, in order to adequately design and assess long-term regulations, and market structure modifications, that can create the market conditions required to deliver sustainable and efficient power systems.

The improvement of the flexibility characteristics of conventional generation cannot only have great impact in cost saving and security improvement terms, but also boost the efficient and effective integration of renewable resources. More flexible generation is able to follow and adjust to net-demand quicker, more effectively and with less stress. This translates into massive reductions of renewable energy curtailment levels for large penetration levels of renewables, apart from operation cost savings.

IMPACT OF DEMAND FLEXIBILITY ON GEP

Demand flexibility and its smart coordination with system objectives attract significant interest due to the increasing penetration of renewable generation into power systems and the progressive electrification of transport and heat sectors. The expected decarbonisation of power systems proposes unprecedented challenges for the operation and expansion of those power systems. In this context, the role of demand, and the development and penetration of smart (flexible) demand technologies, attracts great interest as they can be a potential source of flexibility which can help reducing the requirements for new flexible thermal generation, reduce carbon emissions, and also contribute to the effective and efficient integration of renewables.

Developed GEP models have largely ignored the technology-specific inter-temporal characteristics and constraints of flexible demand, or resorted to very simplified representations of those. Within available flexible demand technologies, EV constitute one of the most representative technologies, not only due to their present and expected penetration, but also due to the flexibility potential they offer.

In this chapter, the role of EV flexibility in the expansion of future power systems is analysed through a set of case studies, which show evidence of not only the relevance of including flexible demand modelling in generation expansion planning, but also the value that investing in such flexibility may generate in terms of costs savings, CO₂ emissions reduction and the efficient integration of renewable resources.

6.1 IMPACT OF EV FLEXIBILITY ON GEP

The role of the demand side attracts increasing interest in modern power systems. Given the desired integration of renewable generation, the traditional paradigm of controllability provision using only generation side resources will not be economically efficient, neither sustainable. Furthermore, environmental and energy security concerns have also paved the way for the electrification of transport and heat sectors, which are expected to introduce a significant amount of new demand in power systems. If these new loads are operated inflexibly, i.e. if their power demand is not smartly controlled, following the temporal patterns of users' driving and heating requirements, the generation and network costs required to support such new demand will be disproportionately larger than the increase in the total electric energy consumption [247].

Technological developments have and are enabling the wide penetration of flexible demand technologies, which have the ability of rescheduling electric demand requirements in time

[248]. The smart coordination of this flexibility could yield significant economic, environmental and technical benefits across different timescales and sectors of the power system. Although significant work has been done on analysing the effects of flexible demand on operational aspects of power systems, the impacts on GEP have not been analysed in depth and with sufficient detail.

In the following case study, the effects of EV flexibility on GEP are studied using the Strategic-GEP model. The following assumptions were made for this case study:

- Energy-only-market.
- Target year 2030 according to input data (table A.7).
- Given EV penetration levels: 10%, 30%, 50% and 100%.¹
- Given flexible EV penetration levels: 0% and 100%.²
- EV flexibility can be used at no cost.
- Only day-ahead information is used for the coordination of flexible EV in the operational timescale (intra-day flexibility).
- Different levels of wind capacity: 10GW, 30GW and 50GW.
- Power system is built from scratch.
- For the system CO₂ intensity limit two scenarios are considered. In the first one, the CO₂ emissions limit constraint is relaxed (not enforced), while in the second is enforced and the limit is set at 50 [gCO₂/kWh]. The CO₂ price is set at £76/tonneCO₂ in both cases.
- Two different scenarios concerning EV operation are considered. In the first one, i.e. “0%-FEV” or “Fully inflexible EV operation”, all EV are assumed to be inflexible and start charging their batteries immediately after they are plugged into the grid and until they are fully charged. The resulting total power demand of the EV population constitutes a fixed input to the model, which is not optimally scheduled. The second scenario, i.e. “100%-FEV” or “Fully flexible EV operation”, assumes flexible charging capability for all EV, the demand of which can be optimally scheduled by the Strategic-GEP model.
- The examined scenarios involve the application of the Strategic-GEP model in the context of UK, for different EV and flexible EV penetration and wind generation levels.³
- Data regarding the size and the average driving patterns of the UK vehicle fleet was taken from [318] and [319]. Based on this data, each EV is assumed to make two journeys per day and a set of 103 different types of EV has been produced, each defined by the combination of the start time, end time, and electrical energy requirements of each of its two daily journeys (tables A.5 and A.6). The values of the rest of the EV parameters have been assumed identical for the different EV types and set in line with [252] (table A.4).

¹ In the figures of this section, the penetration level of EV is denoted as “X%-EV”, where $X = \{10, 30, 50, 100\}$.

² In the figures of this section, the penetration level of flexible EV is denoted as “Y%-FEV”, where $Y = \{0, 100\}$.

³ EV penetration level is defined as the percentage of vehicles that are assumed to be electric, and wind generation level as the amount of wind generation capacity installed in the power system.

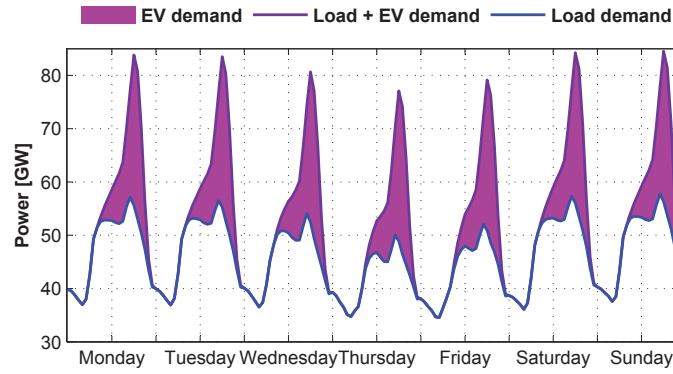


Figure 6.1: Load demand and EV demand during the winter week considering 50 [gCO₂/kWh] limit, 10GW of wind capacity, 100% EV penetration (100%-EV) and fully inflexible EV operation (0%-FEV).

- EV are assumed connected to the grid during the period between the end of their second and the start of their first journey, in line with the home charging scenario.⁴
- The base case scenarios do not consider EV in the system, and there is one base case scenario for each wind capacity level.⁵

Users' travelling patterns are aligned to the base case load demand pattern as shown in figure 6.1, which means that inflexible EV power demand will be mostly concentrated during peak hours. This translates into increased peak demand levels (figure 6.2 shows a comparison of the net-demand load duration curves),⁶ and consequently into larger requirements of mid-merit and peaking gas-fired generation capacity (CCGT, CCGT-CCS and OCGT), and in the reduction of baseload nuclear generation, as the latter becomes less cost-effective given the increased net-demand unpredictability and variability. The previous effects can be observed in figure 6.6, where the evolution of the optimal conventional generation mix for increasing wind capacity levels and increasing EV penetration levels is shown.⁷ Table 6.1 and figures 6.3 and 6.4 compare the BC-10GW case against the cases where there is a CO₂ emissions limit of 50 [gCO₂/kWh], 10GW of wind generation capacity, and all EV are either flexible or inflexible.⁸

The integration of inflexible EV in the system yields increased operation cost proportions due to more expensive generation, i.e. gas-fired generation units, is needed to satisfy demand, as shown in figure 6.7. As clearly depicted in figure 6.8, where the percentage increase in total conventional generation capacity and total system cost with respect to the base case scenarios are plotted, it is evident that the inflexible operation of EV will lead to significantly larger requirements in total generation capacity and higher costs.

The power demand of flexible EV, on the other hand, can be optimally rescheduled towards off-peak hours, as shown in figure 6.5. This allows keeping peak demand and total generation capacity almost unchanged with respect to the base case scenarios for all EV penetration levels

⁴ The charging of EV only when parked at home is deemed as the most plausible scenario in the literature [257].

⁵ In the figures of this section, the base case scenarios are denoted as "BC-ZGW", where Z = {10, 30, 50}.

⁶ Load demand (non-EV demand) plus inflexible and flexible EV power demand minus wind and solar PV power dispatched.

⁷ All EV operation modes are also shown in this figure. It must be noted that, as analysed in Section 5.2, when the CO₂ emissions limit is enforced, CCGT generation capacity is replaced by CCGT-CCS, as the latter allows reducing the CO₂ emissions by 90% with respect to the traditional CCGT generation technology.

⁸ Additional data regarding the base case scenarios can be found in tables B.2 and B.3.

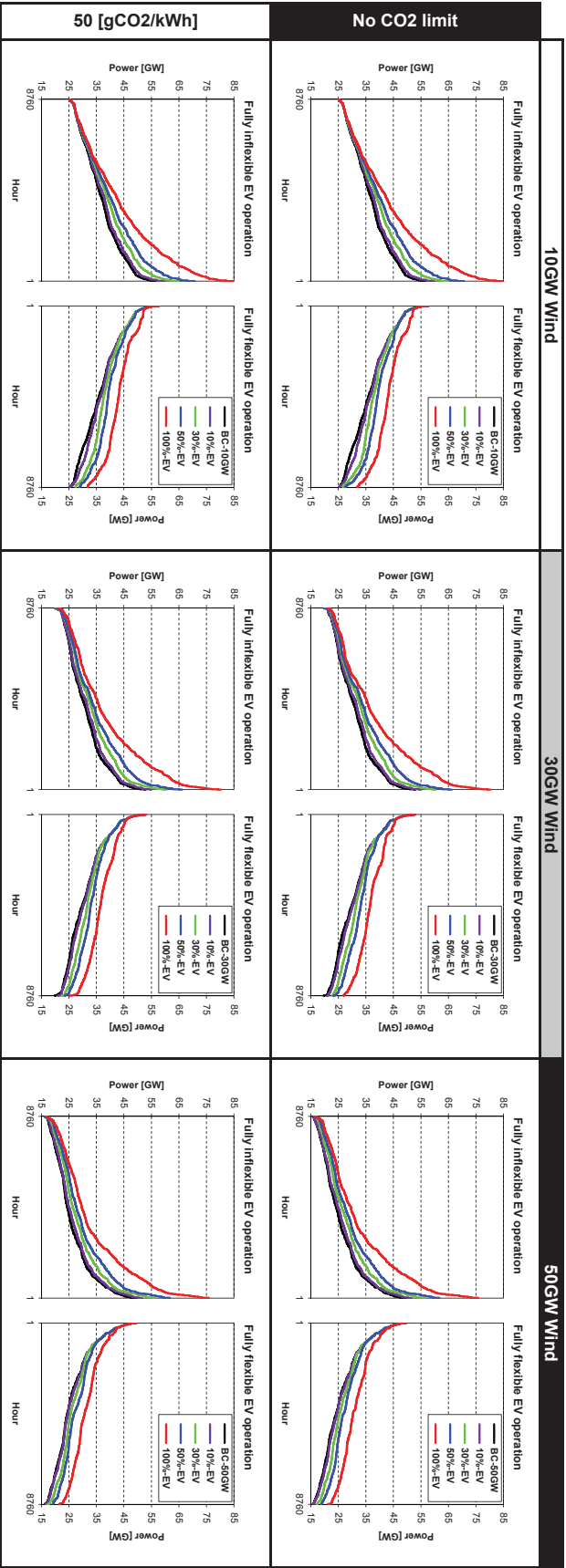


Figure 6.2: Comparison of the net-demand load duration curves in the case that the CO_2 emissions limit is not enforced, and when it is enforced and equal to 50 [gCO₂/kWh], for different levels of wind capacity.

Table 6.1: Generation capacity, system costs, curtailment levels, CO₂ emissions and renewables utilization factors when considering 50 [gCO₂/kWh] limit and 10GW of wind capacity, in the cases that there are no EV in the system (BC-10GW), and when there is a 100% EV penetration (100%-EV) and either all of them are inflexible (0%-FEV) or all flexible (100%-FEV).

	Parameter	Units	Scenario		
			0%-EV	100%-EV	
			BC-10GW	0%-FEV	100%-FEV
Generation Capacity	Nuclear	GW	27.00	27.00	34.50
	Coal	GW	0.00	0.00	0.00
	CCGT	GW	12.00	15.75	9.75
	OCGT	GW	12.30	22.80	9.45
	Oil	GW	0.00	0.00	0.00
	Coal-CCS	GW	0.00	0.00	0.00
	CCGT-CCS	GW	9.12	23.18	6.84
	Solar PV	GW	15.81	15.81	15.81
	Wind	GW	10.00	10.00	10.00
	TOTAL	GW	86.23	114.54	86.35
Costs	Investment	bn£	16.89	20.22	19.91
	Operation	bn£	9.38	13.84	9.23
	TOTAL	bn£	26.26	34.06	29.14
Curtailment	Load	TWh	0.00	0.00	0.00
	Generation	TWh	0.00	0.00	0.00
	Wind	TWh	1.16	1.24	0.11
	Solar PV	TWh	0.70	0.40	0.25
	Renewable energy curtailment	TWh	1.86	1.64	0.36
CO ₂	Emissions	MtonneCO ₂	17.90	20.88	19.01
	Intensity	gCO ₂ /kWh	50.00	50.00	45.50
UF	Wind Utilization Factor	%	95.8	95.4	99.6
	Solar PV Utilization Factor	%	94.9	97.1	98.2

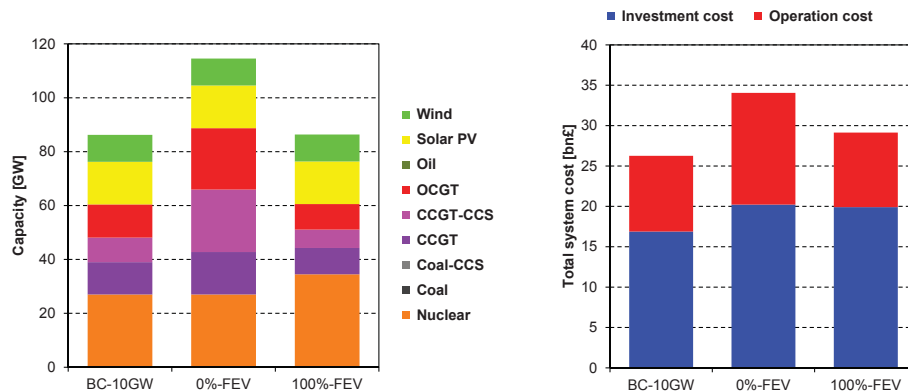


Figure 6.3: Comparison of the optimal generation mixes (left plot) and the total system costs (right plot) when considering 50 [gCO₂/kWh] limit and 10GW of wind capacity, in the cases that there are no EV in the system (BC-10GW), and when there is a 100% EV penetration (100%-EV) and either all of them are inflexible (0%-FEV) or all flexible (100%-FEV).

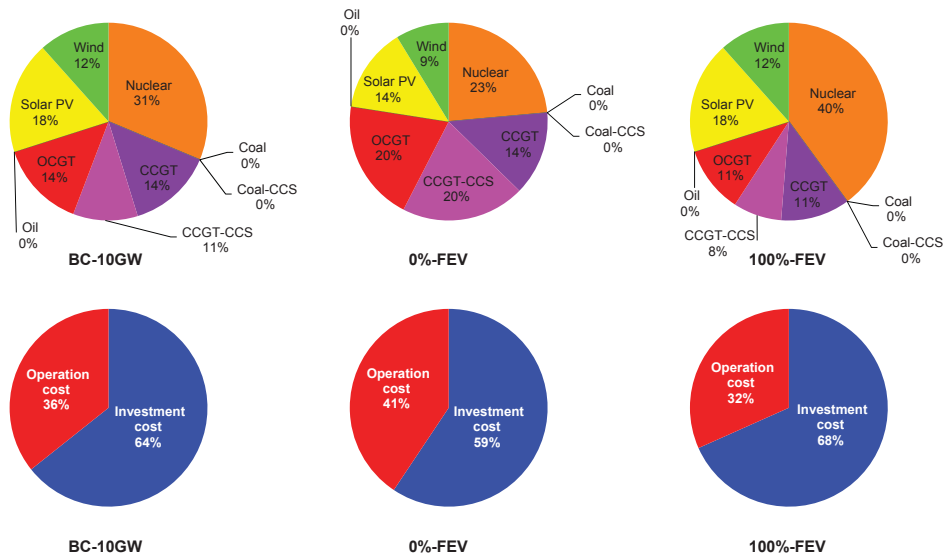


Figure 6.4: Comparison of the generation matrix composition (*top pie charts*), and the costs structure composition (*bottom pie charts*), when considering 50 [gCO₂/kWh] limit and 10GW of wind capacity, in the cases that there are no EV in the system (BC-10GW), and when there is a 100% EV penetration (100%-EV) and either all of them are inflexible (0%-FEV) or all flexible (100%-FEV).

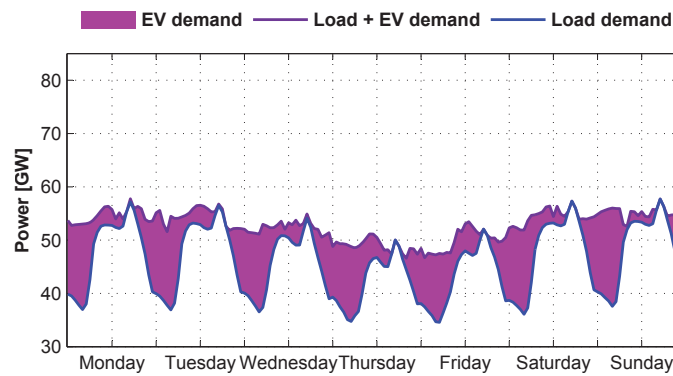


Figure 6.5: Load demand and EV demand during the winter week considering 50 [gCO₂/kWh] limit, 10GW of wind capacity, 100% EV penetration (100%-EV) and fully flexible EV operation (100%-FEV).

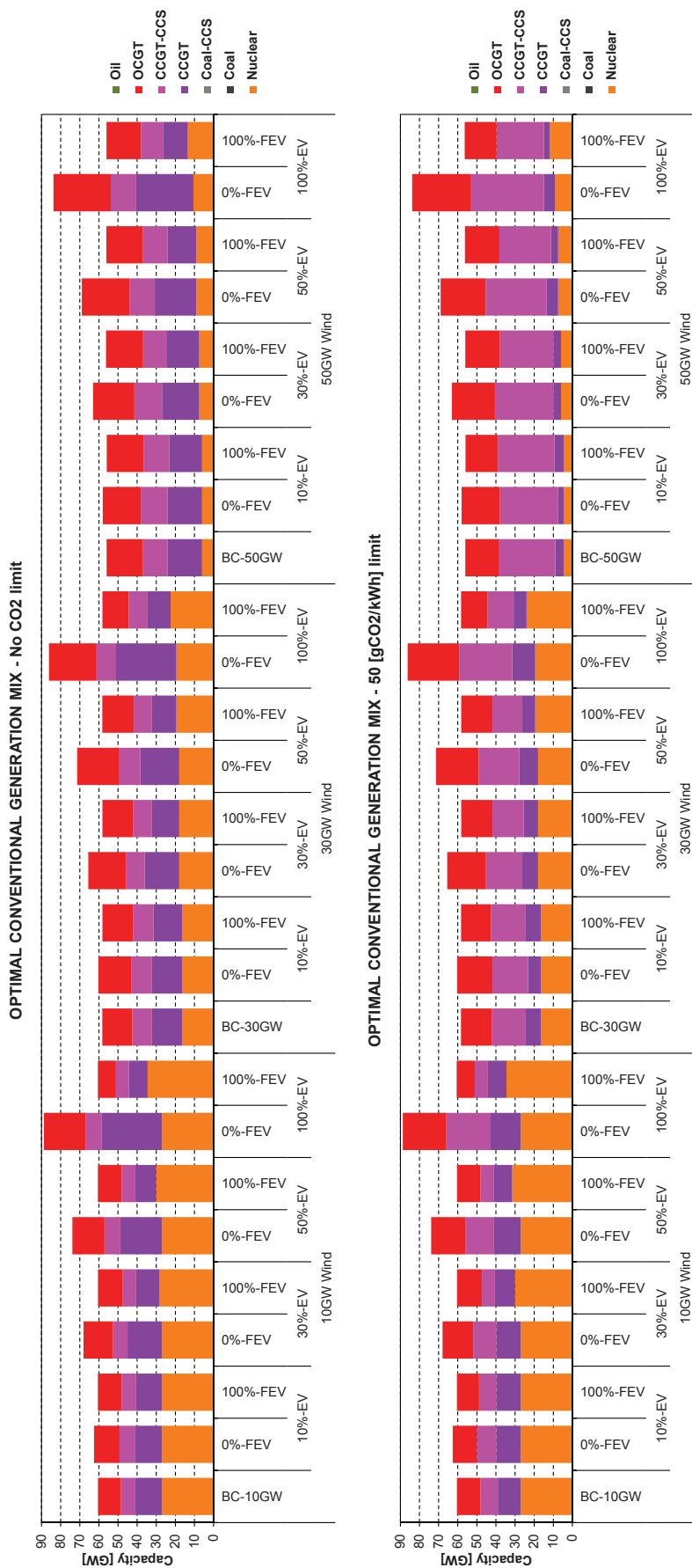
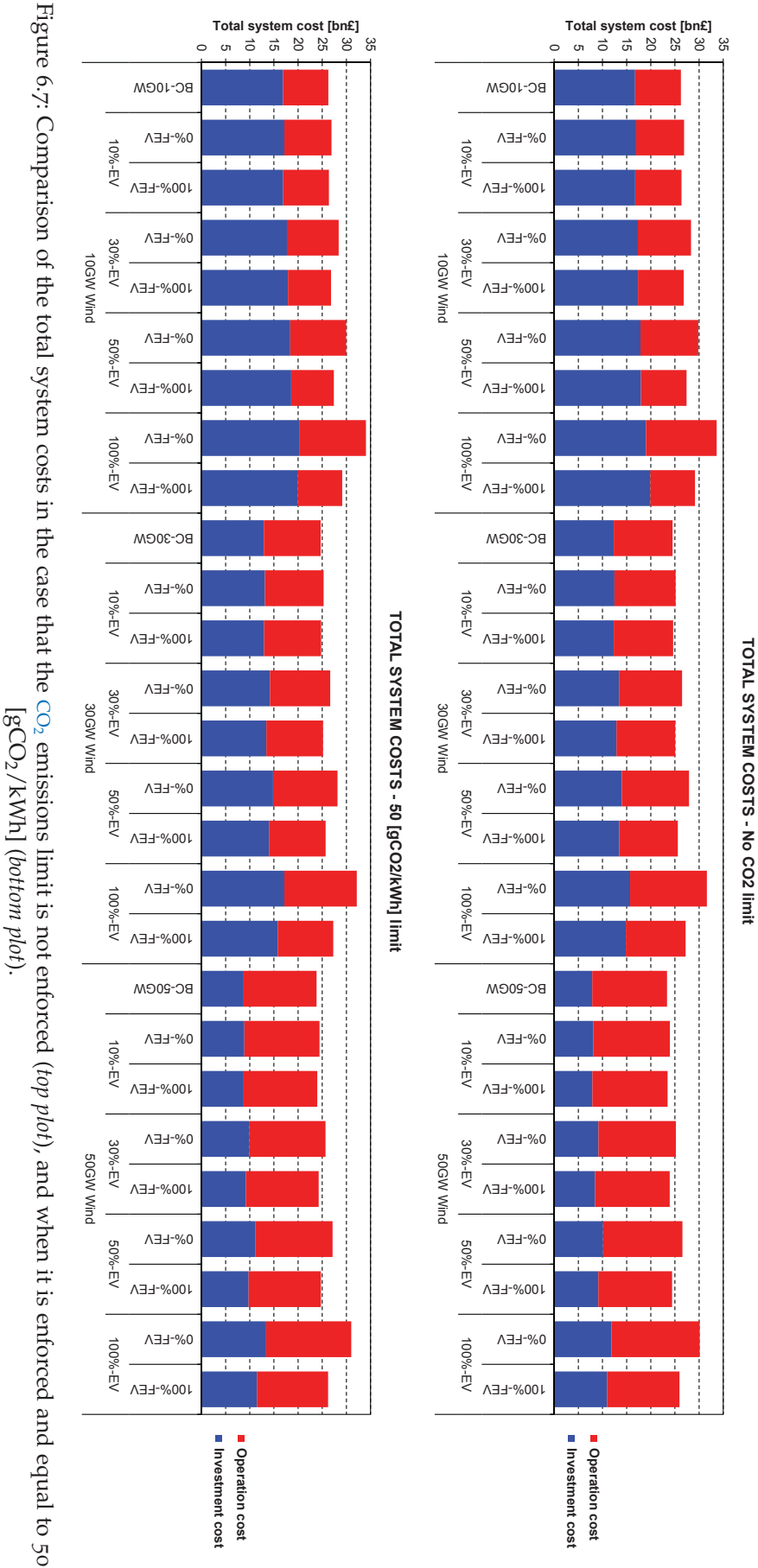


Figure 6.6: Comparison of the optimal conventional generation mixes in the case that the CO_2 emissions limit is not enforced (*top plot*), and when it is enforced and equal to 50 $[\text{gCO}_2/\text{kWh}]$ (*bottom plot*).



considered, as shown in figures 6.2 and 6.8 respectively. Furthermore, the resulting flattening of the demand profile increases the proportion of baseload nuclear generation in the system, as shown in figure 6.6. This leads to more capital intensive generation systems, but with significantly smaller total operation cost for larger EV penetration levels, as shown in figure 6.7.

Figure 6.8 clearly shows the economic value that EV flexibility generates, since the total cost, i.e. investment and operation, of the power system is significantly lower compared to the respective fully inflexible EV scenario, and also close to the total cost in the base case scenarios. From an environmental point of view, the increased capacity of nuclear generation, the increased utilization of available wind power, and the reduction of traditional gas-fired generation capacity (CCGT and OCGT), translates into a significant reduction of the CO₂ emissions if EV are operated flexibly, as shown in figures 6.9 and 6.10, where the level of renewable energy curtailment and the CO₂ emissions intensity are shown.

EV flexibility allows absorbing more renewable energy, improving the use of renewable energy in at least 20% for low levels of EV penetration, and up to almost 100% for high levels of EV penetration as shown in figure 6.9. It must be noted that although flexible EV allow reducing the levels of CO₂ emissions, their penetration and quantity does not allow reducing them in order to achieve the CO₂ emissions limit established for the power system as shown in figure 6.10, and then additional measures are required, i.e. limit the total carbon emissions and/or increase the CO₂ price, as analysed in Section 5.2.

The benefits from EV flexibility can have a big impacts in power system that expects large amounts of renewables to be incorporated in the near future. Their flexibility, in combination with the amount of these assets and their temporal and spatial diversity can allow, in the operational timescale, handling quick variations of intermittent generation (and also outages of conventional generation and transmission lines), improving security of supply and helping to reduce the thermal stress to which conventional generation is expected to be exposed. Flexible EV movability will allow also avoid operating baseload generation at their minimum stable operation level when the power produced by VRE resources is capable of supplying most or entire electricity demand, and also reduce the cycling regime of conventional generation, leading to reduced system operation costs, and thus, to improve the efficiency of the power system. The contribution of flexible EV to system flexibility will improve the usage of the available renewable energy, and reduce the amount of flexibility required from the generation side.

Finally, the absorption effect introduced by flexible EV could help reducing the volatility of energy prices, as EV flexibility can be used to stabilize net-demand, which can improve the certainty for investors in capital intensive generation technologies, and can translate into reduced energy costs for electricity consumers. This will be topic for further research.

6.2 CO-OPTIMIZATION OF GEP & EV FLEXIBILITY

Environmental and energy security concerns have paved the way for the wide decarbonisation of energy systems through the large-scale integration of renewable generation and the electrification of transport and heat sectors. This paradigmatic change however introduces

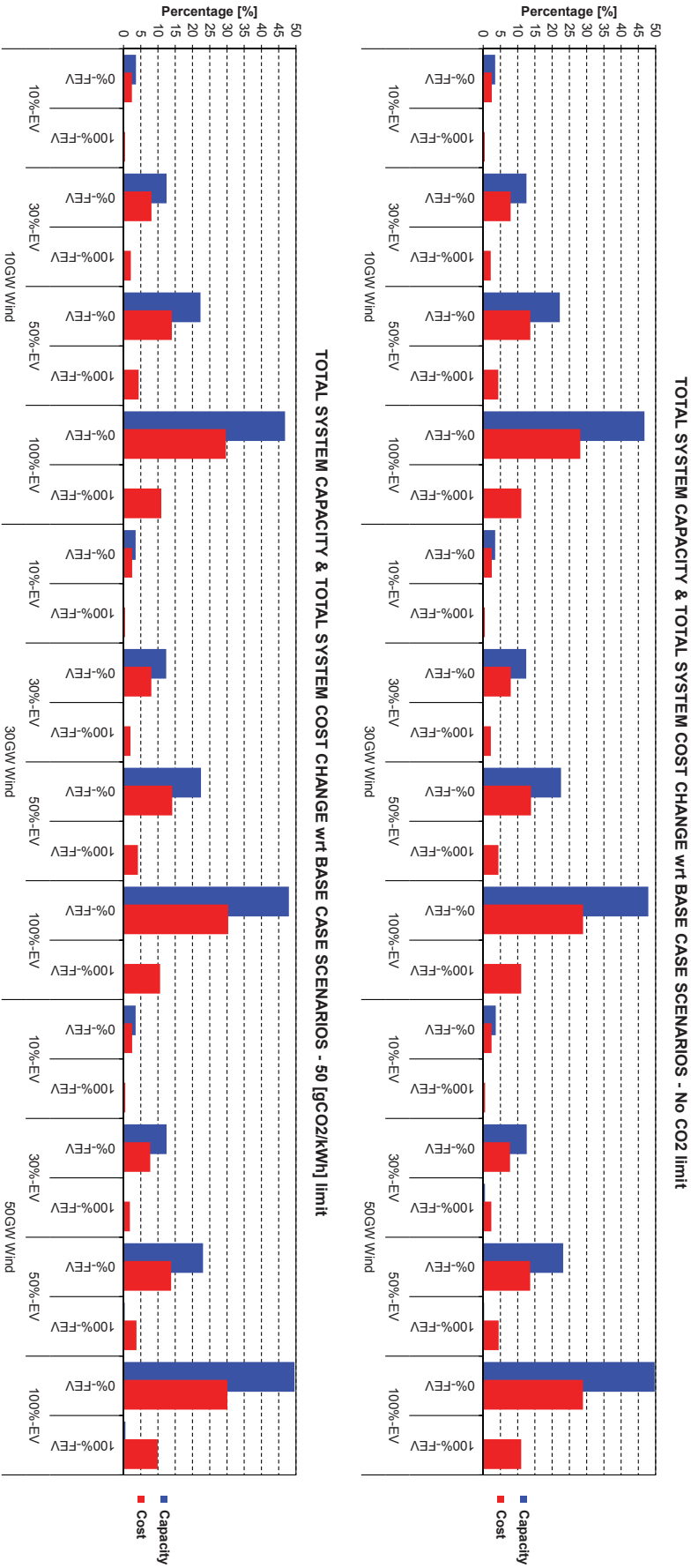


Figure 6.8: Comparison of the total system conventional generation capacity (*blue bars*) and total system cost (*red bars*) change with respect to the base case scenario of each wind generation level in the case that the CO₂ emissions limit is not enforced (*top plot*), and when it is enforced and equal to 50 [gCO₂/kWh] (*bottom plot*).

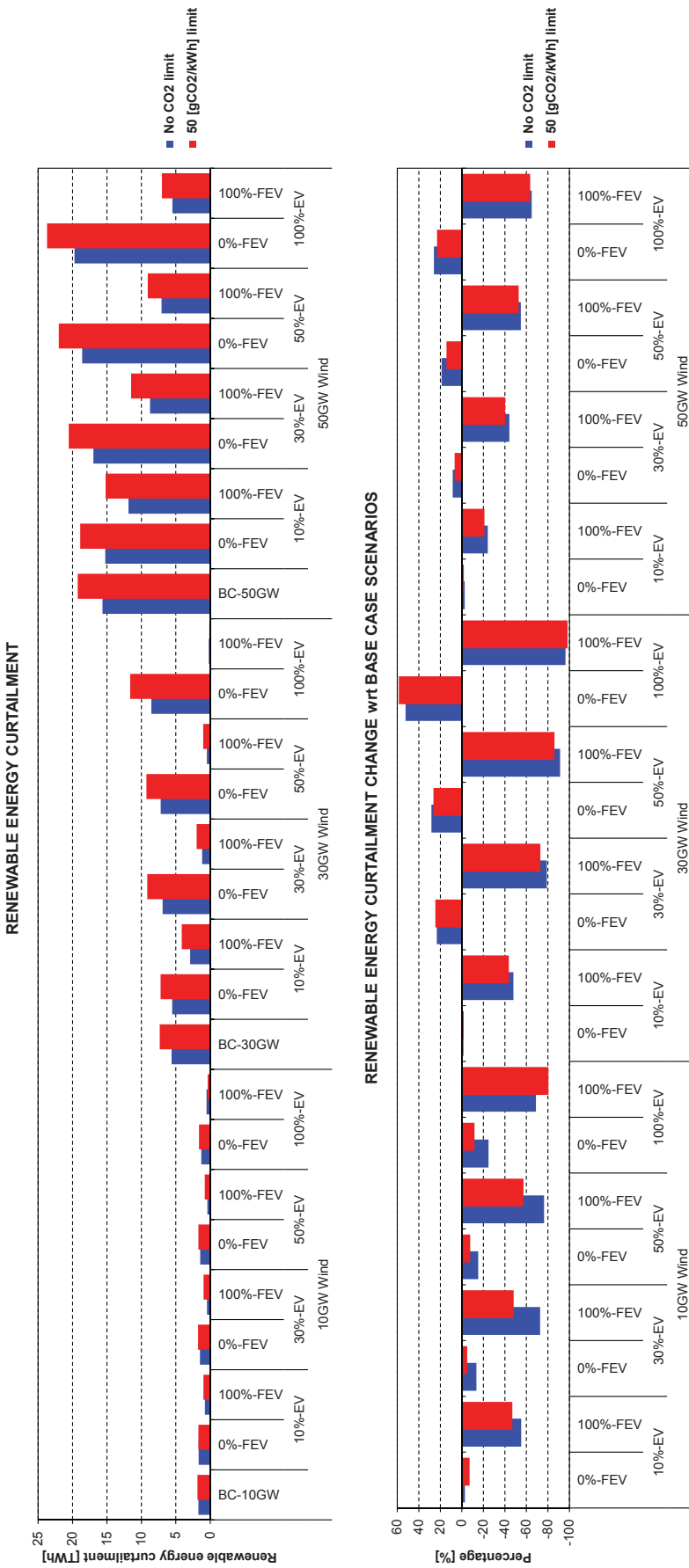


Figure 6.9: Comparison of the level of renewable energy curtailment (*top plot*), and the renewable energy curtailment change with respect to the base case scenario of each wind capacity level (*bottom plot*), in the case that the CO₂ emissions limit is not enforced (*blue bars*), and when it is enforced and equal to 50 [gCO₂/kWh] (*red bars*).

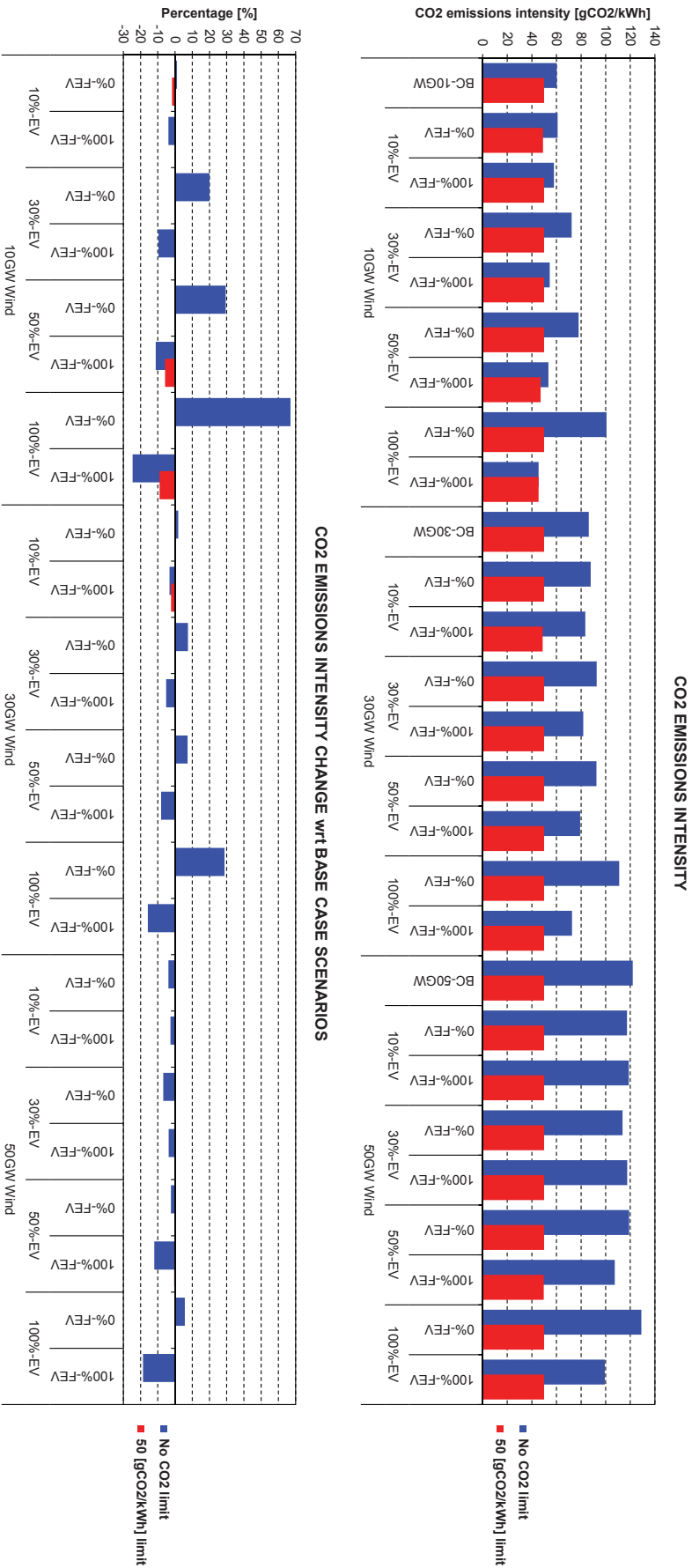


Figure 6.10: Comparison of the level of CO₂ emissions intensity (*top plot*), and the CO₂ emissions intensity change with respect to the base case scenario of each wind capacity level (*bottom plot*), in the case that the CO₂ emissions limit is not enforced (*blue bars*), and when it is enforced and equal to 50 gCO₂/kWh (*red bars*).

significant challenges to the operation and development of modern power systems. The limited controllability and predictability of renewable generation is expected to require large volumes of flexible conventional generation, implying adverse economic effects. Furthermore, the envisaged electrification of transport and heat sectors will lead to disproportionately larger demand peaks—and subsequently higher generation and network costs—than the increase in the total electrical energy consumption, due to the temporal patterns of users' driving and heating requirements [247].

In this context, flexible demand technologies attract great interest due to their ability to redistribute users' electricity demand requirements in time, through the employment of different types of storage [248]. Smart coordination of such demand flexibility could reduce the requirements for flexible generation capacity and limit peak demand levels, improving significantly the economic efficiency of future low-carbon power systems. Despite the significant potential and great interest in flexible demand, its incorporation into system planning has yet to be analysed in depth and with sufficient detail.

Most of the works that can be found in literature, as discussed in Section 4.6, consider fixed flexible demand penetrations and do not account for the cost of introducing and coordinating flexibility at the demand side. In reality, the realization of the flexible demand potential involves the installation and operation of suitable metering, control and communication infrastructure. The benefits of flexible demand in system development can only be accurately assessed if the costs of such enabling infrastructure are also considered in generation expansion planning.

In the following case study, the effects of EV flexibility, and their enabling costs, on GEP are studied using the Strategic-GEP model. This case study, unlike the previous one, does not assume fixed penetration levels of flexible EV but instead determines the optimal number of flexible loads along with the optimal portfolio of generation assets. The assumptions made for this case study are similar to those presented in Section 6.1, but with the following modifications:

- The system CO₂ intensity limit was set at 50 [gCO₂/kWh], and the CO₂ price at £76/tonneCO₂.
- Flexible demand involves EV with smart (controllable) charging capability, the realization and coordination of which requires certain costs per EV. Although the total EV penetration constitutes a fixed input of the model, the proportion of flexible EV is a decision variable in this case. Flexible EV demand is optimally scheduled in the operational timescale and constitutes a decision variable, whilst that of each inflexible EV is a fixed input and is derived by assuming that they start charging their batteries immediately after they are plugged into the grid and until they are fully charged. However, the total inflexible EV demand is not fixed, but a function of the number of flexible EV.
- The examined scenarios involve the application of the Strategic-GEP model in the context of UK, for different EV penetration and wind generation levels.

- The enabling cost of EV flexibility, i.e. $FC_v^{EV-Flexibility}$,⁹ is changed from 0 to £2,000/EV-yr, in steps of £20/EV-yr, and it is assumed to be equal for all EV types.
- The base case scenarios do not consider EV in the system, and there is one base case scenario for each wind capacity level.

When EV flexibility can be deployed without cost, i.e. when the EV flexibility enabling cost is equal to £0/EV-yr, all EV on the system become flexible. As this cost increases, the proportion of flexible EV decreases, and beyond a flexibility enabling cost of approximately £1,020/EV-yr, deployment of flexibility for any type of EV in the system cannot be economically justified in any of the examined EV penetration and wind generation scenarios.¹⁰

Given the assumed home-charging scenario, in combination with the fact that most users return home during evening hours (17:00-20:00), inflexible EV demand coincides with the non-EV system demand peak as shown in the previous section in figure 6.1. This results in increased peak demand levels as can be seen in figure 6.11, where a comparison of the net-demand load duration curves is made for fully inflexible and fully flexible EV operation.¹¹

The larger peak demand levels under inflexible EV operation result in larger requirements for mid-merit and peaking gas-fired generation, i.e. CCGT, CCGT-CCS and OCGT, with respect to the base cases, and in reduced requirements for baseload nuclear generation, because the increased variability and unpredictability of net-demand due to the VRE resources makes this generation technology a less-cost-effective option for installation. This is shown in the top plot of figure 6.12, where the optimal conventional generation matrix composition is depicted for different values of $FC_v^{EV-Flexibility}$, and different EV penetration and wind generation levels. The share of baseload generation is also reduced as the installed wind capacity increases, since more flexible generation is required to absorb the increased variability introduced by wind and solar PV generation, to provide the higher reserve requirements, and also to satisfy the CO₂ emissions limit constraint. Given that mid-merit and peaking generation are characterized by higher operational and lower investment costs with respect to baseload generation, increased inflexible EV penetrations and wind generation levels yield systems with larger operation cost proportions, as shown in the bottom plot of figure 6.12.

On the other hand, under flexible EV operation EV demand is optimally rescheduled towards off-peak (valley) hours, which allows reducing peak demand levels and significantly flattening the net-demand profile, as shown in figures 6.11 and 6.5. The reduced levels of net-demand variability translate into larger requirements for baseload nuclear generation with respect to the inflexible EV operation scenario, reduced requirements for mid-merit and peaking generation, and subsequently into systems with higher investment cost proportions, as shown in the

⁹ $FC_v^{EV-Flexibility}$ corresponds to the annuitized cost in metering, control and communication infrastructure, required to enable and coordinate the flexible operation of a single EV of type v .

¹⁰ It must be noted that the EV flexibility enabling cost level for which all EV are inflexible is not the same for all EV penetration and wind generation levels. Such level depends on how much value can be extracted from EV flexibility, which is given by the different uses that can be given to their movability potential, such as lowering peak demand levels, absorption of excess of renewable energy, and provision of reserve services, among others. In this case study it is assumed that EV flexibility can only help reducing peak demand levels and also diminish primary and secondary reserve demand levels. The other potential benefits of flexible EV are not explored and will be topic for further research.

¹¹ $FC_v^{EV-Flexibility}$ equal to 1,020 and £0/EV-yr respectively.

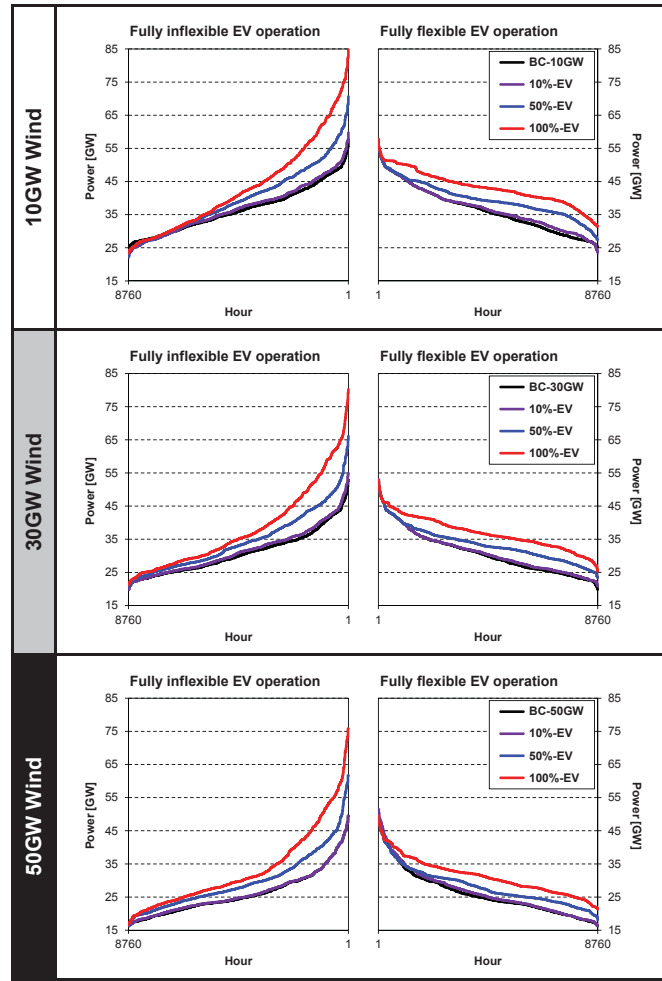


Figure 6.11: Comparison of the net-demand load duration curves for the extreme EV flexibility enabling costs, i.e. £1,020/EV-yr (fully inflexible EV operation) and £0/EV-yr (fully flexible EV operation), and different EV penetration and wind generation levels.

top and bottom plots of figure 6.12 respectively. These effects are enhanced as the enabling cost of EV flexibility decreases, since a higher number of flexible EV are cost-effectively integrated into the system, and thus a more significant flattening of the demand profile is achieved.

Figure 6.13 illustrate the total system conventional capacity, total system cost and renewable energy curtailment levels, when the option of EV flexibility deployment is available and function of the EV flexibility enabling cost.¹² Table 6.2, on the other hand, compares the extreme cases, i.e. full inflexible EV and full flexible EV operation, to show the savings in terms of conventional generation capacity, system cost, renewables curtailment and energy price that EV flexibility can generate. As the enabling cost of EV flexibility decreases, the number of flexible EV is increased, and therefore the net-value of EV in terms of total costs and generation capacity is enhanced. This can also be visualised in figure 6.14, where the load weighted energy price is shown as a function of the EV flexibility enabling cost, for the different EV penetration and wind generation levels analysed. Flexible EV operation can help reducing energy prices between 2% and 18% with respect to the full inflexible EV operation scenario, which can

¹² The optimal conventional generation mix, and the investment and operation costs can be found in figures B.1 and B.2.

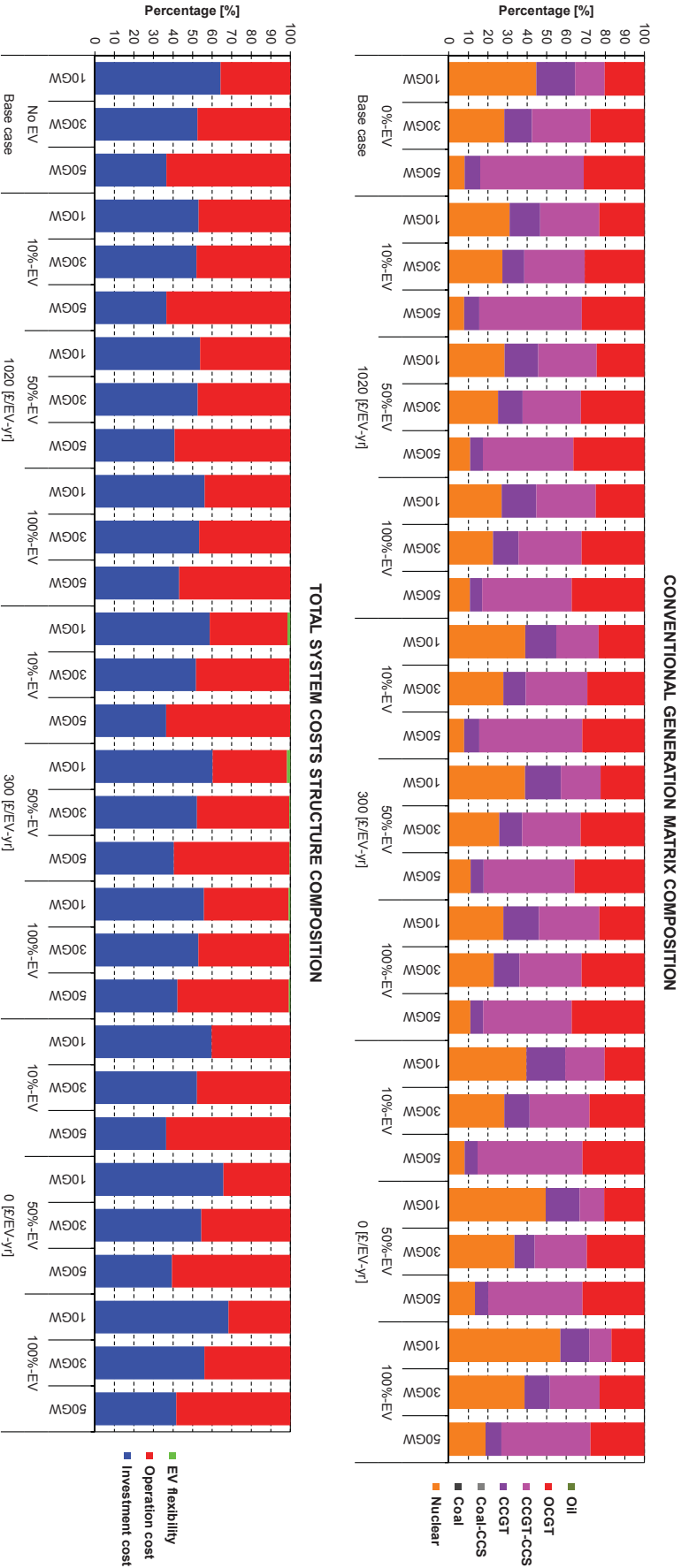


Figure 6.12: Comparison of the optimal conventional generation matrix composition (*top plot*), and the total system costs structure composition (*bottom plot*), for different EV flexibility enabling costs, and different EV penetration and wind generation levels.

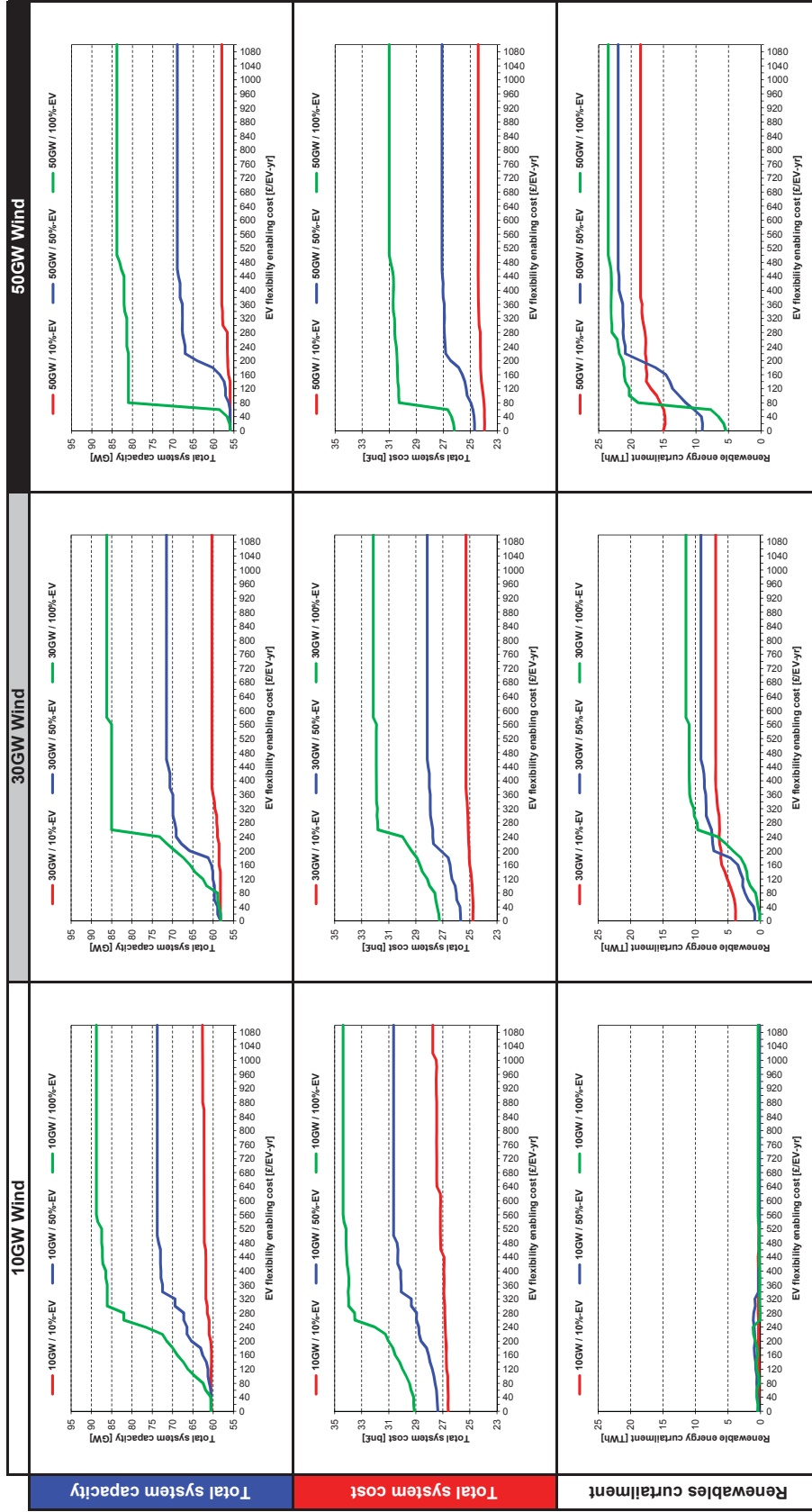


Figure 6.13: Total system conventional capacity (*first row*), total system cost (*second row*), and renewable energy curtailment (*third row*) levels as a function of the EV flexibility enabling cost for different EV penetration and wind generation levels.

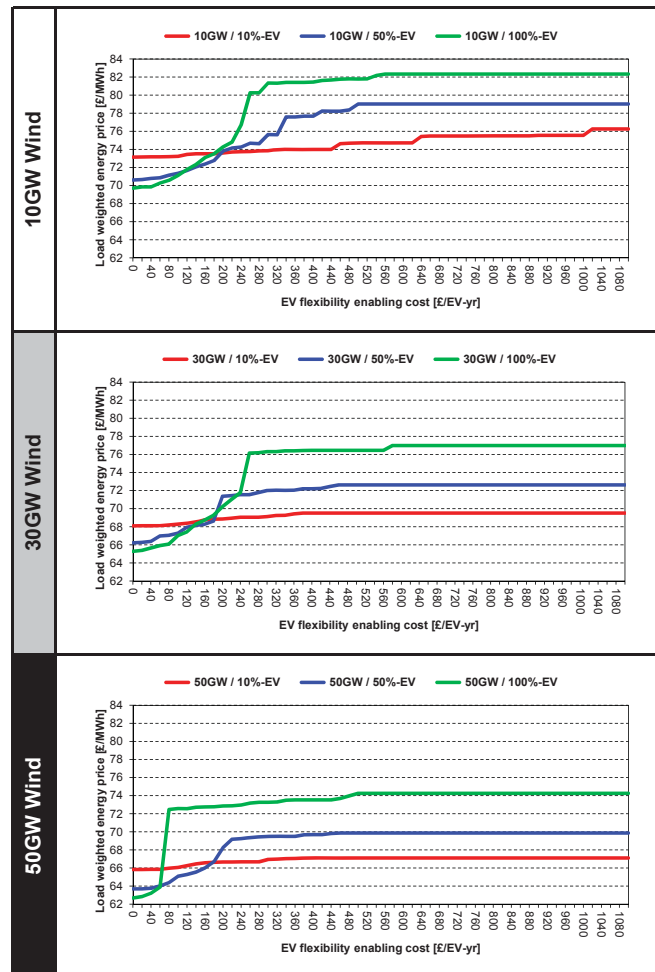


Figure 6.14: Load weighted energy price level as a function of the EV flexibility enabling cost for different EV penetration and wind generation levels.

Table 6.2: Comparison of the total system conventional capacity, total system cost, renewable energy curtailment and load weighted energy price increments with respect to the full flexible EV operation, and also with respect to the base case scenarios.

Basis of comparison	EV operation scenario	Wind capacity	EV penetration	Total system conv.		Total system		Renewable energy		Load weighted	
				capacity increment (GW)	increment (%)	cost increment (bn£)	cost increment (%)	curtailment (TWh)	curtailment increment (%)	energy price increment (£/MWh)	energy price increment (%)
Full inflexible EV operation	N/A	10GW	10%	2.19	4%	1.14	4%	0.00	0%	3.12	4%
			50%	13.24	22%	3.26	12%	0.00	0%	8.41	12%
			100%	28.24	47%	5.27	18%	0.00	0%	12.62	18%
		30GW	10%	2.11	4%	0.52	2%	3.06	79%	1.42	2%
			50%	13.35	23%	2.48	10%	8.31	925%	6.40	10%
			100%	28.07	48%	4.89	18%	11.34	6810%	11.71	18%
	EV operation	50GW	10%	2.03	4%	0.46	2%	3.52	23%	1.27	2%
			50%	13.04	23%	2.40	10%	12.95	143%	6.18	10%
			100%	27.92	50%	4.84	18%	18.11	334%	11.59	18%
		10GW	10%	2.23	4%	1.51	6%	0.00	0%	2.89	4%
			50%	13.37	22%	4.40	17%	0.00	0%	5.65	8%
			100%	28.36	47%	8.15	31%	0.00	0%	8.96	12%
Base case scenarios	Full inflexible EV operation	30GW	10%	2.04	4%	0.78	3%	-0.40	-6%	0.60	1%
			50%	13.25	23%	3.65	15%	1.87	25%	3.71	5%
			100%	27.96	48%	7.64	31%	4.18	57%	8.08	12%
		50GW	10%	1.96	3%	1.06	5%	-0.67	-3%	0.53	1%
			50%	12.93	23%	3.73	16%	2.75	14%	3.29	5%
			100%	27.79	50%	7.65	33%	4.29	22%	7.67	12%
	Full flexible EV operation	10GW	10%	0.04	0%	0.38	1%	0.00	0%	-0.23	0%
			50%	0.13	0%	1.14	4%	0.00	0%	-2.76	-4%
			100%	0.12	0%	2.88	11%	0.00	0%	-3.66	-5%
		30GW	10%	-0.07	0%	0.27	1%	-3.47	-47%	-0.82	-1%
			50%	-0.10	0%	1.17	5%	-6.44	-88%	-2.69	-4%
			100%	-0.11	0%	2.75	11%	-7.17	-98%	-3.64	-5%
	50GW	10%	-0.07	0%	0.60	3%	3%	-4.19	-22%	-0.75	-1%
		50%	-0.11	0%	1.34	6%	6%	-10.20	-53%	-2.89	-4%
		100%	-0.13	0%	2.81	12%	12%	-13.82	-72%	-3.91	-6%

Table 6.3: Comparison of the EV flexibility deployment threshold with respect to the plug-in time for different EV penetration and wind generation levels.

Plug-in time	EV flexibility enabling cost (£/EV-yr)								
	10GW Wind			30GW Wind			50GW Wind		
	10%-EV	50%-EV	100%-EV	10%-EV	50%-EV	100%-EV	10%-EV	50%-EV	100%-EV
10:00	640	60	20	120	100	40	140	80	60
11:00	460	100	20	100	60	40	100	100	120
12:00	120	60	60	80	60	40	120	60	40
13:00	100	140	100	80	60	60	80	80	100
14:00	60	80	100	80	60	100	80	80	100
15:00	100	100	120	100	120	100	80	100	100
16:00	200	160	160	120	120	140	120	100	40
17:00	640	220	260	280	200	240	220	220	140
18:00	1,020	340	540	380	460	580	580	380	500
19:00	1,020	500	560	240	440	580	220	460	480
20:00	1,020	400	300	240	280	340	180	240	280
21:00	460	140	180	160	140	160	140	160	40
22:00	460	20	20	60	40	40	80	40	40
23:00	80	20	20	40	20	20	60	80	20

translate into savings of between £1.27 and £12.62 per megawatt-hour of energy consumed in average.

It is worth stressing that for the same value of $FC_v^{EV-Flexibility}$, the value of EV flexibility increases with an increasing EV penetration, as the economic implications of inflexible EV operation—in terms of employment of peaking generation with high operational costs—are aggravated. On the other hand, the value of EV flexibility is lower as the renewables penetration increases. This is justified by the fact that the increased variability introduced by VRE resources in net-demand translates into higher requirements for reserve services, and due to EV are assumed to be not able of providing any type of reserve their flexibility value decreases.¹³ This highlights the potential and additional value that using EV to provide reserve services, and also to inject power into the grid, can generate for future power systems and for the wide decarbonisation of demand and power generation.

Interesting conclusions are also drawn by analysing the types of EV that are selected by the optimization model to become flexible. For the sake of this analysis, the different EV are categorized according to: a) the time they get plugged into the grid (after the end of their second journey); and b) the daily distance of their journeys (two categories are considered, i.e. EV with short and long journeys, which group the EV with daily travelled distances smaller and larger than 30 kilometres respectively). Tables 6.3 and 6.4 present the minimum value of $FC_v^{EV-Flexibility}$ for which EV flexibility is not deployed in each of the previously defined categories (none of the EV of the respective category is selected to become flexible), for the different EV penetration and wind generation levels analysed.

¹³ It must be noted that EV flexibility in the Strategic-GEP model current formulation, can help reducing the demand levels for reserve services. The rescheduling capability of flexible EV can reduce the levels of electricity demand during peak hours when renewable generation is low, and thus reduce the reserve requirements during those hours. However, only for low levels of renewables penetration this generates clear benefits. The reserve requirements are proportional to the renewables power available and their forecast errors, and also to the load and EV demand levels at each hour. For large-scale renewables penetration, and during hours of high levels of generation from those VRE resources, the value of rescheduling flexible EV consumption to those hours decrease, as they only help to increase the demand levels of reserve services that can only be provided by conventional generation. This is the reason why, for larger levels of EV penetration, the value of their flexibility decreases at a higher rate, and also the reason why flexible EV penetration becomes more sensitive to the EV flexibility enabling cost.

Table 6.4: Comparison of the EV flexibility deployment threshold with respect to the journey's length for different EV penetration and wind generation levels.

Journey's length	EV flexibility enabling cost (£/EV-yr)								
	10GW Wind			30GW Wind			50GW Wind		
	10%-EV	50%-EV	100%-EV	10%-EV	50%-EV	100%-EV	10%-EV	50%-EV	100%-EV
Short	640	260	300	300	380	260	300	200	220
Long	1,020	400	540	340	460	580	580	460	500

Table 6.3 demonstrates that the threshold value of $FC_v^{EV-Flexibility}$ is very large for EV that are plugged-in at around peak demand times (18:00-19:00) and gradually decreases as we move to plug-in times away from this peak period.¹⁴ This result reveals the increased value of flexibility deployment in EV the plug-in time of which coincides with the demand peak, as their inflexible operation would aggravate the economic implications of peaks. This can be visualized in figure 6.15 that shows the evolution of the total inflexible EV demand as a function of the EV flexibility enabling cost, for the different EV penetration and wind generation scenarios analysed. Furthermore, the value of flexibility deployment is higher for EV with larger travelling distances, as shown in table 6.4, as their total electrical energy requirements are higher, and therefore they offer a higher amount of re-distributable energy to the system when they become flexible.

The developed simulations demonstrate that EV flexibility significantly flattens net-demand profile by reducing peak demand levels and absorbing the variability introduced by wind generation, and subsequently impacts the optimal generation mix by allowing the cost-effective integration of a larger proportion of baseload nuclear generation. The value of EV flexibility in terms of total system cost savings and total installed conventional generation capacity reduction are shown to increase with an increasing electrification of the transport sector, highlighting the enhanced potential of flexible demand in a future with wide decarbonisation of demand and power generation.

Furthermore, the results illustrate the dependency of the optimal number of flexible EV and the net-value of EV flexibility on the cost of the enabling equipment, and quantify upper bounds for this cost at the different EV penetration and wind generation levels, above which deployment of EV flexibility is not economically justifiable. Finally, the value of EV flexibility is shown to depend on the travelling patterns of EV users, with EV plugged into the grid during demand peak periods and EV with larger travelling distances yielding higher system benefits when becoming flexible.

¹⁴ For low levels of EV penetration, an increase in the threshold value of $FC_v^{EV-Flexibility}$ for initial plug-in hours can be observed. This behaviour is due to the electricity demand has a first peak between 10:00 and 14:00 approximately, that increases the flexibility value of the EV that connect to the grid before reaching that peak. This is demonstrated by the decrease of the threshold value that can be observed between the first and second peaks of the demand, which is because the EV demand contribution makes the total electricity demand level smaller than the level of the first peak. This behaviour gets reduced as the EV penetration level increases, which demonstrates that for larger EV penetration levels, their power demand contribution during the valley between the non-EV system demand peaks increases total demand above the level of the first peak.

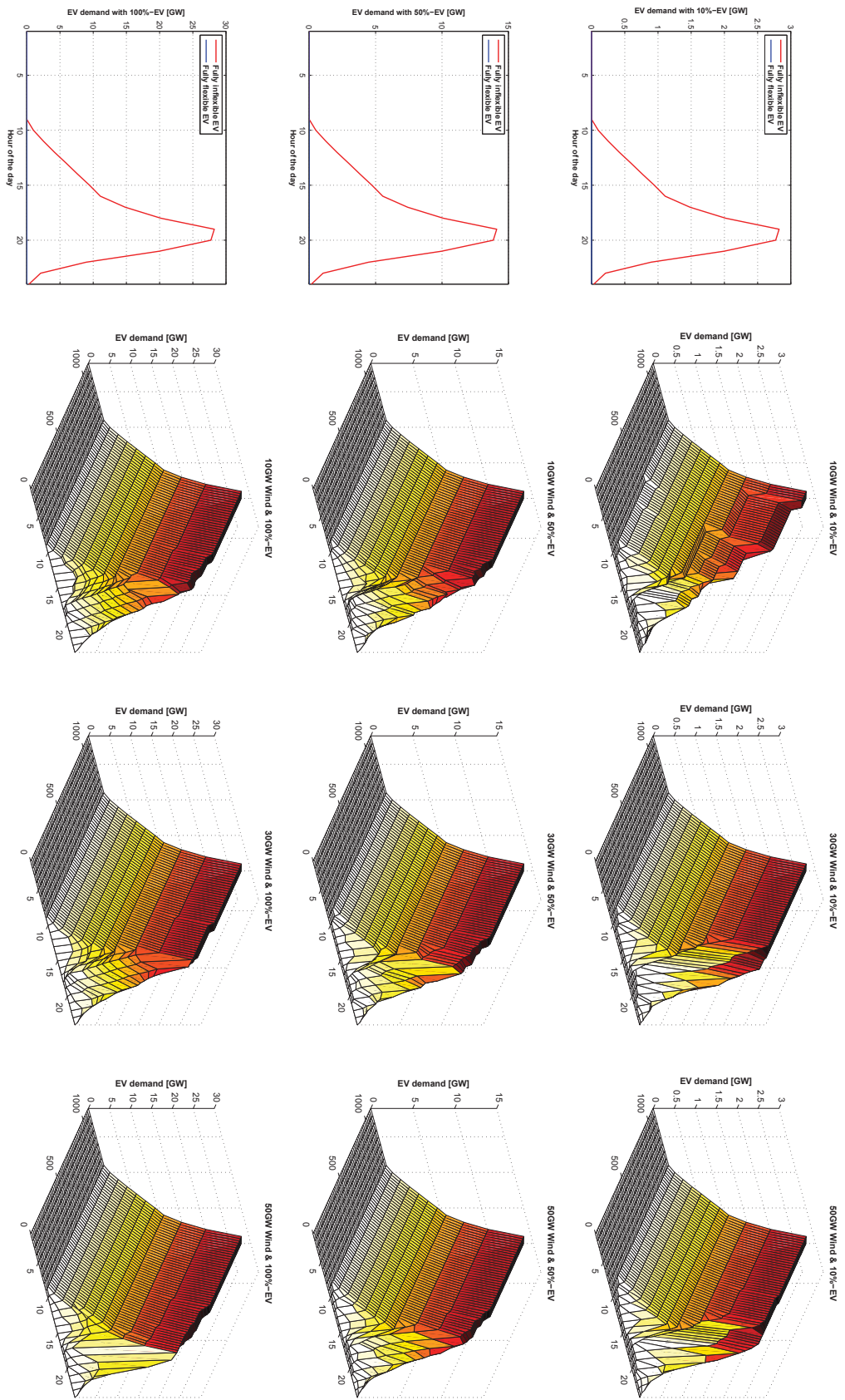


Figure 6.15: Inflexible EV demand evolution as a function of the EV flexibility enabling cost for different EV penetration and wind generation levels. The x -axis corresponds to the hours of the day, the y -axis to the EV flexibility enabling cost, and the z -axis to the total electricity demand from inflexible EV.

6.3 CONCLUSIONS

Electricity demand plays a mayor role in the future evolution of power systems, and also in the effective and efficient integration of renewables. The relevance of this role is being intensified even further by the envisaged electrification of other energy sectors such as transport and heating, and also by the large-scale penetration of renewables. Rapid developments and wide penetration of flexible demand technologies, which allow smartly controlling electricity demand in time, offer the chance of using demand as a potential and critical source of flexibility for power systems.

Incorporating a detailed modelling of the flexible demand dynamics can lead to notorious changes in the optimal generation mix and in its operation. Generation expansion planning needs not only to consider conventional generation flexibility, but also the flexibility characteristics of the demand side, in order to achieve a richer and more realistic representation of the real operation of power systems that will allow improving the assessment of the long-term generation investment decisions. This will also help regulators in their decision making processes, which will allow them designing better, more stable and long-term energy policies.

Among all available flexible demand technologies, electric vehicles offer a great potential not only due to their penetration, technological developments and compatibility, but also due to they can help mitigate CO₂ emissions. Movability of flexible EV, combined with their temporal and spatial diversity, can allow damping electricity demand peaks, reducing the demand for flexible generation, and increasing baseload capacity. If EV flexibility is smartly used, it will facilitate the integration of renewable generation, since will allow to increase and improve power systems flexibility, and thus, it will help absorbing renewables unpredictable variability, which will translate into improved renewable energy utilization and net-demand levelling, and therefore into more efficient power systems.

Demand flexibility is critical for expansion of future low-carbon power systems as it can help to massively reduce CO₂ emissions. This suggests that policies pro-flexible demand technologies will critically help governments in achieving their decarbonisation targets, and also in their effort to maintain electricity supply secure and affordable for consumers.

Part IV

FINAL WORDS

CONCLUSIONS & FUTURE WORK

Over the next decades a significant increase in the amount of renewable generation is expected in many countries around the world. The inherent intermittency and stochasticity of those energy sources and their contribution to electricity demand will greatly increase the time dynamics of net-demand. The electrification of other energy sectors, distributed generation, new storage technologies, and flexible and efficient demand side resources, among others, will also contribute by introducing new dynamics at multiple timescales in net-demand.

This new scenario is creating great concern in governments, who begin to fear an imminent compromise of the resource adequacy and security of supply of their power systems. This is due to the multiple challenges to which the electricity industry is and will be exposed, especially those related to the large-scale deployment of renewables that are required to meet the ambitious carbon emissions reduction targets to which governments have committed themselves.

These commitments to maintain electricity supply secure and affordable require the delivery of advanced, reliable, cost-effective and sustainable power systems. All these objectives demand revisiting the generation expansion planning methodologies and tools that are used today, because the vast majority are based on practices, assumptions and simplifications that have become less valid in current and future low-carbon power systems.

The challenge to keep the lights on is today a worldwide issue, which has many dimensions for all electric industry stakeholders. One of those dimensions was the key driver of this research: the study and modelling of the generation expansion planning of power systems with a high degree of renewables and vehicle electrification, with the specific objective of analysing and understanding the role that flexibility will have in this economic process and future scenario.

The previous objective was achieved by developing a methodology for capturing and modelling flexible demand and conventional generation technical and operational characteristics, and also by proposing a novel computationally efficient generation expansion planning model that successfully includes the flexibility characteristics of conventional generation and flexible demand resources, specifically electric vehicles.

The methodologies and the model developed in this thesis facilitate the successful merging of power system operation modelling and generation expansion planning into a single model. This allows the calculation of optimal generation mixes that are operationally feasible for the different flexibility scenarios expected due to the large-scale deployment of renewable generation and vehicle electrification, and that can ensure carbon emissions targets are met.

Finally, the developed model and case studies allow an understanding, assessment and quantification of the short and long-term economic and environmental value of generation and electric vehicles flexibility, as well as the dependence of this value on the enabling costs, and users' travelling patterns (in the case of electric vehicles).

7.1 RESEARCH CONTRIBUTIONS

The following original contributions are made by this thesis:

- Development of a computationally efficient generation expansion planning model that allows the assessment of the short and long-term economic and environmental performance of power systems with large volumes of renewables and high degrees of transport electrification.
- Development of a methodology for capturing, modelling and incorporating a detailed representation of the technical and operational characteristics of flexible demand, in the form of large fleets of smart charging electric vehicles, in generation expansion planning. Electric vehicles are grouped into different types using the concept of clustering, which allows avoiding non-linearities in the model formulation.
- The developed generation expansion model, apart from including the full set of different conventional generation technologies flexibility characteristics, allows to optimally scheduling the electricity demand of flexible electric vehicles according to a detailed model of their users' travelling requirements and batteries/grid connections' technical properties.
- In contrast to previous works, the enabling costs for introducing and coordinating electric vehicles flexibility are explicitly incorporated in the proposed model. This allows determining the optimal number of flexible electric vehicles along with the optimal portfolio of generation assets.
- Compare and quantify the economic and environmental implications of considering conventional generation flexibility characteristics in generation expansion planning, with respect to traditional expansion planning that neglects them.
- Analyse and quantify the economic and environmental impacts of carbon emissions regulations and their potential interaction with power system flexibility.
- Estimate and quantify the economic and environmental benefits that can be achieved by investing in the improvement of conventional generation flexibility characteristics and how those benefits change depending on the enabling costs, under different scenarios of renewable generation and vehicle electrification.
- Comprehensive assessment of the economic and environmental implications of inflexible electric vehicles operation, and the benefits that can be obtained by smartly controlling their electricity consumption.

- Analyse the relationship between the value delivered by electric vehicles flexibility, the cost of the technology required to enable such flexibility, and the users' travelling patterns. This allows identifying and informing industry stakeholders regarding the types of electric vehicles that create more value when becoming flexible.

7.2 CONCLUSIONS

- A novel large-scale mixed integer generation expansion planning that includes a detail representation of the conventional generation and electric vehicles flexibility characteristics is proposed in this thesis (Section 4.6). Computational tractability and efficiency of the model are achieved by clustering conventional generation and flexible demand resources, which allows using integer instead of binary decision variables (Sections 4.2.4, 4.3.3 and 4.4.3). The use of integer variables allows reducing the model size in terms of both decision variables and constraints as quantitatively explored in Section 4.6.11, and also avoids non-linearities in the model formulation. The proposed integer formulation allows reducing the number of discrete decision variables and constraints by 500x and the solution time by approximately 58x with respect to the binary traditional formulation, as shown in table 4.3.
- The developed case studies show clear evidence of:
 1. the implications of simplifying or ignoring system flexibility characteristics in generation expansion planning (Section 5.1);
 2. the role of generation and demand flexibility in the integration of renewables and carbon emissions reduction (Chapters 5 and 6);
 3. the potential interactions between carbon emissions regulations and power system flexibility (Section 5.2);
 4. the economic and environmental value of improving conventional generation flexibility (Section 5.3);
 5. the economic and environmental value of using electric vehicles flexibility (Section 6.1);
 6. and, the value of demand flexibility and how it change depending on the cost of the flexibility enabling technology and EV users' travelling patterns (Section 6.2).
- The power output of renewable generation fluctuates depending on the available resource. Such fluctuations impact net-demand, increasing its variability in amplitude, frequency and rate of change, as analysed in Section 3.3 and clearly shown in figures 3.17, 3.19 and 3.21. In the case of the simulations presented in Section 3.3, i.e. for a 50% share of renewable generation (approximately 73GW between wind and solar PV), the peak-to-peak amplitude of net-demand variability is 2x bigger, the standard deviation of net-demand increases by 55%, and the rate of change inter-period is 2.7x bigger compared to original demand. This requires demand and supply side components to change

their consumption or output faster and more frequently in order to maintain system balance.

- The fluctuations introduced by VRE resources in net-demand will also increase its unpredictability and result in the need for larger amounts of reserve services to compensate for these unexpected variations in power output, as analysed in Section 3.3 and clearly shown in figures 3.18 and 3.20. In the case of the simulations presented in Section 3.3, upward spinning reserve demand level are between 1.3x and up to 8.4x bigger compared to the original demand case. The increased demand for reserve services will require more flexible resources, which have been traditionally associated with quickly dispatchable generation. For example, comparing the base case scenario BC-50GW with respect to the base case scenario BC-10GW presented in Section 5.3, flexible gas generation share increases by 24%, while inflexible baseload capacity reduces by 77%, when the amount of renewable generation increases by 78%.
- The wide electrification of heat and transport, and the development of smart-grid technologies, can enable the use of alternative resources from generation and demand to provide flexibility, and also to potentially supply reserve services. For example, as shown in table 6.2, if the flexibility potential of flexible EV is not utilized, the installed capacity can increase by up to 50%, the total system costs can rise by up to 18%, the level of renewables curtailment can become up to 69x bigger, and the average energy prices can climb by up to 18%, with respect to the case in which EV flexibility is fully utilized.
- Generation planning of power systems that expect large-scale deployments of renewable resources need to evaluate the appropriate amount of system flexibility required to securely and reliably satisfy electricity demand. This means giving consideration to the flexibility characteristics of available and future resources in order to ensure that future power systems can integrate renewables effectively and efficiently and also satisfy carbon emissions targets. Oversimplifying or omitting the modelling of the technical and operational limitations of generation and flexible demand resources can have serious implications in the individual decision-making processes of all electricity industry stakeholders, potentially leading to:
 1. suboptimal or even infeasible generation mixes that can threaten renewables integration, greenhouse gas emissions reduction targets and security of supply as shown in Section 5.1;
 2. underestimate the investment and operating costs of power systems. For example, in Section 5.1, the traditional LP expansion planning approach underestimates the total costs of the system by approximately bn£4, i.e. 24% less than the value obtained with the Strategic-GEP model, and if the power system calculated with the GEP-LP model is dispatched respecting the flexibility characteristics of conventional generation, the system operation costs are approximately 16x bigger compared to those calculated by the GEP-LP model;
 3. overestimate the capability of power systems to follow net-demand and absorb renewable energy. For example, in Section 5.1, the power system obtained ignor-

- ing the flexibility characteristics of conventional generation leads to approximately 0TWh of load curtailment, and 0.5TWh of renewable energy spillage, while if the system is operated under real operational requirements those figures change to 8TWh and 10TWh respectively;
4. overestimate the contribution of renewable generation and the consequential reduction in carbon emissions;
 5. higher energy prices for consumers;
 6. and, lead to unstable, short-term and suboptimal market structures and energy regulations, which can result in power systems that are less reliable, inefficient and potentially more expensive for consumers.
- Improving conventional generation flexibility characteristics can translate into a series of economic and environmental benefits such as:
 1. Achieve significant cost savings in terms of investment and operation as analysed in Section 5.3 and shown in figures 5.11 to 5.13, and 5.16 to 5.18. From the investment point of view, increased flexibility can allow larger shares of low-carbon baseload generation to be cost-effectively accommodated, allowing larger portions of electricity demand to be supplied with cheap and clean energy, and reduce the share of gas-fired peaking generation (potentially less CCS equipped generation). It could also reduce total generation capacity, because more flexible generation units can operate over a wider range of their capabilities, i.e. operate at lower power output levels, provide larger amounts of reserve services, start-up and shut-down more frequently, etc. From an operating cost point of view, on the other hand, flexibility improvements can allow generating units to operate more efficiently and with less stress. This can significantly reduce the operating costs, as well as the costs associated with increased cycling. For example, reducing the minimum stable generation of CCGT generation can reduce the system operation cost by up to 20%, and improving the ramping capability of Nuclear generation can reduce the system operation cost by up to 31%.
 2. Improve the absorption of renewable energy, as shown in figures 5.14 and 5.19 (Section 5.3), by reducing the minimum stable generation of the whole system, as well as increasing its ramping capability, thereby reducing the burning levels of fossil fuels, and thus, carbon emissions. For example, reducing the minimum stable generation of CCGT generation can reduce renewables curtailment by up to 73%, and improving the ramping capability of Nuclear generation can reduce renewables curtailment by up to 67%.
 3. Help to extend the physical and economic lifetime of conventional generation.
 4. Help governments in their effort to ensure a clean, secure and affordable energy future for their citizens.
 - Providing the levels of flexibility required to securely supply demand and satisfy carbon emissions constraints by only building new conventional generation will be costly and

economically inefficient, as it ignores the key role of demand in the electricity production and consumption process as analysed in Chapter 6. The envisaged electrification of other energy sectors, such as transport and heating, intensifies even further the role of demand and the benefits that can be obtained from improvements in its side. Electricity demand from electric vehicles, if smartly controlled, is a potential source of flexibility that can help reducing the demand for new flexible generation, as it can be used to reduce net-demand's variability and unpredictability. In Section 6.1 is shown that, if the potential flexibility from EV is not used can increase total system capacity between 4% and 50%, i.e. between 2GW and 28GW of additional generation capacity, and total system costs between 3% and 30%, i.e. between bn£0.6 and bn£7.8. Renewable energy curtailment, on the other hand, can be reduced by between 1TWh and 12TWh by using EV flexibility.

7.3 KEY MESSAGES

- The proposed model generation expansion model will be useful for government, regulators, system planners, and energy and environmental analysts, amongst others, as it allows:
 1. the assessment of economic and environmental performance, at different timescales, for power systems that expect large volumes of renewable generation and electric vehicle penetration;
 2. the assessment of the impact of new market structures and regulations under different scenarios of renewable generation and electric vehicles penetration;
 3. the assessment of the economic and environmental implications of not using potential flexibility from electric vehicles;
 4. the assessment of the economic and environmental benefits that can be gained by improving conventional generation flexibility characteristics and by enabling electric vehicles flexibility;
 5. and, the identification of electric vehicle functionality that will enhance the value from flexibility.
- For small penetration levels of VRE resources, available generation and demand side resources can handle new net-demand. However, increasing deployments of renewable generation will make balancing the system a complex and challenging task, not only due to increased variability of net-demand, but also due to renewables power output clashing more frequently with the fluctuations of electricity demand. Such situations will be more severe and frequent for larger amounts of renewables, requiring more flexible resources to ensure security of supply.
- The effective and efficient integration of renewables will require governments, regulators and system planners to ensure there is suitable and sufficient system flexibility and also that such flexibility is available and can be reliably operated by grid operators. The need for system flexibility requires: a) access to sufficient physical flexibility on

the generation and demand side; and b) market structures and regulations that allow access to this physical flexibility. Power systems with insufficient levels of flexibility will need supplementary markets, incentives or new measures that can value flexibility. This is required to create price signals for new flexible resources and also to compensate flexibility providers for the additional costs incurred.

- Promoting and making use of the potential flexibility from electric vehicles can have, as shown in Section 6.2, economic and environmental benefits such as:
 1. Lead to significant cost savings in terms of investment and operation, as shown in figure 6.13 and table 6.2. EV flexibility allows rescheduling of their electricity demand towards low net-demand periods, which can allow the reduction of peak demand levels and a significant flattening of net-demand (see figures 6.1 and 6.5), allowing larger portions of electricity demand to be supplied by cheap and clean generation resources. It can also allow a reduction in the need for gas-fired flexible generation, and thus lower system operating costs. Investing in EV flexibility can also help extending the physical and economic life of existing and new conventional generation units, by reducing the mechanical stress to which they are expected to be exposed due to the large-scale penetration of renewables.
 2. EV flexibility can allow a reduction in the levels of renewables curtailment during periods of excess of energy, as they can permit increasing net-demand level, and thus, reduce the gap between such level and the minimum stable operation level of the whole system. Demand shifting of flexible EV can also allow the ramping needs of generation units to be reduced as they can be rescheduled in order to smooth net-demand when there are large variations between consecutive time periods. This can also contribute to a reduction in the levels of renewable energy curtailment and load shedding. Lower levels of renewable energy curtailment can result in lower fossil fuels consumption and carbon emissions, and lower energy prices (see figures 6.13 and 6.14).
- Generation and demand flexibility will play a key role in the development of future power systems, and the investment in improving and/or using such flexibility more effectively can also have considerable economic and environmental benefits as shown in this thesis. However, high technology costs can dominate over the benefits of such additional flexibility as analysed in Section 6.2, highlighting the role that regulators have in creating the compensation framework required for incentivising such efforts.
- The lengthy time required to build new generation facilities and to create awareness amongst electricity consumers as prospective demand side participants, requires taking immediate action in order to achieve the greenhouse gas emissions reduction targets for 2050.

7.4 FUTURE WORK

The work developed in this research, the limitations and potential expansions of the Strategic-GEP model, the assumptions made, the data limitations, together with its conclusions and findings summarized in this thesis have identified several important topics for further research:

IMPACT OF OTHER FLEXIBLE DEMAND TECHNOLOGIES This thesis only focused its attention on the potential flexibility of electric vehicles but there are other promising flexible demand technologies, such as electric heating and deferrable domestic appliances, which can also be analysed in order to compare and assess their impact on system planning. EV are only one of many electric consuming devices that can be smartly controlled, and thus, the flexibility that can be provided by the demand side could be much more, thereby reducing the need for additional generation side flexibility.

IMPACT OF STORAGE FLEXIBILITY Electricity storage technologies can be extremely useful for absorbing excess of renewable energy, which can be used later to supply demand at peak hours. Their flexibility as demand, and also as energy sources needs to be understood, as they will be critical for the effective and efficient integration of renewables, for alleviating the stress to which conventional generation will be exposed during extreme system operating conditions, as well as to diminish the need for new flexible generation capacity.

RESERVE SERVICES FROM FLEXIBLE DEMAND In this thesis, flexible electric vehicles are considered only for energy arbitrage. The additional flexibility that can be gained by using electric vehicles and other flexible demand technologies as sources of reserve services needs to be explored as it could lead to significant cost savings and environmental benefits.

ENERGY PRICES VOLATILITY REDUCTION Flexibility of EV and other flexible demand technologies can be used to stabilize net-demand, thereby reducing the volatility of energy prices. Such potential needs to be studied and understood as it could provide more certainty to low-carbon generation investors and result in lower energy costs for electricity consumers.

MULTI-PERIOD MODEL This thesis assumes a long-run equilibrium approach, using a set of representative periods to model a longer assessment horizon. However, as the Strategic-GEP allows the needs for additional generation flexibility to be identified, the remaining question is: when such flexibility needs to be operative? The formulation of a multi-period model will allow such an important question to be answered and also understanding and assessing the impacts that conventional generation construction times and demand flexibility can have on those generation investment decisions.

TRANSMISSION SYSTEM The model developed in this thesis does not consider a transmission system. Expanding the Strategic-GEP model to incorporate transmission constraints

can help understanding how a non-optimal transmission system can impact the operational flexibility of a power system, and therefore, how such scenario could impact the generation expansion of future low-carbon power systems. On the other hand, it could also help to understand how generation and demand side flexibility can modify the expansion of transmission systems.

UNCERTAINTY FROM OTHER ENERGY SOURCES In this thesis only wind and solar PV generation are considered. Expanding the Strategic-GEP model formulation to consider other renewables resources can be useful in the understanding of how they will contribute to changing the net-demand's dynamics, and how they will impact the needs for system flexibility.

MARKET-BASED FORMULATION In this thesis the generation expansion problem is addressed from a centralized cost minimization perspective. However, investment and operating decisions of generation and demand participants in a market-based environment are taken in a decentralized fashion, according to the individual participants' objectives. The derivation of suitable market mechanisms for the realization of the cost-minimizing solution in a deregulated environment is then an essential area of future work.

NOMENCLATURE

INDEXES, SETS & SUB-SETS

$g \in G$	Generation units ($g = 1, \dots, N^G$).
$G^\kappa \subseteq G$	Sub-set of generation units that can provide κ reserve. ($\kappa = \{\text{FRR-Up}, \text{FRR-Dwn}, \text{SPR-Up}, \text{SPR-Dwn}, \text{QSR}\}$)
$i \in I$	Generation technology types ($i = 1, \dots, N^I$). (Screening curves: $i = \text{Baseload (B)}, \text{Mid-merit (M)} \text{ or } \text{Peaking (P)}$)
$I^\kappa \subseteq I$	Sub-set of generation technologies that can provide κ reserve.
$I^{\text{mr}} \subseteq I$	Sub-set of must-run generation technologies.
$l \in L$	Segments of the piecewise linear production cost, or fuel consumption, function ($l = 1, \dots, N^L$).
$n \in N$	Periods ($n = 1, \dots, N^N$).
$t \in T$	Demand segments ($t = 1, \dots, N^T$).
$T^{\text{ed}} \subseteq T$	Sub-set of last demand segments of each day.
$T^{\text{gc}} \subseteq T$	Sub-set of demand segments during which each EV of type v is connected to the grid.
$v \in V$	Electric vehicle (EV) types ($v = 1, \dots, N^V$).

VARIABLES

$\hat{K}_i$	Capacity of generation technology i to be installed (LP model).
$\hat{P}_{ti}$	Power output of generation technology i per demand segment t (LP model).
μ_{ti}	Marginal value of capacity per demand segment t per generation technology i .
π^K	Marginal value of capacity in the forward market, or capacity price.
π_t	Electricity price per demand segment t .
cf_i	Capacity factor of generation technology i .
$D_{nt}^{\text{EV-Flexible}}$	Electricity demand of all flexible EV of type v per period n per demand segment t .
$D_{nt}^{\text{EV-Inflexible}}$	Electricity demand of all inflexible EV of type v per period n per demand segment t .
D_{nt}^{PS}	Power consumed by the hydro pumped-storage power plants per period n per demand segment t .
d_t^{PS}	Power consumed by the hydro pumped-storage power plant to pump water into the upper reservoir per demand segment t .

D_{nt}^{System}	Total system-wide electricity demand per period n per demand segment t .
E_{ntv}^{EV}	Total battery energy level of all flexible EV of type v per period n per demand segment t .
e_{tv}^{EV}	Energy level in the battery of an EV of type v per demand segment t .
$F_{nti}^{\text{fuel-use}}$	Instantaneous fuel consumption of generation technology i per period n per demand segment t .
$f_{tg}^{\text{fuel-use}}$	Instantaneous fuel consumption of generation unit g per demand segment t .
K^S	Total capacity of the system.
K_1^S	Total capacity of the system under a spike-pricing regulation.
K_2^S	Total capacity of the system under a price-cap regulation.
$K_{\pi\text{Cap}}^S$	Same as K_2^S .
K_{VOLL}^S	Same as K_1^S .
K^T	Target capacity level.
K_i	Capacity of generation unit of technology i (Strategic-GEP model). (Screening curves: installed capacity of generation technology i)
K_{MB}	Total capacity of mid-merit and baseload generation technologies.
L_{nt}^{curt}	Load curtailment per period n per demand segment t .
$N_v^{\text{EV-Flex-new}}$	Number of new EV of type v that are converted into flexible EV.
$N_v^{\text{EV-Flex}}$	Number of flexible EV of type v (can be a parameter as well).
$N_i^{I\text{-new}}$	Number of new generation units of technology i to be built.
N_i^I	Number of installed generation units of technology i (can be a parameter as well).
p_{nt}^{curt}	Conventional generation curtailment per period n per demand segment t .
p_{ntv}^{EV}	Total electric power demand of all flexible EV of type v per period n per demand segment t .
p_{tv}^{EV}	Electric power demand of an EV of type v per demand segment t .
p_{nt}^{PS}	Power output of the hydro pumped-storage power plants per period n per demand segment t .
p_t^{PS}	Power generated by the hydro pumped-storage power plant per demand segment t .
p_{tgl}^{seg}	Power output of generation unit g per segment l of the piecewise linear production cost function per demand segment t .
$p_{nt}^{\text{solar-curt}}$	Solar PV generation curtailment per period n per demand segment t .
p_{nt}^{solar}	Solar PV power dispatched per period n per demand segment t .
$p_{nt}^{\text{wind-curt}}$	Wind generation curtailment per period n per demand segment t .
p_{nt}^{wind}	Wind power dispatched per period n per demand segment t .

P_{nti}	Power output of generation technology i per period n per demand segment t .
p_{tg}	Power output of generation unit g per demand segment t .
R_{nti}^κ	κ reserve provided by generation technology i per period n per demand segment t .
r_{tg}^κ	κ reserve provided by generation unit g per demand segment t .
S_{nti}^{Dwn}	Number of shut-down events of generation technology i per period n per demand segment t .
s_{tg}^{Dwn}	Shut-down event of generation unit g per demand segment t .
$S_{nt}^{\text{PS-Dwn-p}}$	Number of shut-down events of pumps of the hydro pumped-storage power plants per period n per demand segment t .
$s_t^{\text{PS-Dwn-p}}$	Shut-down event of the pump of the hydro pumped-storage power plant per demand segment t .
$S_{nt}^{\text{PS-Dwn-t}}$	Number of shut-down events of turbines of the hydro pumped-storage power plants per period n per demand segment t .
$s_t^{\text{PS-Dwn-t}}$	Shut-down event of the turbine of the hydro pumped-storage power plant per demand segment t .
$S_{nt}^{\text{PS-Up-p}}$	Number of start-up events of pumps of the hydro pumped-storage power plants per period n per demand segment t .
$s_t^{\text{PS-Up-p}}$	Start-up event of the pump of the hydro pumped-storage power plant per demand segment t .
$S_{nt}^{\text{PS-Up-t}}$	Number of start-up events of turbines of the hydro pumped-storage power plants per period n per demand segment t .
$s_t^{\text{PS-Up-t}}$	Start-up event of the turbine of the hydro pumped-storage power plant per demand segment t .
S_{nti}^{Up}	Number of start-up events of generation technology i per period n per demand segment t .
s_{tg}^{Up}	Start-up event of generation unit g per demand segment t .
t^M	Optimal capacity factor of the mid-merit generation technology.
t^{PS}	Price spike hours duration.
t_1^{PS}	Price spike hours duration under a spike-pricing regulation.
t_2^{PS}	Price spike hours duration under a price-cap regulation.
t^P	Optimal capacity factor of the peaking generation technology.
$U_{nt}^{\text{PS-p}}$	Number of committed pumps in all hydro pumped-storage power plants per period n per demand segment t .
$u_t^{\text{PS-p}}$	Binary unit commitment status of the pump of the hydro pumped-storage power plant per demand segment t ($u_t^{\text{PS-p}} = 1$ if the power plant is pumping water at demand segment t , and $u_t^{\text{PS-p}} = 0$ otherwise).

NOMENCLATURE

$U_{nt}^{\text{PS-t}}$	Number of committed turbines in all hydro pumped-storage power plants per period n per demand segment t .
$u_t^{\text{PS-t}}$	Binary unit commitment status of the turbine of the hydro pumped-storage power plant per demand segment t ($u_t^{\text{PS-t}} = 1$ if the power plant is generating electricity at demand segment t , and $u_t^{\text{PS-t}} = 0$ otherwise).
U_{nti}	Number of committed generation units of technology i per period n per demand segment t (integer commitment status).
u_{tg}	Binary unit commitment status of generation unit g per demand segment t ($u_{tg} = 1$ if the generation unit g is online at demand segment t , and $u_{tg} = 0$ if offline).
$X_{nt}^{\text{PS-Lower}}$	Total lower reservoir energy stored in all hydro pumped-storage power plants per period n per demand segment t .
$x_t^{\text{PS-Lower}}$	Level of energy stored in the lower reservoir of the hydro pumped-storage power plant per demand segment t .
$X_{nt}^{\text{PS-Upper}}$	Total upper reservoir energy stored in all hydro pumped-storage power plants per period n per demand segment t .
$x_t^{\text{PS-Upper}}$	Level of energy stored in the upper reservoir of the hydro pumped-storage power plant per demand segment t .
AC_i^K	Average cost of capacity of generation technology i .
$EMI_{nti}^{\text{CO}_2}$	CO ₂ emissions of generation technology i per period n per demand segment t .
ICAP-P_i	Installed capacity payment of generation technology i .
MM_i	Missing-money of generation technology i .
PER_i	Peak energy revenue of generation technology i .
ScR_i	Scarcity rent of generation technology i .
SRP_i	Short-run profit of generation technology i .

PARAMETERS

$\alpha_{\text{QSR-SPR}}^{\text{MAX-contrib}}$	Fraction of the system-wide upward spinning reserve demand level that can be provided by quick-start generation units.
Δ_i^{Dwn}	Ramp-down rate limit of a generation unit of technology i (same as Δ_g^{Dwn}).
Δ_i^{Up}	Ramp-up rate limit of a generation unit of technology i (same as Δ_g^{Up}).
η_v^{chg}	Charging efficiency of each EV of type v (battery's and grid connection power electronics' charging efficiency).
η_v^{elec}	Self-discharging energy efficiency of the battery of an EV of type v .
η^{ptc}	Efficiency of the pumping/turbine cycle.
$\overline{\mathcal{A}}_i$	Capacity derating factor (firm capacity or average availability ratio) per generation technology i .

Φ_n	Weighting factor per period n .
$\pi_i^{\text{fix-O\&M}}$	Annual fix O&M costs of generation technology i .
π_i^{fuel}	Cost of the fuel used by generation technology i (same as π_g^{fuel}).
π^{GC}	Conventional generation curtailment value.
π_{gl}^{inc}	Incremental cost of production of generation unit g per segment l of the piece-wise linear production cost function.
π_i^{inc}	Incremental (or marginal) cost of generation of generation technology i .
π^{LC}	Load curtailment value.
π_g^{NL}	No-load cost of generation unit g at the minimum stable generation level.
$\pi_i^{\text{O\&M}}$	Variable O&M cost of generation technology i (same as $\pi_g^{\text{O\&M}}$).
$\pi^{\text{PS-SDwn-p}}$	Cost of shutting down a pump of a hydro pumped-storage power plant.
$\pi^{\text{PS-SDwn-t}}$	Cost of shutting down a turbine of a hydro pumped-storage power plant.
$\pi^{\text{PS-SUp-p}}$	Cost of starting a pump of a hydro pumped-storage power plant.
$\pi^{\text{PS-SUp-t}}$	Cost of starting a turbine of a hydro pumped-storage power plant.
π^{PVC}	Solar PV generation curtailment value.
$\pi_i^{\text{SDwn-fuel}}$	Fuel cost of taking offline a generation unit of technology i (same as $\pi_g^{\text{SDwn-fuel}}$).
$\pi_i^{\text{SDwn-O\&M}}$	Fixed O&M cost associated with taking offline a generation unit of technology i (same as $\pi_g^{\text{SDwn-O\&M}}$).
$\pi_i^{\text{SDwn-CO}_2}$	CO ₂ cost associated with the shut-down event of a generation unit of technology i .
$\pi_i^{\text{SUp-fuel}}$	Fuel cost of bringing online a generation unit of technology i (same as $\pi_g^{\text{SUp-fuel}}$).
$\pi_i^{\text{SUp-O\&M}}$	Fixed O&M cost associated with bringing online a generation unit of technology i (same as $\pi_g^{\text{SUp-O\&M}}$).
$\pi_i^{\text{SUp-CO}_2}$	CO ₂ cost associated with the start-up event of a generation unit of technology i .
π^{WC}	Wind generation curtailment value.
π^{Cap}	Price-cap.
π^{CO_2}	CO ₂ price for the whole power system.
$\pi_i^{\text{CO}_2}$	Incremental CO ₂ cost associated with the electricity production of generation technology i .
SEI	System-wide CO ₂ emissions intensity limit.
$\sigma_i^{\text{FRR-Dwn}}$	Slope of downward frequency regulation reserve contribution of a generation unit of technology i (same as $\sigma_g^{\text{FRR-Dwn}}$).
$\sigma_i^{\text{FRR-Up}}$	Slope of upward frequency regulation reserve contribution of a generation unit of technology i (same as $\sigma_g^{\text{FRR-Up}}$).

τ_t	Duration of demand segment t .
$d_{ntv}^{\text{EV-Inflex}}$	Electricity demand of and inflexible EV of type v per period n per demand segment t .
D^{MAX}	Peak demand.
$d^{\text{PS-MAX}}$	Maximum power of the pump of the hydro pumped-storage power plant.
$d^{\text{PS-min}}$	Minimum power of the pump of the hydro pumped-storage power plant.
D_t	Demand level per demand segment t .
$e_v^{\text{bat-MAX}}$	Maximum state of charge of the battery of an EV of type v .
$e_v^{\text{bat-min}}$	Minimum state of charge of the battery of an EV of type v .
e_v^{ed}	Required energy level in the battery of an EV of type v at the end of the day.
e_{ntv}^{tr}	EV type v user's energy requirements for travelling purposes per period n per demand segment t .
K^{solar}	Solar PV capacity.
K^{wind}	Wind capacity.
L_{nt}	Load demand (Non-EV system demand) per period n per demand segment t .
$N_v^{\text{EV-Flex-old}}$	Initial number of flexible EV of type v at the beginning of the assessment horizon.
$N_v^{\text{EV-Flex}}$	Number of flexible EV of type v (can be a variable as well).
$N_v^{\text{EV-Inflex}}$	Number of inflexible EV of type v (can be a variable as well).
N_v^{EV}	Total number of EV of type v .
N^{PS}	Number of hydro pumped-storage power plants.
$N_i^{I-\text{MAX}}$	Upper bound for the number of new generation units of generation technology i .
$N_i^{I-\text{old}}$	Number of generation units of technology i at the beginning of the assessment horizon.
N_i^I	Number of installed generation units of technology i (can be a variable as well).
$p_v^{\text{chg-MAX}}$	Maximum power charging rate of the battery of an EV of type v .
p_{gl}^{Eb}	Power output elbow of segment l of the piecewise linear production cost function of generation unit g .
p_i^{MAX}	Maximum stable power output level of generation technology i (same as p_g^{MAX}).
p_i^{min}	Minimum stable power output level of generation technology i (same as p_g^{min}).
$p^{\text{PS-MAX}}$	Maximum power output of the turbine of the hydro pumped-storage power plant.
$p^{\text{PS-min}}$	Minimum power output of the turbine of the hydro pumped-storage power plant.
$p_{nt}^{\text{solar-pwr-av}}$	Solar PV power available per period n per demand segment t .

$P_{nt}^{\text{wind-pwr-av}}$	Wind power available per period n per demand segment t .
$x^{\text{PS-Lower-ed}}$	Required energy level in the lower reservoir of a hydro pumped-storage power plant at the end of the day.
$x^{\text{PS-Lower-MAX}}$	Maximum energy level of the lower reservoir of the hydro pumped-storage power plant.
$x^{\text{PS-Lower-min}}$	Minimum energy level of the lower reservoir of the hydro pumped-storage power plant.
$x^{\text{PS-Upper-ed}}$	Required energy level in the upper reservoir of a hydro pumped-storage power plant at the end of the day.
$x^{\text{PS-Upper-MAX}}$	Maximum energy level of the upper reservoir of the hydro pumped-storage power plant.
$x^{\text{PS-Upper-min}}$	Minimum energy level of the upper reservoir of the hydro pumped-storage power plant.
$EF_i^{\text{CO}_2}$	CO ₂ emissions factor of generation technology i .
$ER_i^{\text{CCS-CO}_2}$	CO ₂ emissions reduction factor due to a CCS system.
$FC_v^{\text{EV-Flexibility}}$	Annuitized EV flexibility enabling cost per EV of type v .
FC_i	Fixed costs of generation technology i .
$FRR_i^{\text{MAX-Dwn}}$	Maximum downward frequency regulation reserve deployment of a generation unit of technology i (same as $FRR_g^{\text{MAX-Dwn}}$).
$FRR_i^{\text{MAX-Up}}$	Maximum upward frequency regulation reserve deployment of a generation unit of technology i (same as $FRR_g^{\text{MAX-Up}}$).
HR_{il}^{inc}	Incremental heat rate of generation technology i per segment l of the piecewise linear fuel consumption function (same as HR_{gl}^{inc}).
H_i^{SDwn}	Heat consumed during the shut-down event of a generation unit of technology i .
H_i^{SUP}	Heat consumed during the start-up event of a generation unit of technology i .
MT_i^{Dwn}	Minimum down time of a generation unit of technology i (same as MT_g^{Dwn}).
MT_i^{Up}	Minimum up time of a generation unit of technology i (same as MT_g^{Up}).
$NLH@0_{il}$	Hypothetical no-load fuel usage at zero power output of generation technology i per segment l of the piecewise linear fuel consumption function (same as $NLH@0_{gl}$).
QSR_i^{MAX}	Maximum quick-start reserve deployment of a generation unit of technology i (same as QSR_g^{MAX}).
RR_{nt}^{κ}	System-wide κ reserve demand level per period n per demand segment t .
RR^K	Reserve requirement factor.
$SPR_i^{\text{MAX-Dwn}}$	Maximum downward spinning reserve deployment of a generation unit of technology i (same as $SPR_g^{\text{MAX-Dwn}}$).

NOMENCLATURE

$SPR_i^{\text{MAX-Up}}$	Maximum upward spinning reserve deployment of a generation unit of technology i (same as $SPR_g^{\text{MAX-Up}}$).
$WACC_i$	Annual weighted average cost of capital in generation technology i .
$CAPEX_i$	Capital expenditures of generation technology i .
LDC_t	Load duration curve level per demand segment t .
LT_i	Expected lifetime of a generation unit of technology i .
RM	Reserve margin.
VOLL	Value Of Lost Load.

UNITS

\$	US Dollar
%	Percentage
£	British Pound Sterling
bn£	Billions of £
gCO ₂	Grams of CO ₂
GW	Gigawatt
h	hour
kWh	Kilowatt-hour
MtonneCO ₂	Million tonnes of CO ₂
MW	Megawatt-hour
MW	Megawatt
pu	per unit
TWh	Terawatt-hour
yr	year

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Part V

APPENDIXES

STRATEGIC-GEP INPUT DATA

This appendix includes a summary of the assumptions made for the Strategic-GEP model formulation, and the input data used for the case studies developed in Chapters 5 and 6.

Summary Strategic-GEP model assumptions

Finally, the main assumptions made for the Strategic-GEP model formulation can be summarized in the following list:

- Deterministic long-run equilibrium.
- Perfectly competitive market.
- Centralized total system cost minimization.
- There is an energy price regulation that caps the electricity prices at a centrally defined value when demand is larger than the total available capacity, i.e. when there is load curtailment.
- There are N^I conventional generation technology types.
- Three types of ancillary services: FRR, SPR and QSR.
- CO₂ emissions are penalized through a CO₂ price, and there is a system-wide total carbon emissions limit restriction.
- Inelastic load and inflexible EV demand.
- Flexible EV cannot inject power into the grid (no V2G capability), nor provide any type of ancillary services.
- Single node and aggregated demand.
- Assessment horizon of N^N representative periods, and hourly time resolution.
- There is a cost associated to convert an inflexible EV into a flexible one.
- There is only one cluster with N^{PS} hydro pumped-storage power plants, and they do not provide any type of reserve services.¹
- Two types of renewable resources: wind and solar PV generation.

¹ It must be noted that hydro pumped-storage facilities are highly flexible and can provide the different types of reserve services. However, and as it was noted earlier in this thesis, the modelling of this type of storage was part of the work developed during this research, but they were not included in the analyses presented in Chapters 5 and 6, and will be subject for further research. Because this reason, the hydro pumped-storage capacity was not considered in the reserve services constraints.

Table A.1: Conventional generation cost parameters.

<i>Generation technology</i>	<i>Fixed O&M (£/kW-yr)</i>	<i>Variable O&M (£/MWh)</i>	<i>Capital Cost (£/kW-yr)</i>	<i>Lifetime (yr)</i>	<i>WACC (%)</i>	<i>Fixed Costs (£/kW-yr)</i>
Nuclear	72.0	2.00	4,067	30	10	503
Coal Large	56.9	2.40	2,200	30	10	290
Coal Small	56.9	2.40	2,605	30	10	333
CCGT Large	22.0	2.20	608	30	10	86
CCGT Small	22.0	2.20	800	30	10	107
OCGT	14.0	5.85	415	30	10	58
Oil	42.0	6.31	990	30	10	147
Coal-CCS	56.9	3.80	2,632	30	10	336
CCGT-CCS	25.0	3.20	1,379	30	10	171

Conventional generation

The conventional generation portfolio includes nuclear, coal, gas and oil technologies, whose economic, technical and operational parameters are presented in tables A.1 and A.2.

The data was extracted and adapted from several sources including Mott MacDonald [320, 321] and Parsons Brinckerhoff [322] consulting companies, ARUP [323], IEA [324], IEA-ETSAP [325, 326, 327], Organisation for Economic Co-operation and Development (OECD)/IEA [15], US Energy Information Administration (EIA) [328, 329], UK Department of Energy & Climate Change (DECC) [330, 17, 331], European Photovoltaic Industry Association (EPIA) [332], World Nuclear Association (WNA) [317, 333], PJM [334], National Renewable Energy Laboratory (NREL) [23], among others.

For the calculation of the primary and secondary reserve services demand levels it was assumed that the forecast errors of load demand, wind and solar PV generation are normally distributed, following the approach described in [335]. The forecast error standard deviations are assumed to be proportional to the magnitude of the load demand, wind and solar PV power available at each demand segment, scaled by the empirical standard deviation forecast errors calculated from the input data, which are presented in table A.3.²

Finally, for the operation of the conventional generation a single affine function is assumed for the fuel consumption of each generation technology i , i.e. a constant incremental heat rate with an offset³, which replaces the convex piecewise linear fuel consumption function described in Section 4.2.3.⁴

Load demand & renewable generation profiles

Five weeks representing the four seasons plus an extreme winter week are used in the case studies for representing the load demand. The load (non-EV) system demand was generated using historical data obtained from UK NGET website.⁵ The employed wind generation profile was produced based on the model developed in [153, 154] and has a load factor of 31.3%. On the other hand, the solar PV generation profile was obtained from The Centre for Sustain-

² The contribution of wind and solar PV to primary reserve requirements are assumed proportional to their power available half-hourly forecast error standard deviation, while for secondary reserve services requirements are assumed proportional to their power available 4-hours forecast error standard deviation.

³ Hypothetical no-load fuel usage at zero power output.

⁴ This is equivalent to say that the cardinality of the set L is equal to one. This simplification allows reducing the number of constraints by $(N^T \times N^I \times [N^L - 1])$.

⁵ www.nationalgrid.com/uk/Electricity/Data/.

Table A.2: Conventional generation technical and operational parameters.

Generation technology	Generation unit size (MW)	Power Output Limits		Start-Up		No-Load Heat @0MW (MBTU/h)	Incremental Heat Rate (BTU/kWh)	CCS CO2 Emi. Reduction (pu)		Minimum times		Ramp rate	
		Minimum (pu)	Maximum (pu)	Heat (MBTU/start)	Fix cost (\$/start)					Up (h)	Down (h)	Up (pu/h)	Down (pu/h)
Nuclear	1,500	0.80	1.00	N/A	N/A	4,756	10,400	0.0	0.0	48	24	0.1	0.1
Coal Large	525	0.50	1.00	2,102	1,722	266	8,800	0.0	0.0	24	12	0.3	0.3
Coal Small	250	0.50	1.00	1,001	820	138	9,600	0.0	0.0	24	12	0.3	0.3
CCGT Large	750	0.30	1.00	1,105	10,325	759	6,400	0.0	0.0	6	12	1.0	1.0
CCGT Small	350	0.30	1.00	516	4,818	409	7,100	0.0	0.0	6	12	1.0	1.0
OCGT	150	0.25	1.00	134	3,321	137	9,700	0.0	0.0	0	0	1.0	1.0
Oil	50	0.25	1.00	0	142	33	11,000	0.0	0.0	0	0	1.0	1.0
Coal-CCS	650	0.50	1.00	2,602	2,132	330	12,000	0.9	0.9	24	12	0.3	0.3
CCGT-CCS	380	0.30	1.00	582	5,435	525	7,500	0.9	0.9	6	12	1.0	1.0

Generation technology	Must-run generation	Reserve provision capability				Maximum reserve deployment (pu)							
		Frequency Regulation		Spinning		Quick-start		Frequency Regulation		Spinning		Quick-start	
		Up	Down	Up	Down	Up	Down	Up	Down	Up	Down	Up	Down
Nuclear	YES	NO	NO	NO	NO	NO	NO	0.00	0.00	0.00	0.00	0.00	0.00
Coal Large	NO	YES	YES	YES	YES	NO	NO	0.03	0.03	0.50	0.05	0.05	0.00
Coal Small	NO	YES	YES	YES	YES	NO	NO	0.03	0.03	0.50	0.05	0.05	0.00
CCGT Large	NO	YES	YES	YES	YES	NO	NO	0.08	0.08	0.50	0.17	0.17	0.00
CCGT Small	NO	YES	YES	YES	YES	NO	NO	0.08	0.08	0.50	0.17	0.17	0.00
OCGT	NO	YES	YES	YES	YES	YES	YES	0.50	0.50	1.00	1.00	1.00	1.00
Oil	NO	YES	YES	YES	YES	YES	YES	0.50	0.50	1.00	1.00	1.00	1.00
Coal-CCS	NO	YES	YES	YES	YES	NO	NO	0.03	0.03	0.50	0.05	0.05	0.00
CCGT-CCS	NO	YES	YES	YES	YES	NO	NO	0.08	0.08	0.50	0.17	0.17	0.00

Table A.3: Forecast error standard deviation of load demand and power available from renewable resources.

<i>Renewable resource</i>	<i>Forecast error standard deviation</i>	<i>Value (%)</i>
Load demand	0.5h	1.0
	4h	1.0
Wind	0.5h	1.7
	4h	7.8
Solar PV	0.5h	2.3
	4h	3.9

Table A.4: EV battery technical parameters.

<i>Parameter</i>	<i>Units</i>	<i>Value</i>
Max. charging power	kW	3.00
Battery energy capacity	kWh	15.00
Energy level end of day	pu	0.50
Max. energy limit	pu	1.00
Min. energy limit	pu	0.20
Charging efficiency	pu	0.93
Energy efficiency	pu	1.00

able Electricity and Distributed Generation,⁶ and has a load factor of 8.8%.⁷ The wind and solar PV generation profiles were converted into five representative weeks using the approach described in [29].

Electric vehicles

As mentioned at the beginning of Section 6.1, the EV data presented in tables A.5 and A.6, was produced using UK's vehicle fleet size and average driving patterns [318, 319], and assuming that each EV makes two journeys per day [252]. The technical characteristics of the EV batteries are presented in table A.4, and are assumed identical for all EV types [256].

Other parameters

The rest of the parameters used for the case studies presented in Chapters 5 and 6 were obtained from NGET [152], DECC [336, 138], Element Energy & Imperial College London [337], and [338].

⁶ www.sedg.ac.uk.

⁷ The representativeness of the wind and solar PV profile is not further explored because it is beyond the scope of this thesis to accurately predict the optimal generation mix considering the full diversity of wind and solar PV outputs.

Table A.5: EV types, travelling times and requirements, and quantity (table 1 of 2).

EV type	1st Journey			2nd Journey			100% pen.
	Start	End	Energy	Start	End	Energy	EV quantity
	(hh:mm)	(hh:mm)	(kWh)	(hh:mm)	(hh:mm)	(kWh)	(#)
1	8:00	8:00	2.235	9:00	9:00	2.155	331,280
2	8:00	8:00	2.235	10:00	10:00	2.155	226,515
3	8:00	8:00	2.235	11:00	11:00	2.155	248,259
4	8:00	8:00	2.235	12:00	12:00	2.155	256,132
5	8:00	8:00	2.235	13:00	13:00	2.155	256,050
6	8:00	8:00	2.235	14:00	14:00	2.155	260,137
7	8:00	8:00	2.235	15:00	15:00	2.155	254,873
8	8:00	8:00	2.235	16:00	16:00	2.155	283,491
9	8:00	8:00	2.235	17:00	17:00	2.155	307,960
10	8:00	8:00	2.235	18:00	18:00	2.155	341,285
11	8:00	8:00	2.235	19:00	19:00	2.155	242,589
12	8:00	8:00	2.235	20:00	20:00	2.155	187,553
13	8:00	9:00	1.118	16:00	16:00	2.155	196,271
14	8:00	9:00	1.118	17:00	17:00	2.155	213,211
15	8:00	9:00	1.118	18:00	18:00	2.155	236,283
16	9:00	9:00	2.235	10:00	10:00	2.155	423,434
17	9:00	9:00	2.235	11:00	11:00	2.155	464,081
18	9:00	9:00	2.235	12:00	12:00	2.155	478,798
19	9:00	9:00	2.235	13:00	13:00	2.155	478,646
20	9:00	9:00	2.235	14:00	14:00	2.155	486,285
21	9:00	9:00	2.235	15:00	15:00	2.155	476,446
22	9:00	9:00	2.235	16:00	16:00	2.155	529,943
23	9:00	9:00	2.235	16:00	17:00	1.077	193,060
24	9:00	9:00	2.235	17:00	17:00	2.155	575,684
25	9:00	9:00	2.235	17:00	18:00	1.077	237,106
26	9:00	9:00	2.235	18:00	18:00	2.155	637,980
27	9:00	9:00	2.235	18:00	19:00	1.077	222,720
28	9:00	9:00	2.235	19:00	19:00	2.155	453,483
29	9:00	9:00	2.235	20:00	20:00	2.155	350,601
30	9:00	9:00	2.235	21:00	21:00	2.155	232,164
31	9:00	9:00	2.235	17:00	18:00	2.394	196,733
32	9:00	9:00	2.235	18:00	19:00	2.394	198,504
33	9:00	10:00	1.118	16:00	16:00	2.155	197,813
34	9:00	10:00	1.118	17:00	17:00	2.155	214,887
35	9:00	10:00	1.118	18:00	18:00	2.155	238,140
36	10:00	10:00	2.235	11:00	11:00	2.155	306,599
37	10:00	10:00	2.235	12:00	12:00	2.155	316,321
38	10:00	10:00	2.235	13:00	13:00	2.155	316,221
39	10:00	10:00	2.235	14:00	14:00	2.155	321,268
40	10:00	10:00	2.235	15:00	15:00	2.155	314,767
41	10:00	10:00	2.235	16:00	16:00	2.155	350,111
42	10:00	10:00	2.235	17:00	17:00	2.155	380,330
43	10:00	10:00	2.235	18:00	18:00	2.155	421,486
44	10:00	10:00	2.235	19:00	19:00	2.155	299,597
45	10:00	10:00	2.235	20:00	20:00	2.155	231,627
46	11:00	11:00	2.235	12:00	12:00	2.155	345,120
47	11:00	11:00	2.235	13:00	13:00	2.155	345,010
48	11:00	11:00	2.235	14:00	14:00	2.155	350,517
49	11:00	11:00	2.235	15:00	15:00	2.155	343,424
50	11:00	11:00	2.235	16:00	16:00	2.155	381,986

Table A.6: EV types, travelling times and requirements, and quantity (*table 2 of 2*).

EV type	1st Journey			2nd Journey			100% pen.
	Start	End	Energy	Start	End	Energy	EV quantity (#)
	(hh:mm)	(hh:mm)	(kWh)	(hh:mm)	(hh:mm)	(kWh)	
51	11:00	11:00	2.235	17:00	17:00	2.155	414,956
52	11:00	11:00	2.235	18:00	18:00	2.155	459,859
53	11:00	11:00	2.235	19:00	19:00	2.155	326,873
54	11:00	11:00	2.235	20:00	20:00	2.155	252,715
55	12:00	12:00	2.235	13:00	13:00	2.155	357,177
56	12:00	12:00	2.235	14:00	14:00	2.155	362,877
57	12:00	12:00	2.235	15:00	15:00	2.155	355,535
58	12:00	12:00	2.235	16:00	16:00	2.155	395,456
59	12:00	12:00	2.235	17:00	17:00	2.155	429,588
60	12:00	12:00	2.235	18:00	18:00	2.155	476,075
61	12:00	12:00	2.235	19:00	19:00	2.155	338,399
62	12:00	12:00	2.235	20:00	20:00	2.155	261,626
63	13:00	13:00	2.235	14:00	14:00	2.155	363,643
64	13:00	13:00	2.235	15:00	15:00	2.155	356,285
65	13:00	13:00	2.235	16:00	16:00	2.155	396,290
66	13:00	13:00	2.235	17:00	17:00	2.155	430,495
67	13:00	13:00	2.235	18:00	18:00	2.155	477,080
68	13:00	13:00	2.235	19:00	19:00	2.155	339,113
69	13:00	13:00	2.235	20:00	20:00	2.155	262,178
70	14:00	14:00	2.235	15:00	15:00	2.155	361,865
71	14:00	14:00	2.235	16:00	16:00	2.155	402,496
72	14:00	14:00	2.235	17:00	17:00	2.155	437,237
73	14:00	14:00	2.235	18:00	18:00	2.155	484,551
74	14:00	14:00	2.235	19:00	19:00	2.155	344,424
75	14:00	14:00	2.235	20:00	20:00	2.155	266,284
76	15:00	15:00	2.235	16:00	16:00	2.155	394,686
77	15:00	15:00	2.235	17:00	17:00	2.155	428,752
78	15:00	15:00	2.235	18:00	18:00	2.155	475,148
79	15:00	15:00	2.235	19:00	19:00	2.155	337,741
80	15:00	15:00	2.235	20:00	20:00	2.155	261,117
81	15:00	16:00	1.118	18:00	18:00	2.155	187,756
82	16:00	16:00	2.235	17:00	17:00	2.155	482,145
83	16:00	16:00	2.235	17:00	18:00	1.077	198,580
84	16:00	16:00	2.235	18:00	18:00	2.155	534,320
85	16:00	16:00	2.235	18:00	19:00	1.077	186,532
86	16:00	16:00	2.235	19:00	19:00	2.155	379,800
87	16:00	16:00	2.235	20:00	20:00	2.155	293,634
88	16:00	16:00	2.235	21:00	21:00	2.155	194,442
89	16:00	17:00	1.118	18:00	18:00	2.155	215,603
90	17:00	17:00	2.235	18:00	18:00	2.155	592,439
91	17:00	17:00	2.235	18:00	19:00	1.077	206,822
92	17:00	17:00	2.235	19:00	19:00	2.155	421,112
93	17:00	17:00	2.235	20:00	20:00	2.155	325,574
94	17:00	17:00	2.235	21:00	21:00	2.155	215,592
95	17:00	17:00	2.235	18:00	19:00	2.394	184,334
96	17:00	18:00	1.118	19:00	19:00	2.155	193,754
97	18:00	18:00	2.235	19:00	19:00	2.155	474,521
98	18:00	18:00	2.235	20:00	20:00	2.155	366,866
99	18:00	18:00	2.235	21:00	21:00	2.155	242,935
100	18:00	18:00	2.235	22:00	22:00	2.155	189,925
101	19:00	19:00	2.235	20:00	20:00	2.155	251,237
102	8:00	9:00	2.483	17:00	17:00	2.155	197,324
103	8:00	9:00	2.483	18:00	18:00	2.155	218,677

Table A.7: Strategic-GEP model general parameters.

	<i>Parameter</i>	<i>Units</i>	<i>Value</i>
	Typical periods	week	5
	Demand segments	h	168
	Peak demand (Non-EV)	MW	60,842
	Wind capacity	MW	56,941
	Solar PV capacity	MW	15,813
	Alpha contrib. QSR-SPR	%	50.0
	VOLL	£/MWh	10,000
	Cost of over generation	£/MWh	1,000,000
	Cost of wind curtailment	£/MWh	0
	Cost of solar PV curtailment	£/MWh	0
<i>EV</i>	Number of types	#	103
	Penetration level	%	9.3
<i>CO2</i>	Emissions limit	gCO2/kWh	50.0
	Price	£/tonneCO2	76.0
<i>Fuel cost</i>	LWR	£/MBTU	0.410
	Coal	£/MBTU	4.469
	Gas	£/MBTU	7.023
	Oil	£/MBTU	15.807
<i>CO2 emi. factor</i>	LWR	tonneCO2/MBTU	0.000
	Coal	tonneCO2/MBTU	0.097
	Gas	tonneCO2/MBTU	0.053
	Oil	tonneCO2/MBTU	0.087
<i>Weighting factor</i>	Winter	week/yr	16.75
	Extreme winter	week/yr	0.25
	Spring	week/yr	9.00
	Summer	week/yr	13.00
	Autumn	week/yr	13.00

ADDITIONAL RESULTS

Additional tables and figures are included in this appendix to complement those presented in Chapter 5 and 6.

Table B.1: Generation capacity, system costs, curtailment levels, CO₂ emissions and renewables utilization factors in the simulated scenarios.

	<i>Parameter</i>	<i>Units</i>	<i>Scenario</i>		
			<i>GEP-LP</i>	<i>STR-GEP</i>	<i>STR-GEP*</i>
<i>Generation Capacity</i>	Nuclear	GW	16.49	19.50	0.00
	Coal	GW	0.00	0.00	0.00
	CCGT	GW	17.23	17.25	12.00
	OCGT	GW	13.82	12.00	11.70
	Oil	GW	0.00	0.00	0.00
	Coal-CCS	GW	0.00	0.00	0.00
	CCGT-CCS	GW	2.77	1.52	26.60
	Solar PV	GW	15.81	15.81	15.81
	Wind	GW	56.94	56.94	56.94
	TOTAL	GW	123.06	123.02	123.05
<i>Costs</i>	Investment	bn£	11.05	12.25	6.26
	Operation	bn£	5.55	5.60	14.34
	TOTAL	bn£	16.59	17.84	20.60
<i>Curtailment</i>	Load	TWh	0.00	0.00	0.00
	Generation	TWh	0.00	0.00	0.00
	Wind	TWh	0.52	13.63	0.52
	Solar PV	TWh	0.00	0.23	0.00
	Renewable energy curtailment	TWh	0.52	13.86	0.52
<i>CO₂</i>	Emissions	MtonneCO ₂	18.17	18.00	17.87
	Intensity	gCO ₂ /kWh	50.00	49.53	49.16
<i>UF</i>	Wind Utilization Factor	%	99.7	91.2	99.7
	Solar PV Utilization Factor	%	100.0	98.3	100.0

Table B.2: Generation capacity, system costs, curtailment levels, CO₂ emissions and renewables utilization factors in the base case scenarios when the CO₂ emissions limit is not enforced.

	Parameter	Units	Base Case Scenario		
			BC-10GW	BC-30GW	BC-50GW
Generation Capacity	Nuclear	GW	27.00	16.50	6.00
	Coal	GW	0.00	0.00	0.00
	Coal-CCS	GW	0.00	0.00	0.00
	CCGT	GW	14.25	15.75	18.00
	CCGT-CCS	GW	7.22	10.26	12.92
	OCGT	GW	12.00	15.75	19.05
	Oil	GW	0.00	0.00	0.00
	Solar PV	GW	15.81	15.81	15.81
	Wind	GW	10.00	30.00	50.00
	TOTAL	GW	86.28	104.07	121.78
Costs	Investment	bn£	16.74	12.32	7.88
	Operation	bn£	9.50	12.19	15.48
	TOTAL	bn£	26.24	24.51	23.36
Curtailment	Load	TWh	0.00	0.00	0.00
	Generation	TWh	0.00	0.00	0.00
	Wind	TWh	1.02	5.11	14.59
	Solar PV	TWh	0.70	0.50	1.06
	Renewable energy curtailment	TWh	1.72	5.61	15.65
CO ₂	Emissions	MtonneCO ₂	21.57	30.87	43.68
	Intensity	gCO ₂ /kWh	60.27	86.23	122.03
UF	Wind Utilization Factor	%	96.2	93.7	89.3
	Solar PV Utilization Factor	%	94.9	96.3	92.2

Table B.3: Generation capacity, system costs, curtailment levels, CO₂ emissions and renewables utilization factors in the base case scenarios when the CO₂ emissions limit is enforced and equal to 50 [gCO₂/kWh].

	Parameter	Units	Base Case Scenario		
			BC-10GW	BC-30GW	BC-50GW
Generation Capacity	Nuclear	GW	27.00	16.50	4.50
	Coal	GW	0.00	0.00	0.00
	Coal-CCS	GW	0.00	0.00	0.00
	CCGT	GW	12.00	8.25	4.50
	CCGT-CCS	GW	9.12	17.48	29.64
	OCGT	GW	12.30	16.05	17.40
	Oil	GW	0.00	0.00	0.00
	Solar PV	GW	15.81	15.81	15.81
	Wind	GW	10.00	30.00	50.00
	TOTAL	GW	86.23	104.09	121.85
Costs	Investment	bn£	16.89	12.93	8.73
	Operation	bn£	9.38	11.74	15.11
	TOTAL	bn£	26.26	24.67	23.83
Curtailment	Load	TWh	0.00	0.00	0.00
	Generation	TWh	0.00	0.00	0.00
	Wind	TWh	1.16	6.79	18.02
	Solar PV	TWh	0.70	0.54	1.23
	Renewable energy curtailment	TWh	1.86	7.33	19.25
CO ₂	Emissions	MtonneCO ₂	17.90	17.90	17.88
	Intensity	gCO ₂ /kWh	50.00	50.00	49.95
UF	Wind Utilization Factor	%	95.8	91.7	86.8
	Solar PV Utilization Factor	%	94.9	96.1	91.0

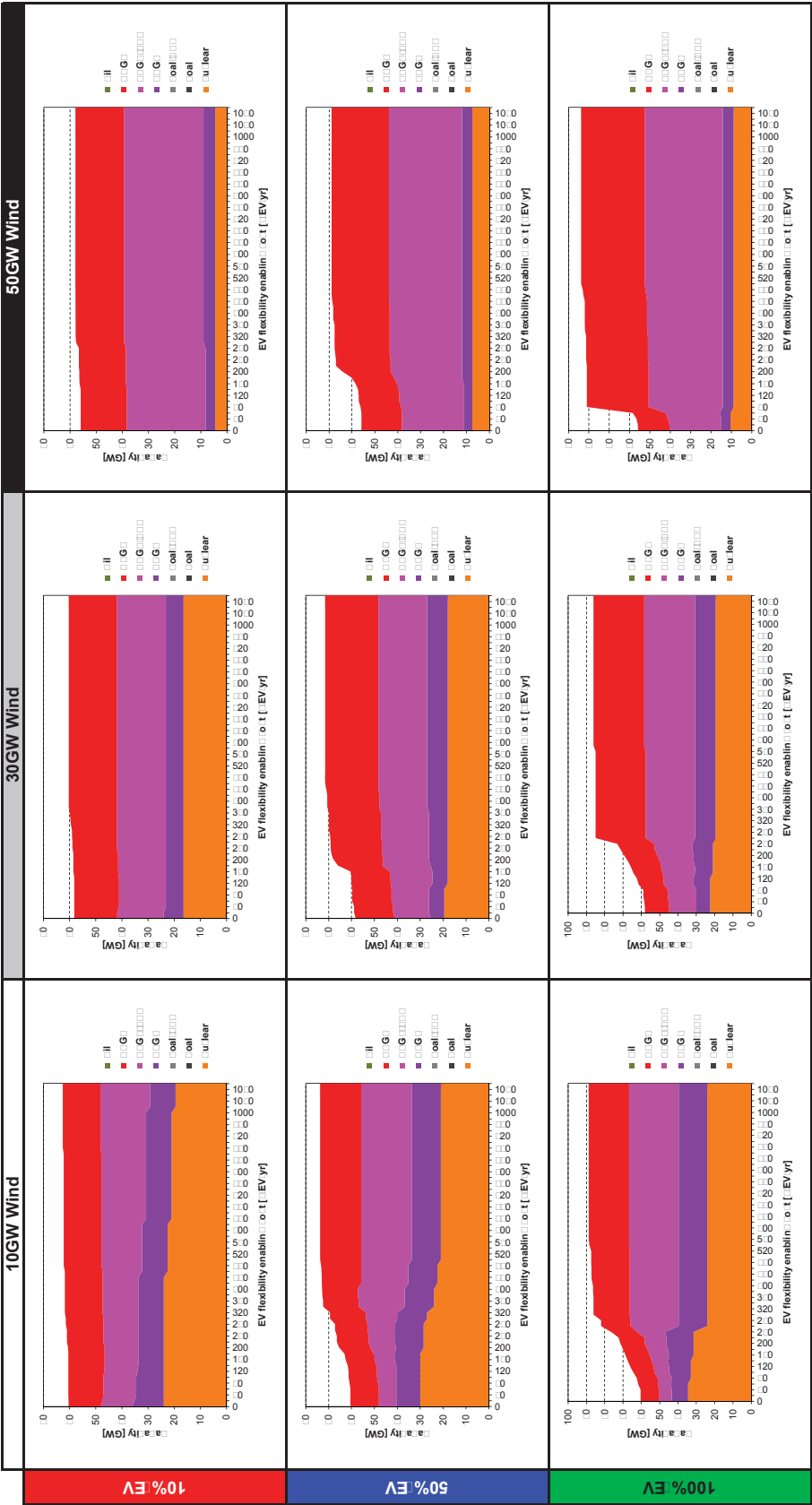
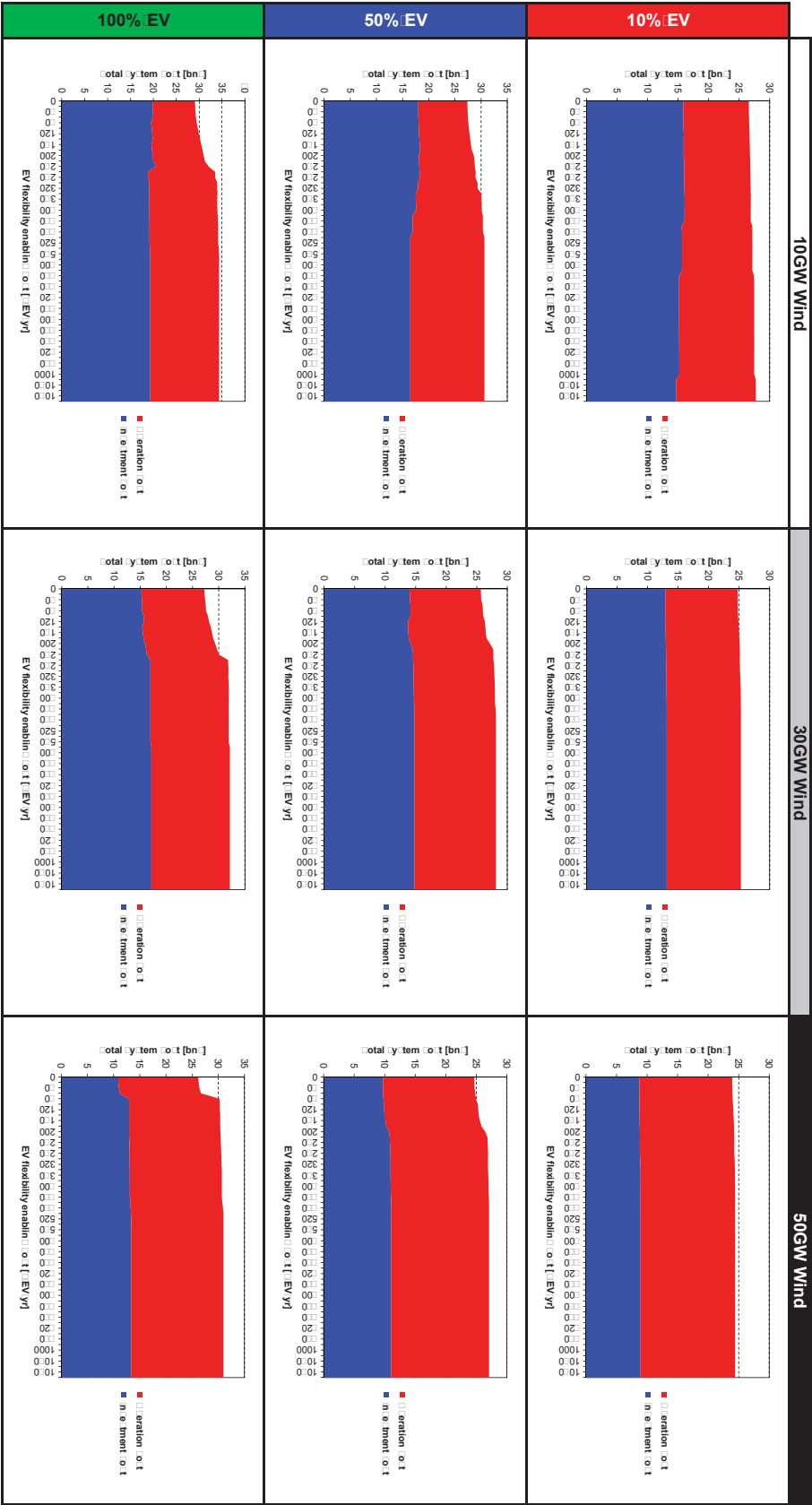


Figure B.1: Comparison of the optimal conventional generation mixes as a function of the EV flexibility enabling cost for different EV penetration and wind generation levels.

Figure B.2: Comparison of the total system costs as a function of the EV flexibility enabling cost for different EV penetration and wind generation levels.



COLOPHON

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