Ph.D. Thesis Dissertation

Thesis defended on the 5^{th} of December 2017 to obtain the degree of Doctor in Electrical Engineering
by
Lazaros Exizidis

Electricity Markets with High Wind Power Penetration: Information Sharing and Incentive-Compatibility

Members of the Jury

Prof. Marc Pirlot (UMONS, Chairman)
Prof. Damien Ernst (ULg, External member)
Prof. François Glineur (UCL, External member)
Prof. Dirk Van Hertem (KUL, External member)
Prof. Georges Kariniotakis (MINES ParisTech, External member)
Prof. Jacques Lobry (UMONS, Secretary)
Prof. Jalal Kazempour (DTU, Co-supervisor)
Dr. Zacharie De Grève (UMONS, Co-supervisor)
Prof. François Vallée (UMONS, Supervisor)

December 2017

Introduction

Availability of information about various properties of an electricity market has an indispensable role for meeting involved market agents objectives. On the one hand, market operators are entities entitled to secure the reliable operation of the market with minimum social cost. Thus, they should have qualitative and truthful information with respect to participants properties and interests. This consists mainly, but not exclusively, of costs and valuations regarding traded energy, their available energy capacity and reserves. On the other hand, producers and consumers that participate in an electricity pool are self-interested entities aiming at maximizing profits (or utility respectively) by their participation in the market. To meet their objective, the possession, to the best possible degree, of a transparent and clear view of the market rules and rivals information is rendered essential.

The inherent variability of wind power generation exposes the market and, inevitably market agents, to new additional challenges. Market operators need qualitative wind power forecasts in order to secure the smallest possible power imbalance in real-time operation, which could possibly lead to system instability. Moreover, well-informed day-ahead market scheduling can lead to increased social welfare and decreased operational costs. Forecasting wind power, however, is in fact a very arduous task, whose results depend greatly on the available to the forecaster resources. Producers, on the other hand, are also interested in anticipating wind power generation, in order to optimize their offering strategies to the market. To this end, this thesis evaluates the solution of *information sharing*, in which market players share their own wind power forecasts with others in the day-ahead market. This approach capitalizes on bilevel optimization modeling and on a two-stage stochastic market-clearing model, in order to explore whether an improvement to the functioning of the sequential market-clearing process can be achieved, by creating better-informed day-ahead schedules, which reduce the need for balancing resources in the real-time operation.

Transparency in electricity markets is also an essential ingredient for the efficient market operation. System and market operators worldwide are taking increasing initiatives towards the publication of various market-related information that may assist efficiency in the market. Favored by the ambitious plans for publishing qualitative aggregate wind power forecasts by market operators, this thesis distinguishes the various impacts of this initiative which, not being by definition positive, may jeopardize the vision of an increased market efficiency due to the imperfect competition that characterizes modern markets. For that purpose, an equilibrium study is incorporated for a setting where strategic power producers consider public forecast information in their decision-making tools and results are evaluated towards different values of the forecast.

Finally, motivated by the bottlenecks caused by strategic behaviors, this thesis investigates the potential of an *incentive-compatible* market mechanism, which has the ability to induce from market participants truthful information regarding their private costs and valuations. Thus, it can eventually lead to increased transparency and market efficiency. The mechanism, which is adapted from the economics literature, is applied in a two-stage stochastic market and compared to the traditional market-clearing mechanism over several, dominant for market operation, criteria. To this end, this work is tailored to evaluate its potential applicability and quantify related caveats in practice.

In a nutshell, the overall objective of the present dissertation can be summarized as addressing the present and future challenges related to the impact of information availability and transparency in electricity pools characterized by high shares of wind power. This is achieved by leveraging mathematical modeling tools, such as stochastic and bilevel optimization, as well as branches of the economic theory, namely game and mechanism design theory.

Thesis Organization

The original contributions of this dissertation are divided into two parts. The organization and description of each chapter is presented below:

General Context and Background

Chapter 1 is a comprehensive introduction of the dissertation. It first introduces the basic aspects of modern electricity markets, involved agents and market mechanisms. Then, the concepts of market power and game theory are briefly introduced along with some economic aspects related to the main chapters of the thesis.

Part I: Impact of Wind Forecast Information Availability in Electricity Markets with High Penetration of Wind Power

Chapter 2 explores a three-step evaluation framework for the impact of sharing wind power forecasts between a wind producer and the market operator. The framework is based on a bilevel model that induces strategic offers from the wind producer which are submitted to a stochastic two-stage market. Finally, an extensive out-of-sample simulation analysis is performed considering a large number of unforeseen wind power realizations for clearing the real-time market.

Chapter 3 extends the model of the previous chapter by assuming that an additional wind power producer is present in the market. The effect of this additional source of uncertainty on strategic wind producer's offering decisions and the anticipated market operation is evaluated.

Chapter 4 evaluates a market where multiple strategic producers are present. Under this setup, it studies the impact of aggregate wind forecasts, published by the system operator, on the market outcomes and the producers objectives. For the scope of this chapter, an equilibrium analysis is performed based on a non-cooperative multi-leader-follower game.

Part II: Mechanism Design Towards Incentive-Compatibility in Electricity Markets with High Penetration of Wind Power

Chapter 5 explores the application of a Vickrey-Clarke-Groves (VCG) incentive-compatible mechanism in a two-stage stochastic electricity market. More specifically, an incentive-compatible VCG-based payment scheme is proposed for a stochastic market and compared to the corresponding traditional market mechanism under both perfect and imperfect competition. Furthermore, the study is extended to include network constraints and the results are evaluated for increasing levels of wind power penetration. Finally, this chapter proposes a redistribution mechanism for recovering revenue-adequacy in the market.

Global Conclusions, Contributions and Future Perspectives

Chapter 6 concludes this dissertation providing a summary, conclusions and the main contributions of the thesis. Finally, suggestions for future research and perspectives, which emerged from the results of the thesis, are additionally presented.

Appendices

Appendix A provides a brief summary of the main concepts associated with mathematical modeling and optimization.

Appendix B lists the technical data and details pertaining to the modified 24-bus system used in the case study of Chapter 5.

Appendix C provides a description of the DC power flow models and the corresponding constraints in market-clearing problems.

Contents

List of Figures

List of Tables

Notation

For convenience, detailed notation tables are given at the formulation section of each chapter. However, in the following lines we introduce some generic principles regarding notation used in this dissertation, in order to ease the reading of mathematical formulations. Those guidelines include the following:

- In order to make a clear distinction between symbols that refer to the model variables and those referring to the model parameters, variables are denoted with lower-case letters, e.g., p^G, while parameters are denoted with upper-case letters, e.g., P^G.
- Set i always refers to conventional units.
- Set d always refers to demands.
- Sets ω, s and h are indices for wind power scenarios.
- With the Greek letter λ we denote either market prices or agents price offers. Thus, for example λ^{DA} and λ^{RT} are the day-ahead and real-time prices, respectively, while λ_i^{G} is the conventional generation price offer of conventional unit i.
- An overline above a parameter, e.g., $\overline{P}$, denotes the maximum value that corresponding variable p can take, and the opposite is denoted by an underline, e.g., $\underline{P}$.
- Dual variables of the lower-level problem of a bilevel optimization model are given after the corresponding constraints following a colon, e.g., $0 \leq p \ : \ \phi$, where ϕ is the dual variable of the corresponding inequality constraint.

Acronyms

TSO Transmission System Operator

ISO Independent System Operator

MO Market Operator

ENTSO-E European Network of Transmission System Operators for Electricity

ACER Agency for the Cooperation of Energy Regulators

DA Day-Ahead

RT Real-Time

LMP Locational Marginal Price

GNE Generalized Nash Equilibrium

NE Nash Equilibrium

MDT Mechanism Design Theory

VCG Vickrey-Clarke-Groves

NWP Numerical Weather Prediction

MPEC Mathematical Program with Equilibrium Constraints

EPEC Equilibrium Problem with Equilibrium Constraints

KKT Karush-Kuhn-Tucker conditions

SDT Strong Duality Theorem

MILP Mixed-Integer Linear Program

LL Lower-Level

UL Upper-Level

IEEE Institute of Electrical and Electronics Engineers

RTS Reliability Test System

SW Strategic Wind (Producer)

RW Rival Wind (Producer)

Glossary

Arbitrage Arbitrage is the simultaneous purchase and sale of an asset to profit from a difference in the price. Arbitrage exists as a result of market inefficiencies.

Budget Balance Budget balance refers to the condition where the difference between the payments that a market operator receives from consumers and payments made to producers is zero.

Competitive Agent see price-taker.

Cost-Recovery Cost-recovery refers to recovering the expenses that an agent has for participating in the auction; in the framework of electricity markets, it refers to the condition in which a producer's profit is non-negative.

Dominant Strategy A strategy is dominant if, regardless of what any other agents do, the strategy earns an agent the largest payoff.

Incentive-Compatibility A mechanism is called incentive-compatible if every participant can maximize its objective just by acting according to its true preferences.

Imperfect Competition Imperfect competition refers to a market where strategic agents are present.

Individual Rationality The incentive an individual economic agent has to participate in a given auction; in the framework of electricity markets, individual rationality refers to the condition where negative profits for producers are not acceptable, i.e., cost-recovery.

Marginal Producer Marginal producer is the producer who would be eliminated from competition by a drop in the market price or a rise in its production costs. Its production costs define the current market price.

Market Efficiency Market efficiency in financial economics refers to the condition in which the price of a commodity fully reflects all available information; in the framework of electricity markets, market efficiency is maximized when market outcomes align with the minimum system cost (or maximum social welfare).

Market Power Market power is the ability of a seller to profitably raise the market price of a good or service over marginal cost. Additionally, market power can also be defined for a consumer as its ability to reduce the market price. In perfectly competitive markets, market participants have no market power.

Perfect Competition Perfect competition refers to the condition where all participating agents reveal their true preferences, i.e., do not exercise market power.

Price Elasticity of Demand Price elasticity of demand measures the responsiveness of demand after a change in the price of the product. In the framework of electricity markets, inelastic demand refers to the case where consumers are not willing to withdraw their demand from the market, despite potential high prices.

Price-Maker Price-maker is an agent who exercises market power in order to change market prices for its own benefit.

Price-Taker Price-taker is an agent who acts competitively with respect to its price, i.e., reveals its true preferences to the market.

Revenue-Adequacy Revenue-adequacy refers to the condition where the central authority of a market receives enough revenue to recover the expenses of the market operation.

Strategic Agent see price-maker.

Social Choice A social choice is an aggregation of the preferences of the different participants toward a single joint decision.

Social Welfare Social welfare in economics refers to the utility gained through an economic activity; in the framework of electricity markets, it refers to the maximization of producers and consumers surplus, i.e., market surplus.

Chapter 1

General Context and Background

This first chapter serves as an introduction to this dissertation and provides all the relevant background information that is needed for understanding all chapters to follow. Under this context, in Section 1.1 we present an overview of electricity market operation. Operation of modern electricity markets is explained by presenting the most common applied market mechanisms but, also, extending the presentation to include mechanisms derived from recent research efforts, which hold particular interest for markets with high penetration of wind power.

It becomes apparent by now that this thesis lies on the crossroad of power systems, operations research and energy economics. Thus, concepts and definitions which depart from the economics society are present throughout this dissertation. In Section 1.2, we attempt to introduce those concepts and terms from an engineering viewpoint, offering a better understanding of the work to follow without, however, going deep into economical aspects.

Modern electricity markets come with a great deal of challenges for all the involved agents. Self-interested market agents may try to manipulate markets by exercising market power. The impact of such strategic behaviors is investigated throughout this thesis and, thus, it is essential to provide an overview of imperfect competition in electricity markets.

Finally, this introductory chapter concludes by presenting the motivation and objectives of the present thesis.

1.1 An Introduction to Electricity Markets

Definition 1.1.1. The term commodity refers to an economic good or service, the demand for which has no qualitative differentiation across a market.

To elaborate more on the above definition, an item is defined as a commodity if it is indifferent for the consumer to buy it from one or the other seller. The item should, thus, be in raw state only and should be available to be used right away. Definitely, electricity retains the main characteristic of a commodity: it is exactly the same for the consumer, independently from where it is produced, e.g. wind or nuclear. However, electricity has properties that differentiate it from other commodities:

- electricity is subject to physical rules: it should be used immediately once generated, since it cannot be stored in large quantities yet,
- supply of electricity should exactly meet the demand,
- transportation of electricity is subject to physical laws, which lead to associated costs and losses.

It was only until the very recent past, that electricity has been commercialized as a commodity. Before, power systems were managed by state-owned entities in a centralized way. However, the so-called economic liberalization lead worldwide to the separation of the various features involved in electrical power systems, namely generation, transmission, distribution and retail. Thus, generation and retail of electricity have been commercialized, promoting the competition of private entities under a certain market scheme. On the other hand, due to the aforementioned specific properties of electricity, transmission in most cases remained a monopoly managed by non-commercial entities, which are entrusted to transmit electrical power from the generation plants to consumers and distribution operators through the electrical grid, having the responsibility to maintain safety and reliability [2, 3]. In Europe those entities are, in regional or national level, the *Transmission System Operators* (TSO) which are interconnected to each other in order to minimize grid instability or failure and to secure supply-demand adequacy. In that sense TSOs, being natural monopolies, are subject to regulations. Under this context, trading electricity is organized in pools or exchanges. A detailed overview of the most important trading floors and the main market participants of the aforementioned electricity pools is presented in the following subsections.

1.1.1 Organization of Electricity Markets

Definitely, the indispensable "ingredients" of a market are the market agents that interact under the determined rules, serving individual or, in cases, societal interests. The main participants of an electricity market are reported below [4]:

- **Producers**

  Power producers have as main objective to increase their profits by selling generated power. A power producer can sell energy produced by traditional means such as nuclear generators, combined heat and power units, coal operated power plants, etc., as well as from renewable energy sources such as wind, solar or hydro power plants. The highest the number of producers participating in the electricity market, the more competitive the market becomes. As a result, electricity prices are expected, in principle, to become lower as the number of participating producers increases. However, as it will be illustrated in the upcoming sections, markets are -by design- vulnerable to strategic behaviors which can lead to increased prices due to the presence of producers with market power.

- **Consumers**

  Consumers are the end-users, i.e., the ones who consume the energy produced by power producers. They can vary from individuals to major industrial players. Large consumers can be connected to the high-voltage grid and purchase energy from the pool. On the other hand, smaller consumers are connected to the distribution systems, being supplied energy from bilateral contracts or by retailers. The target of a consumer is to maximize the utility it obtains from consuming electricity. This means that a consumer desires to maximize the difference between the price it is willing to pay and the actual price of the market. Generally, due to the special features of electricity as a commodity, demand does not significantly change with the variations in electricity prices. Therefore, in many cases demand is considered inelastic, meaning that consumers are not willing to withdraw their demand despite potential high prices.

- **Market Operator**

  Economic management of the market is the responsibility of the market operator. Market operator manages the market following a set of predefined and transparent rules and clears the market in order to define the energy price. In most cases market-clearing procedures are based on matching offers from producers and bids from consumers in order to derive market prices, as well as the economic dispatch of each producer and consumer. The main objective of market operators in performing the market-clearing is to maximize social welfare or minimize the generation-side costs when demand is inelastic. In Europe, there are several energy exchanges operators, e.g., the European Power Exchange (EPEX SPOT) which operates short-term electricity markets for Belgium, as well as Germany, France, United Kingdom and other.

- **Transmission System Operators / Independent System Operators (ISO)**

  Transmission System Operators in Europe are entities responsible for reliably and efficiently running the high voltage transmission systems, being independent from other electricity market players. They are entrusted to ensure equal access to the power grid to all market participants according to non-discriminatory and transparent rules. In order to ensure the security of supply, they also guarantee the safe operation and maintenance of the system. In Europe, the electricity market also stretches across borders, and the interconnections between European transmission systems allow countries to help each other and enable cross-border energy exchanges. For this reason, coordination among TSOs is crucial and, thus, the entity entrusted for this role is the "European Network of Transmission System Operators for Electricity (ENTSO-E)", where each European TSO is equally represented [5]. By March 2017, ENTSO-E consisted of 43 members including ELIA, which is the TSO of Belgium.

Similarly, Indepent System Operators in the United States are non-profit organizations that coordinate, control and monitor the operation of the electrical power system. Their operating area may be within a single US State (e.g., the California ISO) or sometimes expands to multiple states (e.g., the Midcontinent ISO), while in contrast to TSOs in Europe, they additionally operate the electricity market serving as market operators. Finally, ISOs are entitled to provide non-discriminatory access to transmission grid and, thus, must be independent of the transmission grid owners [6].

- **Balance Responsible Parties (BRPs)**

  In Europe, even though the responsibility for maintaining the instantaneous balance between generation and consumption lies with the TSO, the latter outsources the responsibility to private entities called Balance Responsible Parties (BRP). For example, in Belgium a balance responsible party, also called an Access Responsible Party (ARP), must be appointed for every grid access point, i.e., at every point where energy injections or off-takes are performed, for which is responsible for maintaining the balance. Electricity producers, major consumers, electricity suppliers or traders can all be BRPs and are tasked with maintaining the quarter-hourly balance between all grid user injections and off-takes for which they are responsible, based on a contract with the TSO of Belgium, i.e., ELIA [7].

- **Regulators**

  Regulators are independent entities that are entrusted to guarantee market transparency and competitiveness. They are expected to serve public interests and defend consumers interests as well as advising authorities on energy issues. The corresponding entity serving this role at a European level is the "Agency for the Cooperation of Energy Regulators (ACER)". The "Commission for Electricity and Gas Regulations (CREG)", is the corresponding authority for Belgium, being a member of ACER.

1.1.2 Electricity Pools: Day-Ahead and Real-Time Markets

In transmission level, there are mainly two trading floors for the aforementioned agents to interact: (1) the futures markets and (2) the electricity pools (or spot markets).

A *futures market* is an auction market in which participants buy and sell physical or financial products for delivery on a specified future date. The most important feature of futures markets is that they allow trading physical or financial products in the future at today prices. Thus, futures markets are useful if the price of electricity is highly uncertain in the pool, which is the case in pool-based electricity markets.

An *electricity pool*, under which context this dissertation lies, is a marketplace where energy is traded on a short-term time scale. It typically includes a day-ahead (DA) market and several shorter-term markets, called intraday adjustment markets. For example, in Belgium apart from the DA market there is also the "Continuous Intraday Market", which provides a trading floor for market participants to sell and purchase electricity on a continuous basis (from 14:00 the trading day prior to delivery until 5 minutes before delivery). Additionally, the electricity pool includes the balancing market which ensures the real-time balance between supply and demand. In Belgium, the individual BRPs might face a real-time imbalance, which should be then confronted by the TSO by activating upward or downward reserves, depending on whether there is a need for upward regulation, i.e., grid injection, or downward regulation, i.e., decrease in grid injections [8]. In the DA and adjustment markets, producers submit energy blocks and their corresponding minimum selling prices for every hour of the market horizon and every production unit. At the same time, retailers and consumers submit energy blocks and their corresponding maximum buying prices for every hour of the market horizon. The market operator collects purchase bids and sale offers, and clears the market (both DA and adjustment) using a market-clearing procedure [9]. Market-clearing procedures are comprehensively explained in the following paragraphs.

The most commonly preferred trading floor in an electricity pool is the DA market, while adjustment markets are used to make adjustments to the energy cleared in the DA market. The DA energy exchange takes place one day in advance and settles contracts for the delivery of energy on an hourly basis. The balancing market serves to competitively settle the energy adjustments required to ensure the constant balance between electricity supply and demand [9]. As observed in Figures 1.1 and 1.2, Begium presents an example of the increasing role of spot markets, since the traded volumes in DA and Intraday markets increased significantly through the last decade.

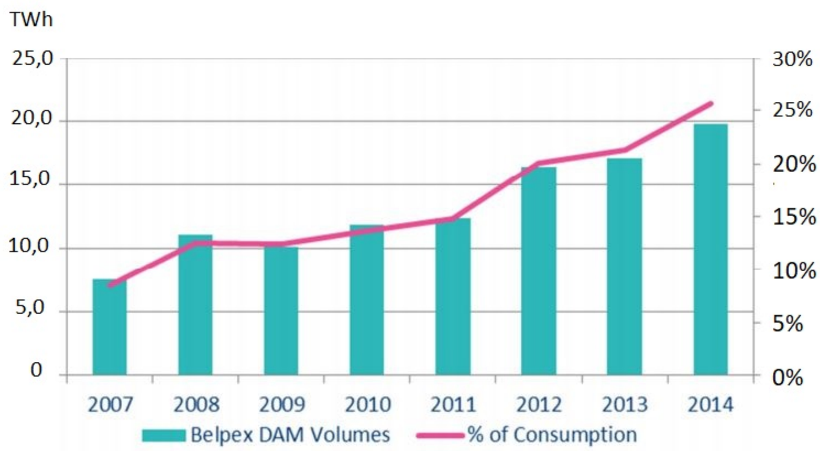

Figure 1.1: Belpex (currently EPEX SPOT Belgium) DA market volumes through the years 2007 - 2014 [1]

In the following lines, we illustrate the aforementioned definitions with qualitative examples. In a DA market, producers submit their production blocks of energy along with the minimum selling prices for the DA market. At the same time, consumers submit their energy consumption quantities along with the maximum price they are willing to pay. The above offers and bids are submitted to the market operator at least 24 hours ahead energy delivery and, most commonly, on an hourly basis for the following day. In the case that transmission constraints are not considered in the market-clearing process, e.g., in most European DA markets including Belgium, market operator aggregates demand bids and generation offers into the so-called *merit order* curve. This curve has typically the shape of Fig. 1.3.

As seen from the figure, producers offers (supply curve) are ranked with increasing price order while consumers bids (demand curve) are ranked oppositely with decreasing bids order. Accordingly, the intersec-

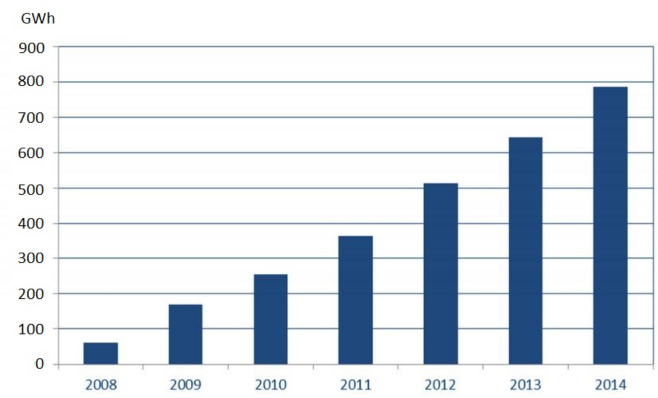

Figure 1.2: Belpex (currently EPEX SPOT Belgium) continuous intraday market volumes through the years 2008 - 2014 [1]

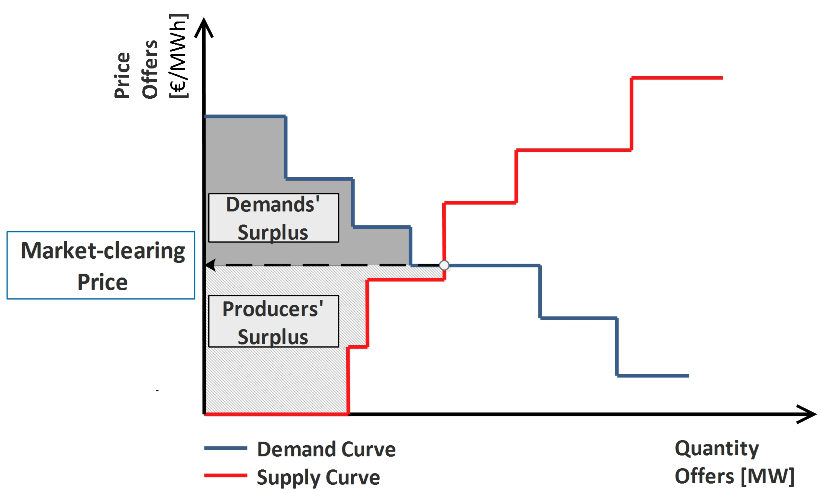

Figure 1.3: Merit order curves

tion point of the supply-demand curves sets the market price. Following the definition of the market price, all producers with a lower price offer are scheduled and paid on the market-clearing price and, thus, they profit the difference between the market price and their generation cost. Similarly, all consumers with higher price bid than the market price are expected to pay each energy unit in the market-clearing price, benefiting as well. Under this context, we can define the maximization of *social* *welfare* as the exact objective of a market-clearing mechanism: that is, to find the equilibrium between the maximization of aggregate producers and consumers surplus, indicated by the sum of the corresponding shaded areas in Fig. 1.3.

The aforementioned market-clearing problem can be mathematically formulated as an optimization problem, which objective function is the maximization of the social welfare function subject to a number of constraints, as illustrated in Fig. 1.4. A market-clearing process results in

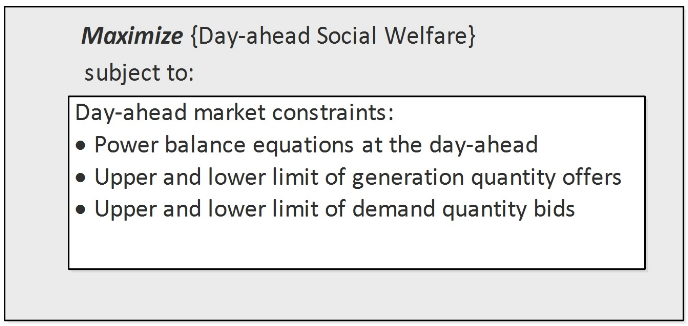

Figure 1.4: DA market-clearing formulation

market-clearing prices, as well as production and consumption schedules. If the transmission grid is not considered in the market-clearing process, the resulting market-clearing price is identical for all market agents. This is, for example, the case in Belgium. On the other hand, if the transmission network is taken into account for clearing the market, instead of a single market-clearing price, a locational marginal price (LMP) is associated with each node of the power system. Most notable LMP markets are the markets of PJM Interconnection, ERCOT, New York, and New England in the US. The LMPs differ across nodes due to line congestion. If a transmission line is congested, more expensive generation is needed to be dispatched on the downstream side of the congested line. This increase in expensive generation yields an increase in the market-clearing prices in those nodes placed on the downstream side of the congested line. The corresponding optimization model is presented in Fig. 1.5.

With respect to the balancing market, reserve capacity may be sequentially procured in a series of auctions run once the DA energy dispatch has been determined. These auctions are organized to procure

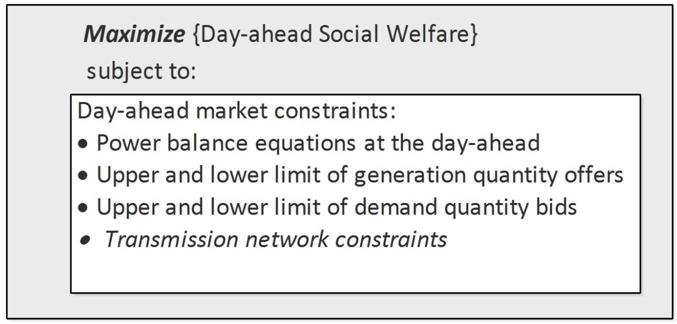

Figure 1.5: DA market-clearing formulation considering transmission constraints (LMP)

reserves with different activation times. The rationale behind this approach is that the free capacity that has not been successfully placed in one market can then be offered in the following auctions where the required activation time for the traded reserve is not as demanding. Consequently, reserve capacity offers that are successful in one market are not considered in the subsequent ones. On the other hand, DA and balancing markets may be simultaneously procured using an optimization algorithm that captures the strong coupling between the supply of energy and operation of real-time (RT) market [2]. This approach is illustrated in Fig. 1.6 and will be given special attention throughout this dissertation. For a comprehensive example of the stochastic two-stage market-clearing mechanism see book [2] (pages 64-70).

1.1.2.1 Nodal and Zonal Pricing Schemes

As explained in this section, electricity markets around the world share some common characteristics but they also have significant differences. More specifically, most of electricity markets in the US operate under the LMP scheme, which aims in maximizing social welfare considering transmission network constraints, thus leading to different prices in congested network nodes. For this reason, we refer to this pricing scheme also as nodal pricing. On the contrary, Europe is currently under a transmission phase completing the internal market in electricity [10], which aims in a single European energy market, through the implementation of the so-called Target Model [11]. However, this is an ongoing pro-

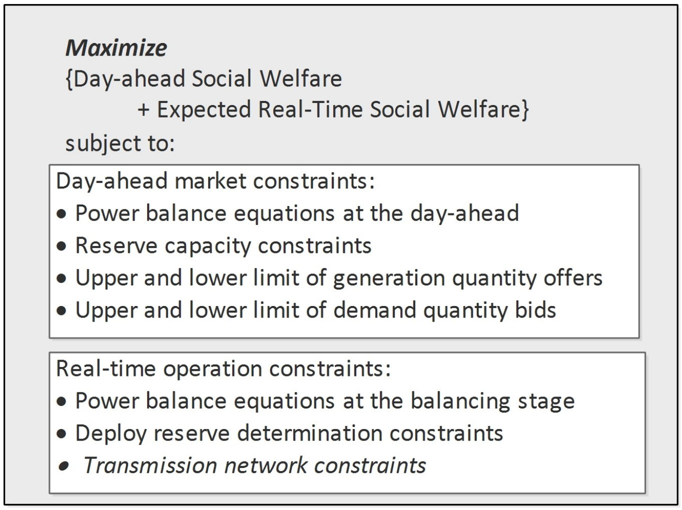

Figure 1.6: Stochastic two-stage DA market-clearing formulation

cess and electricity markets in European countries are still subject to continuous changes. Electricity markets in Europe follow a zonal pricing scheme, where the prices may change among different geographical zones, in contrast to the nodal pricing where prices change among different network nodes. A market zone usually comprises a country, e.g. the case of Belgium, but there are examples of zones which consist of multiple countries, e.g., Germany and Austria, or countries which are divided in multiple zones, e.g., the case of Italy [12].

The advantages and disadvantages of the two different schemes have been investigated in the technical literature. In [13, 14], authors show that nodal pricing might be better in preventing market power compared to the zonal pricing, while [15, 16, 17] indicate problems in market efficiency and highlight the difficulties in optimally defining zones in large networks. Furthermore, author in [18] notes a greater risk for inefficient dispatches in the zonal scheme under increased uncertainty, e.g., due to increased wind power penetration, appraising the possibility of varying prices across a country (referring to the UK), which would reflect the true state of the transmission system and give incentives to reduce generation and investment in constrained areas. Finally, in review paper [19], author concludes that nodal pricing yields better outcomes in the short and long term, since congestion is directly reflected in optimal spot prices. On the other hand, nodal pricing comes with several disadvantages mainly related to complexity, such as the possibly complex coordination of the corresponding sub-markets and the high number of nodal prices that have to be calculated. The latter, along with political reasons related to the fact that Europe consists of independent countries, makes zonal pricing more applicable since it avoids different prices throughout the territory of a single country.

To this end, in Chapters 2, 3 and 4 we adapt a market-clearing process without considering network constraints, i.e., a single zone is considered. On the other hand, in Chapter 5 we evaluate a novel mechanism for market-clearing and, thus, it is rendered crucial to investigate the model under a nodal pricing system (LMP market), in order to better reflect the state of the transmission system and potential congestion on the optimal market-clearing.

1.1.3 Challenges Related to High Penetration of Wind Power in Electricity Markets

In principle, the operational cost of wind power generation is very low [20, 21, 22, 23, 24] or even negative due to incentive schemes that offer premiums to renewable energy production on top of the market-clearing price [25]. The result of this important feature is that wind power generation is scheduled before conventional generation, thus entering the merit order curve from the left-hand side [2]. Naturally, wind power influences market prices by shifting the supply curve and, consequently, the intersection point of the two curves to the right. This is illustrated in Fig. 1.7, where the dashed red curve is shifted to the right due to the introduction of zero-cost wind power generation on the left-hand side. Thus, the corresponding price is lower, being the intersection of the supply-demand curves.

In addition to the decreasing market-clearing prices, wind power penetration introduces important variability in the generation-side of the power system, due to its stochastic nature. As indicated before, high wind power penetration means lower prices, as the result of the supply curve moving to the right. However, the inherent variability of wind power generation increases the need for backup power generation in RT in order to fix supply and demand imbalance caused by the unpredicted

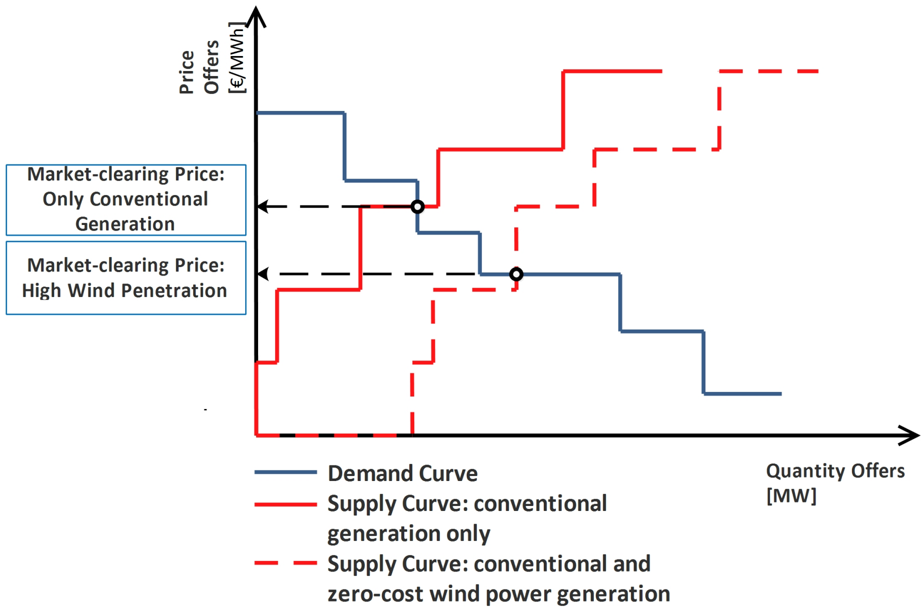

Figure 1.7: The *merit order effect*: Increasing penetration of renewable energy in the market tends to lower the average market price of electricity since those sources have very low marginal costs, thus entering the merit order curve from the left-hand side.

wind power fluctuations. To this end, balancing markets are important for wind power producers, since they form the trading floor that allows them to adjust their contracts in order to match their actual output [2]. Obviously, this leads to increased needs for balancing resources in real time, which increase the market cost of the RT market.

Considering the above, there is an apparent need for increased flexibility in the market as well as for optimal DA scheduling, to reduce real-time imbalances. The former corresponds to the need for flexible generation units, i.e., units that can quickly and efficiently alter the level of power generation (either increase it or decrease it), in order to provide reserves for securing supply-demand balance in real time. However, the increased competitiveness of RES out-competes conventional generation and along with the introduced increased need for flexible resources, jeopardizes supply-demand balance in real time. Thus, complementary services/products are introduced in a number of electricity markets in order to ensure balance in RT, e.g., capacity remuneration mechanisms (CRM) in Belgium, also known as "strategic reserves" [26]. Additionally, sources of flexibility can be also found in the demand side of the power system, where demand-response products can help in maintaining the balance in real time, by paying consumers to voluntarily withdraw their demand in times of supply scarcity. Lastly, the second challenge refers to the need for optimal wind power and reserve scheduling, in order to avoid -to the best possible degree- imbalances in the real time. In this vein, researchers focus on novel approaches and improvements on wind power forecasting (e.g., [27]) and new market-clearing mechanisms, which in contrast to the traditional deterministic ones, are tailored for accounting stochasticity in the market (e.g., [28]).

1.2 Competition in Electricity Markets and Economic Aspects

1.2.1 Design Principles of Electricity Markets

The main purpose of restructuring electricity markets is to increase competition which is expected to lead in decreasing electricity prices and increased social welfare. The new market design creates an open environment by allowing producers to compete and consumers to choose from whom they will be delivered their energy. Even though the implementation of the market design principles varies from region to region, successful operation of electricity markets should satisfy some common criteria. Therefore, market operator's success is subject to ensuring the following properties [3]:

- **Power System Reliability**

  Power system reliability refers to ensuring supply and demand balance. To achieve this goal, market operator coordinates with the system operator, while in many cases the two actors can be a single entity (e.g., US markets CAISO, NYISO, etc.). System operator contributes to the design of the market in order to ensure that market rules will support reliable power system operations. During operation, market operator exchanges information with the system operator about the state of the power system and reliability needs.

- **Market Transparency**

  Transparency is of great importance for a market to be competitive. Market rules should be clear and market signals should be predictable for each participating market agent. Therefore, there is the need for a market design in which actual power system operating conditions are reflected in the market results. In this context, transparency is the ability of individual participants to understand that the market signals they receive are consistent with minimizing the system cost, with maximizing the individual participant's revenue and with power system operating conditions. For example, in the case of an LMP market, market transparency is supported by publishing the binding constraints and market prices. The prices are consistent with the constraints, providing incentives that reinforce participants behavior to maintain and/or increase reliability.

- **Revenue-Adequacy**

  While maintaining system reliability and transparency, the market must also be consistent with *revenue-adequacy* principles, ensuring that the revenue it collects from consumers is enough to pay the producers costs. In cases where electricity markets are cleared considering the transmission network constraints, revenue-adequacy translates in collecting sufficient congestion charges in order to support the price incentives given to producers and consumers to maintain system reliability.

- **Cost-Recovery** Additionally to the market operator, financial certainty should also be ensured for market participants as well. That said, *cost-recovery* should be secured for market-participants, which means that market participants should be ensured that they are not going to face losses by participating in the market.

- **Market Efficiency**

  Market efficiency describes how well the market applies available resources to maximize market objectives, i.e., maximization of social welfare. Efficiency is included in the market-clearing objective function which models the production costs, demand bids and, in many cases, network constraints. The resulting operational instructions (e.g., unit dispatch) and prices are consistent with the optimal dispatch, thus achieving transparency and, at the same time, operational efficiency.

1.2.2 Market Power

Under the assumption of perfect competition, i.e., there is no market agent that exercises market power, the design of the DA and the RT markets, as presented previously, guarantees all the aforementioned properties. However, electricity market offers in practice a trading arena where participating agents may have the opportunity to exercise market power in order to alter market-clearing outcomes and increase individual interests. Under this context, competitive behavior is not to be confused with market power which may have crucial impact on social welfare and electricity prices.

Based on their ability to exercise market power, producers can be divided in two categories, namely *strategic producers* or *price-makers* which have the capacity to exercise market power and *competitive producers* or *price-takers*. A price-taker producer is willing to sell its generated electricity as long as it is paid in a price at least equal to its marginal production cost, ensuring cost-recovery. In case the market-clearing price is equal to producer's marginal cost, the latter is called *marginal producer*, being the one that defines the market price. On the other hand, a price-maker producer can behave differently and exercise market power in two ways: (1) by withholding a part of its capacity in order to let more expensive units to become the marginal ones or (2) by raising its price offer in order to increase market-clearing prices.

Given that an optimal market design is important to satisfy the three main properties of revenue-adequacy, efficiency and cost-recovery, strategic behaviors may jeopardise the optimal operation of a market. In the case of the traditional market-clearing models, those three properties are satisfied only under the assumption that all participants are price-takers, which is rather unrealistic. If price-makers are present in the market, then market-clearing results may be manipulated leading to increased prices and decreased social welfare. It is, therefore, of great interest to investigate market mechanisms considering the impact of potential strategic behaviors. To this end, in the following lines we present some basic concepts with respect to markets that include strategic agents, which compete in non-cooperative environments and exercise market power.

1.2.3 Basic Concepts of Game Theory and Mechanism Design

1.2.3.1 Game theory

Game theory aims to help us in understanding situations in which decision-makers interact. A game in the everyday sense, i.e., a competitive activity in which players compete with each other according to a set of rules, is an example of such a situation, but the scope of game theory is vastly larger. In the last 50 years, game theory has become a useful analytic tool for the assessment of strategic behavior of market players in an oligopoly setup [29, 30]. An example of adapting game theory to power systems is the following: in an oligopolistic electricity market the producer may be seen as a market player submitting offers higher than the marginal cost and aiming to its surplus maximization. The objective function of the market-clearing optimization problem is altered by replacing producers marginal costs with their strategic offers [31]. In order to provide some general definitions related to game theory as a subfield of the economic theory, we will adapt, for the following lines, the terms *"game"* and *"player"*, which under the context of this thesis naturally correspond to *electricity market* and *market agents*.

A strategic game is a model of interacting players, where each player has a set of possible actions. The model captures the interactions among the players by allowing each player to be affected by the actions of all players, not only by its own action. Specifically, each player has preferences about the action profile, which represents the list of all the players actions. More formally, a strategic game consists of:

- a set of players,

- for each player, a set of actions,
- for each player, preferences over the set of action profiles.

The most common models in the literature analyzing market power in electricity markets are presented briefly below:

1. **Cournot model**

   The Cournot model, a generalization of the duopoly game formulated by A. Cournot in [32], describes a setup where each producer wants to maximize profits by offering production quantities, assuming that the output of other producers does not depend on its output decisions. The Cournot approach yields a direct outcome in terms of price and quantities as a function of the demand function.

2. **Stackelberg model**

   The Stackelberg model, first introduced in [33], is a non-cooperative competition game with a dominant player which is called leader and a number of other players called followers. The leader of the game maximizes its profit by anticipating the responses of the rest of the players, which are perfectly known. Then, given the leader's strategic decisions, followers compete with each other in a non-cooperative manner. The Stackelberg model is used in this thesis, and more particularly in Chapters 2 and 3, where the leader is a wind power producer with large enough capacity to exercise market power, while the rest of conventional or wind producers are the followers with no strategic behaviors.

3. **Multi-leader-follower game**

   A multi-leader-follower game [34] is an extension of the Stackelberg game where there exist more than one leaders in the game competing non-cooperatively with each other. This process is realized by each leader anticipating the strategy of the rival leaders in its offering strategy. A specific case of this game is the multi-leader-common-follower game, which realizes if the follower responses are common across all leaders. The equilibrium reached in such a game can be identified as Generalized Nash Equilibrium (GNE), which is a generalization of the standard Nash Equilibrium, presented in the following paragraph. Such a game is considered under the context of Chapters 4 and 5, where multiple strategic producers are considered in the market competing each other in a non-cooperative manner. The role of the common follower is taken by the market operator, whose objective and decision-making strategy is anticipated by the competing producers.

Nash Theory or *Nash Equilibrium* is a solution theory of non-cooperative games involving two or more players, according to which no player has the incentive to move from this solution by unilaterally changing its strategy. Let us assume that each player chooses the best available action. In a game, the best action for any given player depends, in general, on the other players actions. Thus, when choosing an action, a player must have in mind the actions other players may choose. That is, each player must form a belief about the other players actions. The assumption underlying the analysis, under the context of a Nash game, is that each player's belief is derived from its past experience playing the game, and that this experience is sufficiently extensive that it knows how its opponents will behave [*]. Although we assume that each player has experience playing the game, we assume that it views each play of the game in isolation. It does not become familiar with the behavior of specific opponents and consequently does not condition its action on the opponent it faces; nor does it expect its current action to affect the other players future behavior.

In summary, the Nash solution theory has two components: (1) each player chooses its action according to the model of rational choice (that is being self-interested), given its belief about the other players actions and (2) every player's belief about the other players actions is correct. These two components are embodied in the following definition:

Definition 1.2.1. A Nash equilibrium is an action profile, a^*, with the property that no player i can do better by choosing an action different from a_i^*, given that every other player j adheres to a_j^* .

[*] On the contrary, multi-agent reinforcement learning provides a framework where agents learn an optimal behavior through trial-and-error interactions with their environment, see e.g. [35, 36].

Based on the above definition, in the framework of this thesis and more specifically Chapters 4 and 5, searching for the Nash equilibrium of the market corresponds to finding a set of strategic producers price offers, under which no producer wishes to change its strategy unilaterally, given that a change in his strategy would only result in lower profits.

1.2.3.2 Mechanism design

Mechanism Design Theory (MDT) [37] is another branch of economic theory that differs from game theory in the sense that game theory takes the rules of the game as given, while MDT asks about the consequences of different types of rules. Naturally, this relies heavily on game theory. Questions addressed by MDT include the design of compensation and wage agreements that effectively spread risk while maintaining incentives, and the design of auctions to maximize revenue, or achieve other goals. MDT is, thus, a subfield of economic theory that is rather unique within economics in having an engineering perspective and is interested in designing economic mechanisms [38]. In order to formally define MDT, let us first define *social choice*. A social choice is an aggregation of the preferences of the different participants toward a single joint decision. MDT attempts implementing desired social choices in a strategic setting - assuming that the different members of society each act rationally in a game-theoretic sense, being self-interested. Such a strategic design is necessary since usually the preferences of the participants are private and, thus, the main assumption of the Nash Equilibrium, does not usually hold in practice.

The MDT is, thus, the science, belonging to the family of game theory, of designing the rules of a game in order to achieve outcome, even though each participant may be self-interested. This is done by setting up a structure in which each player has the incentive to behave as the designer intends. Based on this, it is commonly referred to as reverse game theory. In MDT, it is important for the designers of a game to achieve the following four main properties:

- *Incentive-compatibility*, meaning that every participant can achieve the best outcome to itself just by acting according to its true preferences, i.e., being non-strategic. We can distinguish two different categories of incentive-compatible mechanisms:

1. a mechanism that imposes truthfulness to be each player's best strategy, independently of other players actions, called also *dominant strategy incentive-compatible* or *strategy-proof mechanism*.
2. a mechanism that, being incentive-compatible in a weaker degree, imposes truthfulness to be each player's best strategy only if all rivals also act truthfully, i.e., truthfulness is a *Nash Equilibrium*.

- *Individual rationality*, meaning that a solution is only acceptable if participants gain value by participating in the game, ensuring that way their participation. Therefore, individual rationality ensures cost-recovery in electricity markets.

- *Budget balance*, which ensures that the market collects enough revenue from purchasers in order to pay the suppliers. Obviously, budget deficit is an undesirable result in a market, requiring external budget to support market functioning. On the other hand, in some markets it is preferable to maintain as much wealth as possible within the group of agents and, thus, budget surplus is as well to be minimized. In electricity markets, budget surplus might appear (e.g., in LMP markets) due to congestion, which corresponds to payments transferred to the grid operator.

- *Social welfare maximization*, achieved by aggregating all participants preferences into a common preference. In electricity markets, maximizing social welfare is equivalent to maximizing market efficiency.

Unfortunately, it is impossible to guarantee all four properties in a market design. Hurwicz in [39] first showed a conflict between efficiency and strategy-proofness in a simple two agent model, summarized by the theorem, also called *Hurwicz Impossibility Theorem*, which states that "it is impossible to implement an efficient, budget-balanced, and strategy-proof mechanism in a simple exchange economy with quasi-linear preferences". Hurwicz Impossibility Theorem was extended later by the *Myerson and Satterthwaite impossibility theorem* [40], which proves that no mechanism is capable of achieving individual rationality, efficiency, and budget balance at the same time for general valuation functions, even if solution is loosened to refer to Bayes-Nash equilibrium [41]. Albeit negative this result is, fortunately, it is possible to achieve incentive-compatibility, efficiency, cost-recovery and *weak* budget balance in a number of interesting domains. This possibility is studied under the context of Chapter 5, exploring the Vickrey-Clarke-Groves mechanism in electricity markets and comparing it with the LMP market scheme.

1.2.3.3 Vickrey-Clarke-Groves mechanism

In MDT, a Vickrey-Clarke-Groves (VCG) mechanism is a generic truthful mechanism for achieving a socially-optimal solution [29, 38]. It forms a generalization of the VCG auction which is the collective outcome of the research works of Vickrey [42], Clarke [43] and Groves [44]. The property of truthfulness that VCG secures in a market is the motivation behind the work presented in Chapter 5. Therefore, in the following lines we introduce the mechanism and its basic features.

Nash equilibrium, as previously presented, is based on the assumption that all players preferences are known perfectly, either from previous experience or because agents report them truthfully. However, in settings with self-interested agents, such as electricity markets, it is rather unlikely that agents would be willing to publicly reveal their true preferences. To this end, VCG is explored in Chapter 5 under the context of electricity markets. The main idea behind VCG mechanism lies in the fact that each player is paid an amount equal to the sum of the values of other players. In other terms, VCG has the property to eliminate incentives for misreporting values, by penalizing any player by the cost of the distortion it causes.

Before we give the formal definition of the VCG mechanism, based on [38], the notation is explained hereafter: the preference of each player $i \in I$, is modeled by a valuation function $v_i \in V_i$ and its payment by p_i. The players that win in the auction, i.e., their bids/offers are accepted, are denoted by α. Let $v_i = (v_1, ..., v_n)$ be an n-dimensional vector, then we denote by $v_{-i} \in V_{-i}$ the $(n-1)$-dimensional vector in which the i^{th} coordinate is removed, i.e., $v_i = (v_1, ..., v_{i-1}, v_{i+1}, ..., v_n)$. Lastly, the aggregate utilities of all players, i.e., social welfare function, is denoted by $f(v_1, ..., v_n)$.

Based on the above, the formal definition of the VCG mechanism is given below:

Definition 1.2.2. A mechanism $(f, p_1, ..., p_n)$ is called a Vickrey-Clarke-Groves (VCG) mechanism if

- $f(v_1, ..., v_n) \in \text{argmax}_{\alpha \in A} \sum_i v_i(\alpha)$; that is, f maximizes the social welfare, and
- for some functions $h_1, ..., h_n$, where $h_i : V_{-i} \rightarrow \mathbb{R}$ (i.e., h_i does not depend on v_i), we have that for all $v_1 \in V_1, ..., v_n \in V_n$: $p_i(v_1, ..., v_n) = h_i(v_{-i}) - \sum_{j \neq i} v_j(f(v_1, ..., v_n))$.

The main idea lies in the term $-\sum_{j \neq i} v_j(f(v_1, ..., v_n))$, which means that each player is paid an amount equal to the sum of the values of all other players. When this term is added to its own value $v_i(f(v_1, ..., v_n))$, the sum becomes exactly the total social welfare of $f(v_1, ..., v_n)$. Thus, the mechanism aligns all players incentives with the social goal of maximizing social welfare, which is exactly achieved by telling the truth. The term $h_i(v_{-i})$ does not depend on what player i reports and, thus, it has no strategic value for i. A similar proof regarding incentive-compatibility in VCG mechanism, but specifically for the electricity market model of Chapter 5, is presented in the corresponding chapter.

1.3 Thesis Features and Objectives

This PhD thesis copes with the importance of information in modern electricity markets and market-clearing mechanisms. Its main objective is to evaluate potential solutions for increasing market efficiency, based on information sharing and incentive-compatible market mechanisms. Under this context, a number of exact mathematical programs are developed that aim to capture the impact of information availability as well as incentive-compatibility, for improving market-functioning. In an effort to accurately represent interactions among various market agents in modern electricity markets, the following features are present throughout the thesis:

- The spot market (DA and RT) is cleared by the market operator based on producers offers and demands bids.
- Market operator aims in maximizing social welfare (or minimizing operational costs for inelastic demand).
- Producers aim in maximizing their profits, by optimizing their offering portfolio, while they may have strategic behavior. This translates in a decision-making process where producers anticipate market operation in their strategy in order to alter market results on their individual benefit.
- Stochastic co-optimization of DA and RT markets is preferred in Chapters 2, 3 and 5 over a deterministic DA market-clearing approach, in order to better capture the stochastic nature of wind generation, given that traditional market-clearing mechanisms are strongly focused on deterministic conventional generation.

Under the above general context, this thesis work sets the following two research objectives:

1. **Impact of Wind Forecast Information Availability in Electricity Markets with High Penetration of Wind Power.**

   The first set of objectives concerns the increasing value of wind forecasts on market outcomes and agents interactions in the market. Chapters 2-4 are dealing with the above objective, and more specifically:

   - Chapter 2 evaluates the impact of sharing individual and, *a priori*, private wind power forecasts on the market outcomes. A three-step evaluation framework is explored which consists of the strategic wind producer's offering model, a stochastic DA and RT co-optimized market model and, lastly, an out-of-sample deterministic analysis of RT market-clearing. Following a numerical study based on the aforementioned framework, the impact of sharing forecasts between the wind producer and the market operator is evaluated with respect to both market agents objectives.

- Chapter 3 capitalizes on the same setup but additionally considers a second wind power producer who adds another source of uncertainty to strategic wind producer's decision-making problem. Under this context, the impact of the additional source of uncertainty is studied.
- Lastly, Chapter 4 further extends the context of the previous chapters by considering multiple strategic producers in the market, some of them including in their generation portfolios wind power. Driven by recent directives regarding publication of data, the effect of aggregate wind forecasts, published by market operators worldwide, is evaluated with respect to producers strategies and market outcomes.

2. **Mechanism Design Towards Incentive-Compatibility in Electricity Markets with High Penetration of Wind Power.**

   Today's electricity markets are vulnerable to manipulation. In order to maximize its objective, market operator would optimally avoid receiving manipulated and false information regarding market participants information, i.e., their production costs, consumption values, generation capacity, etc.. Thus, the scope of Chapter 5 is to investigate a new payment scheme, based on the economic theory of MDT, which aims in eliciting truthful information from all participants, by incorporating into their payments the distortion they cause to the market.

   Under this context, Chapter 5 copes with the following specific objectives:

   - Propose a VCG model for a two-stage stochastic market, where the first stage is the DA market-clearing and the second is the expected RT power adjustments based on a set of wind power scenarios.
   - Comprehensively compare the VCG mechanism with the corresponding LMP mechanism under perfect and imperfect competition for increasing levels of wind power penetration.
   - Evaluate the results from both producers and demands viewpoints, i.e., producers profits and demands payments, respectively.

- Evaluate the impact of congestion in the transmission network and compare the results with market-clearing excluding the transmission constraints.
- Suggest a solution scheme for partially recovering the negative budget imbalance of the market under VCG, in order to ensure revenue-adequacy.

Part I

Impact of Wind Forecast Information Availability in Electricity Markets with High Penetration of Wind Power

Chapter 2

Sharing Wind Power Forecasts in Electricity Markets

2.1 Introduction

In this chapter we investigate a stochastic day-ahead (DA) market setup, where the wind producer and the market operator may have different forecasts for wind power generation. Under this context, the impact of sharing private forecast information on market outcomes as well as on producers interests is evaluated.

2.1.1 Motivation

In an electricity pool with significant share of wind power, all generators including conventional and wind power units are generally scheduled in a DA market based on wind power forecasts. Then, a real-time (RT) market is cleared given the updated wind power forecast and fixed DA decisions to adjust power imbalances. This sequential market-clearing process may cope with serious operational challenges such as severe power shortage in real time due to erroneous wind power forecasts in DA market. To overcome such situations, several solutions can be considered such as adding flexible resources to the system, e.g., peaking units and demand response providers [45, 46]. In this chapter, we address another potential solution based on information sharing in which market players share their own wind power forecasts with others in DA market. This solution may improve the functioning of sequential market-clearing process through leading to more informed DA schedules, which reduces the need for balancing resources in RT operation. The potential value of sharing forecasts for the whole system in terms of system cost reduction is numerically evaluated. Additionally, its impact on each market player's profit is analyzed. The framework of this study is based on a stochastic two-stage market setup, which allows us to gain further insights into the impact of information sharing, as well as complementarity modeling, which refers to optimization models which are complemented (constrained) by other optimization problems (see Appendix A).

2.1.2 Literature Review and Contributions

Over the last decade, the share of wind power has rapidly grown. For example, wind power is the generating technology with the highest rate for new installations in Europe, reaching 128.8 GW of installed capacity [47]. Germany is currently the leading country in terms of installed capacity with more than 39 GW installed by the end of 2014, while Denmark is a pioneer country in terms of the high share of wind power production, covering the same year almost 40% of its electricity consumption from wind power [48]. However, uncertainty and variability in wind power production pose operational challenges in electricity markets. Under this context, wind power forecast and the level of its accuracy are key factors in modern power systems. This rises up a need for re-thinking the design of electricity markets as the share of stochastic non-dispatchable production increases.

The importance of wind power forecast accuracy for improving the operation of wind-integrated power systems is investigated in a large number of papers and technical reports in the existing literature. Reference [27] gives an overview of the recent advances in wind power forecast techniques. Although such techniques are constantly improving, wind forecasts are still followed by a considerable error especially in DA timescale [49, 50, 51]. This error leads to several operational challenges in electricity markets addressed in [52, 53, 54, 55]. One potential solution to cope with those challenges is to add various operational flexible resources to the market such as peaking units and demand response providers [45, 46]. The operational value of those resources is evaluated in [56, 57, 58].

However, in this chapter we address another potential solution for system functioning improvement, i.e., sharing wind power forecasts among different players, which may assist market players to build a more accurate wind power distribution than the one they individually forecast. Note that this sharing mechanism can improve the forecast of each player only if the shared forecasts are not fully correlated. This condition is consistent with the real-world electricity markets because the forecast of each market player is dependent not only on public numerical weather prediction (NWP) models, but also on the forecasting methodology of that player and its historical forecast error data. In case we assume that all players have the same beliefs about all technical characteristics of the system except the future wind power, sharing wind power forecasts allows to characterize the market competition as a game-theoretic model with complete information (instead of one with incomplete information).

A short-run electricity market is considered with two sequential trading floors: DA and RT markets. The DA market is cleared based on all bids and offers, such as wind producers offers. Given the fixed DA decisions, the market operator clears RT market based on updated wind power forecasts, which might be different than the wind producers dispatch in DA market. Two different setups are generally available in the literature to manage wind power uncertainty within a sequential DA-RT framework: deterministic and stochastic. In the first one, the market operator clears DA market based on all submitted bids and offers (including wind producers offers) and determines the DA schedules, while no other possibility for future wind power realization is considered. However, the market operator accommodates a number of market products, e.g., flexiramp [59], based on exogenous minimum requirements to provide operational flexibility against future wind power mismatch. In contrast, DA market is cleared stochastically in the second setup in which the market operator clears the DA market considering submitted bids and offers (including wind producers offers) as well as a number of scenarios for future wind power realization [28, 60, 61, 62, 63, 64, 65]. In this work, a stochastic market setup is used for two main reasons. Firstly, it results in more informed DA schedules than the deterministic one, and therefore, reduces the total expected system cost, given that wind scenarios represent accurately enough the actual realization [28]. Secondly, the nature of information sharing is stochastic, i.e., the deterministic setup avoids appropriately capturing different features of shared information. Under this stochastic setup, the mathematical problem for clearing DA market is formed as a stochastic two-stage programming problem [9], whose outcomes are scenario-independent DA schedules (here-and-now decisions) and scenario-dependent RT operations (wait-and-see decisions).

Under the above context, a market is considered in which the wind producer and the market operator independently forecast wind production in DA timescale. It is intuitively expected that sharing wind power forecasts among wind producers and market operator may yield improved social welfare (or reduced system cost) through generating a more qualified wind forecast distribution, though not necessarily at the benefit of each individual market player. This potential value is numerically evaluated from system perspective in terms of expected system cost, i.e., the total cost across all market players, as well as from producers point of view.

Under the considered market setup, one potential concern is that sharing wind power forecasts among wind producers and market operator may bring market power for wind producers to alter market-clearing outcomes to their own profit. In other words, each wind producer may behave more strategically if it has better knowledge on its stochastic production. To address such a concern, a complementarity approach [66, 67] is used to model the strategic behavior of a wind producer with and without sharing forecasts. This requires solving a stochastic mathematical program with equilibrium constraints (MPEC) to determine an optimal offering strategy of the wind producer (regarding MPECs see Appendix A). Considering multiple wind producers forms a stochastic equilibrium problem with equilibrium constraints (EPEC), which is generally hard-to-solve since it aggregates in an optimization model a number of MPECs equal to the number of strategic agents. A relevant analysis considering multiple wind producers is the topic of the following two chapters (Chapters 3 and 4).

Another potential concern is that the analysis of this study is subject to the realized wind power in real time. To address such a concern, an extensive out-of-sample assessment [68] is carried out, considering a large number of different wind power realizations. This numerical analysis allows us to compare the expected system cost and the profit of each individual producer with and without sharing wind power forecasts.

Under this context, the contribution of this study is threefold:

- To propose a three-step evaluation framework that numerically assesses the value of sharing wind power forecasts between a wind producer and the market operator, which allows them to generate more qualified scenarios. This potential value is evaluated in terms of a reduction in expected system cost.
- To numerically analyze the impact of sharing wind power forecasts on potential strategic behavior of wind producer and on conventional producers expected profits. The former is investigated through a sensitivity analysis.
- To carry out an extensive out-of-sample assessment that allows us to compare expected system cost and expected profit of different players with and without sharing wind power forecasts.

2.1.3 Chapter Organization

The rest of the chapter is organized as follows: Section 2.2 proposes a three-step evaluation framework for sharing wind power forecasts in electricity markets and provides the corresponding mathematical formulations. Section 2.3 provides numerical results for a large case study based on the IEEE one-area reliability test system and discusses the main findings. Finally, Section 2.4 concludes the chapter and summarizes its main features.

2.2 Evaluation Framework

2.2.1 Features and Assumptions

For the purpose of this Chapter, a number of assumptions were considered which are listed below:

1. An imperfectly competitive electricity market is considered, in which the wind producer and conventional units may offer strategically [69, 70].

2. To avoid forming an EPEC, the strategic offering problem of wind producer is solved while assuming the offer curves of rival conventional units as fixed parameters. These parameters are generally uncertain, which brings another source of uncertainty. In line with [71, 72, 73, 74], we exclude such an uncertainty. Therefore, we assume that the wind producer perfectly knows the offering strategy of its conventional rivals.

3. Similarly to [70, 71, 73] and for the sake of simplicity, transmission constraints are not enforced. A relevant formulation considering transmission constraints can be found in Chapter 5.

4. Unlike coal or gas-fired power plants, the operational cost of wind producers is negligible since they are not incurred by the fuel costs. In some realistic electricity markets, this cost is even negative due to renewable incentives [25]. As it is customary in the technical literature, e.g., [20, 21, 22, 23, 24], we assume that the wind production cost is zero.

5. Given that network constraints are not considered, it is assumed that a single wind power producer carries all wind power uncertainty in the market. This designing decision is based on the following two features:

   - From the market operator perspective, given that network constraints are not considered, the economic dispatch of several wind producers with the same operational costs would be indifferent compared to a single wind power farm, summing up to the aggregate capacity.
   - On the other hand, considering several wind producers with price-making offering behavior, the formulation of a non-cooperative game would be unavoidable, forming an EPEC which is out of the scope of the current chapter. This extension is, however, investigated under a different context in Chapter 4.

6. In addition, the inter-temporal constraints, e.g., ramping limits of conventional power units, are not enforced and thus a single-hour auction is considered, which is consistent with the relevant literature [70, 71, 74, 75].

7. Finally, demand is assumed to be inelastic to price, as in [76]. Inelastic demand refers to the case where consumers are not willing to withdraw their demand from the market, despite potential high prices. Demand is also considered deterministic in order to avoid additional sources of uncertainty.

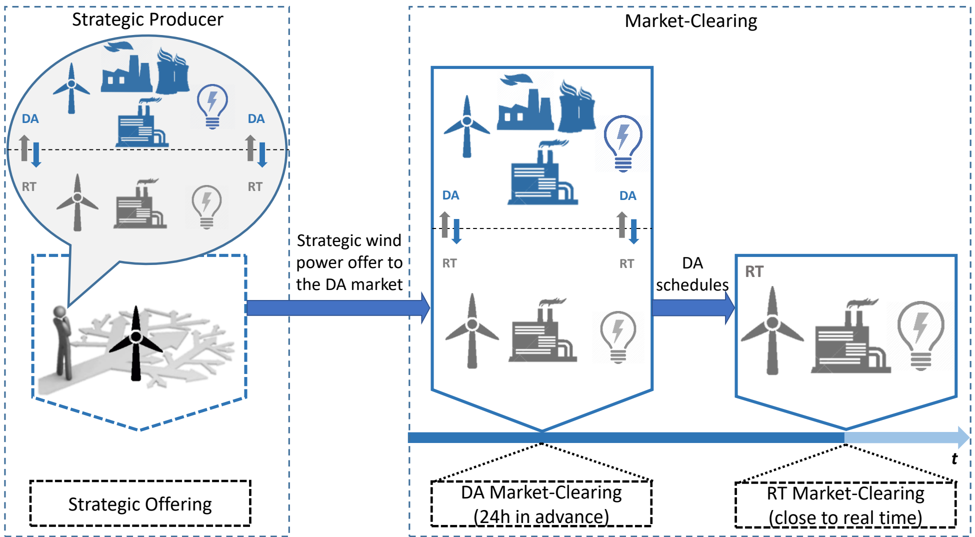

Figure 2.1: Illustrative representation of the market setup of Chapter 2

The aforementioned setup is illustrated in Fig. 2.1. As shown, wind producer anticipates the stochastic two-stage electricity market, based on the available information which include offers from conventional producers, demand bids and a wind power forecast. In this chapter, we consider a single strategic wind power producer, while the offers of the rest market participants are fixed and assumed to be perfectly known. After solving the strategic offering optimization problem, wind producer submits its strategic wind power offer to the DA market. Then, the DA market is cleared one day in advance, based on the strategic wind power offer of wind producer along with the fixed offers of the rest producers and demands. Note that due to the two-stage DA market-clearing approach, the DA market is cleared anticipating RT market-clearing based on a set of wind power scenarios. Finally, the RT market is solved, where imbalances with respect to DA schedules, are adjusted by reserves, load shedding or wind power curtailment.

2.2.2 Proposed Three-Step Framework

The proposed three-step evaluation framework is schematically depicted in Fig. 2.2 and explained in detail as follows:

1. Step 1 derives the offering strategy of wind producer through a complementarity model, whose objective is to maximize wind producer's expected profit. Three offering options are available for the wind producer to exert its market power: i) strategic offering in terms of quantity, ii) strategic offering in terms of price, and iii) strategic offering in terms of both quantity and price. Note that the market impacts of all options are similar. In this study, we consider the first option, i.e., the wind producer derives its strategic quantity offers. This allows the wind producer to withhold a part of its production. However, it offers its quantity at a non-strategic price, i.e., its marginal cost (zero). This offering setup for the wind producers is more consistent with the real-world markets since they usually offer at zero (or even negative [25]) price.

2. Given the quantity offer of the wind producer in Step 1, the market operator stochastically clears DA market considering foreseen wind power scenarios.

3. Given the DA schedules in Step 2, the RT market is cleared for a large number of wind power realization scenarios, which are not necessarily the same with wind producer or market operator forecasts in DA (out-of-sample assessment).

Note that scenarios involved in Steps 1 and 2 are generated based on available wind power forecasts in DA market, while Step 3 is solved based on actual realizations in RT.

The aforementioned three-step framework is investigated for two different analyses. The first analysis (so-called non-sharing analysis) considers that the wind power producer and the market operator use their

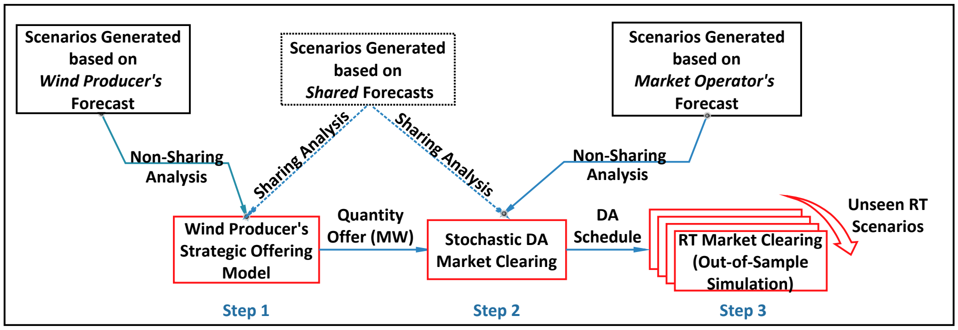

Figure 2.2: The proposed three-step evaluation framework: non-sharing and sharing analyses

own forecasts which may follow different distributions. Therefore, different sets of scenarios are considered in Steps 1 and 2. The second analysis (so-called sharing analysis) considers that the market operator and wind producer share their forecast information, and therefore, the decisions of the first and second steps are made based on an identical set of scenarios.

The proposed three-step framework is mathematically explained in the following subsections. The symbols used in this chapter are defined below. Note that superscript (.) within variables refers to the corresponding step of that symbol. For example, $p_i^{\mathrm{G},(\mathrm{S1})}$ is a variable in Step 1.

Notation

Sets:

Ω	Set of wind producer's scenarios
$\mathcal{S}$	Set of market operator's wind power scenarios
$\mathcal{I}$	Set of conventional power units
$\mathcal{D}$	Set of demands

Indices:

ω	Index for scenarios generated based on wind producer's forecast
s	Index for scenarios generated based on market operator's forecast
i	Index for conventional power units
d	Index for demands

Parameters:

$\overline{P}_d^{\mathrm{D}}$	Quantity bid of demand d [MW]
$\overline{P}_i^{\mathrm{G}}$	Quantity offer of conventional power unit i [MW]
P^{act}	Actual wind power realization [MW]
P_s^{MO}	Wind power forecast of market operator under scenario s [MW]
P_ω^{W}	Wind power forecast of wind producer under scenario ω [MW]
λ_i^{G}	Offer price of conventional power unit i [€/MWh]
λ_i^{U}	Operational cost of conventional power unit i for providing upward reserve [€/MWh]
λ_i^{D}	Operational cost of conventional power unit i for providing downward reserve [€/MWh]
γ_ω	Probability of scenario ω
π_s	Probability of scenario s
R_i^{U}	Upward reserve capacity of conventional power unit i [MW]
R_i^{D}	Downward reserve capacity of conventional power unit i [MW]
V_d^{shed}	Value of lost load for demand d [€/MWh]

DA Variables:

$\lambda^{\mathrm{DA},(.)}$	DA market-clearing price [€/MWh]
$p_i^{\mathrm{G},(.)}$	DA dispatch of conventional power unit i [MW]
$p^{\mathrm{W},(.)}$	DA dispatch of wind producer [MW]
$p^{\mathrm{W,of},(.)}$	Quantity offer of wind producer [MW]

RT Variables:

$\lambda_\omega^{\mathrm{RT},(.)}$	Probability-weighted RT market-clearing price under scenario ω [€/MWh]
$p_\omega^{\mathrm{spill},(.)}$	Wind power spillage under scenario ω [MW]
$r_{i,\omega}^{\mathrm{U},(.)}$	Upward power adjustment of unit i under scenario ω [MW]
$r_{i,\omega}^{\mathrm{D},(.)}$	Downward power adjustment of unit i under scenario ω [MW]
$l_{d,\omega}^{\mathrm{shed},(.)}$	Involuntarily load shedding of demand d under scenario ω [MW]

Note that the definition of each RT variable with subscript s is similar to that with subscript ω, but under market operator's scenarios.

2.2.3 Step 1: Offering Strategy of the Wind Producer

The strategic quantity offer of a wind producer is derived in this step using a stochastic complementarity model, which is similar to one proposed in [71] and [72] but derives strategic quantity offers instead of price offers. To this end, we use bilevel model (2.1), whose upper-level (UL) problem, i.e., (2.1a)-(2.1b), maximizes wind producer's expected profit and derives strategic offers, and whose lower-level (LL) problem, i.e., (2.1c)-(2.1m), clears the market through minimizing the expected system cost. Dual variables are indicated in each LL constraint after a colon. Note that in bilevel model (2.1), the wind producer's own scenarios ($\omega \in \Omega$) are considered (referring to non-sharing analysis), and therefore, variables and stochastic parameters are indexed by ω. In the case of the sharing analysis, index ω needs to be replaced by a new one, e.g., index h, referring to the shared scenarios.

More precisely, the UL objective function (2.1a) below, maximizes the wind producer's expected profit and includes:

- The wind producer's profit in DA market, being the product of DA market-clearing price, i.e., $\lambda^{\mathrm{DA,(S1)}}$, and scheduled quantity, i.e., $p^{\mathrm{W,(S1)}}$.
- The wind producer's expected profit/cost in RT market, being the product of the probability-weighted RT market-clearing price, i.e., $\lambda_\omega^{\mathrm{RT,(S1)}}$, and wind power excess/deficit in RT, i.e., $P_\omega^{\mathrm{W}} - p^{\mathrm{W,(S1)}} - p_\omega^{\mathrm{spill,(S1)}}$.

$$\underset{p^{\mathrm{W,of,(S1)}},\ \Xi^{\mathrm{LL,P}}\ \cup\ \Xi^{\mathrm{LL,D}}}{\text{Maximize}}$$
$$\lambda^{\mathrm{DA,(S1)}}\ p^{\mathrm{W,(S1)}} + \sum_{\omega\in\Omega} \lambda_\omega^{\mathrm{RT,(S1)}} \left(P_\omega^{\mathrm{W}} - p^{\mathrm{W,(S1)}} - p_\omega^{\mathrm{spill,(S1)}}\right) \tag{2.1a}$$

The UL objective function (2.1a) is subject to the UL constraint (2.1b) and to the whole LL problem (2.1c)-(2.1m). The UL constraint (2.1b) below, imposes the strategic quantity offer of wind producer, i.e., $p^{\mathrm{W,of,(S1)}}$, to be non-negative.

$$p^{\mathrm{W,of,(S1)}} \geq 0 \tag{2.1b}$$

The LL objective function (2.1c) minimizes the expected system cost including generation-side costs in DA and RT as well as load shedding costs in RT and is subject to the constraints (2.1d)-(2.1m). Recall that, the formulation of the LL problem, i.e., the two-stage electricity market-clearing, has been illustratively presented in Chapter 1, Fig. 1.6.

$$\lambda^{\mathrm{DA,(S1)}}, p^{\mathrm{W,(S1)}}, \lambda_\omega^{\mathrm{RT,(S1)}}, p_\omega^{\mathrm{spill,(S1)}} \in \arg \underset{\Xi^{\mathrm{LL,P}}}{\text{minimize}} \Bigg\{$$

$$\sum_{i\in\mathcal{I}} \lambda_i^{\mathrm{G}}\ p_i^{\mathrm{G},(\mathrm{S1})} + \sum_{\omega\in\Omega} \gamma_\omega \Bigg[\sum_{i\in\mathcal{I}} \Big(\lambda_i^{\mathrm{U}}\ r_{i,\omega}^{\mathrm{U},(\mathrm{S1})} - \lambda_i^{\mathrm{D}}\ r_{i,\omega}^{\mathrm{D},(\mathrm{S1})} \Big) + \sum_{d\in\mathcal{D}} V_d^{\mathrm{shed}}\ l_{d,\omega}^{\mathrm{shed},(\mathrm{S1})} \Bigg] \tag{2.1c}$$

The LL constraint (2.1d) represents the power balance in DA, whose dual variable, i.e., $\lambda^{\mathrm{DA},(\mathrm{S1})}$, provides the DA market-clearing price.

$$\sum_{d\in\mathcal{D}} \overline{P}_d^{\mathrm{D}} - \sum_{i\in\mathcal{I}} p_i^{\mathrm{G},(\mathrm{S1})} - p^{\mathrm{W},(\mathrm{S1})} = 0 \ : \lambda^{\mathrm{DA},(\mathrm{S1})} \tag{2.1d}$$

Constraints (2.1e) and (2.1f) below, bind the DA schedule of conventional power units and wind producer, respectively, based on their quantity offers.

$$0 \leq p_i^{\mathrm{G},(\mathrm{S1})} \leq \overline{P}_i^{\mathrm{G}} \ : \underline{\phi}_i^{(\mathrm{S1})}, \overline{\phi}_i^{(\mathrm{S1})} \ \forall i \tag{2.1e}$$

$$0 \leq p^{\mathrm{W},(\mathrm{S1})} \leq p^{\mathrm{W,of},(\mathrm{S1})} \ : \underline{\sigma}^{(\mathrm{S1})}, \overline{\sigma}^{(\mathrm{S1})} \tag{2.1f}$$

Load shedding is the result of inadequacy in terms of supply meeting demand, representing the unserved load in RT due to unavailable generation. Additionally, wind power spillage might be needed in order to balance generation and demand in RT, e.g., when additional wind power production in the RT market (compared to DA scheduled) exceeds available downward reserves. Thus, constraint (2.1g) refers to power balance in RT that adjusts the energy imbalance by power adjustments in RT as well as wind power spillage and load shedding. Note that its corresponding dual variable provides the probability-weighted RT market-clearing price, i.e., $\lambda_\omega^{\mathrm{RT},(\mathrm{S1})}$.

$$\sum_{i\in\mathcal{I}} \Big(r_{i,\omega}^{\mathrm{D},(\mathrm{S1})} - r_{i,\omega}^{\mathrm{U},(\mathrm{S1})} \Big) - \sum_{d\in\mathcal{D}} l_{d,\omega}^{\mathrm{shed},(\mathrm{S1})} - \big(P_\omega^{\mathrm{W}} - p^{\mathrm{W},(\mathrm{S1})} - p_\omega^{\mathrm{spill},(\mathrm{S1})} \big) = 0 \ : \lambda_\omega^{\mathrm{RT},(\mathrm{S1})} \ \forall \omega \tag{2.1g}$$

Constraint (2.1h) implies that wind power spillage should be equal to or lower than the wind power realization.

$$0 \leq p_{\omega}^{\text{spill},(\text{S1})} \leq P_{\omega}^{\text{W}} \quad : \underline{\tau}_{\omega}^{(\text{S1})}, \overline{\tau}_{\omega}^{(\text{S1})} \ \forall \omega \tag{2.1h}$$

The load shedding quantity is restricted by the maximum consumption, imposed by constraint (2.1i) below:

$$0 \leq l_{d,\omega}^{\text{shed},(\text{S1})} \leq \overline{P}_{d}^{\text{D}} \quad : \underline{\psi}_{d,\omega}^{(\text{S1})}, \overline{\psi}_{d,\omega}^{(\text{S1})} \ \forall d, \forall \omega \tag{2.1i}$$

Finally, operational reserves in RT are bounded by reserve quantity offers and DA dispatch through (2.1j)-(2.1m).

$$0 \leq r_{i,\omega}^{\text{D},(\text{S1})} \leq R_{i}^{\text{D}} \quad : \underline{\mu}_{i,\omega}^{\text{D},(\text{S1})}, \overline{\mu}_{i,\omega}^{\text{D},(\text{S1})} \ \forall i, \forall \omega \tag{2.1j}$$

$$0 \leq r_{i,\omega}^{\text{U},(\text{S1})} \leq R_{i}^{\text{U}} \quad : \underline{\mu}_{i,\omega}^{\text{U},(\text{S1})}, \overline{\mu}_{i,\omega}^{\text{U},(\text{S1})} \ \forall i, \forall \omega \tag{2.1k}$$

$$r_{i,\omega}^{\text{U},(\text{S1})} \leq \left(\overline{P}_{i}^{\text{G}} - p_{i}^{\text{G},(\text{S1})} \right) \quad : \overline{\mu}_{i,\omega}^{(\text{S1})} \ \forall i, \forall \omega \tag{2.1l}$$

$$\left. r_{i,\omega}^{\text{D},(\text{S1})} \leq p_{i}^{\text{G},(\text{S1})} \quad : \underline{\mu}_{i,\omega}^{(\text{S1})} \ \forall i, \forall \omega \right\}. \tag{2.1m}$$

Some of the aforementioned constraints may refer exclusively to either the DA or the RT stage of the two-stage programming model, but some also link the DA and RT stages. More specifically, constraints (2.1d)-(2.1f) are associated with the DA stage of the two-stage optimization problem, while (2.1h)-(2.1k) are associated with the RT stage. The power balance equation in RT, i.e., (2.1g), apart from the RT variables, also involves DA variable $p^{\text{W},(\text{S1})}$. Also, constraints (2.1l) and (2.1m), which refer to the upper bounds of the reserves in RT, depend on the DA schedules $p_i^{\text{G},(\text{S1})}$. Thus, constraints (2.1g), (2.1l) and (2.1m) link the DA and RT stages, highlighting the need for a two-stage programming solution.

The set of primal variables of LL problem (2.1c)-(2.1m) is $\Xi^{\text{LL,P}} = \{p_i^{\text{G},(\text{S1})},\ p^{\text{W},(\text{S1})},\ r_{i,\omega}^{\text{U},(\text{S1})},\ r_{i,\omega}^{\text{D},(\text{S1})},\ l_{d,\omega}^{\text{shed},(\text{S1})},\ p_{\omega}^{\text{spill},(\text{S1})}\}$.

Furthermore, the set of dual variables of the LL problem is $\Xi^{\text{LL,D}} = \{\underline{\phi_i}^{(\text{S1})},\ \overline{\phi_i}^{(\text{S1})},\ \underline{\sigma}^{(\text{S1})},\ \overline{\sigma}^{(\text{S1})},\ \lambda^{\text{DA},(\text{S1})},\ \underline{\tau}_{\omega}^{(\text{S1})},\ \overline{\tau}_{\omega}^{(\text{S1})},\ \lambda_{\omega}^{\text{RT},(\text{S1})},\ \underline{\psi}_{d,\omega}^{(\text{S1})},\ \overline{\psi}_{d,\omega}^{(\text{S1})},\ \underline{\mu}_{i,\omega}^{\text{D},(\text{S1})},\ \overline{\mu}_{i,\omega}^{\text{D},(\text{S1})},\ \underline{\mu}_{i,\omega}^{\text{U},(\text{S1})},\ \overline{\mu}_{i,\omega}^{\text{U},(\text{S1})},\ \underline{\mu}_{i,\omega}^{(\text{S1})},\ \overline{\mu}_{i,\omega}^{(\text{S1})}\}$.

Finally, the primal variables of the UL problem (2.1a)-(2.1b) are $p^{\mathrm{W,of,(S1)}}$ as well as all members of variable sets $\Xi^{\mathrm{LL,P}}$ and $\Xi^{\mathrm{LL,D}}$.

Note that LL problem (2.1c)-(2.1m) is continuous, linear, and therefore convex. This allows bilevel model (2.1) to be recast as a single-level mathematical program with equilibrium constraints (MPEC) through replacing LL problem (2.1c)-(2.1m) by its Karush-Kuhn-Tucker (KKT) optimality conditions [66, 67] as given by (2.3). The mathematical background on bilevel models and their recasting into MPECs using the KKT conditions is provided in more detail in Appendix A. The KKT conditions are derived from the Lagrangian function associated with the LL, which for (2.1c)-(2.1m) is given by (2.2) below:

$$
\begin{aligned}
\mathcal{L} = & \sum_{i\in\mathcal{I}} \lambda_i^{\mathrm{G}}\, p_i^{\mathrm{G,(S1)}} + \sum_{\omega\in\Omega} \gamma_\omega \Bigg[\sum_{i\in\mathcal{I}} \left(\lambda_i^{\mathrm{U}}\, r_{i,\omega}^{\mathrm{U,(S1)}} - \lambda_i^{\mathrm{D}}\, r_{i,\omega}^{\mathrm{D,(S1)}} \right) \\
& + \sum_{d\in\mathcal{D}} V_d^{\mathrm{shed}}\, l_{d,\omega}^{\mathrm{shed,(S1)}} \Bigg] + \lambda^{\mathrm{DA,(S1)}} \Bigg[\sum_{d\in\mathcal{D}} \overline{P}_d^{\mathrm{D}} - \sum_{i\in\mathcal{I}} p_i^{\mathrm{G,(S1)}} - p^{\mathrm{W,(S1)}} \Bigg] \\
& + \sum_{\omega\in\Omega} \lambda_\omega^{\mathrm{RT,(S1)}} \Bigg[\sum_{i\in\mathcal{I}} \left(r_{i,\omega}^{\mathrm{D,(S1)}} - r_{i,\omega}^{\mathrm{U,(S1)}} \right) - \sum_{d\in\mathcal{D}} l_{d,\omega}^{\mathrm{shed,(S1)}} \\
& - \left(P_\omega^{\mathrm{W}} - p^{\mathrm{W,(S1)}} - p_\omega^{\mathrm{spill,(S1)}} \right) \Bigg] - \sum_{i\in\mathcal{I}} \underline{\phi}_i^{(\mathrm{S1})} p_i^{\mathrm{G,(S1)}} \\
& - \sum_{i\in\mathcal{I}} \overline{\phi}_i^{(\mathrm{S1})} (\overline{P}_i^{\mathrm{G}} - p_i^{\mathrm{G,(S1)}}) - \underline{\sigma}^{(\mathrm{S1})} p^{\mathrm{W,(S1)}} - \overline{\sigma}^{(\mathrm{S1})} (p^{\mathrm{W,of,(S1)}} - p^{\mathrm{W,(S1)}}) \\
& - \sum_{\omega\in\Omega} \underline{\tau}_\omega^{(\mathrm{S1})} p_\omega^{\mathrm{spill,(S1)}} - \sum_{\omega\in\Omega} \overline{\tau}_\omega^{(\mathrm{S1})} (P_\omega^{\mathrm{W}} - p_\omega^{\mathrm{spill,(S1)}}) - \sum_{\omega\in\Omega} \sum_{d\in\mathcal{D}} \underline{\psi}_{d,\omega}^{(\mathrm{S1})} l_{d,\omega}^{\mathrm{shed,(S1)}} \\
& - \sum_{\omega\in\Omega} \sum_{i\in\mathcal{I}} \overline{\mu}_{i,\omega}^{\mathrm{D,(S1)}} (R_i^{\mathrm{D}} - r_{i,\omega}^{\mathrm{D,(S1)}}) - \sum_{\omega\in\Omega} \sum_{i\in\mathcal{I}} \underline{\mu}_{i,\omega}^{\mathrm{U,(S1)}} r_{i,\omega}^{\mathrm{U,(S1)}} \\
& - \sum_{\omega\in\Omega} \sum_{i\in\mathcal{I}} \overline{\mu}_{i,\omega}^{\mathrm{U,(S1)}} (R_i^{\mathrm{U}} - r_{i,\omega}^{\mathrm{U,(S1)}}) - \sum_{\omega\in\Omega} \sum_{i\in\mathcal{I}} \underline{\mu}_{i,\omega}^{(\mathrm{S1})} (p_i^{\mathrm{G,(S1)}} - r_{i,\omega}^{\mathrm{D,(S1)}}) \\
& - \sum_{\omega\in\Omega} \sum_{i\in\mathcal{I}} \overline{\mu}_{i,\omega}^{(\mathrm{S1})} \left(\overline{P}_i^{\mathrm{G}} - p_i^{\mathrm{G,(S1)}} - r_{i,\omega}^{\mathrm{U,(S1)}} \right).
\end{aligned}
\tag{2.2}
$$

The KKT conditions are calculated by differentiating the Lagrangian each time with the corresponding primal variable of the LL problem. Thus, we can replace the LL problem (2.1c)-(2.1m) by its KKT conditions as shown below:

$$\underset{p^{\mathrm{W,of,(S1)}},\ \Xi^{\mathrm{LL,P}}\ \cup\ \Xi^{\mathrm{LL,D}}}{\text{Maximize}} \quad (2.1a) \tag{2.3a}$$

subject to

$$(2.1b),\ (2.1d) \text{ and } (2.1g) \tag{2.3b}$$

$$\frac{\partial \mathcal{L}}{\partial p_i^{\mathrm{G,(S1)}}} = \lambda_i^{\mathrm{G}} - \lambda^{\mathrm{DA,(S1)}} - \underline{\phi_i}^{\mathrm{(S1)}} + \overline{\phi_i}^{\mathrm{(S1)}} + \sum_{\omega} (\overline{\mu}_{i,\omega}^{\mathrm{(S1)}} - \underline{\mu}_{i,\omega}^{\mathrm{(S1)}}) = 0 \ \forall i \tag{2.3c}$$

$$\frac{\partial \mathcal{L}}{\partial p^{\mathrm{W,(S1)}}} = -\lambda^{\mathrm{DA,(S1)}} - \underline{\sigma}^{\mathrm{(S1)}} + \overline{\sigma}^{\mathrm{(S1)}} + \sum_{\omega} \lambda_{\omega}^{\mathrm{RT,(S1)}} = 0 \tag{2.3d}$$

$$\frac{\partial \mathcal{L}}{\partial r_{i,\omega}^{\mathrm{U,(S1)}}} = \gamma_\omega \lambda_i^{\mathrm{U}} - \lambda_{\omega}^{\mathrm{RT,(S1)}} - \underline{\mu}_{i,\omega}^{\mathrm{U,(S1)}} + \overline{\mu}_{i,\omega}^{\mathrm{U,(S1)}} + \overline{\mu}_{i,\omega}^{\mathrm{(S1)}} = 0 \ \forall i, \forall \omega \tag{2.3e}$$

$$\frac{\partial \mathcal{L}}{\partial r_{i,\omega}^{\mathrm{D,(S1)}}} = -\gamma_\omega \lambda_i^{\mathrm{D}} + \lambda_{\omega}^{\mathrm{RT,(S1)}} - \underline{\mu}_{i,\omega}^{\mathrm{D,(S1)}} + \overline{\mu}_{i,\omega}^{\mathrm{D,(S1)}} + \underline{\mu}_{i,\omega}^{\mathrm{(S1)}} = 0 \ \forall i, \forall \omega \tag{2.3f}$$

$$\frac{\partial \mathcal{L}}{\partial l_{d,\omega}^{\mathrm{shed,(S1)}}} = \gamma_\omega V_d^{\mathrm{shed}} - \lambda_{\omega}^{\mathrm{RT,(S1)}} + \overline{\psi}_{d,\omega}^{\mathrm{(S1)}} - \underline{\psi}_{d,\omega}^{\mathrm{(S1)}} = 0 \ \forall d, \forall \omega \tag{2.3g}$$

$$\frac{\partial \mathcal{L}}{\partial p_{\omega}^{\mathrm{spill,(S1)}}} = \lambda_{\omega}^{\mathrm{RT,(S1)}} + \overline{\tau}_{\omega}^{\mathrm{(S1)}} - \underline{\tau}_{\omega}^{\mathrm{(S1)}} = 0 \ \forall \omega \tag{2.3h}$$

Lastly, complementarity slackness conditions, which refer to the relationship between the positivity in a primal constraint and the positivity of its associated dual variable, are given below by (2.3i)-(2.3v):

$$0 \leq p_i^{\mathrm{G},(\mathrm{S1})} \perp \underline{\phi_i}^{(\mathrm{S1})} \geq 0 \ \forall i \tag{2.3i}$$

$$0 \leq (\overline{P}_i^{\mathrm{G}} - p_i^{\mathrm{G},(\mathrm{S1})}) \perp \overline{\phi_i}^{(\mathrm{S1})} \geq 0 \ \forall i \tag{2.3j}$$

$$0 \leq p^{\mathrm{W},(\mathrm{S1})} \perp \underline{\sigma}^{(\mathrm{S1})} \geq 0 \tag{2.3k}$$

$$0 \leq (p^{\mathrm{W,of},(\mathrm{S1})} - p^{\mathrm{W},(\mathrm{S1})}) \perp \overline{\sigma}^{(\mathrm{S1})} \geq 0 \tag{2.3l}$$

$$0 \leq p_\omega^{\mathrm{spill},(\mathrm{S1})} \perp \underline{\tau}_\omega^{(\mathrm{S1})} \geq 0 \ \forall \omega \tag{2.3m}$$

$$0 \leq (P_\omega^{\mathrm{W}} - p_\omega^{\mathrm{spill},(\mathrm{S1})}) \perp \overline{\tau}_\omega^{(\mathrm{S1})} \geq 0 \ \forall \omega \tag{2.3n}$$

$$0 \leq l_{d,\omega}^{\mathrm{shed},(\mathrm{S1})} \perp \underline{\psi}_{d,\omega}^{(\mathrm{S1})} \geq 0 \ \forall d, \forall \omega \tag{2.3o}$$

$$0 \leq (\overline{P}_d^{\mathrm{D}} - l_{d,\omega}^{\mathrm{shed},(\mathrm{S1})}) \perp \overline{\psi}_{d,\omega}^{(\mathrm{S1})} \geq 0 \ \forall d, \forall \omega \tag{2.3p}$$

$$0 \leq r_{i,\omega}^{\mathrm{D},(\mathrm{S1})} \perp \underline{\mu}_{i,\omega}^{\mathrm{D},(\mathrm{S1})} \geq 0 \ \forall i, \forall \omega \tag{2.3q}$$

$$0 \leq (R_i^{\mathrm{D}} - r_{i,\omega}^{\mathrm{D},(\mathrm{S1})}) \perp \overline{\mu}_{i,\omega}^{\mathrm{D},(\mathrm{S1})} \geq 0 \ \forall i, \forall \omega \tag{2.3r}$$

$$0 \leq r_{i,\omega}^{\mathrm{U},(\mathrm{S1})} \perp \underline{\mu}_{i,\omega}^{\mathrm{U},(\mathrm{S1})} \geq 0 \ \forall i, \forall \omega \tag{2.3s}$$

$$0 \leq (R_i^{\mathrm{U}} - r_{i,\omega}^{\mathrm{U},(\mathrm{S1})}) \perp \overline{\mu}_{i,\omega}^{\mathrm{U},(\mathrm{S1})} \geq 0 \ \forall i, \forall \omega \tag{2.3t}$$

$$0 \leq (\overline{P}_i^{\mathrm{G}} - r_{i,\omega}^{\mathrm{U},(\mathrm{S1})} - p_i^{\mathrm{G},(\mathrm{S1})}) \perp \overline{\mu}_{i,\omega}^{(\mathrm{S1})} \geq 0 \ \forall i, \forall \omega \tag{2.3u}$$

$$0 \leq (p_i^{\mathrm{G},(\mathrm{S1})} - r_{i,\omega}^{\mathrm{D},(\mathrm{S1})}) \perp \underline{\mu}_{i,\omega}^{(\mathrm{S1})} \geq 0 \ \forall i, \forall \omega, \tag{2.3v}$$

where operator $\perp$ (perpendicular) enforces the perpendicular condition between the vectors on the left-hand and right-hand sides, i.e., their element-by-element product is zero.

MPEC (2.3) is non-linear due to the following two sources of non-linearities:

- the bilinear terms $\lambda^{\mathrm{DA},(\mathrm{S1})} p^{\mathrm{W},(\mathrm{S1})}$, $\lambda_\omega^{\mathrm{RT},(\mathrm{S1})} p^{\mathrm{W},(\mathrm{S1})}$ and $\lambda_\omega^{\mathrm{RT},(\mathrm{S1})} p_\omega^{\mathrm{spill},(\mathrm{S1})}$ included in the objective function (2.1a), and
- complementarity conditions (2.3i)-(2.3v).

The bilinear terms inside the objective function are linearized based on an approach without approximation, which was firstly introduced in [77]. Accordingly, we deploy the strong duality theorem (SDT) [78] and mathematical expressions (2.3c) - (2.3v). The SDT states that if a problem is convex then the objective functions of the primal and dual problems have the same value at the optimum, and for the investigated problem this writes as in (2.4) below:

$$\begin{aligned}
&\sum_{\omega \in \Omega} \gamma_\omega \left[\sum_{i \in \mathcal{I}} (\lambda_i^{\mathrm{U}} \ r_{i,\omega}^{\mathrm{U,(S1)}} - \lambda_i^{\mathrm{D}} \ r_{i,\omega}^{\mathrm{D,(S1)}}) + \sum_{d \in \mathcal{D}} V_d^{\mathrm{shed}} \ l_{d,\omega}^{\mathrm{shed,(S1)}} \right] \\
&+ \sum_{i \in \mathcal{I}} \lambda_i^{\mathrm{G}} \ p_i^{\mathrm{G,(S1)}} = - \sum_{i \in \mathcal{I}} \overline{\phi}_i^{\mathrm{(S1)}} \ \overline{P}_i^{\mathrm{G}} + \sum_{d \in \mathcal{D}} \overline{P}_d^{\mathrm{D}} \ \lambda^{\mathrm{DA,(S1)}} - \overline{\sigma} \ p^{\mathrm{W,of,(S1)}} \\
&- \sum_{\omega \in \Omega} \overline{\tau}_\omega \ P_\omega^{\mathrm{W}} - \sum_{\omega \in \Omega} \lambda_\omega^{\mathrm{RT,(S1)}} \ P_\omega^{\mathrm{W}} - \sum_{\omega \in \Omega} \sum_{i \in \mathcal{I}} \overline{\mu}_{i,\omega}^{\mathrm{D}} \ R_i^{D} - \sum_{\omega \in \Omega} \sum_{d \in \mathcal{D}} \overline{\psi}_{d,\omega} \ \overline{P}_d^{\mathrm{D}} \\
&- \sum_{\omega \in \Omega} \sum_{i \in \mathcal{I}} \overline{\mu}_{i,\omega}^{\mathrm{U}} \ R_i^{\mathrm{U}} - \sum_{\omega \in \Omega} \sum_{i \in \mathcal{I}} \overline{\mu}_{i,\omega} \ \overline{P}_i^{\mathrm{G}}.
\end{aligned} \tag{2.4}$$

Multiplying (2.3d) by $p^{\mathrm{W,(S1)}}$ we get:

$$\begin{aligned}
&- \lambda^{\mathrm{DA,(S1)}} \ p^{\mathrm{W,(S1)}} - \underline{\sigma}^{\mathrm{(S1)}} \ p^{\mathrm{W,(S1)}} + \overline{\sigma}^{\mathrm{(S1)}} \ p^{\mathrm{W,(S1)}} \\
&\quad + \sum_{\omega} \lambda_\omega^{\mathrm{RT,(S1)}} \ p^{\mathrm{W,(S1)}} = 0.
\end{aligned} \tag{2.5}$$

Due to (2.3k)-(2.3l), equation (2.5) becomes:

$$-\lambda^{\mathrm{DA,(S1)}} \ p^{\mathrm{W,(S1)}} + \overline{\sigma}^{\mathrm{(S1)}} \ p^{\mathrm{W,of,(S1)}} + \sum_{\omega} \lambda_\omega^{\mathrm{RT,(S1)}} \ p^{\mathrm{W,(S1)}} = 0. \tag{2.6}$$

Similarly, considering complementarities (2.3m)-(2.3n) and multiplying (2.3h) by $p_\omega^{\mathrm{spill,(S1)}}$, we finally obtain:

$$\lambda_\omega^{\mathrm{RT,(S1)}} \ p_\omega^{\mathrm{spill,(S1)}} + \overline{\tau}_\omega^{\mathrm{(S1)}} \ P_\omega^{\mathrm{W}} = 0. \tag{2.7}$$

Considering (2.4) and the above transformations, the objective function finally writes as (2.8a). The complementarity conditions (2.3i)-(2.3v), are linearized using the Big-M approach, but at the cost of introducing a set of auxiliary binary variables [79, 80]. For more information on the linearization process, we refer to Appendix A. Following these two linearization techniques, MPEC (2.3) is transformed into the mixed-integer linear programming (MILP) problem (2.8) [66], below:

$$\underset{p^{\mathrm{W,of,(S1)}},\ \Xi^{\mathrm{LL,P}}\ \cup\ \Xi^{\mathrm{LL,D}}}{\text{Maximize}}$$

$$\Bigg\{ -\sum_{\omega\in\Omega}\gamma_{\omega}\left[\sum_{i\in\mathcal{I}}(\lambda_i^{\mathrm{U}}\ r_{i,\omega}^{\mathrm{U,(S1)}} - \lambda_i^{\mathrm{D}}\ r_{i,\omega}^{\mathrm{D,(S1)}}) + \sum_{d\in\mathcal{D}} V_d^{\mathrm{shed}}\ l_{d,\omega}^{\mathrm{shed,(S1)}}\right]$$
$$- \sum_{i\in\mathcal{I}}\lambda_i^{\mathrm{G}}\ p_i^{\mathrm{G,(S1)}} + \sum_{d\in\mathcal{D}}\overline{P}_d^{\mathrm{D}}\lambda^{\mathrm{DA,(S1)}} - \sum_{i\in\mathcal{I}}\overline{\phi_i}^{\mathrm{(S1)}}\ \overline{P}_i^{\mathrm{G}}$$
$$- \sum_{\omega\in\Omega}\left[\sum_{d\in\mathcal{D}}\overline{\psi}_{d,\omega}\overline{P}_d^{\mathrm{D}} + \sum_{i\in\mathcal{I}}\overline{\mu}_{i,\omega}^{\mathrm{D}}R_i^{D} + \sum_{i\in\mathcal{I}}\overline{\mu}_{i,\omega}^{\mathrm{U}}R_i^{\mathrm{U}} + \sum_{i\in\mathcal{I}}\overline{\mu}_{i,\omega}\overline{P}_i^{\mathrm{G}}\right]\Bigg\} \quad (2.8a)$$

subject to

$$(2.1b),\ (2.1d),\ (2.1g) \text{ and } (2.3c) - (2.3h) \quad (2.8b)$$
$$0 \le \underline{\phi}_i \le \underline{M}_i^{(1)}\ \underline{u}_i^{(1)}\ \forall i \quad (2.8c)$$
$$0 \le p_i^{\mathrm{G,(S1)}} \le \underline{M}_i^{(1)}\ (1-\underline{u}_i^{(1)})\ \forall i \quad (2.8d)$$
$$0 \le \overline{\phi}_i \le \overline{M}_i^{(1)}\ \overline{u}_i^{(1)}\ \forall i \quad (2.8e)$$
$$0 \le (\overline{P}_i^{\mathrm{G}} - p_i^{\mathrm{G,(S1)}}) \le \overline{M}_i^{(1)}\ (1-\overline{u}_i^{(1)})\ \forall i \quad (2.8f)$$
$$0 \le \underline{\sigma}^{\mathrm{(S1)}} \le \underline{M}^{(2)}\ \underline{u}^{(2)} \quad (2.8g)$$
$$0 \le p^{\mathrm{W,(S1)}} \le \underline{M}^{(2)}\ (1-\underline{u}^{(2)}) \quad (2.8h)$$
$$0 \le \overline{\sigma}^{\mathrm{(S1)}} \le \overline{M}^{(2)}\ \overline{u}^{(2)} \quad (2.8i)$$
$$0 \le (\overline{P}^{\mathrm{W,of,(S1)}} - p^{\mathrm{W,(S1)}}) \le \overline{M}^{(2)}\ (1-\overline{u}^{(2)}). \quad (2.8j)$$

The remaining equations of the complementarity constraints follow the same pattern with (2.8c)-(2.8j), where parameters $M^{(\cdot)}$ are large enough constants and u are binary variables. The resulting MILP problem can be solved with available optimization solvers, e.g., CPLEX [81], Gurobi [82], etc.. In our case CPLEX optimization solver was used, associated with GAMS software [83].

2.2.4 Step 2: Stochastic Day-Ahead Market-Clearing

In this step, the market operator clears stochastically the DA market considering all foreseen wind power scenarios. The aim of the market operator is to minimize the expected overall system cost in DA and RT. To this purpose, it solves stochastic two-stage programming problem (2.9). Note that the scenarios considered in (2.9) are those generated based on market operator's forecast (indexed by s), which refers to the non-sharing analysis. In the sharing analysis, this index is replaced by h referring to the shared scenarios. Note also that the quantity offer of wind producer denoted by $P^{\mathrm{W,of,(S1)}}$ is a parameter in Step 2, whose value is obtained from Step 1. The two-stage programming problem (2.9) below, is similar to the LL of bilevel model (2.1) and clears the market based on producers offers.

Objective function (2.9a) below, minimizes the expected overall system cost in DA and RT markets in Step 2, based on producers offers:

$$\underset{p_i^{\mathrm{G,(S2)}}, p^{\mathrm{W,(S2)}}, r_{i,s}^{\mathrm{U,(S2)}}, r_{i,s}^{\mathrm{D,(S2)}}, l_{d,s}^{\mathrm{shed,(S2)}}, p_s^{\mathrm{spill,(S2)}}}{\text{Minimize}} \sum_{i \in \mathcal{I}} \lambda_i^{\mathrm{G}} \; p_i^{\mathrm{G,(S2)}} + \sum_{s \in \mathcal{S}} \pi_s \Bigg[\sum_{i \in \mathcal{I}} \left(\lambda_i^{\mathrm{U}} \; r_{i,s}^{\mathrm{U,(S2)}} - \lambda_i^{\mathrm{D}} \; r_{i,s}^{\mathrm{D,(S2)}} \right) + \sum_{d \in \mathcal{D}} V_d^{\mathrm{shed}} \; l_{d,s}^{\mathrm{shed,(S2)}} \Bigg] \tag{2.9a}$$

Objective function (2.9a) is subject to constraints (2.9b) - (2.9k), below, which are similar to constraints (2.1d)-(2.1m) of the LL of bilevel model (2.1) at Step 1, but are solved based on received producers offers and market operator's wind scenarios:

$$\sum_{d \in \mathcal{D}} \overline{P}_d^{\mathrm{D}} - \sum_{i \in \mathcal{I}} p_i^{\mathrm{G,(S2)}} - p^{\mathrm{W,(S2)}} = 0 \tag{2.9b}$$

$$0 \leq p_i^{\mathrm{G,(S2)}} \leq \overline{P}_i^{\mathrm{G}} \;\; \forall i \tag{2.9c}$$

$$0 \leq p^{\mathrm{W,(S2)}} \leq P^{\mathrm{W,of,(S1)}} \tag{2.9d}$$

$$\sum_{i \in \mathcal{I}} \left(r_{i,s}^{\mathrm{D,(S2)}} - r_{i,s}^{\mathrm{U,(S2)}} \right) - \sum_{d \in \mathcal{D}} l_{d,s}^{\mathrm{shed,(S2)}}$$

$$- \left(P_s^{\text{MO}} - p^{\text{W,(S2)}} - p_s^{\text{spill,(S2)}}\right) = 0 \ \forall s \tag{2.9e}$$

$$0 \leq p_s^{\text{spill,(S2)}} \leq P_s^{\text{MO}} \ \forall s \tag{2.9f}$$

$$0 \leq l_{d,s}^{\text{shed,(S2)}} \leq \overline{P}_d^{\text{D}} \ \forall d, \forall s \tag{2.9g}$$

$$0 \leq r_{i,s}^{\text{D,(S2)}} \leq R_i^{\text{D}} \ \forall i, \forall s \tag{2.9h}$$

$$0 \leq r_{i,s}^{\text{U,(S2)}} \leq R_i^{\text{U}} \ \forall i, \forall s \tag{2.9i}$$

$$r_{i,s}^{\text{U,(S2)}} \leq \left(\overline{P}_i^{\text{G}} - p_i^{\text{G,(S2)}}\right) \ \forall i, \forall s \tag{2.9j}$$

$$r_{i,s}^{\text{D,(S2)}} \leq p_i^{\text{G,(S2)}} \ \forall i, \forall s. \tag{2.9k}$$

2.2.5 Step 3: Real-Time Market-Clearing (Out-of-Sample Assessment)

In this step, we fix the DA schedule of conventional power units and wind producer to those obtained in Step 2. Then, RT market is cleared versus different wind power realizations, which are not necessarily the same as the scenarios considered in Steps 1 and 2. The RT market for a particular wind power realization is given by the deterministic optimization problem (2.10). Note that symbols with superscript (S2) correspond to parameters (DA schedules), whose values are obtained from Step 2.

$$\underset{r_i^{\text{U,(S3)}}, r_i^{\text{D,(S3)}}, l_d^{\text{shed,(S3)}}, p^{\text{spill,(S3)}}}{\text{Minimize}}$$

$$\sum_{i \in \mathcal{I}} \left(\lambda_i^{\text{U}} \ r_i^{\text{U,(S3)}} - \lambda_i^{\text{D}} \ r_i^{\text{D,(S3)}}\right) + \sum_{d \in \mathcal{D}} V_d^{\text{shed}} \ l_d^{\text{shed,(S3)}} \tag{2.10a}$$

Objective function (2.10a) minimizes the imbalance cost incurred, by operational reserve deployment and/or involuntarily load shedding and is subject to the following set of constraints:

$$\sum_{i \in \mathcal{I}} \left(r_i^{\text{D,(S3)}} - r_i^{\text{U,(S3)}}\right) - \sum_{d \in \mathcal{D}} l_d^{\text{shed,(S3)}}$$

$$- \left(P^{\text{act}} - P^{\text{W,(S2)}} - p^{\text{spill,(S3)}}\right) = 0 \tag{2.10b}$$

$$0 \leq p^{\text{spill,(S3)}} \leq P^{\text{act}} \tag{2.10c}$$

$$0 \leq l_d^{\text{shed,(S3)}} \leq \overline{P}_d^{\text{D}} \ \forall d \tag{2.10d}$$

$$0 \leq r_i^{\mathrm{D,(S3)}} \leq R_i^{\mathrm{D}} \ \forall i \tag{2.10e}$$

$$0 \leq r_i^{\mathrm{U,(S3)}} \leq R_i^{\mathrm{U}} \ \forall i \tag{2.10f}$$

$$r_i^{\mathrm{U,(S3)}} \leq \left(\overline{P}_i^{\mathrm{G}} - P_i^{\mathrm{G,(S2)}}\right) \ \forall i \tag{2.10g}$$

$$r_i^{\mathrm{D,(S3)}} \leq P_i^{\mathrm{G,(S2)}} \ \forall i. \tag{2.10h}$$

Constraints (2.10b)-(2.10h) are similar to LL constraints (2.1g)-(2.1m) in Step 1 and constraints (2.9b)-(2.9k) in Step 2, but at real-time operation based on the fixed DA schedules of Step 2.

2.3 Case Study

2.3.1 Data

A case study based on a modified version of the IEEE reliability test system (RTS) is considered, which is differentiated from [84] in order to better accommodate wind farms [85]. Seven conventional units are considered, which are grouped for the sake of simplicity. Each conventional unit offers at a quantity identical to its installed capacity and at a price given in Table 2.1. In addition to the conventional units, a single wind power farm is considered. The system load is 2,200 MW, and the value of lost load is assumed to be €200/MWh.

Table 2.1: Technical Characteristics of Conventional Units

Unit (i)	$\overline{P}_i^{\mathrm{G}}$ [MW]	λ_i^{G} [€/MW]	R_i^{U} [MW]	λ_i^{U} [€/MWh]	R_i^{D} [MW]	λ_i^{D} [€/MWh]
G1	304	13.32	80	15	80	11
G2	350	19.7	70	24	70	16
G3	591	20.93	180	25	180	17
G4	60	26.11	60	28	60	23
G5	610	10.52	120	15	120	7
G6	800	5.47	0	-	0	-
G7	650	12.89	40	16	40	8

The distribution of the wind power forecast errors has been investigated in the recent literature. It was reported that due to the variable skewness and kurtosis values, forecast errors cannot be described by a Gaussian curve but rather by a Weibull [86] or a Beta [51] distribution. In this study, Beta distribution is used to represent the uncertainty around the wind power forecast, since it is found to appropriately model wind power output [55, 87, 88]. The mean value of the distribution function is the predicted power, which along with the variance of the prediction error for that predicted power, define a probability distribution Beta function [55]. Definitely, utilizing a state-of-the-art prediction model would be desirable, however, Beta distribution is chosen over a prediction model in order to make findings more tractable and ease the selection of the different scenarios with respect to the level of wind power penetration, similarly to [71]. Beta probability density functions for various sets of shape parameters (a, b) [55] are presented in Fig. 2.3, for illustration reasons. In this case study, a Beta distribution with shape parameters $(a^{\mathrm{R}}, b^{\mathrm{R}})$ is considered and 5,000 samples are generated representing potential wind power realizations. These samples are in per-unit, i.e., wind production divided by installed wind capacity. The number of samples is arbitrarily chosen to make an appropriate trade-off between accuracy and computational burden. These samples are used in Step 3 for an extensive out-of-sample assessment. The wind producer's and the market operator's forecasts, to be used in Steps 1 and 2, are also modeled using a Beta distribution but with different shape parameters, i.e., $(a^{\mathrm{W}}, b^{\mathrm{W}})$ and $(a^{\mathrm{MO}}, b^{\mathrm{MO}})$, respectively. The wind producer and the market operator generate 2,000 scenarios each, and then they reduce them into three scenarios using a scenario reduction approach, e.g., the K-means method [89]. This provides wind producer's scenarios, denoted by ω_1, ω_2 and ω_3, with their corresponding probabilities. Similarly, the market operator's scenarios are generated, denoted by s_1, s_2 and s_3, with different probabilities. In the non-sharing analysis, wind producer solves Step 1 considering its own scenarios, and then market operator solves Step 2 based on its own different set of scenarios. However, they both use the same set of scenarios in the sharing analysis including all six scenarios, i.e., $h = \{\omega_1, \omega_2, \omega_3, s_1, s_2, s_3\}$, in Steps 1 and 2. Note that the probability of each scenario in the sharing analysis is half of that in the non-sharing one.

In this case study, three different sets for Beta distribution shape parameters are examined as given in Table 2.2, which yield different distribution shapes in order to evaluate different conditions with respect

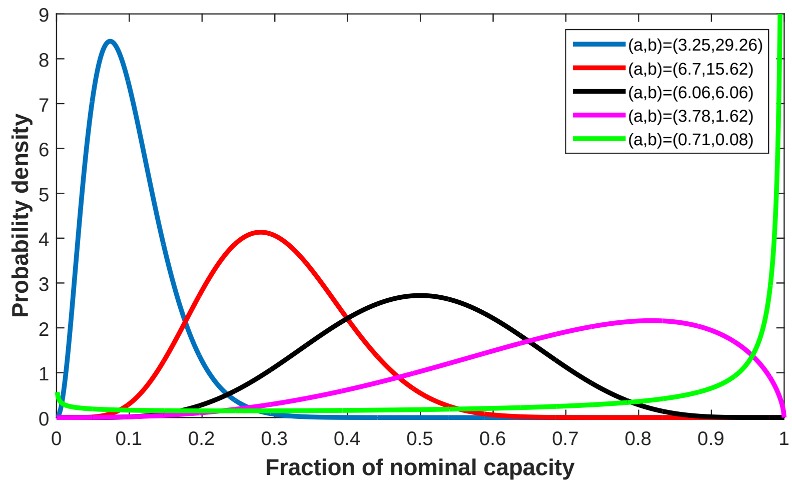

Figure 2.3: Beta probability density function for various sets of (a, b) parameters

to the level of wind power penetration. These three sets correspond to cases with high-mean, mid-mean and low-mean distributions, i.e., $a > b$, $a \simeq b$, $a < b$. We refer to those cases as Sets 1, 2 and 3, respectively. It is assumed that forecasts of wind producer and market operator have different distributions but they still predict the same shape of distribution, i.e., high-mean, mid-mean or low-mean. For clarity, the distribution shapes of actual wind power realization are illustrated in Fig. 2.4 considering values of a^{R} and b^{R} across different sets. Based on the considered shape parameters representing actual realizations (5,000 samples), the average wind power production is 38%, 25% and 15% of the total system load for Set 1, Set 2 and Set 3, respectively.

2.3.2 Results: Non-sharing Analysis

In this subsection, we assume that the wind producer and the market operator do not share their forecast distributions. The wind producer solves bilevel model (2.1) in Step 1 considering its own three scenarios, and derives its most beneficial quantity offer as depicted in Fig. 2.5 by blue bars. Given producer's quantity offer, market operator solves problem (2.9) in Step 2 to clear DA market considering its own three scenarios, which are different from the wind producer's ones. This step provides the DA wind

Table 2.2: Shape Parameters of Beta Distributions

Shape Parameters	Set 1 $a > b$	Set 2 $a \simeq b$	Set 3 $a < b$
$(a^{\mathrm{R}}, b^{\mathrm{R}})$	(3.78,1.62)	(5.37,5.37)	(1.89,4.48)
$(a^{\mathrm{MO}}, b^{\mathrm{MO}})$	(4.18,1.42)	(5.17,5.77)	(1.69,4.88)
$(a^{\mathrm{W}}, b^{\mathrm{W}})$	(3.38,1.82)	(5.57,4.97)	(2.09,4.08)

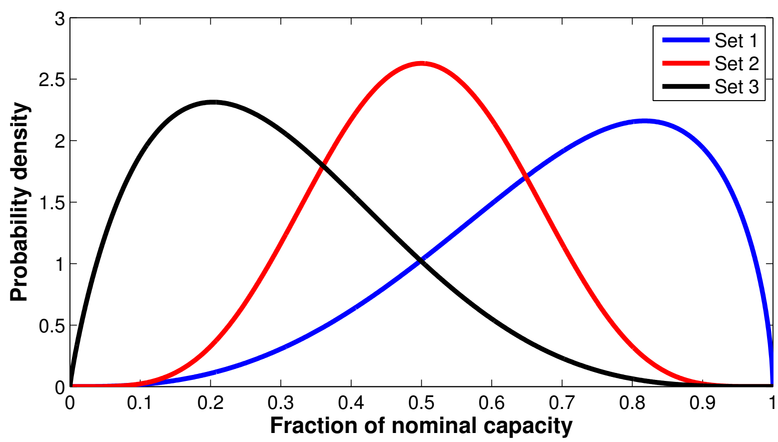

Figure 2.4: Actual wind power distribution considering Set 1 ($a^{\mathrm{R}} > b^{\mathrm{R}}$), Set 2 ($a^{\mathrm{R}} = b^{\mathrm{R}}$) and Set 3 ($a^{\mathrm{R}} < b^{\mathrm{R}}$)

power dispatch as depicted in Fig. 2.5 by green bars. Additionally, the expected wind power production, considering 5,000 samples as potential realizations in Step 3, is illustrated by red bars.

According to the results obtained for Set 1, the market operator forecasts a comparatively higher production than the wind producer. However, the DA wind power schedule cannot exceed the producer's quantity offer. Therefore, the DA wind schedule is equal to the wind producer's quantity offer. The expected wind realization in this case is higher than the scheduled wind power in DA market.

Regarding Set 2, the wind producer forecasts a comparatively higher

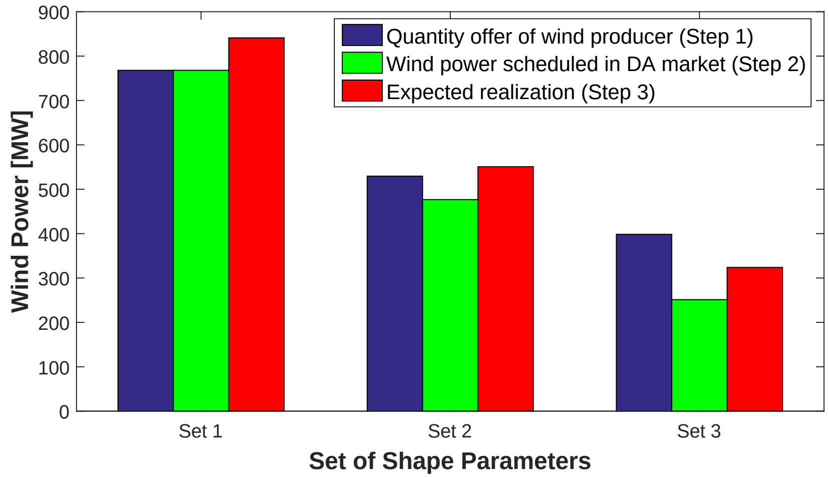

Figure 2.5: Non-sharing analysis: wind producer's quantity offer to DA market (Step 1), scheduled wind power in DA market (Step 2), and expected wind power realization in RT (Step 3)

wind production with respect to the market operator. Therefore, the market operator schedules the wind producer at a quantity lower than the wind producer's quantity offer. The expected actual wind power is higher than both wind producer's power offer and the scheduled wind power.

Finally, in Set 3, the wind producer and the market operator forecast lower wind power generation, but wind producer offers a greater quantity than the final scheduled wind power. The expected wind realization in this case is in between.

2.3.3 Results: Sharing Analysis

In this subsection, we consider that the wind producer and the market operator share their wind power forecast distributions. Therefore, an identical scenario set including six scenarios is considered within both Steps 1 and 2. Fig. 2.6 depicts the wind quantity offer (Step 1), the scheduled wind power in DA (Step 2) and the expected wind power realization (Step 3) obtained from the sharing analysis. In this analysis, the producer's quantity offer and the scheduled DA wind power are equal in each set since the wind producer and the market operator have the same beliefs on wind power production.

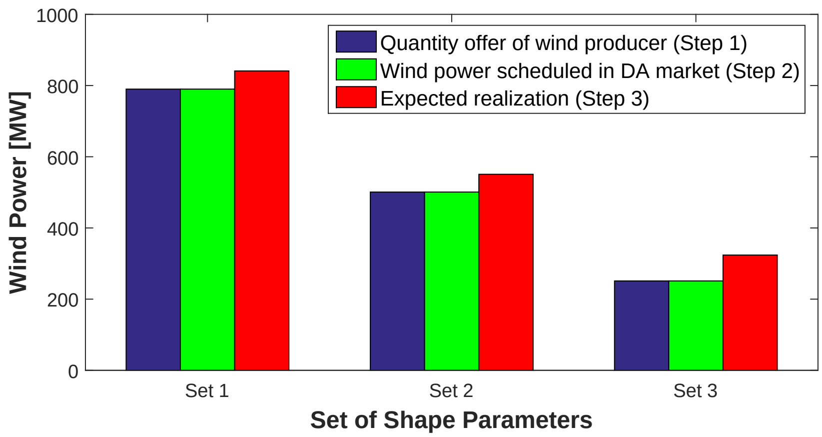

Figure 2.6: Sharing analysis: wind producer's quantity offer to DA market (Step 1), scheduled wind power in DA market (Step 2), and expected wind power realization in RT (Step 3)

2.3.4 Extensive Out-of-Sample Assessment

In this subsection, the RT market is cleared in Step 3 for 5,000 samples representing different wind power realizations, while DA decisions are fixed to those obtained from Step 2. Then, the *actual* system cost is computed, that consists of the system cost in DA obtained from Step 2 plus the expected system cost in RT obtained from Step 3. As it is given in Table 2.3, the actual system cost in the sharing analysis is comparatively lower than (in case of Sets 1 and 2) or equal to (in case of Set 3) that in the non-sharing analysis. This numerically concludes for this case study that sharing forecasts can potentially reduce the system cost in systems with high penetration of wind.

Moreover, the DA and the expected RT market-clearing prices in both sharing and non-sharing analyses are reported in Tables 2.4 and 2.5. Note that the DA market-clearing price is derived from Step 2, whereas the expected RT market-clearing price is derived from Step 3 considering 5,000 wind generation samples. The results of Table 2.4 imply that the DA market-clearing price for Set 1 increases at the sharing analysis which

Table 2.3: Actual System Cost [€]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	11500	14631	17634
Sharing	11406	14553	17634

consequently results in increased profits for most producers. The set of shared scenarios leads to increased DA market-clearing price because market operator anticipates in the RT market stage the need for reserves from producers G2 and G3. This increases the DA price, since those reserves are more expensive and prices in the DA and RT stages are correlated in the two-stage market setup. However, anticipating the need of these reserves leads to better schedules in DA, decreasing the cost in RT. The increased DA price has a positive impact on all producers profits, apart from producers G2 and G3 (see Table 2.7), which benefit in the non-sharing analysis by the less informed DA schedules. Lastly, it is observed that despite the same DA market-clearing price for Set 2, the RT price is different between the two analyses. In contrast to Set 3, wind power schedules in DA are different, which eventually leads to different power adjustments in RT.

Table 2.4: Day-Ahead Prices [€/MWh]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	10.52	12.89	12.89
Sharing	11.66	12.89	12.89

In addition to the impact of sharing forecasts on actual system cost and market-clearing prices as social measures, its impact on different players profit needs to be investigated. The expected profit of each player includes its profit in DA market (Step 2) plus its expected profit/cost in RT market (Step 3). Table 2.6 gives the wind producers expected profit for the three different sets, while Table 2.7 presents the expected profit

Table 2.5: Expected Real-Time Prices [€/MWh]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	11.62	10.24	11.11
Sharing	11.23	11.56	11.11

Table 2.6: Expected Profit of The Wind Producer [€]

Analysis	Set 1	Set 2	Set 3
Non-Sharing	6527	5880	2750
Sharing	7474	5918	2750

of each conventional unit. According to the results reported in Table 2.6, the wind producer benefits from sharing forecasts as its profit increases in the first two sets while in Set 3 it remains unchanged. These results numerically reveal that sharing forecasts is beneficial for the wind producer obtaining better knowledge on its future stochastic production. Besides, this information sharing might bring more market power to wind producer to alter the market-clearing outcomes to its own benefit. Further discussion on wind producer's increased profit is provided in the next subsection. Unlike the wind producer, the conventional units may lose profit or may gain higher profit if the market operator and the wind producer share their forecasts. For example, the expected profit of units G2 and G3 considering Set 1 in the sharing case is comparatively lower with respect to that in the non-sharing case. The reason for this, as explained before, is that these units profit from trading reserves in the RT market, which was not anticipated in the RT stage of the two-stage DA market. In contrast, the expected profit of conventional power units G5 and G6 considering Set 1 considerably increases by information sharing. This is the result of the comparatively higher DA market-clearing price in the sharing analysis. Finally, note that the expected profit of producer G4 in the non-sharing analysis is negative. The reason is that the two-stage stochastic market guarantees cost-recovery only in expectation, based on the available wind power scenarios. However, in the analysis of this section, expected profits consist of the DA profits plus the expected profits from the RT market derived from the out-of-sample analysis, which are different than the ones anticipated by the two-stage market. On the contrary, wind power scenarios of the sharing analysis lead to better schedules avoiding negative profits in expectation for producer G4.

Table 2.7: Expected Profit of The Conventional Units [€]

Unit	Analysis	Set 1	Set 2	Set 3
G1	Non-Sharing	243.68	274.52	317.61
	Sharing	331.85	290.72	317.61
G2	Non-Sharing	95.32	2.43	2.85
	Sharing	84.64	5.13	2.85
G3	Non-Sharing	234.5	0	0
	Sharing	204.95	0	0
G4	Non-Sharing	-44.17	0	0
	Sharing	66.05	0	0
G5	Non-Sharing	473.54	1543	1601
	Sharing	1022.8	1552	1601
G6	Non-Sharing	4040	5936	5936
	Sharing	4956	5936	5936
G7	Non-Sharing	73.65	90.67	115.37
	Sharing	116.46	101.88	115.37

2.3.5 Sensitivity Analysis

As reported in the previous subsection, wind producer's expected profit increases by sharing forecasts. A part of this profit increment happens due to the generation of a more qualified set of scenarios. Besides, it may happen as the wind producer is able to behave more strategically with more information access. This subsection numerically measures wind producer's market power in sharing and non-sharing cases through a sensitivity analysis. To this end, we use the value obtained for dual variable corresponding to the upper bound of constraint (2.9d) in Step 2, i.e., constraint $p^{\mathrm{W},(\mathrm{S2})} \leq P^{\mathrm{W},\mathrm{of},(\mathrm{S1})}$. This value implies the sensitivity of system cost with respect to the wind producer's strategic quantity offer. As given in Table 2.8, its absolute value for Sets 2 and 3 is zero in the non-sharing analysis, while it becomes non-zero in the sharing analysis. This reveals that sharing forecasts with market operator for these sets increases the ability of wind producer to exert market power. More specifically, regarding Set 3 wind producer's increased strategic behavior in the sharing analysis contributes to retain the same DA schedules as in the non-sharing one and, thus, its profit remains at the same level, instead of decreasing (see Table 2.6). On the other hand, in Set 1 the absolute value of sensitivity factor is non-zero in both analyses and decreases in the sharing one. Based on the wind power scenarios of the non-sharing analysis, DA market price is lower and, thus, wind producer acts more intensively as an arbitrager between DA and RT markets, in order to take advantage of the different prices between the two markets. This is the reason of the increased value of the sensitivity factor. Considering the shared scenarios, DA market-clearing price increases and it is more beneficial for wind producer to be scheduled in the DA market rather than in the RT.

Table 2.8: Value of Sensitivity Factor: Dual Variable Corresponding to the Upper Bound of Constraint (2.9d) in Step 2. This value implies the sensitivity of system cost with respect to the wind producer's strategic quantity offer.

Analysis	Set 1	Set 2	Set 3
Non-Sharing	-3.11	0	0
Sharing	-1.23	-1.55	-1.48

Finally, note that the negative value for this dual variable means that system cost in DA market (Step 2) increases with the strategic behavior of wind producer. However, recall that the actual system cost, i.e., the system cost in DA (obtained from Step 2) plus the expected system cost in RT (obtained from Step 3), can potentially decrease with information sharing as it has been already reported in Table 2.3. The reduction of total actual cost in sharing cases is the result of anticipating better the balancing resources that are needed in real time.

2.3.6 Computational Performance

This subsection offers an insight to the computational needs of this case study. For the simulations of this chapter we have used CPLEX under GAMS associated with Matlab R2015b. The softwares were installed on a Windows 8.1, 64-bit operating system with 2-core processor running at 2.4 GHz and 12 GB of RAM. The total computational time was approximately 70 min., the greatest part of which is due to the extensive out-of-sample simulation (60 min.). Note that by increasing the number of wind power scenarios considered in the two models of Steps 1 and 2, would increase computational times, since scenarios of the sharing analysis are double than the ones of the non-sharing. Additionally, increased number of scenarios make the selection of the Big-M parameters challenging. Lastly, despite the high computational time that the out-of-sample analysis demands, we should highlight the fact that the corresponding model, i.e., model of Step 3, is only solved for the needs of this evaluation framework and is not an operational process. In fact, the clearing of the RT market is a simple deterministic optimization problem, which can be solved in RT within some seconds.

2.4 Summary and Conclusions

In this chapter, the value of sharing wind power forecasts between a single wind power producer and the market operator is analyzed. This potential value is numerically evaluated in terms of the system cost. To this purpose, a three-step evaluation framework is proposed. In the first step, a stochastic bilevel optimization model is formulated, which allows the wind producer to derive its most beneficial quantity offer. In the second step, the market operator clears stochastically the DA market considering all foreseen wind power realizations in real time. In the last step, the RT market is cleared deterministically for a large number of wind power realizations constrained by fixed DA schedules. This framework is applied in two cases: (i) the wind producer and the market operator use different wind power scenarios (non-sharing analysis), and (ii) the wind producer and the market operator share their wind power scenarios (sharing analysis). In addition, the impact of sharing wind power forecasts on strategic offering of wind producer is analyzed through a relevant sensitivity analysis.

Under the above context, this chapter has numerically concluded for a large case study that sharing wind forecasts among a wind power producer and the market operator:

- can potentially decrease the expected market cost for high-wind penetration, while it retains it at the same levels for low-wind penetration,
- affects the expected profits of each conventional producer which, subject to each considered case, may increase or decrease,
- may help wind producer to alter the market-clearing outcomes to its own benefit, by increasing its market power due to the presence of better wind forecast information. To this end, a sensitivity analysis is performed to investigate wind producer's market power in both cases of sharing and non-sharing analyses and, lastly,
- it may lead to increased profit in expectation for the wind power producer, mainly as a result of wind producer's increased market power and better DA scheduling.

2.5 Future Perspectives

The interaction of multiple wind producers is not considered in this study. Thus, evaluating the concept of sharing wind power forecasts among multiple producers and the market operator is of interest for future research. The consideration of multiple price-making wind power producers yields a stochastic EPEC [68, 90]. Under such a framework, it is also relevant to analyze how sharing wind power forecasts affects the market equilibria.

Naturally, market agents will more likely conceive any information-asset they might have, including qualitative wind power forecasts, as a potential strategic advantage rather than an information that they will willingly share. Thus, the concept of sharing information in electricity markets, eventually coincides with the concept of an "information-trading" market. Under this framework, the approach followed in this study can be associated with ongoing research advances on trading information in other scientific domains, such as in [91, 92].

Finally, as noted in this chapter the impact of sharing wind power forecasts in an electricity market was investigated under the assumption that only one wind power producer is present in the market. In the following chapters, electricity markets with additional wind power producers are investigated. More precisely, Chapter 3 extends the presented setup into a stochastic DA market with an additional price-taking wind power producer, investigating the impact of the additional source of uncertainty in the market. Moreover, Chapter 4 further extends the market setup into a non-cooperative game of price-making power producers, with mixed wind and conventional power offering portfolios.

2.6 Chapter Publications

This chapter has led to the following publication:

- L. Exizidis, S. J. Kazempour, P. Pinson, Z. D. Grève, and F. Vallée, *Sharing wind power forecasts in electricity markets: A numerical analysis*, Applied Energy, vol. 176, pp. 65-73, 2016.

Chapter 3

Strategic Wind Power Trading Considering Rival Wind Power Production

3.1 Introduction

In this chapter we investigate a stochastic day-ahead (DA) market setup where, in contrast to Chapter 2, additional price-taking wind power producers are present. Under this context, the main focus of this chapter is to evaluate the impact of the additional source of wind uncertainty on the offering strategies and market outcomes, considering various levels of wind penetration.

3.1.1 Motivation and Literature Review

In recent years, a lot of attention is drawn on wind power and its impact on electricity markets. Political decisions as well as technological advances mitigating climate change, have led to an increased penetration of wind power in energy systems, transforming wind power producers into dominant market players. As mentioned in 2.1.2, the mix of energy generation is rapidly changing in many countries, such as Denmark, Spain and Germany, where wind power generation is holding an increasing share of the total power generation. Under this context, benefits and premiums for wind power generation are not anymore the case in many countries and wind power producers are forced to compete under the same rules with conventional ones [93], being able in some cases to exercise market power in order to increase profits. However, uncertainty and variability in wind power production pose operational challenges in electricity markets, for both power producers and market operators. The cost for backup reserves is considerably high in order to guarantee reliability, while energy storage is still not mature enough [94]. Therefore, intensive research in wind power forecasting, as for example presented in [27], has led to mature forecasting tools, which are used widely in the related decision-making processes. Furthermore, advanced stochastic optimization as well as game theory are deployed by researchers in the technical literature, in an effort to address the problem of wind power trading under uncertainty in liberalized electricity markets.

Initial research efforts were focused on models where wind power producers are not accountable for exercising market power, i.e., being price-takers. Furthermore, due to political decisions for increasing wind power penetration, wind producers were even considered to receive additional support when participating in a forward electricity market [55, 95, 96, 97]. However, as a result of the low operational costs associated with wind power generation, wind producers competitiveness increased considerably resulting, in due time, to a change in the aforementioned policies forcing now wind producers to participate in the electricity markets under full competition and following the same rules as conventional producers [98]. Under this context, authors in [71] consider that wind power producers are price-makers in the real-time (RT) market, by strategically offering less wind power than the difference between the anticipated generation and the DA scheduled wind power, while they are price-takers in the DA market due to large volumes of traded energy. The impact of the forecast distribution on the producers decision-making problem is additionally investigated. The problem of a price-maker wind power producer in the DA market, being a deviator in the RT market, was later addressed in [72]. More specifically, the problem was formulated as a stochastic optimization tool for market participation, where uncertainty pertaining to wind power production is represented through scenarios. Study [73] has contributed to the aforementioned research problem by evaluating the impact of a price-maker wind power producer on DA electricity prices as well as on the resulted imbalances for a market without regulated tariffs. Both aforementioned studies were focusing on the uncertainty introduced by wind power producers. Research paper [74] offered an insight to the same problems by additionally considering, in the form of scenarios, the uncertainties in demand and bidding strategies of strategic conventional generators focusing on the problem of strategic wind power trading. Recent study [99], proposed a multi-stage risk-constrained stochastic complementarity model to derive the optimal offering strategy of a wind power producer that participates in both the DA and the RT markets. Uncertainties concerning wind power production, market prices, demands bids and rivals offers were modeled in this study using a set of scenarios.

Aforementioned studies focus on a single strategic wind power producer and its strategic offering problem since, as highlighted in [99], there are countries where even a single wind power producer owns large enough wind capacity that enables him to behave strategically. However, it can naturally be argued that this setup, including only one strategic producer with stochastic generation, is rather unrealistic. The consideration of more than one strategic producers with uncertain generation would, naturally, lead to a game-theoretic approach, which is a problem generally hard to cope with and is the topic of Chapter 4. Moreover, given that each producer owns its private wind power forecast, the problem would lead to a game under incomplete information, yielding a Bayesian approach [100]. Motivated by the above challenges, in [101] authors approach the problem of an electricity market with multiple stochastic producers based on a minority game, studying the competition among them using a set of learning tools to identify their actions. Under the same context, the contribution of this chapter is to address the impact of additional wind power producers on the wind power offering strategy of a price-maker wind power producer. In this approach, avoiding a more complex setup, i.e., equilibrium problem with equilibrium constraints (EPEC), rival wind power production is represented by a number of foreseen scenarios followed by the corresponding probabilities. In parallel, various levels of wind power generation for both wind power producers are considered, investigating their impact on the strategic producer's offering strategy and profits, as well as on anticipated market outcomes. The problem is formulated as a bilevel stochastic optimization model, following a complementarity approach [66], similarly to the model of Chapter 2.

3.1.2 Chapter Organization

The rest of the chapter is organized as follows: Section 3.2 presents the mathematical formulation of the decision-making problem for a wind power producer, considering the uncertainty introduced by rival wind power generation. Section 3.3 presents the results for a large case study with respect to producers offering strategies, strategic behavior as well as market outcomes. Lastly, Section 3.4 concludes the chapter and summarizes the main results.

3.2 Mathematical Formulation

3.2.1 Model Assumptions and Uncertainty Characterization

A pool-based electricity market is assumed, where producers submit power and price offers for the DA and RT markets. The assumed DA market-clearing mechanism is a two-stage stochastic optimization program, as introduced in [28]. The aforementioned market mechanism, which is similar to that used in Chapter 2, co-optimizes DA and RT markets and enables better operational results in markets with considerable sources of uncertainty, given a set of qualitative scenarios. Under the investigated framework, two main sources of uncertainty are considered, namely:

- wind power generation of investigated strategic wind producer,
- wind power generation of competitive rival wind producer,

both of which are introduced as independent wind power scenarios. Note that in contrast to [72], real-time prices are driven by the optimization model and not predicted. Furthermore, the approach of this chapter differs from [71, 72, 74, 102], as well as the model of Chapter 2, in the sense that it additionally considers the uncertainty of rival wind power producer.

A number of assumptions are made for the purpose of this study, namely:

1. An imperfectly competitive electricity market is considered, in which the wind producers and conventional units may offer strategically [69, 70].
2. In line with [71, 72, 73, 74] and similarly to Chapter 2 we assume that the wind producer perfectly knows the offering strategy of its

rival power producers. Consideration of multiple strategic producers with different private forecasts, would lead to a non-cooperative game with incomplete information, which exceeds the scope of this thesis and is left for future research. However, an extension of Chapters 2 and 3 considering multiple strategic power producers with private wind power forecasts is investigated under the context of Chapter 4.

3. Similarly to [70, 71, 73], and for the sake of simplicity, transmission constraints are not enforced. A relevant formulation considering transmission constraints can be found in Chapter 5.

4. In addition, the inter-temporal constraints, e.g., ramping limits of conventional power units, are not enforced and thus a single-hour auction is considered, which is consistent with the relevant literature [70, 71, 74, 75].

5. The operational cost of wind power producers is negligible since they are not incurred by the fuel costs. In some realistic electricity markets, this cost is even negative due to renewable incentives [25]. As it is customary in the technical literature, e.g., [20, 21, 22, 23, 24], we assume that the wind production cost is zero.

6. Finally, demand is assumed to be deterministic and inelastic to price, as in [76], in order to avoid additional sources of uncertainty.

The aforementioned setup is illustrated in Fig. 3.1. As shown, in contrast to Chapter 2 and the corresponding illustration 2.1, in this study we consider two wind power producers. However, only one wind producer is considered to be strategic, distinguished in Fig. 3.1 by the circle. Strategic wind producer anticipates the stochastic two-stage electricity market, based on the available information which, in addition to conventional producers offers and demand bids, also include a forecast for its own wind power generation and a forecast for its rival price-taker wind producer's generation. Note that in contrast to Chapter 2, in this chapter we focus only on strategic producer's viewpoint, so the actual clearing of DA and RT markets is omitted. Thus, the results that correspond to the market-clearing outcomes are the anticipated results from strategic wind producer's point of view.

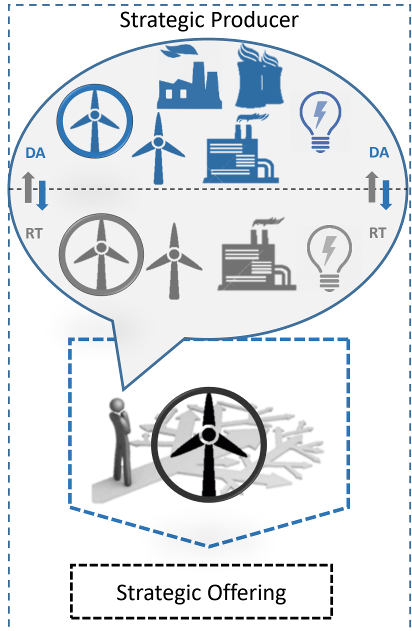

Figure 3.1: Illustrative representation of the market setup of Chapter 3

3.2.2 Model Formulation

The symbols used in this chapter are defined below:

Notation

Sets:

Ω	Set of strategic wind producer's scenarios.
$\mathcal{S}$	Set of rival wind producer's scenarios.
$\mathcal{I}$	Set of conventional power units.
$\mathcal{D}$	Set of demands.

Indices:

ω — Index for scenarios generated based on strategic wind producer's forecast (referred to as SW).

s — Index for scenarios generated based on rival wind producer's forecast (referred to as RW).

i — Index for conventional power units.

d — Index for demands.

Parameters:

$\overline{P}_d^{\mathrm{D}}$ — Quantity bid of demand d [MW].

$\overline{P}_i^{\mathrm{G}}$ — Quantity offer of conventional power unit i [MW].

$P_\omega^{\mathrm{F,SW}}$ — Wind power forecast of strategic wind producer under scenario ω [MW].

$P_s^{\mathrm{F,RW}}$ — Wind power forecast of rival wind producer under scenario s [MW].

λ_i^{G} — Offer price of conventional power unit i [€/MWh].

λ_i^{U} — Operational cost of conventional power unit i for providing upward reserve [€/MWh].

λ_i^{D} — Operational cost of conventional power unit i for providing downward reserve [€/MWh].

γ_ω — Probability of scenario ω.

π_s — Probability of scenario s.

R_i^{U} — Upward reserve capacity of conventional power unit i [MW].

R_i^{D} — Downward reserve capacity of conventional power unit i [MW].

V_d^{shed} — Value of lost load for demand d [€/MWh].

Day-Ahead Variables:

λ_s^{DA} DA market-clearing price under scenario s [€/MWh].

$p_{i,s}^{\mathrm{G}}$ DA dispatch of conventional power unit i under scenario s [MW].

$p_s^{\mathrm{DA,SW}}$ DA dispatch of strategic wind producer under scenario s [MW].

$p_s^{\mathrm{DA,RW}}$ DA dispatch of rival wind producer under scenario s [MW].

$p^{\mathrm{Of,SW}}$ Quantity offer of strategic wind producer [MW].

Real-time Variables:

$\lambda_{\omega,s}^{\mathrm{RT}}$ Probability-weighted RT market-clearing price under scenario ω and scenario s [€/MWh].

$p_{\omega}^{\mathrm{spill,SW}}$ Wind power spillage under scenario ω for strategic wind producer [MW].

$p_{\omega,s}^{\mathrm{spill,RW}}$ Wind power spillage under scenario ω and scenario s for rival wind producer [MW].

$r_{i,\omega,s}^{\mathrm{U}}$ Upward power adjustment of unit i under scenario ω and scenario s [MW].

$r_{i,\omega,s}^{\mathrm{D}}$ Downward power adjustment of unit i under scenario ω and scenario s [MW].

$l_{d,\omega,s}^{\mathrm{shed}}$ Involuntarily load shed of demand d under scenario ω and scenario s [MW].

The offering strategy of the strategic wind power producer is modeled through a stochastic complementarity approach [66, 72]. We use a bilevel model, i.e., (3.1), whose upper-level (UL) problem (3.1a)-(3.1b) maximizes wind producer's expected profit, and lower-level (LL) problem (3.1c)-(3.1o) clears the stochastic two-stage market through minimizing the expected system cost. Note that in model (3.1), the strategic wind producer's scenarios for its own generation are indicated by $\omega \in \Omega$ and for its rival by $s \in \mathcal{S}$. Dual variables are indicated in each LL constraint after a colon.

The UL objective function (3.1a) maximizes strategic wind producer's expected profit, considering wind power generation scenarios for rival wind producer ($s \in \mathcal{S}$), and consists of:

- wind producer's profit in DA market, being the product of DA market-clearing price, i.e., λ_s^{DA}, and scheduled quantity, i.e., $p_s^{\mathrm{DA,SW}}$,
- wind producer's expected profit/cost in RT market, being the product of the probability-weighted RT market-clearing price, i.e., $\lambda_{\omega,s}^{\mathrm{RT}}$, and wind power excess/deficit in RT, i.e., $P_\omega^{\mathrm{F,SW}} - p_s^{\mathrm{DA,SW}} - p_\omega^{\mathrm{spill,SW}}$.

$$\underset{p^{\mathrm{Of,SW}},\ \Xi^{\mathrm{LL,P}} \cup \Xi^{\mathrm{LL,D}}}{\text{Maximize}}$$

$$\sum_{s \in \mathcal{S}} \pi_s \left[\lambda_s^{\mathrm{DA}}\ p_s^{\mathrm{DA,SW}} + \sum_{\omega \in \Omega} \lambda_{\omega,s}^{\mathrm{RT}} (P_\omega^{\mathrm{F,SW}} - p_s^{\mathrm{DA,SW}} - p_\omega^{\mathrm{spill,SW}}) \right] \quad (3.1a)$$

The UL objective function (3.1a) is constrained by both UL constraint (3.1b) and LL problem (3.1c)-(3.1o). The UL constraint (3.1b), below, imposes the strategic quantity offer of wind producer, i.e., $p^{\mathrm{Of,SW}}$, to be non-negative.

$$p^{\mathrm{Of,SW}} \geq 0 \quad (3.1b)$$

The LL objective function (3.1c) minimizes the expected system cost including generation-side costs in DA and RT as well as load shedding costs in RT.

$$\lambda_s^{\mathrm{DA}}, p_s^{\mathrm{DA,SW}}, \lambda_{\omega,s}^{\mathrm{RT}} \text{ and } p_\omega^{\mathrm{spill,SW}} \in \arg \underset{\Xi^{\mathrm{LL,P}}}{\text{minimize}} \Bigg\{$$

$$\sum_{i\in\mathcal{I}} \lambda_i^{\mathrm{G}} p_{i,s}^{\mathrm{G}} + \sum_{\omega\in\Omega} \gamma_\omega \Bigg[\sum_{i\in\mathcal{I}} (\lambda_i^{\mathrm{U}}\ r_{i,\omega,s}^{\mathrm{U}} - \lambda_i^{\mathrm{D}}\ r_{i,\omega,s}^{\mathrm{D}}) + \sum_{d\in\mathcal{D}} V_d^{\mathrm{shed}}\ l_{d,\omega,s}^{\mathrm{shed}} \Bigg] \tag{3.1c}$$

Objective function (3.1c) is constrained by (3.1d) - (3.1o), below:

$$\sum_{d\in\mathcal{D}} \overline{P}_d^{\mathrm{D}} - \sum_{i\in\mathcal{I}} p_{i,s}^{\mathrm{G}} - p_s^{\mathrm{DA,SW}} - p_s^{\mathrm{DA,RW}} = 0\ \ : \lambda_s^{\mathrm{DA}} \tag{3.1d}$$

The LL constraint (3.1d) represents the power balance in DA, whose dual variable, i.e., λ_s^{DA}, provides the DA market-clearing price.

$$0 \le p_{i,s}^{\mathrm{G}} \le \overline{P}_i^{\mathrm{G}}\ \ : \underline{\phi}_{i,s}, \overline{\phi}_{i,s}\ \forall i \tag{3.1e}$$

$$0 \le p_s^{\mathrm{DA,SW}} \le p^{\mathrm{Of,SW}}\ \ : \underline{\sigma}_s^{\mathrm{SW}}, \overline{\sigma}_s^{\mathrm{SW}} \tag{3.1f}$$

$$0 \le p_s^{\mathrm{DA,RW}} \le P_s^{\mathrm{F,RW}}\ \ : \underline{\sigma}_s^{\mathrm{RW}}, \overline{\sigma}_s^{\mathrm{RW}} \tag{3.1g}$$

Constraints (3.1e)-(3.1g), above, bind the DA schedule of conventional power units and wind producers, based on their quantity offers (or expected generation for rival wind producer).

Constraint (3.1h), below, refers to power balance in RT that adjusts the energy imbalance by operational reserve deployment, wind power spillage and load shedding. Note that its corresponding dual variable provides the probability-weighted RT market-clearing price, i.e., $\lambda_{\omega,s}^{\mathrm{RT}}$.

$$\sum_{i\in\mathcal{I}} (r_{i,\omega,s}^{\mathrm{D}} - r_{i,\omega,s}^{\mathrm{U}}) - \sum_{d\in\mathcal{D}} l_{d,\omega,s}^{\mathrm{shed}} - (P_\omega^{\mathrm{F,SW}} - p_s^{\mathrm{DA,SW}} - p_\omega^{\mathrm{spill,SW}}) - (P_s^{\mathrm{F,RW}} - p_s^{\mathrm{DA,RW}} - p_{s,\omega}^{\mathrm{spill,RW}}) = 0\ \ : \lambda_{\omega,s}^{\mathrm{RT}}\ \forall\omega \tag{3.1h}$$

Constraints (3.1i)-(3.1j) imply that wind power spillage should be equal to or less than the wind power realization.

$$0 \leq p_{\omega}^{\text{spill,SW}} \leq P_{\omega}^{\text{F,SW}} \;\; : \underline{\tau}_{\omega}^{\text{SW}}, \overline{\tau}_{\omega}^{\text{SW}} \; \forall \omega \tag{3.1i}$$

$$0 \leq p_{\omega,s}^{\text{spill,RW}} \leq P_{s}^{\text{F,RW}} \;\; : \underline{\tau}_{\omega,s}^{\text{RW}}, \overline{\tau}_{\omega,s}^{\text{RW}} \; \forall \omega \tag{3.1j}$$

Constraint (3.1k) restricts the load shedding quantity. Lastly, operational reserves in RT are bounded by reserve quantity offers and DA dispatch through (3.1l)-(3.1o).

$$0 \leq l_{d,\omega,s}^{\text{shed}} \leq \overline{P}_{d}^{\text{D}} \;\; : \underline{\psi}_{d,\omega,s}, \overline{\psi}_{d,\omega,s} \; \forall d, \forall \omega \tag{3.1k}$$

$$0 \leq r_{i,\omega,s}^{\text{D}} \leq R_{i}^{\text{D}}, \; : \underline{\mu}_{i,\omega,s}^{\text{D}}, \overline{\mu}_{i,\omega,s}^{\text{D}} \; \forall i, \forall \omega \tag{3.1l}$$

$$0 \leq r_{i,\omega,s}^{\text{U}} \leq R_{i}^{\text{U}}, \; : \underline{\mu}_{i,\omega,s}^{\text{U}}, \overline{\mu}_{i,\omega,s}^{\text{U}} \; \forall i, \forall \omega \tag{3.1m}$$

$$r_{i,\omega,s}^{\text{U}} \leq (\overline{P}_{i}^{\text{G}} - p_{i,s}^{\text{G}}), \; : \overline{\mu}_{i,\omega,s} \; \forall i, \forall \omega \tag{3.1n}$$

$$r_{i,\omega,s}^{\text{D}} \leq p_{i,s}^{\text{G}}, \; : \underline{\mu}_{i,\omega,s} \; \forall i, \forall \omega \tag{3.1o}$$

$$\Big\} \; \forall s.$$

The set of primal variables of the LL problem is $\Xi^{\text{LL,P}} = \{p_{s}^{\text{DA,SW}}, p_{s}^{\text{DA,RW}}, p_{\omega}^{\text{spill,SW}}, \; p_{i,s}^{\text{G}}, \; r_{i,\omega,s}^{\text{U}}, \; r_{i,\omega,s}^{\text{D}}, \; l_{d,\omega,s}^{\text{shed}}, \; p_{\omega,s}^{\text{spill,RW}}\}$.

Furthermore, the set of dual variables of the LL problem is $\Xi^{\text{LL,D}} = \{\lambda_{s}^{\text{DA}}, \; \underline{\phi}_{i,s}, \; \overline{\phi}_{i,s}, \; \underline{\sigma}_{s}^{\text{SW}}, \; \overline{\sigma}_{s}^{\text{SW}}, \; \underline{\sigma}_{s}^{\text{RW}}, \; \overline{\sigma}_{s}^{\text{RW}}, \; \lambda_{\omega,s}^{\text{RT}}, \; \underline{\tau}_{\omega}^{\text{SW}}, \; \overline{\tau}_{\omega}^{\text{SW}}, \; \underline{\tau}_{\omega,s}^{\text{RW}}, \; \overline{\tau}_{\omega,s}^{\text{RW}}, \underline{\psi}_{d,\omega,s}, \; \overline{\psi}_{d,\omega,s}, \; \underline{\mu}_{i,\omega,s}^{\text{D}}, \; \overline{\mu}_{i,\omega,s}^{\text{D}}, \; \underline{\mu}_{i,\omega,s}^{\text{U}}, \; \overline{\mu}_{i,\omega,s}^{\text{U}}, \; \underline{\mu}_{i,\omega,s}, \; \overline{\mu}_{i,\omega,s}\}$.

Finally, the primal variables of the UL problem (3.1a)-(3.1b) are $p^{\text{Of,SW}}$, as well as all members of variable sets $\Xi^{\text{LL,P}}$ and $\Xi^{\text{LL,D}}$.

Given that LL problem (3.1c)-(3.1o) is continuous, linear and therefore convex, bilevel model (3.1) can be recast as a single-level mathematical program with equilibrium constraints (MPEC), by replacing the LL problem by its Karush-Kuhn-Tucker (KKT) optimality conditions [66]. The procedure is similar to that of Chapter 2 and explained at Appendix A. As in Chapter 2, the KKT conditions are derived by the Lagrangian function associated with the LL, by differentiating the Lagrangian each time with the corresponding primal variable of the LL problem. Thus, we can replace the LL problem (3.1c)-(3.1o) by its KKT conditions as shown below:

$$\underset{p^{\mathrm{Of,SW}},\ \Xi^{\mathrm{LL,P}} \cup \Xi^{\mathrm{LL,D}}}{\text{Maximize}} \ (3.1\text{a}) \tag{3.2a}$$

subject to

$$(3.1\text{b}),\ (3.1\text{d}) \text{ and } (3.1\text{h}) \tag{3.2b}$$

$$\frac{\partial \mathcal{L}}{\partial p^{\mathrm{G}}_{i,s}} = \lambda^{\mathrm{G}}_{i} - \lambda^{\mathrm{DA}}_{s} - \underline{\phi}_{i,s} + \overline{\phi}_{i,s} + \sum_{\omega \in \Omega} (\overline{\mu}_{i,\omega,s} - \underline{\mu}_{i,\omega,s}) = 0 \ \forall i,\ \forall s \tag{3.2c}$$

$$\frac{\partial \mathcal{L}}{\partial p^{\mathrm{DA,SW}}_{s}} = -\lambda^{\mathrm{DA}}_{s} - \underline{\sigma}^{\mathrm{SW}}_{s} + \overline{\sigma}^{\mathrm{SW}}_{s} + \sum_{\omega \in \Omega} \lambda^{\mathrm{RT}}_{\omega,s} = 0 \ \forall s \tag{3.2d}$$

$$\frac{\partial \mathcal{L}}{\partial p^{\mathrm{DA,RW}}_{s}} = -\lambda^{\mathrm{DA}}_{s} - \underline{\sigma}^{\mathrm{RW}}_{s} + \overline{\sigma}^{\mathrm{RW}}_{s} + \sum_{\omega \in \Omega} \lambda^{\mathrm{RT}}_{\omega,s} = 0 \ \forall s \tag{3.2e}$$

$$\frac{\partial \mathcal{L}}{\partial r^{\mathrm{U}}_{i,\omega,s}} = \gamma_{\omega} \lambda^{\mathrm{U}}_{i} - \lambda^{\mathrm{RT}}_{\omega,s} - \underline{\mu}^{\mathrm{U}}_{i,\omega,s} + \overline{\mu}^{\mathrm{U}}_{i,\omega,s} + \overline{\mu}_{i,\omega,s} = 0 \ \forall i, \forall \omega,\ \forall s \tag{3.2f}$$

$$\frac{\partial \mathcal{L}}{\partial r^{\mathrm{D}}_{i,\omega,s}} = -\gamma_{\omega} \lambda^{\mathrm{D}}_{i} + \lambda^{\mathrm{RT}}_{\omega,s} - \underline{\mu}^{\mathrm{D}}_{i,\omega,s} + \overline{\mu}^{\mathrm{D}}_{i,\omega,s} + \underline{\mu}_{i,\omega,s} = 0 \ \forall i, \forall \omega,\ \forall s \tag{3.2g}$$

$$\frac{\partial \mathcal{L}}{\partial l^{\mathrm{shed}}_{d,\omega,s}} = \gamma_{\omega} V^{\mathrm{shed}}_{d} - \lambda^{\mathrm{RT}}_{\omega,s} + \overline{\psi}_{d,\omega,s} - \underline{\psi}_{d,\omega,s} = 0 \ \forall d, \forall \omega,\ \forall s \tag{3.2h}$$

$$\frac{\partial \mathcal{L}}{\partial p^{\mathrm{spill,SW}}_{\omega,s}} = \lambda^{\mathrm{RT}}_{\omega,s} + \overline{\tau}^{\mathrm{SW}}_{\omega} - \underline{\tau}^{\mathrm{SW}}_{\omega} = 0 \ \forall \omega,\ \forall s \tag{3.2i}$$

$$\frac{\partial \mathcal{L}}{\partial p^{\mathrm{spill,RW}}_{\omega,s}} = \lambda^{\mathrm{RT}}_{\omega,s} + \overline{\tau}^{\mathrm{RW}}_{\omega,s} - \underline{\tau}^{\mathrm{RW}}_{\omega,s} = 0 \ \forall \omega,\ \forall s \tag{3.2j}$$

Lastly, complementarity slackness conditions, which refer to the relationship between the positivity in a primal constraint and the positivity of its associated dual variable, are given below by (3.2k)-(3.2zc):

$$0 \leq p^{\mathrm{G}}_{i} \perp \underline{\phi}_{i,s} \geq 0 \ \forall i,\ \forall s \tag{3.2k}$$

$$0 \leq (\overline{P}_i^{\mathrm{G}} - p_{i,s}^{\mathrm{G}}) \perp \overline{\phi}_i \geq 0 \ \forall i, \ \forall s \tag{3.2l}$$

$$0 \leq p_s^{\mathrm{DA,SW}} \perp \underline{\sigma}_s^{\mathrm{SW}} \geq 0 \ \forall s \tag{3.2m}$$

$$0 \leq (p^{\mathrm{Of,SW}} - p_s^{\mathrm{DA,SW}}) \perp \overline{\sigma}_s^{\mathrm{SW}} \geq 0 \ \forall s \tag{3.2n}$$

$$0 \leq p_s^{\mathrm{DA,RW}} \perp \underline{\sigma}_s^{\mathrm{RW}} \geq 0 \ \forall s \tag{3.2o}$$

$$0 \leq (P_s^{\mathrm{F,RW}} - p_s^{\mathrm{DA,RW}}) \perp \overline{\sigma}_s^{\mathrm{RW}} \geq 0 \ \forall s \tag{3.2p}$$

$$0 \leq p_\omega^{\mathrm{spill,SW}} \perp \underline{\tau}_\omega^{\mathrm{SW}} \geq 0 \ \forall \omega \tag{3.2q}$$

$$0 \leq (P_s^{\mathrm{W,F,SW}} - p_\omega^{\mathrm{spill,SW}}) \perp \overline{\tau}_\omega^{\mathrm{SW}} \geq 0 \ \forall \omega \tag{3.2r}$$

$$0 \leq p_{\omega,s}^{\mathrm{spill,RW}} \perp \underline{\tau}_{\omega,s}^{\mathrm{RW}} \geq 0 \ \forall \omega, \forall s \tag{3.2s}$$

$$0 \leq (P_s^{\mathrm{F,RW}} - p_\omega^{\mathrm{spill,RW}}) \perp \overline{\tau}_\omega^{\mathrm{RW}} \geq 0 \ \forall \omega, \forall s \tag{3.2t}$$

$$0 \leq l_{d,\omega,s}^{\mathrm{shed}} \perp \underline{\psi}_{d,\omega,s} \geq 0 \ \forall d, \forall \omega, \forall s \tag{3.2u}$$

$$0 \leq (\overline{P}_d^{\mathrm{D}} - l_{d,\omega,s}^{\mathrm{shed}}) \perp \overline{\psi}_{d,\omega,s} \geq 0 \ \forall d, \forall \omega, \forall s \tag{3.2v}$$

$$0 \leq r_{i,\omega,s}^{\mathrm{D}} \perp \underline{\mu}_{i,\omega,s}^{\mathrm{D}} \geq 0 \ \forall i, \forall \omega, \forall s \tag{3.2w}$$

$$0 \leq (R_i^{\mathrm{D}} - r_{i,\omega,s}^{\mathrm{D}}) \perp \overline{\mu}_{i,\omega,s}^{\mathrm{D}} \geq 0 \ \forall i, \forall \omega, \forall s \tag{3.2x}$$

$$0 \leq r_{i,\omega,s}^{\mathrm{U}} \perp \underline{\mu}_{i,\omega,s}^{\mathrm{U}} \geq 0 \ \forall i, \forall \omega, \forall s \tag{3.2y}$$

$$0 \leq (R_i^{\mathrm{U}} - r_{i,\omega,s}^{\mathrm{U}}) \perp \overline{\mu}_{i,\omega,s}^{\mathrm{U}} \geq 0 \ \forall i, \forall \omega, \forall s \tag{3.2za}$$

$$0 \leq (\overline{P}_i^{\mathrm{G}} - r_{i,\omega,s}^{\mathrm{U}} - p_{i,s}^{\mathrm{G}}) \perp \overline{\mu}_{i,\omega,s} \geq 0 \ \forall i, \forall \omega, \forall s \tag{3.2zb}$$

$$0 \leq (p_{i,s}^{\mathrm{G}} - r_{i,\omega,s}^{\mathrm{D}}) \perp \underline{\mu}_{i,\omega,s} \geq 0 \ \forall i, \forall \omega, \forall s. \tag{3.2zc}$$

The perpendicular ($\perp$) enforces the perpendicular condition between the vectors on the left-hand and right-hand sides, i.e., their element-by-element product is zero.

The MPEC (3.2) includes two sources of non-linearities:

- the bilinear terms $\lambda_s^{\mathrm{DA}} \ p_s^{\mathrm{DA,SW}}$, $\lambda_{\omega,s}^{\mathrm{RT}} \ p_s^{\mathrm{DA,SW}}$ and $\lambda_{\omega,s}^{\mathrm{RT}} \ p_\omega^{\mathrm{spill,SW}}$ included in the objective function (3.1a), and
- complementarity conditions (3.2k)-(3.2zc).

Similarly to Chapter 2, bilinear terms of the objective function are linearized using the strong duality theorem (SDT) along with the complementarity constraints (3.2k)-(3.2zc). The SDT states that if a problem is convex then the objective functions of the primal and dual problems have the same value at the optimum, and for the investigated problem this writes as in (3.3) below:

$$\Bigg\{ \sum_{i \in \mathcal{I}} \lambda_i^{\mathrm{G}} p_{i,s}^{\mathrm{G}} + \sum_{\omega \in \Omega} \gamma_\omega \Bigg[\sum_{i \in \mathcal{I}} (\lambda_i^{\mathrm{U}} \; r_{i,\omega,s}^{\mathrm{U}} - \lambda_i^{\mathrm{D}} \; r_{i,\omega,s}^{\mathrm{D}}) + \sum_{d \in \mathcal{D}} V_d^{\mathrm{shed}} \; l_{d,\omega,s}^{\mathrm{shed}} \Bigg] =$$
$$- \sum_{i \in \mathcal{I}} \overline{\phi}_{i,s} \overline{P}_i^{\mathrm{G}} - \overline{\sigma}_s^{\mathrm{SW}} p^{\mathrm{Of,SW}} - \overline{\sigma}_s^{\mathrm{RW}} P_s^{\mathrm{F,RW}} + \sum_{d \in \mathcal{D}} \overline{P}_d^{\mathrm{D}} \lambda_s^{\mathrm{DA}}$$
$$- \sum_{\omega \in \Omega} \Bigg[P_\omega^{\mathrm{F,SW}} \lambda_{\omega,s}^{\mathrm{RT}} + P_s^{\mathrm{F,RW}} \lambda_{\omega,s}^{\mathrm{RT}} + P_\omega^{\mathrm{F,SW}} \overline{\tau}_\omega^{\mathrm{SW}} + P_s^{\mathrm{F,RW}} \overline{\tau}_{\omega,s}^{\mathrm{RW}}$$
$$+ \sum_{d \in \mathcal{D}} \overline{\psi}_{d,\omega,s} \overline{P}_d^{\mathrm{D}} + \sum_{i \in \mathcal{I}} R_i^{\mathrm{D}} \overline{\mu}_{i,\omega,s}^{\mathrm{D}} + \sum_{i \in \mathcal{I}} R_i^{\mathrm{U}} \overline{\mu}_{i,\omega,s}^{\mathrm{U}} + \sum_{i \in \mathcal{I}} \overline{P}_i^{\mathrm{G}} \overline{\mu}_{i,\omega,s} \Bigg] \Bigg\} \; \forall s. \tag{3.3}$$

Finally, non-linear complementarities are linearized based on the Big-M approach [77, 79], at the cost of introducing a set of auxiliary binary variables. Following this linearization approach, MPEC is transformed into a mixed-integer linear programming (MILP) problem, similarly to Chapter 2, which is solved with available solvers.

3.3 Case Study

3.3.1 Data

A case study based on the IEEE one-area reliability test system [84] is considered, in which conventional units are grouped for the sake of simplicity. Each conventional unit offers at a quantity identical to its installed capacity and at a price given in Table 3.1. In addition to the conventional units, two wind power producers, i.e., the investigated strategic producer (indicated by SW) and its rival wind producer (indicated by RW), are considered with the same installed capacity of 800 MW each. The system load is 2,850 MW, and its value of lost load is set to €200/MWh.

Table 3.1: Technical Characteristics of Conventional Units

Unit (i)	P_i^{G} [MW]	λ_i^{G} [€/MW]	R_i^{U} [MW]	λ_i^{U} [€/MWh]	R_i^{D} [MW]	λ_i^{D} [€/MWh]
G1	451	35.88	250	40	0	-
G2	500	30.12	200	35	0	-
G3	80	45.00	40	50	0	-
G4	300	5.00	300	7	300	2
G5	474	18.72	290	25	125	10
G6	800	20.56	300	27	200	12
G7	800	7.53	400	15	100	5

In this chapter, we investigate the market from the strategic wind power producer's viewpoint. In order for the producer to optimally offer its wind power generation to the market, it needs an uncertainty forecast, e.g., in the form of wind power scenarios. As discussed already in Chapter 2, there are numerous techniques in the technical literature to generate scenarios of wind power generation, such as [103, 104, 105, 106, 107]. In this study, strategic wind power producer needs to forecast wind generation of both its own wind units as well as those of its rival. We assume that both wind power forecasts follow a Beta distribution with shape parameters (a, b). Strategic wind producer generates 2,000 scenarios for its own wind power generation and the same number of scenarios for its rival units, based on the corresponding forecast distribution. Then, scenarios are reduced to three in order to reduce computational cost, using a scenario reduction approach such as the K-means method [89]. Note that these samples are in per-unit, i.e., wind production divided by installed wind capacity. This procedure provides strategic wind producer's scenarios, denoted by ω_1, ω_2 and ω_3, and, similarly, rival wind producer's scenarios s_1, s_2 and s_3 with their corresponding probabilities.

To evaluate the impact of rival generation uncertainty on strategic producer's offering decisions, we investigate different levels of wind power generation for both producers. Therefore, three different sets for the parameters of Beta distribution are examined in this case study, as given in Table 3.2, which yield different distribution shapes for both producers. These sets are selected to represent the three cases with the most characteristic differences in distribution shapes, i.e., cases with high-mean, mid-mean and low-mean distributions, for each of the producers. The three sets correspond to shape parameters $a > b$, $a \simeq b$ and $a < b$, respectively. Thus, we investigate the impact of forecast distributions on the market outcomes as well as on strategic wind producer's profits, for all combinations of the aforementioned distributions.

Table 3.2: Shape Parameters of Beta Distributions

Shape Parameters	Set 1 $a > b$	Set 2 $a \simeq b$	Set 3 $a < b$
(a, b)	(3.78,1.62)	(5.37,5.37)	(1.89,4.48)

3.3.2 Results

In this section, we present the results for the case study assuming that each of the wind power producers can have high-mean, mid-mean or low-mean forecast distribution. Therefore, nine scenarios are investigated in total with respect to their impact on strategic wind producer's profits and on market results.

In Fig. 3.2, one can see the wind power offers of the strategic wind power producer for all the investigated cases. First, we evaluate the outcomes in the case where strategic wind power producer expects high wind power production, i.e., the blue curve of the plot. As anticipated, offers are the highest compared to the cases where own wind generation is expected to be lower. Consequently, from Fig. 3.3, expected profits for this case are higher as well, independently of the expectations of rival wind generation. However, albeit its own wind power forecast is the same for the three RW scenarios, its wind power offers are different. As observed from Fig. 3.2 wind offers are lower for RW scenarios 1 and 3. This is the result of wind producer's strategic behavior in those two cases. More precisely, wind producer withholds a part of its expected wind generation in RW scenarios 1 and 3, in order to increase the market prices. To confirm producer's strategic behavior we perform a sensitivity analysis and observe the value of the dual variable that corresponds to the upper bound of constraint (3.1f). This value indicates the sensitivity of the producer's profit with respect to its quantity offer. It is indeed observed, from the first line of Table 3.3, that for RW scenarios 1 and 3, the value of the dual variable is greater than RW scenario 2, which indicates that wind producer's profit maximization is more sensitive to a change in its quantity offer. Similar observation is also noticed in the case of mid-mean distribution for the strategic wind power producer, i.e., red curve. It is noticed that producer offers less at RW scenario 3, compared to the other two scenarios, indicating its increased strategic behavior. From the second line of Table 3.3, it is confirmed that wind producer's strategic behavior is increased in scenario 3, since the dual variable has a high value compared to being zero for RW scenarios 1 and 2. As a result, slightly higher profits are also observed for this case in Fig. 3.3. For low-mean distribution (black curve), wind power producer offers the same power quantity for all three RW scenarios, acting strategically, as indicated at Table 3.3. However, its strategic behavior increases with decreasing expectations of rival generation. This result is also observed by the increased profits of strategic wind producer in Fig. 3.3.

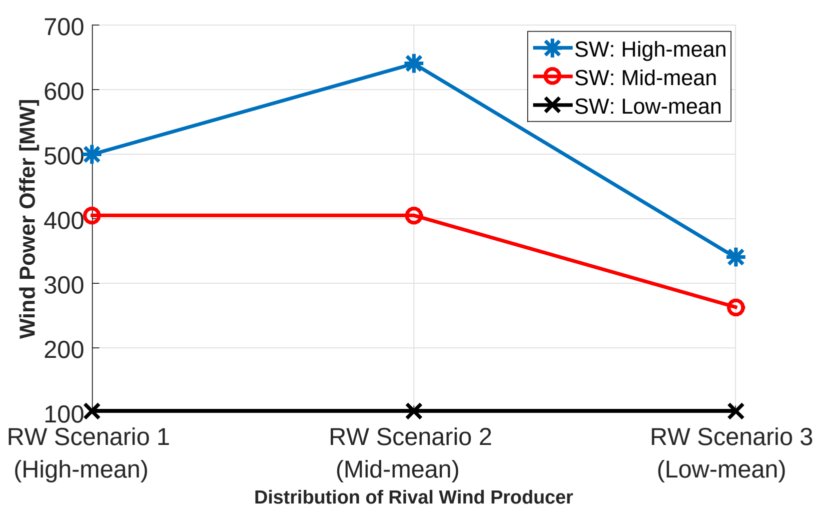

Figure 3.2: The strategic wind producer's quantity offer to DA market

Fig. 3.4 reflects the expected DA market-clearing prices for all investigated cases. As expected, the highest prices are seen when both producers are expected to have low wind power generation. Furthermore,

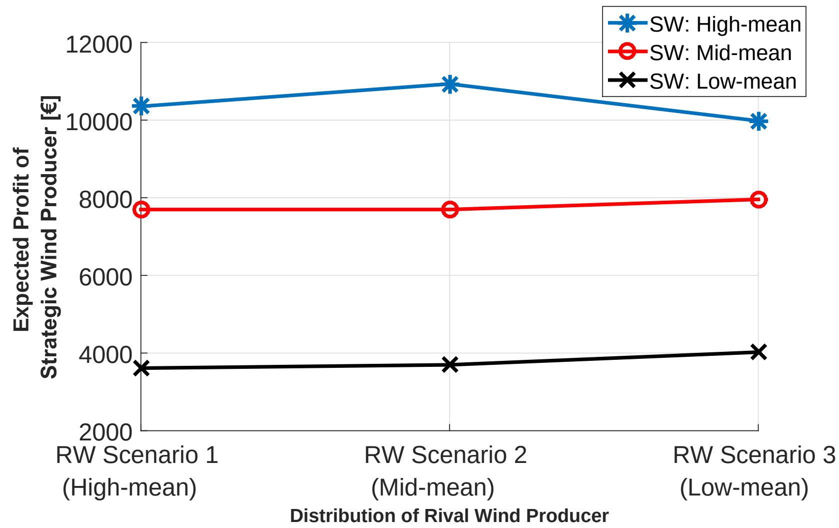

Figure 3.3: Profit of strategic wind power producer

Table 3.3: Value of Sensitivity Factor: Dual Variable Corresponding to the Upper Bound of Constraint (3.1f)

SW \ RW	Scenario 1	Scenario 2	Scenario 3
	High-mean	Mid-mean	Low-mean
High-mean	6.334	0.220	12.772
Mid-mean	0	0	8.653
Low-mean	4.885	5.712	14.841

comparatively high prices are observed for RW scenario 3. Recalling the high values of the sensitivity factor at the last column of Table 3.3, it is apparent that exercising market power has contributed to the increased market-clearing prices. Finally, Fig. 3.5 presents the expected market cost, i.e., expected DA and RT system cost, for the investigated cases. In line with the descriptions above, the cost is higher when total expected wind penetration in the market is the lowest, since wind comes with greatly lower costs. Similarly, strategic behaviors at RW scenario 3 are followed, as well, by an increase in the expected market cost, explained by the fact that in these cases strategic wind producer withholds a part of its expected generation.

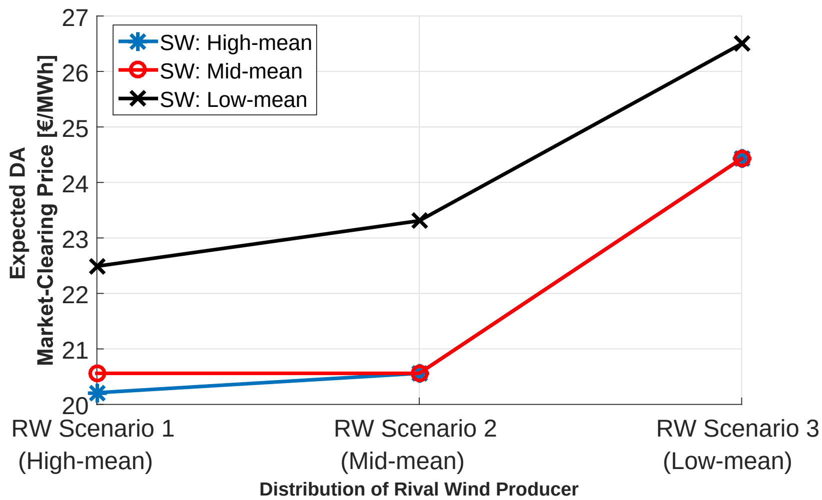

Figure 3.4: Expected DA market-clearing price

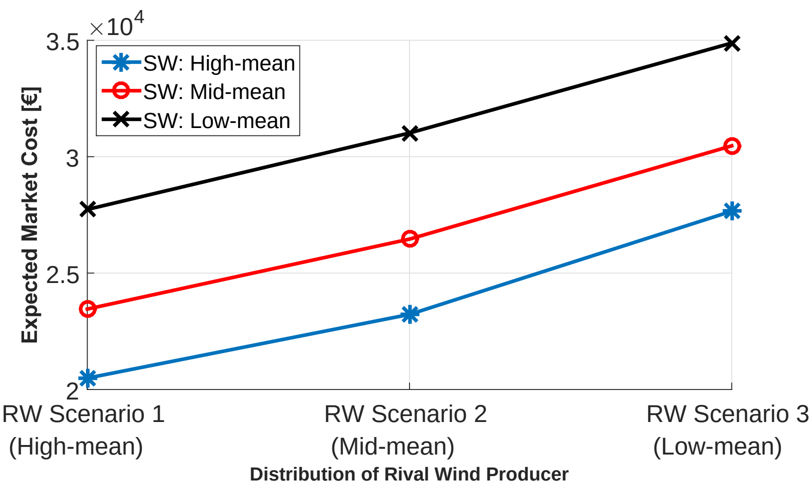

Figure 3.5: Expected total system cost

3.3.3 Computational Performance

For the simulations of this chapter we have used CPLEX under GAMS on a Windows 8.1, 64-bit operating system with 2 cores processor running at 2.4 GHz and 12 GB of RAM. The computational time for each model of the case study was approximately 2 min.

3.4 Summary and Conclusions

As wind power producers become dominant market players in a number of electricity markets, it is expected that they offer their generation strategically. This chapter extends the model of Chapter 2 to include more than one wind power producer. Under this context, it addresses the impact of the uncertainty introduced by a rival wind power producer on the offering strategy of the price-maker one. The price-maker wind power producer forecasts the generation of its rival and makes optimal power offers to a stochastic DA market. The results of a large case study lead to the following observations:

1. Strategic wind power producer's offering strategy depends highly on the introduced power uncertainty of its rival. More precisely, it exercises more market power when the expected wind power generation of the rival wind producer is relatively low but is independent of the rival's expected generation when its own wind forecast is low as well.

2. Under both the aforementioned conditions, strategic wind producer withholds a part of its generation in order to increase DA market prices to its own benefit.

3. Finally, it is observed that the expected total market cost is, as anticipated, higher when both producers are expected to produce low wind power as well as in cases where there is increased strategic behavior, i.e., price-maker producer withholds a part of its expected generation. Increased cost is the result of the increased energy prices caused by the present strategic behaviors.

3.5 Future Perspectives

This study was made under the assumption that strategic wind power producer has a forecast of its rival, which acts as a price-taker. It can be extended by assuming both or more producers as price-makers in the market. The consideration of all participating wind power producers as price-makers, would yield a more complex study which can be seen as a non-cooperative game. Under this context, Chapter 4 extends this study, and the relevant one of Chapter 2, to a non-cooperative game with multiple strategic producers. However, the private nature of individual wind power forecasts would lead to a game of incomplete or imperfect information [100], which is left for future research. In the following chapter, this bottleneck of missing wind forecast information is bypassed by accommodating an aggregate wind power forecast in the decision-making models, motivated by the fact that an increasing number of market operators and/or TSOs are publishing this information as a part of their transparency initiatives.

3.6 Chapter Publications

This chapter has led to the following publication:

- L. Exizidis, J. Kazempour, P. Pinson, Z. D. Grève, and F. Vallée, *Strategic wind power trading considering rival wind power production*, Proceedings of 2016 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia), Melbourne, Australia, Nov. 2016.

Chapter 4

Impact of Public Aggregate Wind Forecasts on Electricity Market Outcomes

4.1 Introduction

Under the scope of the previous chapters, we investigated market setups where there was only one strategic producer. However, in actual electricity markets it is expected that multiple producers will try to exercise market power. Thus, in this chapter we investigate a market where there exist multiple strategic power producers which include in their offering portfolio both wind and conventional power generation units. Under this setting, the main focus of this chapter is to evaluate how public forecasts of the aggregate wind power generation can affect market-clearing outcomes and participants revenues. Due to the presence of multiple strategic producers, the market is represented by a non-cooperative game and the market outcomes are evaluated at the equilibrium point.

4.1.1 Background and Motivation

European electricity market regulators, representatives of EU countries and stakeholders gathered in June 2015 in Florence to discuss the implementation of the so-called "third energy package", which aims at improving the functioning of the internal energy markets [108]. Among other, participants agreed on the importance of renewable energy in the energy mix, stressing however the fact that renewable power producers should follow the same rules with conventional producers and compete them without any support, under the current framework of a liberalized market [93]. Moreover, European Union escalated the importance for increased transparency in electricity market operations, which has already improved over the past few years following *Regulation (EU) No 543/2013* on the submission and publication of data in electricity markets [98]. The latter implies that TSOs shall calculate and provide for their control areas, among other information, a forecast of wind power generation (MW) per bidding zone, per each market time unit of the following day to the European Network of Transmission System Operators for Electricity (ENTSO-E). Following this directive, TSOs started publishing aggregate forecasts of wind power generation in their control area. For example, the TSO of Belgium, i.e., ELIA, publishes day-ahead (DA) and week-ahead forecasts of wind power [109] in order to "provide the basis for a harmonised, transparent environment and create a level playing field between all market players, which will potentially foster the development of the electricity market"[110]. To this end, ENTSO-E Transparency Platform [111] provides free, continuous access to Pan-European electricity market data for all users, across six main categories: load, generation, transmission, balancing, outages and congestion management. However, Europe is not alone in taking decisive steps towards public forecast-related information. The interest for public aggregate forecasts is shared by more system operators in other geographical areas, such as the Independent System Operator of New England [112], Midcontinent Independent System Operator [113] and Alberta Electric System Operator [114], which provide aggregate DA and/or week-ahead forecasts for their control areas.

Challenged by the aforementioned political decisions and policy regulations, the main contribution of this chapter is to offer an insight into how public forecasts and the level of their deviation can potentially impact market operation as well as market participants interests. The study is performed for a DA market setup with increased share of wind power. A joint energy and reserve auction is considered, where strategic conventional power producers may also include within their offering portfolio wind power, which they offer at generation cost based on a forecast. In contrast to the previous chapters, wind power is offered based on a deterministic forecast and RT market-clearing stage is not anticipated in the DA. However, reserve quantities are allocated in order to balance the system in case of generation-demand inadequacy in real time. Given that producers may exercise market power, it comes naturally to represent the market by a non-cooperative game played among all producers. We consider all producers as strategic players, as they all have the capacity to exercise market power. Therefore, a game-theoretic approach is followed where each producer builds a mathematical program with equilibrium constraints (MPEC) in order to optimally decide its offering strategy. An iterative diagonalization approach [115, 116, 117, 118] is then incorporated to search for the equilibrium of the game, which is found when no producer has incentive to change its strategy unilaterally.

4.1.2 Literature Review and Contributions

The major drawback for the large-scale integration of wind power in electricity markets is its intermittent nature. The cost for backup flexibility reserves is considerably high in order to guarantee reliability, while energy storage is still not mature enough [94]. Despite the fact that wind power forecasting will never be perfectly accurate, it has improved significantly through intensive research spanning over the last two decades [27]. Following the emergence of advanced methods for wind power forecasting, the latter has been distinguished as a dominant tool for market participation. Under this context, an ever-increasing number of contributions is focusing on suggesting tools for wind power trading in electricity markets with significant share of wind power generation.

Initial studies adopted models where wind power producers are non-strategic players, i.e., price-takers, and/or receiving additional support when participating in a forward electricity market [55, 95, 96, 97]. However, as the cost of wind power production is low and the competitiveness of wind power increases, wind power producers are forced to participate in the electricity markets under full competition and following the same rules as conventional producers [98]. Under this context, [71] considers that wind power producers strategically offer their power in the balancing market. It is anticipated that wind producer acts as a price-taker in DA market, due to the large volume of traded energy. In addition, [71] investigates how the shape of the forecast distribution impacts the offering strategy of producer. The problem of a price-maker wind power producer in DA market, being a deviator in the balancing market, is addressed in [72]. More specifically, the problem is formulated as a stochastic optimization tool for market participation, where uncertainty pertaining to wind power production is represented through scenarios. The impact of a price-maker wind power producer on electricity prices as well as on the resulting imbalances is studied in [73] for a market without regulated tariffs. Furthermore, study [74] additionally considers, through scenarios, the uncertainties in demand, wind power generation and bidding strategies of strategic conventional generators focusing on the problem of strategic wind power trading.

A more realistic setup would suggest the consideration of multiple strategic power producers competing each other in an effort to increase their own profits. Considering various market players that offer their generation strategically acting as price-makers, the investigated market can be seen as a non-cooperative game assuming complete information knowledge, i.e., the offers of rival producers are perfectly known. For example, in [75], the equilibria reached by strategic producers in a pool-based electricity market are investigated. The behavior of each power producer is described by an MPEC, whose joint solution constitutes an equilibrium problem with equilibrium constraints (EPEC). Moreover, in [90], strategic electricity producers react to both prices and rival production changes, in both the spot and the futures markets. The proposed model allows deriving analytical expressions that characterize such multi-market equilibria. Motivated by the increasing levels of wind power penetration in electricity markets, [70] investigates the equilibria in a pool-based oligopolistic electricity market, including a DA and several real-time (RT) markets, where wind power is also considered within the generation portfolio of the strategic producers. Then, the resulting EPEC is solved, in the search of the equilibrium point. Following the same approach, [119] proposes a stochastic model to find the equilibria that, compared to [70], additionally considers the transmission constraints and proposes a different approach for RT market-clearing.

In view of the above, the central contribution of this chapter is to investigate the impact of public aggregate wind forecasts in an imperfectly competitive market environment. Even though availability of public aggregate wind forecasts is expected to improve market operation, strategic behaviour of market players could merely jeopardize this vision. More precisely, the impact of aggregate forecasts on the market results should be investigated, given a market with strategic players. Therefore, we study a market setup where producers, which include within their portfolio both wind and conventional units, offer their conventional power strategically to the DA market, while their wind power is offered at generation cost based on a forecast. Producers determine their optimal offering strategy considering individual forecasts for their own wind units as well as the public aggregate forecast. Their decision-making tool is formulated as a bilevel optimization model. Then, the interaction of all participating producers is represented by a non-cooperative game with complete information, whose equilibrium is investigated through an iterative diagonalization procedure. Energy and reserve prices as well as social welfare are compared for under- and over-forecasting at the equilibrium points. Additionally, the results are analyzed from the producers point of view by evaluating the impact of different aggregate forecasts on their profits.

4.1.3 Chapter Organization

The rest of the chapter is organized as follows: Section 4.2 proposes a bilevel optimization model for the strategic offering of power producers and provides the corresponding mathematical formulation. Additionally, it presents the methodology followed for the equilibrium study among the various power producers. Section 4.3 presents the results for a case study based on the IEEE reliability test system, as well as an additional numerical study considering uncertainty of wind generation and RT prices. Finally, Section 4.4 concludes the chapter.

4.2 Mathematical Formulation

Notation:

Sets:

$\mathcal{I}$	Set of all conventional power units.
$\mathcal{I}_J$	Set of conventional power units belonging to producer J.
$\mathcal{W}$	Set of all wind power units.
$\mathcal{W}_J$	Set of wind power units belonging to producer J.

$\mathcal{D}$	Set of demands.
$\mathcal{B}_i$	Set of generation blocks of unit i.
Ω	Set of wind power generation scenarios.
S	Set of real-time market price scenarios.

Indices:

J	Index for producers.
i	Index for conventional power units.
b	Index for generation blocks of conventional units.
d	Index for demands.
l	Index for wind power units.
ω	Index for wind power generation scenarios.
s	Index for real-time market price scenarios.

Variables:

$p^{\mathrm{G}}_{i,b}$	Scheduled generation for the b-th block of conventional power unit i [MW].
r^{U}_i	Committed upward reserve from conventional power unit i [MW].
r^{D}_i	Committed downward reserve from conventional power unit i [MW].
λ^{DA}	Energy price [€/MWh].
μ^{U}	Price of capacity for committed upward reserve [€/MWh].
μ^{D}	Price of capacity for committed downward reserve [€/MWh].
$\alpha^{\mathrm{G}}_{i,b}$	Price offer for the b-th block of unit i [€/MWh].

p_d^{D} Scheduled consumption for demand d [MW].

p_l^{W} Scheduled wind power generation for wind power unit l [MW].

$p_{l,\omega}^{\mathrm{W,RT}}$ Power sold/bought in the real-time market by the l-th wind power unit under scenario ω [MW].

Parameters:

$C_{i,b}^{\mathrm{G}}$ Marginal cost of the b-th block of unit i [€/MWh].

λ_d^{D} Price bid of demand d [€/MWh].

γ, δ Non-negative factors representing the minimum reserve requirements of the market as percentage of total demand and total installed wind capacity, respectively.

$\overline{W}_l$ Installed wind power capacity of the wind power unit l [MW].

$\overline{P}_{i,b}^{\mathrm{G}}$ Maximum generation capacity of the b-th block of unit i [MW].

$\overline{P}_d^{\mathrm{D}}$ Maximum consumption of demand d [MW].

$\overline{R}_i^{\mathrm{U}}$ Maximum upward reserve capacity of unit i [MW].

$\overline{R}_i^{\mathrm{D}}$ Maximum downward reserve capacity of unit i [MW].

F_l Wind power forecast of the l-th unit as private data, provided by its owner [MW].

F^{MO} Aggregate wind power forecast as public information, provided by market operator [MW].

$P_{l,\omega}^{\mathrm{W,P}}$ Wind power produced by the l-th wind power unit under scenario ω [MW].

λ_s^{RT} Real-time market price under scenario s [€/MWh].

π_ω Probability of scenario ω.

π_s^λ Probability of scenario s.

This section is divided into four parts: Section 4.2.1 presents the main features and assumptions of the model used in this chapter. Section 4.2.2 provides the mathematical formulation of producers decision-making tool. The iterative diagonalization process followed to identify the equilibrium of the game is described in Section 4.2.4. Lastly, an additional step is taken in Section 4.2.5, where the actual DA market is cleared based on the offers of producers at the equilibrium point.

4.2.1 Features and Assumptions

Under the scope of this study, a number of necessary assumptions are made which are presented hereafter:

1. An imperfectly competitive electricity market is considered, in which power producers include within their generation portfolio both conventional and wind power generation, in contrast to previous Chapters 2 and 3 where the focus was on strategic wind power producers. Moreover, we consider conventional producers to offer their generation in blocks of increasing generation cost.

2. Producers behave strategically with respect to price offers of conventional generation [69, 70], but not regarding their wind generation, which they offer deterministically based on a forecast.

3. For the sake of simplicity, transmission constraints are not enforced [70, 71, 73]. A relevant formulation considering transmission constraints can be found in the formulation of Chapter 5.

4. Inter-temporal constraints, e.g., ramping limits of conventional units, are not enforced and thus a single-hour auction is considered, which is consistent with the relevant literature [70, 71, 74, 75].

5. This study only focuses on the DA market and evaluates its impact on market outcomes in that stage. Thus, the RT stage, in which the actual wind power is realized, is not considered for simplicity. However, market operator commits in DA a specific level of reserve capacity, which manages potential DA forecast errors in real time.

The required reserve capacity is exogenously sized based on the total demand as well as on the installed wind capacity.

6. For the sake of clarity, in view of the aforementioned assumption, a complementary numerical study is additionally presented in Section 4.3.3, offering an insight on the same problem considering uncertainty on wind power generation and RT prices.

7. Being consistent with the previous chapters, the operational cost of wind power producers is considered zero, as it is customary in the technical literature, e.g., [20, 21, 22, 23, 24]. In some realistic electricity markets, this cost is even negative due to renewable incentives [25].

8. In order to identify an equilibrium, a game of complete information is considered where producers anticipate perfectly the offers of their rivals, in line with the necessary assumptions of a Nash game. On the other hand, individual wind power forecasts are private information used for solving the individual decision-making problem of each producer along with an aggregate wind power forecast, with the latter being publicly available by the TSO.

9. Finally, demand is assumed to be elastic with respect to price and deterministic in order to avoid additional sources of uncertainty. This difference with the models of Chapters 2 and 3 is depicted in the formulation of the market-clearing problem, which in this chapter maximizes social welfare, i.e, aggregate demand utility minus aggregate generation cost, instead of minimizing market cost. This feature additionally models the possibility of consumers to withdraw from the market if the price is lower than their corresponding bids.

The aforementioned setup is illustrated in Fig. 4.1. As shown, in contrast to previous Chapters 2 and 3, in this study we consider conventional producers that might include wind power in their offering portfolio. Furthermore, all producers are considered to be strategic in the DA market, which means that they all anticipate the DA market-clearing procedure in their decision-making model based on the available information. A game of complete information is considered, where all strategic producers have perfect knowledge of their rivals offers to the market. Additionally to this information, all producers have access to a public aggregate wind power forecast, which is published by the system operator as well as a private wind power forecast for their own wind power plants (where applicable). The output of the game is the strategic price offers of power producers, regarding the conventional part of their generation portfolio, at the equilibrium. Then, the DA market is cleared based on the price offers as well as the quantity offers of producers, which for the wind power plants correspond to their private forecasts. Note that in contrast to Chapters 2 and 3, the DA market is a deterministic market, which however commits a specific level of reserve capacity in order to manage potential DA forecast errors in real time.

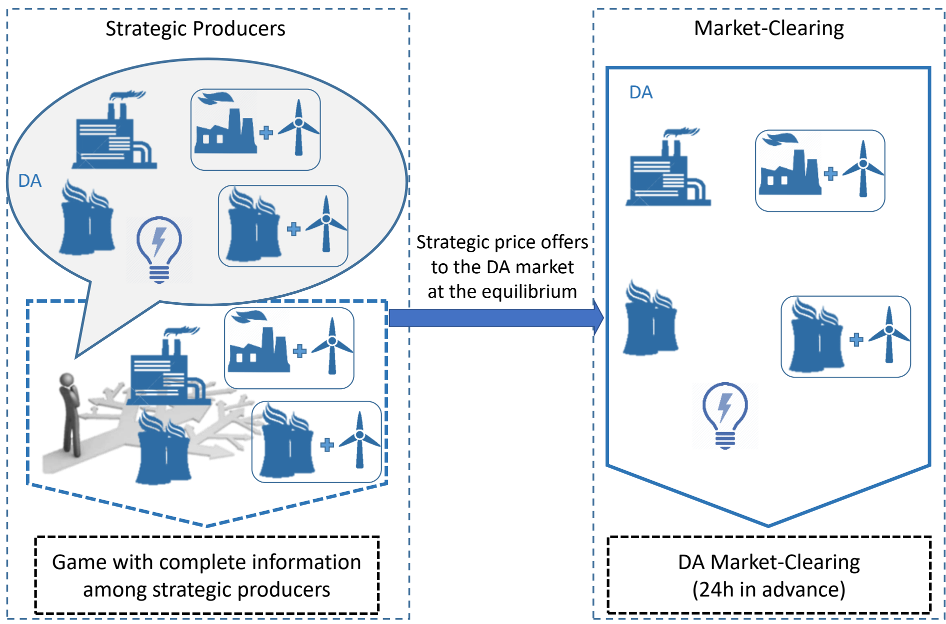

Figure 4.1: Illustrative representation of the market setup of Chapter 4

4.2.2 Model Formulation Considering Aggregate Wind Forecasts

In this subsection, the mathematical formulation of the producers offering tool is presented. Each producer solves bilevel problem (4.1) in order to optimize its offer, considering its privately owned wind power forecast as well as the available public aggregate wind power forecast. The problem is formulated as a bilevel model for each producer J, whose upper-level (UL), i.e., (4.1a)-(4.1c), maximizes producer's profit and derives its strategic price offers and whose lower-level (LL) problem, i.e., (4.1d)-(4.1o), clears the DA market through maximizing social welfare. Note that dual variables are indicated in each LL constraint after a colon.

The UL objective function, i.e., (4.1a), maximizes the profit of producer J, and consists of:

- Producer's profit due to conventional generation after deducting the generation costs, i.e., $\sum_{i\in\mathcal{I}_J}\sum_{b\in\mathcal{B}_i}(\lambda^{\mathrm{DA}} - C^{\mathrm{G}}_{i,b})\ p^{\mathrm{G}}_{i,b}$.
- Producer's profit due to wind generation, i.e., $\sum_{l\in\mathcal{W}_J}(\lambda^{\mathrm{DA}} p^{\mathrm{W}}_l)$.
- Associated profits for allocation of upward and downward reserve capacities, i.e., $\sum_{i\in\mathcal{I}_J}(\mu^{\mathrm{U}} r^{\mathrm{U}}_i + \mu^{\mathrm{D}} r^{\mathrm{D}}_i)$.

$$\left\{ \underset{\alpha^{\mathrm{G}}_{i,b},\ \Xi^{\mathrm{LL,P}}\ \cup\ \Xi^{\mathrm{LL,D}}}{\text{Maximize}} \sum_{i\in\mathcal{I}_J}\sum_{b\in\mathcal{B}_i}(\lambda^{\mathrm{DA}} - C^{\mathrm{G}}_{i,b})\ p^{\mathrm{G}}_{i,b} \right.$$
$$+\sum_{l\in\mathcal{W}_J}(\lambda^{\mathrm{DA}}\ p^{\mathrm{W}}_l) + \sum_{i\in\mathcal{I}_J}(\mu^{\mathrm{U}}\ r^{\mathrm{U}}_i + \mu^{\mathrm{D}}\ r^{\mathrm{D}}_i) \tag{4.1a}$$

The UL objective function (4.1a) is subject to UL constraints (4.1b)-(4.1c) below, and LL problem (4.1d)-(4.1o).

$$0 \le \alpha^{\mathrm{G}}_{i,b} \quad \forall i \in \mathcal{I}_J, \forall b \tag{4.1b}$$
$$\alpha^{\mathrm{G}}_{i,b-1} \le \alpha^{\mathrm{G}}_{i,b} \quad \forall i \in \mathcal{I}_J, \forall b \ge 2 \tag{4.1c}$$

The UL constraints (4.1b)-(4.1c) impose the strategic price offer for the conventional units, i.e., $\alpha^{\mathrm{G}}_{i,b}$, to be non-negative and non-decreasing from the first offer block to the last.

The LL objective function (4.1d), below, maximizes social welfare of the market based on producers offers and demand bids, which is constrained by (4.1e)-(4.1o).

$$\lambda^{\mathrm{DA}},\ p_l^{\mathrm{W}},\ r_i^{\mathrm{U}},\ r_i^{\mathrm{D}},\ \mu^{\mathrm{U}},\ \mu^{\mathrm{D}} \text{ and } p_{i,b}^{\mathrm{G}}\ \forall i \in \mathcal{I}_J,\ \forall l \in \mathcal{W}_J,\ \forall b \in \arg\Big\{$$

$$\underset{\Xi^{\mathrm{LL,P}}}{\text{maximize}} \sum_{d\in\mathcal{D}} \lambda_d^{\mathrm{D}}\, p_d^{\mathrm{D}} - \sum_{i\in\mathcal{I}} \sum_{b\in\mathcal{B}_i} \alpha_{i,b}^{\mathrm{G}}\, p_{i,b}^{\mathrm{G}} \tag{4.1d}$$

The power balance in DA is enforced by constraint (4.1e), below:

$$\sum_{i\in\mathcal{I}} \sum_{b\in\mathcal{B}_i} p_{i,b}^{\mathrm{G}} + \sum_{l\in\mathcal{W}} p_l^{\mathrm{W}} = \sum_{d\in\mathcal{D}} p_d^{\mathrm{D}} \quad : \lambda^{\mathrm{DA}} \tag{4.1e}$$

Constraints (4.1f) and (4.1g) impose the minimum reserve requirements of the market:

$$\sum_{i\in\mathcal{I}} r_i^{\mathrm{U}} \geq \gamma \sum_{d\in\mathcal{D}} \overline{P}_d^{\mathrm{D}} + \delta \sum_{l\in\mathcal{W}} \overline{W}_l \quad : \mu^{\mathrm{U}} \tag{4.1f}$$

$$\sum_{i\in\mathcal{I}} r_i^{\mathrm{D}} \geq \gamma \sum_{d\in\mathcal{D}} \overline{P}_d^{\mathrm{D}} + \delta \sum_{l\in\mathcal{W}} \overline{W}_l \quad : \mu^{\mathrm{D}} \tag{4.1g}$$

The level of minimum reserve requirements is introduced as a portion of the total load level plus a portion of the level of installed wind power capacity, using non-negative factors γ and δ, respectively. Note that the dual variables of constraints (4.1e), (4.1f) and (4.1g) indicate the prices for energy, upward and downward committed reserves, respectively.

Constraints (4.1h)-(4.1l), below, bind the generation and reserve capacities by the corresponding maximum capacity offers.

$$0 \leq r_i^{\mathrm{U}} \leq \overline{R}_i^{\mathrm{U}} \ : \ \underline{\rho}_i^{\mathrm{U}},\ \overline{\rho}_i^{\mathrm{U}}\ \forall i \tag{4.1h}$$

$$0 \leq r_i^{\mathrm{D}} \leq \overline{R}_i^{\mathrm{D}} \ : \ \underline{\rho}_i^{\mathrm{D}},\ \overline{\rho}_i^{\mathrm{D}}\ \forall i \tag{4.1i}$$

$$0 \leq p_{i,b}^{\mathrm{G}} \leq \overline{P}_{i,b}^{\mathrm{G}} \ : \ \underline{\tau}_{i,b},\ \overline{\tau}_{i,b}\ \forall i,\ \forall b \tag{4.1j}$$

$$\sum_{b\in\mathcal{B}_i} p_{i,b}^{\mathrm{G}} + r_i^{\mathrm{U}} \leq \sum_{b\in\mathcal{B}_i} \overline{P}_{i,b}^{\mathrm{G}} \ : \ \overline{\phi}_i^{\mathrm{G}}\ \forall i \tag{4.1k}$$

$$0 \le \sum_{b \in \mathcal{B}_i} p^{\mathrm{G}}_{i,b} - r^{\mathrm{D}}_i \ : \ \underline{\phi}^{\mathrm{G}}_i \ \forall i \tag{4.1l}$$

Constraint (4.1m) binds the scheduled demand by the maximum demand bids:

$$0 \le p^{\mathrm{D}}_d \le \overline{P}^{\mathrm{D}}_d \ : \ \underline{\psi}_d, \ \overline{\psi}_d \ \forall d \tag{4.1m}$$

Constraint (4.1n), below, sets the scheduled wind for the investigated producer to be less than or equal to its own private forecast.

$$0 \le p^{\mathrm{W}}_l \le F_l \ : \ \underline{\sigma}_l, \ \overline{\sigma}_l \ \forall l \in \mathcal{W}_J \tag{4.1n}$$

Finally, constraint (4.1o) enforces the aggregate scheduled wind power of rival wind units to be lower than or equal to the public aggregate forecast minus producer's individual forecast for its own wind generation.

$$0 \le \sum_{l \notin \mathcal{W}_J} p^{\mathrm{W}}_l \le F^{\mathrm{MO}} - \sum_{l \in \mathcal{W}_J} F_l \ : \ \underline{\sigma}^{\mathrm{MO}}, \ \overline{\sigma}^{\mathrm{MO}} \Big\} \tag{4.1o}$$

$$\Big\} \ \forall J.$$

The set of primal variables of LL problem (4.1d)-(4.1o) is $\Xi^{\mathrm{LL,P}} = \{p^{\mathrm{W}}_l, p^{\mathrm{G}}_{i,b}, p^{\mathrm{D}}_d, r^{\mathrm{U}}_i, r^{\mathrm{D}}_i\}$.

Furthermore, the set of dual variables of the LL problem is $\Xi^{\mathrm{LL,D}} = \{\lambda^{\mathrm{DA}}, \mu^{\mathrm{U}}, \mu^{\mathrm{D}}, \underline{\rho}^{\mathrm{U}}_i, \overline{\rho}^{\mathrm{U}}_i, \underline{\rho}^{\mathrm{D}}_i, \overline{\rho}^{\mathrm{D}}_i, \overline{\tau}_{i,b}, \underline{\tau}_{i,b}, \underline{\phi}^{\mathrm{G}}_i, \overline{\phi}^{\mathrm{G}}_i, \underline{\psi}_d, \overline{\psi}_d, \underline{\sigma}_l, \overline{\sigma}_l, \underline{\sigma}^{\mathrm{MO}}, \overline{\sigma}^{\mathrm{MO}}\}$.

Finally, the primal variables of the UL problem (4.1a)-(4.1c) are $\alpha^{\mathrm{G}}_{i,b}$ as well as all members of variable sets $\Xi^{\mathrm{LL,P}}$ and $\Xi^{\mathrm{LL,D}}$.

Lower-level problem (4.1d)-(4.1o) is continuous, linear and, therefore, convex. This allows bilevel problem (4.1) to be recast as a single-level MPEC through replacing the LL problem by its Karush-Kuhn-Tucker (KKT) optimality conditions. The procedure is similar to the one in

Chapters 2, 3 and is explained in Appendix A. As in Chapter 2, the KKT conditions are derived by the Lagrangian function associated with the LL, by differentiating the Lagrangian each time with the corresponding primal variable of the LL problem. Thus, we can replace the LL problem (4.1d)-(4.1o) by its KKT conditions as shown below:

$$\begin{cases} \underset{\alpha^{\mathrm{G}}_{i,b},\ \Xi^{\mathrm{LL,P}} \cup \Xi^{\mathrm{LL,D}}}{\text{Maximize}} \quad (4.1\text{a}) \end{cases} \tag{4.2a}$$

subject to:

$$(4.1\text{b}),\ (4.1\text{c}) \text{ and } (4.1\text{e}) \tag{4.2b}$$

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial p^{\mathrm{G}}_{i,b}} &= \alpha^{\mathrm{G}}_{i,b} - \lambda^{\mathrm{DA}} + \overline{\phi}^{\mathrm{G}}_i - \underline{\phi}^{\mathrm{G}}_i + \overline{\tau}_{i,b} - \underline{\tau}_{i,b} \\
&= 0\ \forall i, \forall b && (4.2\text{c})\\
\frac{\partial \mathcal{L}}{\partial p^{\mathrm{D}}_{d}} &= -\lambda^{\mathrm{D}}_d + \lambda^{\mathrm{DA}} + \overline{\psi}_d - \underline{\psi}_d = 0\ \forall d && (4.2\text{d})\\
\frac{\partial \mathcal{L}}{\partial p^{\mathrm{W}}_{l}} &= -\lambda^{\mathrm{DA}} + \overline{\sigma}_l - \underline{\sigma}_l = 0\ \forall l \in \mathcal{W}_J && (4.2\text{e})\\
\frac{\partial \mathcal{L}}{\partial \sum_{l \notin \mathcal{W}_J} p^{\mathrm{W}}_{l}} &= -\lambda^{\mathrm{DA}} + \overline{\sigma}^{\mathrm{MO}} - \underline{\sigma}^{\mathrm{MO}} = 0 && (4.2\text{f})\\
\frac{\partial \mathcal{L}}{\partial r^{\mathrm{U}}_{i}} &= -\mu^{\mathrm{U}} + \overline{\rho}^{\mathrm{U}}_i - \underline{\rho}^{\mathrm{U}}_i + \overline{\phi}^{\mathrm{G}}_i = 0\ \forall i && (4.2\text{g})\\
\frac{\partial \mathcal{L}}{\partial r^{\mathrm{D}}_{i}} &= -\mu^{\mathrm{D}} + \overline{\rho}^{\mathrm{D}}_i - \underline{\rho}^{\mathrm{D}}_i + \underline{\phi}^{\mathrm{G}}_i = 0\ \forall i && (4.2\text{h})
\end{aligned}$$

Lastly, complementarity slackness conditions, which refer to the relationship between the positivity in a primal constraint and the positivity of its associated dual variable, are given below by (4.2i)-(4.2x):

$$0 \leq \left(\sum_{i \in \mathcal{I}} r^{\mathrm{U}}_i - \gamma \sum_{d \in \mathcal{D}} \overline{P}^{\mathrm{D}}_d - \delta \sum_{l \in \mathcal{W}} \overline{W}_l \right) \perp \mu^{\mathrm{U}} \geq 0 \tag{4.2i}$$

$$0 \leq \left(\sum_{i \in \mathcal{I}} r^{\mathrm{D}}_i - \gamma \sum_{d \in \mathcal{D}} \overline{P}^{\mathrm{D}}_d - \delta \sum_{l \in \mathcal{W}} \overline{W}_l \right) \perp \mu^{\mathrm{D}} \geq 0 \tag{4.2j}$$

$$0 \leq r_i^{\mathrm{U}} \perp \underline{\rho}_i^{\mathrm{U}} \geq 0 \ \forall i \tag{4.2k}$$

$$0 \leq (\overline{R}_i^{\mathrm{U}} - r_i^{\mathrm{U}}) \perp \overline{\rho}_i^{\mathrm{U}} \geq 0 \ \forall i \tag{4.2l}$$

$$0 \leq r_i^{\mathrm{D}} \perp \underline{\rho}_i^{\mathrm{D}} \geq 0 \ \forall i \tag{4.2m}$$

$$0 \leq (\overline{R}_i^{\mathrm{D}} - r_i^{\mathrm{D}}) \perp \overline{\rho}_i^{\mathrm{D}} \geq 0 \ \forall i \tag{4.2n}$$

$$0 \leq p_{i,b}^{\mathrm{G}} \perp \underline{\tau}_{i,b} \geq 0 \ \forall i, \ \forall b \tag{4.2o}$$

$$0 \leq (\overline{P}_{i,b}^{\mathrm{G}} - p_{i,b}^{\mathrm{G}}) \perp \overline{\tau}_{i,b}^{\mathrm{G}} \geq 0 \ \forall i, \ \forall b \tag{4.2p}$$

$$0 \leq (\sum_{b \in \mathcal{B}_i} p_{i,b}^{\mathrm{G}} - r_i^{\mathrm{D}}) \perp \underline{\phi}_i^{\mathrm{G}} \geq 0 \ \forall i \tag{4.2q}$$

$$0 \leq (\sum_{b \in \mathcal{B}_i} \overline{P}_{i,b}^{\mathrm{G}} - \sum_{b \in \mathcal{B}_i} p_{i,b}^{\mathrm{G}} - r_i^{\mathrm{U}}) \perp \overline{\phi}_i^{\mathrm{G}} \geq 0 \ \forall i \tag{4.2r}$$

$$0 \leq p_d^{\mathrm{D}} \perp \underline{\psi}_d \geq 0 \ \forall d \tag{4.2s}$$

$$0 \leq (\overline{P}_d^{\mathrm{D}} - p_d^{\mathrm{D}}) \perp \overline{\psi}_d \geq 0 \ \forall d \tag{4.2t}$$

$$0 \leq p_l^{\mathrm{W}} \perp \underline{\sigma}_l \geq 0 \ \forall l \in W_J \tag{4.2u}$$

$$0 \leq (F_l - p_l^{\mathrm{W}}) \perp \overline{\sigma}_l \geq 0 \ \forall l \in W_J \tag{4.2v}$$

$$0 \leq \sum_{l \notin \mathcal{W}_J} p_l^{\mathrm{W}} \perp \underline{\sigma}^{\mathrm{MO}} \geq 0 \tag{4.2w}$$

$$0 \leq \left(F^{\mathrm{MO}} - \sum_{l \notin \mathcal{W}_J} p_l^{\mathrm{W}} - \sum_{l \in \mathcal{W}_J} F_l \right) \perp \overline{\sigma}^{\mathrm{MO}} \geq 0 \tag{4.2x}$$

$$\Bigg\} \ \forall J.$$

The perpendicular ($\perp$) enforces the perpendicular condition between the vectors on the left-hand and right-hand sides, i.e., their element-by-element product is zero.

MPECs (4.2), one per producer, are non-linear due to the following two sources of non-linearities:

- the bilinear terms $\lambda^{\mathrm{DA}} \ p_{i,b}^{\mathrm{G}}$, $\lambda^{\mathrm{DA}} \ p_l^{\mathrm{W}}$, $\mu^{\mathrm{U}} \ r_i^{\mathrm{U}}$ and $\mu^{\mathrm{D}} \ r_i^{\mathrm{D}}$ included in the objective function (4.2a), and
- complementarity conditions (4.2i)-(4.2x).

The bilinear terms inside the objective function are linearized based on an approach without approximation, deploying the strong duality theorem (SDT) and mathematical expressions (4.2c)-(4.2x), as in [75] and Chapters 2 and 3. The SDT states that if a problem is convex then the objective functions of the primal and dual problems have the same value at the optimum, and for the investigated problem this writes as in (4.3) below:

$$\begin{aligned}
&\sum_{i\in\mathcal{I}}\sum_{b\in\mathcal{B}_i}\alpha^{\mathrm{G}}_{i,b}\,p^{\mathrm{G}}_{i,b}-\sum_{d\in\mathcal{D}}\lambda^{\mathrm{D}}_{d}\,p^{\mathrm{D}}_{d}=\\
&\mu^{\mathrm{U}}\left(\gamma\sum_{d\in\mathcal{D}}\overline{P}^{\mathrm{D}}_{d}+\delta\sum_{l\in\mathcal{W}}\overline{W}_{l}\right)+\mu^{\mathrm{D}}\left(\gamma\sum_{d\in\mathcal{D}}\overline{P}^{\mathrm{D}}_{d}+\delta\sum_{l\in\mathcal{W}}\overline{W}_{l}\right)\\
&-\sum_{i\in\mathcal{I}}\overline{R}^{\mathrm{U}}_{i}\overline{\rho}^{\mathrm{U}}_{i}-\sum_{i\in\mathcal{I}}\overline{R}^{\mathrm{D}}_{i}\overline{\rho}^{\mathrm{D}}_{i}-\sum_{i\in\mathcal{I}}\sum_{b\in\mathcal{B}_i}\overline{P}^{\mathrm{G}}_{i,b}\overline{\tau}_{i,b}-\sum_{i\in\mathcal{I}}\sum_{b\in\mathcal{B}_i}\overline{P}^{\mathrm{G}}_{i,b}\overline{\phi}^{\mathrm{G}}_{i}\\
&-\sum_{d\in\mathcal{D}}\overline{P}^{\mathrm{D}}_{d}\overline{\psi}_{d}-\sum_{l\in\mathcal{W}}F_{l}\overline{\sigma}_{l}-\overline{\sigma}^{\mathrm{MO}}\left(F^{\mathrm{MO}}-\sum_{l\in\mathcal{W}_J}F_{l}\right).
\end{aligned} \tag{4.3}$$

Finally, complementarity conditions are linearized based on an SOS1 approach [66, 120] but at the cost of introducing a set of auxiliary SOS1 variables. The SOS1 method is used in this study because it has the advantage, over the previously used Big-M approach, that it does not need to be manually adjusted every time the optimization problem is solved. Thus, it is preferred over the previously used Big-M approach, given that the optimization problem of this chapter is iteratively solved multiple times in order to reach an equilibrium. The SOS1 approach is further explained in Appendix A.

The corresponding MPEC is linearized and then solved, as a mixed-integer linear program (MILP), similarly to Chapters 2 and 3 and as explained in Appendix A. The collection of all MPECs, one per producer, forms an EPEC, whose solution identifies the equilibrium point. Unlike [70, 75, 90] in which the LL problem of all producers is common (equilibrium with shared constraints), the LL problems of producers in this chapter are different, because each producer anticipates DA wind power schedules based on the public aggregate forecast as well as the individual one, which is different for each producer. This prevents the use of EPEC solution techniques proposed in [70, 75, 90]. Alternatively, we use an iterative diagonalization approach to solve EPEC, in which each producer determines sequentially its strategy considering the rivals strategies fixed. The iterations continue until no producer changes its strategy unilaterally or until the maximum number of iterations is reached. Further description is available in Section 4.2.4.

4.2.3 Benchmark: Model Formulation Assuming Public Knowledge of Individual Wind Forecasts

In this section, we consider a different setup that will serve as a reference throughout this chapter: individual wind power forecasts are assumed to be public knowledge and available to all market agents. Thus, strategic producers have access to the individual wind power forecasts of rivals and do not consider the public aggregate forecast in their decision-making tools. This forms a well-defined non-cooperative game with complete information, which is already studied in the relevant literature from various viewpoints such as [62, 70, 119].

The problem is formulated as a bilevel model whose UL, i.e.,(4.4a)-(4.4c), maximizes producer's profit and derives strategic price offers and whose LL problem, i.e., (4.4d)-(4.4n), clears the DA market through maximizing social welfare. The UL objective function (4.4a) is constrained by both UL constraints (4.4b)-(4.4c) and LL problem (4.4d)-(4.4n). Dual variables are indicated in each LL constraint after a colon.

The UL objective function, i.e.,(4.4a), maximizes producer's profit and includes as before:

- Producer's profit due to conventional generation after deducting the generation costs, i.e., $\sum_{i\in\mathcal{I}_J}\sum_{b\in\mathcal{B}_i}(\lambda^{\mathrm{DA}}-C^{\mathrm{G}}_{i,b})\,p^{\mathrm{G}}_{i,b}$.
- Producer's profit due to wind generation, i.e., $\sum_{l\in\mathcal{W}_J}(\lambda^{\mathrm{DA}}p^{\mathrm{W}}_l)$.
- Associated profits for allocation of upward and downward reserve capacities, i.e., $\sum_{i\in\mathcal{I}_J}(\mu^{\mathrm{U}}r^{\mathrm{U}}_i+\mu^{\mathrm{D}}r^{\mathrm{D}}_i)$.

$$\Bigg\{\underset{\alpha^{\mathrm{G}}_{i,b},\ \Xi^{\mathrm{LL,P}}\ \cup\ \Xi^{\mathrm{LL,D}}}{\text{Maximize}}\sum_{i\in\mathcal{I}_J}\sum_{b\in\mathcal{B}_i}(\lambda^{\mathrm{DA}}-C^{\mathrm{G}}_{i,b})\ p^{\mathrm{G}}_{i,b}+\sum_{l\in\mathcal{W}_J}(\lambda^{\mathrm{DA}}\ p^{\mathrm{W}}_l)$$

$$+\sum_{i\in\mathcal{I}_J}(\mu^{\mathrm{U}}\ r_i^{\mathrm{U}}+\mu^{\mathrm{D}}\ r_i^{\mathrm{D}}) \tag{4.4a}$$

Constraints (4.4b)-(4.4c) and (4.4e)-(4.4m) are similar to (4.1b)-(4.1c) and (4.1e)-(4.1m) which correspond to the model of Section 4.2.2.

$$0\le\alpha_{i,b}^{\mathrm{G}}\quad\forall i\in\mathcal{I}_J,\forall b \tag{4.4b}$$

$$\alpha_{i,b-1}^{\mathrm{G}}\le\alpha_{i,b}^{\mathrm{G}}\quad\forall i\in\mathcal{I}_J,\forall b\ge 2 \tag{4.4c}$$

where $\lambda^{\mathrm{DA}},\ p_l^{\mathrm{W}},\ r_i^{\mathrm{U}},\ r_i^{\mathrm{D}},\ \mu^{\mathrm{U}},\ \mu^{\mathrm{D}}$ and $p_{i,b}^{\mathrm{G}}\ \forall i\in\mathcal{I}_J,$
$\forall l\in\mathcal{W}_J,\ \forall b\in\arg\Big\{$

$$\underset{\Xi^{\mathrm{LL,P}}}{\text{maximize}}\sum_{d\in\mathcal{D}}\lambda_d^{\mathrm{D}}\ p_d^{\mathrm{D}}-\sum_{i\in\mathcal{I}}\sum_{b\in\mathcal{B}_i}\alpha_{i,b}^{\mathrm{G}}\ p_{i,b}^{\mathrm{G}} \tag{4.4d}$$

subject to:

$$\sum_{i\in\mathcal{I}}\sum_{b\in\mathcal{B}_i}p_{i,b}^{\mathrm{G}}+\sum_{l\in\mathcal{W}}p_l^{\mathrm{W}}=\sum_{d\in\mathcal{D}}p_d^{\mathrm{D}}\quad:\lambda^{\mathrm{DA}} \tag{4.4e}$$

$$\sum_{i\in\mathcal{I}}r_i^{\mathrm{U}}\ge\gamma\sum_{d\in\mathcal{D}}\overline{P}_d^{\mathrm{D}}+\delta\sum_{l\in\mathcal{W}}\overline{W}_l\quad:\mu^{\mathrm{U}} \tag{4.4f}$$

$$\sum_{i\in\mathcal{I}}r_i^{\mathrm{D}}\ge\gamma\sum_{d\in\mathcal{D}}\overline{P}_d^{\mathrm{D}}+\delta\sum_{l\in\mathcal{W}}\overline{W}_l\quad:\mu^{\mathrm{D}} \tag{4.4g}$$

$$0\le r_i^{\mathrm{U}}\le\overline{R}_i^{\mathrm{U}}\ :\ \underline{\rho}_i^{\mathrm{U}},\ \overline{\rho}_i^{\mathrm{U}}\ \forall i \tag{4.4h}$$

$$0\le r_i^{\mathrm{D}}\le\overline{R}_i^{\mathrm{D}}\ :\ \underline{\rho}_i^{\mathrm{D}},\ \overline{\rho}_i^{\mathrm{D}}\ \forall i \tag{4.4i}$$

$$0\le p_{i,b}^{\mathrm{G}}\le\overline{P}_{i,b}^{\mathrm{G}}\ :\ \underline{\tau}_{i,b},\ \overline{\tau}_{i,b}\ \forall i,\ \forall b \tag{4.4j}$$

$$\sum_{b\in\mathcal{B}_i}p_{i,b}^{\mathrm{G}}+r_i^{\mathrm{U}}\le\sum_{b\in\mathcal{B}_i}\overline{P}_{i,b}^{\mathrm{G}}\ :\ \overline{\phi}_i^{\mathrm{G}}\ \forall i \tag{4.4k}$$

$$0\le\sum_{b\in\mathcal{B}_i}p_{i,b}^{\mathrm{G}}-r_i^{\mathrm{D}}\ :\ \underline{\phi}_i^{\mathrm{G}}\ \forall i \tag{4.4l}$$

$$0\le p_d^{\mathrm{D}}\le\overline{P}_d^{\mathrm{D}}\ :\ \underline{\psi}_d,\ \overline{\psi}_d\ \forall d \tag{4.4m}$$

However, constraint (4.4n), below, is different from (4.1o) and sets the scheduled wind power of each wind farm l to be less than or equal to the corresponding producer's forecast (which is now considered common knowledge).

$$0 \leq p_l^{\mathrm{W}} \leq F_l \; : \; \underline{\sigma}_l, \; \overline{\sigma}_l \; \forall \; l \qquad (4.4n)$$

$$\Big\} \; \forall J.$$

The set of primal variables of LL problem (4.4d)-(4.4n) is $\Xi^{\mathrm{LL,P}} = \{p_l^{\mathrm{W}}, p_{i,b}^{\mathrm{G}}, p_d^{\mathrm{D}}, r_i^{\mathrm{U}}, r_i^{\mathrm{D}}\}$.

Furthermore, the set of dual variables of the LL problem is $\Xi^{\mathrm{LL,D}} = \{\lambda^{\mathrm{DA}}, \mu^{\mathrm{U}}, \mu^{\mathrm{D}}, \underline{\rho}_i^{\mathrm{U}}, \overline{\rho}_i^{\mathrm{U}}, \underline{\rho}_i^{\mathrm{D}}, \overline{\rho}_i^{\mathrm{D}}, \overline{\tau}_{i,b}, \underline{\tau}_{i,b}, \underline{\phi}_i^{\mathrm{G}}, \overline{\phi}_i^{\mathrm{G}}, \underline{\psi}_d, \overline{\psi}_d, \underline{\sigma}_l, \overline{\sigma}_l\}$.

Finally, the primal variables of the UL problem (4.4a)-(4.4c) are $\alpha_{i,b}^{\mathrm{G}}$ as well as all members of variable sets $\Xi^{\mathrm{LL,P}}$ and $\Xi^{\mathrm{LL,D}}$.

Given that wind power is offered by all producers at zero price, individual producers optimization models are only affected by the summation of scheduled wind power for all rival producers, as included in constraints (4.1e) and (4.4e). Thus, assuming that producers know exactly the individual wind power forecasts of rival producers equals to having knowledge only about the summation of individual forecasts. Concluding, due to the aforementioned description the case study with public individual forecasts yields the same result with the one where public aggregate forecast is equal to the summation of individual private ones. This notion eases the computations, since we can represent the solution of the problem of this subsection by the case where public aggregate forecast is equal to the summation of individual ones.

4.2.4 Identifying the Equilibrium Point Among Producers

We represent the game among all strategic producers by an iterative diagonalization process, which is illustrated in Fig. 4.2. Producers make their offering decisions sequentially, while at each step each producer considers the offers of rivals being fixed. The game is, therefore, described by the following three steps:

1. Iteration counter (c), maximum number of iterations (c_{max}), convergence tolerance (ε) and price offering strategies ($x(c)$) are initialized. For the first step of the iterative process, producers price

offering strategies, i.e., vector of price offers, are initialized to be equal to their marginal costs.

2. Through iteration c, each power producer solves the corresponding MPEC in order to determine its optimal offering strategy, keeping rivals offers fixed to their value at iteration $c-1$. The vector of price offers is, thus, updated by the solution of the corresponding MPEC for all producers.

3. Finally, vector of price offers at iteration c is compared to the one at iteration c-1. If their mathematical distance is greater than ε, then a new iteration starts. The iterations stop either if this distance is smaller than the value of tolerance, i.e., an equilibrium is found, or if the maximum number of iterations has been reached, indicating that no equilibrium is found.

4.2.5 Day-Ahead Market-Clearing

The answer to the central question of this work, i.e., investigating the impact of public aggregate wind forecast on market results, requires taking an additional step where DA market is actually cleared by the market operator based on producers offers and demand bids. Note that each producer subjectively anticipates DA market-clearing, taking into consideration the aggregate wind power forecast. However, the market is actually cleared by the market operator based solely on producers wind power offers, which are equal to their private wind power forecast. Price offers for conventional generation at the equilibrium point, derived by the model presented in Section 4.2.2, are also considered for market-clearing. Therefore, the formulation of the DA market is given by (4.5) below:

$$\underset{p^{\mathrm{G}}_{i,b}, p^{\mathrm{W}}_{l}, p^{\mathrm{D}}_{d}, r^{\mathrm{U}}_{i}, r^{\mathrm{D}}_{i}}{\text{Maximize}} \quad \sum_{d \in \mathcal{D}} \lambda^{\mathrm{D}}_{d} \; p^{\mathrm{D}}_{d} - \sum_{i \in \mathcal{I}} \sum_{b \in \mathcal{B}_i} \alpha^{\mathrm{G}}_{i,b} \; p^{\mathrm{G}}_{i,b} \tag{4.5a}$$

subject to:

$$(4.1\text{e}) - (4.1\text{m}) \tag{4.5b}$$

$$0 \leq p^{\mathrm{W}}_{l} \leq F_l \quad \forall l. \tag{4.5c}$$

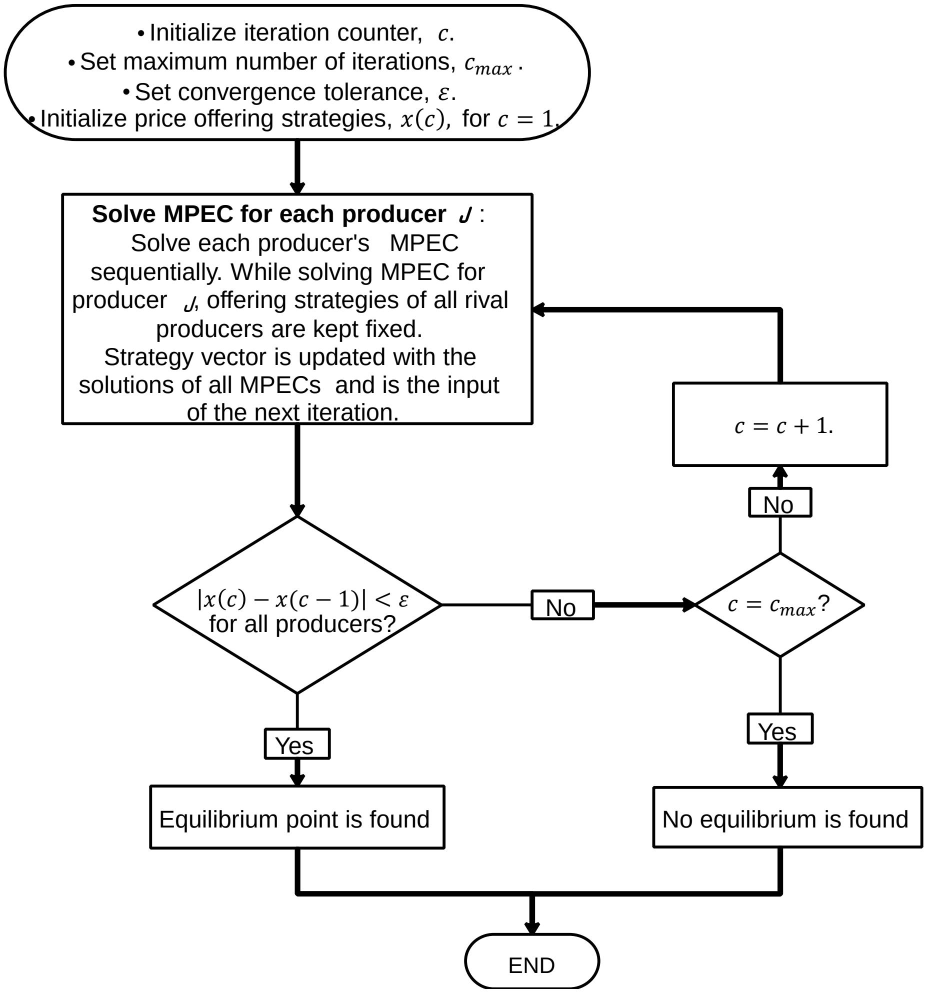

Figure 4.2: The iterative diagonalization approach to identify the equilibrium point

Note that the results obtained from LL problem in model (4.1) and those obtained from model (4.5) are not necessarily the same, though their optimization structure is similar. In the LL problem of producers models, the market is cleared from the producer's perspective based on the available data for that producer, i.e., forecast for its own wind power units and public aggregate wind forecast. However, model (4.5) actually clears the market from market operator's point of view considering the price offers received from (4.1) and the private wind forecasts of producers. Therefore, constraints (4.5b) are the same as LL problem (4.1e)-(4.1m) of each producer but LL constraints (4.1n) and (4.1o) are now replaced by (4.5c) for all producers. In addition $\alpha^{\mathrm{G}}_{i,b}, \forall i, \forall b$ are now parameters, derived from the equilibrium model presented in Section 4.2.4.

4.3 Case Study

4.3.1 Data

A single-hour case study based on the IEEE one-area reliability test system [84] is considered. For the sake of simplicity, conventional units are grouped by type. Each conventional unit offers at a quantity identical to its installed capacity, given in Table 4.1, and at a strategic price that can differ from its marginal costs, which are presented in Table 4.2. Among eight producers competing in this case study, four of them, namely producers $j1, j2, j3$ and $j4$, own wind power units in addition to their conventional generation capacity. Each of those producers forecasts its own wind power generation deterministically. The forecasted values are listed in the last column of Table 4.1. Note that these individual forecasts are private data and are not shared with the rivals. The demand levels and the corresponding bids are presented in Table 4.3, while the factors defining the minimum reserve requirements are arbitrarily chosen as $\gamma = 0.05$ and $\delta = 0.1$.

Table 4.1: Technical Characteristics of Power Generation Units [MW]

Producer J with generation portfolio i and l	Conventional generation offers for unit i and block b				Reserve capacity offers for unit i		Wind power forecast by producer
	$\overline{P}^{\mathrm{G}}_{i,b1}$	$\overline{P}^{\mathrm{G}}_{i,b2}$	$\overline{P}^{\mathrm{G}}_{i,b3}$	$\overline{P}^{\mathrm{G}}_{i,b4}$	$\overline{R}^{\mathrm{D}}_{i}$	$\overline{R}^{\mathrm{U}}_{i}$	F_l
$j1$	60.8	91.2	91.2	60.8	80	80	200
$j2$	75	75	90	60	75	75	350
$j3$	206.85	147.75	118.2	118.2	120	120	450
$j4$	12	18	18	12	0	0	400
$j5$	217	155	124	124	180	180	-
$j6$	200	200	240	160	80	80	-
$j7$	300	0	0	0	0	0	-
$j8$	140	87.5	52.5	70	80	80	-

Table 4.2: Marginal Costs of Conventional Units [€/MWh]

Producer J	$C^{\mathrm{G}}_{i,b1}$	$C^{\mathrm{G}}_{i,b2}$	$C^{\mathrm{G}}_{i,b3}$	$C^{\mathrm{G}}_{i,b4}$
$j1$	11.46	11.96	21.67	22.72
$j2$	18.60	20.03	21.67	22.72
$j3$	19.20	20.32	21.22	22.13
$j4$	23.41	23.78	26.84	30.4
$j5$	9.92	10.25	10.68	11.26
$j6$	5.31	5.38	5.53	5.66
$j7$	2.00	-	-	-
$j8$	10.08	10.66	11.09	11.72

4.3.2 Results

In real-world markets, producers with wind power within their generation portfolio usually make their offers to the market based on a deterministic forecast, which is privately generated and accessible. Undoubtedly, the summation of these individual forecasts differs from the aggregate forecast of the market operator. A special case, according to which the summation of private individual wind forecasts equals the public aggregate one, is used throughout this study as a reference. As described in Section 4.2.3, under the context of this chapter this problem leads to the same results with the producers knowing exactly the individual wind forecasts of rivals. In this case, the public aggregate wind forecast is 1400 MW, which is equal to the summation of individual wind forecasts reported in the last column of Table 4.1.

For the reference case, the strategic price offers of producers are derived and presented in Table 4.4. Producers $j1, j2, j5, j6$ and $j8$ offer their cheap generation blocks at zero price in order to get scheduled. The energy price is €18.601/MWh as presented in Table 4.5. However, the corresponding capacity prices for committed downward and upward reserve are both zero. This is explained by the last two columns of Table 4.6, where it is observed that producers $j1$, $j2$ and $j3$, $j8$ have still additional available downward and upward reserve capacity, respectively. Therefore, constraints (4.1f) and (4.1g), which enforce the minimum reserve requirements of the market, are not binding and the corresponding dual variables are zero. Table 4.6 additionally presents producers total profits for the reference case, as well as the scheduled power for each gen-

Table 4.3: Demand Characteristics

Demand d	Demand level [MW]	Demand bid [€/MWh]
$d1$	550	65
$d2$	300	60
$d3$	500	55
$d4$	300	55
$d5$	200	52
$d6$	450	52
$d7$	500	50
$d8$	200	50
$d9$	300	50
$d10$	200	50
Total	3500	-

eration block of each producer. Note that each wind farm is scheduled in DA market at a quantity equal to its owner's wind power forecast. Those results are used as a benchmark for comparison with the corresponding results for different values of aggregate wind forecast.

Table 4.4: Strategic Price Offers at the Equilibrium Point for the Reference Case [€/MWh]

Producer J	$\alpha^{\mathrm{G}}_{i,b1}$	$\alpha^{\mathrm{G}}_{i,b2}$	$\alpha^{\mathrm{G}}_{i,b3}$	$\alpha^{\mathrm{G}}_{i,b4}$
$j1$	0	18.600	18.601	18.602
$j2$	0	18.601	18.602	18.603
$j3$	18.601	18.602	18.603	18.604
$j4$	18.601	18.602	18.603	18.604
$j5$	0	0.001	0.002	18.600
$j6$	0	0.001	0.002	18.601
$j7$	18.600	-	-	-
$j8$	0	0.001	0.002	18.601

Table 4.5: Energy and Reserve Prices for the Reference Case

Price [€/MWh]	
μ^{U}	0
μ^{D}	0
λ^{DA}	18.601

Table 4.6: Schedules and Producers Profits at the Equilibrium Point for the Reference Case

Producer J	Profit [€]	Scheduled power in DA for each unit i and block b [MW]				Committed capacity for reserves [MW]	
		$p^{G}_{i,1}$	$p^{G}_{i,2}$	$p^{G}_{i,3}$	$p^{G}_{i,4}$	r^{U}_{i}	r^{D}_{i}
$j1$	4760	60.8	91.2	0	0	80	0
$j2$	6510	75.0	0	0	0	75	35
$j3$	8370	0	0	0	0	70	0
$j4$	7382	12.0	0	0	0	0	0
$j5$	5070	217.0	155.0	124.0	124.0	0	180
$j6$	8711	200.0	200.0	240.0	21.0	80	80
$j7$	4980	300.0	0	0	0	0	0
$j8$	2282	140.0	87.5	52.5	0	70	80

Based on model (4.1) we investigate the impact of deviations between public aggregate wind forecast and the summation of private ones, on market results and on producers profits. For this purpose we search the equilibrium under different values of aggregate forecast, which may not be equal to the one corresponding to the reference case. The problem is solved for aggregate forecast that takes values in a wide range around the reference case, which is used for comparison. More specifically, aggregate forecast is considered to take different values between 900 MW and 1900 MW in 10-MW steps. Recall that the summation of private forecasts is 1400 MW (reference case). Note that for values of aggregate forecast for which no equilibrium is found, there are no results to be presented.

Figure 4.3 shows energy and reserve prices at the equilibrium point for different aggregate wind forecast values. It is observed that energy price is zero for low values of aggregate forecast, i.e., below 1030 MW. Then, following some small fluctuations, it stabilizes at €18.601/MWh. Zero energy price for small values of aggregate wind forecast is explained by producers price offers. More particularly, when the aggregate wind forecast is low, the producers expect low wind power penetration in the market based on their decision-making model (4.1). The producers do not have information on rivals wind offers and, therefore, anticipate market outcomes based on the available aggregate wind forecast. Thus, from producers perspective, the expected low wind power penetration (low aggregate forecast) indicates potentially high market-clearing price. This motivates some producers to offer at zero price in order to get scheduled.

However, it has the opposite result in terms of actual market outcomes. Producers zero price offers along with the total wind power (which is higher than producers anticipated) lead to zero market-clearing price. Moreover, prices for committed downward reserve are always zero in this study, which is explained by the fact that there is sufficient capacity for downward reserve, without incurring extra cost. In other words, the corresponding reserve requirement never changes the power schedule of generators. However, prices for committed upward reserve can take non-zero values, especially for values of aggregate forecast below and around 1400 MW.

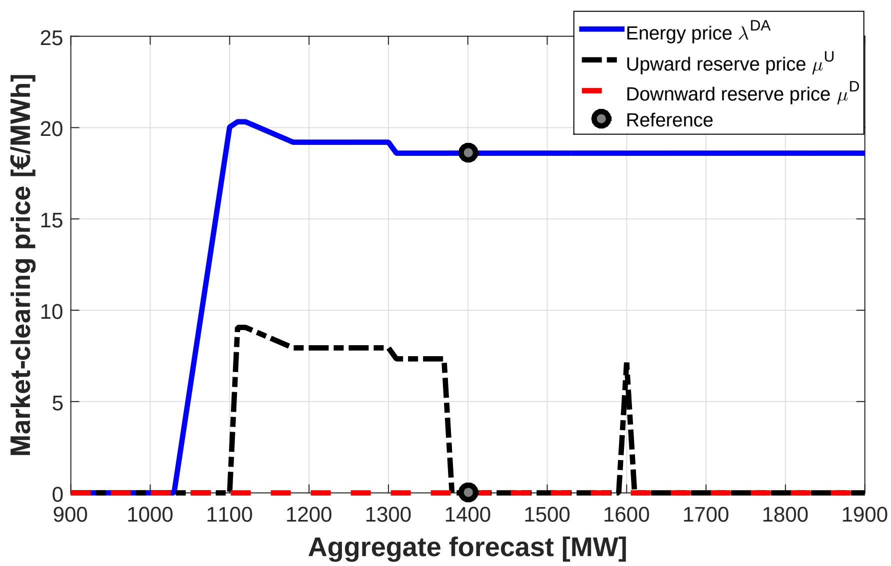

Figure 4.3: Energy and reserve prices versus different aggregate wind forecast values

From Fig. 4.4 it is observed that for small values of aggregate forecast, profits of all producers are either zero or negative. This result is again explained by the producers expectations for high energy prices, which inevitably leads to the opposite results, i.e., zero prices, with the consequent impact on producers profits. It should be noted that the producers offers are derived from model (4.1) and are based on their available information. Accordingly, producers do not anticipate their profits to be negative. For example, Fig. 4.5 shows that, apart from producer $j7$ (red

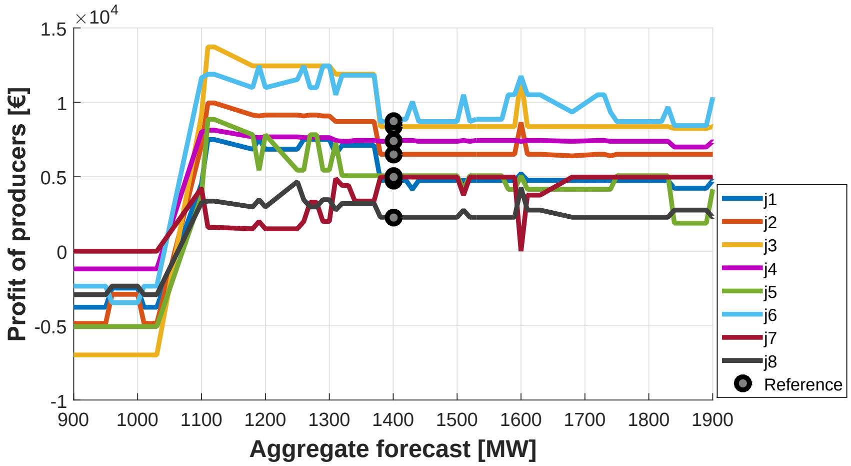

Figure 4.4: Producers profits versus different aggregate wind forecast values

bars) who is not scheduled for aggregate forecasts below 1030 MW, all other producers are scheduled in the DA market. As already discussed, in the case of small aggregate forecasts, producers mostly offer their generation at zero price in order to get scheduled, expecting that the energy price will actually be high. However, energy price is eventually zero, leading to negative profits for producers. Obviously, this is an unfavorable result for the producers, which happened due to their decision-making process that depends on public aggregate forecasts. This result can be better understood by comparing models (4.1) and (4.5) of Sections 4.2.2 and 4.2.5, respectively. Producers anticipate market outcomes based on their model that considers the public aggregate forecast, i.e., constraint (4.1o), while the actual market is cleared based on wind offers, which are fixed and equal to the individual wind forecasts of producers, i.e., constraint (4.5c).

In addition, social welfare is also affected by the level of aggregate forecast. In Fig. 4.6, we present the social welfare calculated as the value obtained for objective function (4.5a). Social welfare is not directly affected by public aggregate forecast - which has a direct impact on the producers decision-making model. In turn, producers strategic decisions, i.e., price offers of conventional generation, have a direct impact on the market-clearing results and, thus, on social welfare. Even though pro-

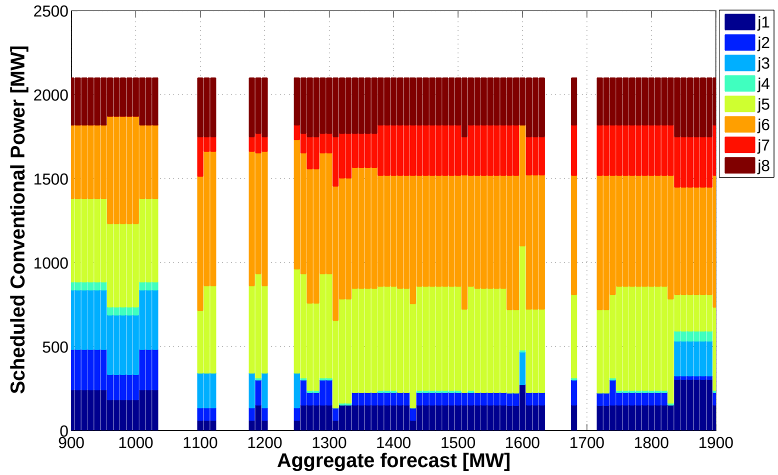

Figure 4.5: Day-Ahead schedules of conventional generators versus different aggregate wind forecast values

ducers always offer their wind power generation based solely on their private wind forecast, their price offers for conventional generation are highly affected by the level of public aggregate forecast, with consequent impact on market-clearing outcomes and social welfare. In line with the previous description, low values of aggregate forecast lead to low price offers from producers and, therefore, cheaper energy is scheduled in the market. Consequently, social welfare is increased for low aggregate wind forecast. Likewise, higher values of aggregate forecast lead to lower social welfare, caused by comparatively high price offers.

For further clarity, the supply-demand curves for some cases of specific interest are presented in Fig. 4.7. As described earlier, the wind power offers are always equal to the producers individual forecasts at zero price. However, price offers for conventional generators are different, derived from model (4.1), which depends on the level of aggregate wind forecast. Hence, one can see that the price offers at F^{MO}=1030 MW lead to zero energy price while in cases of F^{MO}=1400 MW and F^{MO}=1500 MW energy price is €18.601/MWh. The case of F^{MO}=1200 MW is of specific interest given that the upward reserve constraint is active. Therefore, even though the supply-demand curve sets the energy price at €11.26/MWh, which is the marginal producer's price offer (see

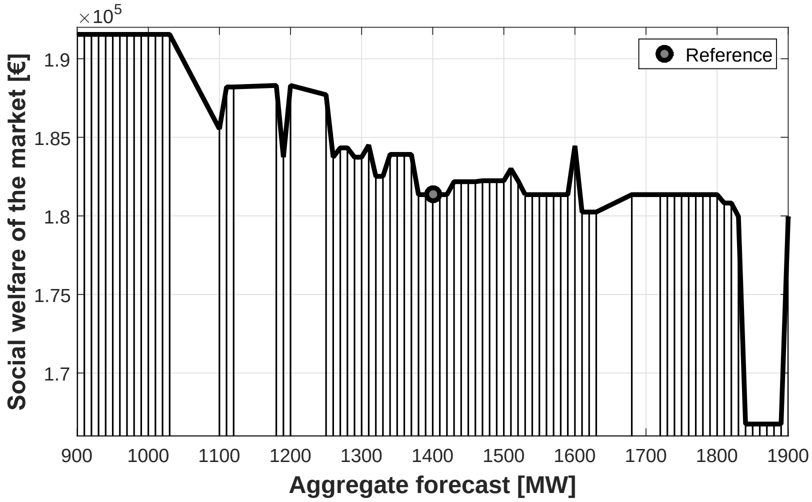

Figure 4.6: Social welfare of the market versus different aggregate wind forecast values

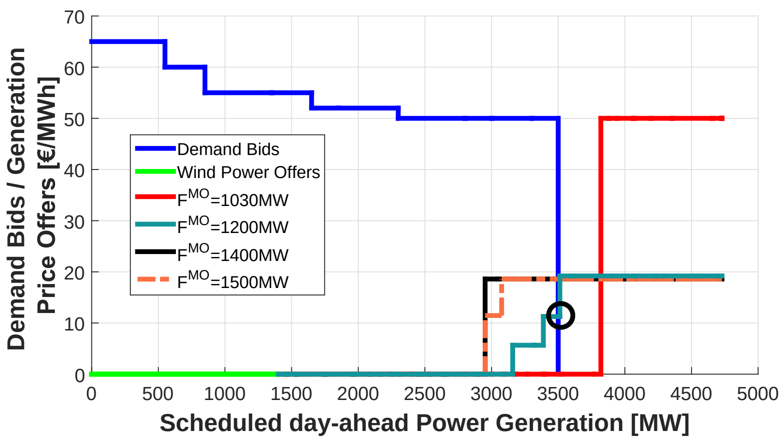

Figure 4.7: Supply-demand curves versus different aggregate wind forecast values

point in circle in Fig. 4.7), the actual energy price derived from model (4.5) is €19.20/MWh, being the summation of marginal price offer and the corresponding price for upward reserve. This condition illustrates the coupling between DA energy and reserve auctions, as introduced by constraints (4.4k) and (4.4l).

4.3.3 Uncertainty of Wind Forecasts and Real-Time Prices

In the previous paragraphs we have focused on a DA market setup only. However, it is of further interest to investigate the validity of the aforementioned results based on a case study accommodating a certain degree of uncertainty stemming from the RT market stage. Indeed, considering the uncertainty of wind power generation along with the anticipation of the RT market prices can enable the derivation of advanced strategies for wind power producers, avoiding additional costs due to forecast errors in the RT stage. Using as a basis the presented models, we will additionally investigate the equilibrium of the market under a number of scenarios for the RT wind power generation as well as the RT prices, following the approach of [72]. According to the above, model (4.1) is transformed into the new model (4.6), the formulation of which is presented below:

$$\Bigg\{ \underset{\alpha^{\mathrm{G}}_{i,b},\ p^{\mathrm{W,RT}}_{l,\omega},\ \Xi^{\mathrm{LL,P}} \cup \Xi^{\mathrm{LL,D}}}{\text{Maximize}}$$

$$\sum_{i \in \mathcal{I}_J} \sum_{b \in \mathcal{B}_i} (\lambda^{\mathrm{DA}} - C^{\mathrm{G}}_{i,b})\, p^{\mathrm{G}}_{i,b} + \sum_{l \in \mathcal{W}_J} (\lambda^{\mathrm{DA}}\ p^{\mathrm{W}}_l)$$

$$+ \sum_{i \in \mathcal{I}_J} (\mu^{\mathrm{U}}\ r^{\mathrm{U}}_i + \mu^{\mathrm{D}}\ r^{\mathrm{D}}_i) - \sum_{\omega \in \Omega} \pi_\omega \sum_{s \in \mathcal{S}} \pi^{\lambda}_s \left[\sum_{l \in \mathcal{W}_J} \lambda^{\mathrm{RT}}_s p^{\mathrm{W,RT}}_{l,\omega} \right] \tag{4.6a}$$

subject to:

$$(4.1\text{b}) - (4.1\text{c}) \tag{4.6b}$$

$$P^{\mathrm{W,P}}_{l,\omega} + p^{\mathrm{W,RT}}_{l,\omega} = p^{\mathrm{W}}_l \quad \forall l \in \mathcal{W}_{\mathcal{J}}, \forall \omega \tag{4.6c}$$

where $\lambda^{\mathrm{DA}},\ p^{\mathrm{W}}_l$ and $p^{\mathrm{G}}_{i,b}$ $\forall i \in \mathcal{I}_J$,

$\forall l \in \mathcal{W}_J,\ \forall b \in \arg\big\{$

$$\underset{\Xi^{\mathrm{LL,P}}}{\text{maximize}} \sum_{d \in \mathcal{D}} \lambda^{\mathrm{D}}_d\ p^{\mathrm{D}}_d - \sum_{i \in \mathcal{I}} \sum_{b \in \mathcal{B}_i} \alpha^{\mathrm{G}}_{i,b}\ p^{\mathrm{G}}_{i,b} \tag{4.6d}$$

subject to:

$$(4.1\text{e}) - (4.1\text{o}) \quad \big\} \tag{4.6e}$$

$$\Bigg\} \ \forall J,$$

where constraint (4.6c) ensures that the power imbalance due to the difference between the DA scheduled wind power and the actual generated one under scenario ω, is adjusted in RT by the traded RT wind power. A positive value of $p_{l,\omega}^{\mathrm{W,RT}}$ indicates that wind power production is lower than the scheduled one in DA market, incurring an additional cost for the producer. Lastly, we assume that wind power producers are price-takers in the RT market and, thus, they do not strategically affect RT prices, similarly to [72].

The input data for this numerical case study are presented in Tables 4.7 and 4.8, defining three scenarios for each source of uncertainty. Note that the deterministic forecast used in the previous sections, is equal to the expected values of the three wind scenarios. Furthermore, similarly to [72], we assume that wind power producers are price-takers in the RT market and, thus, they do not affect RT prices.

Table 4.7: Scenarios for Wind Power Generation ($P_{l,\omega}^{\mathrm{W,P}}$) [MW]

	ω_1	ω_2	ω_3
π_ω	0.2	0.3	0.5
$j1$	160	250	186
$j2$	260	320	404
$j3$	400	430	482
$j4$	320	380	444
$j5...j8$	-	-	-

Table 4.8: Scenarios for Real-Time Prices [€/MWh]

	s_1	s_2	s_3
π_s^λ	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
λ_s^{RT}	10	20	30

Following the same presentation as before, we present the two most interesting figures, i.e, social welfare and producers profits for various levels of aggregate forecasts. In Fig. 4.8, a similar trend with the analysis of Section 4.3.2 is observed. Social welfare is comparatively lower for greater values of aggregate forecasts. However, the possibility of having high RT prices may weaken the aforementioned decreasing profile of social welfare. Finally, Fig. 4.9 is similar to Fig. 4.4 of the DA-only study, where it is observed that for very small values of aggregate forecasts producers may earn zero or even negative profits. The interpretation of this outcome is already presented in detail in Section 4.3.2.

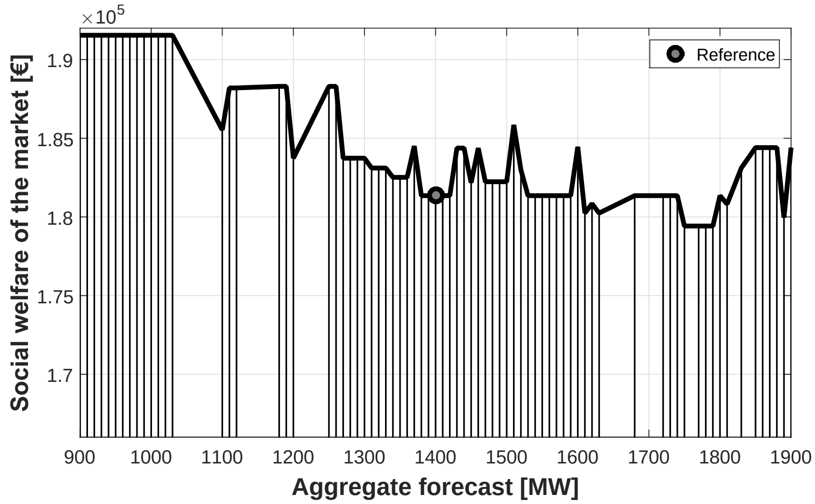

Figure 4.8: Social welfare of the market versus different aggregate wind forecast values considering uncertainty in wind power generation and real-time prices

4.3.4 Computational Performance

This subsection offers an insight to the computational needs of this case study. For the simulations of this chapter we have used CPLEX under GAMS associated with Matlab R2015b on a Windows 8.1, 64-bit operating system with 2 cores processor, running at 2.4 GHz and 12 GB of RAM. The total computational time for the whole case study was 720 s. Furthermore, for the cases where equilibrium was found (82 out of 101) it took less than 5 iterations to find the equilibrium. The computational time depends highly on whether an equilibrium is found or if the process terminates after maximum number of iterations, the latter requiring more time. The convergence tolerance was set at $\epsilon = 0.3$ and the maximum number of iterations $c_{max} = 10$. In this chapter, we use an

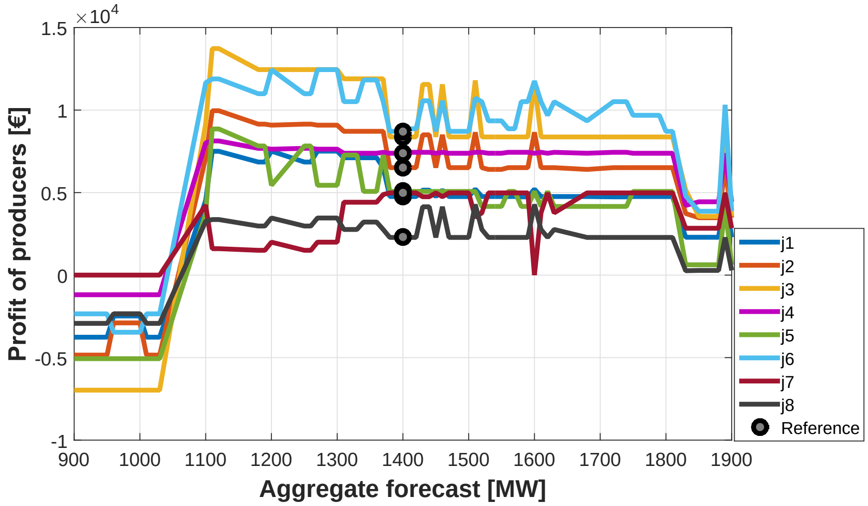

Figure 4.9: Producers profits versus different aggregate wind forecast values considering uncertainty in wind power generation and real-time prices

iterative diagonalization approach, which is simple but at the risk of not converging in the predefined number of iterations. One sort of alternatives is to augment the current diagonalization technique by increasing the number of iterations and/or providing different starting points. Another alternative is to use non-iterative equilibrium solution techniques where applicable (e.g., in [70]), but at the cost of increased complexity. Lastly, the setup that was chosen for this study allows us to get an insight into the role of public aggregate forecasts in electricity markets without constructing a complicated tool.

4.4 Summary and Conclusions

An increasing interest towards transparency and competitiveness in energy markets has led to decisions and directives for the publication of various market-related information. To this end, system operators invest in generating and publishing qualitative market data, including aggregate wind power forecast, envisioning an improved and transparent market operation. In the presence of a public aggregate wind forecast, participating producers may consider this information in their decision-making tool. This chapter uses a complementarity model that provides producers with the strategic price offers for their conventional generation, while wind power is offered at zero price based on an individual forecast. The main scope of the study is, by using the aforementioned model, to investigate how the availability of public aggregate forecasts can affect electricity market outcomes. To this end, we considered multiple strategic producers and described the market as a non-cooperative game, whose equilibrium is identified through an iterative diagonalization technique.

The results of this equilibrium study lead to a number of interesting conclusions that contribute to a better understanding of the impact of available aggregate wind power forecasts on the electricity market outcomes:

1. Market-clearing prices (energy and reserve) could be significantly affected by the public aggregate wind forecast. More precisely, the under-forecast of aggregate wind power leads to comparatively low or even zero energy prices. Producers expect high prices due to decreased wind power penetration and thus make low price offers for a portion of their generation portfolio in order to get scheduled.

2. In view of the above, social welfare is also affected. Low price offers inevitably impact social welfare, which increases accordingly. The opposite effect is observed for aggregate forecasts of greater values than the reference, i.e., social welfare decreases.

3. As anticipated, energy prices affect producers profits as well. For small values of aggregate forecast, producers profits are very low and in some cases even negative. Producers offer their power in lower -than the corresponding generation cost- prices, mislead by the aggregate forecast causing them negative instead of positive profits. Note that cost-recovery is not guaranteed in a market with strategic behaviors.

4. Similar outcomes are observed when uncertainty around wind forecasts as well as RT prices is considered. Social welfare is comparatively lower for greater values of aggregate forecasts. However, the possibility of having high RT prices may weaken the aforementioned decreasing profile of social welfare.

Under such a setup, it is evident that the level of public aggregate forecast can indeed misguide producers strategic behaviour. In turn, this has a major impact on social welfare, which is considerably decreased or increased, for over- or under-forecasts. To this end, note that this observation should not be considered in isolation from the main assumptions that wind power producers have market power and, additionally, they consider the public aggregate forecast in their decision-making tool. Lastly, the motivation of this study is based on the likely situation where deviations in public aggregate forecast are the result of forecast errors and not the result of a potential strategy from the system operator's side. Besides, the initiative of publishing this information is taken on the grounds of increased market transparency.

4.5 Future Perspectives

The outcomes of this study contribute towards the discussion on the importance of sharing and publishing wind power forecasts on the benefit of market operation, initially discussed in Chapter 2. Favored by ambitious plans for high quality market-related data, it is strongly believed that understanding the role of forecast information and their status, being public or private, can have a crucial impact on electricity market functioning. To this end, it is highly relevant to account for incentive-compatible mechanisms, such as mechanism design [121] or consensus-based distributed market-clearing [64], which can elicit truthful decisions from market parties, increasing the transparency of the electricity market. Under this context, an incentive-compatible mechanism is thoroughly investigated and compared against the LMP market-clearing mechanism in Chapter 5.

Lastly, in this work wind power was offered deterministically to the market based on a forecast, even though uncertainty around forecasts and RT prices was additionally considered. It is of future interest to investigate how aggregate forecasts would impact the results under a stochastic two-stage market setup, similar to the ones presented in Chapters 2 and 3, where DA and RT markets are co-optimized to improve market operation under uncertainty.

4.6 Chapter Publications

This chapter has led to the following publication:

- L. Exizidis, J. Kazempour, P. Pinson, Z. D. Grève, and F. Vallée, *Impact of public aggregate wind forecasts on electricity market outcomes*, IEEE Transactions on Sustainable Energy, vol. 8, no. 4, pp. 1394-1405, Oct. 2017.

Part II

Mechanism Design Towards Incentive-Compatibility in Electricity Markets with High Penetration of Wind Power

Chapter 5

An Efficient and Incentive-Compatible Two-Stage Stochastic Market with High Wind Power Penetration

5.1 Introduction

In the previous chapters, we have investigated imperfectly competitive markets, which are vulnerable to strategic behaviors. Under such setups there exist market agents, in particular power producers, that have the capacity to exercise market power and alter market-clearing outcomes for their own benefit. This can eventually decrease social welfare, increase prices and, thus, pose a negative impact on market efficiency. Motivated by this drawback of traditional market mechanisms, we investigate in this chapter a different payment scheme, which has the capacity to eliminate producers market power. The payment scheme is based on the *mechanism design theory* and more specifically the Vickrey-Clarke-Groves (VCG) auction. In the following sections we perform a literature survey on market power in electricity markets and then present the relevant research on incentive-compatible mechanisms. A novel application of the VCG auction in a two-stage stochastic market is explored and extensively compared to the corresponding traditional market structure under both competitive and strategic settings. In this chapter, we consider a stochastic LMP market mechanism, which is similar to the market-clearing models presented in Chapters 2 and 3 but additionally accounts for transmission network constraints. The VCG and LMP mechanisms are compared for increasing levels of wind power penetration and for both network-constrained and unconstrained market. Finally, we quantify the budget deficit that VCG may lead to and explore a potential solution for partially recovering it, based on the economics research literature.

5.1.1 Motivation

A competitive market can be defined as the market where the large number of participating firms selling a homogeneous commodity along with the small individual share of each firm, lead to a setup where no individual firm is able to influence appreciably the commodity price by varying the quantity of output it sells [122]. Under such a context, market price is turned into a parameter that cannot be controlled by any of the market agents. However, in order to consider a market as perfectly competitive there is an important assumption to be made; each agent should have all the information needed to maintain the equilibrium position with respect to prices. Naturally, though, market agents will more likely conceive any information-asset they might have as a potential strategic advantage, rather than an information that they will willingly share. In previous chapters we have explored cases where private or, even, shared information can be used by power producers in order to exercise market power. This has consequent negative impacts on social welfare and market efficiency. Motivated by this increasing value of information in electricity markets, we explore in this chapter an incentive-compatible mechanism that induces truthful information from market participants. More specifically, VCG motivates market agents (both producers and consumers) to be truthful with respect to their generation offers or demand bids without, however, having to publicly reveal private information. The evaluated mechanism, i.e., VCG auction, is adapted to a two-stage stochastic electricity market and evaluated versus the corresponding stochastic market mechanism, seen in previous chapters 2 and 3, exploring both the advantages and disadvantages of each mechanism for increasing penetration of wind power. As VCG may lead to budget deficit, we quantify it in a network-constrained market and research a partial recovery of the negative budget imbalance, based on an approach that does not affect incentive-compatibility and efficiency [41].

5.1.2 Literature Review and Contributions

The last three decades, power system operation and consequently electricity markets have changed drastically. From state-owned entities, power systems have reformed following a deregulated structure, that has a specific interest in electricity markets. The results of this transformation is the appearance of electricity pools worldwide, which are entrusted to support equal access to the market of any willing agent, either producer or consumer, under the same transparent rules. The main purpose of restructuring electricity markets is to increase competition which is expected to lead in decreasing electricity prices and increased social welfare. Even though the implementation of the market design principles varies from region to region, successful operation of electricity markets aims at satisfying some common criteria, namely (i) power system reliability, (ii) market transparency, (iii) revenue-adequacy, (iv) cost-recovery and (v) efficiency, which are described in detail in Chapter 1. Thus, a market mechanism should ensure accordingly that supply meets demand, rules and conditions of the market are transparent, market operator does not face deficit, agents operational costs are reimbursed and, finally, maximum efficiency is achieved. However, it is impossible to guarantee all the aforementioned properties in a market design. Myerson and Satterthwaite in [40] showed a conflict between efficiency, individual rationality (equivalent to cost-recovery) and budget balance (equivalent to zero budget imbalance of market) building on the *Hurwicz Impossibility Theorem* [39], which states that: "*No mechanism is capable of achieving individual rationality, efficiency, and budget balance at the same time for general valuation functions, even if solution is loosened to refer to Bayes-Nash equilibrium*[*]".

Practically, under the concept of an electricity market as presented in Chapter 1, the aforementioned impossibility theorem could be adapted by saying that there can be no electricity pool that ensures: (i) cost-recovery: agents are not facing loses due to their participation to the market, (ii) efficiency: social welfare is maximized and (iii) revenue-adequacy: market revenue is enough to cover operational and transmission costs, i.e., there

[*]Dominant strategy incentive-compatibility refers to the condition where each agent is induced to tell the truth whatever the other agents report. This constraint is more stringent than the corresponding under a Bayes-Nash implementation, where reporting the truth is dominant strategy only in expectation [29].

is no budget deficit.

Elaborating more on efficiency, in LMP markets it can only be maximized if market participants are truthful with respect to their costs, meaning that producers are price-takers. In practice, this assumption does not usually hold and electricity markets are challenged by the presence of strategic producers [123], which may offer at prices different than their actual production costs in order to increase market prices. Thus, an ever increasing number of researchers have been studying market power in electricity markets, a concept under which market agents submit different offers in order to change market results for their own benefit. Initial research efforts focused on the concepts of Cournot and Stackelberg games, as in papers [124, 125, 126, 127, 128, 129] and [130, 131, 132, 133, 134, 135], respectively, where the investigated markets include firms that exercise market power and firms that are price-takers, distinguished as leaders and followers, respectively. Extending this to a market where all firms are price-makers, [136] presented a mixed-integer linear programming (MILP) solution for finding the Nash equilibrium in a strategic bidding setup and [137] explored an iterative approach for finding multiperiod Nash Equilibria in short-term electricity markets with strategic producers. Considering the increasing penetration of wind power in imperfectly competitive markets, the focus of more recent research efforts was put on the problem of optimal trading or market-clearing under high wind power uncertainty, with some of the studies additionally coping with the problem of strategically trading wind power. Under this context, papers [71, 72, 74] explored the problem of optimal wind power trading in electricity pools, while [62, 70, 75, 119, 138] investigated equilibria in electricity markets with high penetration of wind power under different conditions.

Albeit game theory offers a comprehensive insight into the operation of imperfectly competitive markets, it is subject to weak assumptions with respect to information availability. Reasonably, strategic agents in real markets are not willing to reveal their private information, since in such a case their market power may decrease. Thus, game theory is only a tool for understanding those behaviors and not for solving the problem of market design under the presence of strategic producers. The problem of designing a market based on some specified principles and properties is the topic of an other branch of economics, namely the mechanism design theory. In fact, mechanism design is a theory closely-related to game theory which attempts to implement desired choices in a strategic setting where interested parties are self-interested. Such a strategic design is necessary since the preferences of participants are private and the assumption of complete information knowledge does not hold in practice. In mechanism design, VCG is a truthful mechanism for achieving a socially optimal solution, being a generalization of the VCG auction [42, 43, 44]. The VCG mechanism is incentive-compatible, individual rational and efficient but it does not guarantee budget balance. This is explained by the aforementioned Myerson and Satterthwaite theorem [40], which attracted increased attention due to its importance in most markets. Under this context, a lot of research works in economics literature focused on this problem, including the proposed d'AGVA mechanism [139] for achieving budget balance under a Bayesian (and not dominant-strategy) equilibrium and the proposed solution in [140] which ensures budget balance but at the cost of market efficiency. In the same vein, in [141], the author suggests a budget imbalance redistribution mechanism that is efficient and achieves budget balance in expectation, while in [41] the author characterizes the extent to which budget balance can be approximated in dominant strategies, without affecting the rest of the VCG properties.

Focusing on electricity markets, mechanism design applications are investigated in recent research studies. In [142], authors propose a market design that achieves efficiency in spite of the missing information problem, ensuring incentive-compatibility and cost-recovery. The basic idea of the aforementioned research is that producers payments are divided into two parts, one being the cost-compensation and the other one being an information payment, which is specifically designed to elicit truthful marginal costs from producers. However, the study does not ensure that payments to producers are minimized, due to the nature of the aforementioned dual payment scheme. Authors in [143] investigate the VCG auction for supply and demand bidding in an energy market with conventional producers to motivate truthful bidding. Advantages and shortcomings of VCG are then explored without, however, considering the impact of potential wind power uncertainty as well as the impact of imperfect competition that appears in LMP markets. In [144], an incentive-compatible mechanism is proposed, where market operator makes a generation payment as well as a transfer payment to producers, with the latter one aiming in ex-post recovering the resulting budget deficit. However, maximum market efficiency is not guaranteed due to the ex-post transfer payment, network constraints are not taken into consideration and the impact of wind power uncertainty is not investigated. To this end, [145] introduces an incentive-compatible pool-based market design based on a Bayesian approach in order to cope with some of the aforementioned shortcomings. In this study authors design a mechanism that satisfies incentive-compatibility, cost-recovery and payment-cost minimization but assumes that there exists prior common knowledge of the probability distribution over possible values of producers individual costs. Furthermore, it does not guarantee maximum efficiency nor does it account for wind power uncertainty. Finally, recent research [146] applies the VCG mechanism to wholesale electricity markets considering wind uncertainty, without however anticipating the RT market operation. The study also compares VCG to a competitive LMP market setup but it does not compare it with an imperfectly competitive market. With respect to the resulting budget deficit, authors suggest an ex-post case-specific recovering solution of the negative budget imbalance, without however further exploring it.

Under this context, this chapter aims in deeper exploring the VCG mechanism in electricity markets with high penetration of wind power, and to cope with some of the aforementioned weaknesses. To this end, the contribution of this chapter is manifold and, more specifically, it aims at:

1. proposing a VCG model for a two-stage stochastic market, where the first stage is the DA market-clearing and the second is the expected RT power adjustments based on a set of wind power scenarios,

2. comprehensively comparing the proposed mechanism with the corresponding LMP mechanism under perfect and imperfect competition for increasing levels of wind power penetration,

3. evaluating the results from both producers and demands viewpoints, i.e., producers profits and demands payments, respectively,

4. evaluating the impact of congestion in the transmission network and comparing the results with market-clearing excluding the transmission constraints,

5. and, finally, suggesting a solution scheme for partially recovering the negative budget imbalance of the market under VCG.

5.1.3 Chapter Organization

The remainder of the chapter is organized as follows: Section 5.2 presents the mathematical formulation of the investigated market models. Section 5.3 consists of two parts: (i) a case study considering a single wind power producer and no transmission constraints, and (ii) a large-scale case study considering multiple wind power producers and a network-constrained market. Finally, Section 5.4 concludes the chapter.

5.2 Mathematical Formulation

Notation:

Sets:

$\mathcal{I}$ Set of all conventional units

$\mathcal{I}_J$ Set of conventional units belonging only to producer J

$\mathcal{I}_{-J}$ Set of conventional units excluding the ones belonging to producer J

$\mathcal{D}$ Set of all demands

$\mathcal{D}_{-C}$ Set of demands excluding consumer C

$\mathcal{W}$ Set of all wind power units

$\mathcal{W}_{-L}$ Set of wind power units excluding the ones belonging to wind producer L

Λ Set of transmission lines

$\mathcal{M}_I$ Mapping of the set of conventional units into the set of buses

$\mathcal{M}_D$	Mapping of the set of demands into the set of buses
$\mathcal{M}_W$	Mapping of the set of wind power units into the set of buses
$\mathcal{S}$	Set of wind power scenarios

Indices:

s	Index for scenarios of the wind power forecast
i/j	Indices for conventional units
d	Index for demands
l	Index for wind power units
n/m	Indices for system buses

DA Variables:

δ_n^{DA}	Voltage angle at node n [rad]
α_i^{G}	Offer price of strategic conventional power unit i [€/MWh]
λ_n^{DA}	DA market-clearing price at system node n [€/MWh]
p_i^{G}	DA dispatch of conventional power unit i [MW]
p_l^{W}	DA dispatch of wind power unit l [MW]

RT Variables:

$\delta_{n,s}^{\mathrm{RT}}$	Voltage angle at node n under scenario s [rad]
$\lambda_{n,s}^{\mathrm{RT}}$	Probability-weighted RT market-clearing price at system node n under scenario s [€/MWh]
$p_{l,s}^{\mathrm{spill}}$	Wind power spillage of wind power unit l under scenario s [MW]
$r_{i,s}^{\mathrm{U}}$	Upward power adjustment of conventional unit i in RT under scenario s [MW]

$r_{i,s}^{\mathrm{D}}$ Downward power adjustment of conventional unit i in RT under scenario s [MW]

$l_{d,s}^{\mathrm{sh}}$ Involuntarily load shedding of demand d under scenario s [MW]

Parameters:

$B_{n,m}$ Value of the susceptance of line (n,m) [p.u.]

$F_{n,m}^{\max}$ Capacity of line (n,m) [MW]

$\overline{P}_{d}^{\mathrm{D}}$ Quantity bid of demand d [MW]

$\overline{P}_{i}^{\mathrm{G}}$ Quantity offer of conventional power unit i [MW]

$P_{l,s}^{\mathrm{W,F}}$ Wind power forecast of wind power unit l under scenario s [MW]

λ_{i}^{G} Operational cost of conventional power unit i [€/MWh]

λ_{d}^{D} Price bid of demand d [€/MWh]

λ_{i}^{U} Operational cost of conventional power unit i for providing upward reserve in RT [€/MWh]

λ_{i}^{D} Operational cost of conventional power unit i for providing downward reserve in RT [€/MWh]

π_{s} Probability of scenario s

R_{i}^{U} Upward reserve capacity of conventional power unit i [MW]

R_{i}^{D} Downward reserve capacity of conventional power unit i [MW]

V_{d}^{sh} Value of lost load for demand d [€/MWh]

$\overline{P}_{l}^{\mathrm{W}}$ Installed capacity of wind power unit l [MW]

This section is divided into four parts: Section 5.2.1 presents the main features and assumptions of the models used in this chapter. Section 5.2.2 introduces the formulation of the stochastic LMP market model, which defines optimal DA dispatch anticipating the RT market, assuming that all market agents are price-takers. Then, in Section 5.2.3 the formulation of an LMP market setup is extended into a non-cooperative game of strategic power producers, which compete assuming perfect information knowledge. An iterative diagonalization approach is then used to determine the equilibrium of their strategic decisions. The formulation of the VCG payment scheme is, finally, presented in Section 5.2.4, including a solution for partially recovering budget imbalance under VCG.

5.2.1 Features and Assumptions

Under the scope of this study, a number of necessary assumptions are made, which are presented hereafter:

1. For all the models presented in this section a stochastic two-stage DA market is considered in order to better capture the uncertainty of wind power generation [28, 61].

2. "Competitive Model": Section 5.2.2, presents the case of a perfectly competitive electricity market. In the corresponding model, participants are considered to be price-takers and submit their true costs/utilities to the market operator, who clears the market accordingly. This is an ideal model which is used in this study as a benchmark.

3. "Strategic Model": Section 5.2.3, refers to a market with strategic producers, i.e., price-makers. Under this context, an iterative diagonalization approach is followed, similarly to Chapter 4, in order to define the equilibrium of the market with respect to the strategic offers of producers. Then, market operator clears the market based on offers and bids at the equilibrium. Producers under this model behave strategically with respect to price offers of conventional generation [69, 70], but not regarding quantities and their wind generation.

4. "VCG Model": Section 5.2.4, presents a mechanism based on the VCG auction theory, i.e., each producer is paid and each consumer is charged proportionally to the impact it has on social welfare, making truthful market participation its dominant strategy, i.e., regardless of what any other agents do, the strategy earns the agent the largest payment. Under this model, economic dispatch is defined similarly to the LMP model in order to ensure maximum market efficiency. On the other hand, payments are made differently based on the VCG payment scheme.

5. All aforementioned models are solved both without considering network constraints, as in [70, 71, 73], and with enforcing transmission network constraints, following a lossless DC optimal power flow approach (see Appendix C) which is a reasonable assumption in transmission networks, as for example in [28, 72, 75].

6. Inter-temporal constraints, e.g., ramping limits of conventional units, are not enforced and thus a single-hour auction is considered, which is consistent with the relevant literature [70, 71, 74, 75].

7. Being consistent with the previous chapters, the operational cost of wind power producers is considered zero, as it is customary in the technical literature, e.g., [20, 21, 22, 23, 24]. In some realistic electricity markets, this cost is even negative due to renewable incentives [25].

8. Finally, demand is considered to be deterministic in order to avoid additional sources of uncertainty and demand price bids are high enough so that demand is, to a certain degree, inelastic.

The aforementioned setup and models are illustrated in Fig. 5.1 and 5.2. Figure 5.1 describes the strategic model. Similar to the previous Chapter 4, we consider a market with multiple strategic producers, i.e., they anticipate the DA market-clearing procedure in their decision-making model based on the available information. A game of complete information is considered, where all strategic producers have perfect knowledge of their rivals price offers to the market. Additionally to this information, all producers have access to the same wind power forecast for the wind power plants. For the sake of simplicity, wind power producers

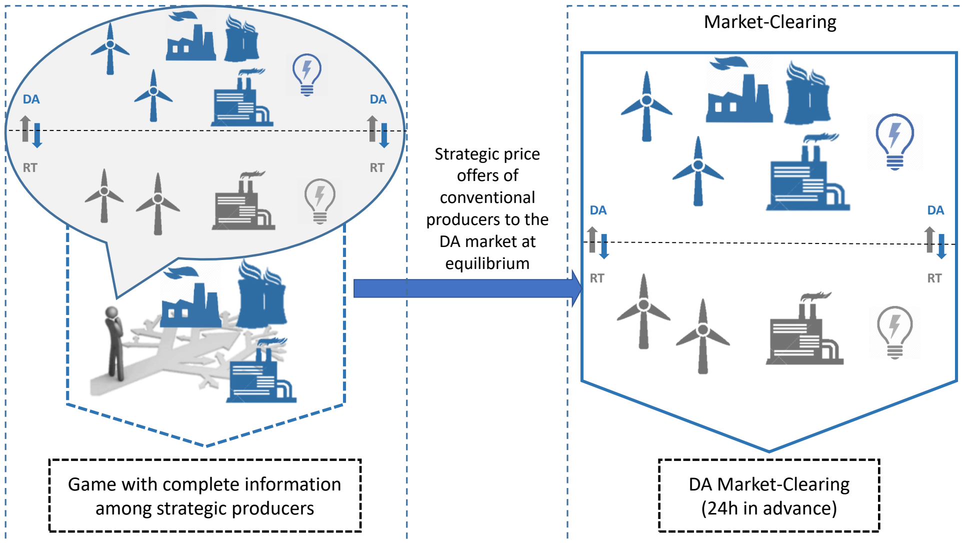

Figure 5.1: Illustrative representation of the market setup under the strategic model of Chapter 5

are not considered strategic in this study. The output of the game is the strategic price offers of conventional power producers at the equilibrium. Then, the DA market is cleared based on the price offers as well as the quantity offers of producers and the same wind power scenarios which are assumed to be common knowledge. Note that similarly to Chapters 2 and 3, a stochastic two-stage DA market is considered, which anticipates the operation of the RT market based on the available wind power scenarios. On the other hand, Fig. 5.2 describes the competitive and VCG models. As described by the illustration, strategic offering is not considered in these models. On the one hand, under the competitive model producers are assumed to behave competitively and not exercise market power. On the other hand, as it will be proved later on, under VCG model producers dominant strategy is to be truthful with respect to their offers. Thus, the two models refer to the same market-clearing setup, even though in the first one perfect competition is an assumption, while in the latter is producers dominant strategy.

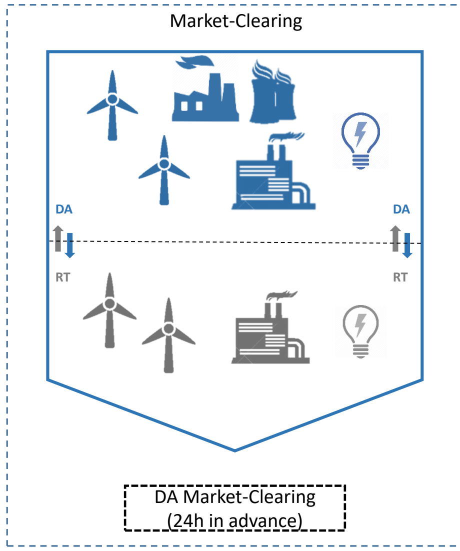

Figure 5.2: Illustrative representation of the market setup under the competitive and VCG models of Chapter 5

5.2.2 Competitive Model: Perfectly Competitive Market

We first explore the case of a perfectly competitive market, where all market participants are price-takers. The market-clearing model is formulated as a two-stage stochastic optimization model, similarly to [28], which is solved in the DA and consists of a DA stage and a RT stage based on a set of wind power scenarios that are generated from an available DA wind power forecast. The DA stage is cleared, while adapting the foreseen RT scenarios, i.e., DA stage anticipates the impacts of DA schedules on future RT adjustments, and therefore, on final expected social welfare (social welfare in DA and expected social welfare in RT). The two-stage model is described in more details in Chapter 1. The objective of the optimization problem is to maximize the expected social welfare. By convention, the standard form of an optimization problem defines a minimization problem and, thus, for illustration reasons the objective function is replaced by its equivalent objective of minimizing the negative expected social welfare. The market-clearing formulation, considering transmission network constraints, is presented below:

$$\underset{\Xi^{\mathrm{P}}}{\text{Minimize}}$$
$$\sum_{i\in\mathcal{I}} \lambda_i^{\mathrm{G}}\, p_i^{\mathrm{G}} - \sum_{d\in\mathcal{D}} \lambda_d^{\mathrm{D}}\, p_d^{\mathrm{D}} + \sum_{s\in\mathcal{S}} \pi_s \Bigg[\sum_{i\in\mathcal{I}} \left(\lambda_i^{\mathrm{U}}\, r_{i,s}^{\mathrm{U}} - \lambda_i^{\mathrm{D}}\, r_{i,s}^{\mathrm{D}}\right) + \sum_{d\in\mathcal{D}} V_d^{\mathrm{sh}}\, l_{d,s}^{\mathrm{sh}} \Bigg] \quad (5.1a)$$

Objective function (5.1a) represents the negative expected social welfare to be minimized. The first term is the aggregate generation cost and the second is the aggregate demands utility in the DA stage, while the third term refers to the RT market and consists of expected generation-side costs as well as load shedding costs in RT.

Objective function (5.1a) is subject to the following constraints:

$$\sum_{d:(d,n)\in\mathcal{M}_D} p_d^{\mathrm{D}} - \sum_{i:(i,n)\in\mathcal{M}_I} p_i^{\mathrm{G}} - \sum_{l:(l,n)\in\mathcal{M}_W} p_l^{\mathrm{W}} + \sum_{m:(n,m)\in\Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} - \delta_m^{\mathrm{DA}}) = 0 : \ \lambda_n^{\mathrm{DA}}\ \forall n \quad (5.1b)$$

Constraint (5.1b) imposes the power balance in DA per node, whose dual variable, i.e., λ_n^{DA}, provides the DA market-clearing price for each node. The term $\sum_{m:(n,m)\in\Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} - \delta_m^{\mathrm{DA}})$ refers to the active power flow from node n to node m (see Appendix C for the corresponding descriptions).

$$\sum_{i:(i,n)\in\mathcal{M}_I} \left(r_{i,s}^{\mathrm{D}} - r_{i,s}^{\mathrm{U}}\right) - \sum_{l:(l,n)\in\mathcal{M}_W} (P_{l,s}^{\mathrm{W,F}} - p_l^{\mathrm{W}} - p_{l,s}^{\mathrm{spill}}) - \sum_{d:(d,n)\in\mathcal{M}_D} l_{d,s}^{\mathrm{sh}} + \sum_{m:(n,m)\in\Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} + \delta_{m,s}^{\mathrm{RT}} - \delta_m^{\mathrm{DA}} - \delta_{n,s}^{\mathrm{RT}}) = 0 : \ \lambda_{n,s}^{\mathrm{RT}}\ \forall n, \forall s \quad (5.1c)$$

Constraint (5.1c) imposes the power balance in RT adjusting the energy imbalance by power adjustments of conventional generators, wind power spillage and load shedding. Its corresponding dual variable, i.e., $\lambda_{n,s}^{\mathrm{RT}}$, provides the probability-weighted RT market-clearing price for each node and scenario.

$$0 \leq p_i^{\mathrm{G}} \leq \overline{P}_i^{\mathrm{G}} \quad : \underline{\phi}_i, \overline{\phi}_i \ \forall i \tag{5.1d}$$

$$0 \leq p_d^{\mathrm{D}} \leq \overline{P}_d^{\mathrm{D}} \quad : \underline{\psi}_d, \overline{\psi}_d \ \forall d \tag{5.1e}$$

$$0 \leq p_l^{\mathrm{W}} \leq \overline{P}_l^{\mathrm{W}} \quad : \underline{\sigma}_l, \overline{\sigma}_l \ \forall l \tag{5.1f}$$

Constraints (5.1d) - (5.1f) bind the DA schedule of conventional units, demands and wind producers based on their maximum quantity offers.

$$0 \leq p_{l,s}^{\mathrm{spill}} \leq P_{l,s}^{\mathrm{W,F}} \quad : \underline{\tau}_{l,s}, \overline{\tau}_{l,s} \ \forall l, \forall s \tag{5.1g}$$

Constraint (5.1g) implies that wind power spillage should be equal to or lower than the wind power realization.

$$0 \leq l_{d,s}^{\mathrm{sh}} \leq p_d^{\mathrm{D}} \quad : \underline{\xi}_{d,s}, \overline{\xi}_{d,s} \ \forall d, \forall s \tag{5.1h}$$

Constraint (5.1h) restricts the load shedding quantity by the demands schedules.

$$0 \leq r_{i,s}^{\mathrm{D}} \leq R_i^{\mathrm{D}} \quad : \underline{\rho}_{i,s}^{\mathrm{D}}, \overline{\rho}_{i,s}^{\mathrm{D}} \ \forall i, \forall s \tag{5.1i}$$

$$0 \leq r_{i,s}^{\mathrm{U}} \leq R_i^{\mathrm{U}} \quad : \underline{\rho}_{i,s}^{\mathrm{U}}, \overline{\rho}_{i,s}^{\mathrm{U}} \ \forall i, \forall s \tag{5.1j}$$

$$r_{i,s}^{\mathrm{U}} \leq \left(\overline{P}_i^{\mathrm{G}} - p_i^{\mathrm{G}}\right) \quad : \underline{\mu}_{i,s}^{\mathrm{U}}, \overline{\mu}_{i,s}^{\mathrm{U}} \ \forall i, \forall s \tag{5.1k}$$

$$r_{i,s}^{\mathrm{D}} \leq p_i^{\mathrm{G}} \quad : \underline{\mu}_{i,s}^{\mathrm{D}}, \overline{\mu}_{i,s}^{\mathrm{D}} \ \forall i, \forall s \tag{5.1l}$$

Constraints (5.1i)-(5.1j) bind power adjustments in RT by the upward and downward reserve capacities. Additionally, constraints (5.1k)-(5.1l) bind power adjustments in RT accounting for the available conventional generation capacity following DA power dispatch. Thus, upward power adjustments for conventional generators cannot be greater than the remaining power capacity after deducting DA scheduled power and, similarly, downward power adjustments cannot be greater than the DA scheduled power.

$$B_{n,m}(\delta_n^{\mathrm{DA}} - \delta_m^{\mathrm{DA}}) \leq F_{n,m}^{\max} \;\; : \epsilon_{n,m}^{\mathrm{DA}} \; \forall (n,m) \in \Lambda \tag{5.1m}$$

$$B_{n,m}(\delta_{n,s}^{\mathrm{RT}} - \delta_{m,s}^{\mathrm{RT}}) \leq F_{n,m}^{\max} \;\; : \epsilon_{n,m,s}^{\mathrm{RT}} \; \forall (n,m) \in \Lambda, \forall s \tag{5.1n}$$

$$-\pi \leq \delta_n^{\mathrm{DA}} \leq \pi \;\; : \underline{\gamma}_n^{\mathrm{DA}}, \overline{\gamma}_n^{\mathrm{DA}} \; \forall n \tag{5.1o}$$

$$-\pi \leq \delta_{n,s}^{\mathrm{RT}} \leq \pi \;\; : \underline{\gamma}_{n,s}^{\mathrm{RT}}, \overline{\gamma}_{n,s}^{\mathrm{RT}} \; \forall n, \forall s \tag{5.1p}$$

$$\delta_{n=1}^{\mathrm{DA}} = 0 \;\; : \gamma^{\mathrm{DA}} \tag{5.1q}$$

$$\delta_{n=1,s}^{\mathrm{RT}} = 0 \;\; : \gamma_s^{\mathrm{RT}} \; \forall s. \tag{5.1r}$$

Constraints (5.1m)-(5.1n) restrict the power flow in transmission lines by the maximum capacity of the line, while constraints (5.1o)-(5.1r) restrict maximum and minimum values of the voltage angles and set node n=1 as reference node.

Some of the aforementioned constraints may refer exclusively to either the DA or the RT stage of the two-stage programming model, but some also link the DA and RT stages. More specifically, constraints (5.1b), (5.1d)-(5.1f), (5.1m), (5.1o) and (5.1q) are associated with the DA stage of the two-stage optimization problem, while (5.1g), (5.1h), (5.1i), (5.1j), (5.1n), (5.1p) and (5.1r) are associated with the RT stage. The power balance equation in RT, i.e., (5.1c), apart from the RT variables, also involves DA variables p_l^{W} and δ_n^{DA}. Also, constraints (5.1k) and (5.1l), which refer to the upper bounds of the reserves in RT, depend on the DA schedules p_i^{G}. Thus, constraints (5.1c), (5.1k) and (5.1l) link the DA and RT stages, highlighting the need for a two-stage programming solution.

In case we neglect transmission network, aforementioned constraints as well as the terms related to power flows through the lines in the power balance equations (5.1b) and (5.1c) are not considered, leading to a market-clearing solution for the whole system and a single market-clearing price, as in Chapters 2 and 3.

Finally, $\Xi^{\mathrm{P}} = \{p_i^{\mathrm{G}},\ p_l^{\mathrm{W}},\ r_{i,s}^{\mathrm{U}},\ r_{i,s}^{\mathrm{D}},\ l_{d,s}^{\mathrm{sh}},\ p_{l,s}^{\mathrm{spill}},\ p_d^{\mathrm{D}},\ \delta_n^{\mathrm{DA}},\ \delta_{n,s}^{\mathrm{RT}}\}$ is the set of primal variables and $\Xi^{\mathrm{D}} = \{\lambda_n^{\mathrm{DA}}, \lambda_{n,s}^{\mathrm{RT}}, \underline{\phi}_i, \overline{\phi}_i, \underline{\psi}_d, \overline{\psi}_d, \underline{\sigma}_l, \overline{\sigma}_l, \underline{\tau}_{l,s}, \overline{\tau}_{l,s}, \underline{\xi}_{d,s}, \overline{\xi}_{d,s}, \underline{\rho}_{i,s}^{\mathrm{D}}, \overline{\rho}_{i,s}^{\mathrm{D}}, \underline{\rho}_{i,s}^{\mathrm{U}}, \overline{\rho}_{i,s}^{\mathrm{U}}, \underline{\mu}_{i,s}^{\mathrm{U}}, \overline{\mu}_{i,s}^{\mathrm{U}}, \underline{\mu}_{i,s}^{\mathrm{D}}, \overline{\mu}_{i,s}^{\mathrm{D}}, \epsilon_{n,m}^{\mathrm{DA}}, \epsilon_{n,m,s}^{\mathrm{RT}}, \underline{\gamma}_n^{\mathrm{DA}}, \overline{\gamma}_n^{\mathrm{DA}}, \underline{\gamma}_{n,s}^{\mathrm{RT}}, \overline{\gamma}_{n,s}^{\mathrm{RT}}, \gamma^{\mathrm{DA}}, \gamma_s^{\mathrm{RT}}\}$ is the set of the dual variables of optimization problem (5.1).

5.2.3 Strategic Model: Imperfectly Competitive Market

The market mechanism of Section 5.2.2 is efficient, ensures cost-recovery and revenue-adequacy in expectation [28] but does not guarantee that market participants will remain price-takers and will not exercise market power. In this subsection, we investigate an LMP market setup which, being more consistent to real markets, additionally considers strategic producers. Under such a context, we consider an imperfectly competitive market and we search for the market equilibrium through the iterative diagonalization approach presented in Chapter 4. Each conventional producer's decision-making model is described by bilevel model (5.2) below.

The upper-level (UL) objective function maximizes the profit of producer J, and consists of:

- Producer's profit due to conventional generation after deducting the generation costs in DA stage, i.e., $\sum_{i\in\mathcal{I}_J}(\lambda^{\mathrm{DA}}_{(n:i\in\mathcal{M}_I)} - \lambda^{\mathrm{G}}_i)\; p^{\mathrm{G}}_i$.
- Associated profits for providing power adjustments in RT stage, i.e., $\sum_{s\in\mathcal{S}}\; \pi_s \left[\sum_{i\in\mathcal{I}_J} r^{\mathrm{U}}_{i,s} (\frac{\lambda^{\mathrm{RT}}_{(n:i\in\mathcal{M}_I),s}}{\pi_s} - \lambda^{\mathrm{U}}_i) - \sum_{i\in\mathcal{I}_J} r^{\mathrm{D}}_{i,s} (\frac{\lambda^{\mathrm{RT}}_{(n:i\in\mathcal{M}_I),s}}{\pi_s} - \lambda^{\mathrm{D}}_i) \right]$.

The UL objective function is, thus, given by (5.2a) and is constrained by constraint (5.2b) and the lower-level (LL) problem (5.2c)-(5.2t), which, similarly to the model of the previous subsection, clears the stochastic two-stage DA market.

$$\underset{\alpha^{\mathrm{G}}_i\;\forall i\in\mathcal{I}_J,\;\Xi^{\mathrm{LL,P}}\;\cup\;\Xi^{\mathrm{LL,D}}}{\text{Maximize}}$$

$$\sum_{i\in\mathcal{I}_J} p^{\mathrm{G}}_i\;(\lambda^{\mathrm{DA}}_n - \lambda^{\mathrm{G}}_i) + \sum_{s\in\mathcal{S}}\;\pi_s \left[\sum_{i\in\mathcal{I}_J} r^{\mathrm{U}}_{i,s}\;(\frac{\lambda^{\mathrm{RT}}_{n,s}}{\pi_s} - \lambda^{\mathrm{U}}_i) - \sum_{i\in\mathcal{I}_J} r^{\mathrm{D}}_{i,s}\;(\frac{\lambda^{\mathrm{RT}}_{n,s}}{\pi_s} - \lambda^{\mathrm{D}}_i) \right] \tag{5.2a}$$

$$\alpha^{\mathrm{G}}_i \geq 0 \;\forall i \in \mathcal{I}_J \tag{5.2b}$$

The UL constraint (5.2b), above, imposes the strategic price offer for the conventional units, i.e., α^{G}_i, to be non-negative.

The lower-level objective function (5.2c) minimizes the negative expected social welfare based on producers offers and demands bids. Note that producers offers under this model are not equal to generation costs but they are strategic price offers. Furthermore, strategic price offer α_i^{G} is a variable for the UL problem, but treated as a parameter within the LL problem.

$$\begin{aligned}
&\underset{\Xi^{\mathrm{P}}}{\text{Minimize}} \\
&\sum_{i\in\mathcal{I}} \alpha_i^{\mathrm{G}}\ p_i^{\mathrm{G}} - \sum_{d\in\mathcal{D}} \lambda_d^{\mathrm{D}}\ p_d^{\mathrm{D}} + \sum_{s\in\mathcal{S}} \pi_s \Big[\sum_{i\in\mathcal{I}} \left(\lambda_i^{\mathrm{U}}\ r_{i,s}^{\mathrm{U}} - \lambda_i^{\mathrm{D}}\ r_{i,s}^{\mathrm{D}}\right) \\
&\qquad + \sum_{d\in\mathcal{D}} V_d^{\mathrm{sh}}\ l_{d,s}^{\mathrm{sh}} \Big] \qquad (5.2\text{c})
\end{aligned}$$

Finally, LL objective function (5.2c), above, is subject to the following constraints:

$$\begin{aligned}
&\sum_{d:(d,n)\in\mathcal{M}_D} p_d^{\mathrm{D}} - \sum_{i:(i,n)\in\mathcal{M}_I} p_i^{\mathrm{G}} - \sum_{l:(l,n)\in\mathcal{M}_W} p_l^{\mathrm{W}} \\
&\qquad + \sum_{m:(n,m)\in\Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} - \delta_m^{\mathrm{DA}}) = 0 :\ \lambda_n^{\mathrm{DA}}\ \forall n \qquad (5.2\text{d}) \\
&\sum_{i:(i,n)\in\mathcal{M}_I} \left(r_{i,s}^{\mathrm{D}} - r_{i,s}^{\mathrm{U}}\right) - \sum_{l:(l,n)\in\mathcal{M}_W} (P_{l,s}^{\mathrm{W,F}} - p_l^{\mathrm{W}} - p_{l,s}^{\mathrm{spill}}) \\
&\quad - \sum_{d:(d,n)\in\mathcal{M}_D} l_{d,s}^{\mathrm{sh}} - \sum_{m:(n,m)\in\Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} + \delta_{m,s}^{\mathrm{RT}} - \delta_m^{\mathrm{DA}} - \delta_{n,s}^{\mathrm{RT}}) \\
&\quad = 0\ :\ \lambda_{n,s}^{\mathrm{RT}}\ \forall n, \forall s \qquad (5.2\text{e}) \\
&0 \le p_i^{\mathrm{G}} \le \overline{P}_i^{\mathrm{G}}\ :\ \underline{\phi}_i^{\mathrm{G}}, \overline{\phi}_i^{\mathrm{G}}\ \forall i \qquad (5.2\text{f}) \\
&0 \le p_d^{\mathrm{D}} \le \overline{P}_d^{\mathrm{D}}\ :\ \underline{\psi}_d^{\mathrm{D}}, \overline{\psi}_d^{\mathrm{D}}\ \forall d \qquad (5.2\text{g}) \\
&0 \le p_l^{\mathrm{W}} \le \overline{P}_l^{\mathrm{W}}\ :\ \underline{\sigma}_l, \overline{\sigma}_l\ \forall l \qquad (5.2\text{h}) \\
&0 \le p_{l,s}^{\mathrm{spill}} \le P_{l,s}^{\mathrm{W,F}}\ :\ \underline{\tau}_{l,s}, \overline{\tau}_{l,s}\ \forall l, \forall s \qquad (5.2\text{i}) \\
&0 \le l_{d,s}^{\mathrm{sh}} \le p_d^{\mathrm{D}}\ :\ \underline{\xi}_{d,s}, \overline{\xi}_{d,s}\ \forall d, \forall s \qquad (5.2\text{j}) \\
&0 \le r_{i,s}^{\mathrm{D}} \le R_i^{\mathrm{D}}\ :\ \underline{\mu}_{i,s}^{\mathrm{D}}, \overline{\mu}_{i,s}^{\mathrm{D}}\ \forall i, \forall s \qquad (5.2\text{k})
\end{aligned}$$

$$0 \leq r^{\mathrm{U}}_{i,s} \leq R^{\mathrm{U}}_{i} \quad : \underline{\mu}^{\mathrm{U}}_{i,s}, \overline{\mu}^{\mathrm{U}}_{i,s} \ \forall i, \forall s \tag{5.2l}$$

$$r^{\mathrm{U}}_{i,s} \leq \left(\overline{P}^{\mathrm{G}}_{i} - p^{\mathrm{G}}_{i}\right) \quad : \overline{\mu}_{i,s} \ \forall i, \forall s \tag{5.2m}$$

$$r^{\mathrm{D}}_{i,s} \leq p^{\mathrm{G}}_{i} \quad : \underline{\mu}_{i,s} \ \forall i, \forall s \tag{5.2n}$$

$$B_{n,m}(\delta^{\mathrm{DA}}_{n} - \delta^{\mathrm{DA}}_{m}) \leq F^{\max}_{n,m} \quad : \epsilon^{\mathrm{DA}}_{n,m} \ \forall (n,m) \in \Lambda \tag{5.2o}$$

$$B_{n,m}(\delta^{\mathrm{RT}}_{n,s} - \delta^{\mathrm{RT}}_{m,s}) \leq F^{\max}_{n,m} \quad : \epsilon^{\mathrm{RT}}_{n,m,s} \ \forall (n,m) \in \Lambda, \forall s \tag{5.2p}$$

$$-\pi \leq \delta^{\mathrm{DA}}_{n} \leq \pi \quad : \underline{\gamma}^{\mathrm{DA}}_{n}, \overline{\gamma}^{\mathrm{DA}}_{n} \ \forall n \tag{5.2q}$$

$$-\pi \leq \delta^{\mathrm{RT}}_{n,s} \leq \pi \quad : \underline{\gamma}^{\mathrm{RT}}_{n,s}, \overline{\gamma}^{\mathrm{RT}}_{n,s} \ \forall n, \forall s \tag{5.2r}$$

$$\delta^{\mathrm{DA}}_{n=1} = 0 \quad : \gamma^{\mathrm{DA}} \tag{5.2s}$$

$$\delta^{\mathrm{RT}}_{n=1,s} = 0 \quad : \gamma^{\mathrm{RT}}_{s} \ \forall s. \tag{5.2t}$$

Constraints (5.2d)-(5.2t) are similar to constraints (5.1d)-(5.1q) of the previous subsection of the two-stage market-clearing model.

The primal variables of the LL are included in the set $\Xi^{\mathrm{P}} = \{p^{\mathrm{G}}_{i},\ p^{\mathrm{W}}_{l},\ r^{\mathrm{U}}_{i,s},\ r^{\mathrm{D}}_{i,s},\ l^{\mathrm{sh}}_{d,s},\ p^{\mathrm{spill}}_{l,s},\ p^{\mathrm{D}}_{d},\ \delta^{\mathrm{DA}}_{n},\ \delta^{\mathrm{RT}}_{n,s}\}$.

In addition, the dual variables of the LL are included in the set $\Xi^{\mathrm{LL,D}} = \{\lambda^{\mathrm{DA}}_{n},\ \lambda^{\mathrm{RT}}_{n,s},\ \underline{\phi}^{\mathrm{G}}_{i},\ \overline{\phi}^{\mathrm{G}}_{i},\ \underline{\psi}^{\mathrm{D}}_{d},\ \overline{\psi}^{\mathrm{D}}_{d},\ \underline{\sigma}_{l},\ \overline{\sigma}_{l},\ \underline{\tau}_{l,s},\ \overline{\tau}_{l,s},\ \underline{\xi}_{d,s},\ \overline{\xi}_{d,s},\ \underline{\mu}^{\mathrm{D}}_{i,s},\ \overline{\mu}^{\mathrm{D}}_{i,s},\ \underline{\mu}^{\mathrm{U}}_{i,s},\ \overline{\mu}^{\mathrm{U}}_{i,s},\ \overline{\mu}_{i,s},\ \underline{\mu}_{i,s},\ \epsilon^{\mathrm{DA}}_{n,m},\ \epsilon^{\mathrm{RT}}_{n,m,s},\ \underline{\gamma}^{\mathrm{DA}}_{n},\ \overline{\gamma}^{0}_{n},\ \underline{\gamma}^{\mathrm{RT}}_{n,s},\ \overline{\gamma}^{\mathrm{RT}}_{n,s},\ \gamma^{\mathrm{DA}},\ \gamma^{\mathrm{RT}}_{s}\ \}$.

Finally, the primal variables of the UL (5.2a)-(5.2b) are α^{G}_{i} $\forall i \in \mathcal{I}_J$ as well as all members of variable sets $\Xi^{\mathrm{LL,P}}$ and $\Xi^{\mathrm{LL,D}}$.

Model (5.2) is solved iteratively for every producer J until equilibrium is reached, following the approach of Chapter 4, assuming perfect information for each player. To solve bilevel model (5.2), we follow the procedure explained in Chapters 2 - 4. The LL problem (5.2c)-(5.2t) is continuous, linear and, therefore, convex. This allows bilevel problem (5.2) to be recast as a single-level mathematical program with equilibrium constraints (MPEC) through replacing the LL problem by its Karush-Kuhn-Tucker (KKT) optimality conditions [66, 67]. Simlarly to Chapters 2-4 and as explained in Appendix A, the KKT conditions are derived from the Lagrangian function associated with the LL, by differentiating it each time with the corresponding primal variable of the LL problem:

$$\frac{\partial \mathcal{L}}{\partial p_i^{\mathrm{G}}} = \alpha_i^{\mathrm{G}} - \lambda_{n:i\in\mathcal{M}_I}^{\mathrm{DA}} - \underline{\phi}_i + \overline{\phi}_i + \sum_{s\in\mathcal{S}}(\overline{\mu}_{i,s} - \underline{\mu}_{i,s}) = 0 \ \forall i \quad (5.3a)$$

$$\frac{\partial \mathcal{L}}{\partial p_l^{\mathrm{W}}} = -\lambda_{n:l\in\mathcal{M}_W}^{\mathrm{DA}} - \underline{\sigma}_l + \overline{\sigma}_l + \sum_{s\in\mathcal{S}} \lambda_{(n:l\in\mathcal{M}_W),s}^{\mathrm{RT}} = 0 \ \forall l \quad (5.3b)$$

$$\frac{\partial \mathcal{L}}{\partial r_{i,s}^{\mathrm{U}}} = \pi_s \lambda_i^{\mathrm{U}} - \lambda_{(n:i\in\mathcal{M}_I),s}^{\mathrm{RT}} - \underline{\mu}_{i,s}^{\mathrm{U}} + \overline{\mu}_{i,s}^{\mathrm{U}} + \overline{\mu}_{i,s} = 0 \ \forall i, \forall s \quad (5.3c)$$

$$\frac{\partial \mathcal{L}}{\partial r_{i,s}^{\mathrm{D}}} = -\pi_s \lambda_i^{\mathrm{D}} + \lambda_{(n:i\in\mathcal{M}_I),s}^{\mathrm{RT}} - \underline{\mu}_{i,s}^{\mathrm{D}} + \overline{\mu}_{i,s}^{\mathrm{D}} + \underline{\mu}_{i,s} = 0 \ \forall i, \forall s \quad (5.3d)$$

$$\frac{\partial \mathcal{L}}{\partial l_{d,s}^{\mathrm{sh}}} = \pi_s V_d^{\mathrm{sh}} - \lambda_{(n:d\in\mathcal{M}_D),s}^{\mathrm{RT}} - \underline{\xi}_{d,s} + \overline{\xi}_{d,s} = 0 \ \forall d, \forall s \quad (5.3e)$$

$$\frac{\partial \mathcal{L}}{\partial p_{l,s}^{\mathrm{spill}}} = \lambda_{(n:l\in\mathcal{M}_W),s}^{\mathrm{RT}} - \underline{\tau}_{l,s} + \overline{\tau}_{l,s} = 0 \ \forall l, \forall s \quad (5.3f)$$

$$\frac{\partial \mathcal{L}}{\partial p_d^{\mathrm{D}}} = \lambda_{n:d\in\mathcal{M}_D}^{\mathrm{DA}} - \lambda_d^{\mathrm{D}} - \underline{\psi}_d + \overline{\psi}_d - \overline{\xi}_{d,s} = 0 \ \forall d, \forall s \quad (5.3g)$$

$$\frac{\partial \mathcal{L}}{\partial \delta_n^{\mathrm{DA}}} = \sum_{m\in\Lambda}(\lambda_n^{\mathrm{DA}} - \lambda_m^{\mathrm{DA}})B_{n,m} - \sum_{m\in\Lambda}\sum_{s\in\mathcal{S}}(\lambda_{n,s}^{\mathrm{RT}} - \lambda_{m,s}^{\mathrm{RT}})B_{n,m} + \sum_{m\in\Lambda}(\epsilon_{n,m}^{\mathrm{DA}} - \epsilon_{m,n}^{\mathrm{DA}})B_{n,m} - \underline{\gamma}_n^{\mathrm{DA}} + \overline{\gamma}_n^{\mathrm{DA}} + (\gamma^{\mathrm{DA}})_{n=1} = 0 \ \forall n \quad (5.3h)$$

$$\frac{\partial \mathcal{L}}{\partial \delta_{n,s}^{\mathrm{RT}}} = \sum_{m\in\Lambda}\sum_{s\in\mathcal{S}}(\lambda_{n,s}^{\mathrm{RT}} - \lambda_{m,s}^{\mathrm{RT}})B_{n,m} + \sum_{m\in\Lambda}(\epsilon_{n,m,s}^{\mathrm{RT}} - \epsilon_{m,n,s}^{\mathrm{RT}})B_{n,m} - \underline{\gamma}_{n,s}^{\mathrm{RT}} + \overline{\gamma}_{n,s}^{\mathrm{RT}} + (\gamma_s^{\mathrm{RT}})_{n=1} = 0 \ \forall n, \forall s \quad (5.3i)$$

Lastly, complementarity slackness conditions, which refer to the relationship between the positivity in a primal constraint and the positivity of its associated dual variable, are given below:

$$0 \le \overline{P}_i^{\mathrm{G}} \perp \underline{\phi}_i^{\mathrm{G}} \ge 0 \ \forall i \quad (5.3j)$$

$$0 \le (\overline{P}_i^{\mathrm{G}} - p_i^{\mathrm{G}}) \perp \overline{\phi}_i^{\mathrm{G}} \ge 0 \ \forall i \quad (5.3k)$$

$$0 \leq \overline{P}_d^{\mathrm{D}} \perp \underline{\psi_d} \geq 0 \ \forall d \tag{5.3l}$$

$$0 \leq (\overline{P}_d^{\mathrm{D}} - p_d^{\mathrm{D}}) \perp \overline{\psi_d} \geq 0 \ \forall d \tag{5.3m}$$

$$0 \leq p_l^{\mathrm{W}} \perp \underline{\sigma}_l \geq 0 \ \forall l \tag{5.3n}$$

$$0 \leq (P_l^{\mathrm{W}} - p_l^{\mathrm{W}}) \perp \overline{\sigma}_l \geq 0 \ \forall l \tag{5.3o}$$

$$0 \leq p_{l,s}^{\mathrm{spill}} \perp \underline{\tau}_{l,s} \geq 0 \ \forall l, \forall s \tag{5.3p}$$

$$0 \leq (P_{l,s}^{\mathrm{W,F}} - p_{l,s}^{\mathrm{spill}}) \perp \overline{\tau}_{l,s} \geq 0 \ \forall l, \forall s \tag{5.3q}$$

$$0 \leq l_{d,s}^{\mathrm{sh}} \perp \underline{\xi}_{d,s} \geq 0 \ \forall d, \forall s \tag{5.3r}$$

$$0 \leq (p_d^{\mathrm{D}} - l_{d,s}^{\mathrm{sh}}) \perp \overline{\xi}_{d,s} \geq 0 \ \forall d, \forall s \tag{5.3s}$$

$$0 \leq r_{i,s}^{\mathrm{D}} \perp \underline{\mu}_{i,s}^{\mathrm{D}} \geq 0 \ \forall i, \forall s \tag{5.3t}$$

$$0 \leq (R_i^{\mathrm{D}} - r_{i,s}^{\mathrm{D}}) \perp \overline{\mu}_{i,s}^{\mathrm{Ds}} \geq 0 \ \forall i, \forall s \tag{5.3u}$$

$$0 \leq r_{i,s}^{\mathrm{U}} \perp \underline{\mu}_{i,s}^{\mathrm{U}} \geq 0 \ \forall i, \forall s \tag{5.3v}$$

$$0 \leq (R_i^{\mathrm{U}} - r_{i,s}^{\mathrm{U}}) \perp \overline{\mu}_{i,s}^{\mathrm{U}} \geq 0 \ \forall i, \forall s \tag{5.3w}$$

$$0 \leq (\overline{P}_i^{\mathrm{G}} - r_{i,s}^{\mathrm{U}} - p_i^{\mathrm{Gs}}) \perp \overline{\mu}_{i,s} \geq 0 \ \forall i, \forall s \tag{5.3x}$$

$$0 \leq (p_i^{\mathrm{G}} - r_{i,s}^{\mathrm{D}}) \perp \underline{\mu}_{i,s} \geq 0 \ \forall i, \forall s \tag{5.3y}$$

$$0 \leq [\overline{F}_{n,m} - B_{n,m}(\delta_n^0 - \delta_m^0)] \perp \epsilon_{n,m}^{\mathrm{DA}} \geq 0 \ \forall n, \forall m \tag{5.3z}$$

$$0 \leq [\overline{F}_{n,m} - B_{n,m}(\delta_{n,s}^{\mathrm{RT}} - \delta_{m,s}^{\mathrm{RT}})] \perp \epsilon_{n,m,s}^{\mathrm{RT}} \geq 0 \ \forall n, \forall m, \forall s \tag{5.3za}$$

$$0 \leq (\delta_n^0 + \pi) \perp \underline{\gamma}_n^0 \geq 0 \ \forall n \tag{5.3zb}$$

$$0 \leq (-\delta_n^0 + \pi) \perp \overline{\gamma}_n^0 \geq 0 \ \forall n \tag{5.3zc}$$

$$0 \leq (\delta_{n,s}^{\mathrm{RT}} + \pi) \perp \underline{\gamma}_{n,s}^{\mathrm{RT}} \geq 0 \ \forall n, \forall s \tag{5.3zd}$$

$$0 \leq (-\delta_{n,s}^{\mathrm{RT}} + \pi) \perp \overline{\gamma}_{n,s}^{\mathrm{RT}} \geq 0 \ \forall n, \forall s, \tag{5.3ze}$$

where operator $\perp$ (perpendicular) enforces the perpendicular condition between the vectors on the left-hand and right-hand sides, i.e., their element-by-element product is zero.

Thus, bilevel model (5.2), is finally replaced by the MPECs below, one per producer:

$$\Bigg\{ \underset{p_i^{\mathrm{G}},\ \Xi^{\mathrm{LL,P}} \ \cup \ \Xi^{\mathrm{LL,D}}}{\text{Maximize}} (5.2a)$$

subject to

$$(5.2b),\ (5.2d) \text{ and } (5.2e) \tag{5.4a}$$

$$(5.3a) - (5.3i) \tag{5.4b}$$
$$(5.3j) - (5.3ze) \tag{5.4c}$$
$$\Big\} \; \forall \mathcal{J}.$$

MPECs (5.4), one per producer, are non-linear due to the following two sources of non-linearities:

- the bilinear terms $p_i^{\mathrm{G}} \; \lambda_n^{\mathrm{DA}}$, $r_{i,s}^{\mathrm{U}} \; \lambda_{n,s}^{\mathrm{RT}}$ and $r_{i,s}^{\mathrm{D}} \; \lambda_{n,s}^{\mathrm{RT}}$ included in the objective function (5.2a), and
- complementarity conditions (5.4c).

The bilinear terms inside the objective function are linearized based on an approach without approximation, deploying the strong duality theorem (SDT) and mathematical expressions (5.3a)-(5.3ze), following the same procedure as in Chapters 2 - 4. The SDT states that if a problem is convex then the objective functions of the primal and dual problems have the same value at the optimum, and for the given problem this writes as in (5.5) below:

$$\begin{aligned}
&\sum_{i\in\mathcal{I}} \alpha_i^{\mathrm{G}} \; p_i^{\mathrm{G}} - \sum_{d\in\mathcal{D}} \lambda_d^{\mathrm{D}} \; p_d^{\mathrm{D}} + \sum_{s\in\mathcal{S}} \pi_s \Bigg[\sum_{i\in\mathcal{I}} \left(\lambda_i^{\mathrm{U}} \; r_{i,s}^{\mathrm{U}} - \lambda_i^{\mathrm{D}} \; r_{i,s}^{\mathrm{D}} \right) + \sum_{d\in\mathcal{D}} V_d^{\mathrm{sh}} \; l_{d,s}^{\mathrm{sh}} \Bigg] = \\
&- \sum_{n\in\Lambda} \; \sum_{l:(l,n)\in\mathcal{M}_W} \; \sum_{s\in\mathcal{S}} P_{l,s}^{\mathrm{W,F}} \lambda_{n,s}^{\mathrm{RT}} - \sum_{i\in\mathcal{I}} \overline{P}_i^{\mathrm{G}} \overline{\phi}_i^{\mathrm{G}} - \sum_{d\in\mathcal{D}} \overline{P}_d^{\mathrm{D}} \overline{\psi}_d^{\mathrm{D}} - \sum_{l\in\mathcal{W}} \overline{P}_l^{\mathrm{W}} \overline{\sigma}_l \\
&- \sum_{l\in\mathcal{W}} \sum_{s\in\mathcal{S}} P_{l,s}^{\mathrm{W,F}} \overline{\tau}_{l,s} - \sum_{i\in\mathcal{I}} \sum_{s\in\mathcal{S}} \left(R_i^{\mathrm{D}} \overline{\mu}_{i,s}^{\mathrm{D}} + R_i^{\mathrm{U}} \overline{\mu}_{i,s}^{\mathrm{U}} + \overline{P}_i^{\mathrm{G}} \overline{\mu}_{i,s} \right) \\
&- \sum_{(n,m)\in\Lambda} F_{n,m}^{\max} \epsilon_{n,m}^{\mathrm{DA}} - \sum_{(n,m)\in\Lambda} \sum_{s\in\mathcal{S}} F_{n,m}^{\max} \epsilon_{n,m,s}^{\mathrm{RT}} \\
&- \sum_{n\in\Lambda} \pi \left(\overline{\gamma}_n^{\mathrm{DA}} + \underline{\gamma}_n^{\mathrm{DA}} + \sum_{s\in\mathcal{S}} \overline{\gamma}_{n,s}^{\mathrm{RT}} + \sum_{s\in\mathcal{S}} \underline{\gamma}_{n,s}^{\mathrm{RT}} \right).
\end{aligned} \tag{5.5}$$

Finally, similarly to Chapter 4 and due to the iterative nature of the equilibrium problem, complementarity conditions are linearized based on the SOS1 approach [66, 120] but at the cost of introducing a set of auxiliary SOS1 variables. The SOS1 method is explained at the end of Appendix A. The corresponding MPEC is linearized and then solved, as a MILP, similarly to Chapters 2 and 3 and according to the procedure explained in Appendix A. The collection of all MPECs, one per producer, forms an equilibrium problem with equilibrium constraints (EPEC), whose solution identifies the equilibrium point. Unlike [70, 90, 75], for consistency with Chapter 4, we use an iterative diagonalization approach to solve EPEC, in which each producer determines sequentially its strategy considering the rivals' strategies fixed. The iterations continue until no producer changes its strategy unilaterally or until the maximum number of iterations is reached, as illustrated in Fig. 5.3. For a detailed description of the iterative diagonalization approach we refer to Section 4.2.4.

5.2.4 VCG Model: Incentive-Compatible Market-Clearing Mechanism for a Two-Stage Stochastic Market

As indicated in Section 5.2.2, the Competitive market-clearing mechanism does not guarantee that market participants will remain price-takers and will not exercise market power. Therefore, in this subsection we evaluate a VCG-based market-clearing mechanism, which induces truthfulness while at the same time ensures market efficiency. However, as elaborated in the introduction section, VCG does not guarantee revenue-adequacy, potentially leading the market to budget deficit. Thus, budget imbalance should be exogenously recovered by additional payments from market agents, which however may lead to losses in market efficiency or cost-recovery depending on the approach, as shown by the *Myerson-Satterthwaite* theorem [40]. In this study we quantify budget imbalance in a large-scale network-constrained market with high wind power penetration and attempt to partially recover it through a redistribution approach based on the contribution of each market agent on the budget imbalance.

The first step of this approach is to ensure efficient economic dispatch by using the same model as Section 5.2.2, which guarantees market efficiency given a perfectly competitive market. To this end, note that the present model ensures a perfectly competitive market being incentive-

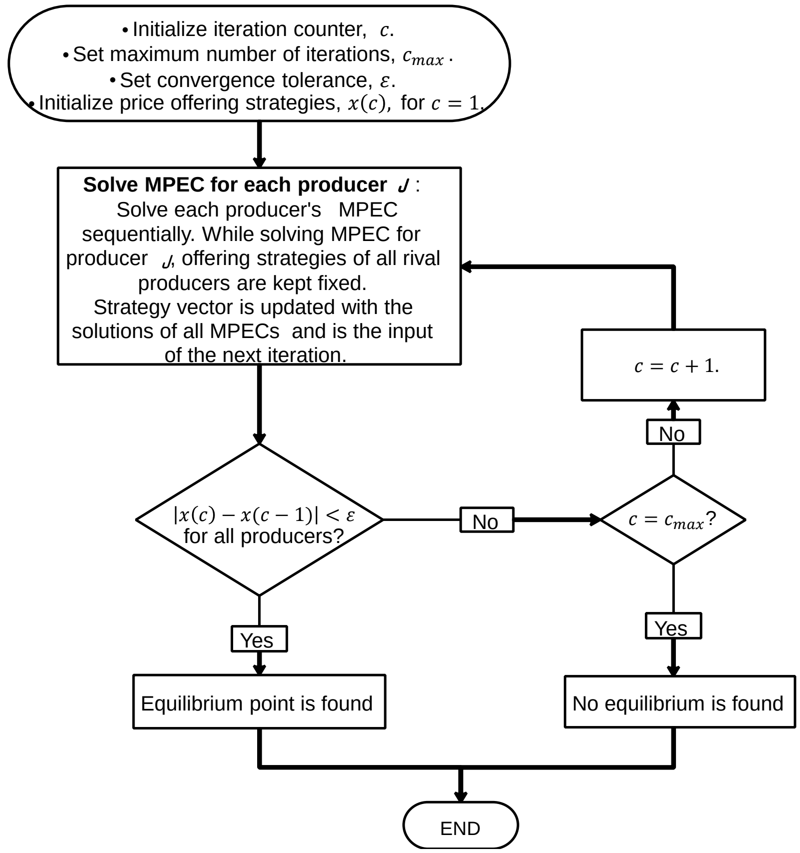

Figure 5.3: (Figure 4.2) The iterative diagonalization approach to identify the equilibrium point for the Strategic LMP model

compatible, as it will be proved in the following paragraphs. This is in contrast with the Competitive model, under which perfect competition is only an assumption. At the second step of the VCG mechanism, demands charges and generation payments are decided based on their individual contribution to market social welfare maximization, which reflects the economic impact of each participant on social welfare.

Regarding producers, the aforementioned payment scheme is designed to endogenize the social welfare function into each producer J's profit-maximizing function, by paying the producer the difference between: (i) the expected social welfare when all agents participate plus producer J's reported operational cost, and (ii) the expected social welfare when J

does not participate, see e.g. (5.7). Demands payments to the market are defined in a similar way.

5.2.4.1 VCG payments to conventional producers

Let producer J be the one whose revenue is to be calculated and $\mathcal{I}_{-J}$ be the set of participating producers excluding J. The social welfare when J does not participate will be derived by the solution of problem (5.6) below. Note that in the below problem, the objective function corresponds to the negative expected social welfare to be minimized, which is equivalent to maximizing expected social welfare.

$$\begin{cases} \underset{\Xi^{\mathrm{P}}}{\text{Minimize}} \end{cases}$$

$$\sum_{i\in\mathcal{I}_{-J}} \lambda_i^{\mathrm{G}}\, p_i^{\mathrm{G}} - \sum_{d\in\mathcal{D}} \lambda_d^{\mathrm{D}}\, p_d^{\mathrm{D}} + \sum_{s\in\mathcal{S}} \pi_s \Bigg[\sum_{i\in\mathcal{I}_{-J}} \left(\lambda_i^{\mathrm{U}}\, r_{i,s}^{\mathrm{U}} - \lambda_i^{\mathrm{D}}\, r_{i,s}^{\mathrm{D}}\right) + \sum_{d\in\mathcal{D}} V_d^{\mathrm{sh}}\, l_{d,s}^{\mathrm{sh}} \Bigg] \tag{5.6a}$$

subject to

$$\sum_{d:(d,n)\in\mathcal{M}_D} p_d^{\mathrm{D}} - \sum_{i:(i,n)\in\mathcal{M}_{\mathcal{I}_{-J}}} p_i^{\mathrm{G}} - \sum_{l:(l,n)\in\mathcal{M}_W} p_l^{\mathrm{W}} + \sum_{m:(n,m)\in\Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} - \delta_m^{\mathrm{DA}}) = 0 \ \forall n \tag{5.6b}$$

$$\sum_{i:(i,n)\in\mathcal{M}_{\mathcal{I}_{-J}}} \left(r_{i,s}^{\mathrm{D}} - r_{i,s}^{\mathrm{U}}\right) - \sum_{l:(l,n)\in\mathcal{M}_W} (P_{l,s}^{\mathrm{W,F}} - p_l^{\mathrm{W}} - p_{l,s}^{\mathrm{spill}}) - \sum_{d:(d,n)\in\mathcal{M}_D} l_{d,s}^{\mathrm{sh}} + \sum_{m:(n,m)\in\Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} + \delta_{m,s}^{\mathrm{RT}} - \delta_m^{\mathrm{DA}} - \delta_{n,s}^{\mathrm{RT}}) = 0 \ \forall n, \forall s \tag{5.6c}$$

$$0 \le p_i^{\mathrm{G}} \le \overline{P}_i^{\mathrm{G}} \ \forall i \in \mathcal{I}_{-J} \tag{5.6d}$$

$$0 \le p_d^{\mathrm{D}} \le \overline{P}_d^{\mathrm{D}} \ \forall d \tag{5.6e}$$

$$0 \le p_l^{\mathrm{W}} \le \overline{P}_l^{\mathrm{W}} \ \forall l \tag{5.6f}$$

$$0 \leq p^{\text{spill}}_{l,s} \leq P^{\text{W,F}}_{l,s} \;\forall l, \forall s \tag{5.6g}$$

$$0 \leq l^{\text{sh}}_{d,s} \leq p^{\text{D}}_{d} \;\forall d, \forall s \tag{5.6h}$$

$$0 \leq r^{\text{D}}_{i,s} \leq R^{\text{D}}_{i} \;\forall i \in \mathcal{I}_{-J}, \forall s \tag{5.6i}$$

$$0 \leq r^{\text{U}}_{i,s} \leq R^{\text{U}}_{i} \;\forall i \in \mathcal{I}_{-J}, \forall s \tag{5.6j}$$

$$r^{\text{U}}_{i,s} \leq \left(\overline{P}^{\text{G}}_{i} - p^{\text{G}}_{i}\right) \;\forall i \in \mathcal{I}_{-J}, \forall s \tag{5.6k}$$

$$r^{\text{D}}_{i,s} \leq p^{\text{G}}_{i} \;\forall i \in \mathcal{I}_{-J}, \forall s \tag{5.6l}$$

$$B_{n,m}(\delta^{\text{DA}}_{n} - \delta^{\text{DA}}_{m}) \leq F^{\max}_{n,m} \;\forall (n,m) \in \mathit{\Lambda} \tag{5.6m}$$

$$B_{n,m}(\delta^{\text{RT}}_{n,s} - \delta^{\text{RT}}_{m,s}) \leq F^{\max}_{n,m} \;\forall (n,m) \in \mathit{\Lambda}, \forall s \tag{5.6n}$$

$$-\pi \leq \delta^{\text{DA}}_{n} \leq \pi \;\forall n \tag{5.6o}$$

$$-\pi \leq \delta^{\text{RT}}_{n,s} \leq \pi \;\forall n, \forall s \tag{5.6p}$$

$$\delta^{\text{DA}}_{n=1} = 0 \tag{5.6q}$$

$$\delta^{\text{RT}}_{n=1,s} = 0 \;\forall s. \tag{5.6r}$$

$$\Bigg\} \;\forall J,$$

where $\Xi^{\text{P}} = \{p^{\text{G}}_{i}, p^{\text{W}}_{l}, r^{\text{U}}_{i,s}, r^{\text{D}}_{i,s}, l^{\text{sh}}_{d,s}, p^{\text{spill}}_{l,s}, p^{\text{D}}_{d}, \delta^{\text{DA}}_{n}, \delta^{\text{RT}}_{n,s}\}$ is the set of primal variables.

The above optimization model is similar to (5.1) but is solved for a number of times equal to the number of conventional producers, excluding one producer at a time. Note, that the set of participating conventional producers has been changed to exclude producer J, i.e., $i \in \mathcal{I}_{-J}$. Finally, the payment to producer J, i.e., Π_J, will be:

$$\Pi_J = \left[\mathbb{E}[\text{SW}] + \sum_{i \in \mathcal{I}_J} \lambda^{\text{G}}_{i} \; p^{\text{G}}_{i}\right] - \mathbb{E}[\text{SW}_{-\text{J}}] \tag{5.7}$$

where $\mathbb{E}[\text{SW}]$ is the expected social welfare of all agents including J, $\mathbb{E}[\text{SW}_{-\text{J}}]$ is the expected market social welfare when producer J is excluded from the auction, i.e., it is the minus value of objective function (5.6a) at the optimal point, and $\sum_{i \in \mathcal{I}_J} \lambda^{\text{G}}_{i} \; p^{\text{G}}_{i}$ is the reported operational cost of producer J for its total scheduled power. Note that the first term of (5.7) inside the brackets is the social welfare considering the contribution of all agents except J. It will be proved in the following subsection that producers dominant strategy is to report their actual cost to the market under this payment scheme.

5.2.4.2 VCG payments to wind producers

Let wind producer L be the one whose revenue is to be calculated and $\mathcal{W}_{-L}$ be the set of all participating wind producers excluding L. The expected social welfare when L does not participate, will be derived by the solution of (5.8) problem below:

$$\left\{ \underset{\Xi^{\mathrm{P}}}{\text{Minimize}} \right.$$

$$\sum_{i \in \mathcal{I}} \lambda_i^{\mathrm{G}}\ p_i^{\mathrm{G}} - \sum_{d \in \mathcal{D}} \lambda_d^{\mathrm{D}}\ p_d^{\mathrm{D}} + \sum_{s \in \mathcal{S}} \pi_s \Bigg[\sum_{i \in \mathcal{I}} \left(\lambda_i^{\mathrm{U}}\ r_{i,s}^{\mathrm{U}} - \lambda_i^{\mathrm{D}}\ r_{i,s}^{\mathrm{D}} \right) + \sum_{d \in \mathcal{D}} V_d^{\mathrm{sh}}\ l_{d,s}^{\mathrm{sh}} \Bigg] \tag{5.8a}$$

subject to

$$\sum_{d:(d,n) \in \mathcal{M}_D} p_d^{\mathrm{D}} - \sum_{i:(i,n) \in \mathcal{M}_I} p_i^{\mathrm{G}} - \sum_{l:(l,n) \in M_{\mathcal{W}_{-L}}} p_l^{\mathrm{W}} + \sum_{m:(n,m) \in \Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} - \delta_m^{\mathrm{DA}}) = 0 \ \forall n \tag{5.8b}$$

$$\sum_{i:(i,n) \in \mathcal{M}_I} \left(r_{i,s}^{\mathrm{D}} - r_{i,s}^{\mathrm{U}} \right) - \sum_{l:(l,n) \in M_{\mathcal{W}_{-L}}} (P_{l,s}^{\mathrm{W,F}} - p_l^{\mathrm{W}} - p_{l,s}^{\mathrm{spill}}) - \sum_{d:(d,n) \in \mathcal{M}_D} l_{d,s}^{\mathrm{sh}} + \sum_{m:(n,m) \in \Lambda} B_{n,m}(\delta_n^{\mathrm{DA}} + \delta_{m,s}^{\mathrm{RT}} - \delta_m^{\mathrm{DA}} - \delta_{n,s}^{\mathrm{RT}}) = 0 \ \forall n, \forall s \tag{5.8c}$$

$$0 \le p_i^{\mathrm{G}} \le \overline{P}_i^{\mathrm{G}} \ \forall i \tag{5.8d}$$

$$0 \le p_d^{\mathrm{D}} \le \overline{P}_d^{\mathrm{D}} \ \forall d \tag{5.8e}$$

$$0 \le p_l^{\mathrm{W}} \le \overline{P}_l^{\mathrm{W}} \ \forall l \in \mathcal{W}_{-L} \tag{5.8f}$$

$$0 \le p_{l,s}^{\mathrm{spill}} \le P_{l,s}^{\mathrm{W,F}} \ \forall l \in \mathcal{W}_{-L}, \forall s \tag{5.8g}$$

$$0 \leq l^{\mathrm{sh}}_{d,s} \leq p^{\mathrm{D}}_{d} \ \forall d, \forall s \tag{5.8h}$$

$$0 \leq r^{\mathrm{D}}_{i,s} \leq R^{\mathrm{D}}_{i} \ \forall i, \forall s \tag{5.8i}$$

$$0 \leq r^{\mathrm{U}}_{i,s} \leq R^{\mathrm{U}}_{i} \ \forall i, \forall s \tag{5.8j}$$

$$r^{\mathrm{U}}_{i,s} \leq \left(\overline{P}^{\mathrm{G}}_{i} - p^{\mathrm{G}}_{i}\right) \ \forall i, \forall s \tag{5.8k}$$

$$r^{\mathrm{D}}_{i,s} \leq p^{\mathrm{G}}_{i} \ \forall i, \forall s \tag{5.8l}$$

$$B_{n,m}(\delta^{\mathrm{DA}}_{n} - \delta^{\mathrm{DA}}_{m}) \leq F^{\max}_{n,m} \ \forall (n,m) \in \Lambda \tag{5.8m}$$

$$B_{n,m}(\delta^{\mathrm{RT}}_{n,s} - \delta^{\mathrm{RT}}_{m,s}) \leq F^{\max}_{n,m} \ \forall (n,m) \in \Lambda, \forall s \tag{5.8n}$$

$$-\pi \leq \delta^{\mathrm{DA}}_{n} \leq \pi \ \forall n \tag{5.8o}$$

$$-\pi \leq \delta^{\mathrm{RT}}_{n,s} \leq \pi \ \forall n, \forall s \tag{5.8p}$$

$$\delta^{\mathrm{DA}}_{n=1} = 0 \tag{5.8q}$$

$$\delta^{\mathrm{RT}}_{n=1,s} = 0 \ \forall s. \tag{5.8r}$$

$$\Bigg\} \ \forall L,$$

where $\Xi^{\mathrm{P}} = \{p^{\mathrm{G}}_{i}, p^{\mathrm{W}}_{l}, r^{\mathrm{U}}_{i,s}, r^{\mathrm{D}}_{i,s}, l^{\mathrm{sh}}_{d,s}, p^{\mathrm{spill}}_{l,s}, p^{\mathrm{D}}_{d}, \delta^{\mathrm{DA}}_{n}, \delta^{\mathrm{RT}}_{n,s}\}$ is the set of primal variables.

The above optimization model is similar to (5.1) but is solved for a number of times equal to the number of wind producers, excluding one wind producer at a time. Note, that the set of participating wind producers has been changed to exclude wind producer L, i.e., $l \in \mathcal{W}_{-L}$. Finally, the payment to wind producer L, i.e., Π_L, will be:

$$\Pi_L = \left[\mathbb{E}[\mathrm{SW}] + \widehat{C}_L\right] - \mathbb{E}[\mathrm{SW}_{-\mathrm{L}}] \tag{5.9}$$

where $\mathbb{E}[\mathrm{SW}]$ is the expected social welfare of all agents including L, $\mathbb{E}[\mathrm{SW}_{-\mathrm{L}}]$ is the expected market social welfare when wind producer L is excluded from the auction, i.e., it is the minus value of objective function (5.8a) at the optimal point, and $\widehat{C}_L$ is the reported operational cost of wind producer L, which in this study is zero for all wind producers.

5.2.4.3 VCG payments from demands

Let demand C be the one whose payment to the market is to be calculated and $\mathcal{D}_{-C}$ be the set of participating consumers excluding C. The social welfare when C does not participate, will be derived by the solution of (5.10) problem below:

$$\Bigg\{ \underset{\Xi^{\mathrm{P}}}{\text{Minimize}}$$

$$\sum_{i \in \mathcal{I}} \lambda_i^{\mathrm{G}}\ p_i^{\mathrm{G}} - \sum_{d \in \mathcal{D}_{-C}} \lambda_d^{\mathrm{D}}\ p_d^{\mathrm{D}} + \sum_{s \in \mathcal{S}} \pi_s \Bigg[\sum_{i \in \mathcal{I}} \left(\lambda_i^{\mathrm{U}}\ r_{i,s}^{\mathrm{U}} - \lambda_i^{\mathrm{D}}\ r_{i,s}^{\mathrm{D}} \right) + \sum_{d \in \mathcal{D}_{-C}} V_d^{\mathrm{sh}}\ l_{d,s}^{\mathrm{sh}} \Bigg] \tag{5.10a}$$

subject to

$$\sum_{d:(d,n) \in \mathcal{M}_{\mathcal{D}_{-C}}} p_d^{\mathrm{D}} - \sum_{i:(i,n) \in \mathcal{M}_I} p_i^{\mathrm{G}} - \sum_{l:(l,n) \in \mathcal{M}_W} p_l^{\mathrm{W}} + \sum_{m:(n,m) \in \Lambda} B_{n,m} (\delta_n^{\mathrm{DA}} - \delta_m^{\mathrm{DA}}) = 0\ \forall n \tag{5.10b}$$

$$\sum_{i:(i,n) \in \mathcal{M}_I} \left(r_{i,s}^{\mathrm{D}} - r_{i,s}^{\mathrm{U}} \right) - \sum_{l:(l,n) \in \mathcal{M}_W} (P_{l,s}^{\mathrm{W,F}} - p_l^{\mathrm{W}} - p_{l,s}^{\mathrm{spill}}) - \sum_{d:(d,n) \in \mathcal{M}_{\mathcal{D}_{-C}}} l_{d,s}^{\mathrm{sh}} + \sum_{m:(n,m) \in \Lambda} B_{n,m} (\delta_n^{\mathrm{DA}} + \delta_{m,s}^{\mathrm{RT}} - \delta_m^{\mathrm{DA}} - \delta_{n,s}^{\mathrm{RT}}) = 0\ \forall n, \forall s \tag{5.10c}$$

$$0 \leq p_i^{\mathrm{G}} \leq \overline{P}_i^{\mathrm{G}}\ \forall i \tag{5.10d}$$

$$0 \leq p_d^{\mathrm{D}} \leq \overline{P}_d^{\mathrm{D}}\ \forall d \in \mathcal{D}_{-C} \tag{5.10e}$$

$$0 \leq p_l^{\mathrm{W}} \leq \overline{P}_l^{\mathrm{W}}\ \forall l \tag{5.10f}$$

$$0 \leq p_{l,s}^{\mathrm{spill}} \leq P_{l,s}^{\mathrm{W,F}}\ \forall l, \forall s \tag{5.10g}$$

$$0 \leq l_{d,s}^{\mathrm{sh}} \leq p_d^{\mathrm{D}}\ \forall d \in \mathcal{D}_{-C}, \forall s \tag{5.10h}$$

$$0 \leq r_{i,s}^{\mathrm{D}} \leq R_i^{\mathrm{D}}\ \forall i, \forall s \tag{5.10i}$$

$$0 \leq r_{i,s}^{\mathrm{U}} \leq R_i^{\mathrm{U}}\ \forall i, \forall s \tag{5.10j}$$

$$r_{i,s}^{\mathrm{U}} \leq \left(\overline{P}_i^{\mathrm{G}} - p_i^{\mathrm{G}}\right) \ \forall i, \forall s \tag{5.10k}$$

$$r_{i,s}^{\mathrm{D}} \leq p_i^{\mathrm{G}} \ \forall i, \forall s \tag{5.10l}$$

$$B_{n,m}(\delta_n^{\mathrm{DA}} - \delta_m^{\mathrm{DA}}) \leq F_{n,m}^{\max} \ \forall (n,m) \in \Lambda \tag{5.10m}$$

$$B_{n,m}(\delta_{n,s}^{\mathrm{RT}} - \delta_{m,s}^{\mathrm{RT}}) \leq F_{n,m}^{\max} \ \forall (n,m) \in \Lambda, \forall s \tag{5.10n}$$

$$-\pi \leq \delta_n^{\mathrm{DA}} \leq \pi \ \forall n \tag{5.10o}$$

$$-\pi \leq \delta_{n,s}^{\mathrm{RT}} \leq \pi \ \forall n, \forall s \tag{5.10p}$$

$$\delta_{n=1}^{\mathrm{DA}} = 0 \tag{5.10q}$$

$$\delta_{n=1,s}^{\mathrm{RT}} = 0 \ \forall s. \tag{5.10r}$$

$$\Big\} \ \forall C,$$

where $\Xi^{\mathrm{P}} = \{p_i^{\mathrm{G}}, p_l^{\mathrm{W}}, r_{i,s}^{\mathrm{U}}, r_{i,s}^{\mathrm{D}}, l_{d,s}^{\mathrm{sh}}, p_{l,s}^{\mathrm{spill}}, p_d^{\mathrm{D}}, \delta_n^{\mathrm{DA}}, \delta_{n,s}^{\mathrm{RT}}\}$ is the set of primal variables.

The above optimization model is similar to (5.1) but is solved for a number of times equal to the number of demands, excluding one demand at a time. Note, that the set of participating demands has been changed to exclude demand C, i.e., $d \in \mathcal{D}_{-C}$. Finally, demand C's charges for its consumption, i.e., Π_C, will be:

$$\Pi_C = \mathbb{E}[\mathrm{SW}_{-\mathrm{C}}] - \left[\mathbb{E}[\mathrm{SW}] - \sum_{d \in \mathcal{D}_C} \lambda_d^{\mathrm{D}} \ p_d^{\mathrm{D}}\right] \tag{5.11}$$

where $\mathbb{E}[\mathrm{SW}_{-\mathrm{C}}]$ is the expected market social welfare when consumer C is excluded from the auction, i.e., it is the minus value of objective function (5.10a) at the optimal point, $\mathbb{E}[\mathrm{SW}]$ is the expected social welfare of all agents including C and $\sum_{d \in \mathcal{D}_C} \lambda_d^{\mathrm{D}} \ p_d^{\mathrm{D}}$ is the reported utility of consumer C, i.e., the total cost it is willing to pay for its consumption p_d.

5.2.4.4 Incentive-compatibility under the VCG mechanism

Based on the above models we are now going to show that the aforementioned mechanism is incentive-compatible. We will prove incentive-compatibility of the VCG mechanism for the case of conventional power producers. However, the corresponding proof for the rest of participants, i.e., wind producers and demands, is straightforward.

Theorem 5.1. *Under a VCG payment scheme, truthful submission of individual operational cost is each producer's dominant strategy.*

Proof. Let us consider producer J, whose revenue under the VCG mechanism is given by (5.12), below:

$$\Pi_J = \left[\mathbb{E}[\mathrm{SW}] + \sum_{i \in \mathcal{I}_J} \lambda_i^{\mathrm{G}} \, p_i^{\mathrm{G}} \right] - \mathbb{E}[\mathrm{SW_{-J}}] \tag{5.12}$$

Producer J's revenue consists of the following two terms:

- the expected social welfare when all producers participate in the market plus J's operational cost, i.e., $\mathbb{E}[\mathrm{SW}] + \sum_{i \in \mathcal{I}_J} \lambda_i^{\mathrm{G}} \, p_i^{\mathrm{G}}$,
- the expected social welfare of the market when producer J does not participate in the auction, i.e., $\mathbb{E}[\mathrm{SW_{-J}}]$.

Producer J, being strategic, optimizes its price offer, which is then submitted to the market instead of its actual operational cost. Producer J's optimal price offer is derived by the optimization problem, whose objective function is (5.13) below:

$$\text{Maximize} \left\{ \Pi_J - \sum_{i \in \mathcal{I}_J} p_i^{\mathrm{G}} \lambda_i^{\mathrm{G}} \right\} \tag{5.13}$$

Objective function (5.13) represents the profit of producer J, being the difference between the payment J receives from the market and its operational cost. Considering (5.12), the above objective function becomes:

$$\text{Maximize} \left\{ \mathbb{E}[\mathrm{SW}] - \mathbb{E}[\mathrm{SW_{-J}}] \right\} \tag{5.14}$$

In (5.14) note that the second term, being the expected social welfare excluding producer J, is a parameter for producer J, i.e., it is independent of its decisions. This reduces its optimization objective into maximizing the first term only. However, the first term is the expected social welfare when all agents participate. Therefore, maximization of social welfare is internalized in producer J's optimization objective, making its dominant strategy to report the actual operational cost, since this will eventually lead to maximum social welfare. Thus, it is proved that VCG payment eliminates producers ability to misreport operational costs exerting market power.

□

5.2.4.5 Cost-recovery under the VCG mechanism

Based on the above models we are now going to show that the aforementioned mechanism ensures cost-recovery of all producers, i.e., non-negative profits.

Theorem 5.2. *Given that truthful submission of individual operational cost is each producer's dominant strategy, payment received by each producer is always not less than its operational cost.*

Proof. Let us consider that the VCG mechanism incurs a profit for each producer J, defined before as:

$$\text{Profit}_J = \mathbb{E}[\text{SW}] - \mathbb{E}[\text{SW}_{-\text{J}}]. \tag{5.15}$$

where $\mathbb{E}[\text{SW}]$ is the expected social welfare when it participates and $\mathbb{E}[\text{SW}_{-\text{J}}]$ is the expected social welfare when J does not participate in the market. Excluding producer J, the market social welfare can only be less than or equal to the social welfare when producer J participates. Indeed, if producer J decreases social welfare in expectation through its participation, then it will not be scheduled by market operator at the optimal dispatch. Thus, the first term of (5.15) is never less than the second term. This leads to the proof that producer J's profit is non-negative and its received revenue is necessarily greater or equal to its operational cost.

□

5.2.4.6 Budget imbalance redistribution under the VCG Mechanism

The VCG-based mechanism is incentive-compatible, efficient and ensures cost-recovery. However, as noted at the beginning of Section 5.2.4, it may lead to budget deficit, i.e., payments received from demand-side are less than payments made to generation-side. Thus, budget imbalance should be exogenously recovered by additional payments from market agents. In [143] authors investigate a VCG mechanism for energy markets, noting that the mechanism will lead to budget deficit, which could potentially be recovered by additional payments from consumers. In more recent research [146], authors calculate the budget deficit and compare it with producers revenues and demands payments to suggest that revenue-adequacy could be achieved by imposing negative constants on generator's payment functions or positive constants to demands payments. However, budget redistribution in [146] is not demonstrated in practice, while the proposed scheme fails to present a fair mechanism for recovering the budget imbalance from the agents that contribute the most towards it.

In this subsection we present a novel redistribution approach, which aims in ex-post recovering the budget imbalance, by charging agents that are responsible for the negative budget imbalance, while rewarding agents that contribute towards revenue-adequacy. The proposed mechanism is motivated by the economics literature, and more particularly paper [41], where the author proves that there exists a maximum VCG surplus guarantee that can be redistributed in demand-side only auctions, without affecting the rest properties of the market. However, it is not straightforward to apply this approach to electricity markets, since the latter include both producers and consumers. Motivated by the aforementioned considerations, we attempt to adapt a similar mechanism in a two-sided electricity market, and evaluate it in a large-scale case study. The proposed redistribution scheme is able to distinguish each agent's positive/negative contribution towards revenue-adequacy and reward/charge them with a corresponding redistribution payment.

Qualitatively, the proposed budget imbalance redistribution scheme is described by the flowchart in Fig. 5.4. The first step is to solve the original VCG market-clearing problem and calculate the value of budget imbalance (S_0), i.e., the difference between aggregate payments received from demands and aggregate revenues of producers, as expressed by (5.16) below:

$$S_0 = \sum_{C \in D} \Pi_C - \left[\sum_{J \in I} \Pi_J + \sum_{L \in W} \Pi_L \right]. \tag{5.16}$$

In order to propose a fair mechanism for charging this additional payment to market participants, we first investigate the contribution of each market agent on the budget imbalance. Thus, we solve the market-clearing problem excluding each time the corresponding market agent and calculate the resulted budget imbalance without agent α, $S_{-\alpha}$. Note that agent α can be either a demand or a producer. If the resulted budget imbalance is positive, i.e., $S_{-\alpha} > 0$, and the initial budget imbalance is negative, i.e., $S_0 < 0$, then agent α's participation in the market contributes towards negative budget imbalance and it should be charged. On the other hand, in cases that initial budget imbalance is positive, i.e., $S_0 > 0$, then if excluding agent α leads to lower budget imbalance, agent α contributes towards higher budget imbalance and should be rewarded accordingly.

The aforementioned redistribution scheme indicates the impact that each agent has on the budget imbalance of the market. Based on this scheme, we can distinguish which agent participation jeopardizes revenue-adequacy and whose participation is helping towards achieving it. Having distinguished the impact of each of the market agents, we should now define the exact redistribution payment of each agent, which should correspond to its individual contribution on revenue-adequacy in order to redistribute budget imbalance in a fair way. To this end, the redistribution payment (RM) in a market with negative imbalance is calculated as the surplus associated with each agent α's absence of the market, divided by the number of participating agents N. Note that agent α redistribution payment, i.e., RM_α, is constrained to be less than or equal to agent α profit/utility, in order to ensure cost-recovery. Similarly, in a market with positive budget imbalance, i.e., revenue-adequacy is satisfied, each agent that helps towards increasing positive budget imbalance

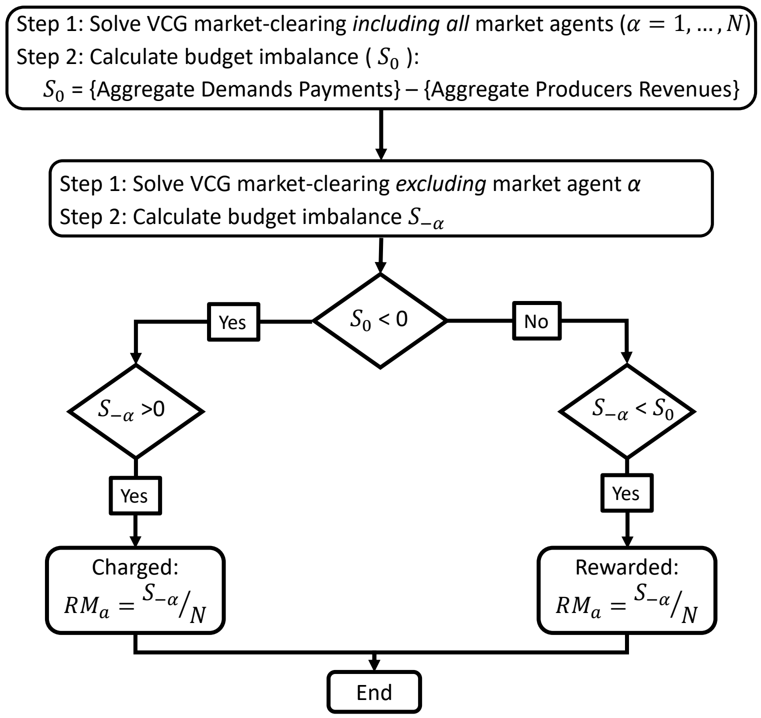

Figure 5.4: Recovery of the market budget imbalance of the VCG market-clearing mechanism

is rewarded by getting paid the surplus associated with its absence in the market divided by the number of participating agents. The proposed approach has the following features:

1. It redistributes budget imbalance of the market in a fair way, rewarding agents that contribute towards revenue-adequacy and charging agents that have negative impact on it.

2. It doesn't affect market efficiency, since DA schedules do not change.

3. It ensures incentive-compatibility, since the redistribution payment RM_α is independent of agent α's decisions, being the VCG budget deficit/surplus when the agent does not participate in the market. Thus, agent α cannot be strategic with its redistribution payment.

4. It ensures ex-post cost-recovery, by constraining the redistribution payment by agent's VCG profit/utility.

However, note that the aforementioned redistribution approach is an ex-post solution, which does not always guarantee full recovery of the negative budget imbalance, i.e., it might just reduce it.

5.3 Case Studies

In order to extensively evaluate the VCG mechanism under the two-stage stochastic market setup, we present in this section two different large-scale case studies. The scope of the case studies is to compare the VCG mechanism in a two-stage stochastic market for increasing levels of wind power penetration, both including and excluding network constraints. Thus, the first case study, i.e., Section 5.3.1, does not consider transmission network constraints, while the second case study considers a transmission network through a lossless DC power flow study. Apart from analyzing the corresponding results for each case study, at the end of this section we additionally evaluate the impact of network congestion in VCG-based market and draw relevant conclusions.

5.3.1 Case Study Excluding Transmission Network Constraints

5.3.1.1 Data and assumptions

A case study based on the IEEE one-area reliability test system [84] is considered, in which transmission network constraints are not considered. For the sake of simplicity, conventional units are grouped by type and price. Nine conventional units are considered and each one of them offers at a quantity identical to its installed capacity and at a price given in Table 5.1.

In addition to conventional units, we consider a large wind power plant. Wind power generation is accommodated by a set of scenarios, derived from a DA forecast. For this purpose, an initial number of 2,000 per-unit wind scenarios are generated from a Beta distribution [51] and then reduced in 10 scenarios for computational efficiency, using the K-means clustering approach [89]. Furthermore, multiple cases are evaluated for increasing penetration of wind power.

Table 5.1: Technical Characteristics of Conventional Units

Conv. Generation Unit	Power Capacity ($\overline{P}_i^{\mathrm{G}}$) [MW]	Oper. Cost (λ_i^{G}) [€/MWh]	Reserve Up Capacity (R_i^{U}) [MW]	Reserve Up Cost (λ_i^{U}) [€/MWh]	Reserve Down Capacity (R_i^{D}) [MW]	Reserve Down Cost (λ_i^{D}) [€/MWh]
G1	304	13.32	80	15	80	11
G2	350	19.7	70	24	70	16
G3	591	20.93	180	25	180	17
G4	60	26.11	60	28	60	23
G5	610	10.52	120	15	120	7
G6	400	6.02	0	-	0	-
G7	400	5.47	0	-	0	-
G8	300	0	0	-	0	-
G9	350	12.89	40	16	40	8

This case study is investigated in the following sections for different levels of wind power penetration. By the term "wind power penetration" we refer to the expected aggregate wind power in the market divided by the total load (i.e., 2,200 MW). Note that in all these cases, 10 per-unit wind power scenarios are generated from a Beta function with shape parameters (a,b)=(5,1). However, a different weight is used to define different penetration levels. Hence, in all cases, the standard deviation of wind power (i.e., level of wind power uncertainty) is the same. The characteristics of wind power scenarios are presented in Table 5.2.

Table 5.2: Characteristics of the Wind Power Scenarios

Case No.	1	2	3	4	5	6	7	8	9
Wind Pen. [%]	13	19	24	27	32	37	43	47.8	53
Std. [MW]	71	99	127	141	170	198	226	255	283
Average [MW]	292	409	528	584	701	818	935	1051	1168
Capacity [MW]	350	490	630	700	840	980	1120	1260	1400

Finally, seven demands are considered in the system, whose bids are given in Table 5.3, and the value of lost load is €200/MWh.

Table 5.3: Demand Data

Demand No.	d1	d2	d3	d4	d5	d6	d7
Maximum Load ($\overline{P}_d^{\mathrm{D}}$) [MW]	200	350	300	400	300	400	250
Bid Price (λ_d^{D}) [€/MWh]	100	100	100	100	100	100	100

5.3.1.2 Results for increasing levels of wind power penetration

In Fig. 5.5 we present the results regarding budget imbalance of the market in expectation, for the three investigated models, i.e., competitive, strategic and VCG. Budget imbalance is calculated as the difference between all payments received from demand-side and payments made to generation-side. In order for a market mechanism to be revenue-adequate, the aforementioned difference should be non-negative, meaning that market operator should not face budget deficit. As shown in [28], the stochastic market model examined in this chapter is revenue-adequate in expectation, under both perfect and imperfect competition. However, note that revenue-adequacy is guaranteed only in expectation and it can be violated for each individual scenario [28].

In Fig. 5.5, it is observed that without enforcing transmission network constraints the stochastic two-stage market mechanism leads to exact budget balance in this case, i.e., budget imbalance is zero. In the same figure, budget imbalance is also presented for the VCG mechanism. From the corresponding black curve it is observed that in contrast to the traditional market mechanism (either competitive or strategic models), VCG mechanism leads to negative budget imbalance for the market operator, i.e., budget deficit. More specifically, analyzing the resulting curve it is apparent that after a certain level of wind power penetration, i.e., around 32%, budget deficit increases notably. Thus, VCG mechanism becomes less appealing for markets with higher wind penetration, since the level of negative budget imbalance increases. As explained further on, the reason for this trend is the decreasing payments of demands as wind power penetration levels increase.

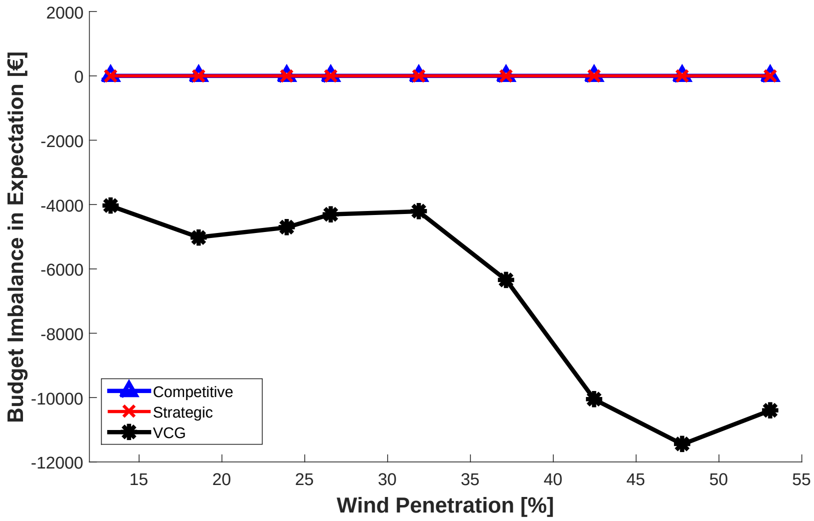

Figure 5.5: Budget imbalance of the market in expectation versus different levels of wind power penetration. Revenue-adequacy refers to the case of having non-negative budget imbalance.

Figure 5.6 presents market expected social welfare for the three investigated models. As mentioned previously, both incentive-compatible VCG and the competitive model (perfect competition) lead to the same social welfare, which is the highest possible, since it considers that all participants in the market submit their true operational costs. The difference between the two models is on the accommodated payment scheme and the calculation of prices, which are ex-post calculations at the optimal dispatch that yields maximum social welfare. Payments under the traditional stochastic two-stage mechanism, i.e., competitive and strategic models, are defined based on the price derived by the optimization model, being the dual variable associated with the power balance equation. On the other hand, VCG payments are made based on a completely different approach. As already explained in Section 5.2.4, payments are based on the contribution of each market participant on social welfare maximization. On the contrary, as anticipated, in a strategic setting social welfare is lower. The market is cleared based on the strategic offers of producers at the equilibrium point, which are not their actual costs. Thus, it is observed, by the red curve in Fig. 5.6, that strategic model results in considerably lower social welfare than the other two mechanisms, indicating the anticipated loss in efficiency caused by producers who act as price-makers. Naturally, though, for all models social welfare increases with increasing penetration of wind power, due to its zero operational cost.

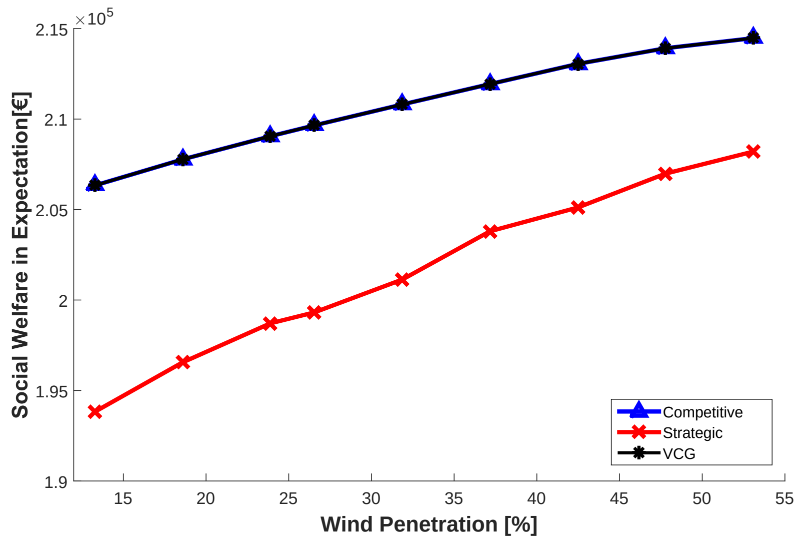

Figure 5.6: Expected market social welfare versus different levels of wind power penetration. Expected social welfare in both competitive and VCG models is the same since they end up in identical dispatch results; the only difference is the pricing scheme used.

Regarding the VCG payment scheme, there is no unique DA market price (even in a case without transmission network) but prices are individually calculated for each market participant. Therefore, for each producer/demand the price is calculated by dividing its revenue/payment by the quantity of power produced/consumed. Individual prices per market participant are presented in Tables 5.4 and 5.5 for producers and demands, respectively. Note that VCG prices which are referred as "Inf" in Table 5.4, are associated with producers who do not trade power in the DA market but affect DA dispatch decisions due to their participation in the RT stage. On the other hand, VCG prices that are referred as "NaN", correspond to cases where no power is traded by that producer in the DA market and, additionally, no payment is made to that producer. For illustration purposes, weighted average prices for aggregate conventional units, aggregate wind power units, and aggregate demands are presented in Fig. 5.7 along with the corresponding prices of the competitive and strategic models. Prices corresponding to "Inf" or "NaN" are replaced by zero at the curves of Fig. 5.7, since they are associated with marginal and zero profits, respectively. The weighted average prices (denoted by $\widehat{\lambda}$) are the summation of all individual prices multiplied by the ratio between individual and total traded power in DA, defined by the expressions below.

Equation (5.17a) below gives the weighted average price for aggregate conventional units under the VCG market mechanism:

$$\widehat{\lambda}^{\mathrm{VCG,G}} = \sum_{i \in \mathcal{I}} \left(\lambda_i^{\mathrm{VCG,G}} \, \frac{p_i^{\mathrm{G}}}{\sum_i p_i^{\mathrm{G}}} \right), \tag{5.17a}$$

where $\lambda_i^{\mathrm{VCG,G}}$ is the VCG market price (€/MWh) of conventional unit i. In addition, p_i^{G} corresponds to its production (MW) dispatched in the market.

Similarly, (5.17b) below gives the weighted average price for aggregate wind power units under the VCG market mechanism:

$$\widehat{\lambda}^{\mathrm{VCG,W}} = \sum_{l \in \mathcal{W}} \left(\lambda_l^{\mathrm{VCG,W}} \, \frac{p_l^{\mathrm{W}}}{\sum_l p_l^{\mathrm{W}}} \right), \tag{5.17b}$$

where $\lambda_l^{\mathrm{VCG,W}}$ is the VCG market price (€/MWh) of wind power unit l. In addition, p_l^{W} corresponds to its production (MW) dispatched in the market.

And, lastly, (5.17c) gives the weighted average price for aggregate demands under the VCG market mechanism:

$$\widehat{\lambda}^{\mathrm{VCG,D}} = \sum_{d \in \mathcal{D}} \left(\lambda_d^{\mathrm{VCG,D}} \, \frac{p_d^{\mathrm{D}}}{\sum_d p_d^{\mathrm{D}}} \right), \tag{5.17c}$$

where $\lambda_d^{\mathrm{VCG,D}}$ is the VCG market price (€/MWh) of demand d, while p_d^{D} corresponds to its consumption (MW) scheduled in the market.

Table 5.4: Generation-side DA Market Prices [€/MWh] in the VCG Market-Clearing Mechanism versus Wind Power Penetration

	Wind Power Penetration								
Producer	13%	19 %	24 %	27 %	32 %	37 %	42 %	48 %	53 %
G1	12.89	13.39	10.52	NaN	Inf	12.44	35.84	Inf	21.13
G2	NaN	Inf	NaN	NaN	NaN	Inf	Inf	Inf	Inf
G3	NaN	Inf	Inf	NaN	Inf	Inf	Inf	Inf	Inf
G4	NaN	NaN	NaN	NaN	NaN	NaN	Inf	Inf	Inf
G5	14.77	13.45	12.87	13.06	13.01	15.53	30.06	32.64	31.77
G6	12.55	13.00	12.74	12.55	11.74	12.02	11.21	10.84	11.23
G7	12.55	13.00	12.74	12.55	11.74	12.02	11.21	10.84	10.27
G8	13.04	12.89	12.69	12.44	11.35	11.52	10.52	10.95	10.19
G9	13.32	22.36	Inf	Inf	Inf	NaN	Inf	Inf	Inf
Wind	13.02	12.96	12.82	12.60	12.26	11.95	11.71	11.76	11.23

*Note: "Inf" stands for the cases where there is payment made to a producer, but producer does not trade any power in the DA market. This is the case of a producer that, even though it does not trade power in the DA market, it has an impact on the DA dispatch of other producers due to its participation in the RT stage. Thus, producer changes social welfare, even though its DA schedule is zero. On the other hand, "NaN" stands for the cases where no power is traded by that producer in the DA market and, additionally, no payment is made to that producer.

Table 5.5: Demands DA Market Prices [€/MWh] in the VCG Market-Clearing Mechanism versus Wind Power Penetration

	Wind Power Penetration								
Demand	13%	19 %	24 %	27 %	32 %	37 %	42 %	48 %	53%
D1	13.46	12.42	12.19	12.28	12.68	12.74	10.60	8.59	5.54
D2	12.20	11.60	11.48	11.53	11.75	10.87	8.64	7.49	6.04
D3	12.48	11.78	11.63	11.70	11.96	11.68	9.07	7.74	5.70
D4	11.99	11.47	11.36	11.40	11.55	10.26	8.31	7.31	6.60
D5	12.48	11.78	11.63	11.70	11.96	11.68	9.07	7.74	5.70
D6	11.99	11.47	11.36	11.40	11.55	10.26	8.31	7.31	6.60
D7	12.87	12.04	11.86	11.93	12.25	12.29	9.68	8.08	5.64

It is observed from Fig. 5.7 that DA prices under the VCG mechanism for all producers, wind and conventional (curves referred as $\widehat{\lambda}^{\mathrm{VCG,G}}$ and $\widehat{\lambda}^{\mathrm{VCG,W}}$), are greater than the prices of the competitive model. This result also confirms similar conclusions reported in [146], where the authors numerically conclude that VCG mechanism leads to higher electricity prices

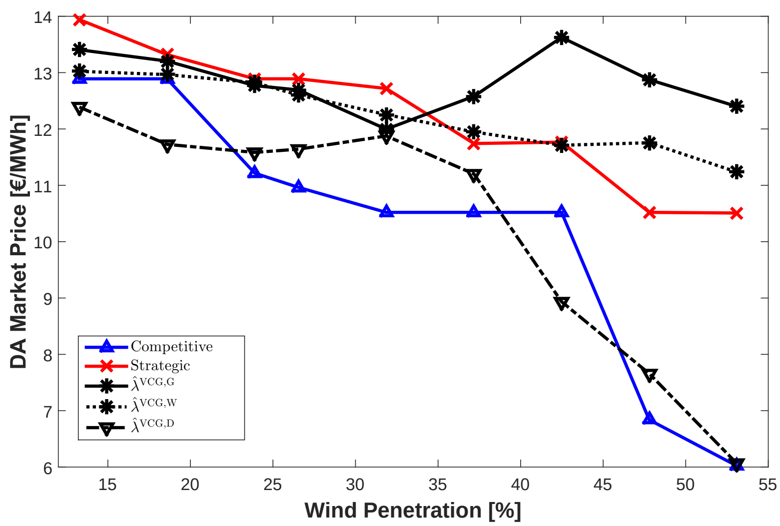

Figure 5.7: Day-Ahead market prices versus different levels of wind power penetration

compared to a perfectly competitive LMP market. Furthermore, as expected, offers in strategic model (red curve) lead to increased electricity prices, as observed by comparing the red curve for imperfect competition and the blue curve for perfect competition. It can be noted that the magnitude of prices of the VCG for producers and the strategic model at the equilibrium point are in comparable levels, being higher than the competitive model, for all levels of wind power penetration. The corresponding weighted average prices for the demand under the VCG model are quite lower, being in some cases lower than the prices of the competitive model. This explains the potential source of budget deficit in the VCG model. Moreover, the discussed observation of increasing budget deficit when wind penetration increases, is also explained by this graph: demands are paying their energy in much lower prices as wind penetration increases (Fig. 5.7). On the contrary, generation-side prices retain comparatively higher values which, eventually, leads to the observed increasing budget deficit. Finally, in both traditional market models (competitive and strategic), a general trend of reducing DA price is observed versus increasing wind power penetration. On the contrary, such a trend is not generally observed in Tables 5.4 and 5.5 reporting the VCG prices for each participant, because VCG payments are based on agents contribution to social welfare maximization and not on a "merit order" approach.

Figures 5.8a and 5.8b compare the expected profits for all participating producers for the three different models. Note that VCG profits refer to the expected profits without considering any ex-post redistribution of the budget imbalance. It is observed that producers expected profits, including wind producer, are generally higher under the VCG mechanism compared to those under the competitive model (yellow and blue bars). In fact, this is explained by the payment scheme that pays each producer based on its contribution to social welfare formation in the optimal point, and not based on a unique DA market price. Thus, for example marginal producer G3, for penetration levels 37%-48%, earns no profit under the competitive model while its profit is positive under the VCG one.

It is worth mentioning that strategic bidding in the electricity market can violate the property of cost-recovery, meaning that if producers offer at different prices than their marginal costs they cannot avoid the risk of negative profits. It is anticipated though, that since all market participants have the same information and reach equilibrium, market-clearing should be perfectly anticipated by producers, ensuring cost-recovery. However, small losses appear for producers due to the existence of multiple available solutions. More precisely, different DA schedules might lead to the same value of social welfare at the optimal. Thus, the returned solution of a producer's profit-maximizing tool corresponds to the dispatch that favors that specific decision-maker while retaining the optimal value of social welfare. On the other hand, the market-clearing tool might return a different solution, with the same optimal social welfare. This result, being a limitation of the diagonalization approach, can potentially be avoided by following a different approach for solving the EPEC model, similarly to [70, 90, 75], which solves all models at a single instance, but comes with higher computational cost. However, the magnitude of these negative values is not high, and generally appears for producers that are not scheduled in the competitive model. On the other hand, as theoretically discussed before, cost-recovery in expectation is successfully achieved for all producers under the VCG and competitive model. Lastly, VCG seems to be the most rewarding model for wind power producer, since its profit under the VCG mechanism is higher compared to that of the competitive model and, for most cases, comparable or higher than the corresponding profit under the strategic model. Note that wind producer, despite being competitive in all cases, still gets benefited by the strategic behavior of conventional producers under the strategic model, since market price is higher due to conventional producers market power. This explains wind producer's increased profits for that case.

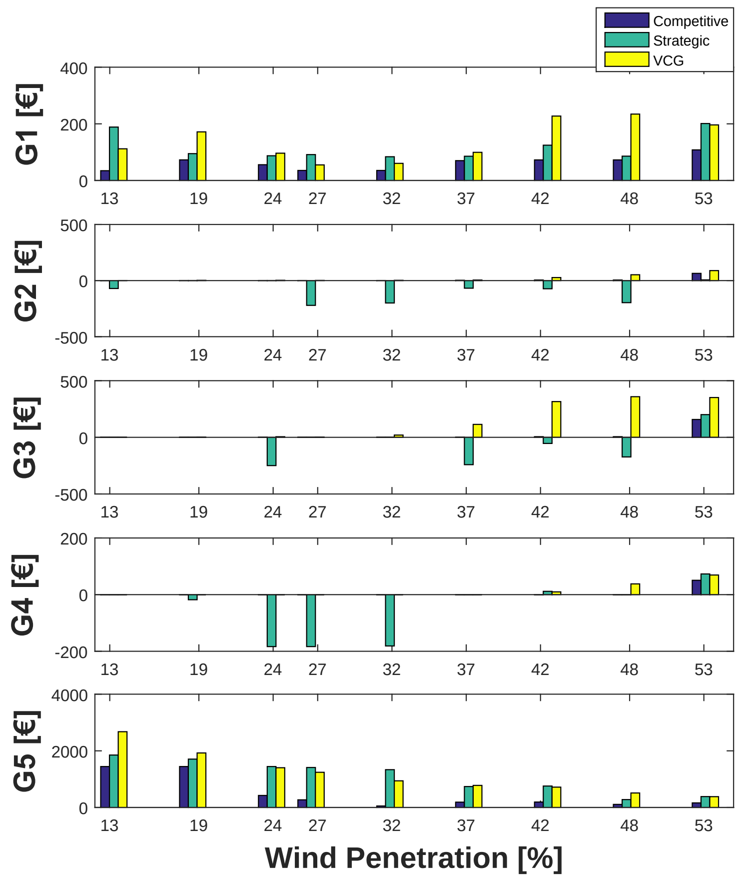

Figure 5.8a: Expected profits of producers G1-G5 across different clearing mechanisms versus different levels of wind power penetration

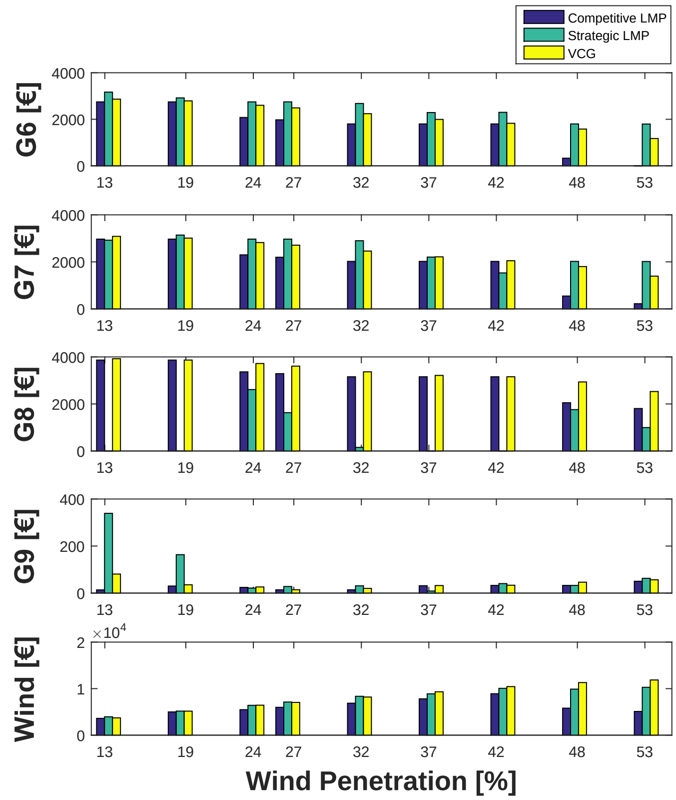

Figure 5.8b: Expected profits of producers G6-G9 and wind producer across different clearing mechanisms versus different levels of wind power penetration

A similar analysis is also provided for the demands payments in Fig. 5.9. It is observed that all consumers pay, comparatively, more in the equilibrium study under the strategic model, as the result of the higher prices due to strategic offering. It is worth mentioning that VCG, before redistribution of budget imbalance, also leads to the lowest payments among the three models, a result which is explained similarly to the VCG results for producers. Similar to conventional and wind producers, demands pay for their consumption based on their contribution to social welfare formation at the optimal point, and not based on a unique price as in traditional market setups. It is also observed that payments further decrease as wind penetration increases. This, on the one hand, indicates the positive impact of wind power on social welfare but, on the other hand, results in the increased budget deficit, observed at the beginning of the section in Fig. 5.5.

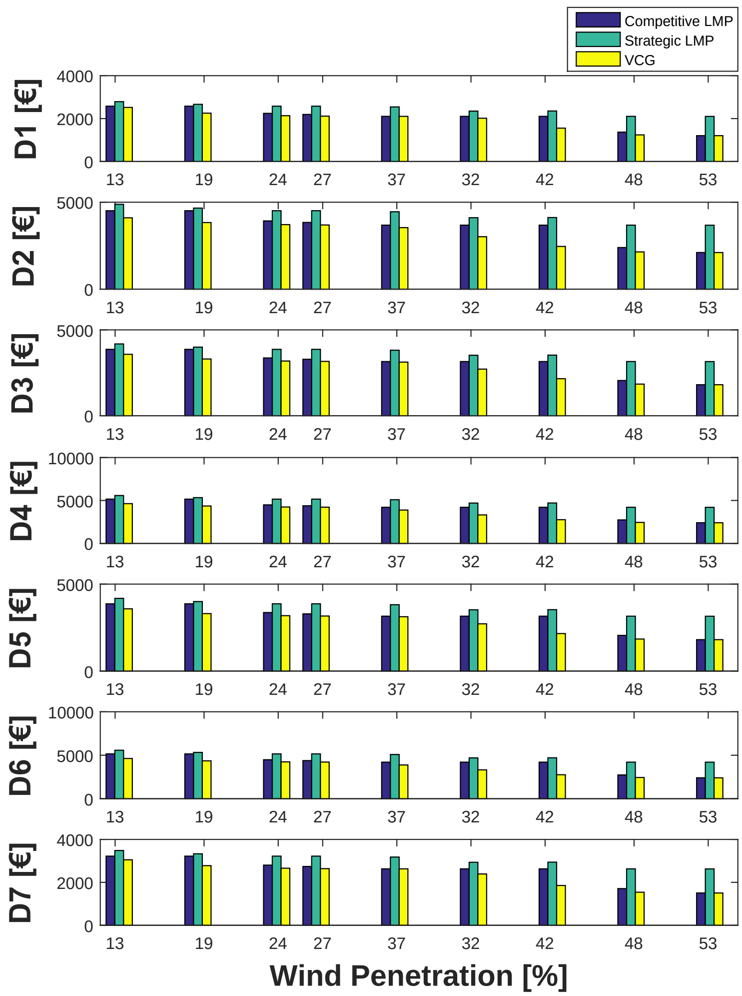

Figure 5.9: Demands expected payment across different clearing mechanisms versus different levels of wind power penetration

Concluding the presentation of the case study, regarding market budget imbalance we initially observed that budget deficit may appear for the

VCG mechanism and, in fact, the deficit increases along with wind power penetration. The result is further highlighted by Fig. 5.8a- 5.8b and 5.9, which show that generation-side revenues are comparatively higher than demand-side payments, ending up in budget deficit for the market operator. Considering that demands payments further decrease with increasing levels of wind generation, the deficit increases as well.

5.3.2 Case Study Considering Transmission Network Constraints

5.3.2.1 Data and assumptions

A large-scale case study based on a modified version of IEEE 24-bus reliability test system (RTS) is considered, which is differentiated from [84] in order to better accommodate wind farms [85]. The details and topology of the network can be found in Appendix B. The case study considers in total 12 conventional units and 17 demands. Each conventional unit offers at a quantity identical to its installed capacity and at a given price, which corresponds to its operational cost. In addition to conventional units, we consider 6 wind power units located at buses n={3, 5, 7, 16, 21, 23}. Similarly to the previous subsection, a set of scenarios is considered, which follow a Beta distribution with shape parameters (a,b)=(5,1), with an initial number of 2,000 wind scenarios [51]. Due to high computational cost, the final number of scenarios is reduced to three, using the K-means clustering method [89]. The values of the three scenarios are per unit values of installed capacity; multiplying them by each producer's installed capacity we obtain its corresponding wind power generation, i.e., for each scenario a set of six values are derived sharing a common probability of occurrence. Furthermore, multiple cases are evaluated for increasing levels of wind power penetration, similarly to the case reported in Subsection 5.3.1, scaling up the same wind power scenarios. Table 5.6 presents wind power scenario characteristics. Demand bids are elastic and the value of lost load for all demand is €200/MWh.

Table 5.6: Characteristics of the Wind Power Scenarios for Aggregate Wind Generation

Case No.	1	2	3	4	5	6	7	8
Wind Pen. [%]	17	23	27	29	34	36	40	50
Std. [MW]	88	116	139	151	174	185	208	255
Average [MW]	378	498	597	647	747	796	896	1095
Capacity [MW]	450	600	715	775	895	950	1070	1310

5.3.2.2 Results for increasing levels of wind power penetration

Figure 5.10 presents the results for budget imbalance of market in expectation versus different levels of wind power penetration. As discussed previously, the stochastic LMP market model was proved to be revenue-adequate in expectation [28], both for perfect and imperfect competition. Figure 5.10 indicates that congested network leads to different results for each model, compared to the case study of Subsection 5.3.1. More specifically, both competitive LMP and strategic LMP models result in positive budget imbalance for all levels of wind power penetration. This positive budget imbalance, which does not appear in market-clearing models without network constraints, is attributable to “transmission/congestion rent” [147, 148]. Transmission rent takes a non-zero value if there is at least one congested line, forming different prices (i.e., nodal LMPs) at the two nodes connected by that line. This term indicates that a change in the line features (e.g., susceptance and thermal capacity) can enable more power exchange between two nodes. In this case, grid operator makes a revenue due to transmission congestion. For a transmission line that carries $P_{n,m}$ power from node n to node m, transmission rent is defined by the following equation:

$$\text{Transmission Rent} = \left(\lambda_m^{\text{DA}} - \lambda_n^{\text{DA}}\right) P_{n,m}. \tag{5.18}$$

One can view the grid operator as a spatial arbitrager, who buys power $P_{n,m}$ at bus n at price λ_n, and then transfers it to bus m, and sells the same amount of power at node m at a different price λ_m. It is obvious that such a revenue is zero if the nodal price at buses n and m is identical, i.e., the connecting line of buses n and m is not congested. Thus, the grid operator profits this positive budget imbalance due to congestion in LMP markets.

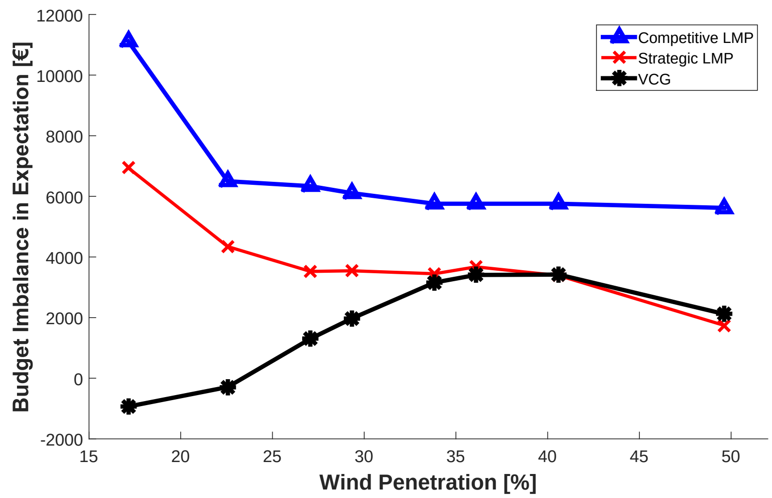

Figure 5.10: Budget imbalance of the market in expectation versus different levels of wind power penetration, considering network constraints. The y-axis value shows the difference of total payments of demand-side and total revenues of generation-side, i.e., the payments to grid operator (e.g., in the form of congestion rent) is not considered.

Note that as before, revenue-adequacy in stochastic LMP is guaranteed in expectation, but not necessarily for each individual scenario. Exploring the results of Fig. 5.10, we note that market budget imbalance in expectation, for both competitive and strategic LMP, is positive, but decreases with increasing penetration level of wind power. This result is explained considering (5.18) and the fact that prices, generally, decrease with the increasing penetration of wind power, as it can be observed by Tables 5.7 and 5.8, presenting the nodal prices for the LMP mechanisms.

Table 5.7: Nodal DA Prices [€/MWh] in Competitive LMP versus Wind Power Penetration

Node	Wind Penetration Level [%]							
n	17%	23%	27%	29%	34%	36%	40%	50%
1	19.18	14.27	14.00	13.78	13.46	13.46	13.46	13.27
2	19.28	14.33	14.05	13.83	13.50	13.50	13.50	13.32
3	15.85	12.50	12.32	12.17	11.95	11.95	11.95	11.82
4	19.60	14.50	14.21	13.99	13.65	13.65	13.65	13.46
5	19.87	14.64	14.35	14.12	13.77	13.77	13.77	13.58
6	20.27	14.85	14.55	14.31	13.95	13.95	13.95	13.75
7	20.22	14.83	14.52	14.29	13.93	13.93	13.93	13.73
8	20.22	14.83	14.52	14.29	13.93	13.93	13.93	13.73
9	19.86	14.63	14.34	14.11	13.77	13.77	13.77	13.57
10	20.58	15.02	14.71	14.46	14.09	14.09	14.09	13.89
11	23.38	16.62	16.23	15.94	15.50	15.50	15.50	15.24
12	19.00	14.06	13.80	13.58	13.25	13.25	13.25	13.07
13	20.93	14.64	14.40	14.09	13.62	13.62	13.62	13.43
14	28.74	20.18	19.56	19.23	18.72	18.72	18.72	18.35
15	9.510	9.13	9.11	9.10	9.07	9.07	9.07	9.06
16	7.88	7.88	7.88	7.88	7.88	7.88	7.88	7.88
17	6.62	6.62	6.62	6.62	6.62	6.62	6.62	6.62
18	6.02	6.02	6.02	6.02	6.02	6.02	6.02	6.02
19	9.74	9.26	9.16	9.16	9.16	9.16	9.16	9.12
20	11.35	10.46	10.28	10.28	10.28	10.28	10.28	10.20
21	5.47	5.47	5.47	5.47	5.47	5.47	5.47	5.47
22	5.92	5.92	5.92	5.92	5.92	5.92	5.920	5.92
23	12.24	11.12	10.89	10.89	10.89	10.89	10.89	10.79
24	11.96	10.44	10.35	10.28	10.18	10.18	10.18	10.13

*Note: The expected RT price at each bus is equal to the DA price at the same bus, under the two-stage stochastic market-clearing model.

Table 5.8: Nodal DA Prices [€/MWh] in Strategic LMP versus Wind Power Penetration

Node	Wind Penetration Level [%]							
n	17%	23%	27%	29%	34%	36%	40%	50%
1	19.55	16.00	14.59	14.00	13.78	13.75	13.42	12.59
2	19.65	16.06	14.63	14.04	13.82	13.80	13.47	12.61
3	16.48	14.13	13.23	12.84	12.24	12.11	11.92	11.81
4	19.94	16.24	14.76	14.15	13.97	13.95	13.62	12.69
5	20.19	16.39	14.87	14.24	14.09	14.09	13.74	12.75
6	20.57	16.62	15.03	14.38	14.28	14.29	13.92	12.84
7	20.52	16.59	15.01	14.36	14.26	14.26	13.90	12.83
8	20.52	16.59	15.01	14.36	14.26	14.26	13.90	12.83
9	20.18	16.39	14.86	14.24	14.09	14.08	13.73	12.75
10	20.85	16.79	15.16	14.49	14.42	14.44	14.06	12.92
11	23.45	18.35	16.33	15.52	15.72	15.82	15.33	13.57
12	19.39	15.92	14.48	13.89	13.69	13.65	13.34	12.54
13	20.14	16.51	14.80	14.16	14.05	14.03	13.70	12.72
14	29.31	21.74	19.00	17.88	18.66	18.97	18.22	15.07
15	10.61	10.57	10.64	10.64	9.32	8.99	9.05	10.33
16	10.01	10.21	10.20	10.05	9.02	8.67	8.75	10.18
17	10.23	10.34	10.01	9.58	9.12	8.78	8.86	10.23
18	10.32	10.40	9.93	9.37	9.17	8.83	8.91	10.26
19	12.23	11.46	11.22	10.97	10.13	9.86	9.85	10.75
20	14.15	12.55	12.12	11.77	11.10	10.90	10.80	11.24
21	10.42	10.45	9.84	9.16	9.22	8.88	8.95	10.28
22	10.34	10.41	9.91	9.33	9.18	8.84	8.91	10.26
23	15.22	13.15	12.61	12.20	11.63	11.47	11.32	11.51
24	12.88	11.95	11.64	11.49	10.45	10.19	10.16	10.90

*Note: The expected RT price at each bus is equal to the DA price at the same bus, under the two-stage stochastic market-clearing model.

Prices, considering transmission network constraints, are different per each node in the LMP mechanisms. Apart from the congested lines, i.e., those lines connecting nodes (15,21), (14,16) and (13,23), all other lines are not congested for any wind power penetration level in this case study. However, the differences in prices among the nodes, observed in Tables 5.7 and 5.8, can also be caused by the coupling among DA and RT prices induced by the two-stage programming approach [28]. Recall that energy prices in the stochastic LMP mechanism anticipate probable system conditions in RT stage under different foreseen scenarios and, thus, DA and

RT prices are strongly coupled. Additionally, in this two-stage stochastic model, DA and RT prices are arbitraged in expectation, i.e., DA and expected RT prices are equal †. However, these prices are totally different from those obtained in a sequential market-clearing model, i.e., a model which clears DA market only, without considering potential realizations in RT, and then sequentially clears the RT market with fixed DA decisions [149].

Since VCG pricing is not nodal but per participant, the market budget imbalance is not directly related to network constraints. From Fig. 5.10 it is observed that market budget imbalance in expectation can be negative for low wind power penetration. This is explained by the comparatively low payments of demands compared to payments made to producers, both wind and conventional. This outcome changes for VCG cases with wind penetration from 23% to 40% where demands payments remain on the same levels; however decreased payments to conventional producers lead to a positive budget imbalance instead of a negative one. Following the increasing wind penetration, payments to wind producers also increase and, thereafter, the market expected budget imbalance decreases, but still remains positive.

For illustration reasons, weighted average prices for aggregate conventional generation, aggregate wind power generation, and aggregate demands are presented in Fig. 5.11, 5.12 and 5.13, respectively. These weighted average prices (denoted by $\widehat{\lambda}$) are the summation of all individual prices multiplied by the ratio of individual and total traded power in DA, defined similarly to equations (5.17a)-(5.17c) of the previous subsection. It is observed that weighted average conventional generation prices are higher for the VCG mechanism at low wind power penetration and then become smaller compared to the competitive LMP, while for all wind power penetration levels, prices under the strategic LMP model are higher. Regarding wind generation prices, VCG and competitive LMP lead to small price difference for low wind power penetration, but for increased wind penetration levels competitive LMP leads to higher prices. Lastly, results for the demand-side prices show that under strategic LMP prices are higher than both competitive LMP and VCG. Furthermore,

†This is explained by equation (5.3b); in a perfectly competitive market dual variables $\underline{\sigma_l}$ and $\overline{\sigma_l}$ have zero values due to the non-binding constraints (5.2h).

for high levels of wind power penetration VCG demand-side prices decrease drastically. Note that up to 30% of wind power penetration the weighted average prices of both wind and conventional generation under VCG decrease, while the corresponding demand-side prices do not change appreciably. This explains partly the fact that budget imbalance increases, and becomes positive, for these penetration levels since payments to producers decrease and payments received from demands remain at the same levels.

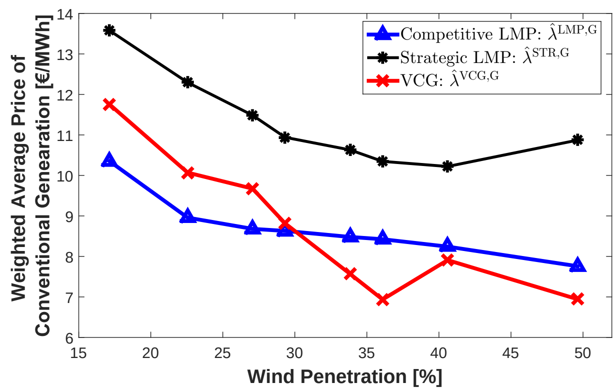

Figure 5.11: Conventional generation weighted average DA market prices versus different levels of wind power penetration

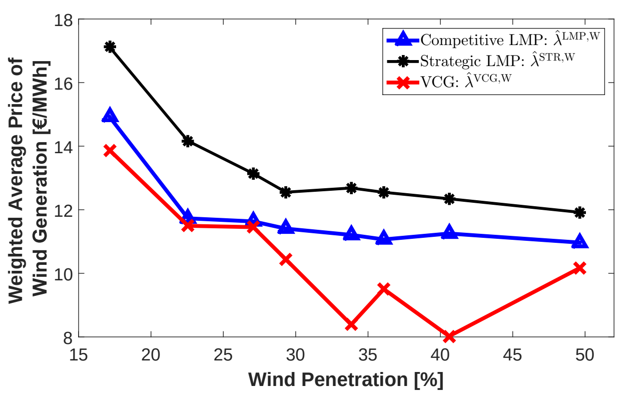

Figure 5.12: Wind generation weighted average DA market prices versus different levels of wind power penetration

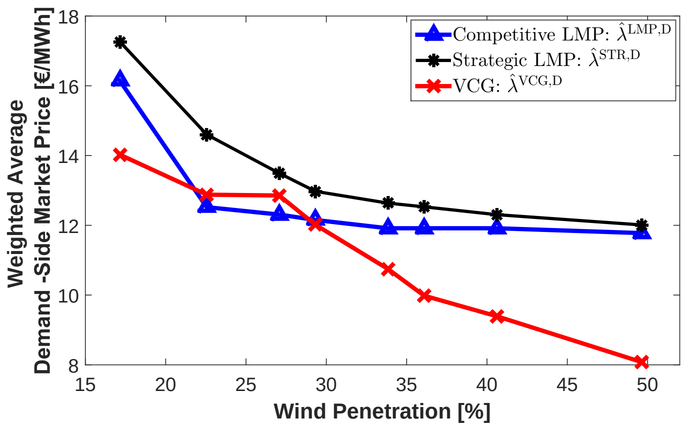

Figure 5.13: Demand-side weighted average DA market prices versus different levels of wind power penetration

The expected social welfare of the market for increasing levels of wind power penetration is plotted in Fig. 5.14. As mentioned previously, incentive-compatible VCG as well as competitive LMP lead to the same social welfare, due to the truthful submission of costs from the generation side. In other words, both of them yield identical production and consumption schedules, but different prices and, thus, payments. Note that truthfulness is an assumption for the competitive LMP model but a dominant strategy for the VCG. On the other hand, under the strategic LMP model, producers offers to the market are not equal to their actual operational costs, but they are strategic decisions aiming to increase DA market prices and, thus, individual profits. It is observed again from Fig. 5.14 that social welfare of strategic LMP is considerably lower than the other two mechanisms, indicating the anticipated loss in efficiency due to existing strategies of the price-making producers. Naturally, though, social welfare increases with the penetration of wind power for all three market mechanisms.

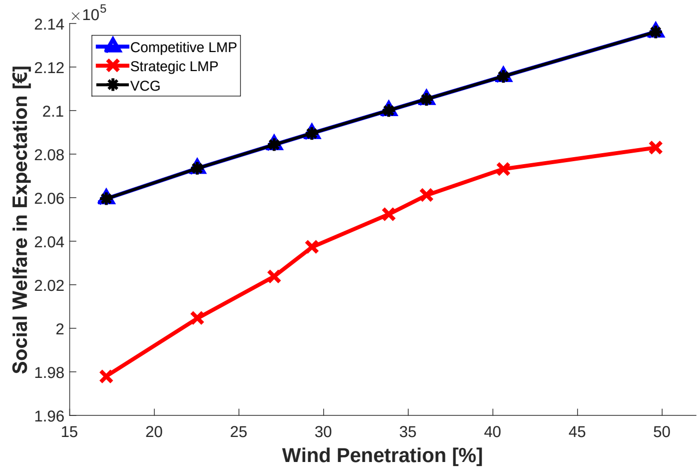

Figure 5.14: Market expected social welfare versus different levels of wind power penetration, considering network constraints. Expected social welfare in both competitive LMP and VCG models is the same since they end up in identical dispatch results; the only difference is the pricing scheme used.

Figure 5.15a and 5.15b compare the profits for all participating producers for the three different market mechanisms. It is observed that producers profits are again higher under the VCG mechanism compared to the competitive LMP. Note that the yellow bars correspond to the VCG payments before potential uplifts, so they might not be the final revenues, since an ex-post budget redistribution step might be required due to negative budget imbalance. Additionally, there are cases, as for example producers G8 and G9, that producers have zero profits under the LMP mechanism due to being marginal producers, but their profits under the VCG mechanism are positive. On the other hand, recall that strategic bidding in the LMP market can violate the property of cost-recovery, meaning that if producers offer at different levels than their marginal costs they cannot avoid the risk of negative profits. It is anticipated though, that since all market participants have the same information and reach equilibrium, market-clearing should be perfectly anticipated by producers. However, similarly to the previous case study, small losses appear for producers due to the existence of multiple available solutions. In Fig. 5.15a this can be observed for producers G3, G4 and G5 who face negative profits, although of low magnitude.

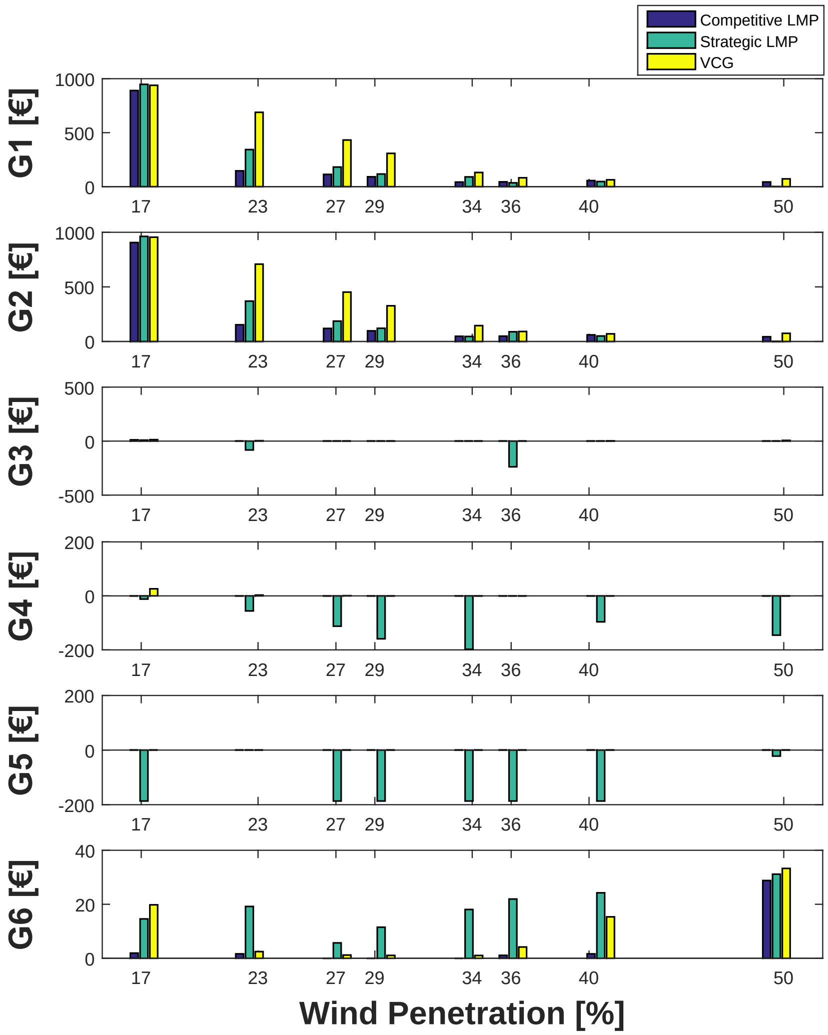

Figure 5.15a: Expected profits of producers G1-G6 versus different levels of wind power penetration, considering network constraints

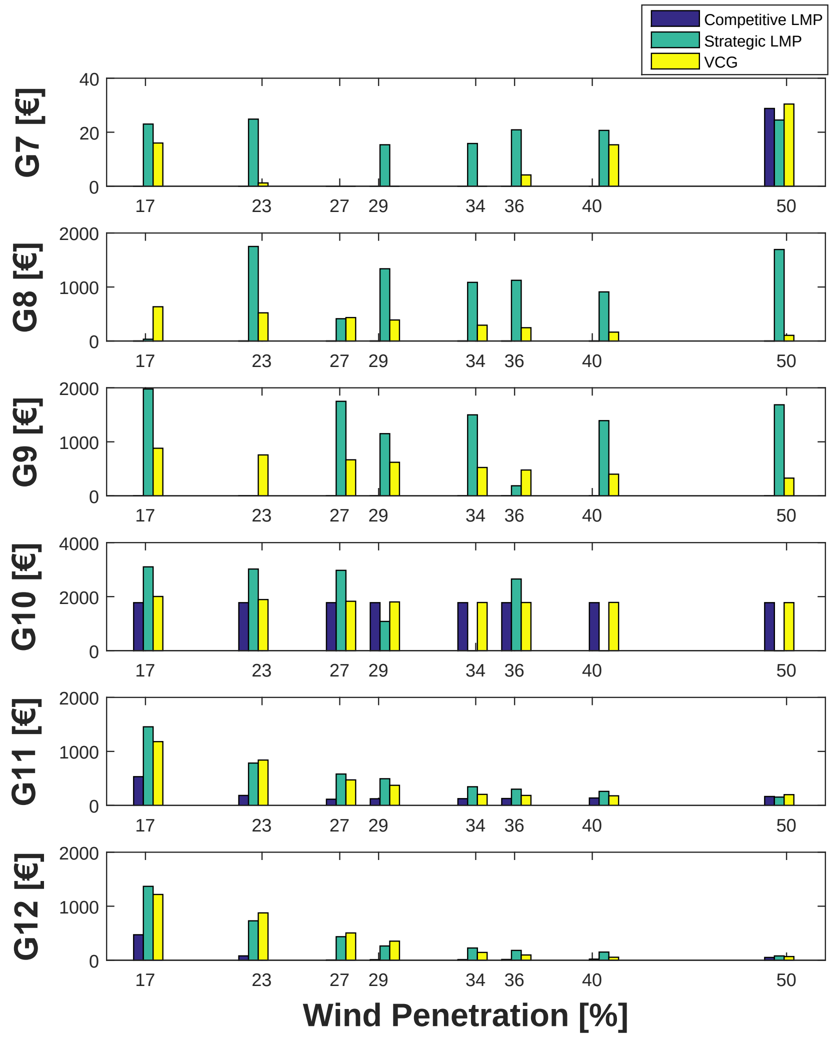

Figure 5.15b: Expected profits of producers G7-G12 versus different levels of wind power penetration, considering network constraints

Figure 5.16 presents the profits of all six wind power producers, W1 to W6. It is evident that in most cases wind producers earn marginally more when strategic offering is adapted by conventional producers, leading to increased prices in strategic LMP. However, VCG is more profitable for wind producers compared to the competitive LMP, since it leads in higher profits that depend on the positive impact of wind producers to social welfare. Transmission network poses additional constraints for the exchange of power between nodes, decreasing the positive impact of wind power on social welfare and, at the same time, reducing payments to wind producers. Recall that wind producers, despite being competitive in all cases, they still get benefited by the strategic behavior of conventional producers under the strategic LMP model, and this explains their higher profits even under congested network.

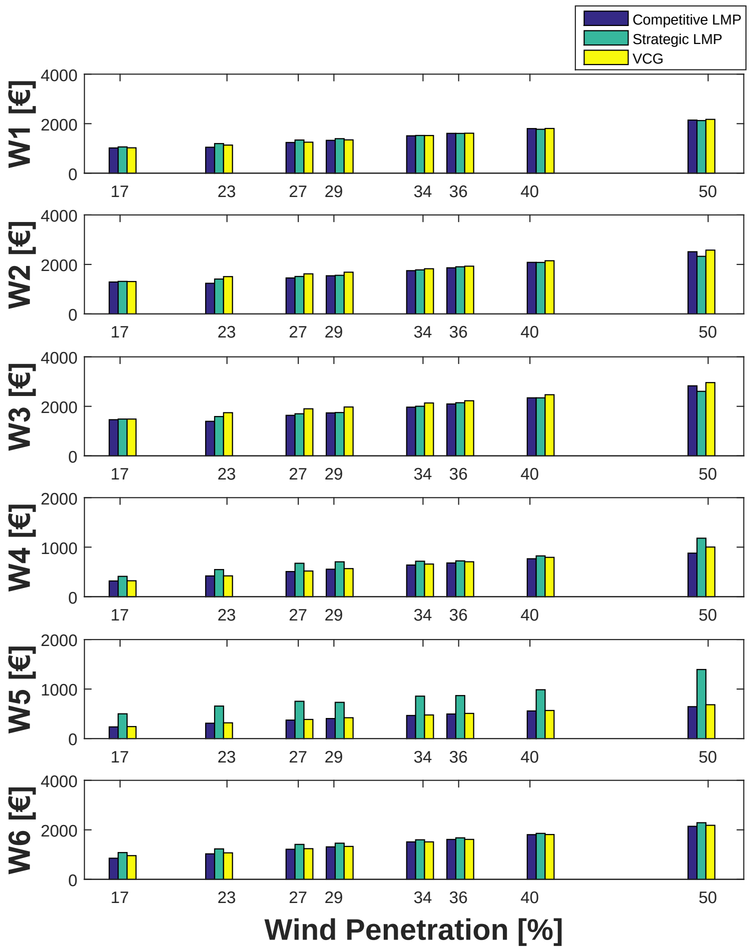

Figure 5.16: Expected profits of wind producers W1-W6 versus different levels of wind power penetration, considering network constraints

Demands payments are presented in Fig. 5.17a-5.17c. It is observed that, generally, consumers pay more under the strategic LMP, similarly to the case ignoring network constraints. This is the result of increased prices caused by strategic offering of conventional producers. It is also observed that demands pay less as wind penetration increases, indicating the positive impact of wind power on social welfare. The VCG model also leads to lower payments and, therefore, it is the most beneficial model for the consumers across all three investigated mechanisms.

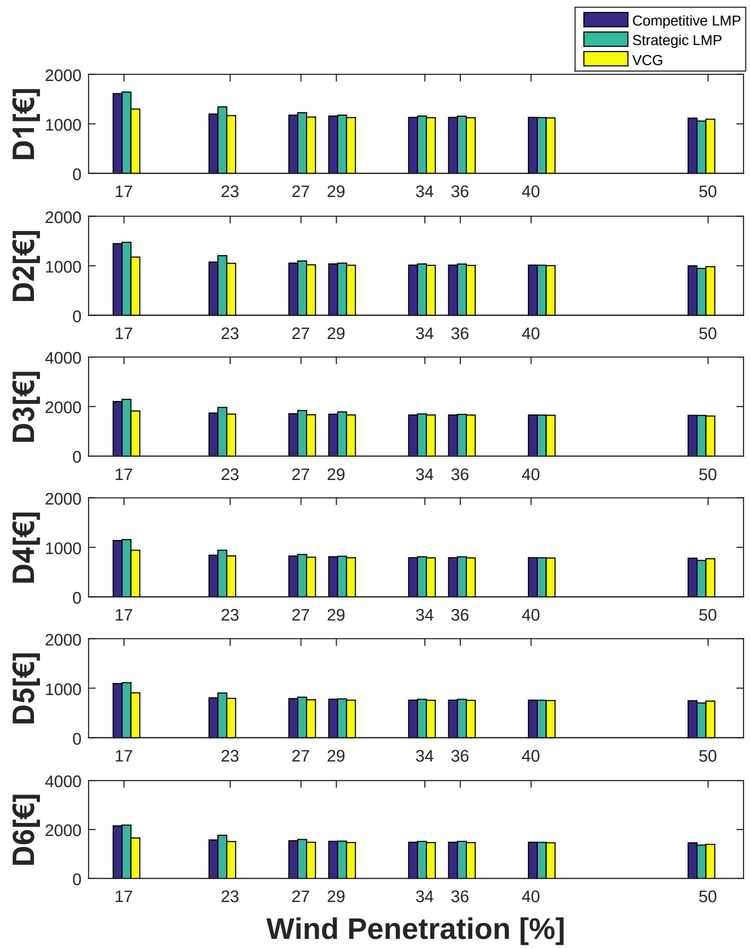

Figure 5.17a: Expected payment of demands D1-D6 versus different levels of wind power penetration, considering network constraints

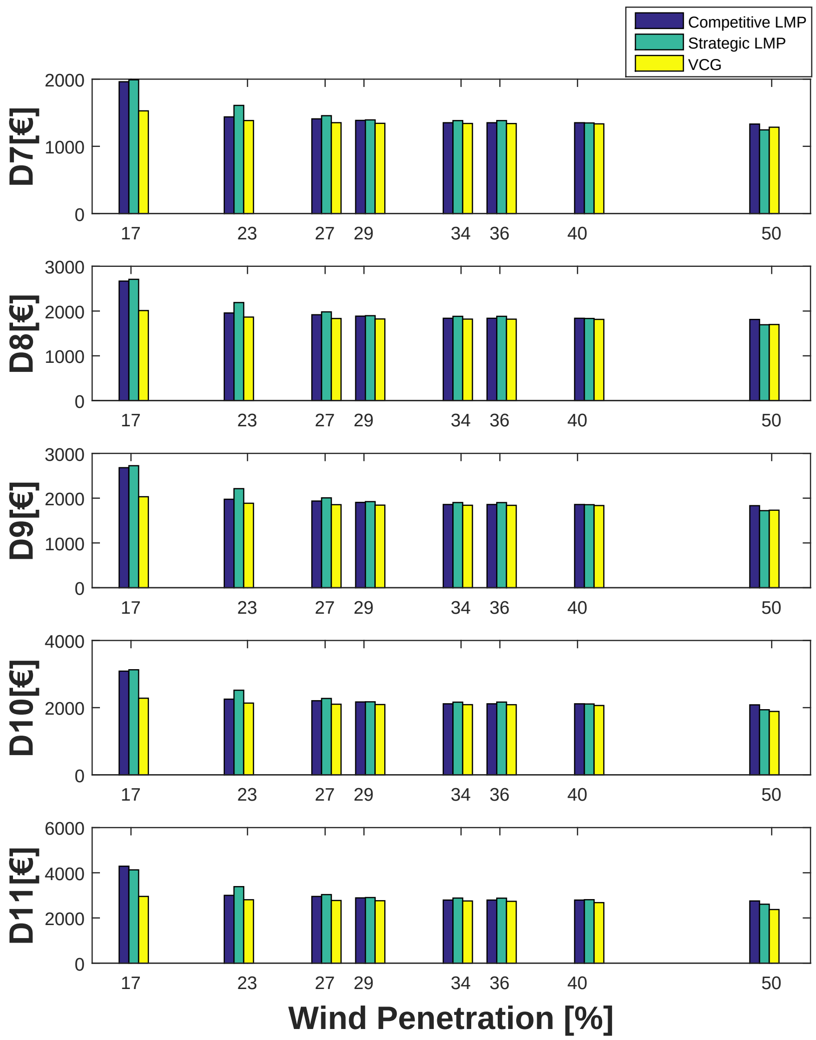

Figure 5.17b: Expected payment of demands D7-D12 versus different levels of wind power penetration, considering network constraints

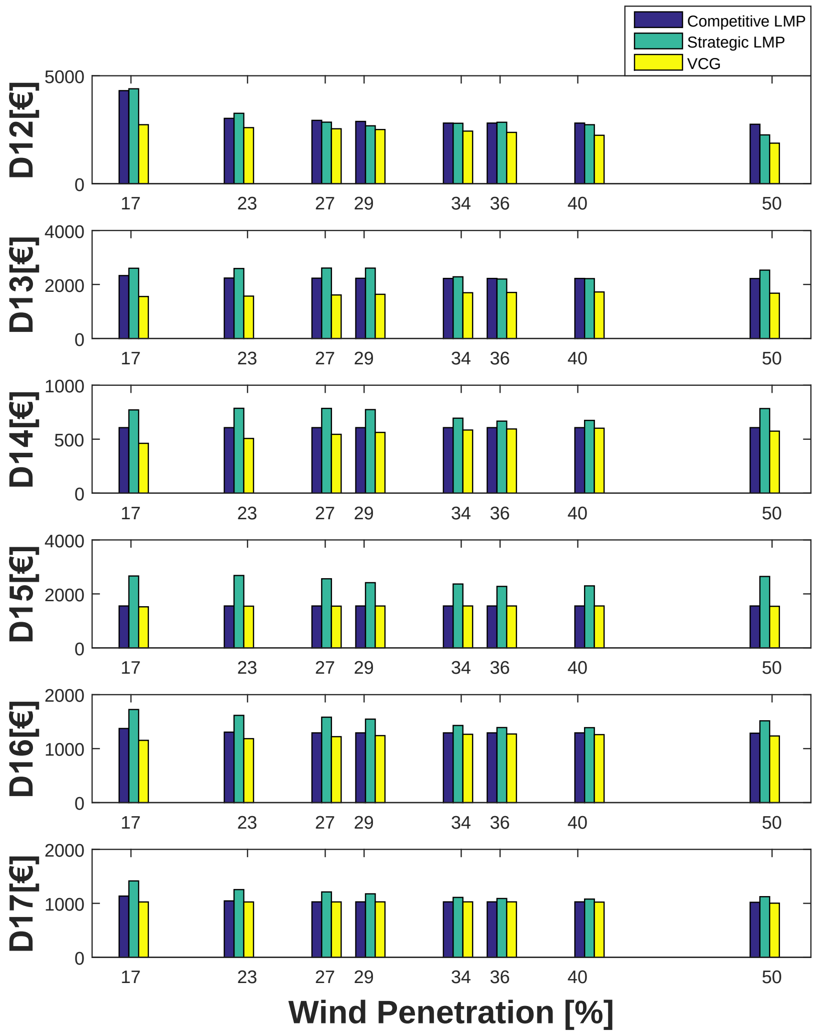

Figure 5.17c: Expected payment of demands D13-D17 versus different levels of wind power penetration, considering network constraints

Elaborating more on the result regarding revenue-adequacy, it was initially presented that negative budget imbalance is very likely to occur under the VCG mechanism. It should be, however, noted that compared to the case that excludes network constraints, negative budget imbalance is decreased when congested network is considered. Moreover, it even becomes positive for increased levels of wind power penetration. Constraints imposed by transmission lines capacity limits reduce the actual impact of producers on social welfare, especially for cheap generation units, which due to congestion cannot be exploited in their highest capacity. Thus, payments to producers are decreased accordingly, compared to the case excluding network constraints. Similarly, these constraints have the same effect on the demand-side, whose impact on social welfare maximization is decreased, followed by increased payments to the market. To better illustrate this result, we solve the same market-clearing problem under VCG, considering increased transmission line capacities in order to avoid congestion in the network. To this end, Fig. 5.18 presents a comparison of demands charges under the VCG mechanism for the case of congested and uncongested network, while Fig. 5.19 presents a comparison of aggregate wind and conventional producers revenues, accordingly.

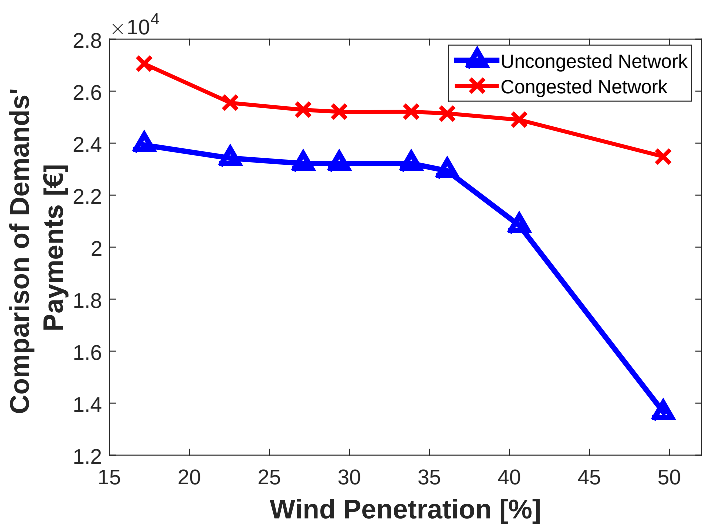

Figure 5.18: Demands payments for both congested and uncongested network, under the VCG mechanism

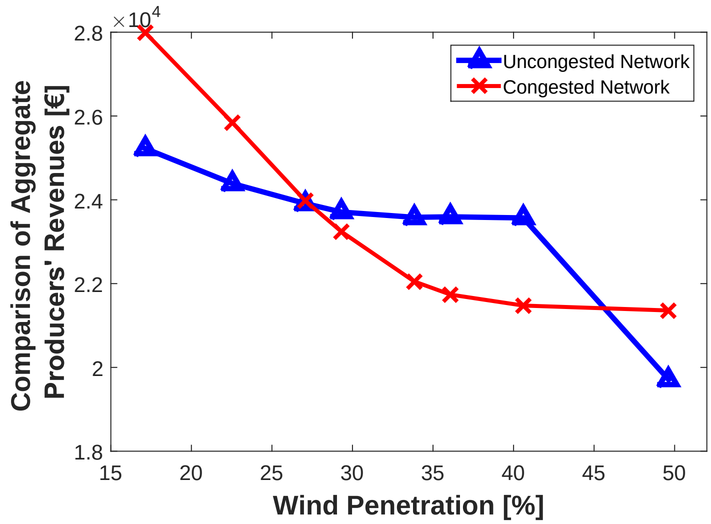

Figure 5.19: Aggregate wind and conventional generation revenues for both congested and uncongested network, under the VCG mechanism

Figure 5.18 shows that demands payments under a congested network are always higher compared to the uncongested network, and the difference increases for large values of wind penetration, i.e., above 35%. This is a first indication that under a congested network negative imbalance is in lower levels, since the received payments from demands are higher. In parallel, Fig. 5.19 shows that aggregate generation revenues are higher under a congested network for penetration levels between 15% and 27%. This is partly balanced by the received high demand payments, leading to small values of negative budget imbalance. However, as penetration level increases the impact of producers under congested network decreases, while the payments received from demands remain on the same high levels. Thus, the difference between demands payments and producers revenues becomes higher, resulting in positive budget imbalance. The case of the uncongested network, though, is different: apart from the last wind penetration scenario, producers revenues as well as demands payments do not change considerably versus increasing levels of wind penetration, maintaining budget imbalance at negative levels. Budget imbalance for the congested and uncongested network is presented in Fig. 5.20.

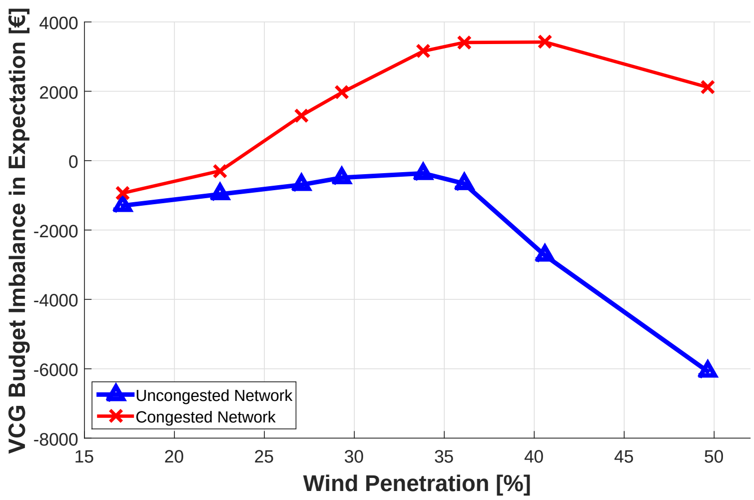

Figure 5.20: Budget imbalance of the market for both congested and uncongested network, under the VCG mechanism

5.3.2.3 Budget imbalance redistribution under the VCG Mechanism

In this subsection we apply the redistribution scheme presented in Section 5.2.4.6 on the case study considering network constraints. Following the process already described, we distinguish which market agents have positive impact towards revenue-adequacy and who have negative impact, leading to negative budget imbalance. The former should be awarded and latter charged for their contribution on market budget imbalance.

Based on the aforementioned approach we present the results for the explored case study with network constraints. Figure 5.21 presents the results of the corrected budget imbalance following the redistribution approach and compares it with the competitive LMP and the VCG before redistribution. Regarding the resulted budget imbalance, we observe that the negative budget imbalance for low wind power penetration levels is fully recovered after redistribution, and it became positive. Furthermore, rewarding market agents that contribute towards revenue-adequacy leads to decreased budget imbalance for the case where revenue-adequacy was met prior redistribution. As mentioned before, LMP markets are characterized by positive budget imbalance in congested networks, which correspond to the payments received by the grid operator. However, the definition of the payments to the grid operator under a VCG mechanism exceeds the scope of this study. Thus, the resulted positive budget imbalance of the proposed redistribution mechanism, should only be seen as a better approximation of budget balance while ensuring the properties of the market, i.e., revenue-adequacy, cost-recovery and incentive-compatibility.

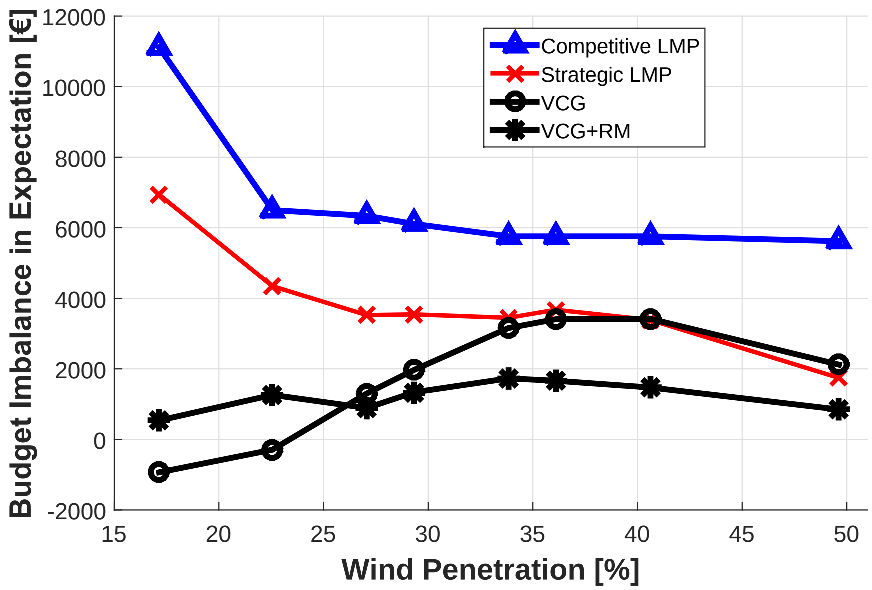

Figure 5.21: Budget imbalance in expectation after redistribution versus different levels of wind power penetration, considering network constraints.

Figures 5.22a - 5.22b present the profits of conventional producers, after applying the aforementioned budget redistribution approach. It is observed that producers G1 and G2 are mostly affected by the redistribution scheme and their profits decrease to levels lower than the competitive LMP mechanism, but only for the lowest wind power penetration scenario. Both producers have increasing profits for all other scenarios of wind power penetration. Moreover, most producers still benefit from the VCG model after redistribution compared to the competitive LMP.

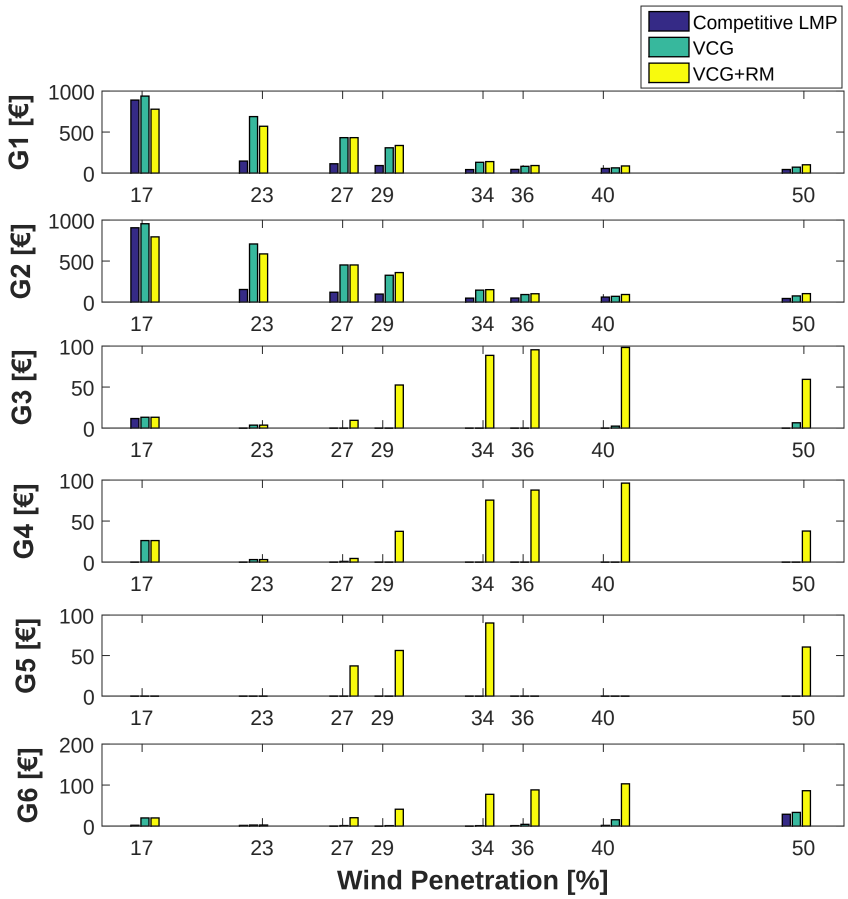

Figure 5.22a: Expected profits of producers G1-G6 after the redistribution of budget imbalance versus different levels of wind power penetration, considering network constraints

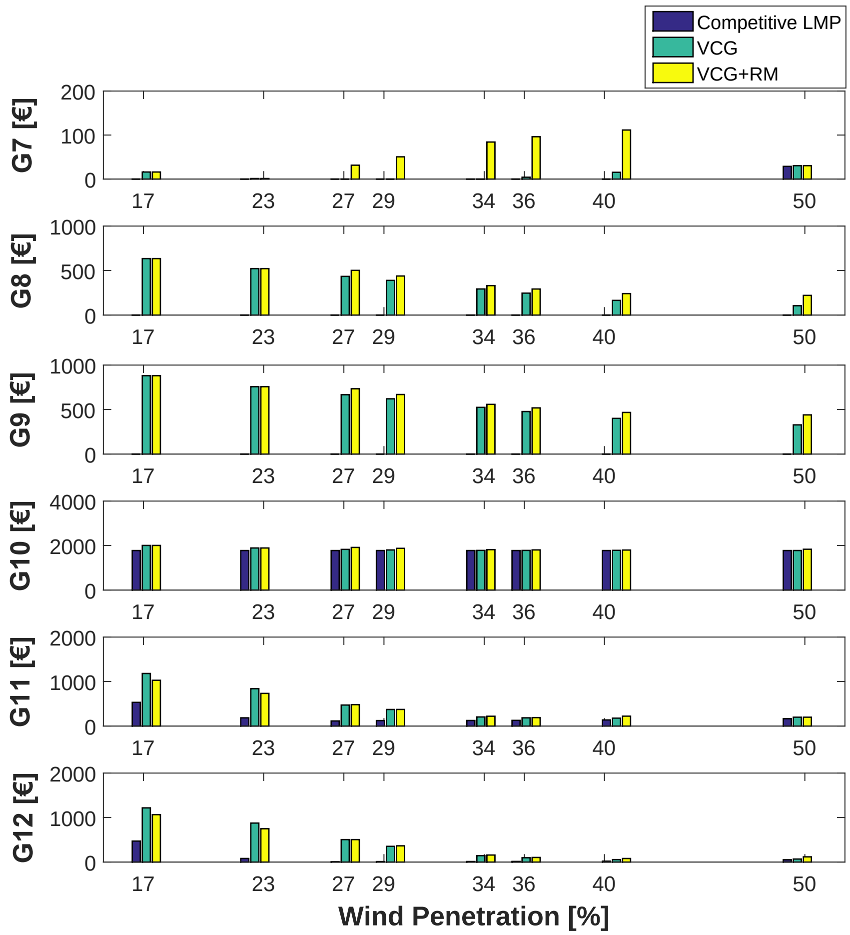

Figure 5.22b: Expected profits of producers G7-G12 after the redistribution of budget imbalance versus different levels of wind power penetration, considering network constraints

Regarding wind producers profits after the redistribution, it is observed in Fig. 5.23 that wind producers participate the least to the redistribution scheme and, thus, their profits do not change considerably. Generally, wind producers still benefit by the VCG model after redistribution.

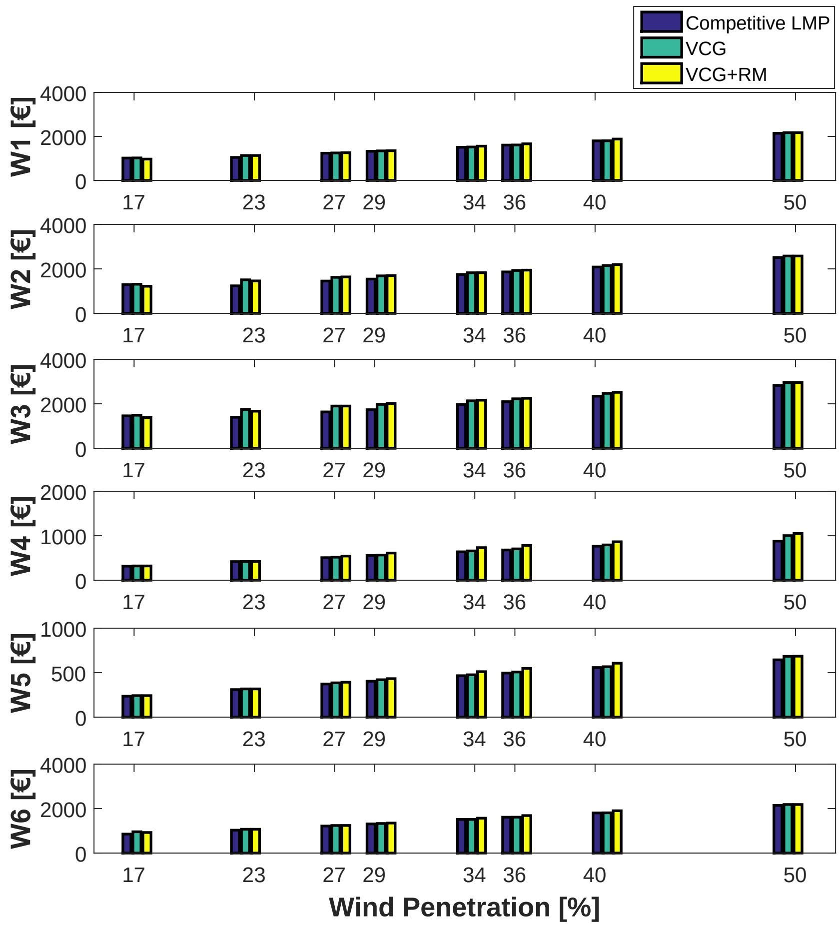

Figure 5.23: Expected profits of wind producers W1-W6 after the redistribution of budget imbalance versus different levels of wind power penetration

Finally, regarding demands payments, as presented in Fig. 5.24a-5.24c, it is observed that some demands, e.g., D14, D15 and D16, have slightly increased payments after redistribution for low wind penetration levels but the opposite for higher penetration levels. In general all demands are due to lower payments under the VCG after redistribution compared to the competitive LMP.

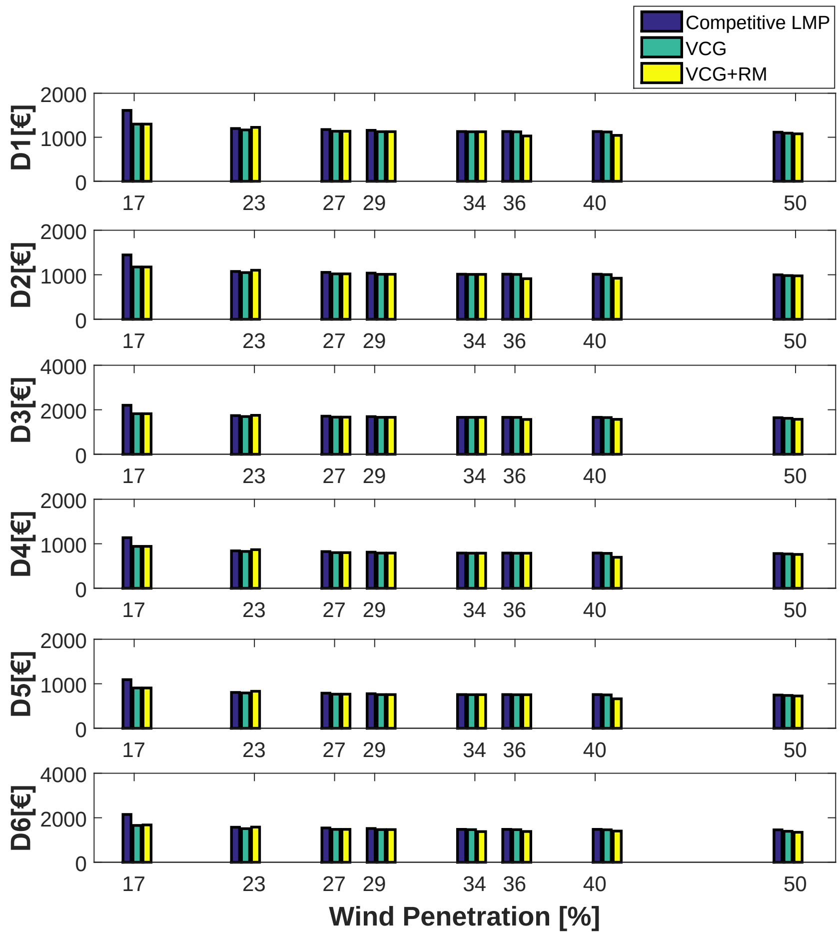

Figure 5.24a: Expected payment of demands D1-D6 after the redistribution of budget imbalance versus different levels of wind power penetration, considering network constraints

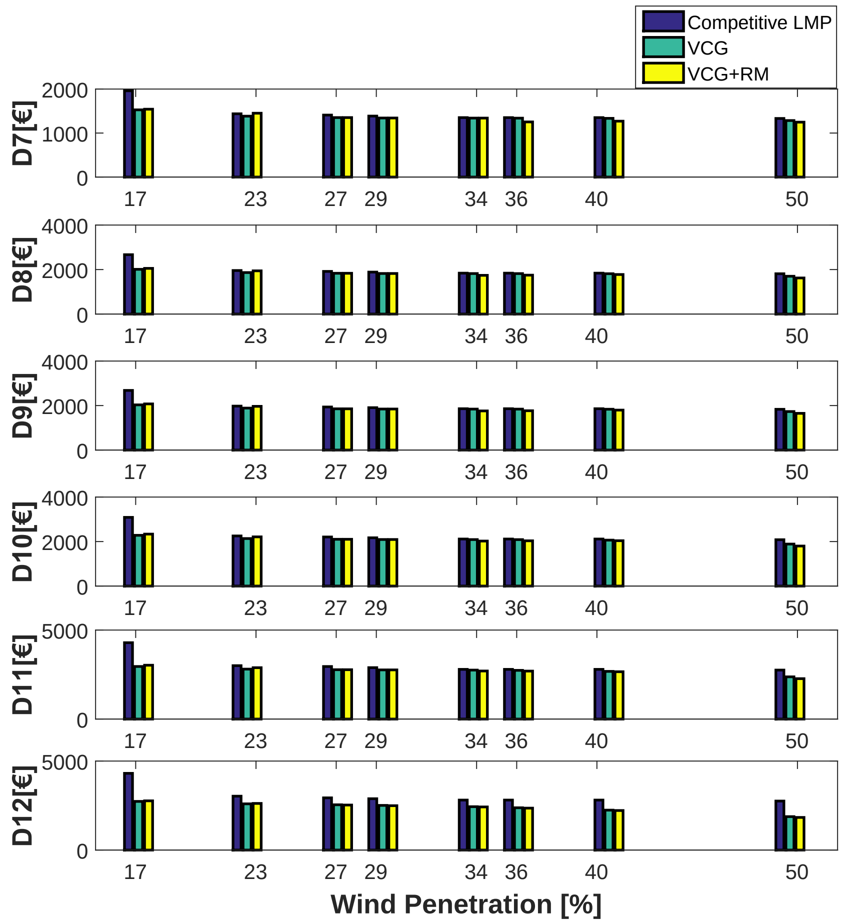

Figure 5.24b: Expected payment of demands D7-D12 after the redistribution of budget imbalance versus different levels of wind power penetration, considering network constraints

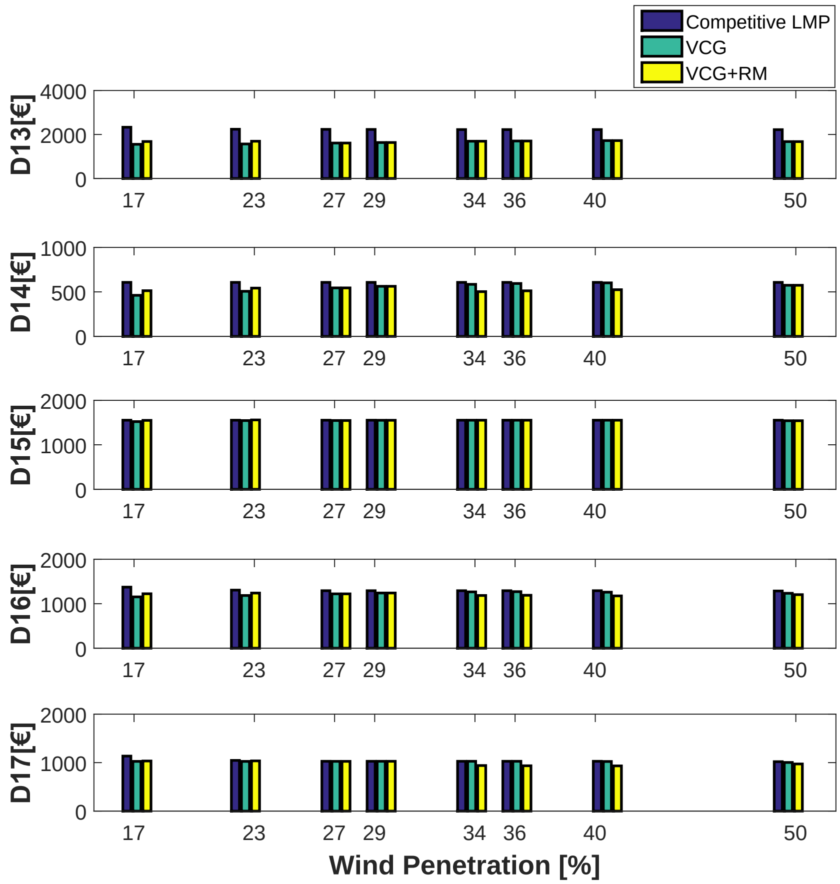

Figure 5.24c: Expected payment of demands D13-D17 after the redistribution of budget imbalance versus different levels of wind power penetration, considering network constraints

Note that the investigated redistribution mechanism succeeds in a fair way to offer a general approach for distinguishing which agents should be charged or rewarded based on their contribution towards revenue-adequacy. However, the solution approach for calculating the exact redistribution payment is only applicable when there are agents whose absence from the market can change the condition of budget imbalance from being negative to being positive. This is not the case, however, for the uncongested network and other approaches should be followed thereafter.

5.3.3 Computational Performance

This subsection offers an insight to the computational needs of the two case studies. For the needs of this chapter we have used CPLEX under GAMS associated with Matlab R2015b on a Windows 8.1, 64-bit operating system with 2 cores processor, running at 2.4 GHz and 12 GB of RAM. The case studies of this chapter are computationally demanding, while the computational times are also multiplied by the number of different wind power penetration levels.

Table 5.9: Computational Times

	Excluding Transmission Network Constraints (10 scenarios)	Including Transmission Network Constraints (3 scenarios)
Competitive LMP	0.3 sec.	0.4 sec.
Strategic LMP	480 sec.	623 sec.
VCG	5 sec.	7.2 sec.

*Note: Computational times in this table refer to simulations for a single wind penetration level.

The computational times are presented in Table 5.9. Similarly to Chapter 4, the most demanding model is the strategic LMP, which requires also multiple iterations until it reaches the equilibrium point. More specifically, for the first case study, i.e., excluding network constraints, the strategic LMP required 480 sec. which is significantly higher than the corresponding computational time of the two-stage stochastic model of the competitive LMP. Lastly, the computational needs of the VCG market mechanism is slightly increased compared to the competitive LMP, mainly because in order to define agents payments the two-stage optimization problem has to be solved a number of times equal to the number of participating agents. However, the computational time remains in comparatively efficient levels.

On the other hand, computational needs considering the transmission network in the market-clearing process increases drastically. For this reason, the number of wind power scenarios considered in this case were reduced to three instead of ten in the unconstrained case study. The solution of the corresponding strategic LMP was 623 sec. for a single wind penetration level. The corresponding computational times for the competitive and VCG models are significantly lower. Even though the reduced computational time of the competitive and the VCG models allows the use of more scenarios, all models were solved with identical sets of scenarios for comparative reasons.

In this chapter, we use an iterative diagonalization approach, which is simple but at the risk of not converging in the predefined number of iterations. One sort of alternatives is to augment the current diagonalization technique by increasing the number of iterations and/or providing different starting points. Another alternative is to use non-iterative equilibrium solution techniques (e.g., in [70]), but at the cost of increased complexity. However, this approach was avoided for both its complexity and its higher computational cost, being also consistent with the method used in Chapter 4.

5.4 Summary and Conclusions

Driven by the importance of electricity market efficiency and competitiveness, this work introduces an incentive-compatible mechanism under a stochastic two-stage market setup, which aims at increasing competitiveness in markets with high penetration of wind power. Given that strategic behaviors can arise under the LMP market mechanism, we investigate a VCG-based market-clearing mechanism and extensively compare it with the LMP mechanism under both perfect and imperfect competition. The VCG mechanism has the ability to induce truthful offers from participants, solving the problem of strategic offering which brings losses in market efficiency. However, both mechanisms come with a set of advantages and disadvantages with respect to market operation, which are explored and reported in this study.

The results of this extensive analysis lead to a number of conclusions that contribute to a better understanding of the aforementioned mechanisms. Table 5.10 attempts to gather and compare the three analysed models, with respect to the most valuable properties of the market, namely market efficiency, cost-recovery, revenue-adequacy and incentive-compatibility. Elaborating on these results and Table 5.10, we conclude that:

- A perfectly competitive LMP mechanism is anticipated to comply with the first three properties, capitalizing however on the assumption of truthfulness and perfect competition. This is an ideal market mechanism used as a benchmark, which in practice does not exist. Thus, the mechanism is not incentive-compatible, providing the capacity for producers to exercise market power.

- Producers, being profit-maximizing and self-interested entities, will take advantage of their ability to exercise market power and, therefore, the LMP will more likely take the form of the investigated strategic LMP model. The latter, as expected, results in decreased market efficiency and, obviously, is not incentive-compatible. However, it still remains revenue-adequate in expectation ensuring that there is no budget deficit for the market operator. Moreover, cost-recovery can be ensured in the equilibrium if all information of the market are perfectly known by all participants. This is usually not realistic and producers that act strategically do not avoid the risk of facing negative profits due to their strategies.

- The VCG mechanism is incentive-compatible, which leads consequently to maximum market efficiency. The mechanism additionally ensures cost-recovery for all participants, by paying them proportionally to their impact on social welfare formation at optimal point. However, it fails to ensure revenue-adequacy in expectation, which mandates an ex-post solution (e.g., in the form of uplifting mechanisms as it is common in U.S. traditional LMP markets [150, 151]) for compensating the potential negative budget imbalance.

Table 5.10: Comparison of Mechanisms and Market Properties

	Competitive LMP*	**Strategic LMP**	**VCG**
Market Efficiency (in exp.)	✓	✗	✓
Cost-Recovery (in exp.)	✓	✓	✓
Revenue Adequacy (in exp.)	✓	✓	✗
Incentive Compatibility	✓(assumed)	✗	✓

*Ideal model, used as benchmark.

Furthermore, the main conclusions of the study, for a network-constrained market, can be summarized by the following points:

1. VCG achieves through incentive-compatibility maximum social welfare, equal to the ideal competitive LMP model. Strategic LMP mechanism, on the other hand, due to the appearance of strategic behaviors leads to reduced social welfare. Lastly, for all models, social welfare increases along with the increasing penetration of wind power.

2. Both conventional and wind producers profits, before redistribution of budget deficit, are higher in the VCG mechanism compared to competitive LMP but, in many cases, producers are still better under a strategic LMP setting. Note that strategic behaviors are eliminated under the VCG model. Conventional producers profits generally decrease for all models as wind power penetration increases.

3. Demand payments are, generally, lower under the VCG mechanism compared to the LMP under both competitive and strategic settings, a condition that indicates that consumers are benefiting from an incentive-compatible mechanism.

4. The VCG market mechanism may lead to a negative budget imbalance, in contrast to the LMP mechanism under which a resulted positive budget imbalance is attributable to the so-called congestion rent. For a network-constrained market, it is numerically concluded

that the negative budget imbalance under the VCG decreases and becomes a surplus, as the penetration of wind power increases.

5. Comparing the results between a market that considers network constraints and one that does not, it is noted that VCG mechanism budget deficit becomes smaller when network constraints are enforced. Excluding network constraints from the market-clearing model, LMP leads to zero budget imbalance, while the VCG model leads always in negative budge imbalance, i.e., budget deficit, which further increases with the increasing penetration of wind power. This outcome, related to physical constraints, is the result of the decreased impact of each agent due to constraints imposed by the capacity of lines. Thus, when network constraints are not considered, generation-side prices are always higher compared to the competitive LMP and demand-side prices are always lower, which is not the case for a network-constrained market.

6. Finally, a potential solution approach for recovering revenue-adequacy under the VCG mechanism is proposed, based on the contribution of each agent on budget imbalance. The approach offers a solution for distinguishing which participants have a negative or positive impact on budget balance, charging or rewarding them respectively, in order to decrease budget imbalance. For a large case study considering transmission constraints, it was concluded that the budget redistribution scheme can achieve partial or, even, full recovery of revenue-adequacy without affecting cost-recovery, efficiency or incentive-compatibility, being at the same time beneficial for most market agents.

Acknowledging that a perfectly competitive LMP market is not realistic, given the self-interested nature of market participants, it is obvious that efficiency loss in the strategic LMP setup should not be neglected. The VCG-based approach manages to increase market efficiency to the levels of the perfectly competitive LMP mechanism, being attractive to power producers by increasing their profits and to consumers by decreasing their payments. However, it comes with the drawback of potential budget deficit. Potential solutions to cope with budget deficit include either ex-ante or ex-post approaches, which aim at recovering revenue loss by market participants.

5.5 Future Perspectives

This chapter has introduced a VCG-based electricity market mechanism, which is adapted in a stochastic two-stage electricity market and evaluated versus both perfect and imperfect LMP market settings. It is of our future research interest to investigate different approaches for coping with the main drawback of the VCG market mechanism, its inability to guarantee revenue-adequacy. To this end, it is of interest as well to investigate a mechanism for estimating payments to the grid operator under congested network which will correspond to the congestion rent under the LMP market. Furthermore, this study can be associated with the concept of sharing wind power forecasts in electricity markets, as discussed already in Chapters 2 and 4. More specifically, instead of the voluntary publication of wind forecasts, it is of great interest to investigate an incentive-compatible mechanism that motivates stochastic producers to reveal their generation forecast.

5.6 Chapter Publications

This chapter has led to the following working articles to be submitted for publication:

- L. Exizidis, J. Kazempour, A. Papakonstantinou, P. Pinson, Z. D. Grève, and F. Vallée, *An Incentive-Compatible Two-Stage Stochastic Electricity Market: Benefits and Costs*, working paper.
- L. Exizidis, J. Kazempour, A. Papakonstantinou, P. Pinson, Z. De Grève, and F. Vallée, *Application of VCG Mechanism on a Two-Stage Stochastic Electricity Market Accommodating a Revenue-Adequacy Recovery Scheme*, working paper.

Chapter 6

Global Conclusions, Contributions and Future Perspectives

This chapter provides a summary and highlights the most interesting conclusions and contributions that this research work has led to. Furthermore, answering a research question will always give birth to multiple new ones and, therefore, in this chapter we present future perspectives and related research questions, which can capitalize on the results and design of this thesis and take it a step forward.

Summary

The main goal of this PhD dissertation is to evaluate the importance of information availability in electricity markets with high penetration of wind power. Modern electricity pools are big arenas for the competition of producers and consumers, all aiming at maximizing individual interests. Motivated by the fact that possession of qualitative information can impact the operation and efficiency of a market, we investigate a number of market setups where market agents make use or share different kinds of information.

More specifically, in Chapter 2 we investigate a two-stage stochastic market-clearing mechanism that co-optimizes DA and RT markets, considering the participation of a large wind power producer that acts strategically. Under this context, a three-step evaluation framework is designed which aims at exploring the benefits of sharing wind power forecasts among different actors and consists of: i) the optimization of wind producer's offering strategy, ii) clearing of the stochastic two-stage market and, finally, iii) an extensive out-of-sample assessment for RT market-clearing, exploring the benefits of the sharing scheme based on unforeseen wind power scenarios. The aforementioned evaluation framework offers a numerical insight into how sharing valuable information about the expected wind power generation can potentially decrease total system cost. Under a similar market setup, in Chapter 3 we investigate how the uncertainty pertaining to a second price-taking wind power producer can impact the decisions and profits of the strategic wind power producer as well as the total system cost.

Chapter 4 is motivated by recent decisions and regulations in a pan-European level for increasing market transparency and publishing information related to aggregate wind power forecasts. This, in addition to the presence of strategic behaviors in electricity pools, motivates the work of this chapter which considers a non-cooperative game to represent the DA market with increased wind power generation and multiple participating producers. Under such context, we evaluate the impact of public aggregate wind power forecasts, ranging from very small to very high magnitudes, in a market where all producers are price-makers, naturally following an equilibrium study.

Lastly, the aforementioned presence of strategic behaviors in electricity markets leads to misinformation regarding generation costs or consumption utility, which inevitably impacts market efficiency. The scope of Chapter 5 is to examine extensively a new approach for incentive-compatible market-clearing mechanisms, under which submitting truthful information would be the dominant strategy for each producer and consumer. To this end, VCG payment scheme is adapted to a stochastic electricity market setting and comprehensively explored. The results of the VCG-based model are then compared and evaluated versus a stochastic LMP model, under both perfect and imperfect competition.

Global Conclusions and Contributions

In this section we present the most important conclusions and contributions of Chapters 2 to 5. Each chapter of this thesis focuses on specific setups and sets well-defined objectives, based on specified features and methodologies. However, the common ground of all chapters is the evaluation of the importance of information, and their status being private or shared, in markets with increased wind power penetration.

This thesis proposes a three-step framework that enables the impact-assessment of sharing wind power forecasts in electricity markets. Motivated by the fact that different actors may have considerably different wind power forecasts for their decision-making problems, it is anticipated that sharing these private information can potentially impact market outcomes as well as individual agents objectives. Indeed, the results of the presented case study indicate that sharing wind forecasts between a wind producer and the market operator can potentially decrease the market cost under high wind penetration levels. Additionally, it leads to increased profits for the wind producer, as the result of better-informed DA schedules or increased market power. The outcomes of this study highlight the interest for a potential parallel market, where agents could trade or obtain relevant information in order to optimize their objectives.

The setup of the aforementioned study considers a single wind power producer that carries all the uncertainty in the market. As a further step, in Chapter 3 an extended setup is considered; the market consists of a strategic wind power producer as well as an additional wind power producer who behaves competitively. The study is procured from the strategic producer's point of view, anticipating the rival wind power generation based on a wind power forecast. It is concluded that the additional source of uncertainty has a significant impact on strategic wind producer's decision-making as well as on market outcomes. More specifically, the price-maker producer is found to exercise more market power when the expected generation of the rival is relatively low. Furthermore, energy prices increase significantly as a result of the increased market power, since strategic producer withholds a part of its generation in order to increase market prices for own benefit. It is, thus, apparent that a stochastic agent should not account only for its own stochasticity but for its rivals as well.

The first two chapters of the thesis indicate, already, the increased importance of forecast information in a market with high wind power penetration. More precisely, acquiring qualitative wind power forecasts for both own and rivals generation is crucial for all market agents, including the market operator. Motivated by the aforementioned results and the increased worldwide interest for transparency in the market and publication of market-related information, we assess in Chapter 4 the potential impact of public aggregate wind power forecasts on electricity market outcomes and agents' objectives. Despite being informative, the first two chapters are built on the assumption that only a single producer might exercise market power, having perfect knowledge of its rivals offers. This limitation is bypassed in Chapter 4, by considering a more complex setup where multiple producers might have market power. The results of the case study indicate that in a market where all producers consider a public aggregate forecast in their strategy, social welfare may increase considerably for low values of aggregate forecast. Additionally, energy prices become zero and producers might face negative profits as a result of the low quality of information. Results indicate that efforts for the publication of forecast-related information should be accompanied by high qualitative standards, otherwise the vision of an improved market operation might be jeopardized.

Strategic behaviors under the presence of increased stochastic power generation in the market, have been investigated in the first part of the thesis in order to offer an understanding of the impact of information-availability in non-cooperative market setups. These results, along with relevant studies in the literature, increase the interest for strategy-proof market mechanisms and motivate the second part of this thesis. Therefore, an incentive-compatible mechanism is explored, in order to cope with the main shortcoming of the traditional market mechanism, which is being vulnerable to strategic behaviors. To this end, VCG auction is adapted on a stochastic electricity market and it is concluded that incentive-compatibility, efficiency and cost-recovery are possible to obtain, but might come on the expense of budget imbalance. More precisely, VCG achieves maximum efficiency, while in most cases it is beneficial for all market players, i.e., producers and demands. However, excluding network constraints VCG leads always to budget deficit that increases with wind power penetration. The corresponding results for an LMP market, considering DC power flow, indicate smaller budget deficit observed only for low wind penetration levels. Finally, a redistribution mechanism is explored that manages to recover revenue-adequacy in the market, retaining at the same time the most important market properties, by charging or rewarding agents based on their contribution towards revenue-adequacy.

As already elaborated, the purpose of this study is to indicate the impact of information in modern markets, that are characterized by increased uncertainty and multiple sources of information. Albeit results should be interpreted accounting for the assumptions and limitations of the accommodated mathematical tools, the main outcomes and the followed approaches offer valuable insights that can assist decision-makers. Regulators and various stakeholders can exploit similar approaches, towards the design of transparent electricity markets with increased operational efficiency. With respect to the increasing needs for information and optimal data-handling, electricity markets are no different from any other operational process today. That said, it is expected that the better coordination among various agents, the benefits of exchanging qualitative information and taking steps towards the improvement of the current market design would certainty lead to improved market functioning and transparency, in markets with high penetration of stochastic power generation.

Future Perspectives

The work of this thesis has highlighted various challenges regarding information in electricity markets and motivates future research paths. Thus, we can summarize in this section the various open research questions that can capitalize on this dissertation and take it a step forward.

The problems of the first part of this thesis have been investigated by representing the market as a non-cooperative game with complete information. This approach offers an insight of market functioning and agents' decision-making at the equilibrium of the game, where each agent has perfect knowledge of the strategies of rivals. However, a more realistic setup would suggest that this kind of information are not generally available and agents' information are rather imperfect, obtained based on their past experience and forecasts of rivals actions. Thus, it would be interesting, instead of deterministic perfect information of rivals actions, to account for a stochastic approach where each agent has only knowledge regarding the distribution of its rivals' actions. More precisely, this can be constructed as a game of incomplete or imperfect information where each market agent is characterized by a "type" that corresponds to its strategy. Each type is associated with a different probability, while the distribution function of the types is considered known by all agents. Even though the knowledge of the distribution is still an assumption, this Bayesian approach would be closer to reality where agents indeed have forecasts of the rivals' actions but not the actual actions, thus being compliant with information being available but not perfect. A Bayesian Nash equilibrium can then be defined as a strategy profile of the agents', which maximizes the objective of each agent given its beliefs regarding other agents' types as well as the actual strategies followed by them. This approach can offer a less stringent solution of the game in the sense that perfect information is not required, however it is followed by increased complexity both on the modeling side as well as on the interpretation of the results, which should be analyzed in expectation with respect to agents' types. Bayesian games are sparsely studied in the context of electricity market and offer a promising field for research.

The concept of sharing information in electricity markets, as investigated in Chapter 2, but also indirectly in Chapters 3-4, can be associated with ongoing research advances on trading information in other scientific domains, such as in [91, 92], towards the construction of "information" and "prediction" markets. In markets with high trading volumes like the energy market, prices do not only reflect the costs of generation but also an increased amount of information about uncertain features of the market, which are more accessible to some agents and less to other. Obtaining this information is an arduous task, since no agent would be willing to share the strategic advantage of qualitative information, that it may have. Thus, social welfare and individual objective optimization depends greatly on the quality and availability of information. Research in this field should answer questions regarding, for example, the value of wind power forecasts in the market, or the value of information regarding future market prices and fuel prices, which is associated not only to market participation but to investment decisions as well.

In the second part of the thesis, an incentive compatible mechanism has been explored for electricity markets with high shares of wind power. It has been concluded that the main shortcoming of the VCG auction under the context of an electricity market is its inability to ensure revenue-adequacy. To this end, a redistribution mechanism has been suggested which is, however, not proved to always guarantee revenue-adequacy or budget balance. Defining such a mechanism is a difficult task, which has not yet been answered in the literature for two-sided markets. Thus, a special focus should be directed towards designing a redistribution approach that can guarantee market principles, offering a solution that would lead to the lowest possible budget imbalance. In network-constrained electricity markets this should be, as well, associated with a mechanism for estimating congestion-rent as a payment to the grid owner, which is naturally associated with budget imbalance since it comprises part of the market budget.

Apart from the aforementioned wider research questions, there are also some technical improvements that can be made regarding specific modeling assumptions and features of this thesis. More precisely:

1. This thesis considers a single-hour auction ignoring inter-temporal constraints. However, investigating agents payoffs on a longer-term time horizon would be impacted by the consideration of inter-temporal constraints. Thus, it is of future interest to include this impact on the models and, potentially, associate it with state-of-the art forecasts for multiple time-steps ahead. This would, additionally, account for the anticipated varying magnitude of forecast errors, as a result of the different forecast horizons.

2. The topics of Chapters 2 and 3 can be further extended to include multiple strategic wind and conventional producers with different individual forecasts. To the case that these forecasts are considered private information, this would eventually relate to a game of incomplete information, as discussed previously.

3. In Chapter 4, wind power was offered deterministically to the market based on a forecast, even though uncertainty around forecasts and RT prices was additionally considered. It is of future interest to investigate how aggregate forecasts would impact the results under a stochastic two-stage market setup, similar to the ones presented in Chapters 2, 3 and 5, where DA and RT markets are co-optimized. Furthermore, given that wind power forecasts are private informa-

tion for each individual, Chapter 4 can also be approached by a Bayesian game, to cope with the missing information problem.

4. Finally, regarding Chapter 5, the study can be extended to include producers being also price-makers in the RT market under a game with perfect information. Furthermore, considering wind power producers being price-makers, motivates the research of incentive-compatible mechanisms to induce private wind power scenarios from wind producers.

Appendices

Appendix A

Mathematical Background

In this appendix we give the basic definitions and information around the mathematical background of the dissertation. The greatest part of this appendix is based on book [2] and references [62, 68, 152, 153, 154], to which the reader can refer for a more detailed reading.

A.1 Optimization Problems

An optimization problem in its most common form is the problem of maximizing or minimizing a real function with respect to a variable which takes values within an allowed set. A simple optimization problem is formulated as:

$$\underset{x}{\text{Minimize}}\ f(x) \tag{A.1a}$$

subject to

$$h(x) = 0 \tag{A.1b}$$

$$g(x) \leq 0 \tag{A.1c}$$

where $x \in \mathbb{R}^n$ is a vector including the n decisions, $f(.) : \mathbb{R}^n \rightarrow \mathbb{R}$ is the objective function of the optimization problem. Typically the objective function represents the minimization of cost or maximization of profit. Function $h(.) : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is vector-valued function of the decision vector x and defines m equality constraints. Lastly, $g(.) : \mathbb{R}^n \rightarrow \mathbb{R}^l$ is vector-valued function of the decision vector x and defines l inequality constraints.

By convention, the standard form of an optimization problem defines a minimization problem and, thus, a maximization problem can be replaced by negating the objective function. The joint enforcement of equalities and inequalities defines the feasibility region of the optimization problem. A decision x is feasible if it satisfies (A.1b)-(A.1c). The aim of optimization problem (A.1) is to determine, among the set of feasible decisions, the one that minimizes objective function (A.1a).

If $f(.)$, $h(.)$ and $g(.)$ are linear, then the optimization problem is a linear programming problem (LP) and can be formulated as:

$$\underset{x}{\text{Minimize}}\ c^\top\ x \tag{A.2a}$$
subject to
$$A_E\ x = b_E \tag{A.2b}$$
$$A_I\ x \geq b_I \tag{A.2c}$$

where the general functions $f(.)$, $h(.)$ and $g(.)$ are replaced by affine expressions involving $c \in \mathbb{R}^n$ being the cost coefficient of the decision vector x, $A_E \in \mathbb{R}^{m\times n}$ and $b_E \in \mathbb{R}^m$ which define the m equality constraints and, finally, $A_I \in \mathbb{R}^{l\times n}$ and $b_I \in \mathbb{R}^l$ which define the l linear inequality constraints.

A.2 Duality in Linear Programming

Given any linear problem, called *primal* problem, there is another related linear problem called the *dual*. The dual problem provides an upper bound to the optimal value of the primal problem and for the primal (A.2) is formulated as below:

$$\underset{\lambda,\ \mu}{\text{Maximize}}\ b_E^\top\ \lambda + b_I^\top\ \mu \tag{A.3a}$$
subject to
$$A_E^\top\ \lambda + A_I^\top\ \mu = c \tag{A.3b}$$
$$\mu \geq 0 \tag{A.3c}$$

where $\lambda \in \mathbb{R}^m$ is a vector associated to the equalities (A.2b) and $\mu \in \mathbb{R}^l$ is a vector associated to the inequalities (A.2c).

Between the primal and the dual problems the following relationship holds:

- The primal problem has n decision variables and $m + l$ constraints while the dual problem has $m + l$ decision variables and n constraints.
- Constraints (A.3b) of the dual problem involve the transposed of the matrices A_E and A_I defining the constraints (A.2b)-(A.2c) of the primal problem.
- The constant vectors b_E and b_I of the primal problem form the cost coefficients of the dual linear objective function (A.3a).
- The cost coefficient vectors c of the primal objective function appear on the right-hand side of the dual constraints (A.3b).

The direction of optimization (minimization or maximization), the sign of the constraints ($\geq, =, \leq$) and the bounds on the variables (≥ 0, free or ≤ 0) for the primal and the dual problem are linked. Specifically, the direction of the dual optimization problem is opposite to the one of the primal one. Furthermore, the signs of the primal constraints set the bounds on the associated dual variables and, conversely, the bounds on the primal variables set the signs of the dual constraints [2].

Finally, note that the dual of the dual problem is the primal problem [152]. The objective function values of the primal and dual problems are related to each other through the so-called weak and strong duality theorems, which are presented bellow without proof.

Theorem A.1. *Weak Duality: If x is feasible for* (A.2)*, and λ, μ are feasible for* (A.3)*, then $c^\top x \geq b_E^\top \lambda + b_I^\top \mu$.*

Theorem A.2. *Strong Duality: If the primal problem has a finite optimal solution x^*, so does the dual problem and at optimality it holds that $c^\top x^* = b_E^\top \lambda^* + b_I^\top \mu^*$.*

Note that λ and μ represent the per-unit change (increase) in the optimal value of the objective function (A.2a) if the right-hand side of the associated constraint is increased marginally. Naturally, $\mu \geq 0$. Indeed, a marginal increase of any element of the vector b_I would result in a smaller feasible space for (A.2), and hence in a larger, i.e., worse, optimal value of the objective function.

A.3 Karush-Kuhn-Tucker Conditions

In this section we will describe the Karush-Kuhn-Tucker conditions for convex problems only, which is related to the problems of this dissertation. For a more complete overview of this topic, see [155]. Let us consider the general formulation (A.1), and suppose that $f(.)$, $g(.)$ are continuously differentiable and convex, and $h(.)$ is affine.

The Lagrangian function for (A.1) is defined as follows:

$$\mathcal{L}(x, \lambda, \mu) = f(x) + \lambda^\top\ h(x) + \mu^\top\ g(x) \tag{A.4}$$

Given the Lagrangian (A.4), the KKT conditions presented below are necessary and sufficient for optimality for problem (A.1). Note that constraint qualifications ensure that KKT are necessary for optimality, while convexity ensures sufficiency.

$$\nabla_x f(x) + \lambda^\top \nabla_x h(x) + \mu^\top \nabla_x g(x) = 0 \tag{A.5a}$$
$$h(x) = 0 \tag{A.5b}$$
$$g(x) \leq 0 \tag{A.5c}$$
$$\mu \geq 0 \tag{A.5d}$$
$$\mu^\top g(x) = 0 \tag{A.5e}$$

Equations (A.5a) are stationary conditions. Constraints (A.5b)-(A.5c) enforce the feasibility of the primal problem, while (A.5d) is a feasibility condition of the dual problem. Finally, (A.5e) enforces complementary slackness. The term *complementary slackness* refers to a relationship between the slackness in a primal constraint and the slackness (positivity) of the associated dual variable. In the aforementioned case, constraint (A.5e) implies that the element-by-element product between μ and $g(x)$ is equal to zero. The terms (A.5c)-(A.5e) are compacted throughout this report into the following nonlinear contraint:

$$0 \geq g(x) \perp \mu \geq 0 \tag{A.6}$$

where the $\perp$ (perpendicular) operator enforces the perpendicular condition between the vectors on the left- and right-hand sides, i.e., their element-by-element product is zero.

A.4 Bilevel Programs and Mathematical Programs with Equilibrium Constraints (MPEC)

Mathematical programs with equilibrium constraints are first reported in [153] and have been widely applied to electricity markets [4, 70, 71, 72, 74, 119, 132]. MPECs are constrained optimization problems where the constraints include variational inequalities or complementarities and are closely related to the Stackelberg games [154]. There are several available methods to solve MPECs, the most popular of which are sequential quadratic programming [67], pertubation and penalty methods [156, 157], interior point methods [158] and relaxation methods [159, 160, 161]. However, due to the non-convex nature of MPECs, methods like the aforementioned cannot guarantee optimality. Therefore, the linearization of MPECs and its transformation into a Mixed Integer Linear Programming (MILP) model can lead to a model that could be solved by standard branch-and-cut solvers. This linearization approach without approximation was used in all chapters of this dissertation.

Bilevel problems [162] are a special class of optimization problems with two levels of optimization task. The outer optimization task is commonly referred to as the upper-level optimization task, and the inner optimization task is commonly referred to as the lower-level optimization task. Recent paper [163] provides an overview of the various formulations of non-cooperative games, including the theoretical foundations, classification and main techniques for solving bilevel games and their applications to power systems. MPECs are closely related to bilevel programs since cases of bilevel programs can be formulated as an MPEC, i.e., the

Stackeberg game [154]. These problems involve two kinds of variables, referred to as the upper-level variables and the lower-level variables. The importance of bilevel optimization in most markets and industries is evident by the fact that related decision processes are two-stage processes, e.g., the first stage being the firm's profit maximization and the second stage being the optimization of operational constraints. Therefore, bilevel programming is gaining more and more attention in operations research. Regarding electricity markets, bilevel problems are becoming very popular for a large variety of problems, such as pricing electricity in an environment with wind producers [28], defining equilibrium models for electricity markets with wind generation [62], evaluating offering strategies for wind producers in a pool [68] and so on.

The general formulation of a bilevel optimization problem is the following:

$$\underset{x,y}{\text{Minimize}}\ f^U(x,y) \tag{A.7a}$$

subject to

$$g^U(x,y) \leq 0 \tag{A.7b}$$

$$h^U(x,y) = 0 \tag{A.7c}$$

$$y \in \arg\ \underset{z}{\text{minimize}}\ \{\ f^L(x,z) \tag{A.7d}$$

subject to

$$h^L(x,z) = 0 \tag{A.7e}$$

$$g^L(x,z) \leq 0 \tag{A.7f}$$

$$\}. \tag{A.7g}$$

Formulation (A.7) includes two optimization problems: an upper-level one that aims at the minimization of $f^U(.)$ and a lower-level one that aims at the minimization of $f^L(.)$. The two problems are interdependent, since in general the upper-level objective function and constraints depend on the lower-level decision variables y. Conversely, the lower-level objective function and constraints depend on the upper-level variable vector x. Model (A.7d)-(A.7f) can accomodate several lower-level optimization problems, simply by concatenating multiple optimality conditions of the type (A.7d)-(A.7f).

Under the assumption that KKT conditions are necessary and sufficient for optimality in the lower-level problem, we can employ them to replace (A.7d)-(A.7f). This results in the following formulation for the bilevel problem:

$$\underset{x,y,\lambda,\mu}{\text{Minimize}}\; f^U(x,y) \tag{A.8a}$$

subject to

$$g^U(x,y) \leq 0 \tag{A.8b}$$

$$h^U(x,y) = 0 \tag{A.8c}$$

$$\nabla_y f^L(x,y) + \lambda^\top \nabla_y h^L(x,y) + \mu^\top \nabla_y g^L(x) = 0 \tag{A.8d}$$

$$h^L(x,y) = 0 \tag{A.8e}$$

$$g^L(x,y) \leq 0 \tag{A.8f}$$

$$\mu \geq 0 \tag{A.8g}$$

$$\mu^\top g^L(x,y) = 0. \tag{A.8h}$$

where λ and μ represent the dual variables associated to constraints $h^L(x,z) = 0$ and $g^L(x,z) \leq 0$, respectively, in the lower-level problem (A.7d)-(A.7f).

The advantage of this formulation is the replacement of the nested lower-level problem with a set of equations and inequalities, which results in a single-level optimization problem that fits the general formulation. However, KKT conditions are in general nonlinear and non-convex, as they involve cross-products between variables in the complementarity condition (A.8h). We cope with these two non-linearities with two different methods: (i) the Big-M approach [79, 80] and (ii) the SOS1 method [66, 120], which are described below.

A.4.1 Linearization of Complementarity Constraints

A.4.1.1 Big-M method

The approach that is used in Chapters 2 and 3 in order to linearize the corresponding MPEC models is based on the so-called Big-M reformulation of the complementarity conditions, employing binary variables

[79, 80]. Under this reformulation we replace conditions of the form:

$$\mu_i \; g_i^L(x,y) = 0 \tag{A.9}$$

by the following:

$$g_i^L(x,y) \geq -u_i \; M_{1i} \; \forall i \tag{A.10a}$$
$$\mu_i \leq (1-u_i) \; M_{2i} \; \forall i \tag{A.10b}$$
$$u_i \in \{0,1\} \; \forall i. \tag{A.10c}$$

The constants M_{1i} and M_{2i} must be large enough so as not to leave the optimal solution out of the feasible space and not too large as they may result in computational inefficiencies in the solution of the resulting MILP. Observing the reformulations above, it is straightforward to show that constraints (A.10a)-(A.10c) are equivalent to (A.9). However, Big-M method follows an engineering approach in the sense that the appropriate values of the M have to be researched each time a problem is solved, which is specifically hard for a problem that is solved iteratively multiple times. Thus, in Chapters 4 and 5 we are using a different method that lifts this constraint, i.e., the SOS1 method.

A.4.1.2 SOS1 method

Despite its ease, the Big-M approach comes with shortcomings. Firstly, choosing the appropriate M values is a trial-and-error approach, which in some cases becomes hard to solve. Furthermore, the confirmation of the successful selection of the M values is rather impossible in the case of multiple repetitive solutions of a problem with varying parameters. Due to the aforementioned reasons, in Chapters 4 and 5 we have used an alternative method for linearizing complementarity constraints, i.e., the SOS1 method [66, 120]. In this case, instead of employing a set of auxiliary binary variables, we use a set of "Special Ordered Sets of type 1 (SOS1)" variables. SOS1 are a set of variables among which at most one can be strictly positive, with all others of the set being zero.

Let us reformulate (A.9), with the help of two SOS1 variables, r_{1i} and r_{2i}:

$$\mu_i + g_i^L(x,y) = r_{1i} + r_{2i} \; \forall i \tag{A.11a}$$

$$\mu_i - g_i^L(x, y) = r_{1i} - r_{2i} \; \forall i \tag{A.11b}$$

Based on the definition of the SOS1 variables, only one of variables r_{1i} and r_{2i} can be strictly positive or they are both zero. It is straightforward to confirm that (A.9) is equivalent to (A.11a)-(A.11b). Despite its ease, SOS1 method increases computational costs compared to the Big-M approach.

Appendix B

IEEE Reliability Test System

B.1 Modified 24-Node IEEE Reliability Test System (RTS)

This appendix presents the modified version of the RTS 24-node network that was used in the case study of Chapter 5. This case study is based on the updated version of the IEEE RTS 24-bus System presented in [85], which can be readily used for electricity markets and accommodate six wind farms. The network topology is presented in Fig. B.1.

The technical data of the generation units and the system demand are presented in Tables B.1 and B.2.

Table B.1: Technical Characteristics and Node Location of Conventional Generation Units

Unit (Gi)	Node n	$\overline{P}_i^{\mathrm{G}}$ [MW]	λ_i^{G} [€/MW]	R_i^{U} [MW]	λ_i^{U} [€/MWh]	R_i^{D} [MW]	λ_i^{D} [€/MWh]
G1	1	152	13.32	40	15	40	11
G2	2	152	13.32	40	15	40	11
G3	7	350	20.70	70	24	70	16
G4	13	591	20.93	180	25	180	17
G5	15	60	26.11	60	28	60	23
G6	15	155	10.52	30	16	30	7
G7	16	155	10.52	30	16	30	7
G8	18	400	6.02	0	0	0	0
G9	21	400	5.47	0	0	0	0
G10	22	300	0	0	0	0	0
G11	23	310	10.52	60	14	60	8
G12	23	350	10.89	40	16	40	8

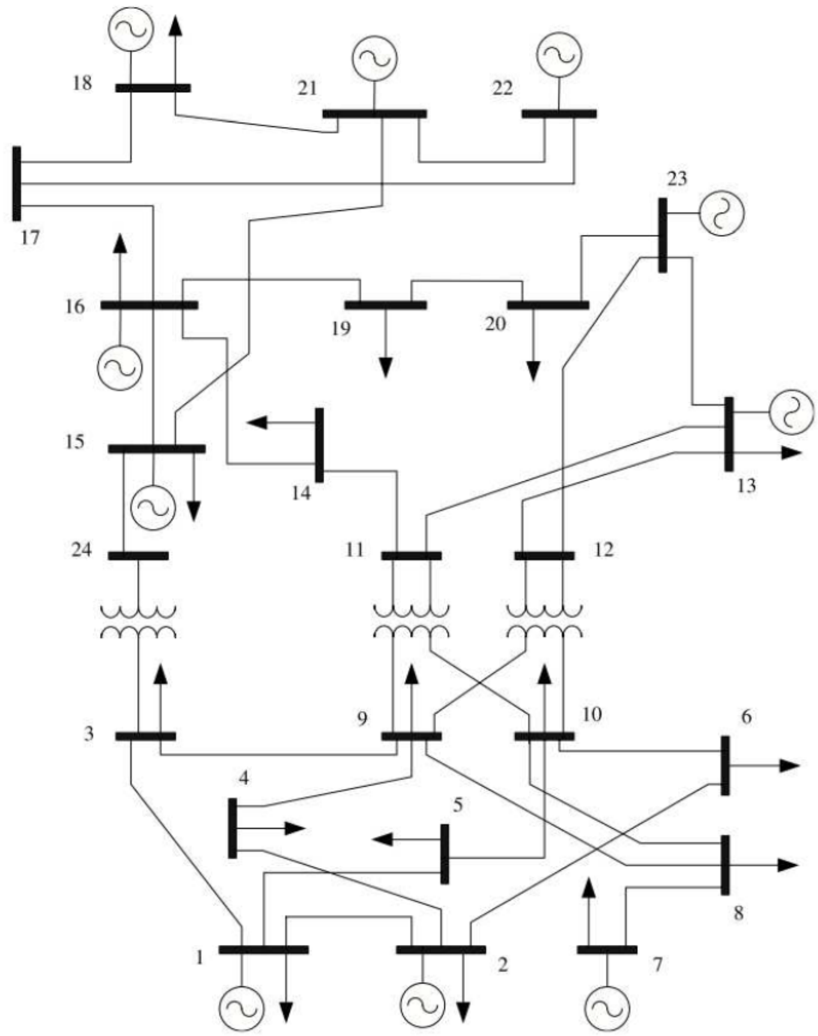

Figure B.1: 24-bus power system - network topology

Table B.2: Node Location and Distribution of the System Demand

Load (D_d)	Node n	$\overline{P}_d^{D}$ [MW]	λ_d [€/MW]	Load (D_d)	Node n	$\overline{P}_d^{D}$ [MW]	λ_d [€/MW]
D1	1	84	100	D10	10	150	100
D2	2	75	100	D11	13	205	100
D3	3	139	100	D12	14	150	100
D4	4	58	100	D13	15	245	100
D5	5	55	100	D14	16	77	100
D6	6	106	100	D15	18	258	100
D7	7	97	100	D16	19	141	100
D8	8	132	100	D17	20	100	100
D9	9	135	100				

In this case study, we consider six wind power producers located at buses n={3, 5, 7, 16, 21, 23}. The operational cost of wind power farms is considered to be zero. Each wind producer's expected wind power generation versus increasing wind penetration levels, i.e., expected wind power generation divided by the total load, is presented in Fig. B.2. The total wind power capacity ranges between 450 MW to 1310 MW and the corresponding penetration levels range from 17.14% to 49.62%.

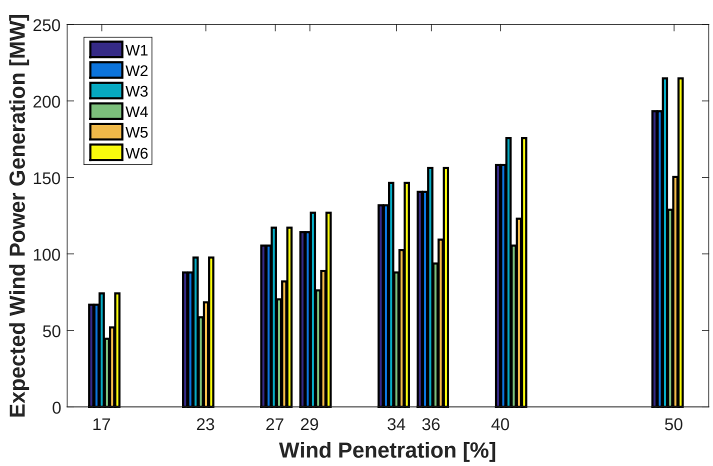

Figure B.2: Wind power producers W1-W6 expected generation versus increasing levels of wind power penetration.

The transmission lines data are presented in Table B.3. The properties of the lines include the connecting nodes, the reactance in [p.u.]

and the capacity of each line in [MVA]. Note that the base for power conversion in p.u. is $S_{base} = 100$MVA.

Finally, according to [164] we have decreased the capacity of lines (15,21), (14,16) and (13,23) from 1000MVA, 500MVA and 500MVA to 400MVA, 250MVA and 250MVA respectively, in order to introduce bottlenecks in the transmission system.

Table B.3: Reactance and Capacity of Transmission Lines

From n	To n	Reactance [p.u.]	Capacity [MVA]	From n	To n	Reactance [p.u.]	Capapcity [MVA]
1	2	0.0146	175	11	13	0.0488	500
1	3	0.2253	175	11	14	0.0426	500
1	5	0.0907	350	12	13	0.0488	500
2	4	0.1356	175	12	23	0.0985	500
2	6	0.205	175	13	23	0.0884	250
3	9	0.1271	175	14	16	0.0594	250
3	24	0.084	400	15	16	0.0172	500
4	9	0.111	175	15	21	0.0249	400
5	10	0.094	350	15	24	0.0529	500
6	10	0.0642	175	16	17	0.0263	500
7	8	0.0652	350	16	19	0.0234	500
8	9	0.1762	175	17	18	0.0143	500
8	10	0.1762	175	17	22	0.1069	500
9	11	0.084	400	18	21	0.0132	1000
9	12	0.084	400	19	20	0.0203	1000
10	11	0.084	400	20	23	0.0112	1000
10	12	0.084	400	21	22	0.0692	500

Appendix C

Transmission Network Constraints

For the sake of simplicity, market models in Chapters 2 to 4 do not account for transmission network constraints. Thus, the location of generation units and demands does not influence balancing market dispatch and prices. However, market models of Chapter 5 are additionally solved considering the transmission network constraints, following the procedure explained in this appendix.

The most common calculation of power flow in electricity grids is the AC power flow. However, AC power flow is computationally heavy, especially if it is incorporated in a stochastic market-clearing problem, as the ones presented in this thesis. Albeit AC power flow study offers a high level of detail in the results, this level of detail is not crucial for the economic dispatch problem. Therefore, it is common to represent network constraints through a DC load flow representation.

The main competences in using a DC power flow model are driven by its linear, non-complex nature. It offers non-iterative, unique and reliable solutions, network data needed for the calculations are limited and easy to acquire while approximated active power flows are reasonably accurate for the heavily loaded branches that might constrain system operation. However, its use is only restricted to power flow oriented applications, where the effects of network voltage and reactive power conditions are minimal [165].

C.1 From the AC to the DC Power Flow Model

Notation

n, m	Node indices
P_n	Active power injection at node n [W]
Q_n	Reactive power injection at node n [VAr]
V_n	Voltage at node n [V]
$R_{n,m}$	Resistance of transmission line (n,m) [Ω]
$X_{n,m}$	Reactance of transmission line (n,m) [Ω]
$Z_{n,m}$	Impedance of transmission line (n,m) [Ω]
$G_{n,m}$	Conductance of transmission line (n,m) [S]
$B_{n,m}$	Susceptance of transmission line (n,m) [S]
$Y_{n,m}$	Admittance of transmission line (n,m) [S]
δ_n	Voltage angle at node n [rad]
$F_{n,m}^{\max}$	Maximum capacity of line (n,m) [W]

In the classical AC power flow model the expressions for the sending (n) and receiving (m) nodes are the following:

$$P_n = \sum_{m=1}^{N} |V_n| \, |V_m| \, \big(G_{n,m} \, \cos(\delta_n - \delta_m) + B_{n,m} \, \sin(\delta_n - \delta_m)\big) \tag{C.1a}$$

$$Q_n = \sum_{m=1}^{N} |V_n| \, |V_m| \, \big(G_{n,m} \, \sin(\delta_n - \delta_m) - B_{n,m} \, \cos(\delta_n - \delta_m)\big) \tag{C.1b}$$

Based on some facts related to transmission networks we can adopt the following assumptions:

1. The resistance of transmission circuits is significantly smaller than the reactance ($R \ll L$) and, thus, grid losses can be neglected as follows [166]:

$$G_{n,m} = \frac{R_{n,m}}{R_{n,m}^2 + X_{n,m}^2} \approx 0 \tag{C.2a}$$

$$B_{n,m} = \frac{-X_{n,m}}{R_{n,m}^2 + X_{n,m}^2} \approx -\frac{1}{X_{n,m}} \tag{C.2b}$$

$$Z_{n,m} \approx j \cdot X_{n,m} \tag{C.2c}$$

$$Y_{n,m} \approx j \cdot B_{n,m} \tag{C.2d}$$

   Applying this assumption to equations (C.1), the latter become:

$$P_n = \sum_{m=1}^{N} |V_n|\ |V_m|\ \big(B_{n,m}\ \sin(\delta_n - \delta_m)\big) \tag{C.3a}$$

$$Q_n = \sum_{m=1}^{N} |V_n|\ |V_m|\ \big(-B_{n,m}\ \cos(\delta_n - \delta_m)\big) \tag{C.3b}$$

2. For typical operation conditions, the angle difference of the voltage phasors at two neighboring nodes n and m, being $\delta_n - \delta_m$, is very small. Therefore, we can generalize that this difference is negligible in transmission circuits. As illustrated in Fig. C.1, if the difference $\delta = \delta_n - \delta_m$ is very small, then $\sin(\delta)$ is approximated in rad by δ itself, while $\cos(\delta)$ is approximating 1. Based on the aforementioned assumptions, (C.3) become:

$$P_n = \sum_{m=1}^{N} |V_n|\ |V_m|\ \big(B_{n,m}\ (\delta_n - \delta_m)\big) \tag{C.4a}$$

$$Q_n = \sum_{m=1}^{N} |V_n|\ |V_m|\ \big(-B_{n,m}\big) \tag{C.4b}$$

3. In the p.u. system, the numerical values of voltage magnitudes $|V_n|$ and $|V_m|$ are very close to 1 p.u, and we can assume that they are one everywhere in the network [165]. Considering this assumption,

(C.4) finally becomes:

$$P_n = \sum_{m=1}^{N} \big(B_{n,m}\ (\delta_n - \delta_m)\big) \tag{C.5a}$$

$$Q_n = \sum_{m=1}^{N} \big(-B_{n,m}\big) \tag{C.5b}$$

4. For techno-economic studies of power systems, such as energy exchanges in transmission level, active power is treated differently than reactive. Active power is a commodity available for trading while reactive power is regarded as an ancillary service. For this reason, DC power flow equations in economic dispatch problems neglect reactive power, while focusing only on the commercial energy exchanges of active power [167]. This assumption eventually leads to a reasonable representation of investigating a circuit's overload by looking at active power flows instead of currents.

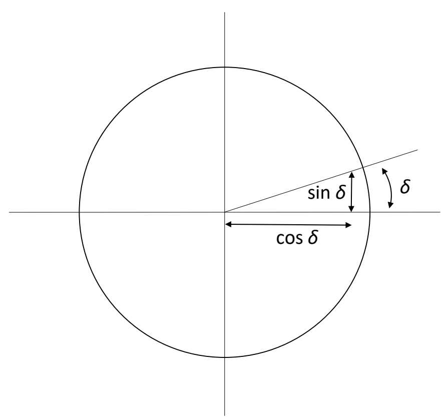

Figure C.1: AC to DC power flow simplification

C.2 DC Power Flow Constraints in Market-Clearing Problems

In this dissertation, being consistent with other techno-economic studies in transmission level, we are considering network constraints through a DC load flow representation. The output of this optimization models are the dispatch of balancing power, which results in power flows that satisfy the network capacity limits. Moreover, it yields LMPs, leading to potentially different energy prices for each node. The optimization models presented in Chapter 5, in contrast to the rest of the chapters, consider network constraints. These constraints are enforced by the following expressions:

- The first constraint refers to the power balance equation per each node. Additionally to power generation and consumption at each node, power exchanges between connected nodes are also taken into account. For example for node n, apart from generated and consumed active power an additional term is considered, i.e., $\sum_m B_{n,m}\,(\delta_n - \delta_m)$, representing the power flow through line connecting node n with every other node m.

- The aforementioned term, representing power flow through a line, is additionally constrained by the maximum power transfer capacity of the line. Thus, the below inequality constraints are also considered:

$$B_{n,m}\,(\delta_n - \delta_m) \leq F_{n,m}^{\max}\ \forall (n,m) \tag{C.6a}$$

Bibliography

[1] EPEX SPOT Belgium, “Belpex - Yearly Overview 2014,” https://www.belpex.be/wp-content/uploads/Power-BE-2014.pdf, [Online; accessed 06-September-2017].

[2] J. M. Morales, A. J. Conejo, H. Madsen, P. Pinson, and M. Zugno, *Integrating Renewables in Electricity Markets: Operational Poblems*. International Series in Operations Research & Management Science. New York, NY, USA: Springer, 2013.

[3] X.-P. Zhang, *Restructured Electric Power Systems*. John Wiley & Sons, Inc., 2010.

[4] C. Ruiz Mora, *Strategic offering and equilibria in electricity markets with stepwise supply functions*. Universidad de Castilla-La Mancha, Spain, 2012 (PhD Thesis).

[5] “ENTSO-E Member Companies,” https://www.entsoe.eu/about-entso-e/inside-entso-e/member-companies/Pages/default.aspx, [Online; accessed 06-September-2017].

[6] “Federal Energy Regulatory Commission (FERC),” https://www.ferc.gov/, [Online; accessed 06-September-2017].

[7] “ELIA: Balance Responsible Parties,” http://www.elia.be/en/products-and-services/balance, [Online; accessed 06-September-2017].

[8] KU Leuven Energy Institute, “The current electricity market design in europe,” https://set.kuleuven.be/ei/images/EI_factsheet8_eng.pdf/, [Online; accessed 06-September-2017].

[9] A. J. Conejo, M. Carrión, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*, International Series in Operations Research & Management Science. New York, NY, USA: Springer, 2010.

[10] *Directive 2003/54/EC*, The European Commission Std., 2003. [Online]. Available: http://eur-lex.europa.eu/eli/dir/2003/54/oj

[11] "ENTSO-E Overview of Internal Electricity Market," https://www.entsoe.eu/Documents/Events/2014/141013_ENTSO-E_Update-on-IEM-related%20project%20work_final.pdf, [Online; accessed 06-September-2017].

[12] K. V. den Bergh, C. Wijsen, E. Delarue, and W. D'haeseleer, "The impact of bidding zone configurations on electricity market outcomes," in *2016 IEEE International Energy Conference (ENERGYCON)*, April 2016, pp. 1–6.

[13] W. W. Hogan, "Transmission congestion: The nodal-zonal debate," *John F. Kennedy School of Government, Harvard University*, [Online; accessed 06-September-2017]. [Online]. Available: https://sites.hks.harvard.edu/fs/whogan/nezn0227.pdf

[14] S. M. Harvey and W. W. Hogan, "Nodal and zonal congestion management and the exercise of market power," *John F. Kennedy School of Government, Harvard University*, [Online; accessed 06-September-2017]. [Online]. Available: https://sites.hks.harvard.edu/fs/whogan/zonal_jan10.pdf

[15] M. Bjorndal and K. Jornsten, "Zonal pricing in a deregulated electricity market," *The Energy Journal*, vol. 1, no. 22, pp. 51–73, 2001.

[16] M. Bjorndal, K. Jornsten, and V. Pignon, "Congestion management in the nordic power market: counter purchases and zonal pricing," *Journal of Network Industries*, vol. 4, pp. 273–296, 2003.

[17] A. Ehrenmann and Y. Smeers, "Inefficiencies in European congestion management proposals," *Utilities Policy*, no. 13, pp. 135–152, 2005.

[18] R. Green, "Are the british electricity trading and transmission arrangements future-proof?" *Utilities Policy*, vol. 18, no. 4, pp. 186 – 194, 2010.

[19] M. Weibelzahl, "Nodal, zonal, or uniform electricity pricing: how to deal with network congestion," *Frontiers in Energy*, vol. 11, no. 2, pp. 210–232, June 2017.

[20] F. Foucault, R. Girard, and G. Kariniotakis, "Wind farm strategic investment considering forecast errors penalties in a nodal prices market," *EWEA 2014*, pp. 1–9, Mar. 2014.

[21] Z. Zhao and L. Wu, "Impacts of high penetration wind generation and demand response on LMPs in day-ahead market," *IEEE Transactions on Smart Grid*, vol. 5, no. 1, pp. 220–229, 2014.

[22] M. Hildmann, A. Ulbig, and G. Andersson, "Empirical analysis of the merit-order effect and the missing money problem in power markets with high RES shares," *IEEE Transactions on Power Systems*, vol. 30, no. 3, pp. 1560–1570, 2015.

[23] J. M. Morales, M. Zugno, S. Pineda, and P. Pinson, "Redefining the merit order of stochastic generation in forward markets," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 992–993, 2014.

[24] Y. Xiao, X. Wang, X. Wang, C. Dang, and M. Lu, "Behavior analysis of wind power producer in electricity market," *Applied Energy*, vol. 171, pp. 325–335, 2016.

[25] L. Deng, B. F. Hobbs, and P. Renson, "What is the cost of negative bidding by wind? A unit commitment analysis of cost and emissions," *IEEE Transactions on Power Systems*, vol. 30, no. 4, pp. 1805 – 1814, Jul. 2015.

[26] "Réserve stratégique en électricité," http://economie.fgov.be/fr/consommateurs/Energie/Securite_des_approvisionnements_en_energie/reserve_strategique_electricite/#.Wch-AYVOJPa, [Online; accessed 02-Oct-2017].

[27] G. Giebel, R. Brownsword, G. Kariniotakis, M. Denhard, and C. Draxl, "The state-of-the-art in short-term prediction of wind power: A literature overview," Tech. Rep., 2011.

[28] J. M. Morales, A. J. Conejo, K. Liu, and J. Zhong, "Pricing electricity in pools with wind producers," *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1366–1376, Aug. 2012.

[29] D. Fudenberg and J. Tirole, *Game Theory.* Cambridge, MA: MIT Press, 1991.

[30] M. J. Osborne, *An Introduction to Game Theory.* Oxford University Press, USA, 2003.

[31] E. Bompard, Y. C. Ma, R. Napoli, G. Gross, and T. Guler, "Comparative analysis of game theory models for assessing the performances of network constrained electricity markets," *IET Generation, Transmission Distribution*, vol. 4, no. 3, pp. 386–399, Mar. 2010.

[32] A. Cournot, *Researches into the Mathematical Principles of the Theory of Wealth.* Kelly, 1897.

[33] H. von Stackelberg, *Market Structure and Equilibrium.* Springer, 1934.

[34] J.-S. Pang and M. Fukushima, "Quasi-variational inequalities, generalized Nash equilibria, and multi-leader-follower games." *Computational Management Science*, vol. 2, no. 1, pp. 21–56, 2005.

[35] J. Nicolaisen, V. Petrov, and L. Tesfatsion, "Market power and efficiency in a computational electricity market with discriminatory double-auction pricing," *IEEE Transactions on Evolutionary Computation*, vol. 5, no. 5, pp. 504–523, Oct. 2001.

[36] Z. Vale, T. Pinto, I. Praca, and H. Morais, "MASCEM: Electricity Markets Simulation with Strategic Agents," *IEEE Intelligent Systems*, vol. 26, no. 2, pp. 9–17, Mar. 2011.

[37] L. Hurwicz and S. Reiter, *Designing Economic Mechanisms.* Cambridge University Press, 2006.

[38] N. Nisan and A. Ronen, "Algorithmic mechanism design," in *Proceedings of the 31st Annual ACM Symposium on Theory of Computing,*, 1999.

[39] L. Hurwicz, *"On Informationally Decentralized Systems" in Decision and Organization.* C.B. McGuire and R.Radner, North Holland, Amsterdam, 1972.

[40] R. Myerson and M. A. Satterthwaite, "Efficient mechanisms for bilateral trading," *Journal of Economic Theory*, vol. 28, pp. 265–281, 1983.

[41] C. Ruggiero, "Optimal decision-making with minimal waste: Strategyproof redistribution of VCG payments," in *5th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2006)*, Hakodate, Japan, May 2006.

[42] W. Vickrey, "Counterspeculation, auctions, and competitive sealed tenders," *The Journal of Finance*, vol. 16, no. 1, pp. 8–37, 1961.

[43] E. H. Clarke, "Multipart pricing of public goods," *Public Choice*, vol. 11, no. 1, pp. 17–33, Sep. 1971.

[44] T. Groves, "Incentives in teams," *Econometrica*, vol. 41, no. 4, pp. 617–631, 1973.

[45] C. De Jonghe, B. F. Hobbs, and R. Belmans, "Value of price responsive load for wind integration in unit commitment," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 675–685, Mar. 2014.

[46] J. Wang, N. E. Redondo, and F. D. Galiana, "Demand-side reserve offers in joint energy/reserve electricity markets," *IEEE Transactions on Power Systems*, vol. 18, no. 4, pp. 1300–1306, Nov. 2003.

[47] I. Pineda and J. Wilkes, "Wind in power," European Wind Energy Association, Tech. Rep., 2015.

[48] "Annual report 2014," Energinet.dk, Tech. Rep., 2014. [Online]. Available: https://en.energinet.dk/About-our-reports/Reports/Annual-Report-2014

[49] B. M. Hodge and M. Milligan, "Wind power forecasting error distributions over multiple timescales," *IEEE Power and Energy Society General Meeting*, pp. 1–8, Jul. 2011.

[50] E. Ela and M. O'Malley, "Studying the variability and uncertainty impacts of variable generation at multiple timescales," *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1324–1333, Aug. 2012.

[51] H. Bludszuweit, J. A. Dominguez-Navarro, and A. Llombart, "Statistical analysis of wind power forecast error," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 983–991, Aug. 2008.

[52] S. Tewari, C. J. Geyer, and N. Mohan, "A statistical model for wind power forecast error and its application to the estimation of penalties in liberalized markets," *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2031–2039, Nov. 2011.

[53] P. Pinson, "Wind energy: Forecasting challenges for its operational management," *Statistical Science*, vol. 28, no. 4, pp. 564–585, 2013.

[54] T. Jonsson, P. Pinson, and H. Madsen, "On the market impact of wind energy forecasts," *Energy Economics*, vol. 32, no. 2, pp. 313–320, Mar. 2010.

[55] A. Fabbri, T. G. S. Roman, J. R. Abbad, and V. H. M. Quezada, "Assessment of the cost associated with wind generation prediction errors in a liberalized electricity market," *IEEE Transactions on Power Systems*, vol. 20, no. 3, pp. 1440–1446, Aug. 2005.

[56] J. Zhao, T. Zheng, and E. Litvinov, "A unified framework for defining and measuring flexibility in power system," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 339–347, 2016.

[57] E. Lannoye, D. Flynn, and M. O'Malley, "Evaluation of power system flexibility," *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 922–931, May 2012.

[58] J. Ma, V. Silva, R. Belhomme, D. S. Kirschen, and L. F. Ochoa, "Evaluating and planning flexibility in sustainable power systems," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 1, pp. 200–209, Jan. 2013.

[59] B. Wang and B. F. Hobbs, "Real-time markets for flexiramp: A stochastic unit commitment-based analysis," *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 846–860, 2016.

[60] S. Wong and J. D. Fuller, "Pricing energy and reserves using stochastic optimization in an alternative electricity market," *IEEE Transactions on Power Systems*, vol. 22, no. 2, pp. 631–638, May 2007.

[61] G. Pritchard, G. Zakeri, and A. Philpott, "A single-settlement, energy-only electric power market for unpredictable and intermittent participants," *Operations Research*, vol. 58, no. 4-part-2, pp. 1210–1219, Apr. 2010.

[62] S. Martin, Y. Smeers, and J. A. Aguado, "A stochastic two settlement equilibrium model for electricity markets with wind generation," *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 233–245, Jan. 2015.

[63] J. M. Morales, M. Zugno, S. Pineda, and P. Pinson, "Electricity market clearing with improved scheduling of stochastic production," *European Journal of Operational Research*, vol. 235, no. 3, pp. 765–774, Jun. 2014.

[64] Y. Zhang and G. B. Giannakis, "Distributed stochastic market clearing with high-penetration wind power," *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 895–906, Mar. 2016.

[65] V. M. Zavala, K. Kim, M. Anitescu, and J. Birge, "A stochastic electricity market clearing formulation with consistent pricing properties," *Operations Research*, vol. 65, no. 3, pp. 557–576, 2017.

[66] S. A. Gabriel, A. J. Conejo, J. D. Fuller, B. F. Hobbs, and C. Ruiz, *Complementarity Modeling in Energy Markets*, New York, NY, USA: Springer, 2012.

[67] Z. Q. Luo, J. S. Pang, and D. Ralph, *Mathematical Programs With Equilibrium Constraints*, Cambridge University Press, 1996.

[68] M. Rahimiyan, J. M. Morales, and A. J. Conejo, "Evaluating alternative offering strategies for wind producers in a pool," *Applied Energy*, vol. 88, no. 12, pp. 4918–4926, 2011.

[69] M. R. Hesamzadeh and M. Yazdani, "Transmission capacity expansion in imperfectly competitive power markets," *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 62–71, 2014.

[70] S. J. Kazempour and H. Zareipour, "Equilibria in an oligopolistic market with wind power production," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 686–697, Mar. 2014.

[71] M. Zugno, J. M. Morales, P. Pinson, and H. Madsen, "Pool strategy of a price-maker wind power producer," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3440–3450, Aug. 2013.

[72] L. Baringo and A. J. Conejo, "Strategic offering for a wind power producer," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4645–4654, Nov. 2013.

[73] A. A. S. de la Nieta, J. Contreras, J. I. Munoz, and M. O'Malley, "Modeling the impact of a wind power producer as a price-maker," *IEEE Transactions on Power Systems*, vol. 29, no. 6, pp. 2723–2732, 2014.

[74] T. Dai and W. Qiao, "Optimal bidding strategy of a strategic wind power producer in the short-term market," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 3, pp. 707–719, 2015.

[75] C. Ruiz, A. J. Conejo, and Y. Smeers, "Equilibria in an oligopolistic electricity pool with stepwise offer curves," *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 752–761, May 2012.

[76] M. Vilim and A. Botterud, "Wind power bidding in electricity markets with high wind penetration," *Applied Energy*, vol. 118, pp. 141–155, 2014.

[77] C. Ruiz and A. J. Conejo, "Pool strategy of a producer with endogenous formation of locational marginal prices," *IEEE Transactions on Power Systems*, vol. 24, no. 4, pp. 1855–1866, Nov. 2009.

[78] B. Mond and T. Weir, *Generalized Concavity and Duality*. Academic Press New York, 1981.

[79] G. L. Nemhauser and L. A. Wolsey, *Integer and Combinatorial Optimization*, Wiley-Interscience, 1988.

[80] J. Fortuny-Amat and B. McCarl, "A representation and economic interpretation of a two-level programming problem," *Journal of the Operational Research Society*, vol. 32, no. 9, pp. 783–792, Sep. 1981.

[81] "Solving mixed integer programming problems (MIP)," https://www.ibm.com/support/knowledgecenter/en/SSSA5P_12.4.0/ilog.odms.cplex.help/CPLEX/User_manual/topics/uss_solveMIP_1.html, [Online; accessed 19-09-2017].

[82] "Gurobi Optimizer: State of the Art Mathematical Programming Solver," http://www.gurobi.com/products/gurobi-optimizer, [Online; accessed 19-09-2017].

[83] GAMS Development Corporation, *General Algebraic Modeling System (GAMS) Release 24.7.4.* Washington, DC, USA, 2016.

[84] Reliability Test System Task Force, "The IEEE reliability test system-1996," *IEEE Transactions on Power Systems*, vol. 14, no. 3, pp. 1010–1020, Nov./Dec. 1999.

[85] C. Ordoudis, P. Pinson, J. M. Morales Gonzalez, and M. Zugno, *An Updated Version of the IEEE RTS 24-Bus System for Electricity Market and Power System Operation Studies.* Technical University of Denmark, 2016.

[86] K. Dietrich, J. Latorre, L. Olmos, A. Ramos, and I. Perez-Arriaga, "Stochastic unit commitment considering uncertain wind production in an isolated system," in *4th Conference on Energy Economics and Technology*, April 2009, pp. 1–6.

[87] H. Louie, "Characterizing and modeling aggregate wind plant power output in large systems," in *IEEE PES General Meeting*, July 2010, pp. 1–8.

[88] ——, "Evaluation of probabilistic models of wind plant power output characteristics," in *2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems*, June 2010, pp. 442–447.

[89] A. Likas, N. Vlassis, and J. J. Verbeek, "The global K-Means clustering algorithm," *Pattern Recognition*, vol. 36, no. 2, pp. 451–461, Feb. 2003.

[90] C. Ruiz, S. J. Kazempour, and A. J. Conejo, "Equilibria in futures and spot electricity markets," *Electric Power Systems Research*, vol. 84, no. 1, pp. 1–9, 2012.

[91] D. Bergemann, A. Bonatti, and A. Smolin, "Selling information in oligopolies," *Yale University*, 2016, discussion paper No.2049. [Online]. Available: http://cowles.yale.edu/sites/default/files/files/pub/d20/d2049.pdf

[92] K. Bimpikis, D. Crapis, and A. Tahbaz-Salehi, "The design and price of information," *Stanford University*, 2016, working paper. [Online]. Available: https://web.stanford.edu/~kostasb/publications/selling_information.pdf

[93] "XXVIII European Electricity Regulatory Forum," https://ec.europa.eu/energy/sites/ener/files/documents/Conclusions_Final_FF_June2015.pdf, 2015, [Online; accessed 28-June-2016].

[94] "Technology roadmap: Energy storage," *International Energy Agency*, 2014.

[95] C. J. Dent, J. W. Bialek, and B. F. Hobbs, "Opportunity cost bidding by wind generators in forward markets: Analytical results," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1600–1608, Aug. 2011.

[96] S. N. Singh and I. Erlich, "Strategies for wind power trading in competitive electricity markets," *IEEE Transactions on Energy Conversion*, vol. 23, no. 1, pp. 249–256, Mar. 2008.

[97] G. N. Bathurst, J. Weatherill, and G. Strbac, "Trading wind generation in short-term energy markets," *IEEE Power Engineering Review*, vol. 22, no. 7, pp. 54–54, Jul. 2002.

[98] "Commission Regulation (EU) no 543/2013," http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:163:0001:0012:EN:PDF, 2013, [Online; accessed 28-June-2016].

[99] L. Baringo and A. J. Conejo, "Offering strategy of wind-power producer: A multi-stage risk-constrained approach," *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 1420–1429, Mar. 2016.

[100] N. Nisan, T. Roughgarden, E. Tardos, and V. V. Vazirani, *Algorithmic Game Theory*. New York, NY, USA: Cambridge University Press, 2007.

[101] A. Papakonstantinou and P. Pinson, "Population dynamics for renewables in electricity markets: A minority game view," in *Proceedings of 2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS 2016)*, Beijing, China, Oct. 2016.

[102] J. M. Morales, A. J. Conejo, and J. Pérez-Ruiz, "Short-term trading for a wind power producer," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 554–564, Jan. 2010.

[103] L. Baringo and A. J. Conejo, "Correlated wind-power production and electric load scenarios for investment decisions," *Applied Energy*, vol. 101, pp. 475 – 482, 2013.

[104] J. M. Morales, R. Minguez, and A. J. Conejo, "A methodology to generate statistically dependent wind speed scenarios," *Applied Energy*, vol. 87, no. 3, pp. 843 – 855, 2010.

[105] S. I. Vagropoulos, E. G. Kardakos, C. K. Simoglou, A. G. Bakirtzis, and J. P. S. Catalao, "ANN-based scenario generation methodology for stochastic variables of electric power systems," *Electric Power Systems Research*, vol. 134, pp. 9 – 18, 2016.

[106] P. Pinson, H. Madsen, H. A. Nielsen, G. Papaefthymiou, and B. Klockl, "From probabilistic forecasts to statistical scenarios of short-term wind power production," *Wind Energy*, vol. 12, no. 1, pp. 51–62, 2009.

[107] G. Diaz, J. Gomez-Aleixandre, and J. Coto, "Wind power scenario generation through state-space specifications for uncertainty analysis of wind power plants," *Applied Energy*, vol. 162, pp. 21 – 30, 2016.

[108] "Electricity Market Regulators, EU countries and stakeholders discuss EU Internal Electricity Market," https://ec.europa.eu/energy/en/news/electricity-market-regulators-

member-states-and-stakeholders-discuss-european-internal/, 2015, [Online; accessed 28-June-2016].

[109] "Elia," http://www.elia.be/en/grid-data/power-generation/wind-power, [Online; accessed 28-June-2016].

[110] "Transparency of Data About the Electricity Market," http://www.elia.be/en/grid-data/transparency/, 2013, [Online; accessed 28-June-2016].

[111] "ENTSO-E Transparency Platform," https://transparency.entsoe.eu/, [Online; accessed 28-June-2016].

[112] "Independent System Operator of New England," http://www.iso-ne.com/isoexpress/web/reports/operations/-/tree/seven-day-wind-power-forecast, [Online; accessed 28-June-2016].

[113] "Midcontinent Independent System Operator," https://www.misoenergy.org/MarketsOperations/RealTimeMarketData/Pages/DayAheadWindForecast.aspx, [Online; accessed 28-June-2016].

[114] "Alberta Electric System Operator," http://www.aeso.ca/gridoperations/18286.html, [Online; accessed 28-June-2016].

[115] J. B. Cardell, C. C. Hitt, and W. W. Hogan, "Market power and strategic interaction in electricity networks," *Resource and Energy Economics*, vol. 19, no. 12, pp. 109–137, 1997.

[116] B. F. Hobbs, C. B. Metzler, and J. S. Pang, "Strategic gaming analysis for electric power systems: an MPEC approach," *IEEE Transactions on Power Systems*, vol. 15, no. 2, pp. 638–645, May 2000.

[117] H. Pandzic, A. J. Conejo, and I. Kuzle, "An EPEC approach to the yearly maintenance scheduling of generating units," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 922–930, May 2013.

[118] S. Steffensen and M. Bittner, "Relaxation approach for equilibrium problems with equilibrium constraints," *Computers & Operations Research*, vol. 41, pp. 333–345, 2014.

[119] T. Dai and W. Qiao, "Finding equilibria in the pool-based electricity market with strategic wind power producers and network constraints," *IEEE Transactions on Power Systems*, vol. 32, no. 1, pp. 389–399, Jan. 2017.

[120] S. Siddiqui and S. A. Gabriel, "An SOS1-based approach for solving MPECs with a natural gas market application," *Networks and Spatial Economics*, vol. 13, no. 2, pp. 205–227, 2013.

[121] T. W. Haring, D. S. Kirschen, and G. Andersson, "Incentive compatible imbalance settlement," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 3338–3346, Nov. 2015.

[122] F. Scherer and D. Ross, *Industrial Market Structure and Economic Performance*. Houghton Mifflin Company, 1990.

[123] D. W. Bunn and F. S. Oliveira, "Evaluating individual market power in electricity markets via agent-based simulation," *Annals of Operations Research*, vol. 121, no. 1, pp. 57–77, 2003.

[124] B. E. Hobbs, "Linear complementarity models of Nash-Cournot competition in bilateral and poolco power markets," *IEEE Transactions on Power Systems*, vol. 16, no. 2, pp. 194–202, May 2001.

[125] B. F. Hobbs and J. S. Pang, "Nash-Cournot equilibria in electric power markets with piecewise linear demand functions and joint constraints," *Operations Research*, vol. 55, no. 1, pp. 113–127, 2007.

[126] C. Metzler, B. F. Hobbs, and J.-S. Pang, "Nash-Cournot equilibria in power markets on a linearized dc network with arbitrage: Formulations and properties," *Networks and Spatial Economics*, vol. 3, no. 2, pp. 123–150, 2003.

[127] V. P. Gountis and A. G. Bakirtzis, "Efficient determination of cournot equilibria in electricity markets," *IEEE Transactions on Power Systems*, vol. 19, no. 4, pp. 1837–1844, Nov. 2004.

[128] W. Jing-Yuan and Y. Smeers, "Spatial oligopolistic electricity models with cournot generators and regulated transmission prices," *Operations Research*, vol. 47, no. 1, pp. 102–112, Jan. 1999.

[129] D. Chattopadhyay, "Multicommodity spatial cournot model for generator bidding analysis," *IEEE Transactions on Power Systems*, vol. 19, no. 1, pp. 267–275, Feb. 2004.

[130] M. de Lujan Latorre and S. Granville, "The stackelberg equilibrium applied to ac power systems-a noninterior point algorithm," *IEEE Transactions on Power Systems*, vol. 18, no. 2, pp. 611–618, May 2003.

[131] L. P. Garces, A. J. Conejo, R. Garcia-Bertrand, and R. Romero, "A bilevel approach to transmission expansion planning within a market environment," *IEEE Transactions on Power Systems*, vol. 24, no. 3, pp. 1513–1522, Aug. 2009.

[132] B. F. Hobbs, C. B. Metzler, and J. S. Pang, "Strategic gaming analysis for electric power systems: an MPEC approach," *IEEE Transactions on Power Systems*, vol. 15, no. 2, pp. 638–645, May 2000.

[133] S. J. Kazempour, A. J. Conejo, and C. Ruiz, "Strategic generation investment using a complementarity approach," *IEEE Transactions on Power Systems*, vol. 26, no. 2, pp. 940–948, Apr. 2011.

[134] M. V. Pereira, S. Granville, M. H. C. Fampa, R. Dix, and L. A. Barroso, "Strategic bidding under uncertainty: a binary expansion approach," *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 180–188, Feb. 2005.

[135] C. Ruiz and A. J. Conejo, "Pool strategy of a producer with endogenous formation of locational marginal prices," *IEEE Transactions on Power Systems*, vol. 24, no. 4, pp. 1855–1866, Nov 2009.

[136] L. A. Barroso, R. D. Carneiro, S. Granville, M. V. Pereira, and M. H. C. Fampa, "Nash equilibrium in strategic bidding: a binary expansion approach," *IEEE Transactions on Power Systems*, vol. 21, no. 2, pp. 629–638, May 2006.

[137] S. de la Torre, J. Contreras, and A. J. Conejo, "Finding multiperiod nash equilibria in pool-based electricity markets," *IEEE Transactions on Power Systems*, vol. 19, no. 1, pp. 643–651, Feb. 2004.

[138] L. Exizidis, J. Kazempour, P. Pinson, Z. D. Grève, and F. Vallée, “Impact of public aggregate wind forecasts on electricity market outcomes,” *IEEE Transactions on Sustainable Energy*, vol. 8, no. 4, pp. 1394–1405, Oct 2017.

[139] C. d’Aspremont and L.-A. Grard-Varet, “Incentives and incomplete information,” *Game Theory in the Tradition of Bob Wilson*, vol. 12, 2002.

[140] B. Faltings, “A budget-balanced, incentive-compatible scheme for social choice.” *Agent-mediated E-commerce AMEC*, 2004.

[141] M. J. Bailey, “The demand revealing process: To distribute the surplus.” *Public Choice*, vol. 91, pp. 107–126, 1997.

[142] C. Silva, B. F. Wollenberg, and C. Z. Zheng, “Application of mechanism design to electric power markets,” *IEEE Transactions on Power Systems*, vol. 16, no. 4, pp. 862–869, Nov. 2001.

[143] B. F. Hobbs, M. H. Rothkopf, L. C. Hyde, and R. P. O’Neill, “Evaluation of a truthful revelation auction in the context of energy markets with nonconcave benefits,” *Journal of Regulatory Economics*, vol. 18, no. 1, pp. 5–32, 2000.

[144] X. Zou, “Double-sided auction mechanism design in electricity based on maximizing social welfare,” *Energy Policy*, vol. 37, no. 11, pp. 4231 – 4239, 2009.

[145] P. Zou, Q. Chen, Q. Xia, C. He, and C. Kang, “Incentive compatible pool-based electricity market design and implementation: A bayesian mechanism design approach,” *Applied Energy*, vol. 158, pp. 508 – 518, 2015.

[146] Y. Xu and S. H. Low, “An efficient and incentive compatible mechanism for wholesale electricity markets,” *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 128–138, Jan. 2017.

[147] K. W. Hedman, R. P. O’Neill, E. B. Fisher, and S. S. Oren, “Optimal Transmission Switching - Sensitivity Analysis and Extensions,” *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1469–1479, Aug. 2008.

[148] H. A. Gil, F. D. Galiana, and E. L. da Silva, "Nodal price control: a mechanism for transmission network cost allocation," *IEEE Transactions on Power Systems*, vol. 21, no. 1, pp. 3–10, Feb. 2006.

[149] J. Kazempour and B. Hobbs, "Value of flexible resources, virtual bidding, and self-scheduling in two-settlement electricity markets with wind generation - part I and part II," *IEEE Transactions on Power Systems*, to be published.

[150] "Uplift in RTO and ISO Markets," https://www.ferc.gov/legal/staff-reports/2014/08-13-14-uplift.pdf, 2014, [Online; accessed 26-September-2017].

[151] F. D. Galiana, A. L. Motto, and F. Bouffard, "Reconciling social welfare, agent profits, and consumer payments in electricity pools," *IEEE Transactions on Power Systems*, vol. 18, no. 2, pp. 452–459, May 2003.

[152] E. Castillo, A. J. Conejo, P. Pedregal, R. Garcia, and N. Alguacil, *Building and Solving Mathematical Programming Models in Engineering and Science.* Pure and Applied Mathematics, Wiley, New York, 2001.

[153] P. T. Harker and J.-S. Pang, "Existence of optimal solutions to mathematical programs with equilibrium constraints," *Operational Research Letters*, vol. 7, no. 2, pp. 61–64, Apr. 1988.

[154] H. V. Stackelberg, *The Theory of Market Economy*, Oxford University Press, Oxford, 1952.

[155] M. S. Bazaraa, H. D. Sherali, and C. M. Shetty, *Nonlinear Programming: Theory and Algorithms, 3rd edn.* Wiley, Hoboken, NJ, 2013.

[156] M. C. Ferris, S. P. Dirkse, and M. A., "Mathematical programs with equilibrium constraints: Automatic reformulation and solution via constrained optimization," *Frontiers in applied general equilibrium modeling: in honor of Herbert Scarf*, p. 67, 2005.

[157] S. Leyffer, G. Lopez-Calva, and J. Nocedal, "Interior methods for mathematical programs with complementarity constraints," *SIAM Journal on Optimization*, vol. 17, no. 1, pp. 52–77, Jan. 2007.

[158] S. Leyffer, "The penalty interior-point method fails to converge," *Optimization Methods and Software*, vol. 20, no. 4, pp. 559–568, Jul. 2005.

[159] A. U. Raghunathan and L. T. Biegler, "An interior point method for mathematical programs with complementarity constraints MPCCs," *SIAM Journal on Optimization*, vol. 15, no. 3, pp. 720–750, 2005.

[160] A. V. de Miguel, M. P. Friedlander, F. J. Nogales, and S. Scholtes, "A two-sided relaxation scheme for mathematical programs with equilibrium constraints," *SIAM Journal on Optimization*, vol. 16, no. 2, pp. 587–609, April 2006.

[161] X. Liu and J. Sun, "Generalized stationary points and an interior-point method for mathematical programs with equilibrium constraints," *Mathematical Programming*, vol. 101, no. 1, pp. 231–261, Aug. 2004.

[162] J. F. Bard, *Practical Bilevel Optimization: Algorithms and Applications*, Springer, Dordrech, 1998.

[163] D. Pozo, E. Sauma, and J. Contreras, "Basic theoretical foundations and insights on bilevel models and their applications to power systems," *Annals of Operations Research*, vol. 254, no. 1, pp. 303–334, Jul 2017.

[164] M. Zugno and A. J. Conejo, "A robust optimization approach to energy and reserve dispatch in electricity markets," *European Journal of Operational Research*, vol. 247, no. 2, pp. 659 – 671, 2015.

[165] B. Stott, J. Jardim, and O. Alsac, "DC power flow revisited," *IEEE Transactions on Power Systems*, vol. 24, no. 3, pp. 1290–1300, Aug. 2009.

[166] K. V. den Bergh, E. Delarue, and W. D'haeseleer, "DC power flow in unit commitment models," *KU Leuven Energy Institute*, 2014, working paper. [Online]. Available: https://www.mech.kuleuven.be/en/tme/research/energy_environment/Pdf/wpen2014-12.pdf

[167] K. Purchala, L. Meeus, D. V. Dommelen, and R. Belmans, "Usefulness of DC power flow for active power flow analysis," in *IEEE Power Engineering Society General Meeting, 2005*, June 2005, pp. 454–459 Vol. 1.

.