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Optimising energy and reserve offers in the Nordic markets under uncertainty

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Abstract

From an energy system perspective, hybrid energy producers with variable renewable energy (VRE) generators should aim to meet their day-ahead market commitments, which have been settled in light of production forecasts. In case of forecast errors, hybrid energy producers can meet these commitments by self-balancing. Self-balancing is possible either by trading in post-day-ahead markets or by adjusting the operation of their flexible generation units. In addition, hybrid producers should contribute to system stability by also offering their flexible generation capacity on ancillary markets. However, the question remains whether current market designs and market prices provide adequate incentives for multi-market participation.

In response to this question, this work presents a profit-maximising offer-strategy optimisation model which generates optimal offer curves for day-ahead and primary reserve markets taking into account uncertainty in dispatch, intraday trading opportunities, VRE generation and imbalance settlement. The primary reserve market considered is the market for up-regulating frequency containment reserve for disturbances (FCR-D). The hybrid producer's portfolio comprises VRE and controllable energy generation technologies. Despite, day-ahead, intraday and reserve markets having been studied previously, the contribution of this work is incorporating all these market opportunities into a coordinated bidding model and studying the benefits of this coordination and the incentives for multi-market participation in the Finnish context. Furthermore, the sensitivity of these results to intraday market liquidity and restrictions on providing reserve are assessed.

The results of the case study indicate that current market design and prices provide incentives for multi-market participation on these three markets. They also illustrate that self-balancing by intraday trading is profitable, but that intraday market liquidity limits this possibility. Furthermore, the results highlight that considering the reserve market in a coordinated manner with the day-ahead market has a significant effect on the reserve market participation. This effect is an increase in reserve market participation in comparison to the setting where offers to the day-ahead and reserve markets are optimised sequentially.

Keywords Electricity markets, offer-strategy optimisation, stochastic programming

Preface

First and foremost, I would like to thank my supervisor Professor Fabricio Oliveira for the opportunity to work in his research group, his guidance in the first steps on my career in research, and connecting me with my advisor Professor Bruno Fanzeres. I would like to thank them both for their advice and feedback during the completion this thesis. I am especially grateful for them providing me the opportunity to visit Pontifical Catholic University of Rio de Janeiro (PUC) and to Professor Bruno Fanzeres for hosting me during my stay. It was not only a professionally insightful research visit but also an amazing experience for me personally.

I would also like to thank my colleagues, whom I also consider my friends, at the Systems Analysis Laboratory for their support. Equally, I would like to thank my colleagues and friends from the Forecasting and Resource Optimization Group at PUC for welcoming me into the group and teaching me survival skills in Portuguese.

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Helmi Hankimaa

Contents

Symbols and abbreviations

Abbreviations

VRE	variable renewable energy
TSO	transmission system operator
FCR	frequency containment reserves
FCR-D	frequency containment reserves for disturbances
FCR-N	frequency containment reserves for normal operation
CCGT	combined cycle gas turbine
CET	Central European time
MW	megawatt
MWh	megawatt hour
BRP	balance responsible party
MIP	mixed-integer program
VPP	virtual power plant
PV	photovoltaic
ESS	energy storage system

Symbols

Sets	
$t \in \mathcal{T}$	Time intervals, each corresponding to an hour on day of dispatch
$i \in \mathcal{I}$	Price steps which form the offer curve to the day-ahead market
$j \in \mathcal{J}$	Offers to the reserve market
$s \in \mathcal{S}$	Price scenarios for day-ahead and reserve market prices
$e \in \mathcal{E}$	Intraday price scenarios
$\omega \in \Omega$	Wind and imbalance settlement scenarios
$k \in \mathcal{K}$	Set of linear functions that form the concave piecewise-linear water value function

Variables	
x_{it}	Volume in price step i of offer curve for hour t to the day-ahead market
y_{ts}	Day-ahead market commitment in hour t
v_{jt}	Volume in offer j for hour t to the reserve market
r_{ts}	Reserve market commitment in hour t
z_{tse}	Volume traded in intraday market for hour t
$\Delta^{+}_{tse\omega}, \Delta^{-}_{tse\omega}$	Positive and negative imbalances in hour t
g^{H}_{tse}	Hydropower generation in hour t
u^{H}_{tse}	On-off state of the hydropower generator in hour t
$u^{H,start}_{tse}, u^{H,stop}_{tse}$	Start up and shut down indicators of hydropower generator in hour t
f_{tse}	Water discharge from reservoir in hour t
f^{spill}_{tse}	Spill from reservoir in hour t
l_{tse}	Reservoir storage level in hour t
l^{k}_{tse}	Reservoir storage level on interval k in hour t
b^{k}_{tse}	Indicator if reservoir storage level is within interval k in hour t
r^{H}_{tse}	Reserve commitment allocated to the hydropower unit in hour t
g^{C}_{tse}	CCGT generation in hour t
u^{C}_{tse}	On-off state of the CCGT in hour t
$u^{C,start}_{tse}, u^{C,stop}_{tse}$	Start up and shut down indicators of the CCGT in hour t
r^{C}_{tse}	Reserve commitment allocated to the CCGT in hour t
$g^{W}_{tse\omega}$	Wind generation in hour t

Parameters

π^S	Probabilities of day-ahead and reserve market price scenarios
π^E	Probabilities of intraday price scenarios
π^Ω	Probabilities of wind and imbalance settlement scenarios
ρ_{ts}	Day ahead market price estimates
ψ_{ts}	Reserve market price estimates
φ_{tse}	Intraday market price estimates
$\lambda^+_{tse\omega}, \lambda^-_{tse\omega}$	Positive and negative imbalance settlement prices
$W_{tse\omega}$	Wind factors in wind availability scenarios
p_i	Price in price step i in the day-ahead market offer curve
p_j	Price in reserve offer j
$S^{H,start}$	Hydropower start up costs
$S^{C,gen}$	CCGT running costs
$S^{C,start}, S^{C,stop}$	CCGT start up and shut down costs
B^k_1, B^k_2	Coefficients of linear function k in the water value function
C^C, C^H, C^W	Installed CCGT, hydropower and wind generation capacities
dt	Length of single time step (1 hour)
U^H_{init}, U^C_{init}	Initial statuses of the hydropower generator and CCGT
F^{min}, F^{max}	Minimum and maximum rate of discharge from reservoir
F^{in}_t	Inflow into reservoir
L^{min}, L^{max}	Minimum and maximum reservoir water level
L^{init}	Initial storage level in reservoir
η	Generation coefficient between rate of discharge and power
U^C_{on}, U^C_{off}	Minimum on and off periods for the CCGT
G^{min}	Minimum stable load factor of the CCGT
G^{init}	Initial generation level of the CCGT
A	Ramping factor of the CCGT
α	Intraday market liquidity parameter

1 Introduction

Electricity is a unique commodity because its supply and demand must always match in real time in order for the electricity grid to remain stable. Since the 1990s, electricity markets have facilitated this matching of supply and demand [1]. These markets typically function at an hourly level of granularity, and they establish hourly plans for producing and consuming energy by evaluating producers' willingness to sell and consumers' willingness to buy energy. Market designs of these markets vary around the world, but in Europe, production and consumption schedules are typically formed each day on the day-ahead market for the 24 hours of the following day, and they are adjusted on the intraday markets up until 30 minutes before the delivery hour [2]. However, deviations from these schedules occur due to disturbances and the intermittent nature of variable renewable energy (VRE) sources, such as wind power. Therefore, the transmission system operators (TSOs), who are responsible for ensuring the stable operation of the electricity grid, procure reserve resources from ancillary markets. The TSOs activate this reserve capacity to compensate for real-time energy excesses and deficits in the grid in order to maintain constant balance between production and consumption.

Recently, installed wind power capacity has grown enormously in Finland. In fact, the capacity increased by 2430 megawatts in 2022, which nearly doubled the original capacity, and an additional 3200 megawatts will be installed within the next three years [3]. In other European countries, the implementation of VRE technologies has increased the significance of intraday trading as a means for adjusting production commitments for producers [4, 5]. Simultaneously, it increases the requirements for reserves [6]. Furthermore, due to the erosion of the price spreads between peak and off-peak electricity prices in Europe, reserve markets have become increasingly important for hydropower generators to maintain their profitability [7]. In light of these changes, it is important to examine how wind and hydropower producers can participate in intraday and reserve markets profitably in Finland and evaluate incentives for multi-market participation.

In the literature, assessing profitability and incentives for multi-market participation has been approached by developing profit-maximising offer-strategy optimisation models. This is because, in market driven energy systems, generation companies participate in electricity markets by submitting offers to sell, which are accepted according to market-clearing prices. Deciding these offers is a complex decision-making process involving many uncertainty factors [8]. Offer-strategy optimisation models tackle the many challenges this problem presents including uncertainties regarding market prices, opportunity costs, market liquidities and VRE generation and constraints due to regulations and technical operating limits. Since many of these issues are location and context specific, numerous models have been proposed for different contexts and under different assumptions [9, 10, 11]. For example, in the Nordic context, multi-market offer-strategy optimisation models have been developed in studies such as [12, 13, 14]. However, all these studies consider only hydropower producers, who do not face production uncertainty. On the other hand, authors in [15] and [16] consider joint bidding of dispatchable and VRE technologies, but do this in contexts where the energy markets are organised differently from their Nordic counterparts. In the Finnish context, optimal bidding has been addressed by for example [17], however with the restriction that they only consider reserve markets. Moreover, modelling intraday markets together with the main market for electricity, the day-ahead market, has rarely been addressed in any context, and considering primary reserve markets has been addressed even less [10].

Therefore, the aim of this thesis is to develop a multi-market offer-strategy optimisation model and to evaluate the benefits of multi-market participation and coordinated bidding in Finland. To assess the benefits of multi-market participation and coordination of bidding, a case study will be presented where the expected profits of the generation company and operating schedules are examined. Additionally, the sensitivity of these profits to intraday market liquidity will be assessed. The focus of this work is modelling market-related decision making in Nordic day-ahead, intraday and primary reserve markets. The primary reserve market considered is the market for up-regulating frequency containment reserve for disturbances (FCR-D). The generation portfolio that will be modelled comprises VRE and controllable energy generation technologies, specifically, wind power, hydropower and thermal generators. However, due to the limited scope of this thesis, the technical features of these generators are modelled linearly and with only hourly granularity. Moreover, sophisticated scenario generation techniques are not implemented within this thesis.

The remainder of this thesis is structured as follows. Chapter 2 introduces the market design and participation guidelines in day-ahead, intraday and FCR-D reserve markets. The chapter also explains the Nordic imbalance settlement scheme. Chapter 3 presents modelling frameworks for offer-strategy optimisation and reviews the state-of-the-art approaches to this problem. Chapter 4 presents the formulation of a mixed-integer linear program for offer strategy optimisation. Chapter 5 evaluates the benefits of multi-market participation and coordinated bidding trough a case study and discusses the results. Finally, Chapter 6 summarises the contributions of and conclusions from this thesis.

2 Nordic energy markets

Since this thesis aims to model multi-market participation in Finland, it is important to understand the context and, especially, the price uncertainty affecting this market-related decision making. In addition to this, since failing to fulfill market commitments incurs financial penalties to a producer, it is also important to understand the imbalance settlement scheme used to determine these penalties. Therefore, this chapter describes the market design of Nordic energy and reserve markets with an emphasis on market price formation and financial contracts. Sections 2.1, 2.2 and 2.4 describe the day-ahead, intraday and up-regulating FCR-D markets, respectively. Section 2.3 describes the Nordic imbalance settlement which relates to the balancing reserve markets.

2.1 Day-ahead market

The primary electricity market where Finnish generation companies sell their energy is the Nordic day-ahead market, operated by Nord Pool. This market is part of the European Single Day-ahead Coupling initiative, which joins together electricity markets around Europe to create a unified and more efficient European day-ahead electricity market [18]. The purpose of the day-ahead market is to find a least-operational cost equilibrium between the supply and demand of electricity for each hour of the delivery day [19]. This is crucial for electricity systems because production and consumption must match at all times in the electricity grid. This section explains the process of price formation and dispatch scheduling in the Nordic day-ahead market and how generation companies can participate in it.

For context, the Nordic day-ahead market, like most day-ahead markets, is organised daily for the 24 hours of the following day. The 24-hour period of the following day is counted from midnight CET [20], and these hours are referred to as delivery hours. Market participants must submit their orders before gate closure at 12:00 CET the day before delivery [21]. After gate closure, market outcomes are calculated. The market outcomes determine the total quantity of electricity that will be produced during each delivery hour and the resulting market-clearing prices.

The Nordic day-ahead market is organised as a uniform price auction, where the market operator establishes an equilibrium between demand and supply by processing orders from consumers and producers. Note that the consumers in the electricity market include electricity retailers and large industrial consumers, not individual private consumers [1]. Orders consist of energy volume and order price pairs, which constitute the order curve. These pairs are also called price steps [21]. Generation companies offers indicate the quantities of electricity they are willing to sell at different prices. Conversely, consumers' bids indicate the prices they are willing to pay for different quantities of energy. Energy volumes and prices are given in units of MWh and €/MWh, respectively [20]. In a uniform price auction, the market operator determines the market equilibrium by maximising total social welfare. In essence, they find the intersection of consumers' willingness to pay and producers' willingness to sell. Determining the market outcome is also called market clearing.

The process of market clearing for a single delivery hour is illustrated in Figure 1, where the orange line represents the aggregated bids of consumers and the blue line represents aggregated offers of producers. In the figure, $\hat{q}$ is the cleared quantity and $\hat{p}$ becomes the market-clearing price. The producers whose offers fall to the left of the equilibrium are cleared, and they will supply the electricity during the delivery hour. In a uniform price auction, all transactions will be settled at the market-clearing price $\hat{p}$. Hence, all producers receive $\hat{p}$ [€/MWh] for the electricity they produce. This process ensures the economically efficient allocation of electricity and that electricity is produced at the lowest possible cost for consumers [19].

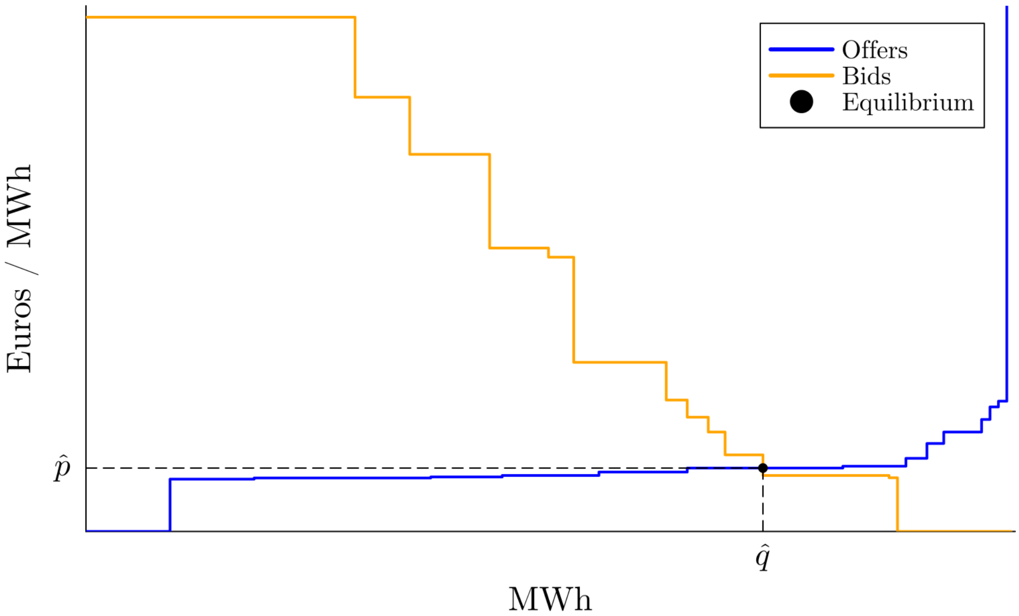


Figure 1: Illustration of the market clearing process in the day-ahead market.

In reality, the market clearing process is more complicated due to the array of different order types and the constraints imposed by the power grid infrastructure. The orders explained above are called hourly orders, and, for the purpose of this thesis, knowledge of the other order types is not necessary. The other complicating factor is the infrastructure of the power grid. The transmission capacity between and within European countries is limited. This constrains the market clearing process because the energy produced must also reach the consumers via the power grid. Therefore, countries are split into bidding areas, and a balance between supply and demand is established for each bidding area. The market outcomes are optimised to maximise welfare across all bidding areas such that the imports and exports across bidding areas comply with transmission capacity limitations. If congestion occurs on the power line between two bidding areas, the allocation of electricity is constrained, and the bidding areas will have different prices. These prices are called area prices, and they reflect the regional market conditions [22]. In the Nordics, the transmission system operators (TSO) decide how many bidding areas are required, and currently, the Nordic countries are split into 12 bidding areas with Finland being a single bidding area [22].

Having explained the governing principles of the day-ahead market, the rest of this section outlines regulations related to and the processing of a single producer's offer curve. As stated above, each producer submits an offer curve consisting of price-volume pairs for each delivery hour. These price steps indicate producers' willingness to sell at different prices. According to the day-ahead market regulations, the price steps on an offer curve must form an increasing series in both price and quantity [21]. The first price step must be at the minimum allowed price of -500 €/MWh, and the final price step must be at the maximum allowed price of 4000 €/MWh [21]. The maximum number of price steps an offer curve may include is 200 [20].

After receiving the offer curve, Nord Pool interpolates the price steps using linear interpolation [21]. The quantity that the producer is ordered to produce is determined by the intersection of the day-ahead price and this interpolated curve [21]. Figure 2 illustrates this process for a single delivery hour. The blue dots indicate the price steps submitted by the producer, and the line connecting them is the linear interpolation calculated by Nord Pool. Note that the first and last price steps at prices -500 €/MWh and 4000 €/MWh exist but are not visible on the graph. In the figure, at market-clearing price $\hat{p}$, the producer is cleared to produce $\bar{q}$ [MWh]. Quantity $\bar{q}$ is also called the producer's day-ahead market commitment.

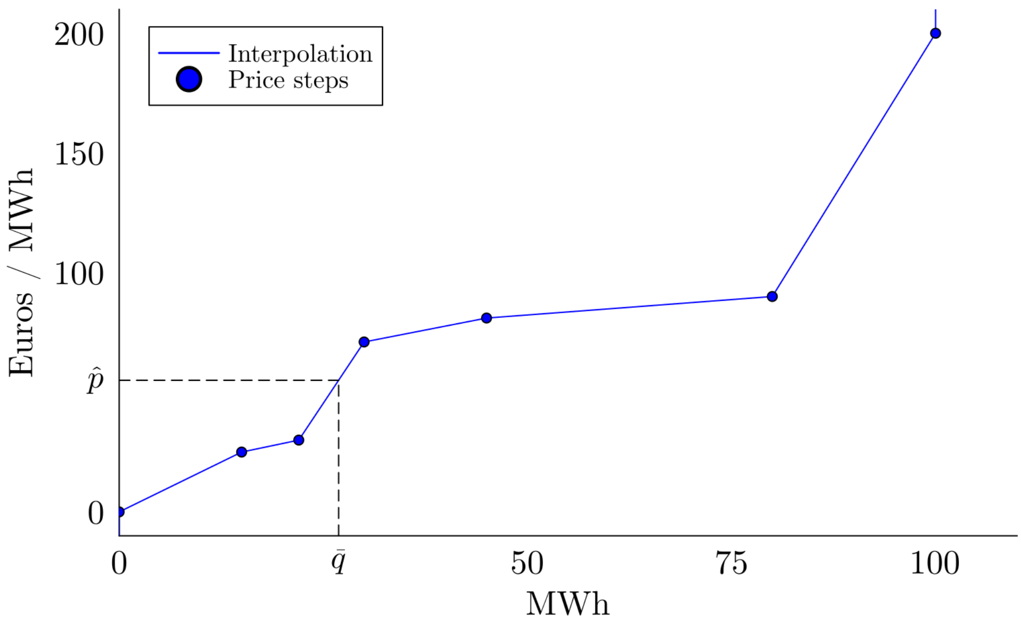


Figure 2: Illustration of determining the commitment of a single producer in the day-ahead market.

2.2 Intraday market

Once the day-ahead market has closed and its market outcome is published, intraday markets open and allow participants to make recourse actions. Intraday market implementations vary around the world, but their defining characteristic is that the trading window typically falls between day-ahead market and balancing market closures [10]. This section outlines the structure and issues of European intraday markets which affect trading and thus the modelling premise in this thesis. In addition, trading behaviour observed in the case study in Chapter 5 will be compared to the typical behaviour seen on these markets.

Finnish electricity producers can participate in the intraday markets organised by Nord Pool. These are joint intraday markets across 14 European countries [23], and they are also part of the Single Intraday Coupling project, which couples markets in 25 European countries [24]. A separate intraday market is organised for each delivery hour of the following day. The markets for all delivery hours open after the day-ahead market outcome has been published at approximately 14:00 CET [20], but the markets close at different times. Gate closure is typically an hour before delivery, but in Finland gate closure is only 30 minutes before delivery [20].

Nord Pool's intraday markets are organised as continuous trading platforms. Therefore, instead of establishing a uniform market-clearing price, as in the day-ahead market, in the intraday markets individual buy and sell orders are matched continuously at varying prices [20]. This matching occurs automatically when a buy order and a sell order are registered on the platform with the order prices being such that the price of the buy order exceeds that of the sell order [20]. The other condition for order matching is that the required transmission capacity is available [24]. It is interesting to note that despite the long opening hours of the intraday markets, most of the trading occurs in the final hours before gate closure [25]. In the intraday markets, participants can make orders with 15, 30 and 60 minute granularity as well as block orders [24]. However, for the purpose of this thesis, only the knowledge of hourly orders is required. Hourly orders are offers to produce or consume a specified amount of energy within a single delivery hour.

Several motivations for generation companies to trade in intraday markets are discussed in [25]. One reason is to reduce imbalances and therefore hedge against uncertain imbalance prices. This is an important motivation for variable renewable energy (VRE) generators, who submit their day-ahead offers based on production forecasts. This type of utilisation of the intraday markets was observed in [4], where they noticed that in Denmark, imbalances due to errors in wind generation forecasts were reduced by intraday trading. Another motivation for intraday trading is buying commitments if producing the energy would be more costly than the prices observed on the intraday market [25]. Finally, producers might also sell their flexibility on the intraday market if the price offered there exceeds the cost of rescheduling and ramping production [25]. Note that the first and third motivations, when acted upon, benefit the entire energy system. This is because trading in the intraday market to reduce imbalances and provide flexibility improves system stability and reduces the need for reserves [25].

Some of the challenges related to intraday trading are volatile prices and low liquidity [10]. Authors in [25] observed that the prices at which trades are made vary greatly within the trading period. However, it has also been observed that the mean of these prices correlates with the day-ahead price for the hour [12, 5]. Therefore, researchers often focus on analysing and predicting the deviation of intraday prices from the day-ahead price instead of the actual intraday prices. This price deviation is also called the intraday price premium. Authors in [26] and [4] analysed intraday price premiums and found that they are affected by generation and consumption forecast errors. These studies also analysed whether the price premiums are symmetric for positive and negative forecast errors, and the author in [26] concluded that in Denmark, the deviations are symmetric. The significance of this information is that asymmetric price premiums would provide an opportunity for strategic trading [26]. Strategic trading means purposely under or over committing in the day-ahead market expecting that it is possible to make advantageous recourse actions in the intraday market.

Low liquidity is a common problem in intraday markets [25]. The main effort to tackle low liquidity has been the implementation of Single Intraday Coupling in 2018 which facilitates sharing energy resources in Europe [24]. Furthermore, it has been expected that liquidity will improve with significant penetration of VRE technologies [10], and this has been observed in Europe [5]. For example, Nord Pool announced that the total intraday trading volume increased by 50% between the years 2021 and 2022 [27]. However, their announcement also revealed that intraday trading still accounts for only 3.5% of all trades on Nord Pool's day-ahead and intraday markets.

2.3 Balancing market and imbalance settlement

The purpose of the day-ahead and intraday markets is to establish an energy balance between production and consumption for each delivery hour. However, real-time production and consumption often deviate from these schedules, and when this happens, it is said that there is a system imbalance. In this case, the energy balance must be maintained using reserve energy units. The significance of this is that if an energy producer is a balance responsible party (BRP) and they contribute to the system imbalance by not fulfilling their commitments accurately, they incur costs for their own imbalance [28]. Therefore, it is important to understand how the imbalances are priced after each delivery hour. Thus, this sections explains the imbalance settlement scheme used in the Nordics.

For context, it is essential to know that the electricity grid faces positive, negative and no imbalance situations, which are caused by having an excess, a deficit or a balance of energy in the system, respectively. Positive imbalances occur when real-time production exceeds consumption and requires the TSO to employ down-regulating reserves to combat over frequency. Conversely, if load exceeds generation, the system faces a negative imbalance which requires the TSO to employ up-regulating reserves to combat under frequency. Up-regulating reserves are resources that increase production or decrease load, and down-regulating reserves decrease production or increase load. Each delivery hour, which in the context of imbalance settlement is often referred to as an operating hour, is defined as an up-regulation, down-regulation or no-regulation hour depending on the regulation needed during that hour [29].

In imbalance settlement, a BRP's deviation from their commitment is charged or paid the imbalance price, λ, if their imbalance is in the same direction as the system imbalance [29]. Otherwise, the imbalance is charged or paid the day-ahead market-clearing price, ρ [29]. The imbalance of a producer is positive if they generate excess energy with respect to their commitments and it is negative if they produce a deficit. These imbalances are measured in MWh and the prices are in €/MWh. In order to process imbalance payments two prices are used: the down-regulation price, λ^+, for positive imbalances, and the up-regulation price, λ^-, for negative imbalances. Note that in each operating hour, one of these prices is equal to the imbalance price, λ, and the other one is equal to the day-ahead price, ρ [1]. Furthermore, the down-regulation price is always less than or equal to the up-regulation price, $\lambda_t^+ \leq \lambda_t^-$, and the day-ahead price falls between them, $\lambda_t^+ \leq \rho \leq \lambda_t^-$ [1]. Note, also that down-regulation prices, λ^+, may be negative [30].

For an individual producer this means that there are five scenarios that may occur if they generate an imbalance:

1. If the system imbalance is negative and the producer's imbalance is positive, the producer will receive the day-ahead price $\rho = \lambda^+$ for every MWh of excess energy they produced.

2. If the system imbalance is negative and the producer's imbalance is negative, the producer has to pay the imbalance price $\lambda = \lambda^- > \rho$ for every MWh of energy they failed to produce.

3. If the system imbalance is positive and the producer's imbalance is positive, the producer will receive the imbalance price $\lambda = \lambda^+ < \rho$ for every MWh of excess energy they produced.

4. If the system imbalance is positive and the producer's imbalance is negative, the producer must pay the day-ahead price $\rho = \lambda^-$ for every MWh of energy it failed to produce. Note, that in this case, the transaction does not incur costs to the producer because they have previously received the same price for the energy from the day-ahead market.

5. If the system has no imbalance, the imbalance price is equal to the day-ahead price. The producer will pay the day-ahead price for a negative imbalance or receive the day-ahead price for a positive imbalance.

Note that this system implies that imbalance costs are in essence an opportunity cost for a producer. They reflect the missed opportunity for higher profits had the producer sold the correct quantity of energy on the day-ahead market. This is due to the day-ahead price always being at least as favourable as the imbalance price. As such, the imbalance price is a significant source of uncertainty for participants in the electricity market. Mitigating this risk, motivates energy producers to offer their energy as accurately as possible in the day-ahead market, aligning their offers with their production capabilities.

The imbalance price λ is determined based on the activation of manual frequency restoration reserves (mFRR) on the balancing energy market [28]. Even though the producer modelled in Chapter 4 does not participate in this market, since the imbalance price is a significant uncertainty affecting the modelling premise, a brief explanation of its price formation follows. The Nordic balancing energy market is used to procure up-regulating and down-regulating energy that the TSOs employ to combat system imbalances. Generation companies and consumers can bid their resources on this market until 45 minutes before delivery [30], and the market price, λ, is determined by the real-time activation of these resources during the operating hour. Due to grid constraints, the balancing prices may differ between bidding areas. Studies have analysed imbalance price premiums, which are the differences between imbalance prices and day-ahead prices. The authors in [25] observed that imbalance price premiums are generally higher in Finland than in the other bidding areas in the Nordics. Between 2012-2013, the mean and standard deviation of this premium were twice bigger in Finland compared to all other Nordic bidding areas. This implies that Finland has had very high variation in imbalance prices and these prices have deviated considerably from day-ahead prices. Furthermore, [31] observed that the imbalance price premiums are weakly correlated with intraday price premiums. These findings illustrate that forecasting imbalance prices based on day-ahead and intraday prices is challenging, and therefore market participants face a significant uncertainty related to them.

2.4 Frequency containment reserve market for disturbances

In order to maintain stable frequency in the electricity grid, the Finnish TSO, Fingrid, procures six types of reserves to handle different frequency situations. These reserves include fast frequency reserves (FFR), automatic frequency restoration reserves, mFRR and three types of frequency containment reserves (FCR) [32]. These products are distinguished by their activation speeds and the frequency situations in which they are activated. The producer whose decision making will be modelled in Chapter 4 provides up-regulating FCR for disturbances (FCR-D). Therefore, this section explains the purpose of FCRs and outlines the organisation of FCR-D markets.

Up-regulating FCR-D is typically provided by electricity producers with flexible generators that can be ramped up with short notice. These reserves are activated if a disturbance drops the frequency below 49.9 Hz and its purpose is to contain the frequency within 500 mHz of its nominal value of 50 Hz [28]. After FFR, FCR-D products have the second strictest activation requirements [28]. They are required to activate 50% of their reserve commitment within 5 seconds and 100% within 30 seconds [28]. Luckily, many generation technologies are capable of providing FCR including nuclear, coal and gas power plants as well as hydropower, batteries and wind turbines [33].

As opposed to energy markets, the commodity traded in reserve markets is generation capacity, measured in units of MW [34]. In the Nordics, TSOs are obligated to procure reserves, and they are responsible for organizing reserve markets [32]. Fingrid organizes yearly and hourly markets for procuring up-regulating FCR-D.

An hourly market is organized daily to procure reserves for all delivery hours of the following day [34]. This market closes at 17:30 CET [34]. Offers to the up-regulating FCR-D hourly market consist of capacity-price pairs in MW and €/MW. These pairs represent the capacity that the producer is willing to reserve for potential under-frequency situations during a specific delivery hour. The minimum offer for up-regulating FCR-D products is 1 MW [34]. A producer is allowed to submit multiple offers, but, in contrast to the day-ahead market, these offers are processed separately and not interpreted as an offer curve. In this market, Fingrid acts as the buyer, and demand represents the obligations Fingrid has not fulfilled in the yearly market. The offers are cleared in order of price, ensuring the most efficient allocation. All sellers whose offers are accepted receive the market-clearing price, known as the capacity fee. If the need for the reserve is realized, producers will also receive an energy fee based on their activation

When participating in the up-regulating FCR-D market, a producer faces a trade-off between offering generation capacity as reserve or utilising it for producing energy to be sold in the day-ahead market. Note that reserving capacity does not incur running costs for the producer; However, they still receive a capacity fee for the reserved capacity. Therefore, producers are primarily concerned with predicting the market prices and evaluating the probability of reserve activation. The FCR market prices have very different statistical characteristics compared to day-ahead market prices [35]. The challenge is that FCR prices face high price peaks, and low and even zero price days [35]. Thus, for example neural networks have been utilised for predicting FCR prices [35, 33, 17]. In terms of reserve activation, the probability of activation varies for different reserve types. Authors in [36] and [35] observed that FCR for normal operation (FCR-N) are activated frequently. In contrast, [36] found that in Denmark, FCR-D tends tends to have relatively rare activations. In line with this finding, Fingrid reported that in Finland, under-frequency situations were rare and brief in 2021. Specifically, the daily average frequency crossings below the 49.9 Hz threshold was 48, and the daily average duration of under-frequency below 49.9 Hz was 12.7 minutes [37]. While these measures do not directly signify the activation of up-regulating FCR-D, they suggest that activations were infrequent. Consequently, participating in the up-regulating FCR-D market could potentially benefit producers, even those with high running costs, if reserving capacity is relatively inexpensive for them. This is due to the low likelihood of reserve activation in this market.

3 Optimising offer strategies in energy markets

Offer-strategy optimisation deals with determining optimal quantities and prices for market offers such that the resulting market commitments yield the highest possible profits. It was shown more than 20 years ago that, in certain settings, it is always optimal to offer at true costs [38]. However, the characteristics of today's energy markets do not meet the requirements for this to always be true. Moreover, the environment of energy trading is continuously changing. Therefore, offer-strategy optimisation remains a topic of active research. Furthermore, this problem remains to be challenging also from a modelling stand point due to its nonlinear structure which optimisation solvers still struggle to handle efficiently. The non-linearity arises from revenue being dependent on the product of two strategic decisions in offer-strategy optimisation: price and quantity.

To establish context for developing a profit-maximising bidding model, which will be done in Chapter 4, this chapter presents a review of the offer-strategy optimisation literature. Section 3.1 outlines offer-strategy optimisation frameworks used to define the modellin premise, Section 3.2 presents how specific challenges related to this problem have been addressed in the literature and Section 3.3 reviews the most relevant multi-market models for the context of this thesis. Despite offer strategies having been optimised using many methodologies, such as optimal control models [39], markov decision processes [40], artificial intelligence [17] and nonlinear programs [15], due to the scope of this thesis, the following sections focus on models that are formulated as mixed-integer programs (MIP) that can be solved with off-the-shelf solvers.

3.1 Offer strategy optimisation frameworks

In the literature, three main frameworks are utilised for optimising offer strategies: endogenous clearing-based models, residual demand curve models and price taker models. Endogenous clearing-based models optimise a producer's offer strategy who has market power, meaning that their offer is expected to have an effect on the market outcome. In this framework the producer's offer strategy is optimised in light of predictions of other producers' offers and demand bids. These models are typically bilevel models, where offer-strategy optimisation is performed in the upper-level problem and market price formation is modelled endogenously in the lower-level problem. The price formation can also yield locational prices if network constraints are incorporated in the model [41]. The lower level problem is traditionally incorporated into the upper level problem using its Karush–Kuhn–Tucker conditions making the problem a mathematical program with equilibrium constraints (MPECs) [42]. In this framework, the non-linearity arising from having to determine offer prices and quantities simultaneously has been approached by developing linearisation methods. For example, [42] presents a binary expansion approach and [43] utilised this in conjunction with a big-M approach. In these models, uncertainty regarding other producers' offers and demand bids can be modelled with stochastic or robust optimisation [41, 44]. Multiple markets, which are sequentially cleared, can be modelled using multiple lower-level problems [43].

Another framework for optimising offer strategies assuming agents can have market power is modelling the residual demand curve. Instead of modelling all individual participants in the market, in this framework, other market participants' aggregate demand and supply are estimated as functions of market-clearing price. The difference between these curves gives the residual demand curve faced by the company in question. This curve quantifies the effect of the company's offer on the market-clearing price [45]. This method has been applied by, for example, authors in [46] for optimising bidding in reserve markets. It was also applied by the authors in [45] to model day-ahead, reserve and balancing markets. However, a residual demand curve was only utilised for modelling the day-ahead market and the reserve and balancing markets were modelled as deterministic second-stage decisions. These studies have represented the problem using MIP formulations by approximating the residual demand curve as a linear or a piece-wise linear function.

In contrast to the frameworks outlined above, in the third framework, the generation company's offers are assumed to have a negligible effect on market-clearing prices. Thus, this framework is used when the company in question is a price-taker. Accordingly, in this approach, market-clearing prices are modelled as exogenous uncertainties. Studies such as [47], [48] and [16] have removed the naturally arising non-linearity by making assumptions about the offer prices and merely optimising the offer quantities. This thesis develops a model for a price-taker company, and therefore this framework with exogenous price-uncertainty is adopted. Thus, the next section explores how challenges in modelling market-related decision making have been addressed in the literature within this framework.

3.2 Model design in price-taker models

The distinguishing characteristic of price-taker models is that market prices are modelled as exogenous uncertainties. However, other than the treatment of this uncertainty, many other challenges are tackled in different ways within this framework. This section reviews some of the key challenges in market-related decision making and solution approaches to them in price-taker optimisation models.

Dealing with non-linearity

As mentioned in the previous section, the non-linearity in price-taker bidding models may be removed by only optimising offer quantities under some assumptions regarding their respective offer prices. At least three different types of assumptions on offer prices have been used for this purpose in the literature. Studies such as [47], [14] and [49] have merely assumed that once optimal offer quantities are determined, offer prices are decided so that these optimal quantities will be cleared in the market. This assumption reduces the offer problem to an optimal self-scheduling problem. In an optimal self-scheduling problem, a profit-maximising dispatch schedule is determined in light of market-price predictions and production constraints. Note that in markets with uniform market-clearing prices, such as day-ahead markets, the revenue of a generation company is independent of their offer prices, assuming that their offered quantity is cleared. Thus, the profits are solely dependent on market-clearing prices, the generation schedule and production costs.

Some studies such as [50] and [51] have developed the optimal self-scheduling approach a step further by defining rules for deciding offer prices after the optimal schedule is determined. The model in [51] optimises the offer strategy of a wind power producer and, as is common practice, they assume wind generation to incur no running costs. Thus, under the assumption that day-ahead market prices are always positive, they suggest that bidding the optimal quantities at zero price is optimal. The offer price rule defined in [50] is more sophisticated. In their study, they utilise the probability density functions of price forecasts to determine optimal offer prices such that the optimal self-schedule will be cleared with a 99% level of confidence. Note that a short-coming of the optimal self-scheduling approach is that it cannot be used to define optimal offer curves, only a single offer volume.

Another approach, which has been adopted for example in [16] and [52] is to utilise market-price forecasts as the offer prices. In these studies, the market-price scenarios for day-ahead prices form a set of offer prices for which offer quantities are optimised. The formulations optimise revenue minus production costs with non-anticipativity constraints, non-decreasing offer curve constraints and production constraints. The non-anticipativity constraints enforce that optimal bid quantities must be equal in price scenarios where market prices are equal, and the non-decreasing offer curve constraints enforce that the bid quantity in one scenario has to be less than or equal to the bid quantity in another scenario if the market price in the first scenario is less than that of the second scenario. Note that in these models it is implicitly assumed that the offer quantities are always cleared for dispatch. Furthermore, they define the offer curve as price steps that are in fact optimal dispatch schedules for different market-price forecasts. Therefore, the limitation of this approach is that it does not account for uncertainty in dispatch and does not consider the linearisation of the offer curve performed by the market operator.

In response to this, the authors of [53] proposed a two-stage stochastic program formulation. They modelled the day-ahead market bid curves and the resulting market commitments of an electricity retailer using separate variables. Building upon this, the authors in [48] adapted the formulation to optimising an offer strategy for a price-taker producer. In this model, an offer curve with multiple price steps is optimised in light of market-price forecasts without assuming dispatch. The offer prices are fixed and offer quantities are modelled as first-stage decisions. Scenario-specific market commitments are determined for each market-price scenario in the second-stage in accordance with the Nordic day-ahead market regulations using a linear interpolation of the price steps. This model has been adapted to include intraday, reserve and balancing market trading as later-stage decisions in [12], [13] and [54], respectively.

Uncertainty in market liquidity

As discussed in the previous chapter, liquidity is a concern in intraday markets. Methods for incorporating this issue in offer-strategy optimisation models have not converged to a well known method [10]. Thus, some studies, such as [55], assume perfect liquidity in markets which are known to have limited liquidity. However, a few approaches have been implemented to model limited liquidity. Authors in [47] and [12] optimised day-ahead and intraday bidding in their models, and imposed a liquidity constraint on intraday trading. This constraint imposed a limit on the volume of energy that could be traded as a percentage of generation capacity. This simple constraint restricted the model from heavily relying on the possibility of trading in the intraday market. Another approach was utilised by the authors in [14]. They modelled post-day-ahead decision making on intraday and balancing markets. They constructed residual demand curves based on historical data on intraday orders to quantify the opportunities for trading in intraday markets with low liquidity. These residual demand curves related decreasing intraday premiums to increasing opportunities for trading. Notice that the use of residual demand curves in this context does not imply market power due to intraday markets not having a uniform clearing price. The most recent approach to modelling limited liquidity was introduced in [14]. They coordinated offering on the Nordic day-ahead and balancing markets. These balancing markets suffer from liquidity issues, and therefore the authors estimated a maximum volume that may be traded in the different price scenarios. This volume was used as a cap on trading in the balancing market in each scenario. Note that this model only considered the possibility of selling to the balancing market. Thus, this approach is not directly applicable to intraday markets where producers can both buy and sell energy.

Uncertainty in reserve activation

A significant uncertainty that generation companies face in reserve markets relates to reserve capacity activation. As discussed in Chapter 2, the commodity in reserve markets is capacity, which can be activated if the demand for reserve is realised. In primary reserve markets, such as FCR-D, the market-clearing process is unconnected to activation. However, in balancing markets, for instance, the market clearing is based on activation, and the market price is determined by the most expensive activated resource. Nevertheless, even when market clearing is performed separately from activation, uncertainties regarding reserve activation remain important for producers. This is because activation incurs costs from generation and yields revenue as energy fees.

Modelling uncertainty in reserve activation has gained little attention in the literature. Nonetheless, every model that optimises bids for reserve markets quantifies this uncertainty. Thus, at least three approaches have been implemented. Some models, such as [16], merely assume the reserve to never be activated. In these models, the profit from reserving capacity is accounted for in the objective, but the revenue or costs from activation are not considered. However, note that despite this assumption, the reserve commitment is still considered in the operational limits of the generator. Whether this is an appropriate assumption depends on the reserve type in question, since the activation frequencies of different reserve resources varies greatly.

Another approach, which was adopted in [56], is to estimate the expected activation time during an operating hour. The model in this study was a deterministic optimal self-scheduling model and they estimated the activation time as a fraction of an hour.

The authors inspected the effect of this parameter on the expected profits from the optimal schedule. Unsurprisingly, they found that this parameter has a significant impact on revenues and the optimal schedule.

The authors in [57] modelled the quantity of activated reserve as a stochastic parameters. They incorporated reserve activation uncertainty in their scenario structure and generated these scenarios from a probability distribution. The value of this stochastic parameter determined the revenue from the reserve market in their objective function.

Sequential and coordinated multi-market offering

In sequentially cleared markets, such as the Nordic ones, the decision-making process of a generation company constitutes a multitude of stages. This is because the markets open and close in succession which leads to market decisions being made in sequence and in an alternating fashion with observing market outcomes. This leads to challenges in modelling the decision-making process because multi-stage optimisation models with uncertainty in many stages are computationally resource intensive. The traditional approach has been to optimise the decision making sequentially. In this approach, each market is represented by a decision stage and the stages are optimised in chronological order so that the optimal solutions from the previous stages are fixed in the following optimisations. This approach was adopted in studies such as [47], where the authors optimised decision making day-ahead, intraday and three reserve markets in Spain already in 2003. Optimising decisions in this many markets in a coordinated manner, where all the decision stages are optimised simultaneously, would not be possible due to the computational complexity of the model. Hence, the clear advantage of the sequential approach, as opposed to coordinated offering, is computational tractability.

However, with the improvements in computing power, a recent research direction has been to evaluate the benefit of coordinated offering in light of the trade-off with tractability [55, 13, 14]. In the most recent of these studies, the authors in [14] evaluated this benefit when optimising offers of a hydropower producer for the Nordic day-ahead and balancing markets. They found that the average increase in profits from coordinated bidding as opposed to sequential bidding was 1.4%. Furthermore, they noted that the value of coordinated offering increases with the uncertainty faced by the company.

However, the authors in [55] reached a very different conclusion on the benefits of coordinated bidding in Nordic day-ahead and balancing markets. They modelled the decision making as a 26-stage problem. The first stage corresponded to day-ahead bidding, stages 2-25 to the 24 balancing markets, which have unique gate closures, and the final stage to the imbalance settlement. Decisions regarding the operating schedule were optimised in stages 3-26. Due to the computational complexity of the model, instead of solving it, the authors evaluated the value of coordinated bidding by deriving lower and upper bounds for the expected gain in profit. They concluded that the expected gains are between 8% and 25%. However, this expected gain estimate may be overly optimistic because the model does not account for liquidity issues in the balancing market. The liquidity issues had been modelled in [14]. Thus, as the model in [55] illustrates, optimising coordinated bidding strategies still presents challenges with tractability because these models grow rapidly with the number of uncertainty factors. This necessitates using simplifications when modelling market structures. The next section reviews models where this multi-stage decision process has been simplified to only a few decision stages.

3.3 Multi-market price-taker models

In order to make coordinated bidding models more computationally tractable, a common approach is to use simplifications when modelling market structures. For instance, post-day-ahead markets with separate gate closures for all delivery hours, such as intraday and balancing markets, are often modelled in a single decision stage. This simplification means that market decisions pertaining to these markets are modelled as if they were made simultaneously. Apart from this, determining the appropriate number of decision stages and deciding the stages in which specific markets are modelled is inherently dependent on the problem and context. This is due to the multitude of markets and their different implementations and regulations around the world. Since common guidelines do not exist, this section reviews a selection of studies that have formulated coordinated bidding problems as multi-stage stochastic optimisation models. The studies were chosen based on them addressing research questions related to benefits of multi-market participation and coordinated bidding strategies. This section also provides context for the model developed in Chapter 4 and reference points for evaluating the results of the case study in Chapter 5.

The authors in [12] studied a closely related problem to the aim of this thesis. They assessed the value of considering intraday trading when optimising day-ahead offers for a Norwegian hydropower producer. For this purpose, they formulated a coordinated offer-strategy optimisation model for Nordic day-ahead offers and intraday trading. As briefly mentioned in the previous section, they formulated this problem as a two-stage decision making process. The first stage represented the day-ahead offer optimisation and the second stage represented all 24 intraday markets of the operating day. Similarly to [47], the authors imposed a limit on the volume of intraday trading as a percentage of generation capacity to account for low liquidity in the market. Furthermore, they constrained the expected intraday trading volume over all price scenarios to zero. This is required in a model where only dispatchable generation technologies such as hydropower are modelled because otherwise the model would merely optimise price arbitrage. The authors evaluated the value of coordinated bidding in day-ahead and intraday markets by comparing the expected profits of day-ahead offer strategies that were optimised with and without considering the intraday market. The baseline for the expected profits was found by first optimising the day-ahead offer strategy with the intraday trading volume set to zero, saving the optimal offer strategy and then re-optimising the model with the day-ahead offer strategy fixed to the optimal one but allowing recourse decisions on intraday markets. These expected profits were compared to the expected profits of the full model that coordinated bidding in both markets. Their results showed that the expected gain in profits from coordinated bidding is between 0.02 and 0.65 % depending on market price volatility and intraday market liquidity. Their results also indicated that more liquid intraday markets lead to increases in profits and in the value of coordination. However, the authors concluded that, within their specific context, coordinated bidding did not have a significant effect on profits or day-ahead offer curves. Nonetheless, they noted that the results may differ for a different type of producer. Note that compared to the context of this thesis, this study did not include reserve markets.

On the other hand, authors in [54] modelled bidding in Nordic day-ahead and balancing markets with a three-stage optimisation model with the purpose of evaluating the benefits of multi-market participation. In their model, the first-stage decisions represented day-ahead bidding and the second stage observed the day-ahead prices and commitments. In the third stage, the balancing market demand and prices were observed, and decisions were made regarding balancing market commitments, generation and imbalances. The authors found that the benefit of participating in the balancing markets is a 3.1% increase in profits. They also concluded that in the current state of balancing markets, the gain in profit from coordinated bidding, when compared to sequential bidding, is negligible. However, they found that even a moderate increase in balancing prices and/or demand would noticeably increase the benefits of coordinated bidding.

In addition to the day-ahead and balancing markets, the authors in [56] incorporated a primary reserve market in their model. This model optimised decision making of a Swedish hydropower producer in day-ahead, FCR-N primary reserve and balancing markets with the aim of assessing the benefit of coordinated bidding. They formulated the offer problem as a deterministic optimal self-scheduling problem. They evaluated the benefit of coordinated bidding in primary reserve markets in conjunction with day-ahead and balancing markets by comparing profits. They found that the revenue increase from participating in the symmetric FCR-N markets was approximately 7%. The comparison was made to the profits from only participating in day-ahead and balancing markets. Note that this profit gain might be over optimistic due to the deterministic formulation of the problem.

In contrast to the deterministic approach in [56], the authors in [13] optimised decision making of a Norwegian hydropower producer under uncertainty in the same three markets. Their purpose was to evaluate the benefits of coordinated versus sequential bidding and assess whether these benefits are dependent on portfolio size. In the problem formulation, the authors simplified the decision-making process into three stages. The first stage optimised day-ahead bidding under price uncertainty by adopting the method developed in [48]. The day-ahead and primary reserve price scenarios were bundled, so that the day-ahead market commitments were observed simultaneously with primary reserve market prices. However, the primary reserve market commitments were optimised only in the second stage. The balancing commitments were then optimised in the third stage. Note that both the second and the third stage decisions were optimised with knowledge of the respective market prices. The authors compared the profits from the coordinated strategy to a sequential approach. The profits used for the comparison were calculated using the optimal offer strategies and the realised prices. The authors concluded that, compared to sequential bidding, coordinated bidding resulted in a profit gain of approximately 1%.

Notice that all the studies reviewed above have optimised bidding strategies for dispatchable energy sources. Therefore, the models do not incorporate production uncertainty. On the contrary, the authors in [57] optimised the offer strategy of a Spanish wind producer. Their aim was to evaluate the benefits of participating in reserve markets. For this purpose, they formulated an optimal self-scheduling model which incorporated decision making in forward markets, day-ahead markets, primary reserve and balancing markets with imbalance settlement. The model was formulated as a three stage problem, where the first stage optimised forward market commitments, the second stage optimised day-ahead, primary reserve and balancing market commitments and the third stage represented imbalance settlement. They found that participating in reserve markets increased expected profits by 9.3% and participating in reserve and forward markets increased expected profits by 16.1%. They concluded that the increase in profits is partially explained by multi-market participation reducing imbalances and therefore reducing imbalance costs. They also inferred that the reduction in imbalances was partly due to multi-market participation resulting in smaller day-ahead market commitments.

Since authors in [57] modelled a wind generator but did not model recourse decisions in the intraday markets, in their model, the producer did not have the opportunity to self-balance. On the contrary, authors in [15] formulated a multi-stage stochastic optimisation model for a virtual power plant (VPP), where they modelled the Iberian day-ahead and six intraday markets with imbalance settlement. The model was an optimal self-scheduling model, which comprised eight decision stages: one for each market and imbalance settlement. The modelled VPP had wind turbines, photovoltaic (PV) units and a battery energy storage system (ESS). Thus, the VPP faced production uncertainty but were able to self-balance by trading in the intraday markets and using the ESS. The aim of the authors was to evaluate the added value of participating in both the day-ahead and intraday markets compared to only participating in the day-ahead market. Their results show that optimising trades for day-ahead and intraday markets result in a 10.1% increase in profits. They concluded that the gain was largely due to the recourse decisions in the intraday markets enabling the company to decrease their imbalances, and therefore to face lower imbalance settlement costs. Intraday trading reduced the imbalance settlement costs to nearly a third of the costs that were incurred in the situation without intraday trading.

Table 1 summarises the results from the most relevant studies outlined in this chapter. As is illustrated by the table, the results of the studies are not directly comparable with each other due to the different markets, contexts and generation technologies that were modelled. However, the table does provide an indication of the order of magnitude in which the gains from multi-market participation and coordinated bidding lie.

3.4 Research gap

As was described in the previous section, a considerable amount of research has been done in the area of offer-strategy optimisation. The contribution of this thesis is that it develops a multi-market offer-strategy optimisation model which generates

Table 1: Summary of studies evaluating benefits of multi-market participation and coordinated bidding.

Study	Markets evaluated	Context	Conclusion
[12]	Day-ahead, Intraday	Hydropower, Norway	Benefits of coordinated bidding were negligible.
[54]	Day-ahead, balancing	Hydropower, Norway	Participating in balancing markets yielded 3.1% increase in profits.
[56]	Day-ahead, FCR-N reserve, balancing	Hydropower, Sweden	Participating in the FCR-N primary reserve markets increased profits by 7%.
[13]	Day-ahead, FCR-N reserve, balancing	Hydropower, Norway	Benefit of coordinated bidding compared to the sequential approach was a 1% increase in profits.
[57]	Forward, day-ahead, primary reserve, balancing	Wind, Spain	Reserve market participation resulted in a 9.3 % increase in profits.
[15]	Day-ahead, intraday	VPP, Iberian market	Added value of participating in intraday markets was a 10.1% increase in profits.
[14]	Day-ahead, Balancing	Hydropower, Norway	Benefits of participating in the balancing market were between 1.4 % and 2.9%.
[55]	Day-ahead, Balancing	Thermal and hydro, Norway	Gains from coordinated bidding were between 8% and 25%.

offer curves for the day-ahead and primary reserve markets. The offer strategy is developed for a hybrid energy producer with dispatchable and VRE technologies under uncertainty regarding market prices, dispatch and wind availability. Despite several models such as [12], [13] and [54] having applied the method developed in [48] to generate offer curves and to account for uncertainty in dispatch, the model developed in this thesis is the first to apply the method for a producer with non-dispatchable generators. Furthermore, applying this method allows generating offer curves instead of single bids, which sets the model apart from other studies such as [57] and [15] who have developed optimal self-scheduling models for VRE producers. Furthermore, in comparison to [15], where only the day-ahead and intraday markets were modelled, the model developed in this thesis also incorporates a primary reserve market. This is noteworthy since modelling intraday trading in a coordinated manner with day-ahead and reserve markets has gained little attention in the literature [10]. Moreover, most studies in the current literature that have modelled reserve markets have mainly focused on balancing markets. Finally, even though benefits of multi-market participation and coordinated bidding have been studied in the Nordic context, as illustrated in Table 1, no study has assessed these benefits with the prices of the Finnish bidding area. Therefore, this thesis aims to evaluate these benefits in the Finnish context.

4 Model

In order to evaluate the benefits of multi-market participation for a generation company, the coordinated bidding process must be modelled. This chapter presents a two-stage multi-period stochastic optimisation model for optimising a price-taker electricity producer's offer strategy under price and production uncertainty in the Finnish context. This producer participates in the day-ahead, intraday and up-regulating FCR-D markets and faces imbalance settlements. Section 4.1 outlines the modelling assumptions and scenario structure. Section 4.2 presents the formulation of the mixed-integer linear program. Section 4.3 defines a second optimisation model which is used to find the solution with the least imbalances out of the degenerate optimal solutions to the first model.

4.1 Modelling assumptions and scenario structure

The model is formulated as a two-stage stochastic optimisation model where the first stage corresponds to day-ahead decisions and the second stage to intraday trading and production planning. In the first stage, in contrast to the model in [13], the day-ahead and up-regulating FCR-D markets are modelled as simultaneous markets since, in reality, their market closures are relatively close (5.5 hours apart). This implies that in the model, the producer does not observe the day-ahead market outcome before submitting offers to the up-regulating FCR-D market. Note that since the modelled producer is a price-taker, their offers are assumed to not affect market prices. Regarding the up-regulating FCR-D market, it is assumed that cleared reserve is never activated, and therefore the model accounts for capacity fees from reserving capacity but does not account for possible energy fees. Furthermore, it is assumed that the minimum offer size of 1 MW [34] is fulfilled organically in the model. Regarding production capabilities, the thermal and hydro units are dispatchable, but the wind power generation is dependent on wind availability, which is modelled using a wind factor. However, wind power can be curtailed. Reserve provision is only possible with the CCGT and hydro power generators, and note that these units must be running in the hours that they are providing reserve. Wind capacity cannot be used to provide reserve because wind power has yet to be qualified to provide automatically activated reserves in Finland [6].

In the second stage of the model, the producer may submit one buy or sell order to the intraday per delivery hour. The intraday markets for all delivery hours are modelled in one stage similarly to [12]. This implies that the 24 intraday markets are modelled as 24 simultaneous decisions. It is assumed that all intraday orders of the producer are matched and that trade prices are observed when trading. These assumptions are motivated by the continuous nature of the markets where participants can observe the orders of other participants. These trades are modelled simultaneously with production planning of hydropower and thermal units, and therefore it is assumed that no costs are related with rescheduling as a result of intraday trading.

Uncertainty is modelled using a scenario tree. The scenario tree structure is seen in Figure 3. Note that each node in the tree comprises values for all 24 delivery hours.

After the first-stage decisions, the day-ahead and up-regulating FCR-D market prices are observed and commitments to both markets are determined for each price scenario $s \in \mathcal{S}$. Each day-ahead and up-regulating FCR-D price scenario $s \in \mathcal{S}$ corresponds to a set of intraday price scenarios $\mathcal{E}$. Second-stage decisions, which consist of intraday trading and production planning, are modelled for each of these intraday price scenarios. The first and second-stage decisions are made under uncertainty of wind generation and imbalance prices. The leaf nodes of the scenario tree correspond to the realisations of these values. This is also the stage where the imbalances of the producer are determined for each hour in each scenario. The set of wind and imbalance price scenarios are denoted by Ω.

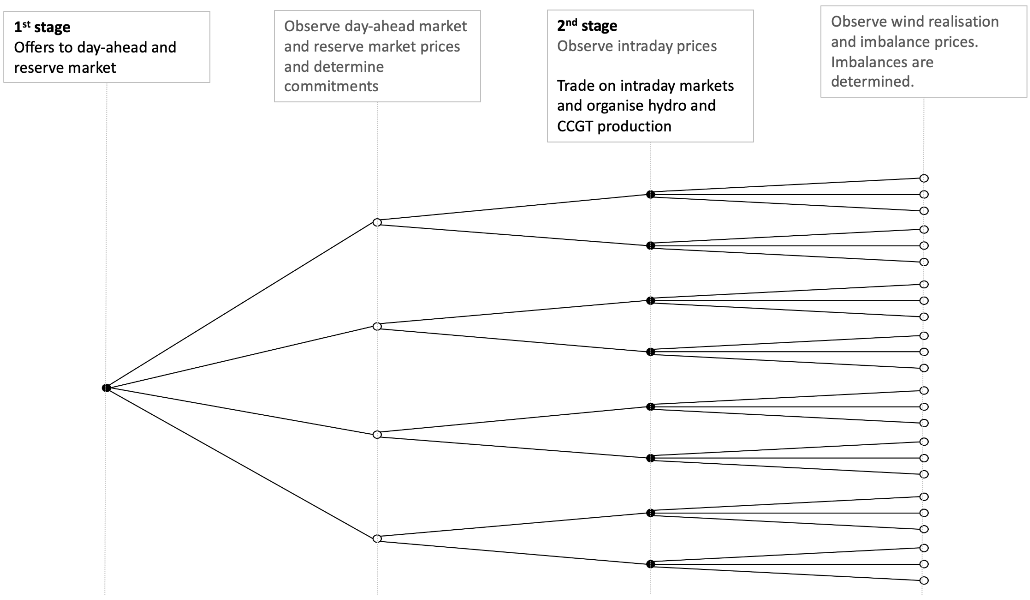


Figure 3: Scenario tree structure. In the figure $|\mathcal{S}| = 4$, $|\mathcal{E}| = 2$ and $|\Omega| = 3$. The figure is adapted from [12].

4.2 Model formulation

Objective

The objective function maximises the expected profit of the generation company. It includes revenue from day-ahead market commitments y_t sold at prices ρ_t, revenue from capacity fees ψ_t received for reserved capacity r_t and revenue or costs from trades z_t in the intraday markets at prices φ_t for each delivery hour $t \in \mathcal{T}$. The quantities traded in the day-ahead and intraday markets are in units of energy (MWh) and the reserve commitments are in units of power (MW). The total revenue for all delivery hours is given by

$$\sum_{t \in \mathcal{T}} \left(\rho_t y_t + \psi_t r_t + \varphi_t z_t \right). \tag{1}$$

Production costs are incurred from start ups of the hydropower generator and running costs, start ups and shut downs of the CCGT. The running costs of the hydropower and wind generators are considered negligible. Thus, the total costs are

$$\sum_{t\in\mathcal{T}}\Big(-S^{H,start}u_t^{H,start}-S^{C,gen}g_t^{C}-S^{C,start}u_t^{C,start}-S^{C,stop}u_t^{C,stop}\Big),\tag{2}$$

where the superscripts of the cost parameters, S, distinguish the specific cost in question. Letters H and C to denote hydropower and CCGT generators, respectively. Binary variables u_t, u_t^{start} and u_t^{stop} represent the on-off state, start up and shut down of units in delivery hours $t \in \mathcal{T}$.

An opportunity cost is associated with hydropower generation. It represents the loss of potential future profit from disposing the water now instead of storing it for later. Similarly to [48], the opportunity cost is modelled using a water value function. The value of water level l in the reservoir is given by the water value function $V(l)$. The opportunity cost incurred in the offer problem is

$$V(l_0)-V(l_{T,se}),\tag{3}$$

where l_0 the initial water level and l_T is the final water level.

The generation company receives the down-regulation price λ_t^+ for excess energy it generates and they are charged the up-regulation price λ_t^- for deficits. As suggested by [1], in the model, the scenarios for these prices internalise the uncertainty regarding the system imbalance in the grid. The positive and negative deviations of the generation company for each hour $t \in \mathcal{T}$ are denoted by variables Δ_t^+ and Δ_t^-, respectively. The revenue from the imbalance settlement is

$$\sum_{t\in\mathcal{T}}\Big(\lambda_t^+\Delta_t^+-\lambda_t^-\Delta_t^-\Big).\tag{4}$$

Water value function

The water value function is defined as a concave piecewise linear function and this section introduces its MIP formulation. The water value function is

$$V(l_t)=\min_{k\in\mathcal{K}}\{B_1^k l_t+B_2^k\},\tag{5}$$

where B_1^k and B_2^k are coefficients of the linear functions $k \in \mathcal{K}$ that constitute the piecewise linear function. Notice that the functions $k \in \mathcal{K}$ are associated with intervals for the water level l_t. We introduce binary variables b_t^k which indicate if the water level is within interval $[L^{k-1}, L^k]$ associated with the function k. The variables l_t^k

capture the exact water levels on the interval k, i.e.,

$$0 \leq l_t^1 \leq L^1 b_t^1 \qquad \forall t \in \mathcal{T} \tag{6}$$

$$L^1 b_t^2 < l_t^2 \leq L^2 b_t^2 \qquad \forall t \in \mathcal{T} \tag{7}$$

$$\vdots$$

$$L^{k-1} b_t^k < l_t^k \leq L^k b_t^k \qquad \forall t \in \mathcal{T}. \tag{8}$$

The water level must be within one of the intervals defining the piecewise water value function; Thus,

$$\sum_{k \in \mathcal{K}} b_t^k = 1 \qquad \forall t \in \mathcal{T}. \tag{9}$$

The interval specific water levels l_t^k, out of which only one is nonzero, are aggregated to define the water level l_t as

$$l_t = \sum_{k \in \mathcal{K}} l_t^k \qquad \forall t \in \mathcal{T}. \tag{10}$$

Thus, in the objective function the opportunity cost of water is formulated as

$$V(l_0) - \sum_{k \in \mathcal{K}} \left(B_1^k l_T^k + B_2^k \right). \tag{11}$$

Note that the term $V(l_0)$ is a constant and does not affect the optimisation. Therefore, in the implementation, it is excluded from the objective function.

Objective function

As explained in the previous section, uncertainty is modelled using a scenario tree. Therefore, scenario specific instances of variables are defined according to information revelation. Scenarios $s \in \mathcal{S}$ model uncertainty in day-ahead and reserve market prices ρ_{ts} and ψ_{ts}, respectively. These prices are observed simultaneously in the model. Uncertainty in intraday market prices φ_{tse} is modelled using scenarios $e \in \mathcal{E}$. Notice that intraday trading coincides with production planning and all these decisions are made after day-ahead and reserve market outcomes have been observed. Finally, during the operating hour, wind production is realised, and thus imbalances are determined. This uncertainty is modelled with scenarios $\omega \in \Omega$. Taking into account the scenario tree structure, the full expression of the objective function is

$$\max \quad \Pi(y, r, z, u^{H,start}, u^C, u^{C,start}, u^{C,stop}, l, \Delta^+, \Delta^-),$$

where the objective function, Π, is defined as

$$\begin{aligned}
&\sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}}\pi_s^S\Big(\rho_{ts}y_{ts}+\psi_{ts}r_{ts}\Big)+\sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}}\sum_{e\in\mathcal{E}}\pi_s^S\pi_e^E\Big(\varphi_{tse}z_{tse}\Big)\\
&+\sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}}\sum_{e\in\mathcal{E}}\pi_s^S\pi_e^E\Big(-S^{H,start}u_{tse}^{H,start}-S^{C,gen}g_{tse}^{C}\\
&-S^{C,start}u_{tse}^{C,start}-S^{C,stop}u_{tse}^{C,stop}\Big)+\sum_{s\in\mathcal{S}}\sum_{e\in\mathcal{E}}\sum_{k\in\mathcal{K}}\Big(B_1^k l_{Tse}^k+B_2^k\Big)\\
&+\sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}}\sum_{e\in\mathcal{E}}\sum_{\omega\in\Omega}\pi_s^S\pi_e^E\pi_\omega^\Omega\Big(\lambda_{tse\omega}^{+}\Delta_{tse\omega}^{+}-\lambda_{tse\omega}^{-}\Delta_{tse\omega}^{-}\Big).
\end{aligned}\tag{12}$$

Day-ahead market

The generation company submits an offer curve with I price steps. The day-ahead offer curve is formulated according to [48]. To avoid a non-linear formulation, the prices p_i for each offer $i\in\mathcal{I}$ are fixed. These prices are ordered such that $p_i<p_{i+1}$ for all $i\in\mathcal{I}\setminus I$. The offer quantities are optimised. They are denoted with positive continuous variables x_{it} for all $i\in\mathcal{I},t\in\mathcal{T}$, and since the day-ahead market regulations require that the offer curve is increasing, the following constraint is imposed on these variables:

$$x_{it}\le x_{i+1,t}\quad\forall i\in\mathcal{I}\setminus\{I\},t\in\mathcal{T}.\tag{13}$$

The day-ahead market commitment for each hour $t\in\mathcal{T}$ and scenario $s\in\mathcal{S}$ is derived using the day-ahead market-clearing price ρ_{ts}. The commitment is determined by the intersection of the offer curve and the market price, given as

$$y_{ts}=\begin{cases}\frac{\rho_{ts}-p_1}{p_2-p_1}x_{2t}+\frac{p_2-\rho_{ts}}{p_2-p_1}x_{1t}, & \text{if } p_1\le\rho_{ts}<p_2\\ \vdots & \\ \frac{\rho_{ts}-p_i}{p_{i+1}-p_i}x_{i+1,t}+\frac{p_{i+1}-\rho_{ts}}{p_{i+1}-p_i}x_{it}, & \text{if } p_i\le\rho_{ts}<p_{i+1}\\ \vdots & \\ \frac{\rho_{ts}-p_{I-1}}{p_I-p_{I-1}}x_{It}+\frac{p_I-\rho_{ts}}{p_I-p_{I-1}}x_{I-1,t}, & \text{if } p_{I-1}\le\rho_{ts}<p_I.\end{cases}\tag{14}$$

The authors in [12] noted that since each scenario $s\in\mathcal{S}$ includes only one market price, the piecewise function above can be written as a single function. Letting $i(t,s)=\max\{i\in\mathcal{I}:p_i\le\rho_{ts}\}$, the day-ahead price intersects the offer curve on the segment between offers $(x_{i(t,s)},p_{i(t,s)})$ and $(x_{i(t,s)+1},p_{i(t,s)+1})$. Thus, the commitment is

$$y_{ts}=\frac{\rho_{ts}-p_{i(s,t)}}{p_{i(t,s)+1}-p_{i(s,t)}}x_{i(t,s)+1}+\frac{p_{i(t,s)+1}-\rho_{ts}}{p_{i(t,s)+1}-p_{i(t,s)}}x_{i(t,s)}\quad\forall t\in\mathcal{T},s\in\mathcal{S}.\tag{15}$$

Reserve market

The generation company submits J up-regulating capacity offers to the reserve market. The offer quantities are denoted with v_j for all offers $j \in \mathcal{J}$. Similarly to the previous section, the offer prices p_j are fixed in order to linearise the problem. The prices are ordered such that $p_j < p_{j+1}$ for all $j \in \mathcal{J} \setminus J$. In contrast to the day-ahead market, the reserve offers are processed separately meaning that all offers with an offer price less than the market price will be cleared. The committed reserve capacity r_{ts} is the sum of all cleared offers for hour t in scenario s, i.e.,

$$r_{ts} = \begin{cases} 0, & \text{if } \psi_{ts} \leq p_1 \\ v_1, & \text{if } p_1 \leq \psi_{ts} \leq p_2 \\ v_1 + v_2, & \text{if } p_2 \leq \psi_{ts} \leq p_3 \\ \vdots & \\ v_1 + v_2 + \ldots + v_J, & \text{if } p_J \leq \psi_{ts}. \end{cases} \tag{16}$$

The generation company cannot bid more than its generation capacity, which is given as the sum of its CCGT, hydro and wind capacities: C^C, C^H and C^W. Therefore, constraint (17) is imposed. Note that reserve offers and capacities are in units of power and they are multiplied by the time interval of one hour dt in order to convert them to units of energy.

$$x_{It} + \sum_{j \in J} v_j dt \leq (C^C + C^H + C^W)dt \qquad \forall t \in \mathcal{T}. \tag{17}$$

Moreover, the generation company cannot generate and reserve more than its generation capacity. Therefore,

$$y_{ts} + r_{ts}dt \leq (C^C + C^H + C^W)dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{18}$$

Reserve commitments must be fulfilled by the hydropower and CCGT generators. This is ensured by the following constraint:

$$r_{ts} = r^H_{tse} + r^C_{tse} \quad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}, \tag{19}$$

where variables r^H_{tse} and r^C_{tse} denote reserve capacity provided by the hydropower and CCGT generators, respectively. Note that the allocation of reserve between the generation technologies can differ in scenarios $e \in \mathcal{E}$.

Intraday market

The generation company can buy or sell energy from the intraday market. These trades are denoted with variables $z_{tse} \in \mathbb{R}$. A positive value of this variable represents selling energy and a negative value represents buying energy. Similar to [12], a limit on intraday trading is imposed, due to the liquidity issues in these markets. The limit is specified as a percentage, α, of the total installed capacity of the generation company, and is stated as

$$| z_{tse} | \leq \alpha(C^C + C^H + C^W)dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{20}$$

Intraday trading is also limited by the generation capacity of the company. Along with day-ahead and reserve commitments, intraday trading cannot exceed the maximum generation capacity in any scenario. Therefore,

$$y_{ts} + r_{ts}dt + z_{tse} \leq (C^C + C^H + C^W)dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{21}$$

Imbalances

The generation company's imbalance is the difference between its real-time generation and its commitments. The real-time generation is captured by variables g^C_{tse}, g^H_{tse} and $g^W_{tse\omega}$, which represent CCGT, hydropower and wind generation, respectively. Note that the realised wind generation is known only in real time, and it is therefore dependent on scenarios $\omega \in \Omega$. Note that the variables denoting excess and deficit in generation both take positive values: $\Delta^+_{tse\omega}, \Delta^-_{tse\omega} \geq 0$. Thus, the overall imbalance of the company is

$$\Delta^+_{tse\omega} - \Delta^-_{tse\omega} = g^C_{tse} + g^H_{tse} + g^W_{tse\omega} - (y_{ts} + z_{tse}) \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}, \omega \in \Omega. \tag{22}$$

Upper bounds on the positive and negative imbalances are imposed according to [1]. These bounds are valid inequalities derived from the problem structure. The positive imbalance can at most be the maximum possible energy generation as expressed in constraint (23). This limit is only met if the generation company does not sell any energy into the markets but generates at maximum capacity conditional on the availability of wind.

$$\Delta^+_{tse\omega} \leq (C^C + C^H)dt + g^W_{tse\omega} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}, \omega \in \Omega. \tag{23}$$

The negative imbalance can at most be the generation capacity of the company as stated in constraint (24). This limit is only met if the generation company commits all of its capacity to the markets but does not produce anything.

$$\Delta^-_{tse\omega} \leq (C^C + C^H + C^W)dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}, \omega \in \Omega. \tag{24}$$

Short term hydropower production

The model for the hydropower generator is adapted from [48]. Constraints (25)–(27) capture the state change when the hydropower generator is turned on or off and restrict it to be either on or off at each time $t \in \mathcal{T}$ in each scenario $(s, e) \in (\mathcal{S}, \mathcal{E})$.

$$u^H_{tse} = u^H_{t-1,se} + u^{H,start}_{tse} - u^{H,stop}_{tse} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E} \tag{25}$$

$$u^H_{tse} \geq u^{H,start}_{tse} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E} \tag{26}$$

$$u^H_{tse} \leq 1 - u^{H,stop}_{tse} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{27}$$

Furthermore, the generator's initial state is

$$u_0^H = U_{init}^H, \tag{28}$$

where parameter U_{init}^H has either value zero or one.

Discharging water generates energy which is modelled using constraint (29). The water discharge from the reservoir at time t in scenario (s, e) is denoted with f_{tse}. The generation coefficient η captures the relationship between discharged water and power, and it also accounts for the efficiency of the generator.

$$g_{tse}^H = \eta f_{tse} dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{29}$$

The minimum and maximum discharge capacities are denoted by F^{min} and F^{max}, and the rate of discharge, f_{tse}, is limited such that

$$f_{tse} + r_{tse}^H/\eta \le u_{tse}^H F^{max} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}, \tag{30}$$

$$u_{tse}^H F^{min} \le f_{tse} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{31}$$

Note that the maximum discharge capacity and the hydropower generation capacity have the relationship $\eta F^{max} = C^H$. Furthermore, since it is assumed that the reserved capacity is not activated, the reserve provided by hydropower, r_{tse}^H, is only accounted for in the upper bound for rate of discharge.

The volume of water in the reservoir is measured using the water level l_{tse} for all $t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}$. The storage level has lower and upper bounds L^{min} and L^{max}, respectively. Therefore,

$$L^{min} \le l_{tse} \le L^{max} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{32}$$

In addition, the reservoir has an initial storage level of

$$l_0 = L^{init}. \tag{33}$$

There is an inter-temporal effect of discharging water on the reservoir storage level. The change in water level is the result of discharging water f_{tse}, spill from the reservoir f_{tse}^{spill} and inflow F_{tse}^{in}, which is an exogenous parameter. This inter-temporal effect is modelled as

$$l_{tse} = l_{t-1,se} - f_{tse} - f_{tse}^{spill} + F_t^{in} dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{34}$$

CCGT generation

The constraints for the thermal generator are adapted from [52]. Constraints (35)–(37) capture the state change when the CCGT is turned on or off and restrict it to be either on or off at each time $t \in \mathcal{T}$ in each scenario $(s, e) \in (\mathcal{S}, \mathcal{E})$.

$$u^C_{tse} = u^C_{t-1,se} + u^{C,start}_{tse} - u^{C,stop}_{tse} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E} \tag{35}$$
$$u^C_{tse} \geq u^{C,start}_{tse} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E} \tag{36}$$
$$u^C_{tse} \leq 1 - u^{C,stop}_{tse} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{37}$$

In addition, the CCGT generator's initial state is restricted by the following constraint:

$$u^C_0 = U^C_{init}, \tag{38}$$

where parameter U^C_{init} has either value zero or one.

Constraints (39) and (40) ensure that the CCGT generator's operation schedule abides its minimum up and down times. The minimum times on and off are U^C_{on} and U^C_{off} time periods, respectively.

$$u^{C,start}_{tse} \leq u^C_{t'se} \qquad \forall t \in \mathcal{T}, t \leq t' \leq \min\{t + U^C_{on}, T\}, s \in \mathcal{S}, e \in \mathcal{E} \tag{39}$$
$$(1 - u^{C,stop}_{tse}) \geq u^C_{t'se} \qquad \forall t \in \mathcal{T}, t \leq t' \leq \min\{t + U^C_{off}, T\}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{40}$$

Furthermore, the CCGT generation and reserve commitments cannot exceed its installed capacity, C^C. Thus,

$$g^C_{tse} + r^C_{tse} dt \leq u^C_{tse} C^c dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{41}$$

The generator also has a minimum stable load. This is the minimum power at which the generator can be operated when it is running. The minimum load is stated as a fraction of installed capacity, and the fraction is denoted by G^{min}. The minimum stable level is imposed using constraint (42). Note that the reserve commitment is not accounted for in this constraint due to the assumption that the need for reserve will not realise.

$$u^C_{tse} C^C G^{min} dt \leq g^C_{tse} \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{42}$$

The generator's ramping capability is limited by ramping factor A, which is stated as a fraction of the generator's capacity. The restrictions on ramping are stated as

$$g^C_{tse} - g^C_{t-1,se} \geq -AC^C dt - u^{C,stop}_{tse}(G^{min} - A)C^C dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E} \tag{43}$$
$$g^C_{tse} - g^C_{t-1,se} \leq AC^C dt + u^{C,start}_{tse}(G^{min} - A)C^C dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{44}$$

Note that the constraints allow the generator to exceed its ramping factor up to minimum load when it is turned on or off.

The final constraint regarding the CCGT relates to its initial level of generation. The generator has an initial generation level of

$$g^C_0 = G^{init}. \tag{45}$$

Wind power

Wind generation is modelled according to [1]. In the model, wind generation is

$$g^{w}_{tse\omega} = W_{tse\omega} C^{W} dt \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}, \omega \in \Omega, \tag{46}$$

where parameter $W_{tse\omega}$ denotes the wind factor that captures the exogenous uncertainty related to wind availability. The wind factor is expressed as fraction of the installed capacity.

4.3 Degenerate solutions

The formulation in the previous section yields optimal solutions with possibly many degenerate solutions. This degeneracy is partly due to at least one of the up or down-regulation prices, λ^- or λ^+, being equal to the day-ahead price. Thus, in some scenarios the model is indifferent between allocating energy to the day-ahead market or generating an imbalance. In these cases, the optimal solution may have non-zero excess and deficit generation such that $\Delta^+, \Delta^- > 0$. This is undesirable because if this happens, the model is exploiting the scenario structure in an unrealistic way. Essentially, it is acting as though it could foresee the system imbalance. For these degenerate solutions there always exists an alternative optimal solution where the difference between Δ^+ and Δ^- is the same but only one of the imbalances is non-zero. In the alternative optimal solution, the quantity of energy that is reduced from both imbalances to make one of them zero, is allocated to day-ahead market.

Since the interest in offer strategy optimisation is primarily on first-stage decisions, an optimal solution where the first stage decision represent the most accurate offers are most interesting for analysis. The first-stage offers which are expected to generate the least imbalances are considered to be the most accurate. A second optimisation model is defined to find the most accurate offer strategy among the degenerate solutions. Thus, once the first optimisation model is solved and the objective value is found, a constraint enforcing that the objective function, seen in Equation (12), is equal to this objective value is added to the model. For solver-friendly formulation, the constraint is added as

$$\Pi(y, r, z, u^{H,start}, u^{C}, u^{C,start}, u^{C,stop}, l, \Delta^+, \Delta^-) \geq \text{objective value} - \epsilon, \tag{47}$$

where ϵ is a small positive value. The aim of the second optimisation is to find an offer strategy that minimises imbalances but achieves the profit found in the first optimisation. Therefore, the formulation of optimisation problem is

$$\begin{aligned} \min \quad & \sum_{t\in\mathcal{T}} \sum_{s\in\mathcal{S}} \sum_{e\in\mathcal{E}} \sum_{\omega\in\Omega} \left(\Delta^+_{tse\omega} + \Delta^-_{tse\omega} \right) \\ \text{s.t.} \quad & (13), (15)\text{–}(46) \text{ and } (47). \end{aligned}$$

5 Case study

This chapter evaluates the benefits of multi-market participation in the Finnish context through a case study using the model developed in Chapter 4. The implementation of the model can be found in [58]. In the case study, a price-taker generation company possesses a hybrid portfolio comprising a combined-cycle gas turbine (CCGT), a hydropower unit and a wind power unit. The benefits of coordinated bidding in day-ahead, intraday and up-regulating FCR-D markets are evaluated based on expected profits. Furthermore, the chapter assesses the sensitivity of the results to intraday market liquidity and factors restricting the provision of reserves.

5.1 Inputs

The day-ahead market offer curve is optimised with 34 price steps, and 17 offers are optimised for the up-regulating FCR-D market. The day-ahead offer curve constitutes prices spanning in increments of 10 from 0 to 300 €/MWh, price 400 €/MWh, and the obligatory minimum and maximum price steps at -500 €/MWh and 4000 €/MWh. The reserve offers are optimised for prices ranging from 0 to 10€/MW in intervals of 1 €/MW, prices ranging from 10 to 20€/MW in intervals of 2 €/MW, price 100 €/MW and price 300 €/MW. The model allows the producer to make one trade per delivery hour in the intraday markets.

The offer strategy is optimised using a scenario tree consisting of 10 scenarios for first-stage decisions, 6 scenarios for second-stage decisions and 3 scenarios for wind and imbalance settlement. Inspired by the methodology introduced in [59], a pure data-driven, non-parametric scenario generation method was utilised. The scenarios for the day-ahead and up-regulating FCR-D prices were chosen from historical data using covariate information. Since implementing a sophisticated scenario generation methodology is beyond the scope of this thesis, merely temporal and market setting information were used as the covariates. The data points were chosen based on year, month and weekday under the assumption that load patterns tend to be similar on Tuesdays and Wednesdays. Furthermore, for all the days chosen, the same market regulations were in effect, and the new Olkiluoto 3 nuclear power plant was not in operation. Using this covariate information, the data set consisted of price and wind generation data from 10 Tuesdays and Wednesdays in mid spring during years 2022 and 2023. The day-ahead market prices were retrieved from the ENTSO-E Transparency Platform [60], the up-regulating FCR-D market price data and wind factors were found in Fingrid's open data sets [61] and intraday trading data was received from Nord Pool.

In the scenario tree, each day-ahead and reserve price scenario $s \in \mathcal{S}$ corresponds to one day in this data set. These scenarios were considered equiprobable. Intraday price scenarios $e \in \mathcal{E}$ were sampled from realised trades in each day $s \in \mathcal{S}$. Three scenarios $\omega \in \Omega$ for wind factors and imbalance settlement prices were generated from data for each day $s \in S$. Wind factors for each hour $t \in \mathcal{T}$ in all scenarios $(s, e) \in (\mathcal{S}, \mathcal{E})$ were sampled from a normal distribution centred at the value of the wind forecast in the data. The standard deviation of the forecast errors in the data set was used as the standard deviation in the sampling. Imbalance settlement scenarios were generated such that the imbalance price λ was varied below, equal to and above its realised value for each hour $t \in T$ on a given day $s \in \mathcal{S}$. The size of the deviation was half of the imbalance price premium in the hour in question. Notice that this scenario generation method results in a scenario tree where the imbalance prices in scenarios $\omega \in \Omega$ are the equal for all intraday price scenarios $e \in \mathcal{E}$ deriving from a single day-ahead price scenario $s \in \mathcal{S}$.

The modelled generation company is not a particular Finnish producer. However, realistic production parameters were estimated considering the Finnish power generation mix. Thus, it was chosen that the modelled producer possesses a total generation capacity of 300.8 MW, consisting of a 170 MW CCGT unit, a 100.8 MW hydropower unit and 40 MW of wind power. The start-up and shut-down costs of the technologies are assumed to be zero, and the water value function is modelled as a single linear function. The parameter values related to production are displayed in Table 2 and the costs are displayed in Table 3.

Table 2: Production parameters used in the case study.

Parameter	Value		
C^H	100.8	[MW]	Hydropower
U^H_{init}	1		
F^{min}	200	[m^3/s]	
F^{max}	1050	[m^3/s]	
F^{in}	400	[m^3/s]	
L^{min}	120	[Mm^3]	
L^{max}	136	[Mm^3]	
L^{init}	128	[Mm^3]	
L^1	136	[Mm^3]	
η	0.096	[MWh/m^3]	
C^C	170	[MW]	CCGT
U^C_{init}	0		
U^C_{on}	7	[h]	
U^C_{off}	2	[h]	
G^{min}	40	[%]	
G^{init}	0	[MW]	
A	100	[%]	
C^W	40	[MW]	Wind

Table 3: Costs of production in the case study.

Parameter	Value	
$S^{H,start}$	0	[€]
$S^{C,gen}$	243.7	[€/MWh]
$S^{C,start}$	0	[€]
$S^{C,stop}$	0	[€]
B_1^1	0.0015	[€/m^3]
B_2^1	0	[€/m^3]

5.2 Results

This section assesses the research question regarding the benefits of multi-market participation for a hybrid generation company. First, the value of sequential versus coordinated bidding is assessed. Then, the effect of intraday market liquidity and additional constraints on reserve provision are evaluated.

5.2.1 Value of multi-market participation and coordinated bidding

The value of considering up-regulating FCR-D and intraday markets is evaluated by examining the percentage differences in profits between four experimental set-ups:

1. **Day-ahead only** Optimising the model with only the day-ahead market and imbalance settlement. In order to do this, variables representing offers and trades in reserve and intraday markets (v, r, z) are set to zero.

2. **3-stage sequential bidding** Optimising the day-ahead, reserve and intraday trading sequentially. This is done by fixing the day-ahead bidding strategy to the optimal strategy found in the day-ahead only set-up and then optimising reserve offers and intraday trading. Note that since the day-ahead offers are optimised separately from the reserve offers, this model has three decision stages.

3. **2-stage sequential bidding** Optimising the first-stage decisions and intraday trading sequentially. This is done by optimising an offer strategy for the day-ahead and reserve markets without considering the intraday markets ($z = 0$). Then, the optimal strategy for the first-stage decisions is fixed and intraday trading is optimised.

4. **Coordinated bidding** Optimising decision making in all three markets in a coordinated manner.

All optimisation models were run on a 1,4 GHz Quad-Core Intel Core i5 with 16 GB of RAM. The solving the offer-strategy optimisation model took between 2 and 73 seconds. Optimising over the degenerate solutions was more computationally demanding, and these models had solution times between 30 and 800 seconds.

Table 4: Breakdown of expected profit in models from different experimental set-ups. The models optimised with $\alpha = 0.05$. The values are in euros.

Revenue term	DA market	3-stage sequential	2-stage sequential	Coordinated
Profit	374 614	380 880	389 889	393 665
Multi-market gain (%)	0	1.7	4.1	5.1
Coordination gain (%)	-	0	2.4	3.4
DA revenue	253 593	253 593	242 946	262 720
DA revenue share (%)	68	67	62	67
Reserve revenue	0	38	19 030	19 836
ID balance	0	-4 876	-9 050	-6 281
Imbalance settlement	-41 313	-24 540	-7 081	-31 205
Final water value	185 534	185 824	185 270	185 048
Operating costs	-23 200	-29 158	-41 226	-36 453

Table 4 displays a breakdown of the expected profits, revenues and costs of the optimal bidding strategies in the different experimental set-ups. The expected outcomes are calculated over the scenarios described in the previous section. These results were generated using an intraday market liquidity parameter of $\alpha = 0.05$, which corresponds to a volume of 15.54 MW. In the table, abbreviations DA and ID are used for day-ahead and intraday markets. The columns correspond to the different experimental set-ups and the rows correspond to different terms in the objective function seen in Equations (1)–(4). In addition, rows have been added which describe the percentage differences in expected profits between the experimental set-ups and the percentage of the profit that comes from the day-ahead market.

Table 4 shows that participation in only the day-ahead market, which serves as the base case in this study, yields the lowest expected profit: 374 614 €. This is expected since only observing the day-ahead market provides a natural lower bound for the multi-market case. In turn, optimising the trading sequentially in 3 stages increases profits by 6 266 €, which corresponds to a 1.7% profit increase. Table 4 indicates that this gain is largely due to decreased imbalance settlement costs. The reduction in imbalances due to recourse decisions in the intraday markets is illustrated in Figure 4, which shows the absolute values of the expected imbalances in each operating hour. Thus, even though intraday trading itself generates more costs than revenue (ID balance -4 876 €), participating in these markets yields gains in profit through a reduction of imbalances. This implies that the benefit of intraday trading is that these recourse decisions permit the company to self-balance. This is an expected result for a wind producer because it is in line with the results found in [57] and [15]. Furthermore, intraday trading has been observed to reduce imbalances of VRE producers in Denmark [4].

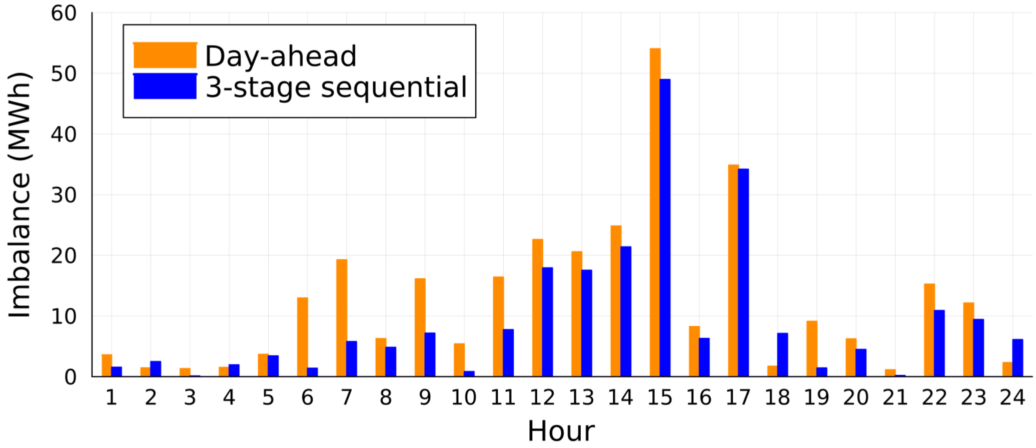


Figure 4: Absolute values of expected hourly imbalances in the day-ahead only and 3-stage sequential bidding experimental set-ups.

Table 5: Expected total market commitments and generation and average hourly imbalances (as absolute values). The models were optimised with $\alpha = 0.05$.

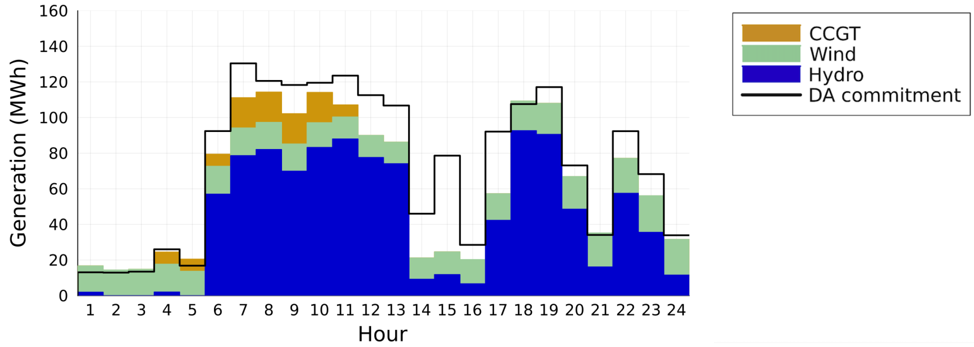
	DA market	3-stage sequential	2-stage sequential	Coordinated
DA commitment (MWh)	1 778	1 778	1 722	1 911
Up-regulating FCR-D commitment (MW)	0	7	409	429
ID sales (MWh)	0	121	92	119
ID purchases (MWh)	0	-180	-169	-221
Total generation (MWh)	1 502	1 529	1 571	1 573
CCGT generation (MWh)	95	120	169	150
Average hourly imbalance	-11	-8	-3	-10

Still comparing the results of the day-ahead only and 3-stage sequential bidding set-ups, it is notable that when the day-ahead offers are optimised independently of the up-regulating FCR-D offers, the optimal reserve offers are small. Table 5 shows that the total expected commitments of up-regulating FCR-D over all hours is only 7 MW. Furthermore, reserve is offered in only two operating hours. It is also noteworthy that operating costs differ by 5 958 € in these set-ups which approximately corresponds to a 25% increase. This is merely due an additional 25 MWh being generated using the CCGT in the optimal operating schedule from the 3-stage sequential bidding strategy.

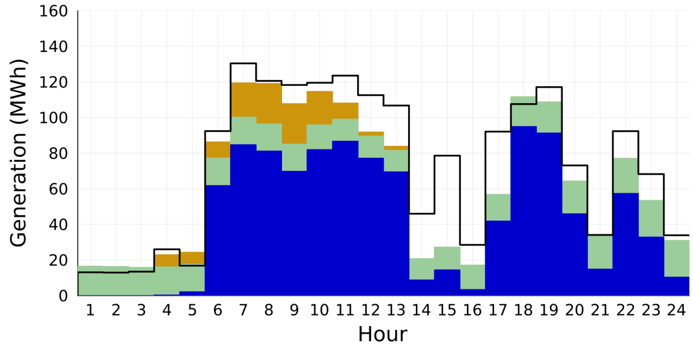
A summary of the optimal generation quantities is seen in Table 5. In turn, Figures 5a and 5b illustrate the optimal operating schedules. These figures show the increased operation of the CCGT does not alter the optimal operating schedule significantly, even though it results in a significant increase in costs. The only noticeable difference in the operating schedules is the fact that in Figure 5b, the CCGT is operated during hours 12 and 13 while in Figure 5a it is off in these hours.

The 2-stage sequential bidding strategy generates greater expected profits than the base case and the 3-stage sequential bidding strategy. This is seen from Table 4. The 2-stage sequential bidding strategy is expected to yield a profit of 389 889 euros, which is a 4.1% and 2.4% improvement compared to the base case and the 3-stage sequential bidding strategy, respectively. Table 4 indicates that this gain stems primarily from higher revenue in the reserve market and reduced costs in imbalance settlement. Note that the increase in reserve market revenue coincides with a decrease in day-ahead market revenue. Table 5 shows that the expected reserve commitment is 409 MW using the 2-stage sequential bidding strategy and only 7 MW using the 3-stage sequential bidding strategy. This is unsurprising since in the 2-stage sequential set-up, the day-ahead and up-regulating FCR-D offers are optimised simultaneously resulting in the model allocating the generation capacity between these markets according to the trade off in expected profits. Figure 6a illustrates the optimal reserve commitment for each hour. It shows that in the majority of hours, the reserve capacity is allocated from the hydropower unit. However, during hours 18 to 22, the CCGT unit also contributes to the reserve supply, indicating a shift in the allocation strategy. In addition, notice from Figure 5 the differences in optimal generation schedules resulting from these bidding strategies. A notable distinction is the utilisation of the CCGT during the evening hours. Furthermore, Tables 5 and 4 show that the increase in CCGT generation is approximately 40% and that this leads to significant operational costs. These observations imply that the opportunities in the up-regulating FCR-D market may motivate significant changes in operating schedules and lead to notable gains in profit if the day-ahead and reserve offers are co-optimised. This is especially notable because the results suggest that the opportunity to provide reserve may even incentivise running a unit with substantial operational expenses, like a CCGT. Additionally, these observations underline the importance of modelling choices regarding how the multi-stage decision-making process in power markets is simplified into fewer stages.

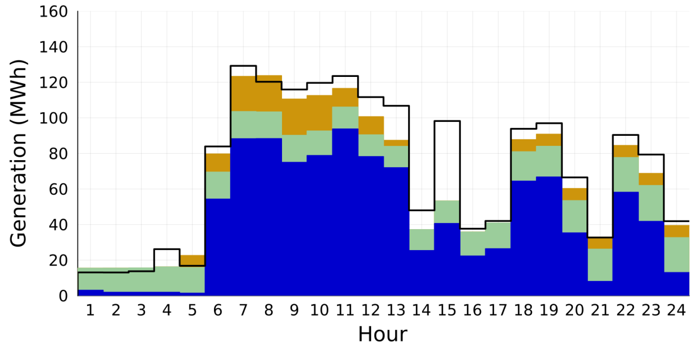
Another contributing factor to the profit increase resulting from the 2-stage bidding strategy is the reduction in costs associated with imbalance settlement. The expected imbalances from this strategy are compared to the expected imbalances from the day-ahead and 3-stage sequential set-ups in Figure 7. The figure confirms that the expected imbalances from the 2-stage sequential set-up are smallest in nearly all of the operating hours. There are a few possible reasons for this. The first is that when generation capacity is allocated between generation and reserve, the portion allocated to reserve cannot contribute to imbalances. In turn, the co-optimised allocation results in smaller day-ahead market commitments, and decreased day-ahead market commitments have been found to be associated with decreases in imbalance costs [57]. It may also be possible that the committed reserve capacity restricts the model's ability to optimise price arbitrage and this influences the imbalances.



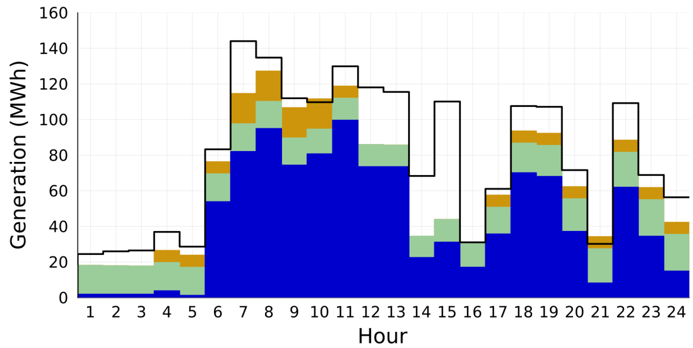
(a) Single market.



(b) 3-stage sequential bidding.

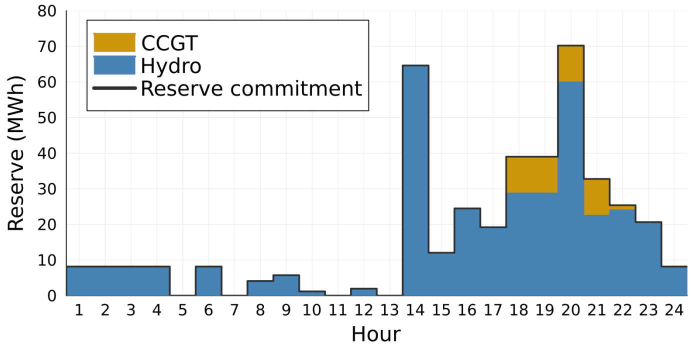


(c) 2-stage sequential bidding.

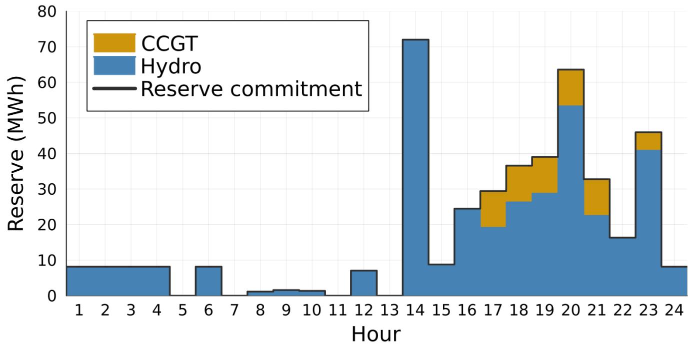


(d) Coordinated bidding.

Figure 5: Optimal generation schedules in different market set-ups.



(a) 2-stage sequential bidding.



(b) Coordinated bidding.

Figure 6: Expected reserve commitments from optimal reserve offer strategies.

While discussing possible reasons for imbalances, it is noteworthy that in Figure 5 all set-ups produce optimal strategies and operating schedules in which the expected energy deficit in hour 15 is very large. The disproportionate imbalance is confirmed in Figure 7. This imbalance is due to the data-driven scenario generation methodology. In all of the data points which were used in the scenario generation, hour 15 was either a no-regulation or a down-regulation hour. Thus, with this data as input, in the model, the generation company is not penalised for energy deficits in hour 15. Similarly, the scenarios for hours 12, 13, 14, 16, and 17 are skewed towards the system imbalance being positive meaning that generating a deficit is profitable. Also the positive imbalances seen in Figure 5 are a result price signals. For example in hour 5, the intraday prices are such that the 3-stage and 2-stage sequential bidding strategies sell to the intraday markets. This is the reason for the expected production in this hour exceeding the day-ahead market commitment.

Table 4 indicates that the coordinated bidding strategy yields the highest expected profit. The gain is 5.1% compared to the base case and 1.0% compared to the 2-stage sequential offer strategy. The coordinated bidding strategy is compared to the 2-stage sequential bidding strategy due to their similar profit levels, and due to only distinction between these set-ups being whether the intraday markets are observed while optimising the first-stage decisions. Table 4 demonstrates that, compared to the 2-stage sequential offer strategy, the coordinated offer strategy gains are due to lower operating costs and increased day-ahead market revenue. Table 5 even exposes

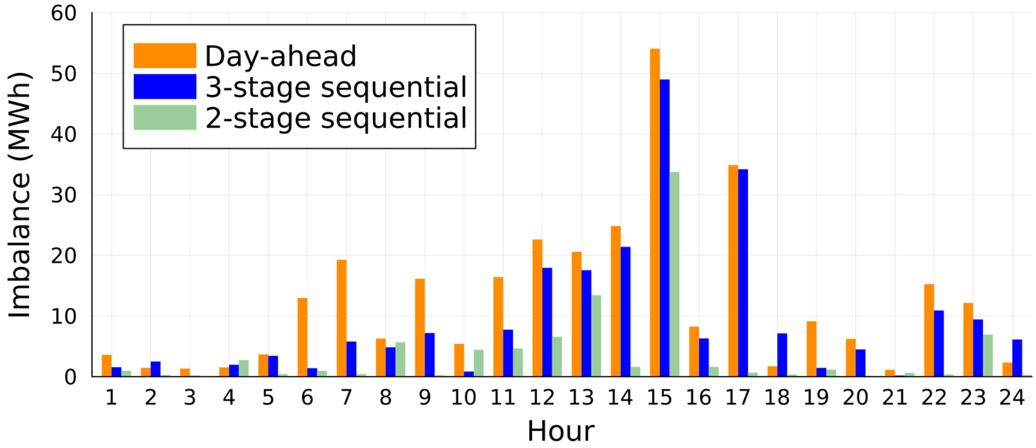


Figure 7: Absolute values of expected hourly imbalances in the day-ahead only, 3-stage sequential and 2-stage sequential bidding set-ups.

that the coordinated strategy achieves the higher expected profits with less generation. Thus, it is clear that the savings in operating costs are achieved by more cost-effective scheduling, in which less energy is generated using the CCGT and more with the wind turbines. Since the wind availability between the models is equal, this implies that the level of wind curtailment is lower in the operating schedule of the coordinated strategy.

Compared to the 2-stage sequential bidding set-up, the optimal coordinated strategy offers more into the day-ahead market and then it relies more on recourse decisions in the intraday markets. The difference in expected intraday trading volumes is seen in Table 5. However, despite the more active intraday trading, the coordinated strategy leads to larger expected imbalances. The expected imbalances are depicted in Figure 8. These observations suggest that the gains from the coordinated strategy are due to strategic bidding that the model naturally pursues when expected intraday and imbalance price premiums are favourable. Thus, this strategy includes intentionally withholding or oversupplying generation to create an imbalance during hours of high imbalance premiums. This kind of strategy is however problematic because purposefully generating imbalances is against the agreements that producers must make with the TSO. Thus, such behaviour will result in the producer loosing their license. The fact that coordinated bidding curves have inherent qualitative properties that seem to violate these contracts was discussed in [54]. Therefore, observing these issues in the offer strategy from the coordinated bidding model is unsurprising.

It is noteworthy that the reserve market bidding strategy does not change considerably between the 2-stage sequential offer strategy and the coordinated offer strategy. Tables 4 and 5 show that the expected revenues and commitments are comparable amongst the strategies. Furthermore, Figure 6 illustrates that the schedules and allocation of the expected reserve commitments over the operating day are quite similar. These observations imply that observing the intraday markets when making first-stage decisions does not largely influence the decisions regarding the reserve market, only the day-ahead offer strategy is noticeably affected.

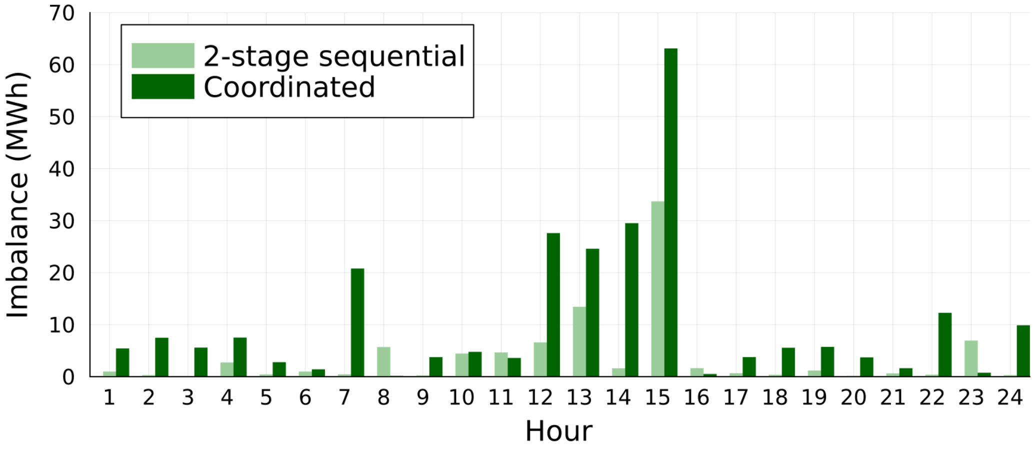


Figure 8: Absolute values of expected hourly imbalances in the different experimental.

5.2.2 Effect of intraday market liquidity

Since uncertainty regarding the liquidity of intraday markets is not incorporated in the model, it is important to assess the sensitivity of the results to the intraday market liquidity parameter α used in constraint (20). The sensitivity will be assessed for the 2-stage sequential and the coordinated bidding strategies. Both of these set-ups incorporate all three markets, and their only difference is whether intraday markets are considered when making first-stage decisions. Table 6 shows breakdowns of profits from models with different intraday market liquidity parameters. In the table, the intraday market liquidity parameter takes values $\alpha = \{0.01, 0.05, 0.1, 0.2\}$. Note that in the table, day-ahead and reserve market revenues from the 2-stage sequential bidding strategies are equal for all values of α. This is because in the 2-stage sequential bidding set-up, intraday markets are not observed when first-stage decisions are made, and therefore intraday market liquidity does not affect the day-ahead and reserve market commitments.

Table 6 shows that the expected profits from multi-market trading are sensitive to the liquidity of intraday markets. The expected profits increase with intraday market liquidity. When the intraday market liquidity parameter is increased from 1% to 20%, the expected profits of the coordinated and 2-stage sequential bidding strategies increase by 6.2% and 4.6%, respectively. These results are in line with the findings of authors in [12], who also concluded that expected profits increase with intraday market liquidity. Notice from the table, that with the coordinated bidding strategy, the day-ahead market revenue and intraday trading costs both increase with intraday market liquidity. Through experiments, it was found that this trend continues when the intraday market liquidity is increased even further than what is shown in the table. However, it was found that the reserve market revenue remains approximately constant when the intraday liquidity parameter is varied.

The last row in Table 6 indicates that the benefit of coordinated bidding increases with intraday market liquidity. The values in the last row show the percentage difference

Table 6: Breakdown of profit in models with different ID market liquidity.

Revenue term		$\alpha = 0.01$	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.2$
Coordinated	Profit	388 003	393 665	400 064	412 148
	DA revenue	246 158	262 720	295 480	347 761
	Reserve revenue	19027	19 836	19 826	19 845
	ID balance	-1127	-6 281	-15 853	-37 654
	Imbalance settlement	26 420	-31 205	-30 145	-47 549
2-Stage Sequential	Profit	386 730	389 889	396 556	404 492
	DA revenue	242 946	242 946	242 946	242 946
	Reserve revenue	19 030	19 030	19 030	19 030
	ID balance	-2 846	-9 050	-9 501	-8 245
	Imbalance settlement	-22 467	-7 081	7 660	16 418
	Profit difference (%)	0.3	1.0	0.9	1.9

in profits between the coordinated and 2-stage sequential strategies. The general trend is that the percentage difference increases with the intraday market liquidity. The values in the table show that the increase is not monotone as the gain from coordinated bidding is lower when $\alpha = 0.1$ than it is when $\alpha = 0.05$. However, this inconsistency can be attributed to numerical inaccuracies. Therefore, the results suggest that the benefit of coordinated bidding increases with intraday market liquidity. However, the increase is moderate; When the intraday market liquidity parameter is increased 20-fold, the benefit of coordinated bidding increases from 0.3% to 1.9%. This result is also consistent with the results in [12], where it was concluded the benefits of coordination increase with intraday market liquidity but that the benefit is very small, even negligible.

5.2.3 Effect of restricting ability to provide reserve

Results in Section 5.2.1, specifically in Table 4, indicate that optimising day-ahead and up-regulating FCR-D offers co-jointly increased expected profits by over 19 000 €, which accounts for approximately 5% of the profits. It also resulted in significantly larger expected reserve market commitments compared to when the day-ahead offers were optimised before observing the reserve market. Table 5 shows that the increase was nearly 60-fold: from 7 MW to over 400 MW. This implies that the reserve market could be a significant source of income for the producer if they withhold generation capacity in their day-ahead offers. However, the question arises if this large reserve commitments are realistic since the demand for up-regulating FCR-D and the ability of the generators to provide it were not explicitly considered in the model in Chapter 4.

Table 7: Breakdown of profit in models with added restrictions on reserve commitments.

Revenue term		Base line	Restricted reserve
Coordinated	Profit	393 665	386 608
	DA revenue	262 720	257 657
	Reserve revenue	19 836	6 713
	ID balance	-6 281	-6 971
	Imbalance settlement	-31 205	-33 167
2-Stage Sequential	Profit	389 889	384 533
	DA revenue	242 946	244 318
	Reserve revenue	19 030	6 749
	ID balance	-9 050	-11 173
	Imbalance settlement	-7 081	-15 078

A simple statistical analysis showed that the hourly average procured volume of up-regulating FCR-D was approximately 53 MW in Finland. This average was calculated over the dates that corresponded to the data points used in the scenario generation, and the data was retrieved from Fingrid's open data sets [62]. In turn, according to [63] the ramp rate of a CCGT is 10% of its capacity per minute. Since the requirement for up-regulating FCR-D is to activate 50% of the committed capacity in 5 seconds, reserve commitments of a CCGT should not exceed 2% of its capacity. This is an approximation under the assumption that the ramp rate is constant within one minute of ramping. Thus, for a 170 MW CCGT generator, its maximum reserve capacity is approximately 3.5 MW. However, Figure 6 illustrates that the expected hourly reserve commitments range from 0 MW to 70 MW, with the CCGT typically accounting for approximately 10 MW of the reserve. Hence, in light of this discussion, it is questionable whether these operating schedules are realistic. Thus, the 2-stage sequential and coordinated bidding models were run with additional constraints which enforced upper bounds on the total hourly reserve commitments and the reserve allocated to the CCGT. The upper bounds were stated as

$$r_{tse} \leq 50 \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E} \tag{48}$$

$$r^C_{tse} \leq 3.5 \qquad \forall t \in \mathcal{T}, s \in \mathcal{S}, e \in \mathcal{E}. \tag{49}$$

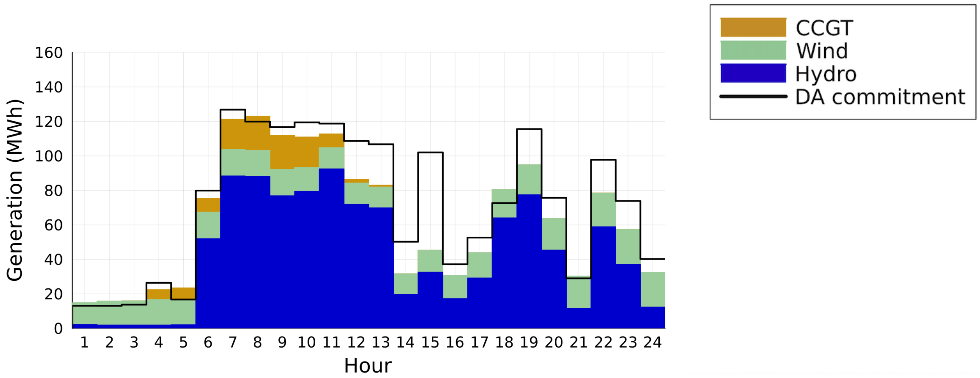
Table 7 shows the results of enforcing these upper bounds. The models were run using intraday market liquidity parameter $\alpha = 0.05$ and the baseline column corresponds to the results analysed in Section 5.2.1. The values indicate that restricting the generators' ability to provide reserve reduces the up-regulating FCR-D market participation. This results in lower expected profits compared to the base line. Figure 9 shows the optimal generation schedule and reserve commitments with the restrictions on providing reserve. Compared to optimal reserve commitments depicted in Figure 6, it is notable that with the additional constraints, no reserve commitments are allocated to the CCGT. Instead, all of the committed reserve is allocated to the hydropower unit. Furthermore, since the CCGT is not providing reserve, it is also not operated in the evening hours. This is a difference compared to the optimal generation schedules depicted in Figure 5. These observations demonstrate that the opportunities in the reserve market can have significant influence on producers' decisions regarding their operating schedules. Furthermore, they underline that modelling the operating limitations of the generation units with specific and accurate constraints is important when optimising offer strategies.

5.3 Discussion

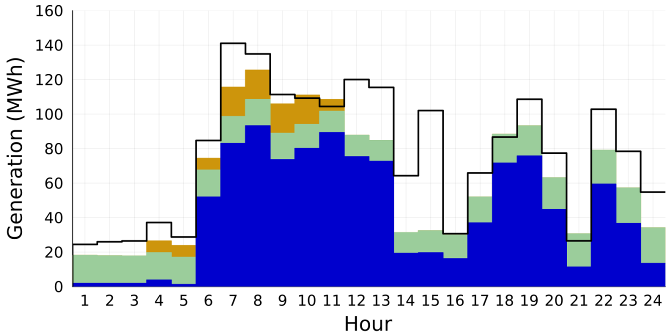
To summarise, multi-market participation in day-ahead, up-regulating FCR-D and intraday markets was observed to increase expected profits of a producer. These gains were between 1.7% and 5.1% compared to the single market case. The exact gain in profit depended on the approach taken to optimise the decision-making process. A coordinated bidding strategy in all three markets yielded the highest profits. A large contributing factor to the increases in profits was intraday trading enabling self-balancing, which was indicated by the lower imbalance settlement costs. Another contributing factor was that when the reserve market offers were optimised co-jointly with day-ahead market offers, more generation capacity was allocated to providing reserves which contributed to significant profit increases. On the contrary, when the day-ahead market offers were optimised separately from the up-regulating FCR-D reserve offers, nearly no reserve capacity was offered. This observation highlights the importance of modelling choices regarding simplifications of the multi-stage decision process. It especially exposes the significance of the decision to model day-ahead and up-regulating FCR-D offers as simultaneous decisions. Further investigation is warranted as to whether this was a faithful choice.

Coordinated bidding resulted in a 1% increase in expected profit over the 2-stage sequential strategy in which first-stage decisions were optimised without considering the intraday markets. This benefit was the result of larger day-ahead market commitments and more active intraday trading. Therefore, the reliance of this strategy on intraday trading exposes the producer to risks resulting from uncertainty in intraday market liquidity. This is a significant concern because Section 5.2.2 demonstrated that the gains from coordinated bidding are sensitive to the liquidity of intraday markets. Furthermore, the coordinated offer strategy resulted in larger expected imbalances than the 2-stage sequential approach; Thus, this strategy also has a higher risk exposure to imbalance prices.

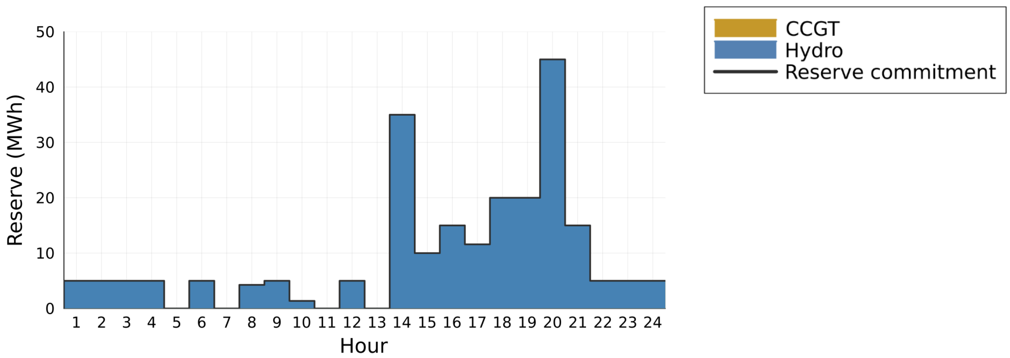
Another noteworthy fact is that all of the experimental set-ups produced offer strategies that anticipated significant negative imbalances in hour 15. This was due to the set of scenarios for hour 15 only including no-regulation and down-regulation system imbalance situations. This kind of day-ahead bidding, which anticipates imbalances is against market agreements set out by the TSO. This finding exposes a



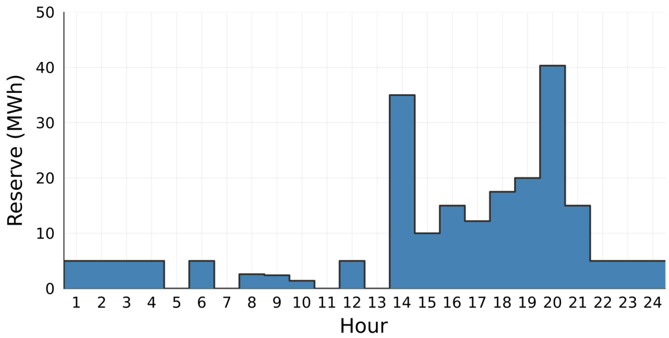
(a) 2-stage sequential bidding generation schedule.



(b) Coordinated bidding generation schedule.



(c) 2-stage sequential bidding reserve commitments.



(d) Coordinated bidding reserve commitments.

Figure 9: Optimal operating schedules and reserve commitments when constrains (49) and (48) are included in the model.

notable challenge in utilising this type of model in practical applications. A remedy for this issue could be employing more sophisticated scenario generation methods. However, it is still imperative to contemplate the appropriateness of attempting to forecast system imbalances. This is because offer strategies optimised in the light of system imbalance predictions will naturally exploit this information. Hence, it should be investigated what would be the effect of using system imbalance scenarios which are by design centered around the no-regulation situation.

The effect of modelling the generator's restricted ability to provide reserve was also evaluated. It was noticed that these constraints reduce expected profits and significantly influence reserve commitments and optimal operating schedules. Therefore, the importance of modelling generation limitations accurately was highlighted. In addition, it was noted that reserve market opportunities are also restricted by the relatively small demand for up-regulating FCR-D. Therefore, it would also be important to consider the uncertainty in demand for up-regulating FCR-D and the proportion of the demand that can be assumed to be fulfilled by a single company.

6 Conclusions

In conclusion, this thesis developed a model for optimising a multi-market offer strategy for day-ahead, up-regulating FCR-D and intraday trading. The model was developed for the Nordic markets and optimised using scenarios generated from Finnish data. In order to develop this model a thorough description of the Nordic day-ahead, intraday, up-regulating FCR-D and balancing markets was provided, and the imbalance settlement scheme was explained. Furthermore, the literature regarding offer-strategy optimisation was reviewed.

The model was utilised to evaluate the benefits of multi-market participation and the value of coordinated bidding as opposed to sequential bidding. The conclusion is that multi-market participation does yield benefits. According to the case study the benefit of multi-market participation is a profit increase between 1.7% and 5.1%. Furthermore, it was observed that intraday trading allowed the producer to self-balance, which reduced imbalance costs. The value of coordinated bidding was moderate, since the profit increase was between 0.26% and 1.8% depending on the intraday market liquidity estimate.

The limitations of the model presented in this thesis include limited modelling of intraday market liquidity and reserve providing capabilities of the producer. Therefore, a direction for future research should be to develop robust methodologies to incorporate uncertainty in market liquidity and demand for reserves into offer-strategy optimisation models. In addition, further examination is warranted regarding the effects that simplifying the multi-stage decision process into fewer decision stages has on the offer strategies.

Despite its limitations, this thesis confirmed multi-market participation derives benefits for Finnish energy producers. Furthermore, the results showed that especially VRE producers can benefit from intraday trading. Additionally, this thesis illustrated and explored several challenging aspects of offer-strategy optimisation and identified directions for possible future research.

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