Optimal revenue strategies for hybrid power plants in the Dutch wholesale energy market

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Challenge the future

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by

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In collaboration with the TNO wind research department

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Abstract

The Netherlands is currently undergoing an energy transition in an effort to decarbonize its electrical grid and build a more sustainable generation model. This transition is being led by the integration of non-controllable, sustainable generation sources such as wind and photovoltaic (PV) power. The Dutch wholesale energy market has an imbalance settlement period in which the TSO penalizes or rewards deviations from the last submitted trading program (based on whether the deviations aggravate or relieve the overall market imbalance), and therefore, non-controllable sources are at a higher risks of suffering undesired deviations. The consequences of this are twofold: on one hand, they impose a strain on the grid and an increased demand of ancillary services; and on the other, they risk the economic profitability of the plant. This issue can be bridged by combining non-controllable generation sources with storage assets.

Although the the dispatch of non-controllable energy sources has been studied extensively, there is a research gap in the proposal of revenue-maximizing strategies for operating hybrid power plants (with wind and PV generation, and energy storage capabilities) in the Dutch wholesale energy market, that account for the stochastic nature of the weather resources and include financial contingency factors. This thesis aims to bridge that gap by setting up an optimization-based dispatch, using Mixed Integer Linear Programming. The optimization was extended to a scenario-based stochastic optimization, and the Conditional Value at Risk was introduced to account for the intrinsic financial risk of the dispatch under random weather conditions. The resulting problem is a two-stage optimization which was solved using a modified Bender's cut. The intra-day optimizations were also adapted as rolling-horizon dispatches, permitting the operation with periodic updates to the weather forecasts.

The study case for this research was the SWITCH lab, a small-scale laboratory developed by TNO to conduct empirical research on the integration of renewable energies and storage into the grid. TNO also provided the basis for a non-optimized dispatch strategy based on price benchmarking, which was used to compare the performance of the optimized strategy.

The optimized dispatch proved to be an effective strategy for producing maximal-revenue trading programs on all market closings. The optimized revenue provided revenues between 85.8 % and 260.1 % higher than a generation-alone plant configuration; and an increase in revenue with respect to a generation-only baseline between 300.0 % and 8962.9 % compared to the non-optimized strategy. Operation under a hybrid configuration using the optmized dispatch also yielded the best economic outlook, having the highest 10-year Net Present Value projections, an average Internal Return on Investment 57.2 % higher than the hybrid plant under a non-optimized scheme and a 47.5 % lower payback time.

The optimized strategy provided the most profitable trading programs for both the case of deficit and surplus of generation at delivery, turning a positive revenue even under unfavourable market conditions. Conversely, the non-optimized dispatch had the lowest economic outlook of any configuration, with worse NPV, IRR, and payback times than the generation-only plant.

These results highlight the importance of developing dispatch strategies that consider the long-term behaviour of generation and prices, as opposed to here-and-now strategies whose performance was shown to be comparatively deficient; and the synergy between storage and renewable generation sources to bridge the non-controllability problem.

Acknowledgements

This report constitutes the final deliverable for the thesis research part of the Sustainable Energy Technology MSc program at the Technical University of Delft, and for me personally it also marks the end of my academic journey.

I am very grateful I got the chance to study my masters in such a young yet exciting topic as sustainable energy engineering. The global switch we are experiencing towards a more sustainable society is a challenging shift that brings a plethora of opportunities for investigation and development. With this thesis I hope to contribute my grain of sand to the advancement of the energy transition; and hopefully motivate you, the reader, to get interested in new advancements in this really interesting area.

The completion of this thesis would have not been possible without the guidance and help from my supervisors. I am most grateful to my TU Delft supervisor, professor Laura Ramírez, for her patience and insight on my research; and to my TNO supervisor, Max Houwing, for his support and advice during my work with TNO. And of course a very special thanks to my PhD supervisor, Joel Alpízar, for not only providing excellent technical guidance but also much needed moral support. I am also very grateful to professors Pavol Bauer and José Rueda for agreeing to be part of the defence committee.

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Maria de Eusebio
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Nomenclature

Acronyms

BRP	Balance Responsible Party
BSP	Balance Service Provider
CVaR	Conditional Value at Risk
DA	Day Ahead
DSO	Distribution System Operator
ESS	Energy Storage Systems
ID	Intraday
IRR	Internal Rate of Return
ISP	Imbalance Settlement Period
MC	Marginal Cost
MILP	Mixed Integer Linear Problem
NPV	Net Present Value
PV	Photovoltaic
RES	Renewable Energy Resources
RT	Real Time
SOC	State of Charge
TSO	Transmission System Operator
VaR	Value at Risk

Symbols

α	Value at Risk cut-off factor	–
β	Risk acceptance factor	–
Δ^{+}_{buy}	Positive difference between energy bought in two market closings	kWh

Δ^{+}_{net}	Positive difference between the net energy traded in two market closings	kWh
Δ^{+}_{sell}	Positive difference between energy sold in two market closings	kWh
Δ^{-}_{buy}	Negative difference between energy bought in two market closings	kWh
Δ^{-}_{net}	Negative difference between the net energy traded in two market closings	kWh
Δ^{-}_{sell}	Negative difference between energy sold in two market closings	kWh
δ_{buy}	Binary variable, 1 if there is a positive Δ^{+}_{buy}	–
δ_{ch}	Binary variable, 1 if battery is charged	–
δ_{net}	Binary variable, 1 if there is a positive Δ^{+}_{net}	–
δ_{sell}	Binary variable, 1 if there is a positive Δ^{+}_{sell}	–
η	Efficiency	–
λ^{+}	Surplus imbalance settlement price	$€/MWh$
λ^{-}	Deficit imbalance settlement	$€/MWh$
λ^{DA}	Day Ahead price	$€/MWh$
λ^{ID}	Intraday price	$€/MWh$
μ	(Local) Conditional Revenue at Risk	€
μ_{1}	Lagrangian equality multiplier	–
ω	Stochastic scenarios ($\omega \in \Omega$)	–
π	Probability of stochastic scenario	€
ρ_{air}	Air density	$\frac{kg}{m^3}$
ρ_{1}	Lagrangian inequality multiplier	–
ξ	Stochastic variables ($\xi \in \Xi$)	–
ζ	(Local) Conditional Value at Risk	€
A	PV panel area	m^2
B_{eq}	Equality constraint matrix	–
b_{eq}	Equality constraint vector	–
B_{ineq}	Inequality constraint matrix	–
b_{ineq}	Inequality constraint vector	–

C	Battery capacity	$-$
D	Wind turbine diameter	m
E_{disch}	Energy discharged from the battery	kWh
$E_{\text{gen sold}}$	Fraction of the generation produced sold to the market	kWh
$E_{\text{gen to batt}}$	Fraction of the generation produced charged to the battery	kWh
$E_{\text{grid to batt}}$	Energy purchased from the grid	kWh
E_{BESS}	Energy stored in the battery the battery	kWh
h	Hourly Day Ahead closings	$-$
J	Irradiance	$\frac{W}{m^2}$
q	Quarterly Intraday closings	$-$
r	Quarterly Real Time dispatch settlements	$-$
T	Temperature	C
u	Linear wind speed	$\frac{m}{s}$
z	Surface roughness	m

List of Figures

List of Tables

Contents

1

Introduction

This chapter presents an overview of the context in which the control of hybrid power plants is relevant. An overview of the shortcomings and challenges of high penetration of noncontrollable Renewable Energy Sources (RES) and their synergy with Energy Storage Systems (ESS) is presented in section 1.1. This is followed by a literature review in section 1.2 introducing the research status and gaps, followed by the proposal of the research objective and research questions in section 1.3. The methodology followed to complete the research is presented in in section 1.4, the scientific contributions of the research are presented in section 1.5, and the organization of the thesis work is shown in section 1.6.

1.1. Motivation

The Netherlands is currently undergoing a process of decarbonization of its electrical grid. Following current European trends [8], the country has set targets to have net zero carbon emissions by 2050 and obtain 16 % of its energy production from sustainable sources [9]. This shift will be supported by the expansion of the wind and solar generation capacity, with a projected 11 GW of offshore wind capacity [10], 6 GW of onshore wind capacity [11], and 27 GW of solar energy capacity [12] by 2030.

The integration of these renewable energies into a grid designed for conventional energy generation (using sources such as coal, oil, and natural gas) comes with a number of technical and socio-economic challenges. The lack of controllability of the energy sources has been highlighted as a main barrier on this problem: in contrast to conventional energy sources, neither the wind nor the irradiation that enable eolic and solar generation can be scheduled or controlled. This lack of control affects the supply security and overall reliability of the system, reduces the flexibility of the grid, and can ricochet in the form of frequency deviation problems, voltage instability, and unpredictable grid loads that can lead to congestion and blackouts. Coping with these problems demands the expansion of ancillary services provision at all levels of the grid, and has led to less predictable and more volatile and spare energy markets [13], [14].

This lack of controllability not only affects the technical performance of the grid, but also poses a threat to the economic viability of renewable energy as a profitable business. This is due to the challenge of scheduling optimal trade programs when the actual energy supply at the moment of delivery is not known, which is a threat to the profits that can be earned by the power producers. Additionally, virtually all TSO's in modern liberalized markets impose some form of fines for deviations between the energy programmed and delivered, and there are contractual obligations to ensure the commitment between buyers and suppliers. These economic challenges derived from the non-controllability nature of RES have also been identified as a key barrier for the social integration of renewable energies by several authors [15], [16].

This central issue of non-controllability demands a shift in the energy dispatch paradigm. The operation of wind and solar power plants for trading in the wholesale and ancillary markets is a multidisciplinary issue, in which weather forecasting plays a central role along power engineering and economic optimization. The topic of short and long-term weather forecasting for power scheduling applications has seen a rise in recent years, with new methods being proposed in a variety of different fields [17], [18]. It has also prompted an expansion of the use of the stochastic optimization methods used for building the energy trading programs, which in the case of noncontrollable sources need to consider supply uncertainty as well as market-related uncertainties.

The dependence on weather resources for energy generation adds the complication of having to deal with seasonal weather patterns [19], which would cause intermittent periods of high and low generation based on the seasonal weather. This can be partially bypassed by using hybrid power plants, which make use of more than one RES [20]. Combining wind and solar production, whose seasonality patterns are complementary (high wind resources during low irradiance months, and vice-versa) [21] would allow to partially override this issue and have stable, year-round energy production.

However, it is becoming increasingly apparent that improvements in the forecasting and dispatching methods for non-controllable RES alone are insufficient for providing flexibility and resilience to these generation sources. This is because this generation is strictly limited to the available weather resources and its dispatch is bound by the forecast accuracy. As several authors have pointed out, the successful overcoming of these barriers has the best outlook through the pairing of sustainable generation with energy storage systems (ESS). This would provide a higher degree of controllability, resilience, and flexibility to the system [22], [23], [24]. Thanks to the variety of storage technologies available, its integration on the electrical grid can serve a variety of roles derived from their technical specifications (such as their power density, frequency response, and capacity) and their positioning on the grid system (for example, as independent resources controlled by the DSO's, or as complementary assets managed by energy producers). Storage systems can then compensate for the shortcomings of high-RES grids by providing serves such as grid frequency support, oscillation damping, voltage control support, and aid in production predictability [25]. From a producer's perspective this last point stands as a particularly interesting one, since it would allow to bypass the problem of weather dependence and reliance on the weather forecasting, as well as add a flexibility factor by acting as both a load and an extra generation source [26]. For the participation in the wholesale energy market, Lithium-ion and redox flow batteries have been pointed as the most promising technologies, owning to their MW-capacity scaling, balance between power and energy density, and long cycle lifetime [26], [27].

Hybrid generation-storage systems that combine noncontrollable RES with ESS then stand as a promising configuration, with the potential to improve the economic and technical viability of large-scale integration of RES [28], [29]. This would use the batteries not only supporting the provision of ancillary services, but acting as support for the participation in the spot energy markets as well.

1.2. Literature review

Energy dispatch strategies for maximizing revenue have long been a matter of interest, both for the scientific community and for the industry alike. Most modern energy dispatch strategies are derived from variations of portfolio theory [30]. There, energy is understood to be a tradeable commodity subject to market and policy constraints, and through which certain benefits can be obtained by exchanging it to suitable parties. This optic allows for the natural integration of energy dispatch within the field of mathematical optimization, through which the assets of a power plant can be managed such that the optimal value of a certain objective function is obtained. The objective function to be attained is up to the strategy followed by the operator of the power plant, with a common objective being the maximizing of the revenue earned in certain markets [31]. Other objective functions can be the maximization of consumer utility [32], minimization of settlement imbalances [33], minimization of financial losses [30], and minimization of the Conditional Value at Risk of the trading [34].

Optimization problems typically have the form

$$\min\left(f(x)\right) \tag{1.1}$$

$$A_{\mathrm{eq}}x^T = b_{\mathrm{eq}} \tag{1.2}$$

$$A_{\mathrm{ineq}}x^T = b_{\mathrm{ineq}} \tag{1.3}$$

In which x is the set of optimization variables, $f(x)$ in Equation 1.1 represents the mathematical expression of the objective function, Equation 1.2 represents the set of equality constraints, and Equation 1.3 represents the set of inequality constraints that the optimization variables are subjected to. Modern computational technology allows to solve optimizations using numerical methods, often based on gradient-based algorithms [35]. The selection of particular numerical solvers depends on the mathematical nature of the objective function and the constraints, as well as the available software tools.

When dealing with the participation non-controllable RES (without battery storage systems) in the wholesale energy market, the optimization problem is expanded into an stochastic optimization, and thus issue of prediction forecasting also has to be taken into account. Several methods have been proposed in the literature to deal with this.

Arguably, the most straightforward formulation of the stochastic dispatch problem without storage resources is that of an stochastic optimization problem with randomly generated scenarios, typically set up with bidding in the spot market with corrections in the settlement period. This results in a two-stage optimization, solved using a two-stage problem decomposition. Formulations of this nature have been proposed by severalauthors. Morales et al. [36], proposed a minimum Conditional Value at Risk (CVaR) strategy, and Salkuti et al. [37] proposed a similar strategy but with a multi-objective dispatch that includes the ageing of the plant components. Usaola et al. [38] proposed a strategy for wind energy trading under known forecast error distribution, and Botterud et al. [39], studied the wind energy dispatch in the US market. Chaves-Ávila et al. [40] tailored the bidding for the Dutch Day-Ahead market and introduced the international trading capacity variable; and Xuan et al. [41] proposed a dispatch based on the minimization of operational costs using the Conditional Value at Risk of the system with Improved Backward Scenario Reduction for a scenario-based stochastic optimization, for an integrated energy system with electric, storage, gas, and heating/cooling systems.

These authors follow similar methodologies to propose optimal energy dispatch strategies, albeit their research varies in terms of the goal of the objective function, the configuration of the power plant, and the rulings of the market they participate in. However, this does not affect the fundamental structure of the optimization problem, which is independent of the generation forecasting methods used and is formulated as a two-stage linear optimization problem solved through stochastic scenario generation.

Other authors have proposed different approaches for the optimization problem. For example, authors like Bashi et al. [42], who proposed a stochastic model to characterize the uncertainty in wind power and market price prediction, which was approached with a genetic algorithm to solve the optimization. Zheng et al. [43] used dynamic uncertainty sets to model the generation uncertainty for the minimization of the Conditional Value at Risk; and the application of robust optimization was used by authors like Thatte et al. [44].

Although there is a variety of methods present in the literature, the dispatch problem follows a common structure:

1. Identify the objective function of interest and the constraints imposed by the system, whether they come from the limitations of the components or the market requirements; and set up the fundamental optimization problem using the objective function and the constraints.

2. Characterize the uncertainty in the stochastic generation variables (through scenario generation or uncertainty sets).

3. Expand the fundamental optimization problem to account for the stochastic variables.

4. Draw an optimization method fit for solving the resulting stochastic optimization problem.

The challenge of operating in the Dutch electricity market has been specifically studied by authors such as Chaves [40] and Mulder [45]. However, there are comparatively few studies done on this particular market, with most of the literature being directed towards a generic market model with doubly-blind price settlement mechanisms.

The combined operation of storage and renewable generation has been extensively applied to microgrids [46], [47], [48] as well as to the spot market under optimized dispatches [49], [50]. The main interest seems to be on the use of storage systems in autonomous grids with high penetration of renewable energy sources and their use for offering ancillary services, as opposed as using storage as an asset for traders in the wholesale market.

The presence of the battery does not affect the general methodology for the optimizations other than adding an extra set of constraints pertaining to the physical limits of the battery and the addition of the State of Charge (SOC) as a state-of-the-system equation.

Research gaps

Although the topic of trading of non-controllable energy sources is a well-researched one, the variety of options for plant configuration, market participation, objective function selection, and optimization methods presents a number of research opportunities for covering any given specific case.

A majority of the literature is focused on the participation on the Day Ahead (DA) market. Participation in the Intraday (ID) market is a topic that has only recently gained more interest, although it has been demonstrated that it is a highly beneficial opportunity for non-controllable RES [51]. The market settlement combination rarely considers a three-closing model with participation in the DA, ID, and imbalance markets, usually being limited to either DA or ID plus settlement when more than one closing is considered.

Given how the Dutch energy market operates on three closings, there is a need for precise stochastic dispatch formulations tailored for this participation model. Furthermore, there is yet another gap pertaining to the particularities of the Dutch energy market, which operates under a dual imbalance settlement price system (as opposed to the majority of European markets, which have a single-settlement price) [52].

There is also a gap in the literature that merges financial risk control mechanisms, such as the CVaR, with the optimal management of a battery storage system. Even though both topics have been studied separately, there is no research into how the flexibility offered by the battery would affect the impact of the CVaR for stochastic energy dispatches.

1.3. Research goal and research questions

The goal of this thesis is to formulate an optimized energy dispatch strategy that would allow operators of hybrid power plants with non-controllable RES and ESS to maximize their profits from participating in the Dutch wholesale energy market. The dispatch would be formulated in Matlab using its native toolboxes offered by Mathworks, without the need for purchasing additional software or licenses; and it would be a generic, ”plug-and-play” optimizer able to generate trading programs independently of how the generation or market conditions are simulated.

The research goals of this thesis are represented in the following research question:

How can the profits of a hybrid power plant, consisting of renewable energy generation and energy storage assets, be maximized through its participation in the Dutch wholesale energy market?

The solution to this research question is further guided by the following sub-research questions:

1. Are there any benefits to proposing the dispatch strategy as an optimization problem, if possible?
2. How can the random nature of the weather inputs be accounted for and managed?
3. What are the benefits of having a hybrid energy generation-and-storage plant, compared to traditional generation-only plants?

Collaboration with TNO and the SWITCH lab

This work is done in collaboration with the Wind Energy Department of the Energy Transition unit at TNO. It is encompassed within the research done around the SWITCH laboratory, a scaled-down facility with wind and solar generation assets totalling 100 kW of rated capacity, and a battery energy storage system with a nominal capacity of 57.6 kW/57.6 kWh. In particular, it is encompassed within the work of the EMERGE project, which aims to study the integration of RES and ESS within the Dutch energy grid [53].

The work done for this thesis is geared towards proposing a dispatch fit for trading with the SWITCH power plant. The association with the project also imposes conditions on the implementation of the optimizations, as it was required that all the work should be done in Matlab/Simulink or Python.

1.4. Scope and methodology of the research

The work done to set up an optimized dispatch fit for maximizing the revenue of a hybrid power plant operator in the Dutch electricity market followed the procedure identified in the literature research of section 1.2. Figure 1.1 presents a schematic overview of the work required to set it up and the relation between all the parts:

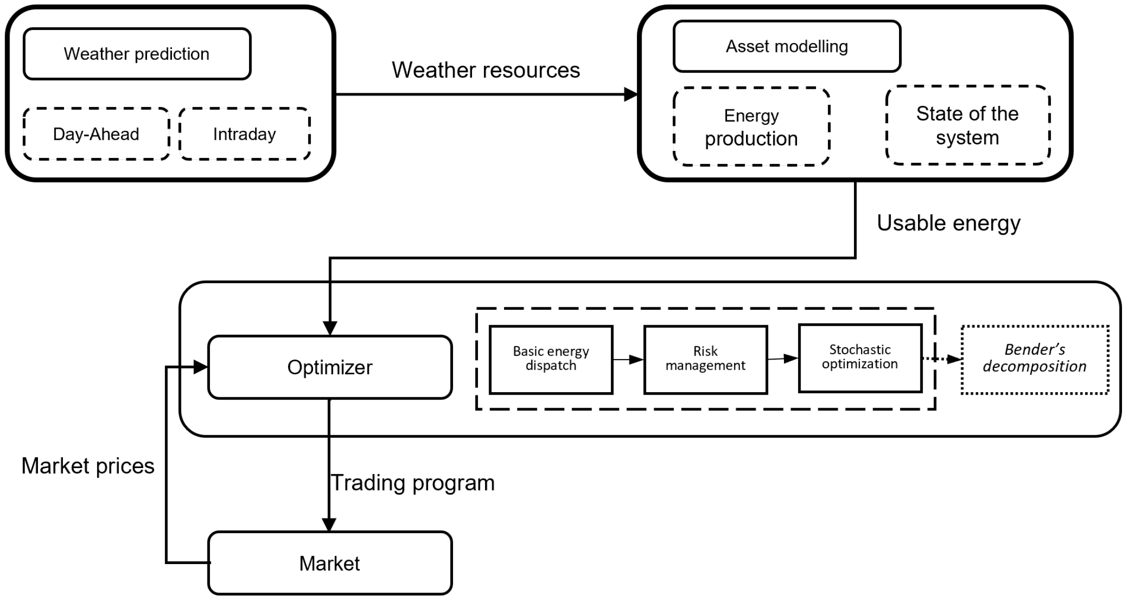


Figure 1.1: Flowchart of the thesis development

The full methodology is then as follows:

1. A literature research covering the workings of the Dutch energy markets, the key issues with the integration of non-controllable energy sources into the energy grid, and the synergy between the energy generation and storage assets, as well as how existing publications tackle the issue of energy dispatch and revenue maximization.

2. Set up of a linear optimization problem to maximize the revenue, tailored for the closings of the Dutch energy market, followed by the addition of the CVaR as a financial risk contention and the expansion to a scenario-based stochastic optimization fit for working with the Conditional Value at Risk. This includes generating stochastic scenarios with known probabilities.

3. Modeling of the predicted and actual weather inputs, based on historical data; and a rolling-horizon set of short-term weather predictions for the ID and Real Time (RT) dispatch, based on random deviations from the actual generation with an accuracy inversely proportional to the optimization horizon.

4. Modelling of wind and PV energy generation and battery assets, which was done in Matlab using simplified high-level mathematical models from standard equations found in the literature.

5. Performance of an economic analysis to determine the payback times and projected long-term revenue using the proposed optimized energy dispatch compared to using a non-optimized dispatch and a generation-only plant.

1.5. Scientific contributions

This research done offers valuable contributions to the field of optimized participation in liberalized energy markets, with a focus on the use of traditional scenario-based stochastic methods for creating maximal revenue programs. Additional contributions include:

- Proposal of an optimized energy dispatch fit for the two-closings plus double-price imbalance settlement, characteristic of the Dutch wholesale energy market.
- The addition of the CVaR for managing potential losses in the revenue, and the implementation of a modified Bender's cut for for solving Mixed-Integer Linear Problems (MILP) with equality and inequality constraints which is needed to solve the resulting problem.
- A comparison between the economic outlook of generation-only power plants versus hybrid power plants, with the added contrasting between operating hybrid power plants with optimized and non-optimized strategies.
- An analysis of the impact of using the CVaR for generating profit-maximizing programs for plants with non-controllable RESS and ESS, based on the consideration of stochastic scenarios.
- A rolling horizon optimization fit for operating with continuously updating intra-day generation forecasts and producing programs with the consideration of the CVaR.

1.6. Thesis outline

This thesis is organized as follows:

The functioning of the Dutch energy market is described in chapter 2, including a brief overview of its general characteristics and an explanation on how the DA, ID, and imbalance settlement markets function. The basic equations needed to set up the optimization problem are presented in chapter 3, including their constraints, bounds, and objective functions, for all market closings. These optimizations are expanded into stochastic ones in chapter 4, which also presents how the CVaR was introduced as a financial contingency mechanism. The generation modeling is presented in chapter 5, including the modeling of the generation and storage assets and the predicted weather resources.

After the aforementioned chapters, which present the construction of the optimizer, chapter 6 describes the SWITCH lab that was used as a case study, and the days that were selected to obtain the results; and chapter 7 describes the assumptions and simplifications that were followed to carry the optimizations.

The resulting trading programs for the two study case days are presented in chapter 8, including the proposed dispatches for the optimized and non-optimized dispatch and an analysis of their respective revenues. These results are complemented by the economic analysis from chapter 9, which compares three fundamental economic indicators for the viability of the project under revenues followed with each strategy. Finally, chapter 10 summarizes the research and proposes recommendations for further related work.

2

The Dutch energy market

This chapter presents the characteristics of the Day Ahead (DA), Intraday (ID) and imbalance settlement Dutch energy markets, including a broad overview of its main actors and their influence, the process through which energy is traded, and the bounds that this imposes for the optimizations.

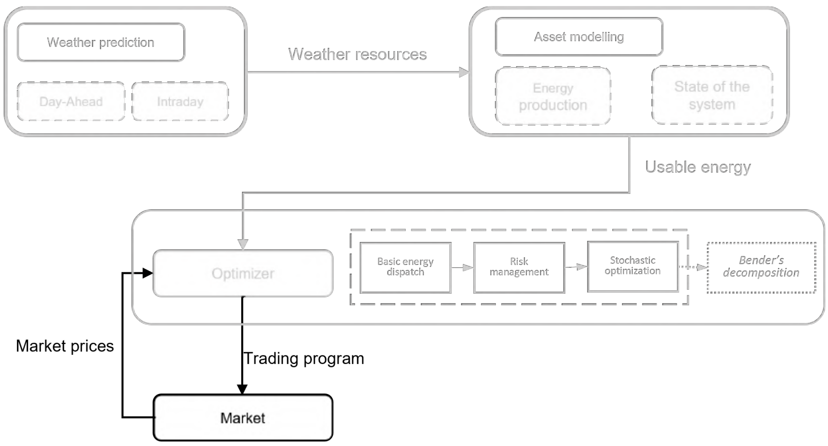


Figure 2.1: Diagram presenting the work flow for setting up the optimizations.

2.1. General overview

The Dutch energy market is a liberalized, deregulated market which allows for free competition among private energy providers [54] through free market supplier selection. The number of energy suppliers in the country has quadrupled since the market liberalization in 2004 [55], with companies offering energy contracts to both private households and corporate institutions. There are currently over 45 energy suppliers active in the market, with the main players being Vatenfall, Essent, E.On, Eneco, and Delta [56].

Energy trading in the market is facilitated by the transmission system operator (TSO). The Dutch TSO is TenneT, a government-owned institution which in addition to overseeing energy transactions also provides power transmission and system services. TenneT's activities include ensuring a secure and continuous supply of energy, transport electricity through the high-voltage grid from producers to consumers, and facilitating a smooth-running, liquid and stable electricity market [57].

A basic feature of this market model is the unbundling of services, in particular, the ownership unbundling between commercial and network operations [58]. This prohibits network operators and generation companies from owning shares in each other's services, a measure that was set in place to prevent monopolies from forming and thus ensuring a fully competitive market. This unbundling requirement led to the creation of distribution system pperators (DSOs), state-owned institutions which handle the distribution of electricity on the medium-and-low-voltage grids.

In addition to locally produced energy, the Netherlands also trades with other European countries such as Belgium, Germany, Norway, and the UK [57]. These connections can be placed in the plan of the European Commission of creating a single European Energy Market [59], and are paired with measures such as the Price Coupling of Regions and joining the European Market Coupling Company.

The actual energy trading is performed by the balance responsible parties (BRP), which manage the physical connections to the grid and correspond with the TSO to submit the forecast energy flows that will cross those connections. There are two types of programs that have to be submitted to the TSO before the energy delivery [60]:

- T-program: a forecast of the actual energy flows that will circulate through the connections. The TSO uses this prognosis to ensure balance between supply and demand, and that there are no congestion problems in the grid. Any participant with a total power consumption or production of more than 2 MW has to submit a T-program on the day before delivery.
- E-program: the aggregate net energy requirement for the next day for every imbalance settlement period (ISP)[1]. These programs have to be approved by the TSO, and are used to calculate the imbalance settlement penalization.

Energy trading takes place in three phases: the DA trading, the ID trading, and the imbalance settlement period. Since the imbalance settlement is calculated based on the actual real time trades, this last period will also be referred to as real time (RT) trading.

2.2. Day Ahead market

The Day Ahead market runs from 00:00 to 12:00 on the day before delivery. BRP submit offers for the selling and purchasing of energy for every hour of the delivery day. These offers can be limit orders (single hourly orders with for certain prices and quantities; can be fractionally accepted or rejected) or block orders (multiple consecutive hourly orders; are either fully accepted or rejected). Trading is carried through the European Power Exchange (EPEX), and

[1] TenneT operates with an ISP of 15 minutes.

thus the Day Ahead prices are also referred to as the EPEX spot prices [61]. These prices are capped at -500 €/ MWh and 3,000 €/MWh. To ensure trading solvency, all trades are fully collateralized by every party.

Supply and demand are matched via a two-sided, double-blind auction, with international trading capacity being assigned on a first-come, first-served basis. The hourly available transmission capacity (ATC) between different countries is published at 11:00 on the day before delivery.

2.3. Intraday market

The ID market has been active since 2006, and is also run through EPEX. The ID spot market allows for energy trading within the delivery day, up to 4 ISP before delivery and with contract lengths in blocks of ISP [62]. Energy is traded continuously 24/7 by immediate offer and demand matching. Prices are capped at -99,999.90€/MWh and 99,999.90€/MWh [63].

2.4. Imbalance settlement

In order to maintain the proper functioning of the grid, the energy injected and extracted from the grid must be balanced at all times. Imbalances will lead to, among others, deviation in the frequency of the grid[2], which can lead to power outages and equipment shutdown if it deviates over certain limits [64].

These grid imbalances are caused by deviations in the energy injected (produced) or withdrawn (consumed) with respect to the values submitted in the E-programs. The TSO is responsible for monitoring these imbalances, which are closed every ISP [1].

Since it is impossible to perfectly forecast the supply and demand at every moment, imbalances are inevitable, and part of the functions of the TSO is to manage and deal with these imbalances.

The way that this is done is by having the TSO act as an artificial market which redirects energy imbalances to parties with designated reserve capacity of production and consumption. These complementary services are known as *ancillary services*, and are provided by the balance service providers (BSP). Ancillary services can be deployed as either balancing energy or balancing capacity.

The reliable provision of ancillary services is ensured through contractual obligations with the large producers (those with more than 60 MW of capacity) and the purchasing from designated parties. There are three different types of spare capacity (emergency capacity, reserve capacity, and adjustment capacity) and three different types of frequency restoration reserves (containment reserve, frequency regulation reserve, and replacement reserve), all of which have different requirements for their function and activation method.

The clearing prices for these services is set through a bid ladder constructed with the offers from the various BSP for purchasing or producing extra energy. The TSO purchases the ancillary services at that clearing price, and those costs are subsequently billed to each BRP

[2]In the Netherlands, the grid operates at a frequency of 50 Hz. A surplus of energy will cause this frequency to increase, and a shortage will cause it to decrease.

based on their particular imbalances. The goal of this fine system is to deter BRP from having imbalances from their program and deliver deliver their energy as closely as possible to their E-program.

The balancing prices are uniform per ISP for all BSP's, and are determined based on the highest or lowest activated bid for the Frequency Restoration Reserve. The final imbalance settlement fine is contingent on three aspects:

1. The overall market state: the overall state of the grid can be in a surplus or in a deficit with respect to the cumulative E-programs submitted by all BRP. The Dutch imbalance pricing system contemplates four possible regulation states of the market per ISP:

   - No regulation (state 0): the overall state of the market matches the overall sum of the E-programs, and no balancing resources are deployed during the ISP.
   - Upwards regulation (state +1): there is a deficit of energy, due to either under-production or over-consumption. Ancillary resources have to be deployed to either inject more energy or curtail consumption.
   - Downwards regulation (state -1): there is an excess of energy in the grid, due to either over-production or under-consumption. Ancillary resources have to be deployed to either increase consumption or reduce injection of energy.
   - Dual regulation (state 2): both up and-down regulation resources have to be deployed alternatively during one ISP[3].

2. The bids submitted by the BSP's: BSP submit fractional bids for their up-and-down regulation services. Bids are arranged by merit order (the upward regulation bids are sorted from low to high and the downward regulation bids are sorted from high to low), and the final price for activation services is based on this bid ladder.

   The balancing energy price for upward bids per ISP is equal to the highest bid price of all activated upward bids within that ISP. The balancing energy price for downward regulation is equal to the lowest bid price of all activated downward regulation bids for that ISP. This process is illustrated in Figure 2.2.

3. The individual imbalance position of every BRP: since the objective of the imbalance fine system is to deter BRP's from having imbalances and thus avoid the deployment of ancillary resources, BRP's can be rewarded or fined depending on whether their individual imbalances harm or balance the market equilibrium. Hence, individual imbalances which skew in the opposite direction of the overall market regulation state will receive a positive financial flow (from the TSO to the BRP), while those in the same direction as the market state will have a negative financial flow (from the BRP to the TSO). A summary of the cash flow direction based on the market regulation state and the imbalance prices can be seen in Figure 2.3.

[3]If the grid is both over-or under balanced during one ISP, but the changes in the grid state are in the same direction - continuously upward or downward - the grid state would be +1 for continuously increasing changes and -1 for continuously decreasing changes.

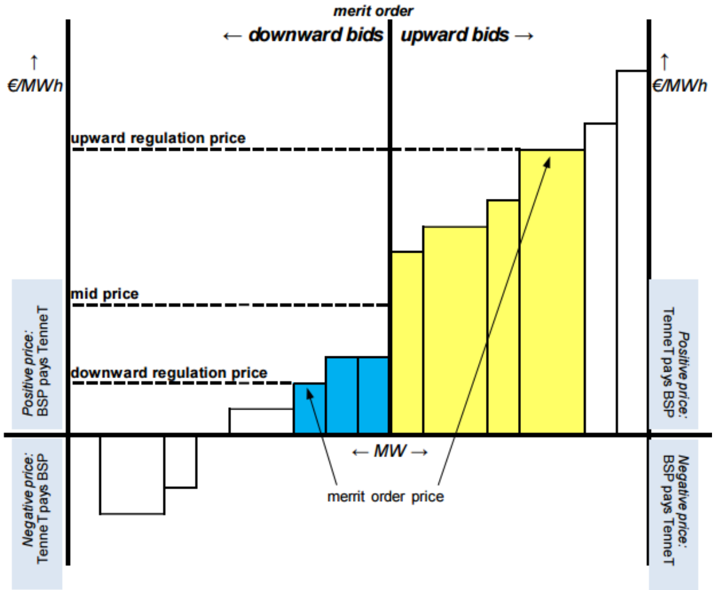


Figure 2.2: Construction of the imbalance energy prices for up-and-down-regulation [1]

During ISP with	Imbalance position BRP	Imbalance price	Direction of payment
Regulation state 0	BRP shortage	P_{mid} (+)	BRP → TSO
		P_{mid} (-)	TSO → BRP
	BRP surplus	P_{mid} (+)	TSO → BRP
		P_{mid} (-)	BRP → TSO

During ISP with	Imbalance position BRP	Imbalance price	Direction of payment
Regulation state +1	BRP shortage	P_{up} (+)	BRP → TSO
		P_{up} (-)	TSO → BRP
	BRP surplus	P_{up} (+)	TSO → BRP
		P_{up} (-)	BRP → TSO

During ISP with	Imbalance position BRP	Imbalance price	Direction of payment
Regulation state -1	BRP shortage	P_{down} (+)	BRP → TSO
		P_{down} (-)	TSO → BRP
	BRP surplus	P_{down} (+)	TSO → BRP
		P_{down} (-)	BRP → TSO

During ISP with	Imbalance position BRP	Imbalance price		Direction of payment
Regulation state 2	BRP shortage	$P_{up} \geq P_{mid}$	P_{up} (+)	BRP → TSO
			P_{up} (-)	TSO → BRP
		$P_{up} < P_{mid}$	P_{mid} (+)	BRP → TSO
			P_{mid} (-)	TSO → BRP
	BRP surplus	$P_{down} \leq P_{mid}$	P_{down} (+)	TSO → BRP
			P_{down} (-)	BRP → TSO
		$P_{down} > P_{mid}$	P_{mid} (+)	TSO → BRP
			P_{mid} (-)	BRP → TSO

Figure 2.3: Direction of imbalance fine payments based on market regulation state, balancing energy prices, and the BRP imbalance position [1]

It is important to note that this imbalance fine payment system is based on a dual pricing system, since the prices for up- and down- regulation can be different during the same ISP. This is a particularity of the Dutch energy market (in opposition to most European markets which have a single-pricing system [65]). An overview of the historical behavior of the market prices for all closings can be found in Appendix A.

The DA prices have the least dispersion and most noticeable seasonality of all closings. Various studies [52] have noted that this market behaves with structured data clusters based on seasonal trends. These trends are influenced by the conditions of offer and demand availability, as well as by various factors of market design and game theory.

The ID market is notably less consistent. Intra-day markets are notably non-liquid under a controllable-heavy production scheme, but have become more liquid with the progressive integration of weather-dependent, non-controllable resources. This liquidity has led to higher price dispersion and extremes. Some degree of seasonality can be found in the historical prices, particularly tied to the natural cycles of weather resources.

The imbalance market prices are notably hard to predict, since prices are influenced by a wide variety of factors including the behavior of the DA and ID markets themselves. This is further complicated by the dual pricing system of the Dutch market, which requires separate analysis for the up-and-down regulation prices instead of for a single, cohesive price. As it can be observed, there is a clear tendency for downward regulation prices to be higher than for upward regulation, with the average downward regulation price being 46.6908 €/MWh and the average upward regulation price being 41.4079 €/MWh.

Note: since the Intraday prices data was only available for October-December 2020, all subsequent work on this thesis will be restricted to studies of that time period.

3

Optimization set up

This chapter presents the basic optimization formulas for building the optimized energy dispatch for each market closing, including the DA market in section 3.1, ID market insection 3.2, and imbalance settlement in section 3.3.

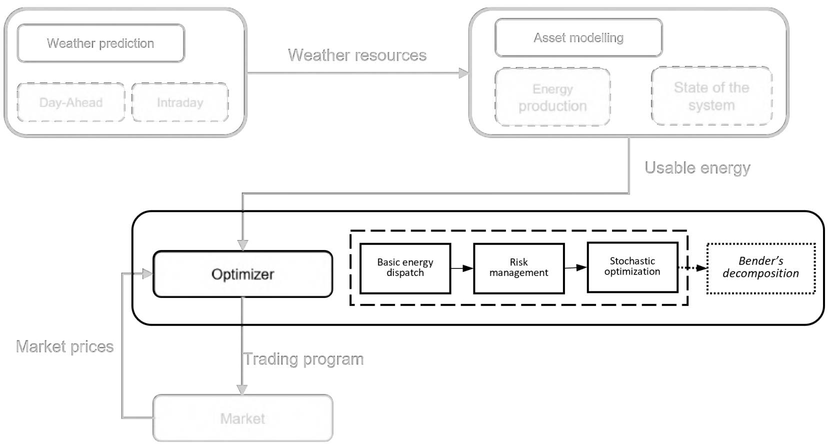


Figure 3.1: Diagram presenting the work flow for setting up the optimizations.
list=no

As presented in chapter 1, the goal of this thesis is to maximize the profits earned by a power plant participating in the Dutch wholesale energy market. In practical terms, this would mean deciding the power allocation between selling, buying, or charging to the battery, considering the physical constraints of the components of the power plant, in order to make as much money as possible through the energy exchanged with the market. If both the revenue earned and the constraints of the system can be modelled mathematically, then the behaviour of those equations could be studied to determine which combination of energy flows would yield the best revenue. Problems of this kind, in which elements are selected among a possible set to obtain the best possible performance with respect to some criterion, belong to the field of mathematical optimization [66].

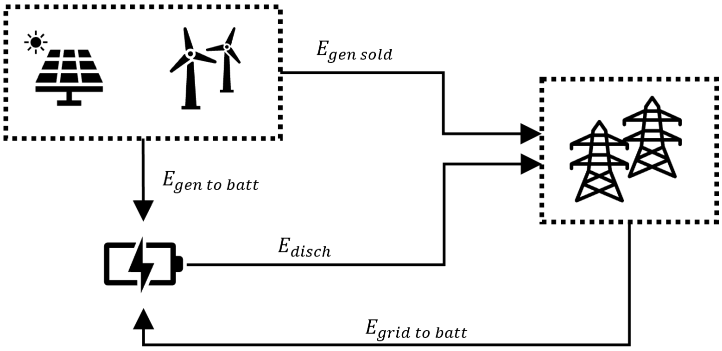


Figure 3.2: Representation of the energy flows which comprise the decision variables that characterize an energy dispatch program.

For the case of a hybrid power plant with generation and storage assets, the variables that would have to be determined in order to plan an energy dispatch are pictured in Figure 3.2, and are defined as follows:

- $E_{\text{gen sold}}$ is the fraction of the energy generated that is sold to the grid.
- $E_{\text{gen to batt}}$ is the fraction of the energy generated that is charged to the battery.
- E_{disch} is the energy extracted from the battery.
- $E_{\text{grid to batt}}$ is the energy purchased from the grid (which, by necessity, has to be stored in the battery).

All of the aforementioned energy flows are positive by definition.

The profits of the plant would be obtained through the selling of energy, corresponding to $E_{\text{gen sold}}$ and E_{disch}. The costs of the plant would be the energy purchased, $E_{\text{grid to batt}}$, and the marginal costs MC of operating the plant. Since the wind and PV generations are assumed to operate under no marginal cost [67], the marginal costs would come from operating the battery. The modeling of these costs is explained in chapter 5.

At this stage of the optimization, each market closing would be treated as the optimal dispatch that should be followed by the plant operator. This means that possible adjustments in later closings are not considered in the optimizations, since this would require introducing predictions of how much energy could be produced in those later market calls.

3.1. Day Ahead dispatch

The DA dispatch is submitted at 11:00h of the day before delivery, and it must present hourly bids for the purchasing and selling of energy for the entire day.

Objective function

The objective function to be maximized (Equation 3.1) are the total profits obtained by participating in H hourly periods of the Day Ahead market. These profits are the revenue earned from selling energy, minus the cost of purchasing energy and the fractional cost of operating the battery. To calculate the dispatch for a full day (24 hours, and therefore 24 closing periods), this sum would be computed for H=24.

$$Profit = \sum_{h=1}^{h=\mathrm{H}} \lambda_h^{\mathrm{DA}} \cdot \left(E_{\text{gen sold},h}^{\mathrm{DA}} + E_{\text{disch},h}^{\mathrm{DA}} - E_{\text{grid to batt},h}^{\mathrm{DA}}\right) - MC_h \tag{3.1}$$

Since all energy generated (or predicted to be generated, $E_{\text{gen pred}}^{\mathrm{DA}}$) has to be dispatched, either by selling or by charging to the battery, $E_{\text{gen to batt}}^{\mathrm{DA}}$ and $E_{\text{gen pred}}^{\mathrm{DA}}$ are linked by Equation 3.2:

$$E_{\text{gen sold},h}^{\mathrm{DA}} + E_{\text{gen to batt},h}^{\mathrm{DA}} = E_{gen\ pred,h}^{\mathrm{DA}} \longrightarrow E_{\text{gen sold},h}^{\mathrm{DA}} = E_{\text{gen pred},h}^{\mathrm{DA}} - E_{\text{gen to batt},h}^{\mathrm{DA}} \tag{3.2}$$

In order to reduce the number of decision variables, $E_{\text{gen sold},h}^{\mathrm{DA}}$ can be reformulated as a function of $E_{\text{gen to batt},h}^{\mathrm{DA}}$, with the objective function in Equation 3.1 being reformulated into Equation 3.3:

$$Profit = \sum_{h=1}^{h=\mathrm{H}} \lambda_h^{\mathrm{DA}} \cdot \left(E_{\text{pred},h}^{\mathrm{DA}} - E_{\text{gen to batt},h}^{\mathrm{DA}} + E_{\text{disch},h}^{\mathrm{DA}} - E_{\text{grid to batt},h}^{\mathrm{DA}}\right) - MC_h \tag{3.3}$$

Constraints

The first constraint is the state of the system, which is represented by the battery state of charge (Equation 3.4)

$$E_{\text{BESS},h}^{\mathrm{DA}} = \left(1 - \eta_{\text{self discharge}}\right) \cdot E_{\text{BESS},h-1}^{\mathrm{DA}} +$$

$$\eta_{\text{charge}} \cdot \left(E_{\text{gen to batt},h}^{\mathrm{DA}} + E_{\text{grid to batt},h}^{\mathrm{DA}}\right) - \eta_{\text{disch}} \cdot E_{\text{disch},h}^{\mathrm{DA}} \tag{3.4}$$

The battery's power has to remain within the defined SOC limits, which defines the upper and lower bounds for the $E_{\text{BESS},h}^{\mathrm{DA}}$ variables (Equation 3.5):

$$C \cdot SOC_{\text{min}}^{\mathrm{DA}} \leq E_{\text{BESS},h}^{\mathrm{DA}} \leq C \cdot SOC_{\text{max}}^{\mathrm{DA}} \tag{3.5}$$

Due to physical constraints, the battery cannot charge and discharge at the same time. This leads to two more constraints (Equation 3.6 and Equation 3.7) which ensure that energy is only either charged (from the grid or from the generation) or discharged at a given time

$$E_{\text{gen to batt},h}^{\mathrm{DA}} \cdot E_{\text{disch},h}^{\mathrm{DA}} = 0 \tag{3.6}$$

$$E^{\mathrm{DA}}_{\text{grid to batt},h} \cdot E^{\mathrm{DA}}_{\text{disch},h} = 0 \tag{3.7}$$

The physical limitations of the battery also require that the charge to the battery does not exceed the maximum charge rate $cr_{\max}$ (Equation 3.8), and that the discharge flows are also less than the maximum discharge rate $dr_{\max}$ (Equation 3.9). The maximum charge and discharge rate are often marked by the manufacturer. This serves as the bounds for the charge and discharge decision variables.

$$0 \leq E^{\mathrm{DA}}_{\text{grid to batt},h} + E^{\mathrm{DA}}_{\text{gen to batt},h} \leq C \cdot cr_{\max} \tag{3.8}$$

$$0 \leq E^{\mathrm{DA}}_{\text{disch},h} \leq C \cdot dr_{\max} \tag{3.9}$$

3.2. Intraday dispatch

The ID market trades energy on the delivery day, and it allows to update energy selling and purchasing bids up to 1 hour before delivery. Assuming that bids are continuously placed (meaning that there are no blank periods in between updated energy trades) with a minimum length contract (15 min), it would result in a total of 96 ID closing periods per day, with Q=4 ID closing periods per hour.

Placing a bid in the ID market necessarily means an increase to the bids placed in the DA market for energy purchased and sold. However, given that certain imbalance settlement prices can result in a profit if imbalances are present, it might be interesting to purposefully cause negative purchasing or selling differences with respect to the DA program. Therefore, the DA bids should not function as a lower bound for the ID bids. The ID dispatch is then conducted as its own optimization, unbounded by (but still coupled to) the DA program.

Since all increases in energy purchased or sold are passed as bids through the ID market, the only way to create a surplus imbalance in the settlement period is by purchasing less energy than submitted in the DA program; and the only way to create a deficit imbalance is by selling less.

The difference between the DA and ID bids can be characterized by the auxiliary variables Δ_{buy} (for changes in the energy purchased) and Δ_{sell} (for changes in the energy sold), defined as per Equation 3.10 and Equation 3.11.

$$\Delta_{\text{buy},h,q} = E^{\mathrm{ID}}_{\text{grid to batt},h,q} - E^{\mathrm{DA}}_{\text{grid to batt},h} \tag{3.10}$$

$$\Delta_{\text{sell},h,q} = \left(E^{\mathrm{ID}}_{\text{pred},h,q} - E^{\mathrm{ID}}_{\text{gen to batt},h,q} + E^{\mathrm{ID}}_{\text{disch},h,q}\right) - \left(E^{\mathrm{DA}}_{\text{gen},h} + E^{\mathrm{DA}}_{\text{disch},h}\right) \tag{3.11}$$

Both Δ_{buy} and Δ_{sell} can be positive (if the ID dispatch is larger than the DA dispatch) or negative (if the ID dispatch is smaller than the DA dispatch). In order to obtain the positive and negative values separately, each Δ can be linearized with the inclusion of the auxiliary positive variables Δ^{+} and Δ^{-}, which represent the positive and negative changes respectively. Equation 3.10 and Equation 3.11 are expanded into Equation 3.12 and Equation 3.13.

$$\Delta_{\text{buy},h,q} = \Delta^{+}_{\text{buy},h,q} - \Delta^{-}_{\text{buy},h,q} = E^{\text{ID}}_{\text{grid to batt},h,q} - E^{\text{DA}}_{\text{grid to batt},h} \tag{3.12}$$

$$\Delta_{\text{sell},h,q} = \Delta^{+}_{\text{sell},h,q} - \Delta^{-}_{\text{sell},h,q} = \left(E^{\text{ID}}_{pred,h,q} - E^{\text{ID}}_{\text{gen to batt},h,q} + E^{\text{ID}}_{\text{disch},h,q}\right) - \left(E^{\text{DA}}_{gen,h} + E^{\text{DA}}_{\text{disch},h}\right) \tag{3.13}$$

Objective function

The profits obtained in each ID closing is the revenue obtained by selling extra energy, minus the cost of purchasing extra energy, minus the foreseen settlement penalty for the surplus and deficit imbalances, and minus the fractional cost of operating the battery (Equation 3.14).

$$Profit = \sum_{h=1}^{h=H} \sum_{q=1}^{q=4} \lambda^{\text{ID}}_{h,q} \cdot \left(\Delta^{+}_{\text{sell},h,q} - \Delta^{+}_{\text{buy},h,q}\right) + \lambda^{+}_{\text{imb}} \cdot \Delta^{-}_{\text{buy},h,q} - \lambda^{-}_{\text{imb}} \cdot \Delta^{-}_{\text{sell},h,q} - MC_{h,q} \tag{3.14}$$

Constraints

The constraints related to the battery remain the same as for the DA dispatch (Equation 3.15-Equation 3.20):

$$E^{\text{ID}}_{\text{BESS},h,q} = \left(1 - \eta_{\text{self discharge}}\right) \cdot E^{\text{ID}}_{\text{BESS},h,q-1} +$$

$$\eta_{\text{charge}} \cdot \left(E^{\text{ID}}_{\text{gen to batt},h,q} + E^{\text{ID}}_{\text{grid to batt},h,q}\right) - \eta_{\text{disch}} \cdot E^{\text{ID}}_{\text{disch},h,q} \tag{3.15}$$

$$C \cdot SOC^{\text{ID}}_{\text{min}} \leq E^{\text{ID}}_{\text{BESS},h,q} \leq C \cdot SOC^{\text{ID}}_{\text{max}} \tag{3.16}$$

$$E^{\text{ID}}_{\text{gen to batt},h,q} \cdot E^{\text{ID}}_{\text{disch},h,q} = 0 \tag{3.17}$$

$$E^{\text{ID}}_{\text{grid to batt},h,q} \cdot E^{\text{ID}}_{\text{disch},h,q} = 0 \tag{3.18}$$

$$0 \leq E^{\text{ID}}_{\text{grid to batt}\ \ h,q} + E^{\text{ID}}_{\text{gen to batt},h,q} \leq C \cdot cr_{\text{max}} \tag{3.19}$$

$$0 \leq E^{\text{ID}}_{\text{disch},h,q} \leq C \cdot dr_{\text{max}} \tag{3.20}$$

The definition of $\Delta^{+}_{\text{buy/sell}}$ and $\Delta^{-}_{\text{buy/sell}}$ requires the introduction of a binary variable $\Delta_{\text{buy/sell}}$, which equals 1 if the difference between ID and DA values is positive (so the ID dispatch is larger than the DA dispatch), and 0 if the difference is negative (the ID dispatch is smaller than the DA dispatch). This results in the addition of constraints Equation 3.21-Equation 3.26:

$$0 \leq \Delta^{+}_{\text{buy},h,q} \leq C \cdot cr_{\max} \cdot \Delta_{\text{buy},h,q} \tag{3.21}$$

$$0 \leq \Delta^{-}_{\text{buy},h,q} \leq C \cdot cr_{\max} \cdot (1 - \Delta_{\text{buy},h,q}) \tag{3.22}$$

$$0 \leq \Delta^{+}_{\text{sell},h,q} \leq (E^{\text{ID}}_{\text{pred},h,q} + C \cdot dr_{\max}) \cdot \Delta_{sell} \tag{3.23}$$

$$0 \leq \Delta^{-}_{\text{sell},h,q} \leq (E_{\text{pred}^{\text{ID}},h,q} + C \cdot dr_{\max}) \cdot (1 - \Delta_{\text{sell},h,q}) \tag{3.24}$$

$$\Delta_{\text{buy},h,q} \in 0, 1 \tag{3.25}$$

$$\Delta_{\text{sell},h,q} \in 0, 1 \tag{3.26}$$

The limits for $\Delta^{+}_{\text{buy/sell}}$ and $\Delta^{-}_{\text{buy/sell}}$ presented in Equation 3.21-Equation 3.24 define the maximum and minimum values that these variables can take:

- Δ^{+}_{buy} can be 0 if exactly the same energy is purchased in the ID and DA markets, and $C \cdot cr_{\max}$ if nothing is bought in the DA but the maximum purchasing capacity is bought in the ID.
- Δ^{-}_{buy} can be 0 if exactly the same energy is purchased in the ID and DA markets, and $C \cdot cr_{\max}$ if the maximum purchasing capacity is bought in the DA nothing is bought in the ID.
- $\Delta_{\text{sell}^{+}}$ can be 0 if exactly the same energy is bought in the ID and DA markets, and $E_{\text{pred},h,q} + C \cdot dr_{\max}$ if nothing is sold in the DA but the maximum production and discharge is sold in the ID.
- $\Delta_{\text{sell}^{-}}$ can be 0 if exactly the same energy is bought in the ID and DA markets, and $E_{\text{pred},h,q} + C \cdot dr_{\max}$ if maximum production and discharge is sold in the DA but the nothing is sold in the ID.

3.3. Imbalance settlement (Real Time dispatch)

The imbalance settlement period is not a market, strictly speaking. However, it still offers the possibility of earning or losing money from the imbalances generated during the actual, energy dispatch, and therefore, this dispatch can be effectively formulated as an optimization for an extra market closing. Since this dispatch (and the subsequent calculation of the profits obtained) are based on the real-time delivery of energy, this period is also referred to as the Real Time (RT) dispatch.

In the RT dispatch, the energy production is known exactly. Since all trading opportunities have closed, the opportunity to earn revenue comes from the exploitation of (predicted) favourable imbalance settlement prices and the avoidance of unfavourable ones. A summary of the cash flow directions based on market imbalance can be found in [1].

Since imbalances are measured every 15 min, there are R=4 imbalance closings per hour h for a total of 96 closings per day. The Real Time dispatch represents the actual, realized dispatch that a plant operator will carry (whereas the DA and ID are the preemptive plans on which this actual realization is based). Therefore, the marginal cost of using the battery on the Real Time dispatch represents the actual cost associated with using the battery.

Similarly to the ID dispatch, the Real Time dispatch is contingent on the differences between the last submitted bid program and the actual delivered energy. However, at this stage any deviation from the last submitted program will be tallied (whether in the ID dispatch, increases in the energy sold and purchased were passed as bids and only reductions were counted as imbalances). For a plant that acts both as a producer and a consumer, its impact on the grid is the net energy exchanged:

$$E_{\mathrm{net}} = E_{\mathrm{sold}} - E_{\mathrm{bought}}$$

Hence, the total imbalance Δ_{net} for the energy delivered at period r within the h hour is defined as per Equation 3.27.

$$\Delta_{\mathrm{net},h,r} = \left(E^{\mathrm{RT}}_{produced,h,r} - E^{\mathrm{RT}}_{\mathrm{gen\ to\ batt},h,r} + E^{\mathrm{RT}}_{\mathrm{disch},h,r} - E^{\mathrm{RT}}_{\mathrm{grid\ to\ batt},h,r}\right) - \left(E^{\mathrm{ID}}_{\mathrm{sold},h,r} + E^{\mathrm{ID}}_{\mathrm{grid\ to\ batt},h,r}\right) \quad (3.27)$$

It should be noted that, in the nomenclature of Equation 3.27, the last program submitted is represented with ID superscripts. This does not necessarily mean that participating in the ID market is compulsory. In the case that only bids for the DA market were submitted, the values used in Equation 3.27 would be $\mathrm{Bid}^{\mathrm{ID}} = \mathrm{Bid}^{\mathrm{DA}}$.

Similarly to the ID dispatch, Δ_{net} could take a positive (net energy delivered is more than net energy bid) or negative (net energy delivered is less than net energy bid) value. This can be linearized by the inclusion of the auxiliary variables $\Delta^{+}_{\mathrm{net}}$ and $\Delta^{-}_{\mathrm{net}}$, which would respectively correspond to the separate positive and negative deviations. Equation 3.27 is then expanded into Equation 3.28:

$$\Delta_{\text{net},h,r} = \Delta^{+}_{\text{net},h,r} - \Delta^{-}_{\text{net},h,r} = \left(E^{\text{RT}}_{\text{produced},h,r} - E^{\text{RT}}_{\text{gen to batt},h,r} + E^{\text{RT}}_{\text{disch},h,r} - E^{\text{RT}}_{\text{grid to batt},h,r}\right) -$$

$$\left(E^{\text{ID}}_{\text{sold},h,r} + E^{\text{ID}}_{\text{grid to batt},h,r}\right) \quad (3.28)$$

Objective function

The earnings in the settlement market period r within hour h is defined as the sum of the positive and negative program deviations multiplied by their respective settlement prices as per Equation 3.29. Depending on the settlement prices the revenue can be positive or negative, with the payment direction between the BRP and the TSO being indicated in [1].

$$Profit = \sum_{h=1}^{h=H} \sum_{r=1}^{r=4} \lambda^{+}_{\text{imb},h,r} \cdot \Delta^{+}_{\text{net},h,r} - \lambda^{-}_{\text{imb},h,r} \cdot \Delta^{-}_{\text{net},h,r} - MC_{h,r} \quad (3.29)$$

Constraints

The constraints related to the battery remain the same as for the DA and ID dispatch (Equation 3.30-Equation 3.35):

$$E^{\text{RT}}_{\text{BESS},h,r} = \left(1 - \eta_{\text{self discharge}}\right) \cdot E^{\text{RT}}_{\text{BESS},h,r-1} +$$

$$\eta_{\text{charge}} \cdot \left(E^{\text{RT}}_{\text{gen to batt},h,r} + E^{\text{RT}}_{\text{grid to batt},h,r}\right) - \eta_{\text{disch}} \cdot E^{\text{RT}}_{\text{disch},h,r} \quad (3.30)$$

$$C \cdot SOC^{\text{RT}}_{\text{min}} \leq E^{\text{RT}}_{\text{BESS},h,r} \leq C \cdot SOC^{\text{RT}}_{\text{max}} \quad (3.31)$$

$$E^{\text{RT}}_{\text{gen to batt},h,r} \cdot E^{\text{RT}}_{\text{disch},h,r} = 0 \quad (3.32)$$

$$E^{\text{RT}}_{\text{grid to batt }h,r} \cdot E^{\text{RT}}_{\text{disch},h,r} = 0 \quad (3.33)$$

$$0 \leq E^{\text{RT}}_{\text{grid to batt }pr} + E^{\text{RT}}_{\text{gen to batt},h,r} \leq C \cdot cr_{\text{max}} \quad (3.34)$$

$$0 \leq E^{\text{RT}}_{\text{disch},h,r} \leq C \cdot dr_{\text{max}} \quad (3.35)$$

The definition of Δ^{+}_{net} and Δ^{-}_{net} requires the introduction of a binary variable δ_{net}, which equals 1 if the difference Δ_{net} is positive (so the net difference in RT dispatch is more than the net energy bid in the last program submission), and 0 if the difference is negative (so the net difference in RT dispatch is less than the net energy bid in the last program submission). This results in the addition of constraints Equation 3.36-Equation 3.38:

$$0 \leq \Delta^{+}_{net,h,r} \leq \left(C \cdot cr_{\text{max}} + C \cdot dr_{\text{max}} + E_{\text{produced},h,r}\right) \cdot \Delta_{\text{net},h,r} \tag{3.36}$$

$$0 \leq \Delta^{-}_{net,h,r} \leq \left(C \cdot cr_{\text{max}} + C \cdot dr_{\text{max}} + E_{\text{produced},h,r}\right) \cdot \left(1 - \Delta_{\text{net},h,r}\right) \tag{3.37}$$

$$\Delta_{net} \in 0, 1 \tag{3.38}$$

The limits for Δ^{+}_{net} and Δ^{-}_{net} presented in Equation 3.36-Equation 3.37 define the maximum and minimum values that these variables can take:

- Δ^{+}_{net} can be 0 if exactly the same energy is traded in the Real Time dispatch as in the last submitted program; and $C \cdot cr_{\text{max}} + C \cdot dr_{\text{max}} + E_{\text{produced},h,r}$ in the case that the only program trade is maximum energy purchase, but in the Real Time dispatch nothing is bought and all available energy was sold.
- Conversely, Δ^{-}_{net} can be 0 if exactly the same energy is traded in the Real Time dispatch as in the last submitted program; and $C \cdot cr_{\text{max}} + C \cdot dr_{\text{max}} + E_{\text{produced},h,r}$ in the case that all available energy is sold in during the last trade program and nothing is bought, but in the Real Time dispatch nothing is sold and energy is purchased to the maximum capacity.

4

Risk and uncertainty management

Putting together a bid program for the DA and ID markets requires consideration of the (predicted) energy generation that will be available during the delivery time. However, the atmospheric conditions that influence the PV and wind energy generation (such as cloud coverage, temperature, wind speed, and solar irradiance) are largely random factors [68] whose broad trends can be foreseen, but precise value is hard to predict. The generation prediction is thus of stochastic nature, which introduces two significant issues for the dispatch optimizations:

1. The stochastic nature of the weather resources and their probable real-time realizations.

2. The intrinsic financial risk linked to possible penalties due to program deviations.

This chapter details how these issues were tackled by introducing the Conditional Value at Risk as a risk management mechanism in section 4.1, how the optimization was expanded to be a stochastic one in section 4.2, how the Conditional Value at Risk was formulated in the optimizations in section 4.3, and the methods needed to solve the resulting optmization in section 4.4.

4.1. Risk management: the Conditional Value at Risk

From a financial perspective, the trading of energy has long been regarded as a subtype of portfolio management [69], meaning that can be handled using the tools from Modern Portfolio Theory (MPT) [70] in order to minimize the damage from potential financial losses. In particular, for the optimization at hand, the focus is on asset allocation in order to maximize returns and minimize losses as represented by the penalties imposed due to program deviations [71].

A fundamental concern of MPT is the estimation and modelling of portfolio losses, and the subsequent selection of risk management methods in order to avoid or minimize them. Traditional MPT methods for loss modelling are typically based on the analysis of either predicted or historical scenarios, based on which different risk measures can be proposed. Investopedia highlights the following commonly used risk measures [72]:

- Standard deviation: used to quantify the volatility of an investment by measuring the actual return dispersion relative to the expected rate of return.
- Sharpe Ratio: used to measure the relative impact of an investment by calculating the ratio between the investment's return and its volatility.
- Beta: compares the volatility of an individual security in relation to that of the entire market. A Beta factor over 1 indicates a volatility higher than that of the broad market.
- R-squared: a statistical measure that indicates the influence exerted by movements in a benchmark index on a particular investment.
- Value at Risk (VaR): a quantile (statistical) risk management tool that measures the maximum (potential) loss associated to a confidence interval, for a given period of time. For example, a portfolio with a one-year 10 % VaR of €1 million means that the portfolio has a 10 % chance of losing €1 million over a one-year period.
- Conditional Value at Risk (CVaR): also referred to as "Expected Shortfall" (ES), the CVaR can be regarded as an extension on the Value at Risk. Instead of just indicating the maximum loss for a confidence interval, the CVaR indicates the likelihood that the Value at Risk will be breached. It is therefore used to indicate the maximum losses that can occur from scenarios that are less likely to occur.

In addition to these methods, various risk measures have been derived in the literature with improved mathematical properties and market risk characterization. In spite of this, the Value at Risk remains widely regarded as the most universally employed method, with the Basel II accord requiring all banks to report the VaR of each of their investment sheets to the regulators, and hold a hedge fund based on this value [73].

However, the use of the VaR has been contended by several authors, who argue that it presents undesirable risk characterization and mathematical properties. The most cited criticisms include the impossibility of properly capturing the most extreme tail-end events, the demand of measuring all risks on normally distirbuted functions, the fact that it is not a coherent risk measure due to its lack of sub-additivity [1].

Seeking to improve upon these shortcomings, Rockafellar and Uryasev proposed the Conditional Value at Risk measure in 1999, and has since become an arguably preferred measure over the Value at Risk. The CVaR is the mean loss in the quantile bounded by the VaR. A visual definition of the CVaR and its relation to the VaR is presented in Figure 4.1.

[1]Coherent risk measures are those that have four distinct mathematical properties: positive homogeneity, translation invariance, sub-additivity and monotonocity [74]. Although an in-depth explanation of the reasons for desiring these properties is beyond the scope of this chapter, suffice to say that they capture the fundamental aspects of portolio risk behaviour.

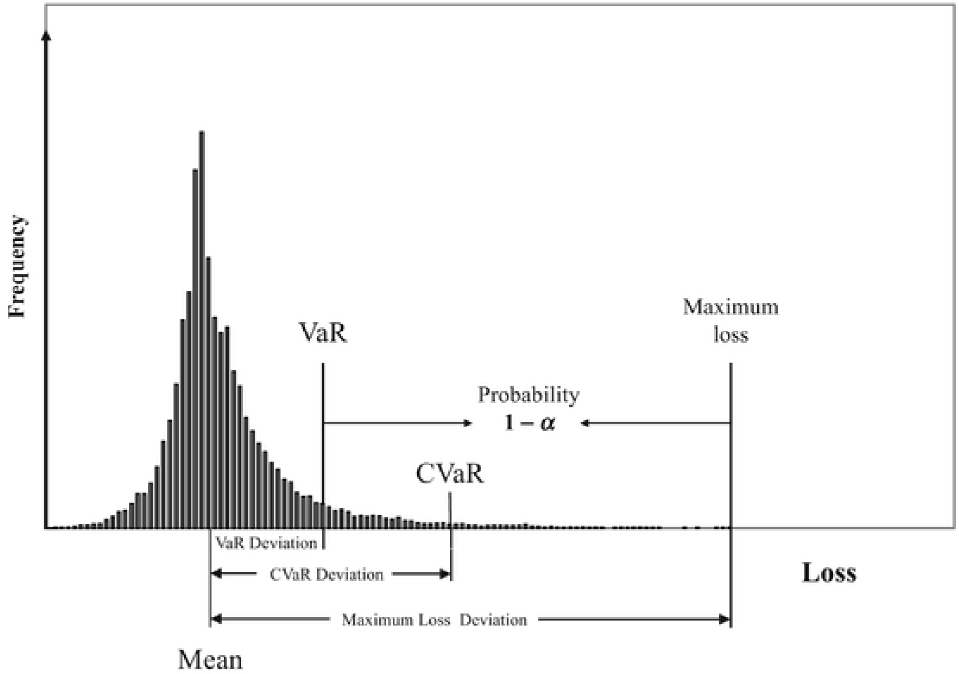


Figure 4.1: Visual representation of the relationship between VaR and CVaR [2].

The Conditional Value at Risk presents a number of mathematical and financial properties that are considered superior to the plain Value at Risk:

- The CVaR is a coherent risk measure which manages to capture the effect of tail-end scenarios above the VaR.
- The CVaR is not contingent on a particular risk probability density function.
- The CVaR is a continuous, convex function that can be optimized through the inclusion of linear constraints. By contrast, the VaR is a discontinuous function that requires extensive manipulation to be applied to large-scale optimizations.

The CVaR is recurrently used as a financial risk measure in energy optimization problems, such as microgrid control, participation in the spot market, and energy policy design [75]. Hence, the CVaR was selected as the risk measure for the optimization problem at hand.

The CVaR is defined as per Equation 4.1:

$$CVaR = min\left(\zeta - \frac{1}{1-\alpha} \cdot \int_0^\alpha [f(x,y) - \zeta]^+ \cdot p(y) \cdot dy\right) \tag{4.1}$$

In Equation 4.1, α is the confidence interval that bounds the CVaR, $f(x,y)$ is the profit function, $p(y)$ is the probability distribution of the loss function, and ζ is an auxiliary variable which tends to the VaR as the CVaR tends to its optimal value. This can be discretized as Equation 4.2.

$$CVaR = min\left(\zeta - \frac{1}{1-\alpha} \cdot \sum_{i=1}^{i=I} \pi_i \cdot [f(x,y) - \zeta]^+\right) \tag{4.2}$$

It should be noted that ζ might not be the same as the historical Value at Risk that can be calculated by analyzing the $1-\alpha$ worst historical cases. Instead, ζ would represent the "local" Value at Risk, calculated by the $1-\alpha$ worst cases within the selected interval I. Therefore, ζ becomes a proxy variable in Equation 4.2, which will assume its proper value as the optimization reaches its optimal point.

The term $[f(x,y)-\zeta]^+$ represents the effective earnings once the VaR has been considered. By its definition, this term will always be positive, and it can be represented by the auxiliary variable μ. This term can be understood as the conditional revenue at risk.

Therefore, the calculation of the CVaR based on Equation 4.2 can be rewritten as an optimization problem with the following objective function (Equation 4.3) and constraints (Equation 4.4):

$$CVaR = \min\left(\zeta - \frac{1}{1-\alpha} \cdot \sum_{i=1}^{i=I} \pi_i \cdot \mu_i\right) \tag{4.3}$$

$$-f(x_i, y_i) - \mu_i + \zeta \leq 0 \tag{4.4}$$

Finally, the risk acceptance factor β can be added to Equation 4.3, in order to quantify the willingness to accept the risk of losing profits up to CVaR, as per Equation 4.5.

$$CVaR = \min\left(\beta \cdot \left[\zeta - \frac{1}{1-\alpha} \cdot \sum_{i=1}^{i=I} \pi_i \cdot \mu_i\right]\right) \tag{4.5}$$

The risk acceptance parameter β represents the *willingness* to accept losing the $1-\alpha$ worst revenue scenarios, and it can take values between 0 and 1. Operating under $\beta = 0$ means that losses are fully accepted and the effect of the stochastic scenarios is not contemplated in the optimization. Operating under $\beta = 1$ is a maximum risk-avoiding strategy in which losses are fully considered on the optimizations.

4.2. Optimizing under uncertainty

As previously stated, participating in the Day Ahead and Intraday markets demands the consideration of values that are not known at the moment of making the bids; namely, the generation that will be available at delivery time. Hence, the nature of the optimizations is an inherently uncertain one, and the stochastic behavior of these inputs has to be considered in order to propose an optimal dispatch.

The selection of an optimization method is not a trivial matter, since it will determine the construction of the problem and the applicability of the solution. The following considerations have to be minded for deciding on one particular method for optimizing using Matlab:

- Matlab's solvers can only deal with deterministic problems.
- The uncertainty in the weather inputs has to be considered for the joint wind and PV generation. This would make deriving uncertainty sets for the generation notably difficult, especially considering that the probability function for both generations is not continuous (unlike the probability function for the weather resources themselves).
- The resulting optimization problem needs to be solved within the allocated time periods to submit bids: 24 hours for the DA bids, and the selected closing time for the ID market (with the minimum contract length being 15 minutes).

4.2.1. Review of stochastic optimization methods

The problem of opimizing with uncertain variables has been a topic of interest since the 1950's, with the first formal paper for linear optimization under uncertainty being published in 1955. Most efforts in the field of optimization under uncertainty focus on solving multistage problems - those in which decisions are taken both before and after the uncertain variables are realized. For the problem at hand, these two stages would be the market bidding and the Real Time delivery. Although imbalance penalizations can be curtailed by taking corrective measures in the Real Time dispatch (once the actual weather resources are known), that dispatch is still influenced by the program submitted in he previous market closings.

A 2018 literature review on methods for solving multistage optimizations with uncertainty revealed that the most prominent methods for tackling such problems are derived from three basic concepts: stochastic programming, robust optimization, and online optimization:

Stochastic optimization

Under this method, the random nature of the stochastic variables ξ is introduced through their probability distribution $\mathcal{F}$. The feasible set of possible realizations of ξ is discretized through the generation of scenarios, and based on the probability distribution $\mathcal{F}$ the expectancy of each scenario can be obtained $\mathbb{E}_{\xi\sim\mathcal{F}}[\cdot]$.

This results in a deterministic second-stage problem of the form

$$\min\left[\mathbb{E}_{\xi\sim\mathcal{F}}\left[f(x,\xi)\right]\right]$$

In which x is the solution to the first-stage problem. The full two-stage optimization with several second stage scenarios is therefore

$$\min\left[c^T x + \mathbb{E}_{\xi_1}\left[f(x,\xi_1)\right] + \mathbb{E}_{\xi_2}[f(x,\xi_2)] + ... + \mathbb{E}_{\xi_S}[f(x,\xi_S)]\right]$$

The stochastic method has the advantage of being a straightforward formulation that provides a feasible solution for any scenario reflected in the optimization, and takes into account the possibility of each being realized. The main downside is that this necessitates generating an array of possible scenarios, knowing the probability of each being realized; and that the inclusion of each scenario exponentially increases the number of decision variables and constraints to the optimization. Figure 4.2 shows an example of this exponential increase using a scenario generation tree with three branch levels, each with two scenarios. The computational burden resulting from this is a major hindrance for the application of the stochastic method [76].

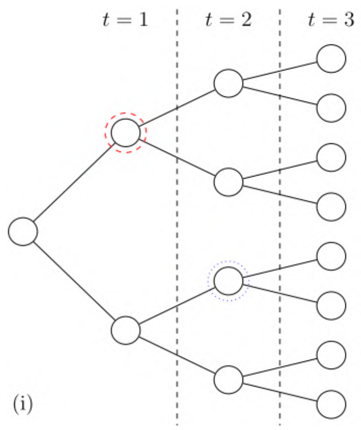


Figure 4.2: Representation of a three-stage scenario decision tree

Therefore, selecting the scenarios has to balance the need to provide a coherent overview of relevant scenario realizations while not causing an unfeasible computational burden. The scenario selection process often consists of generating a pool of scenarios, and then reducing them to select only the most representative ones.

Common scenario generation techniques include random value generation, using methods such as Monte Carlo simulations or time series extrapolations based on historical data; property matching, and growing-and-cutting methods. These multi-scenario generation methods are usually followed by scenario reductions, which aim to cut the number of scenarios to reduce the computational burden while maintaining a comprehensive representation of probable realizations. Probability metrics are often use to eliminate scenarios [77].

The advantages of stochastic optimization is that it is intuitive and straightforard to implement. An array of possible realizations is contemplated, with the likelihood of each being weighted in the final solution.

The downside is that it is very computationally heavy - not only the optimization itself, but the scenario generation and reduction process can also be very dense depending on the number of scenarios generated, the scenario selection criteria, and the generation and reduction methods selected. Consequently, the scenario selection has to be carefully set up, and further mathematical manipulation might be needed to solve the opimization problem.

Robust optimization

Instead of estimating the likelihood of scenario realizations, robust optimization makes use of uncertainty sets bound by the extreme case parameters that contain all possible realizations of the stochastic variables. The uncertainty set conformed by all variables is denoted $\mathcal{U}$. Each possible combination of parameters is called an "instance" i, and under robust optimization the stochastic problem is transformed into a set of deterministic problems $\mathcal{P}_{\mathcal{U}}$ solved under i.

$$\mathcal{P}_{\mathcal{U}} = \{\min\left[f(i,x) : x \in \mathcal{X}(i)\}_{i \in \mathcal{U}}\right]$$

The uncertainty set $\mathcal{U}$ is a multi-dimensional set, and using it straightforwardly leads to an exponential increase in the complexity of the problem, leading to computational and tractabiloty issues. Therefore, the set is often reduced to the so-called primitive uncertainties that bounds the individual variables by a set distance.

Robust optimization is often understood as a ”worst-case-scenario” optimization, since the solution at any bound is unweighted and guaranteed. The solution to the problem will thus be set by the worst-case limits of the uncertainty set U. The advantage is that this guarantees an optimized solution even at the most extreme values of the stochastic variables, albeit this will be an overly conservative solution (and thus not optimal) for non-extreme cases. The downside is that working with uncertainty sets requires extensive processing to ensure feasibility and tractability, and potentially using specialised solvers.

Online optimization

In contrast to the two previous methods, which stem from mathematical optimization, online optimization is based on computer science. In this context, an ”online” refers to a problem for which there is no or incomplete knowledge about the future (as opposed to ”offline” problems, which have complete and closed information). In online optimization decisions are irrevocable (cannot be altered in future instances) and sequential (every decision has to be taken before moving to the next element).

The applications of online optimization are largely limited to the field of computer science, namely, the development of competitive optimizations in which the solutions of online and offline problem formulations are contested. The advantages of online optimization are that it provides quick solutions, with the complexity of the problem at a certain time instance being unaffected by the overall problem size; and it is also independent from probability distributions or certainty sets since no information about subsequent instances is required to make a decision at a certain instance. Much like robust optimization, the solutions are overly conservative and bound by the worst-case-scenario.

The combination of these methods has led to the rise of disciplines like online stochastic programming and robust dynamic stochastic programming. In addition to these basic methods, there are two emerging theories that have generated much interest over the past years: dynamic optimization, and chance-constrained optimization:

Dynamic optimization

Dynamic programming is an optimization method derived from stochastic programming. It is based on Bellman’s optimality principle, which states that an optimal solution between an initial and a final point necessitates the solution in the intermediate points to be optimal as well. Dynamic optimization is linked to Markov’s chains (those in which the next state of the system is exclusively dependent in its previous states), and thus uses the change in state variables to reiterative solve Bellman’s equation until convergence is achieved

$$f_t(i_t) = \min_{x_t \in X_t} \left\{ \mathbb{E}[g_t(x_t, i_t)] + \alpha \sum_{i_t+1} p(i_{t+1}|x_t, i_t) \cdot f_{t+1}(i_{t+1}) \right\}$$

Dynamic programming is technically a solution method, but problems can be specifically tailored to be solved via dynamic optimization. This requires formulating the problem so that the system state is a Markovian process, and changing the objective function to optimize the discounted average costs over the entirety of the process.

Dynamic programming suffers from the curse of dimensionality, with problems growing exponentially and becoming too computationally cumbersome to solve. Methods have been derived to reduce the number of calculations needed, but they usually require extensive processing of the state and action spaces.

Chance-constrained optimization

Chance-constrained optimization is an optimization method that ensures that the solution is feasible for realizations of the stochastic parameters with a certain probability of becoming true. It can be understood as a robust optimization with a restricted uncertainty set. Although a powerful concept, solving problems using this method is notably challenging; with issues such as the difficulty to transform the stochastic bounds into deterministic constraints and the non-convexity of the resulting feasible region.

4.2.2. Stochastic optimization method selection

Given how the Matlab optimization toolboxes can only handle deterministic optimizations, and that the uncertainty distribution functions of the weather resources are not known, the most suitable optimization method would be to use stochastic optimization.

Using this method necessitates drafting a suitable method for scenario selection, which has to both provide a comprehensive representation of possible scenario realizations without generating an unmanageable optimization. Furthermore, since the ID forecasts are dynamic and get updated after every closing, the scenario generation itself also cannot take too long to compute.

As explained in chapter 1, part of the synergy between energy storage sources and non-controllable energy sources is how the former can curtail program imbalances due to errors in weather forecast. Therefore, the stochastic scenarios that are interesting to consider are the potential generation profiles which are within the bounds set by the battery charging and discharging capabilities, since that is the range that can be acted upon for correcting the energy programs. These battery limits therefore serve as the bounds for the scenario generation, as seen in Figure 4.3.

For which the upper bound is the predicted energy plus the maximum charge rate of the battery, and the lower bound is the predicted energy minus the maximum discharge rate. The stochastic scenarios can be drafted through Monte Carlo sampling, and each would define a possible generation profile that could potentially be realized at delivery time with a certain

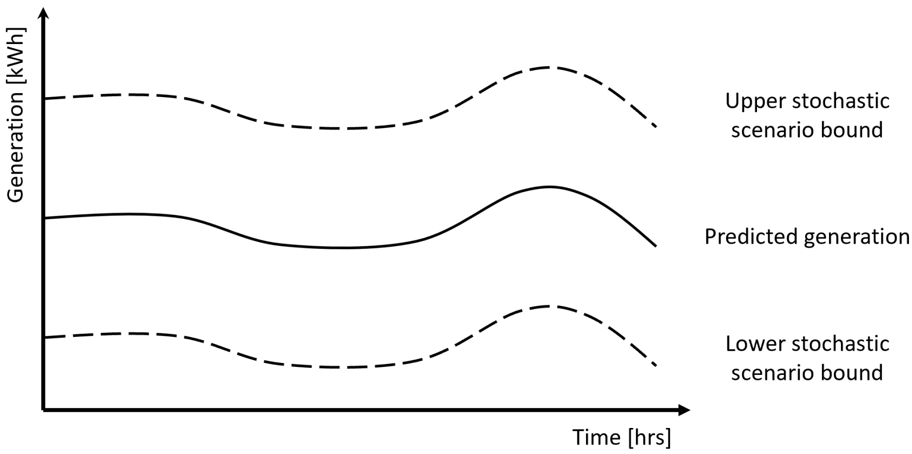


Figure 4.3: Representation of a three-stage scenario decision tree

probability. A detailed explanation on the stochastic scenario generation will be presented in chapter 5.

The scenarios are independent among them, although the CVaR ζ of the overall optimization has to be calculated by considering all the conditional revenues μ from all the scenarios together.

The resulting optimization would be a deterministic one, in which $\omega \in \Omega$ scenarios would be considered, each with a probability π_ω of being realized. The objective function would follow the form described by Equation 4.6.

$$\min\left(c^T x + \pi_{\omega_1} \cdot [f(x,\omega_1)] + \pi_{\omega_2} \cdot [f(x,\omega_2)] + ... + \pi_{\omega_\Omega} \cdot [f(x,\omega_\Omega)]\right) \tag{4.6}$$

4.3. Optimization with CVaR and stochastic scenarios

The stochastic set up described in section 4.2 has an impact in the set up of the optimizations described in chapter 3. While those optimizations consider the generation forecast only for the market closing for which they are set up, the stochastic optimizations also require considering possible realizations of prices and generation for the moment at which the energy will be delivered.

The goal of the stochastic optimizations remains the same as those presented in chapter 3: to maximize the profits, defined as revenue minus losses. However, the stochastic optimizations include an additional term for the calculation of potential losses in the form of the CVaR, that would potentially be incurred in each scenario realization for a given energy dispatch.

4.3.1. Day-Ahead dispatch

The definition of DA optimization depends on whether the plant operator intends to participate in the ID market or not:

- If there is no participation in the ID market, the CVaR would be calculated from the profits or losses incurred in the imbalance settlement period for the net energy traded in the Real Time dispatch. The decision variables would comprise those defined for the DA optimization in section 3.1 and the RT dispatch in section 3.3.

- If there is participation in the ID market, the CVaR would be calculated from the losses incurred in the imbalance settlement period due to deficits in the energy sold or purchased, since increases in the energy sold or purchased would be passed as bids in the ID market. The decision variables would comprise those defined for the DA optimization in section 3.1 and the Intraday dispatch in section 3.2.

Objective function

The objective function is the same with or without ID participation. The predicted revenue for the DA closings would be the revenue earned by selling energy minus the cost of purchasing it and operating the battery, plus the CVaR risked in the next market closing whether that is the ID or RT dispatch. For H hourly DA closings and considering Ω scenarios, the objective function would be defined as per Equation 4.7.

$$Profit = \sum_{h=1}^{h=H} \lambda_{DA,h} \cdot \left(E^{\text{DA}}_{\text{pred},h} - E^{\text{DA}}_{\text{gen to batt},h} + E^{\text{DA}}_{disch,h} - E^{\text{DA}}_{\text{grid to batt},h}\right) - MC_h +$$

$$\beta \cdot \left[\zeta - \frac{1}{1-\alpha} \cdot \sum_{\omega=1}^{\omega=\Omega} \pi_{h,\omega} \cdot \mu_{h,\omega}\right] \quad (4.7)$$

Constraints

The decision of participating or not in the ID market has the biggest effect in the definition of the constraints, particularly the definition of the term μ. Those related to the physical constraints of the system (such as the limits for the battery state of charge, the power equation, or the condition that all energy produced had to be dispatched) remain the same for either case.

Without ID participation

The constraints related to the physical limitations of the system for the DA and RT dispatch remain the same. This covers Equation 3.4-Equation 3.9, Equation 3.28 and Equation 3.30-Equation 3.38. The definition of μ in this case would be as presented in Equation 4.8.

$$-\left[\lambda^{\text{DA}}_{h} \cdot \left(E^{\text{DA}}_{\text{pred},h} - E^{\text{DA}}_{\text{gen to batt},h} + E^{\text{DA}}_{disch,h} - E^{\text{DA}}_{\text{grid to batt},h}\right) + \lambda^{+}_{h,\omega} \cdot \Delta^{+}_{h,\omega} - \lambda^{-}_{h,\omega} \cdot \Delta^{-}_{h,\omega}\right] +$$

$$\zeta - \mu_{\omega} \leq 0 \quad (4.8)$$

With ID participation

The constraints related to the physical limitations of the system for the DA and ID dispatch remain the same. This covers Equation 3.4-Equation 3.9, Equation 3.13, Equation 3.12 and Equation 3.15-Equation 3.26. The definition of μ in this case would be as presented in Equation 4.9.

$$-\left[\lambda_h^{\mathrm{DA}} \cdot \left(E_{\mathrm{pred},h}^{\mathrm{DA}} - E_{\mathrm{gen\ to\ batt},h}^{\mathrm{DA}} + E_{\mathrm{disch},h}^{\mathrm{DA}} - E_{\mathrm{grid\ to\ batt},h}^{\mathrm{DA}}\right) + \lambda_{h,q}^{\mathrm{ID}} \cdot (\Delta_{\mathrm{sell},h,q}^{+} - \Delta_{\mathrm{grid\ to\ batt},h,q}^{+})\right] +$$

$$\left[\lambda_{\mathrm{imb},h,q}^{+} \cdot \Delta_{buy\ h,q,\omega}^{-} - \lambda_{\mathrm{imb},h,q}^{-} \cdot \Delta_{\mathrm{sell}\ h,q,\omega}^{-}\right] + \zeta - \mu_\omega \leq 0 \quad (4.9)$$

4.3.2. Intraday dispatch

In the case of the Intraday dispatch, the stochastic realizations that would be considered for the next market closings would correspond to the Real Time dispatch. The profit or losses in the Real Time dispatch are determined by the net deviations from the ID program in the delivery.

Objective function

The predicted revenue for the ID closings would be the revenue earned by selling energy minus the cost of purchasing it and operating the battery, plus the CVaR risked in the RT dispatch. For H DA closings, each with Q=4 quarterly ID closings and R=4 quarterly RT the objective function is given by Equation 4.10:

$$Profit = \sum_{h=1}^{h=H} \sum_{q=1}^{q=Q} \lambda_{h,q}^{\mathrm{ID}} \cdot \left(\Delta_{\mathrm{sell},h,q}^{+} - \Delta_{\mathrm{buy},h,q}^{+}\right) - MC_{h,q} + \beta \cdot \left[\zeta - \frac{1}{1-\alpha} \cdot \sum_{\omega=1}^{s=\Omega} \pi_\omega \cdot \mu_\omega\right] \quad (4.10)$$

Constraints

The constraints remain the same as those presented in Equation 3.13, Equation 3.12 and Equation 3.15-Equation 3.26, plus the addition of the CVaR definition (Equation 4.11):

$$-\left[\lambda_{h,q}^{\mathrm{ID}} \cdot (\Delta_{\mathrm{sell},h,q}^{+} - \Delta_{\mathrm{buy},h,q}^{+}) + \lambda_{\mathrm{imb},h,r}^{+} \cdot \Delta_{\mathrm{net},h,r,\omega}^{+} - \lambda_{\mathrm{imb},h,r}^{-} \cdot \Delta_{\mathrm{net},h,r,\omega}^{-}\right] + \zeta - \mu_\omega \leq 0 \quad (4.11)$$

Real Time dispatch

Since the Real Time is the last market closing and the generation at the moment of delivery is known, the Real Time dispatch does not have a particular stochastic formulation and remains the same as the one presented in section 3.3.

4.4. Modified Bender's cut for solving the stochastic optimization

The resulting optimization once the CVaR and stochastic scenarios have been incorporated presents a two-stage nature. Two-stage optimizations are those in which certain decisions have to be taken before the value of a set of random variables is known (first stage), and some other decisions have to be made after the value of this set of random variables is known (second stage) [78]. Such a formulation would result in a large-scale optimization prone to suffering from the curse of dimensionality as more stochastic scenarios are considered.

For the optimizations presented in section 4.3, taking the case that there is no ID participation, the first stage decisions would be the DA dispatch (which have to be submitted before the weather at the delivery time is known), and the Real Time dispatch would be the second stage decisions (when the weather conditions, and thus the available generation, are known). Since the trade deviations in the Real Time dispatch are relative to the program submitted for the DA, the second stage variables are coupled to the first stage variables; whereas the formulation of the first stage variables is independent of the second stage variables.

If the Intraday was to be considered, the stochastic optimization would be divided into two: a first problem to get the Day Ahead program, in which the first stage would be the Day Ahead optimization and the second stage would be the Intraday optimization; and a second problem to get the Intraday program, in which the first stage would be the Intraday optimization and the second stage would be the Real Time optimization.

The application of the modified Bender's cut described in this section would not change for any of the problems described above, regardless of what market closings belong to the first and second stage of the stochastic optimizations.

Since the second stage variables are taken once the value of the random variables is "set" (once the weather conditions are known), this second stage is said to be of fixed recourse [79].

The resulting two-stage stochastic problem has the form presented in Equation 4.12.

$$c^T\mathbf{x} + E_\xi \cdot [\min q(\omega)^T\mathbf{y}] \tag{4.12}$$

In Equation 4.12, $\mathbf{x}$ represents the first stage decision variables, and $\mathbf{y}$, the second stage decision variables, $\omega \in \Omega$ is the set of probable stochastic scenario realizations, and E_ξ is the expectation of random variable ξ. The equality and inequality constraints of the first stage would have the form shown in Equation 4.13 and Equation 4.14.

$$A_{\text{eq}}\mathbf{x}^T = b_{\text{eq}} \tag{4.13}$$

$$A_{\text{ineq}}\mathbf{x}^T = b_{\text{ineq}} \tag{4.14}$$

In which A_{eq} is the matrix with the coefficients of the equality constraint equations, and b_{eq} is the vector with the constants of the equality constraint equations. Similarly, A_{ineq} is the matrix with the coefficients of the inequality constraint equations, and b_{ineq} is the vector with the constants of the inequality constraint equations.

And the equality and inequality constraints of the second stage stage would have the form shown in Equation 4.15 and Equation 4.16.

$$B'_{\text{eq}}(\omega)\mathbf{x}^T + A'_{\text{eq}}\mathbf{y}(\omega) = b'_{\text{eq}}(\omega) \tag{4.15}$$

$$B'_{\text{ineq}}(\omega)\mathbf{x}^T + A'_{\text{ineq}}\mathbf{y}(\omega) = b'_{\text{ineq}}(\omega) \tag{4.16}$$

$B'_{\text{eq}(\omega)}$, $b'_{\text{eq}(\omega)}$, $B'_{\text{ineq}(\omega)}$, and $b'_{\text{ineq}(\omega)}$ represent the equality and inequality matrices and vectors for the second stage, whose value depends on the possible realizations of the stochastic scenarios represented by ω. $A'_{\text{eq}(\omega)}$ and $A'_{\text{ineq}(\omega)}$ are the matrices that represent the influence of the first stage solution $\mathbf{y}$ on the second stage solution.

As it can be seen, the terms related to the first stage are effectively a deterministic problem, independent of the realizations of the stochastic variables ξ. Meanwhile, the second stage terms depend both on ω and on the values of the first stage decision variables.

The optimization of the energy dispatch at hand offers an intuitive illustration of the nature of this dependence, illustrated in Figure 4.4.

1. In the first stage, when the Day-Ahead bids have to be calculated, the only information available is a prediction for the possible forecast for the next day.
2. The second stage is the Real Time dispatch, which is done after the weather conditions are known. And, as shown in Equation 3.29, the value of this optimization (namely, the deviations between the energy actually traded and the trade programs) depends on the bids submitted in the Day Ahead.

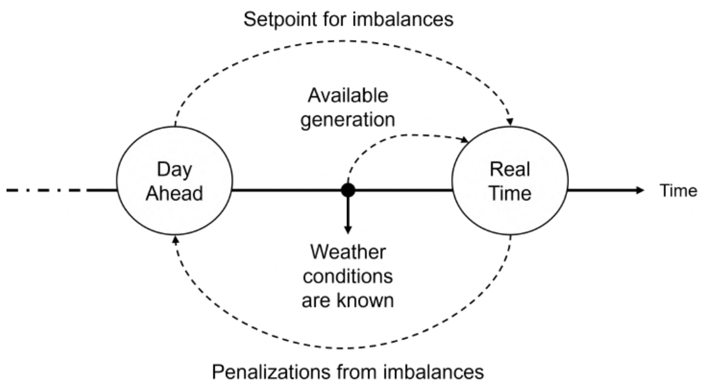


Figure 4.4: Representation of the first and second stage decisions for the optimization, and how they influence each other

The Bender's cut makes use of the dual property of linear problems to generate a series of constraints, or "cuts", that define the feasibility and optimality requirements of the decision variables. These cuts are determined by the extreme points and rays of the subset defined by the second stage variables.

Several methods for solving two-stage optimizations have been described in the literature [80], some of which have been modified to improve computation time and adapt them to different types of optimization problems. Among them, the Bender's cut (also known as the L-shaped cut) remains a popular method for solving two-stage optimization problems [81], and has been successfully adapted for two-stage problems with a Mixed Integer second stage with equality and inequality constraints [82].

Hence, the Bender's cut requires breaking down the original optimization problem into a master problem and Ω sub-problems:

- The master problem, which is a deterministic problem comprising only the first-stage variables, and onto which the cuts are projected.
- The sub-problems, which are solved as equivalent deterministic problems for a fixed first-stage solution and a set realization of the ξ stochastic variables of a given scenario ω. There are as many sub-problems as scenario realizations, which go up to Ω. The solutions to these sub-problems are passed as cuts in the master problem.

The effect of the bBender's cuts on the first-stage objective function are represented in Figure 4.5, which showcases how the feasible solution space of the optimization is delimited by adding succesive feasibility and optimality cuts that act as linear constraints to the master problem.

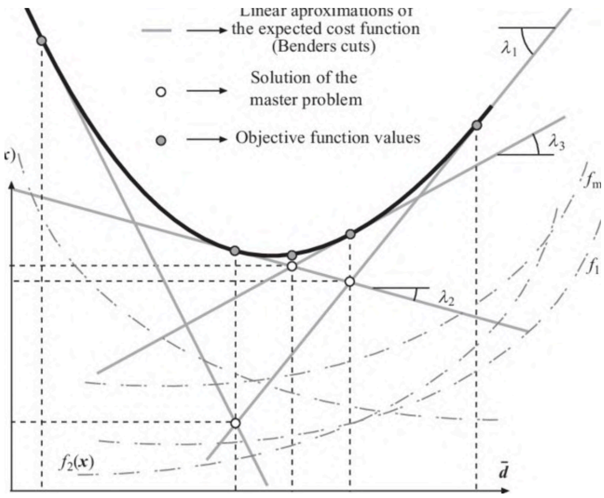


Figure 4.5: Visual representation of the delimitation of the feasible solution subset using successive optimality cuts, following the Bender's decomposition method [3].

The optimizations defined in section 4.3 based on the equations presented in chapter 3 have a non-linear first stage due to the presence of the fractional cost term; and a mixed integer linear second stage. The cut generation method proposed by Gejirifu De et. al [82] for problems with first and second stage Mixed Integer problems can be applied to solve it.

This method is based on an iterative recomputation of the master problem, with subsequent cuts added until the difference between iterations falls below a user-defined threshold. The process is illustrated in Figure 4.6, and explained in further detail below.

i. Initialize the upper bound $UB = +\infty$ and the lower bound $LB = -\infty$

ii. Initialize the fixed first stage solution, $\bar{x}$, by solving the first stage problem without considering the second stage.

1. Using the fixed first stage solution $\bar{x}$, solve the second stage MILP problem considering all scenarios to obtain the Conditional Value at Risk $\bar{\zeta}$ and a preliminary solution for the rest of variables, $\mathrm{y}_{\mathrm{prelim}}$.

2. Using $\bar{x}$, $\bar{\zeta}$, and $\mathrm{y}_{\mathrm{prelim}}$, calculate the value of the original objective function of the full optimization problem (Equation 4.17) to find the updated upper bound UB.

$$c^T\mathbf{x} + E_{\xi} \cdot [\min q(\omega)^T\mathbf{y}] \tag{4.17}$$

3. Check if the difference in upper and lower bounds is below the defined threshold:

$$|UB - LB| < \epsilon \tag{4.18}$$

4. If **not**, add a new optimality cut to the first stage problem.

   For every stochastic scenario ω, analyzed individually:

   4.1. Using $\bar{x}$ and $\bar{\zeta}$, find the solution for the MILP second stage sub-problem. This will yield a solution for the integer variables, $\bar{\delta}_i$.

   Note: Having a set value for the binary variables of the second stage allows to relax the second stage problem into a Linear Problem by treating the binary variables as constants in the constraints.

   4.2. Using $\bar{x}$, $\bar{\zeta}$, and $\bar{\delta}_i$, solve the dual problem of the relaxed second stage to find its Lagrangian multipliers.

   The problem is a Linear optimization problem with equality and inequality constraints, each with the associated multipliers μ_1' and ρ_1' respectively:

$$\min\ (q(\omega)^T\mathbf{y}) \tag{4.19}$$

$$A'_{\mathrm{eq}}\mathbf{y}(\omega) = b'_{\mathrm{eq}}(\omega) - B'_{\mathrm{eq}}(\omega)\bar{x}\ :\ \mu_1' \tag{4.20}$$

$$A'_{\mathrm{ineq}}\mathbf{y}(\omega) = b'_{\mathrm{ineq}}(\omega) - B'_{\mathrm{ineq}}(\omega)\overline{x}\ :\ \rho_1' \tag{4.21}$$

Solving this problem will yield a new solution for the second-stage variables of the sub-scenario, $y_{\text{updated},\omega}$; and the dual objective function that can be used to construct the Bender's cut for this stage.

4.3. Add a Bender's cut to the relaxed second stage optimization. This is done by substituting the objective function Equation 4.19 by the dual objective function of the problem, using the proxy variable α_s . The objective function becomes:

$$\min\ (\alpha_s) \tag{4.22}$$

And the extra constraint defining α_s is added:

$$\alpha_s \geq (b'^T_{\text{eq}} \cdot \rho' + b'^T_{\text{ineq}} \cdot \mu') - (B'^T_{\text{eq}} \cdot \rho' + B'^T_{\text{ineq}} \cdot \mu')^T \cdot \overline{y} \tag{4.23}$$

The resulting constraint matrices, after Equation 4.23 is added, are denoted A''_{eq}, b''_{eq}, B''_{eq}, A''_{ineq}, b''_{ineq}, and B''_{ineq}.

The second stage problem with the added cut is also a Linear Problem with equality and inequality constraints, and its dual solution is associated with the multipliers μ_1'' and ρ_1''.

$$A''_{\text{eq}}\mathbf{y}(\omega) = b''_{\text{eq}}(\omega) - B''_{\text{eq}}(\omega)\overline{x} \ : \ \mu_1'' \tag{4.24}$$

$$A''_{\text{ineq}}\mathbf{y}(\omega) = b''_{\text{ineq}}(\omega) - B''_{\text{ineq}}(\omega)\overline{x} \ : \ \rho_1'' \tag{4.25}$$

Solving this system will yield the dual objective function of the problem, α_ω, which is used to construct the Bender's cut in the first stage.

4.4. Add the Bender's cut to the first stage optimization. The objective function becomes

$$c^T\mathbf{x} - E_\xi \cdot \alpha_\omega \tag{4.26}$$

And the extra constraint is added to the first stage inequality matrix:

$$\alpha_\omega \geq (b''_{\text{eq}} - B''_{\text{eq}} \cdot y)^T \cdot \overline{\mu}'' + (b''_{\text{ineq}} - B''_{\text{ineq}} \cdot y)^T \cdot \overline{\rho}'' \tag{4.27}$$

5. Solve the first stage optimization with the added cuts. This will yield a new fixed first stage solution $\bar{x}$.

6. Gather all solutions to the sub-scenarios, $y_{\text{updated},\omega}$.

7. Use the new $\bar{x}$ and the previously calculated the previously calculated $\bar{\zeta}$ and $y_{\text{updated},\omega}$ to calculate the value of the objective function of the full optimization problem. This value is the lower upper bound, LB.

Steps 1-7 are to be repeated until the convergence criteria in step 3 is fulfilled.

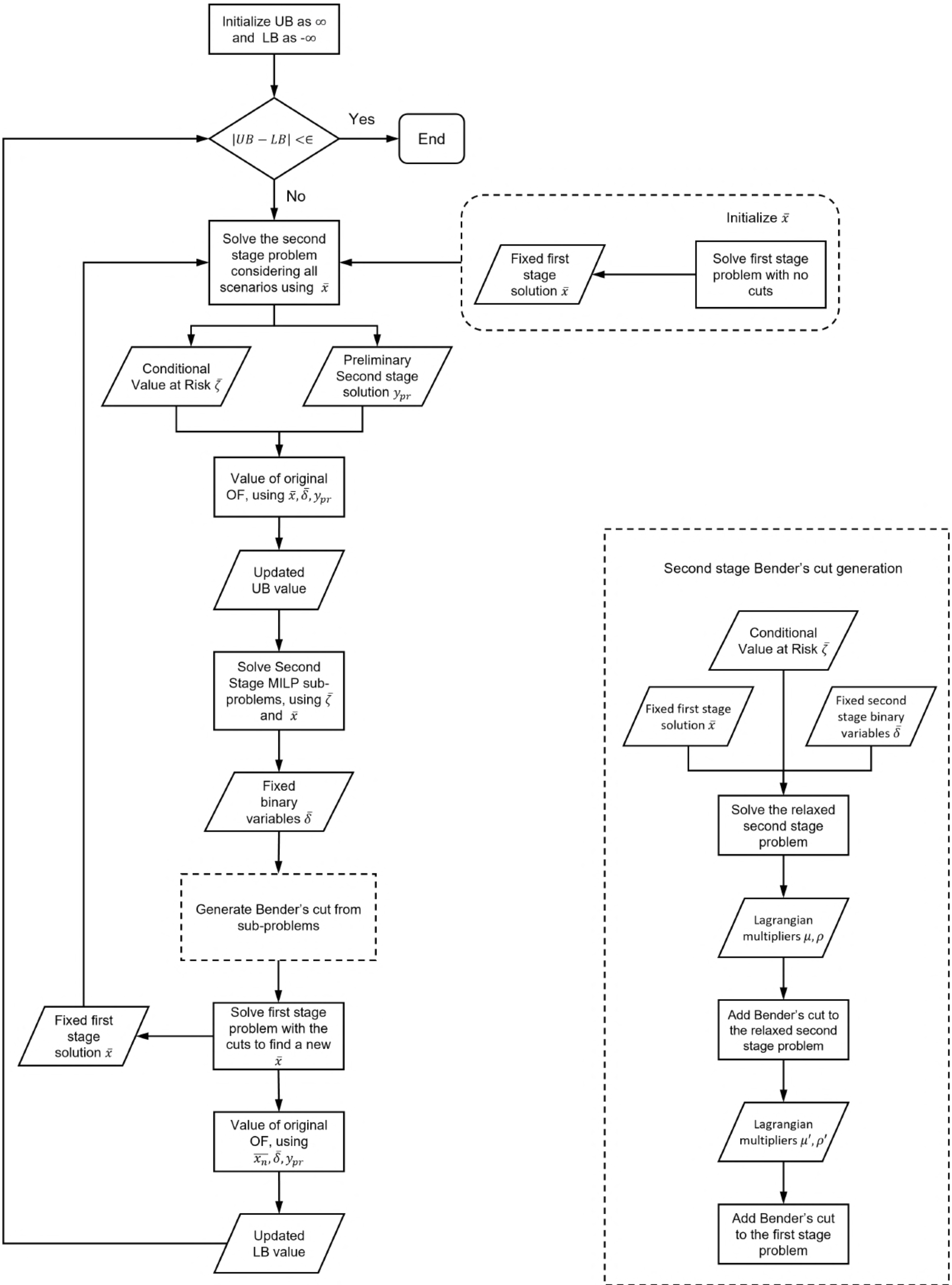


Figure 4.6: Flowchart representing the iterative process to solve the optimization using Bender's decomposition.

5

Input prediction and modelling

This chapter presents the methodology followed to model the energy inputs for the optimizations. It covers three areas: the modeling of the energy assets in section 5.1, the generation of weather forecasts in section 5.3, and the generation of stochastic scenarios in section 5.4.

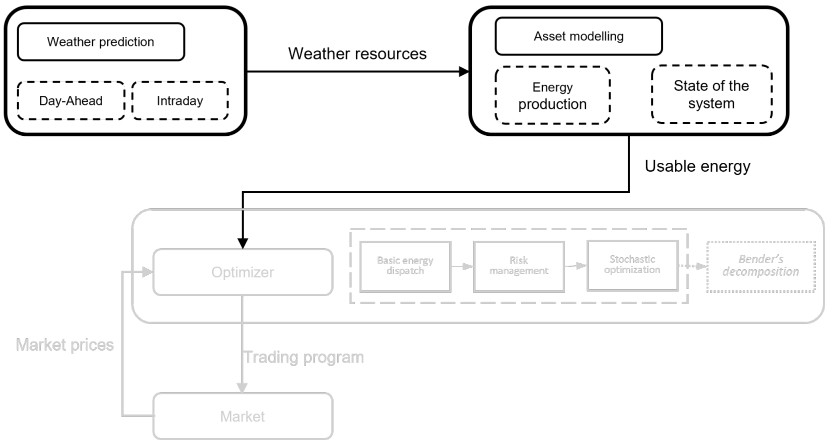


Figure 5.1: Diagram presenting the work flow for the thesis.

It should be noted that the scope of this thesis does not include the proposal or derivation of accurate prediction or modeling methods for either the weather resources or the energy production assets. The optimizations are fit to work with any given set of generation inputs, regardless of how these were obtained. The modeling of the inputs is therefore a relatively trivial matter, since it will not alter the working of the optimizer.

5.1. Energy asset modelling

This section presents the modelling of the energy flows in the hybrid power plant, focusing on the energy generation (which serves as the basic input for the dispatch strategy) and storage (which characterizes the system's state).

The power generated by a generation asset can be converted into energy by using Equation 5.1 [83].

$$E = \int_0^t P(t) \cdot dt \tag{5.1}$$

In which t represents the time interval on which the system is generating a certain power P. If the power production is constant in time, [83] is equivalent to Equation 5.2.

$$E = P \cdot \Delta t \tag{5.2}$$

The modelling of both wind and solar energy generation assets does not include their performance degradation due to extended use or environmental conditions. Their marginal cost operation is assumed to be negligible [84] [67]; and each respective type of generation is modeled as a single asset of each kind, neglecting the differences in performance of the individual turbines and panels and instead taking the total energy produced to be the number of PV panels or wind turbines multiplied by a uniform power output formulation.

This section also presents the weather resources available in the area for wind and PV generation. This data has been extracted from the website of the Dutch National Meteorology Institute (KNMI - Koninklijk Nederlands Meteorologisch Instituut), which has a historical database with recorded hourly average potential wind speeds, irradiance, and temperature at various stations [85]. Although there is no weather data publicly available for the precise location of the SWITCH lab, there is a KNMI station (Station 269) about 8 km away, located at the Lelystad airport [86].

5.1.1. Wind energy generation

The modeling of the power produced by a wind turbine is based on the aerodynamic equations that determine the power that can be extracted from the wind based on momentum and blade element theory, combined with the effect of the power electronics that convert that energy from mechanical to electrical [87].

The overall power that can be produced by a wind turbine is given by Equation 5.3 [88]

$$P_{\text{wind}} = \frac{1}{2} \cdot \rho_{\text{wind}} \cdot \pi \cdot \frac{D^2}{4} \cdot u^3 \cdot \mathrm{c_p} \cdot \eta_{\text{e+m}} \tag{5.3}$$

In which D is the diameter of the wind turbine, ρ_{wind} is the wind density, u is the wind speed, c_p is the power coefficient, and $\eta_{\text{e+m}}$ is the efficiency given by the performance of the electrical and mechanical components.

The power coefficient $\mathrm{c_p}$ is a measure of how much aerodynamic power the turbine is able to extract from the wind, which is contingent on the turbine design. It is bound by the physical interaction between the turbine and the air flow, with its maximum value being 59.3% [1]. Most modern wind turbines have a maximum power coefficient between 40%-50%, although its

[1]This limit is independent of the turbine design.

actual value for a given turbine design has to be determined through experimental testing. The power coefficient is not constant for every wind speed [88].

The effect of the various mechanical and electrical components in the power production is broadly reflected in the additive efficiency $\eta_{\mathrm{e+m}}$ [89]. Much like the power coefficient, this value has to be derived from experimental testing on a case by case basis.

The electrical components also affect the power production by setting the maximum and minimum power that the turbine can produce. This creates three well-defined regions of power production in relation to the wind speed [90], which can be seen in Figure 5.2:

- No production zones ($u < u_{\mathrm{cut-in}}$ and $u > u_{\mathrm{cut-out}}$: in these regions the turbine is idle and no power is produced, either because the wind speed is below the minimum speed needed to make the turbine turn (the cut-in wind speed $u_{\mathrm{cut-in}}$), or because it is so high that it could compromise the turbine's integrity (the cut-out wind speed $u_{\mathrm{cut-out}}$).
- Partial load ($u_{\mathrm{cut-in}} < u < u_{\mathrm{r}}$): when the wind speed is below the rated wind speed (the lowest speed that results in the maximum power production, also called the rated power production), the power increases with the cube of the wind speed as per Equation 5.3.
- Full load ($u_{\mathrm{r}} < u < u_{\mathrm{cut-out}}$): in this region the generator produces its maximum possible power, and thus the power production is kept constant at this maximum (rated) power. The torque on the generator is kept constant by adjusting the blade attitude and deploying mechanical torque reduction mechanisms.

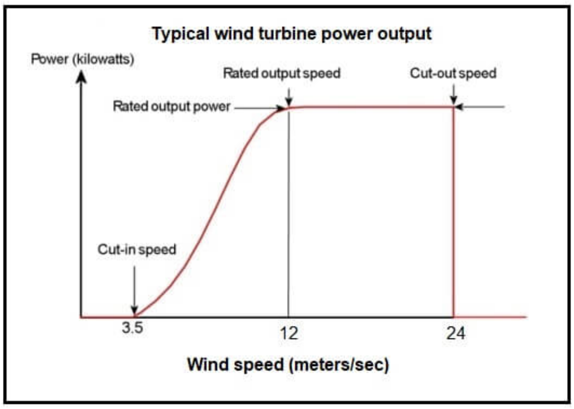


Figure 5.2: Representation of a typical power output graph as a function of the wind speed [4].

If the rated power $P_{\mathrm{wind,r}}$, and cut-in $u_{\mathrm{cut-in}}$ and rated u_{r} wind speeds are known, the partial load generation (Equation 5.3) can be approximated by Equation 5.4 [91]

$$P_{\mathrm{wind}} = P_{\mathrm{wind,r}} \cdot \left(\frac{u - u_{\mathrm{cut-in}}}{u_{\mathrm{r}} - u_{\mathrm{cut-in}}} \right)^3 \tag{5.4}$$

The final modelling of the wind turbine was done using Equation 5.4 for the partial load, with the rated wind speed being derived from Equation 5.3 into Equation 5.5:

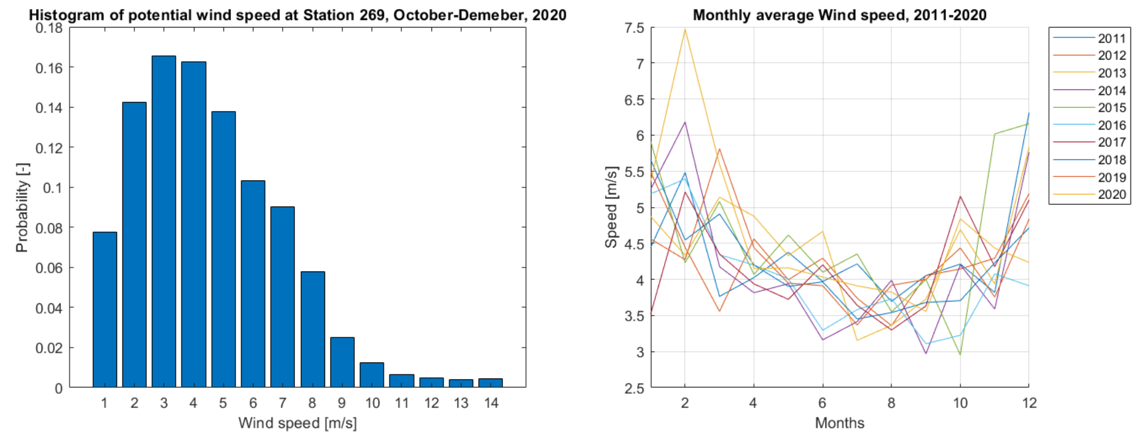
$$u_{\mathrm{r}} = \sqrt[3]{\frac{2 \cdot P_{\mathrm{wind,r}}}{\rho \cdot \frac{\mathrm{D}^4}{4}}} \tag{5.5}$$

The cut-in wind speed $u_{\mathrm{cut-in}}$ has to either be indicated by the manufacturer, or assumed based on data from similar wind turbines.

Since Equation 5.4 does not account for aerodynamic, mechanical or electrical losses, the power modelled will be an overestimation of the actual power generated.

Wind resources in the area

The historical data for average hourly wind speeds recorded at Station 269 can be seen in Figure 5.3. It includes a histogram of the data distribution for the period that will be studied (October-December 2020), and also the average monthly data for a 10-year period (2011-2020). As shown in Figure 5.3b, there is a clear monthly seasonality of the wind speed.



(a) Histogram of the hourly average potential wind speed at Station 269 for the October-December 2020 period.

(b) Monthly average potential wind speeds at Station 269 for the 2011-2020 period.

Figure 5.3: Historical potential wind speed data at Station 269

The wind speed needed to calculate the power in Equation 5.3 and Equation 5.4 is the wind speed at the rotor. However, the data provided by the KNMI is the potential wind speed, which by definition is measured 10 m above the ground. For tower heights below 60 m, wind speeds are scaled using the logarithmic boundary layer law seen in Equation 5.6:

$$u_{\mathrm{rotor}} = u_{\mathrm{pot}} \cdot \frac{\ln\left(\frac{h_{\mathrm{rotor}}}{z_0}\right)}{\ln\left(\frac{h_{\mathrm{pot}}}{z_0}\right)} \tag{5.6}$$

In Equation 5.6 z_0 is the surface roughness length, a factor which accounts for the effects of obstacles in the terrain [92]. The potential wind speed is defined for a very open terrain, usually characterized by a standard roughness length $z_0 = 0.003\mathrm{m}$ [93]. The conversion from potential to rotor wind speed is done by firstly translating the potential wind speed to blending height using the standard surface roughness, and then translating the wind speed at blending height to the rotor height using the local surface roughness. The value of the local surface roughness can be approximated based on data on aerodynamic analysis of various terrains. For a landscape with scattered trees and low buildings, the surface roughness could be approximated at $z = 0.25\mathrm{m}$

5.1.2. PV generation

The power generated by a PV panel is mainly dependent on the solar irradiance absorbed and the temperature of the cells [94]. Although there are a variety of models that correlate these two factors and the technical specifications of the cells to derive the power generated [95], [96], the most basic relation is given by Equation 5.7 [97].

$$P_{\mathrm{PV}} = \eta \cdot \mathrm{A} \cdot J_{\mathrm{a}} \tag{5.7}$$

With the panel efficiency η being defined in Equation 5.8 and Equation 5.9.

$$\eta = \eta_{\mathrm{stc}} \cdot [1 + \mathrm{k} \cdot (T_{\mathrm{m}} - T_{\mathrm{stc}})] \tag{5.8}$$

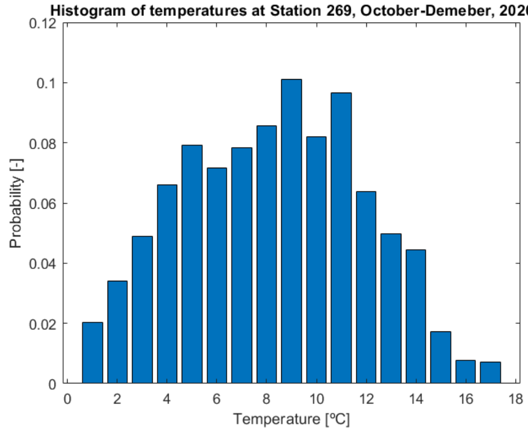
$$T_{\mathrm{m}} = T_{\mathrm{a}} + \frac{T_{\mathrm{nom}} - T_{\mathrm{NMOT}}}{J_{\mathrm{NMOT}}} \tag{5.9}$$

In Equation 5.7 - Equation 5.9, η_{stc} is the efficiency of the panel at standard testing conditions (at a temperature T_{stc} of 25°C and an irradiance of 1000 W/m^2), k is the temperature coefficient at maximum power, T_{nom} is the nominal cell operating temperature, T_{NMOT} is the the nominal module operating temperature at irradiance J_{NMOT}, T_{a} is the ambient temperature, and J_{a} is the ambient irradiance.

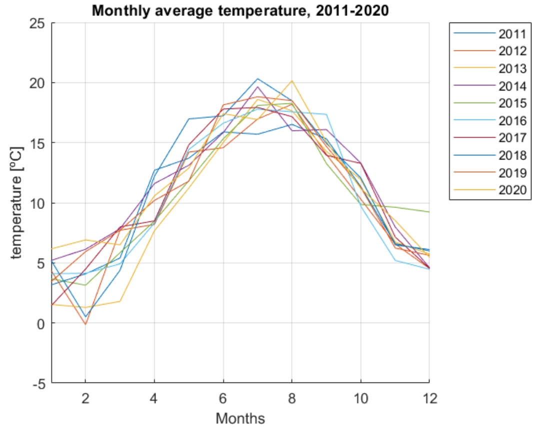
Equation 5.7 - Equation 5.9 assume a perfectly perpendicular irradiance beam that is fully absorbed at ambient temperature. This leads to an over-estimation in the energy produced, since in reality the relative position of the sun with respect to the plate and the irradiance and temperature dispersion would affect the production capacity of the panel.

Temperature and irradiance resources in the area

The KNMI also records historical data for the hourly average temperature and irradiance data. Figure 5.4 and Figure 5.5 present the average temperatures and irradiance recorded at KNMI Station 269 [85]. The figures present histograms for the data distribution for the period that will be studied (October-December 2020), and also the average monthly data for a 10-year period (2011-2020). As it can be seen in Figure 5.4b and Figure 5.5b, there is a clear monthly seasonality of both temperature and irradiance.

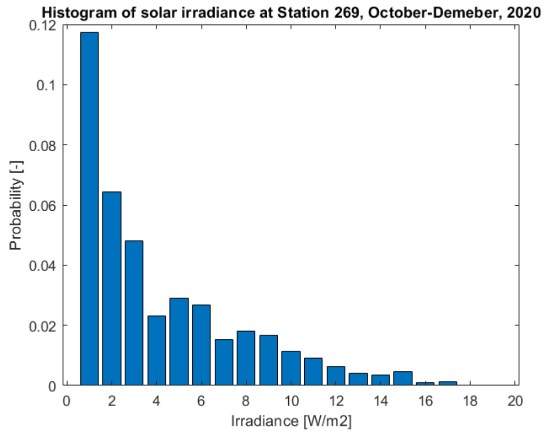


(a) Histogram of the hourly temperature at Station 269 for the October-December 2020 period.

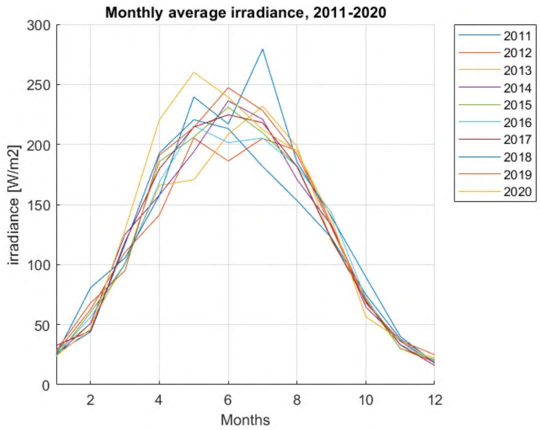


(b) Monthly average temperatures at Station 269 for the 2011-2020 period.

Figure 5.4: Historical temperature data at Station 269



(a) Histogram of the hourly irradiance at Station 269 for the October-December 2020 period.



(b) Monthly average irradiance at Station 269 for the 2011-2020 period.

Figure 5.5: Historical irradiance data at Station 269

5.2. Battery storage

The battery state of charge (SoC) is a fundamental aspect of the system's state. Although its precise behaviour can vary greatly from model to model, the basic expression is given by Equation 5.10 [98]:

$$SoC(t) = SoC(t-1) + \frac{\int_0^t P \cdot dt}{C_{\text{nom}}} \tag{5.10}$$

With C_{nom} being the nominal energy capacity of the battery. Equation 5.10 can be discretized as Equation 5.11:

$$SoC(t) = SoC(t-1) + \frac{P \cdot \Delta t}{C_{\text{nom}}} \tag{5.11}$$

The energy flows to and from the battery can be separated into the energy that is charged and the energy that is discharged, each with their respective efficiencies:

$$SoC(t) = SoC(t-1) + \frac{1}{C_{\text{nom}}} \cdot \int_0^t (\eta_{\text{ch}} \cdot P_{\text{ch}} - \eta_{\text{disch}} \cdot P_{\text{disch}}) \cdot dt \tag{5.12}$$

Equation 5.12 is a non-dimensional factor; however, it can also be left with energy units by removing the normalization by the battery capacity:

$$SoC(t) = SoC(t-1) + \int_0^t (\eta_{\text{ch}} \cdot P_{\text{ch}} - \eta_{\text{disch}} \cdot P_{\text{disch}}) \cdot dt \tag{5.13}$$

Battery energy storage systems are particularly prone to degradation due to use, ageing, and the effect of environmental factors like humidity and temperature. This results in reduced performance, with diminished efficiencies and a progressive capacity fading. Determining how each parameter is affected is usually studied through experimental testing. Although finding general relationships is notably hard and there are significant deviations among individual battery models, empirical relations have been found to characterize the degradation due to different factors. A generic formulation of the capacity fading due to idling time t, the average ambient temperature T, and the state of charge SoC is shown in Equation 5.14 [99]:

$$C_{\text{fade}}(t, SoC) = 1.9775 \cdot 10^{-11} \cdot e^{(0.07511 \cdot T)} \cdot 1.639 \cdot e^{(0.007388 \cdot SoC)} \cdot t_{\text{storage}}^{0.8} \tag{5.14}$$

The capacity degradation due to cycle use could be based on data provided by the manufacturer. For the case at hand, the manufacturer provides a chart with the relationship between certain depths of discharge and the corresponding number of cycles to the end-of-life (EoL) of the battery, as per Figure 5.6.

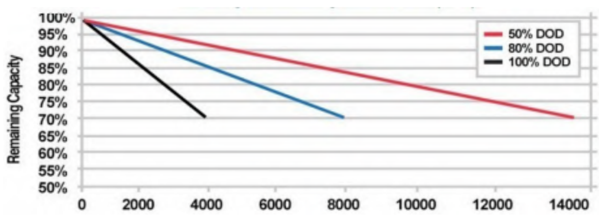


Figure 5.6: Relationship between EoL number of cycles for given DoD, as provided by the battery's manufacturer [5]

The capacity fading due to usage is therefore a linear relationship between the number of cycles experienced by the battery at a certain Depth of Discharge (DoD), the end-of-life capacity loss (which is given to be 30 %), and the end-of-life number of cycles for the DoD at which the cycle takes place (Equation 5.15).

$$FC(DoD) = \frac{0.3}{nc_{EoL}(DoD)} \cdot nc \tag{5.15}$$

The degradation in the battery capacity caused by its use can be factored into the rolling optimization described in subsection 5.3.3, by updating the battery capacity with which the optimizations are set up.

A battery cycle is a full charge plus a full discharge of the battery, whether it is done in a single operation or through the addition of partial charges and discharges (also known as micro-cycles). The cycle counting of the battery was done based on the algorithm proposed by Gundogdu and Gladwin [6], shown in Figure 5.7:

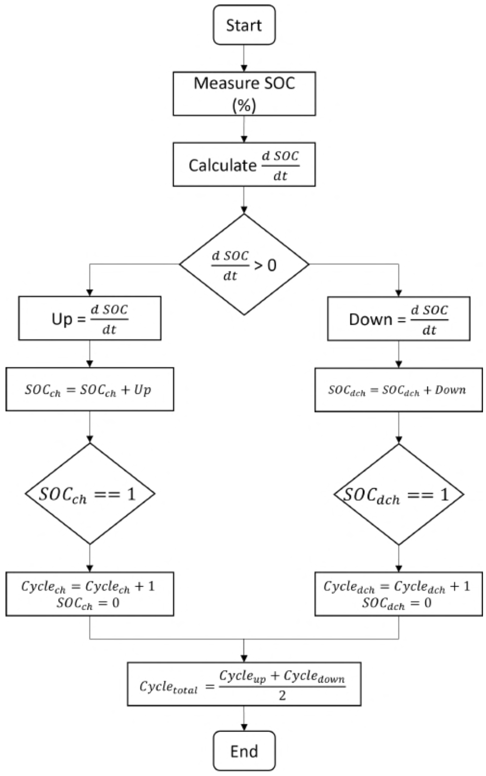


Figure 5.7: Algorithm for charge cycle counting with micro-cycles [6].

The capacity degradation shown in Figure 5.6 can also be used to estimate the marginal cost of the battery. Each movement of the battery will cause a fractional loss in capacity. Since it is assumed that the battery will be replaced once it reaches its end-of-life capacity loss, each movement therefore causes an asSoCiated fractional cost, which can be calculated as per Equation 5.16:

$$MC(DoD) = \frac{Cost\ new\ battery}{nc_{EoL}(DoD)} \cdot (DoD(t) - DoD(t-1)) \tag{5.16}$$

Furthermore, the following aspects of the battery performance were also considered in the model:

- Maximum charge and discharge rate: determine what is the maximum percentage of energy that can be extracted from the battery at a time, and are usually indicated by the manufacturer.
- Maximum and minimum state of charge: for capacity preservation reasons, the battery maximum and minimum charge limits can be reduced by the user. These limits are set

by the user.

- Battery self-discharge from idling [100]: the energy stored in the battery decreases during idle timing due to spontaneous internal chemical reactions in the battery. Lithium-ion batteries have a notably low self-discharge, of about 5% per month.

5.3. Weather resources prediction

This section presents the methodology followed to generate weather predictions needed as inputs for each market closing. The aim of this section is not to propose novel or improved methods for predicting weather or market prices, but to simulate the *process* of generating these forecasts in a way that would mimic how these forecasts would be used in a real-life scenario dispatch. Two types of dispatches have to be generated: one for the Day Ahead dispatch, which is set for the entire optimization; and a dynamic set of predictions for the Intraday tradings, which are updated regularly throughout the day, and instead of covering the entire optimization schedule they only have predictions for a limited optimization horizon.

5.3.1. Day Ahead weather predictions

Since the Day Ahead bids have to be submitted at 11:00 AM on the day before delivery, the Day Ahead weather predictions are set at the time of generating the program. For this research, the weather data of 2019 was used as prediction inputs for the Day Ahead forecasts. A comparison between the energy predicted, using 2019 data; and the actual energy generated for 2020 is shown in Figure 5.8 shows [2].

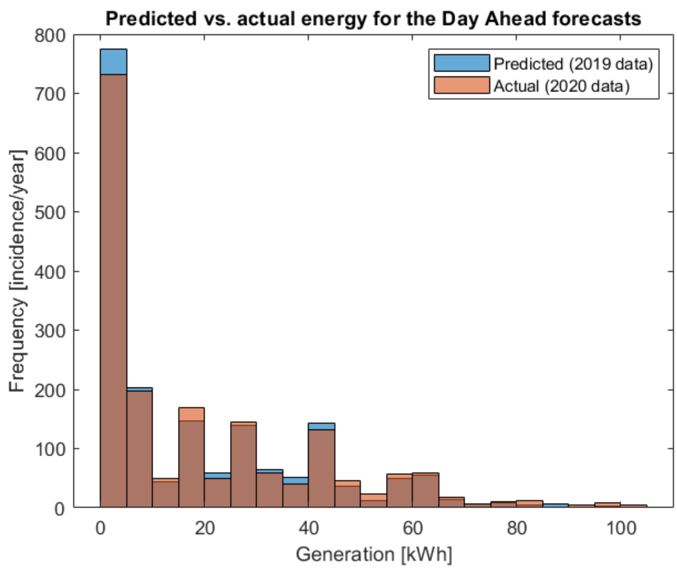


Figure 5.8: Comparison between the 2019 energy generation, used as the Day Ahead forecast, and the 2020 actual generation.

[2] As previously noted, this data study is restricted to the October-December period.

5.3.2. Intraday and Real time prediction generation

As previously explained, the goal of setting up these predictions is not to produce accurate predictions for the bids, but to simulate how these predictions would be generated and updated in a real market participation run. While predictions for the DA have to be closed the day before to submit the trading programs, the ID market allows to update the bids within the delivery day, offering room for updated and weather forecasts as the day progresses.

Deciding how and to update and use these forecasts would be up to the operators of the power plant, based on the available software and time resources. For these predictions, it was assumed that hourly forecasts were generated, meaning that the forecasts are updated every hour and the quarterly energy production is constant for every hour of the forecast.

These predictions were set up with the goal of simulating a forecast that becomes more accurate for next-time predictions after every market closing, and its accuracy decreases the further forward in time the predictions are. The predictions were based on the DA forecast presented in subsection 5.3.1, with the prediction error of the DA predictions multiplied by a weighted random number between 0 and 1 being added to the prediction:

$$P_{\text{ID forecast}}(t) = P_{\text{pred DA}}(t) + \frac{n_t}{N} \cdot rand(0,1) \cdot e_{\text{pred}}(t) \tag{5.17}$$

In Equation 5.17, $P_{\text{ID forecast}}(t)$ is the forecast prediction at time t, $P_{\text{pred DA}}(t)$ is the baseline DA prediction for time t, $e_{\text{pred}}(t)$ is the DA prediction error, n_t is an integer corresponding to the index of t counting from the current market closing, and N is the number of total remaining market closings for which data is being forecast. The random number $rand$ is generated based on a Gaussian distribution.

An example for a 24-hour ID forecast is presented in Figure 5.9. It features 15-minute predictions based on a predicted hourly data series, produced at t=1. As it can be seen, the accuracy of the predictions decreases in time.

5.3.3. Rolling horizon optimization

As explained in subsection 5.3.2, the weather predictions for the ID and RT dispatches are constantly being updated as the day advances. This means that for every market closing there will be a new set of predicted generation for all future closings, with the accuracy of these predictions decreasing the further they are away from the current closing.

Due to this influx of updated generation forecasts, the optimization has a rolling-horizon characterization. This method is based on Model Predictive Control theory [101]. In addition to working with improved energy forecasts, which would yield more fitting dispatches, limiting the decision variables to a certain time horizon reduces the total number of optimization variables, thus improving computation time and accuracy, and produces a dispatch based on the nearest (and thus most accurate) input predictions.

The full optimization would thus be solved by using a rolling horizon algorithm:

1. In order to produce a bid program for the market closing at t=t+1, the optimization problem would be solved considering the predicted weather generation for t=t+1...t+X.

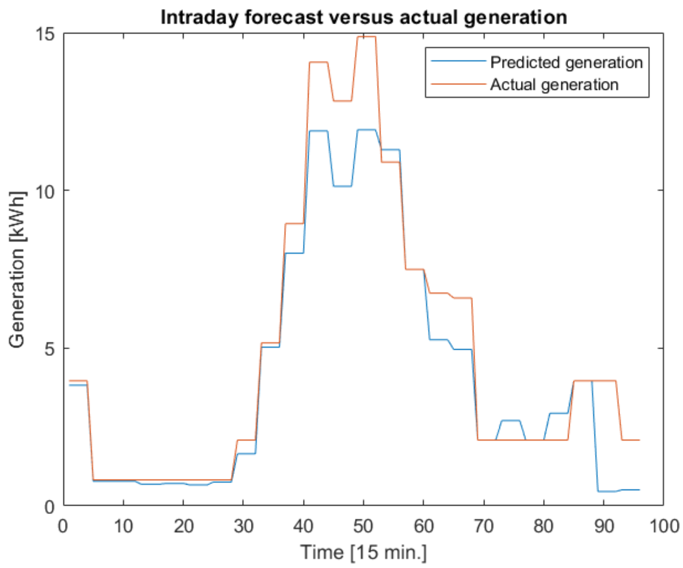


Figure 5.9: Comparison between the Intraday forecast and the actual generation, for a 24-hr horizon.

The resulting dispatch would produce a definitive dispatch for the t=t+1 closing, and a preliminary dispatch for the positions t=t+2...t+X.

2. Changes in the system state would be calculated based on the definitive dispatch for t=t+1 (in this case, this change would be the state of charge of the battery and its subsequent effect in the battery capacity, which can be calculated using Equation 5.14 and Equation 5.15).
3. the same process will be repeated for the next market closing, using a new set of predictions and the new system state values as the initial state.

It is important to note that implementing this solution does not affect the mathematical formulation of the problem as presented in the previous sections.

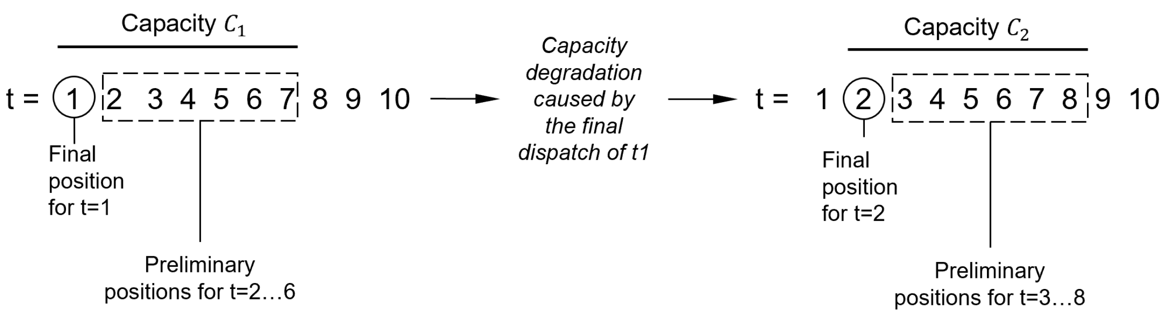


Figure 5.10: Rolling horizon optimization.

5.4. Stochastic scenario generation

As explained in chapter 4, under the assumption that all predicted generation has to be dispatched, the range of action of the optimizer is contingent on the charge and discharge limits of the battery. The stochastic scenario generation was done by random sampling of the area around the predicted energy generation defined by the maximum charge and discharge rate of the battery. This outputs a set of Ω possible generation profiles, each with a probability of being realized.

The random sampling was done by dividing the space defined by the maximum charge and discharge rates around the predicted energy into ω equal segments, with Ω being the total number of stochastic scenarios as defined by the user. The bounds of each segment defined regions for which a random fraction of the maximum charge or discharge rate was added to the predicted generation. Figure 5.11 presents an example of the scenario generation for constant predicted and actual generation, for 24 hours.

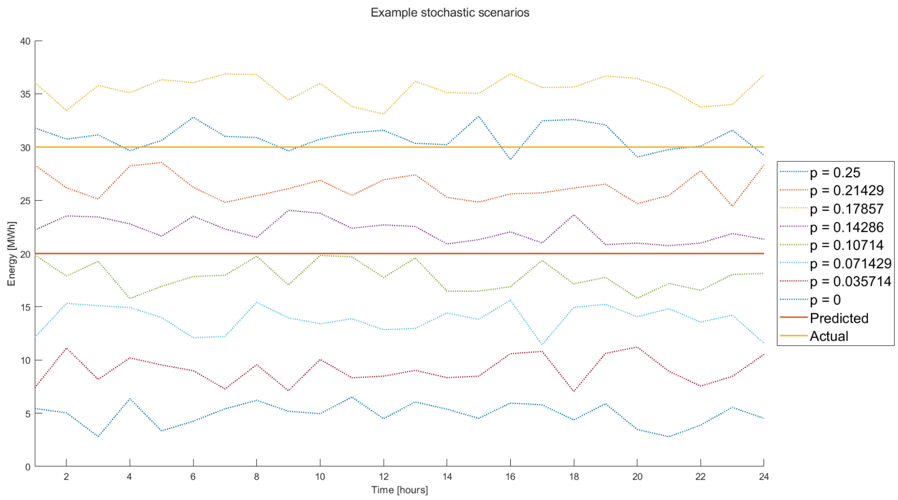


Figure 5.11: Example of the stochastic scenario generation.

The probability of each scenario being realized was calculated by the linear proximity of the total energy predicted per scenario to the total energy actually produced:

1. Calculate the total energy generation per scenario, $E_{\mathrm{T},\omega}$.
2. Calculate the total energy actually generated, $E_{\mathrm{T},actual}$.
3. Calculate the total generation error per scenario e_ω using Equation 5.18

$$e_\omega = |E_{\mathrm{T},actual} - E_{\mathrm{T},\omega}| \tag{5.18}$$

4. Sort in ascending order the stochastic generation profiles based on their corresponding error. This will reorganize the scenarios such that those with a total predicted generation closer to the total actual generation are at the top of the stochastic scenario list. Each scenario has therefore a tier n_ω corresponding to its position on this list. Please note that this does not change the number of scenarios generated, which remains S.
5. Using the reorganized scenario list, the probability π_ω of each scenario can be calculated using Equation 5.19:

$$\pi_\omega = \frac{2}{\Omega} \cdot (\frac{1}{\Omega} \cdot n_\omega + 1) \tag{5.19}$$

The linear distribution of scenario probabilities is given in Equation 5.19, which establishes a linear relationship between the tier of a scenario n_ω, and it probability of taking place, considering that the sum of all probabilities from all scenarios has to be 1. For clarity on this point, Figure 5.12 presents a visual representation between the linear probability distribution per scenario as a function of the scenario's tier n_ω.

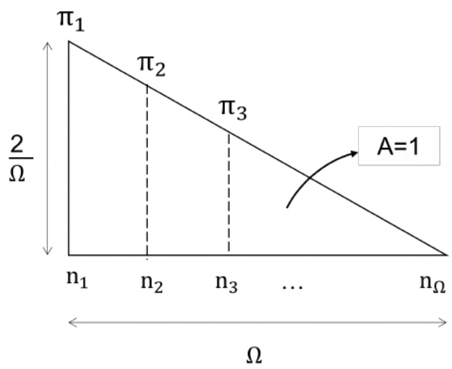


Figure 5.12: Visualization of the linear probability distribution for the stochastic scenarios.

6

Case study

This chapter presents the context in which the optimizations were developed and the case study for which the results were obtained. The TNO SWITCH lab, the power plant used as a case study, is described in section 6.1; and the rationale for selecting the test case days is explained in section 6.2.

6.1. The TNO SWITCH lab

This thesis was developed in collaboration with the Wind Energy research department (which belongs to the Energy Transition research unit) from TNO, the Netherlands Organisation for applied scientific research. In particular, it is encompassed within the work carried around the newly built SWITCH lab, a hybrid renewable power plant laboratory located in the middle of Flevopolder that aims to serve as a scaled-down model to test research related to the integration of renewable energy on the electrical grid [102]. Figure 6.1 displays an airview render of the SWITCH laboratory.

The SWITCH lab consists of the following components:

- 6 pitch-controlled Aircon 10S wind turbines with a rated power of 10 kW.
- 120 Trina335 solar panels, with a maximum power point of 335 W.
- 8 Iron Edison Lithium-Ion 7.2 kWh battery modules, for a total of 57.6 kWh of nominal storage capacity.

The lab also includes an electrolyzer with a 25 kW stack power rating, which was not considered for the optimizations of this thesis.

As of the moment of writing this thesis, there was no empirical data for the generation output of the SWITCH lab. Therefore all the component modeling was done as per chapter 5, and verified against manufacturer data and previously existing models done by TNO. The work done by the Wind Energy research department for the EMERGE project so far has largely

Figure 6.1: Aerial shot of the SWITCH lab [7]

been developed using Matlab/Simulink and Python. It was therefore a requisite that the optimizations were developed for the Matlab environment.

The existing work also includes a non-optimized energy dispatch strategy based on price benchmarking (buying and selling trades are triggered by the market prices being above or below pre-determined selling and purchasing price benchmarks). An example of this price benchmarkign strategy is shown in Figure 6.2.

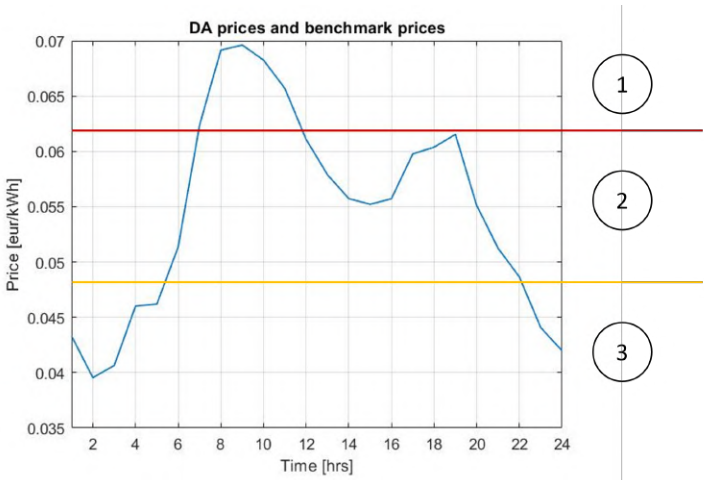


Figure 6.2: Example of the non-optimized dispatch strategy price benchmarking.

In this optimization, the battery operation is controlled by comparing the current market price to some predetermined discharging and purchasing prices. If the market price is above the discharging price (region 1), the battery is discharged to its maximum discharge rate, and all generation is sold. If the market price is below the purchasing price (region 3), energy is charged from the generation, and, if there is enough capacity remaining, purchased from the grid. If the market price is between these two prices (region 2), there is no battery operation and all the generation energy is sold.

The discharge price (in red) and the purchase line (in yellow) are set through an analysis of the historical prices, with the discharge price being the average of the historical high price daily periods (between 07:00 and 21:00), and the purchasing line being the average of the historical low price daily periods (between 22:00 and 06:00). The periods of high and low daily prices was based on the daily seasonality shown in Figure A.1d. The same was done to determine the discharge and purchase prices for the ID market. The value of these reference prices can be seen in Table 6.1:

Table 6.1: Purchase and discharge reference prices for the DA and ID markets.

	Discharge price [€/MWh]	**Purchase price [€/MWh]**
Day Ahead	31.0	21.1
Intraday	43.0	22.0

The non-optimized RT dispatch follows a strategy in which, for every singular closing, the available generation is compared to the program submitted for that closing to calculate the baseline imbalance. If the corresponding closing imbalance price is favorable, the imbalance is exploited by either charging or discharging the battery. If it is unfavorable, the imbalance is mitigated by either charging or discharging the battery.

This existing non-optimized strategy was used as a reference to measure the benefits of having an optimized dispatch strategy, and evaluate the trade-off between the increase in computational demands and the (prospective) increase in earned revenue.

6.2. Test case day selection

The optimizer was evaluated for its performance in two types of days:

1. The predicted energy is less than the actual energy produced. There will therefore be a surplus of generated energy at delivery. The optimizer dispatch for this day serves as a general indication of its general behavior, since surpluses greatly tend to be rewarded in the imbalance market.

2. The predicted energy is more than the actual energy produced. There will therefore be a deficit of generated energy at delivery. This is a critical schedule, since the market tends to punish deficits far more than surpluses, and it will serve to evaluate the effectiveness of the stochastic scenario evaluation in the optimization.

There were no further requisites for the behavior of the market or the prices, and the days were selected randomly based only on whether there was a surplus or a deficit of generation. This was done in order to avoid selecting days with more favorable generation or price profiles, and study the behavior for generic generation and market conditions. The selected days were the 26$^{\text{th}}$ of November for Case 1, and the 17$^{\text{th}}$ of December for Case 2.

7

Assumptions and simplifications

This chapter presents the assumptions and simplifications under which the results were obtained in section 7.1, and the integration in Matlab in section 7.2.

7.1. Assumptions and simplifications

The optimizations were set up under the following assumptions and simplifications:

Regarding the market conditions

- The market prices for all closings are known and deterministic.
- The power plants bids at 0 €/MWh, and acts as a price taker.
- The presence of the power plant does not affect the price settlement or bid capacity of any other market party.
- All bids from the power plant are passed at market price.
- Contractual obligations are not considered, and the plant is free to adjust its trading without any further considerations other than its own gain.
- Government influence in the form of policies, subsidies, and other regulations or economic aid is not considered.

Regarding market participation

- There is a continuous participation in the ID market, trading with the minimum ISP length of 15 minutes.
- For the ID and RT dispatch, new generation forecasts are generated every hour.
- For the ID and RT dispatch, market positions are updated every hour.

Regarding generation modeling

- The exact energy generated is known at delivery time.
- Losses due to mechanical degradation and electrical interfacing of the components are not considered.
- Losses due to transport are not considered.
- All generation from both wind and PV is joined into a single energy generation input.
- The probability of each stochastic generation profile is known.

Regarding the battery use

- The initial battery state of charge was set to half of the nominal capacity for all simulations.
- The full SoC range within the maximum and minimum SoC limits was available for all closings.

Regarding the risk acceptance parameters

- A moderate risk acceptance strategy was followed, with $\alpha = 0.9$ and $\beta = 0.5$ [103].

7.2. Hardware and integration in Matlab

The optimizations were obtained using Matlab R2020a, using the GlobalOptimization toolbox with the globalsearch algorithm under the fmincon solver for the non-linear first stages, and the intlinprog for the second stages. A full explanation on how the solver was selected can be found in Appendix B.

The computer specifications IntelCore i5-9500 CPU @ 3.00 GHz 3.00 GHz, 16 GB of memory.

8

Results

This chapter presents the proposed dispatches for the optimized and non-optimized strategies for the selected case study days, as well as the revenue earned per market closing and in total. The assumptions and simplifications used in the optimizations are explained in section 7.1. The behaviour of the dispatch strategies is illustrated for the results for the 26$^{\text{th}}$ of November in section 8.1, through key points indicated the programs. The results for the 17$^{\text{th}}$ of December are presented in section 8.2, only including the optimized dispatch programs and the overall revenue table.

It should be noted that for the optimzations the power plant was scaled from a 100kWh capacity to 1 MWh capacity. This was done for two reasons: firstly, to set the generation and the market prices on a similar order of magnitude, which improves the convergence time and accuracy of the optimizer; and secondly, to provide a more visually intuitive scale for the revenue[1].

8.1. 26 November 2020 (Constant deficit)

This section presents the proposed strategies for the 26$^{\text{th}}$ of November, 2020; a day for which the generation predicted was more than the actual generation, causing a generation deficit at delivery time. Since the imbalance settlement prices are majorly positive for the day, this is therefore a critical case. The profile for the generation and prices for the day is shown in Figure 8.1.

[1]Due to the relatively small size of the SWITCH lab in comparison to industrial-grade utilities, the relatively low generation during the available data period, and the market dispatch prices being closed in €/MWh, if the actual lab capacity was used it would yield revenues in the order of 10-10^{-2}, making it harder to spot the differences in revenue among market closings and dispatch strategies.

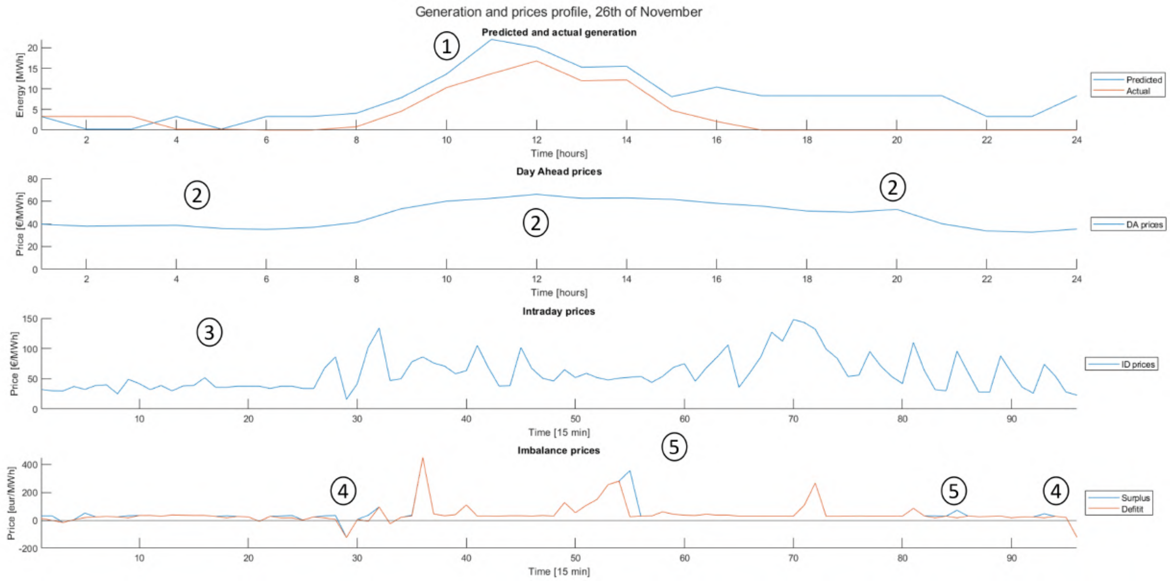


Figure 8.1: Overview of the generation and prices for the 26$^{\text{th}}$ of November.

1. The predicted generation is larger than the actual generation for every hour except 2 AM and 3 AM.
2. The Day Ahead prices have small local fluctuations that create local maxima and minima. They have an average price of 47.6 € and a standard deviation of 11.44 €.
3. The ID prices higher than the Day Ahead prices for 57.29 % of the closings, with an average value of 58.99 € and a standard deviation of 29.18 €.
4. The imbalance settlement prices become negative on two instances, but remain positive for 94.8 % of the settlements.
5. The imbalance settlement prices exhibit dual behaviour for 15.63 % of the settlements.

8.1.1. Optimized dispatch

This section presents the results for the optimized dispatch, with and without ID market participation. The scenario generation for the Day Ahead optimization can be seen in Figure 8.2:

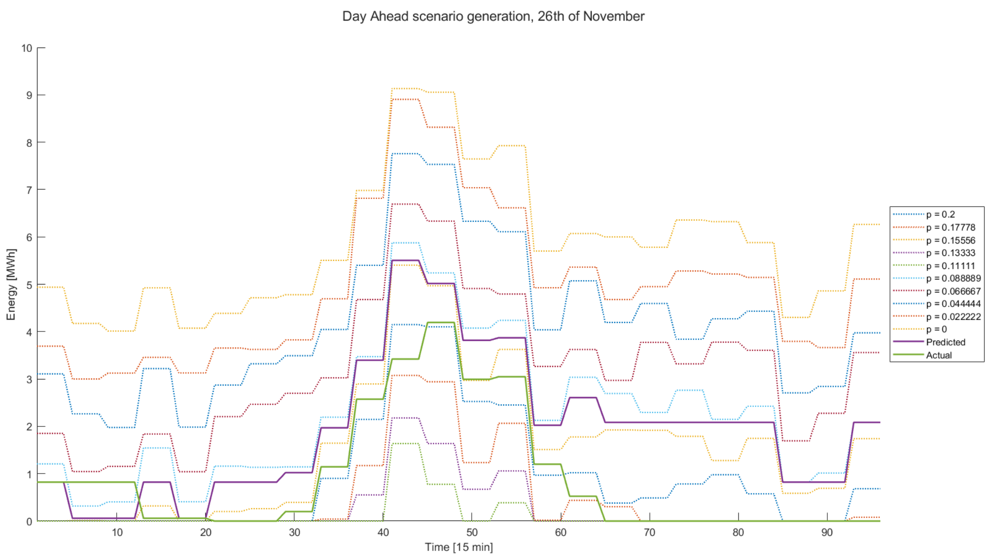


Figure 8.2: Stochastic scenario generation for the Day Ahead, with the respective probabilities of all scenarios for the 26th of November.

Optimized, Day Ahead dispatch- No ID participation

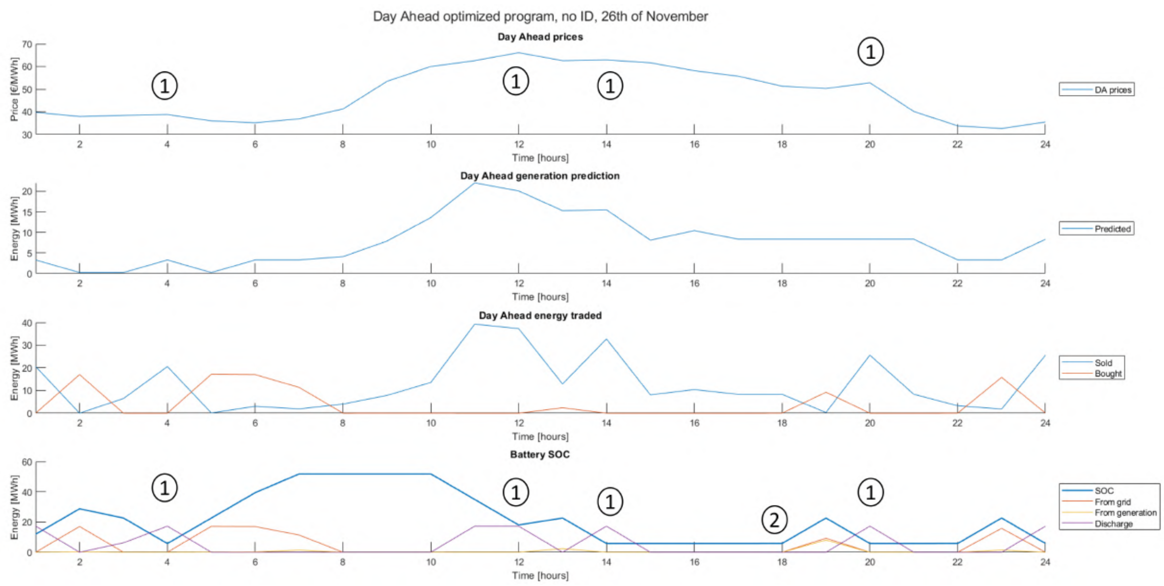


Figure 8.3: Optimized Day Ahead dispatch, without participation in the ID market for the 26th of November.

1. The optimizer discharges the battery on every local price maximum, and uses the following price minimum to recharge the battery.
2. Since no differentiation is made between the power bought from the grid and the power charged from the generation, the optimizer distributes the optimal charge to the battery between both indiscriminately.

Optimized, Real Time dispatch - No ID participation

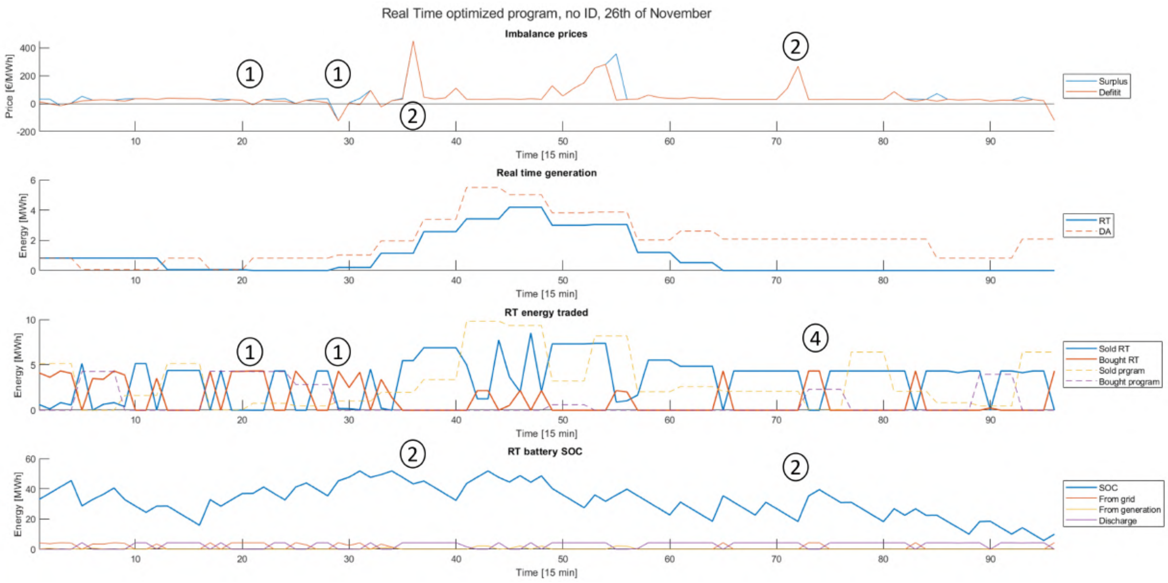


Figure 8.4: Optimized Real time dispatch, without participation in the ID market for the 26$^{\text{th}}$ of November.

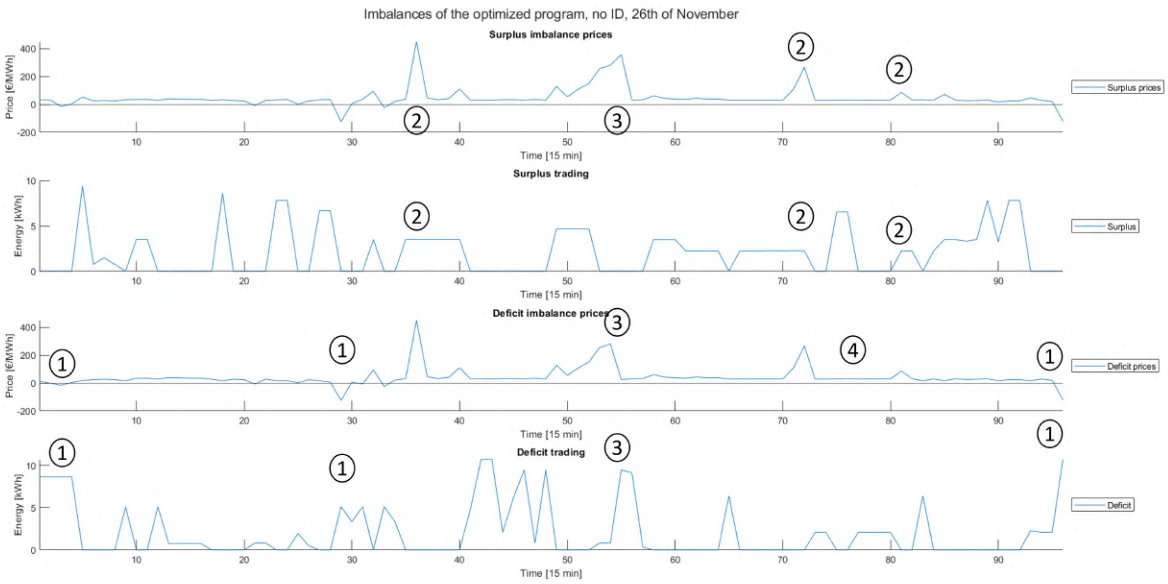


Figure 8.5: Optimized imbalances between the energy delivered and the energy programmed, and their corresponding imbalance settlement prices for the 26$^{\text{th}}$ of November.

1. During negative settlement prices, which reward deficit imbalances, a deficit is generated through an energy purchasing excess and all generation is charged to the battery.

2. All generation is sold and the battery is discharged to take advantage of the peaks in the surplus imbalance prices.

3. During this period in which the deficit imbalance prices are positive but lower than the

surplus imbalance prices, since it is not possible to be in a surplus, the deficit imbalance is minimized during the peak price point.

4. The battery is recharged from both generation and grid during periods of low imbalance settlement prices. During these periods, losses are accepted in order to ensure there is enough available energy to take advantage of the peaks in surplus imbalance prices.

Optimized, Day Ahead dispatch- full market participation

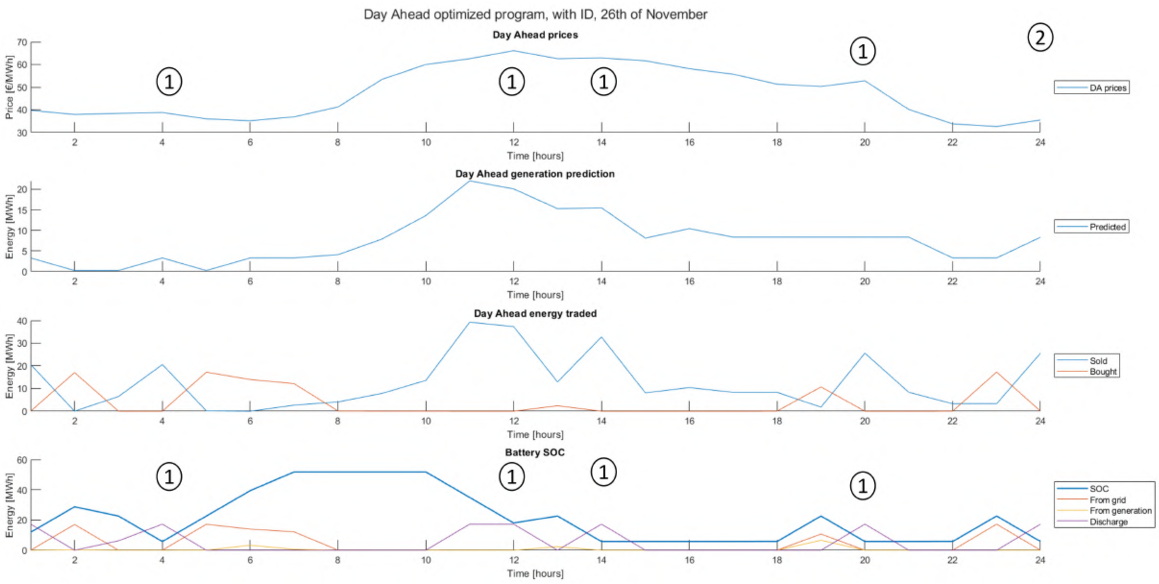


Figure 8.6: Optimized Day Ahead dispatch, with participation in the ID market for the 26th of November.

1. The battery is used following the same strategy seen in Figure 8.3, with discharges at the local price maxima and charges during the minima that are sourced either from the grid or the generation indistinctively.

2. The fact that the optimizer behaves identically to the one without ID market participation shown in Figure 8.3 indicates no effective impact from the use of the CVaR between both cases.

Optimized, ID dispatch - Full market participation

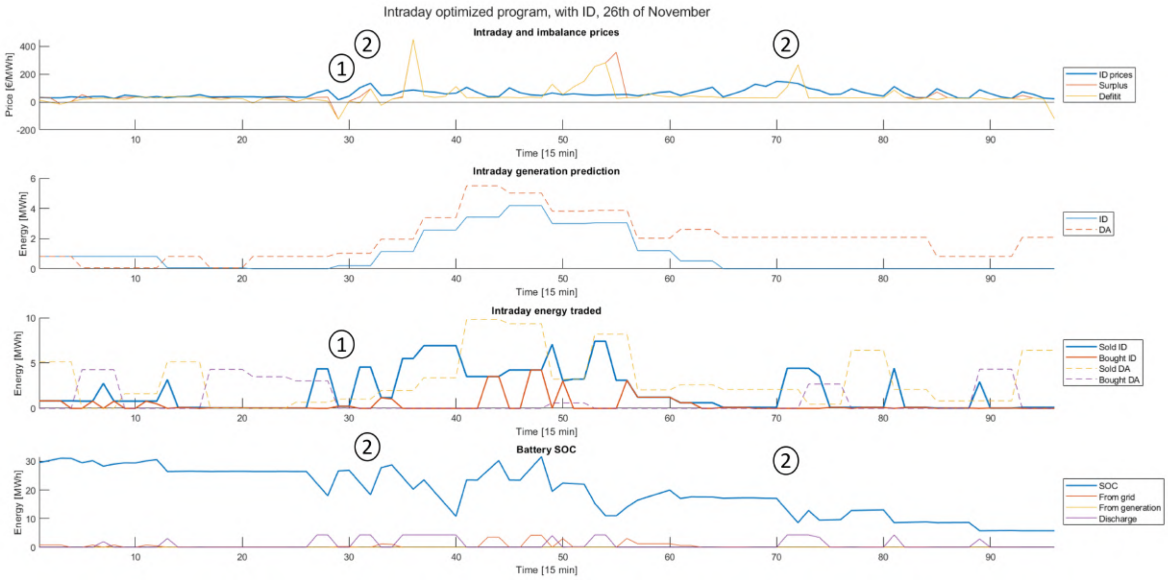


Figure 8.7: Optimized ID dispatch, for participating in the ID market for the 26th of November.

1. Even though these points coincide with local ID prices minima, no energy is purchased to ensure a beneficial deficit in the settlement period.
2. All energy is sold and the battery is discharged during local maxima in prices, and energy is either purchased or charged from the generation during local prices minima.

Optimized, Real Time dispatch - full market participation

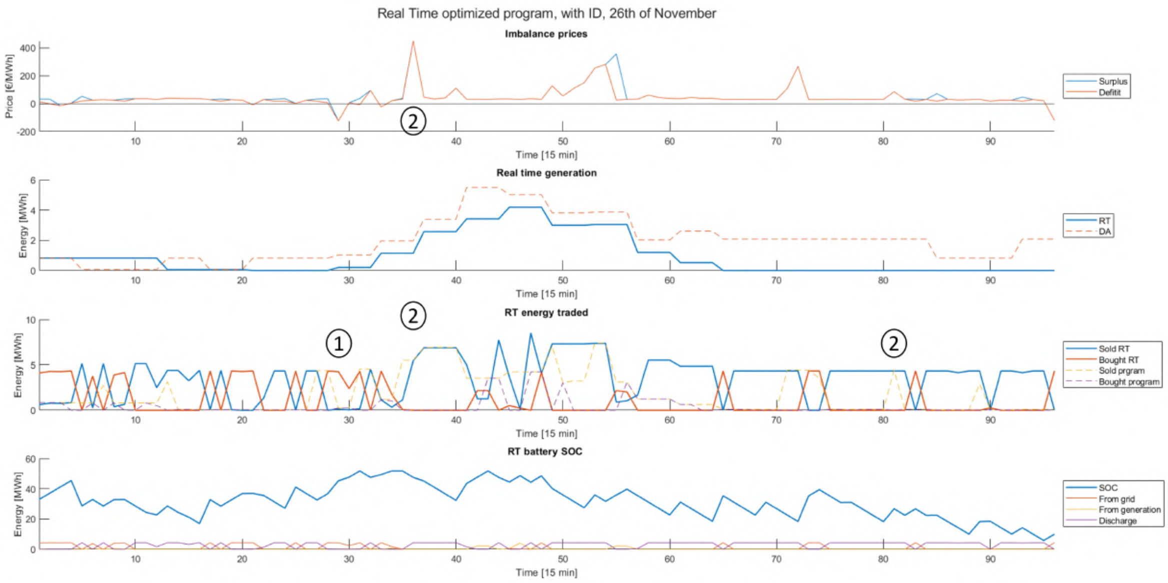


Figure 8.8: Optimized Real time dispatch, with participation in the ID market for the 26th of November.

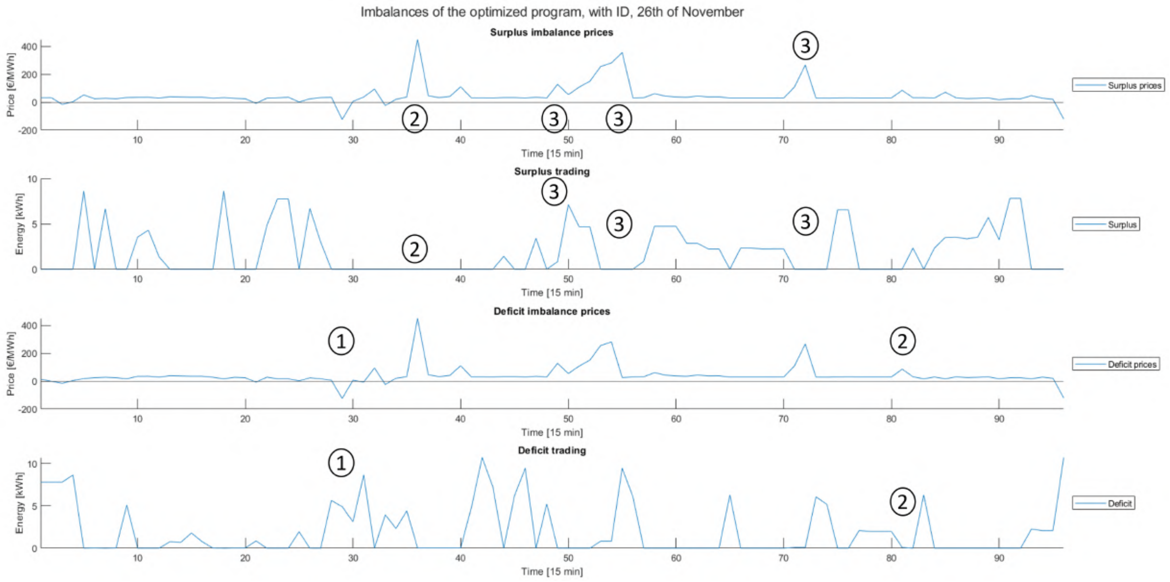


Figure 8.9: Optimized imbalances between the energy delivered and the energy programmed, and their corresponding imbalance settlement prices for the 26th of November.

1. The negative imbalance prices are exploited by an increase in the purchased energy with respect to the ID program, ensuring a deficit.

2. These peaks in the imbalance prices coincide with local maxima of the ID prices, for which bids were passed selling all available (predicted) generation and battery. Since the energy bid is almost the same as the actual energy generated and delivering a surplus is therefore not possible, the only viable way to handle these points is by removing the deficit imbalance as much as possible and avoid a fine due to deficit imbalances.

3. Imbalance price peaks which did not coincide with local maxima of the ID prices are exploited by creating excess in the energy delivered by discharging the battery. Much like for the dispatch shown in Figure 8.4, the fines for deficit imbalances are accepted during low price periods in order to ensure there is enough energy available in the battery to either exploit or cancel the imbalances at the points of peak imbalance prices.

8.1.2. Non-optimized dispatch

Non optimized, Day Ahead dispatch - No ID participation

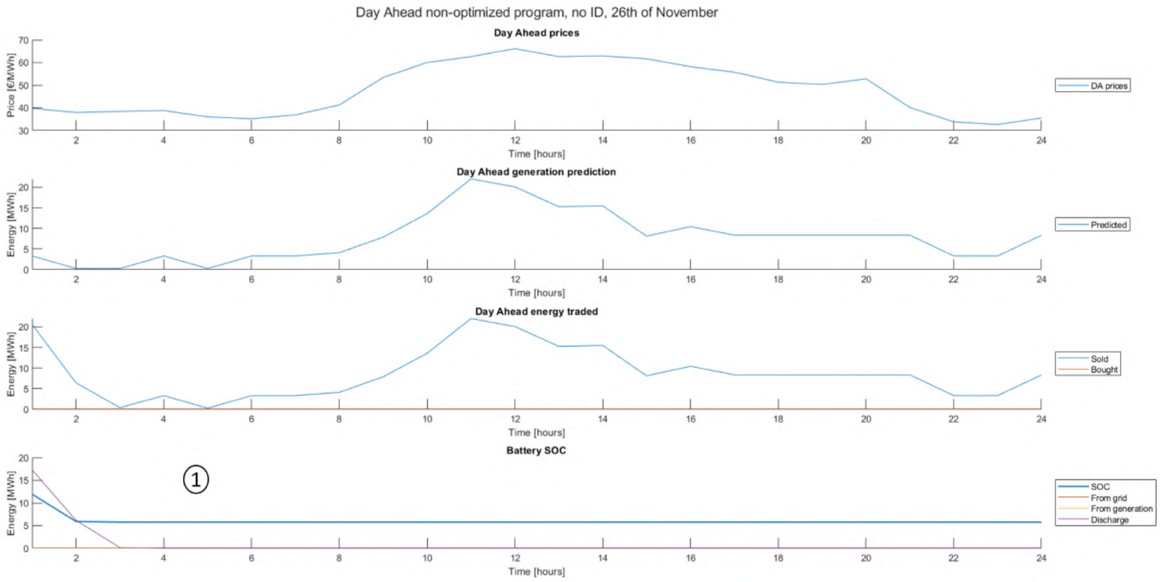


Figure 8.10: Non-optimized Day Ahead dispatch, without participation in the ID market for the 26th of November.

1. The purchasing price benchmarks are never reached, meaning that the signal to charge energy to the battery is never given. As a result, the battery remains effectively useless for the dispatch with a constant minimum state of charge.

Non optimized, Real Time dispatch - No ID participation

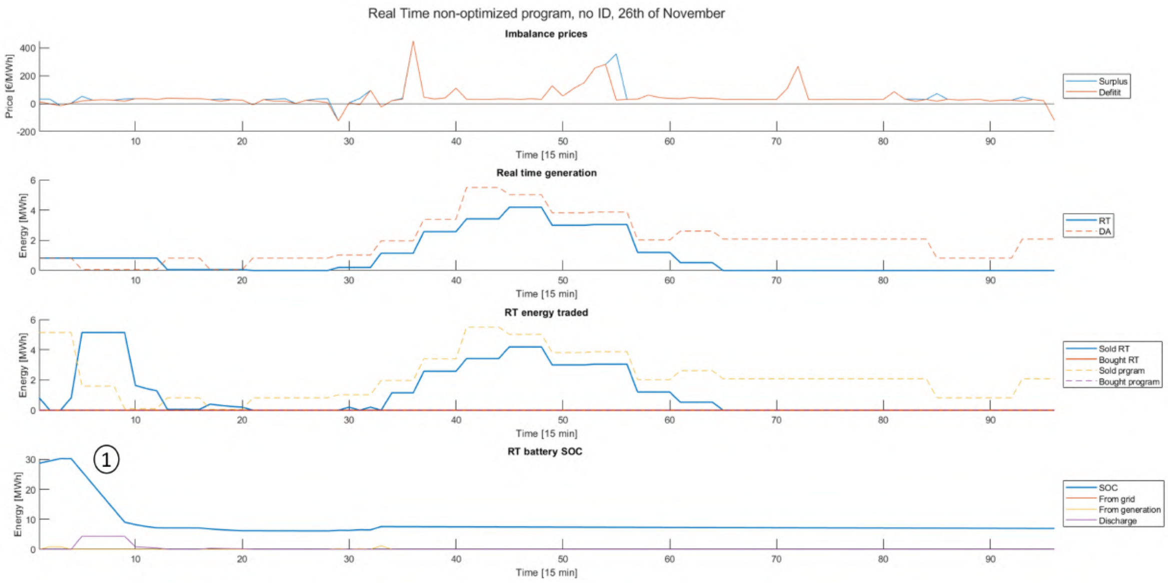


Figure 8.11: Non-optimized Real time dispatch, without participation in the ID market for the 26th of November.

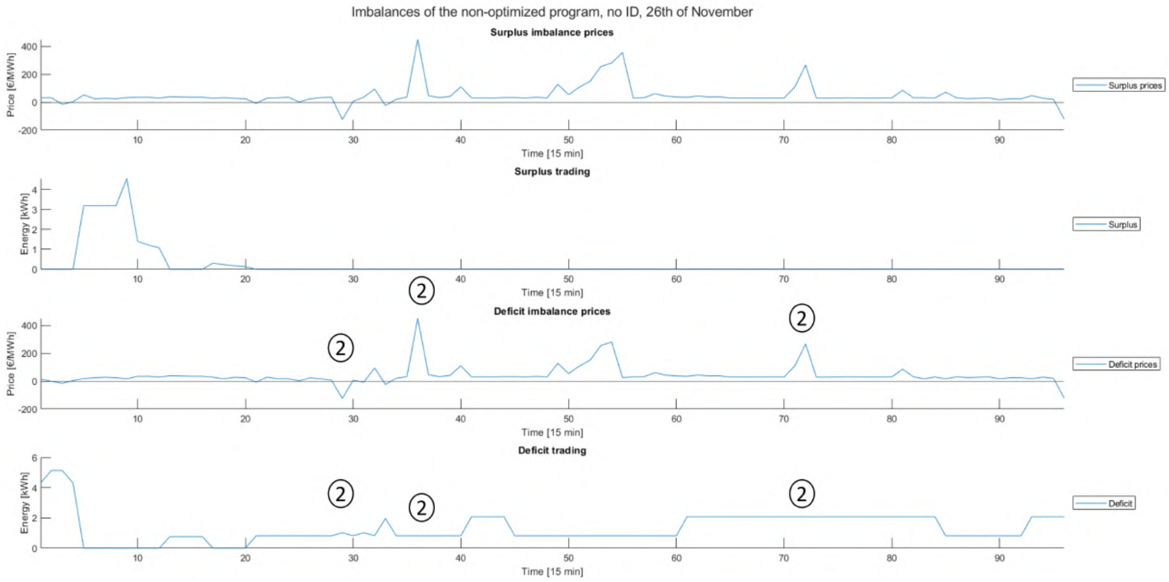


Figure 8.12: Non-optimized imbalances between the energy delivered and the energy programmed, and their corresponding imbalance settlement prices for the 26th of November.

1. These initial prices are exploited with a surplus obtained by discharging the battery. But after this moment, much like with the DA dispatch, the battery remains largely unused at a constant minimum state of charge, since the strategy cannot perform trade-offs between taking penalizations at a low price and exploit future imbalance price peaks, and instead aims to cover every immediate imbalance by selling all the generation and never purchasing from the grid.

2. Due to the inactivity of the battery, the Real Time dispatch is entirely dependent on the generation alone, meaning that there will be constant delivery deficits regardless of the actual imbalance prices.

Non optimized, Day Ahead dispatch - with ID participation

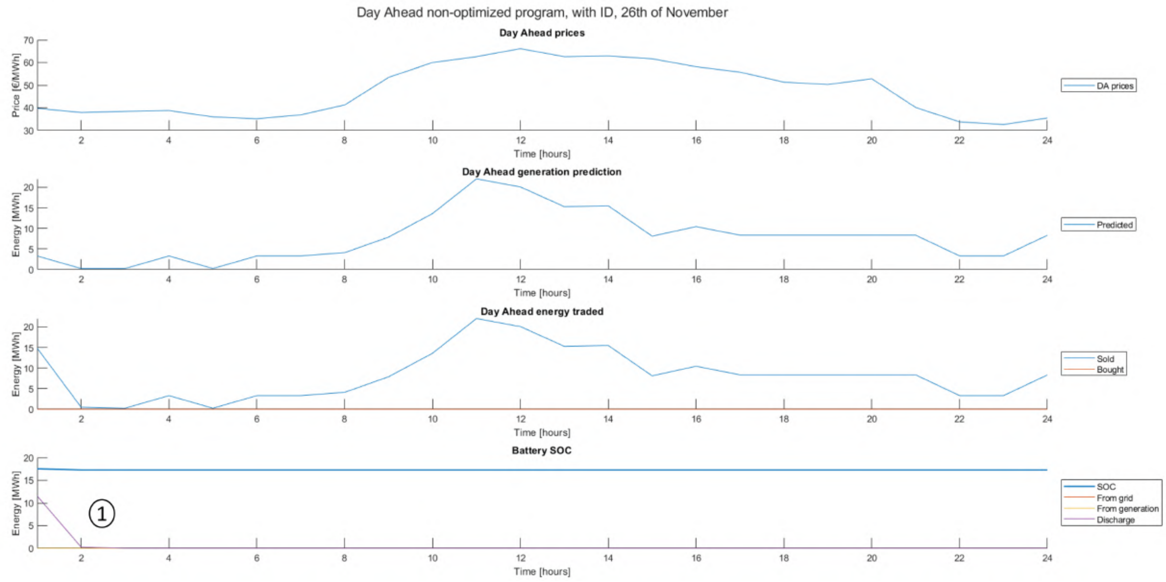


Figure 8.13: Non-optimized Day Ahead dispatch, with participation in the ID market for the 26th of November.

1. The battery remains unused since the purchasing signal is never triggered.

Non optimized, ID dispatch

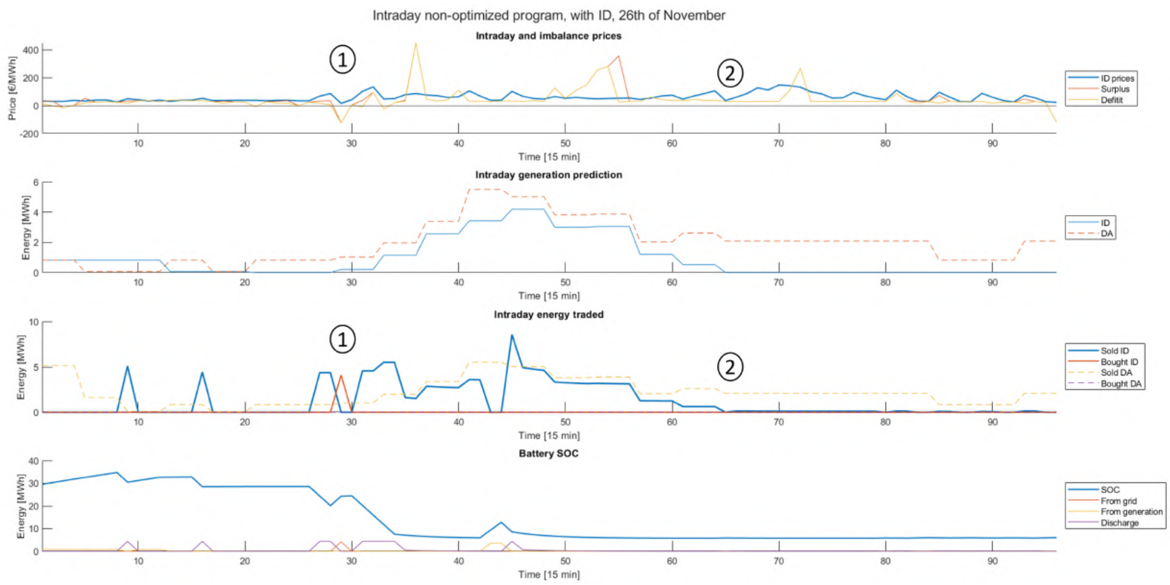


Figure 8.14: Non-optimized ID dispatch, for participating in the ID market for the 26th of November.

1. Since the non-optimized dispatch follows a here-and-now strategy, the purchasing signal is triggered at this local ID price minimum instead of reserving the purchasing to generate a beneficial deficit in the settlement market.

2. The charging and discharge actions are activated when the respective benchmarks are crossed, irrespective of future peaks and valleys in the prices. This eventually leads to an emptying of the battery when the ID prices stay over the charging benchmark for an extended period of time.

Non optimized, Real Time dispatch - with ID participation

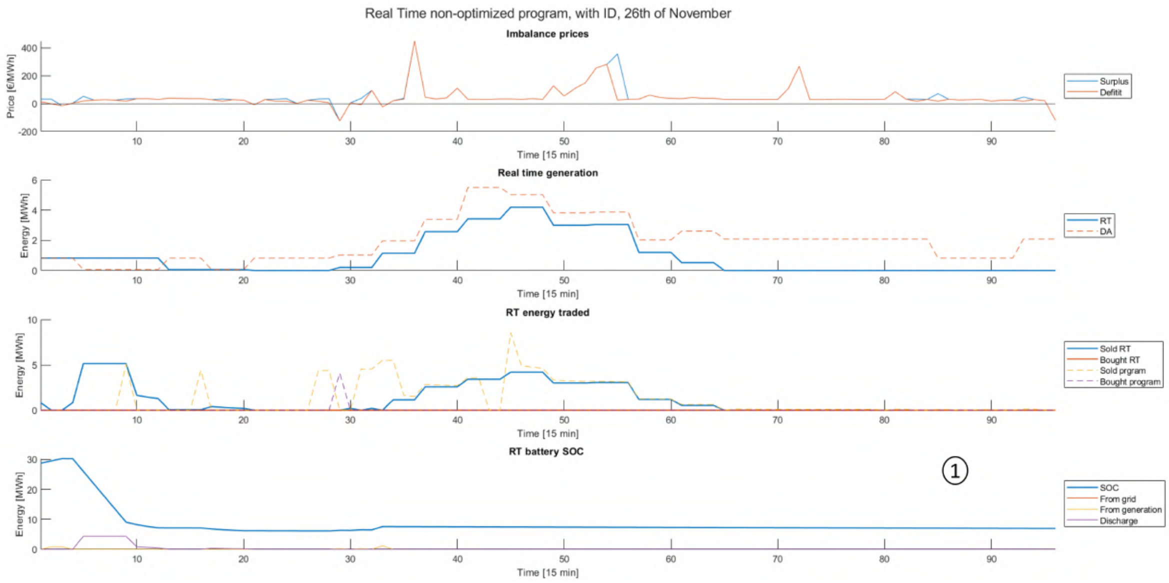


Figure 8.15: Non-optimized Real time dispatch, with participation in the ID market for the 26th of November.

1. The non-optimized dispatch for this case follows the same behavior depicted in Figure 8.11 and Figure 8.12. There is an initial discharge to profit from surplus prices, but since prices are constantly adverse to deficit imbalances, there is never a point at which the battery is recharged sufficiently to take advantage of future price peaks. The imbalance minimization is then left entirely to the generation, which is at a constant deficit.

8.1.3. Revenue table

The revenues obtained per market closings,for each strategy, for the 26th of November can be seen in Table 8.1

As it can be seen in Table 8.1, the optimized strategy manages to turn the highest profits regardless of market configuration, with a revenue 256.8 % higher than the no-battery case with participation in the ID market[2], and 260.1 % higher than the no-battery case without participation in the ID market.

The non-optimized dispatch turns a revenue much closer to that of the case without battery, with a revenue 44.9 % higher for the case with participation in the ID market and 26.31 %

[2]Note: these percentages were obtained using the lowest value of each pair of values being compared as the reference.

Table 8.1: Revenue breakdown for the 26th of November.

Battery	Optimized	Market closings	DA rev. [€]	ID rev. [€]	Imb. rev. [€]	Total rev. [€]
Yes	Yes	With ID	125.93	34.84	54.63	215.42
Yes	Yes	No ID	125.93	-	90.96	216.90
Yes	No	With ID	111.92	24.47	-48.88	87.50
Yes	No	No ID	111.92	-	-36.01	75.90
No	-	With ID	102.66	2.17	-44.45	60.37
No	-	No ID	102.66	-	-42.56	60.09

higher for the case without participation in the ID market. Even though it generates the highest ID revenue, it is at the cost of placing bids that are beneficial in the ID closing but detrimental in the imbalance settlement, which results in the lowest overall revenue in the imbalance settlement period.

It can also be observed that participating in the ID market did not yield significant benefits, with nearly equal profits for the optimized dispatch with and without participating, 15.2 % higher for the non-optimized dispatch, and 0.4 % higher for trading without the battery. This can be explained by the accuracy of the ID prediction, which is quite close to the actual RT value, and the assumption that prices are known. By trading in the ID market, the margin of profitable imbalances in the RT period are reduced, since there will be a larger difference between the DA program and the RT bid compared to the ID program and the RT bid.

Taking the revenue of the generation-alone plant as a baseline, the extra profit generated by having a hybrid power plant can be calculated by subtracting this generation-only to the revenue of the hybrid power plant, resulting in Table 8.2.

Table 8.2: Increase in revenue of the hybrid plant compared to generation-only plant for the 26th of November.

Battery	Optimized	Market closings	Increase in revenue [€]
Yes	Yes	With ID	155.05
Yes	Yes	No ID	156.81
Yes	No	With ID	27.2
Yes	No	No ID	15.81

Subtracting the baseline revenue earned with generation alone, the optimized strategy delivers a revenue 322.9 % higher than the non-optimized dispatch case with participation in the ID market, and 891.8 % higher than the non-optimized dispatch case without participation in the ID market.

A very significant result that should be noted is how the optimized dispatch is the only one that turns a profit in the imbalance market, in spite of having an overwhelmingly positive imbalance price scenario with a deficit of energy at delivery compared to the forecast in the DA trading. This is possible thanks to the efficient management of the storage assets, proving that the combination of non-controllable assets with a sensibly managed battery system offers the flexibility needed to successfully produce trade programs even on market adverse conditions.

8.2. 17 December 2020 (Constant surplus)

This section presents the proposed strategies for the 17$^{\text{th}}$ of December, 2020; a day for which the generation predicted was less than the actual generation, causing a default surplus at delivery time. Since the imbalance settlement prices are majorly positive for the day, this case presents more favourable conditions than the one presented in section 8.1. The profile for the generation and prices for the day is shown in Figure 8.16.

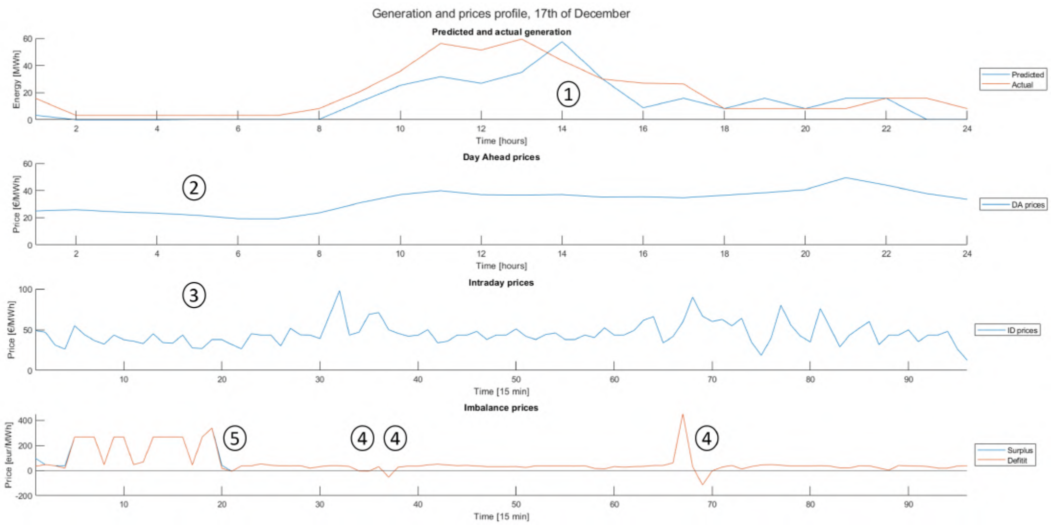


Figure 8.16: Overview of the generation and prices for the day for the 17$^{\text{th}}$ of December.

1. The predicted generation is larger than the actual generation for every hour except at 2 PM and 7 PM.
2. The Day Ahead prices have an average price of 32.75€ and a standard deviation of 8.13 €.
3. The ID prices higher than the Day Ahead prices for 86.46 % of the closings, with an average value of 45.21 € and a standard deviation of 13.86 €.
4. The imbalance settlement prices become negative on six instances, but remain positive for 93.75 % of the settlements.
5. The imbalance settlement prices exhibit dual behavior for 3.13 % of the settlements.

8.2.1. Optimized dispatch

This section presents the results for the optimized dispatch, with and without ID market participation. The scenario generation for the Day Ahead optimization can be seen in Figure 8.17:

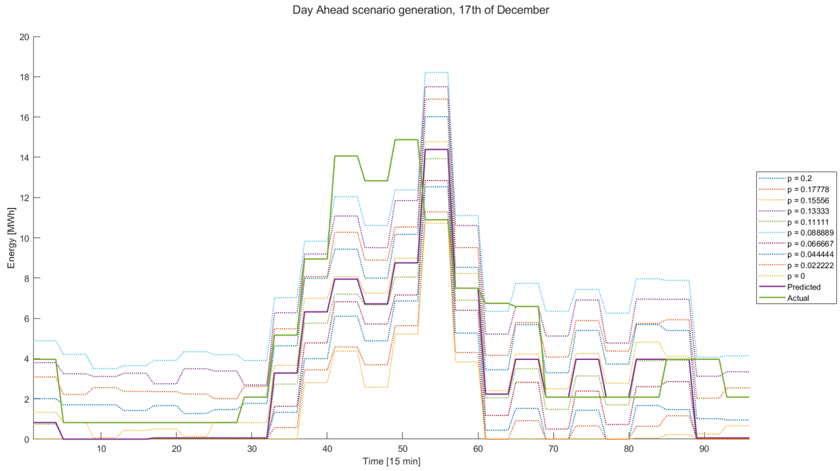


Figure 8.17: Stochastic scenario generation for the Day Ahead, with the respective probabilities of all scenarios for the 17th of December.

Optimized, Day Ahead dispatch- No ID participation

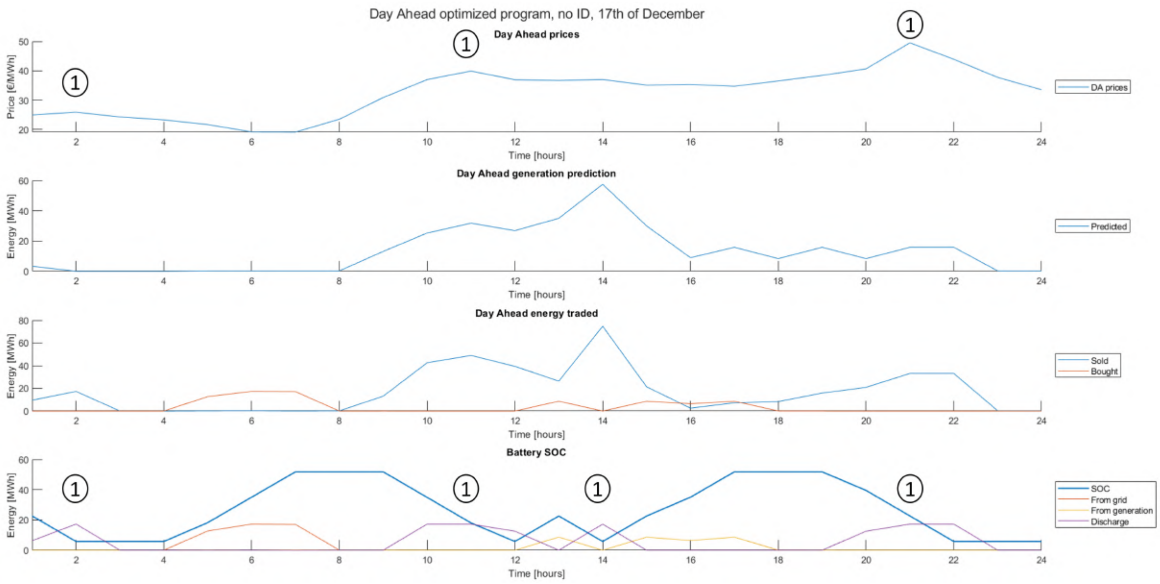


Figure 8.18: Optimized Day Ahead dispatch, without participation in the ID market for the 17th of December.

1. The optimizer follows the same behavior presented in Figure 8.3. The battery is discharged on every local price maximum, and uses the following price minimum to recharge the battery. For maxima separated by longer time periods, the battery is discharged during the interval around this maxima with the highest cumulative prices.

Optimized, Real Time dispatch - No ID participation

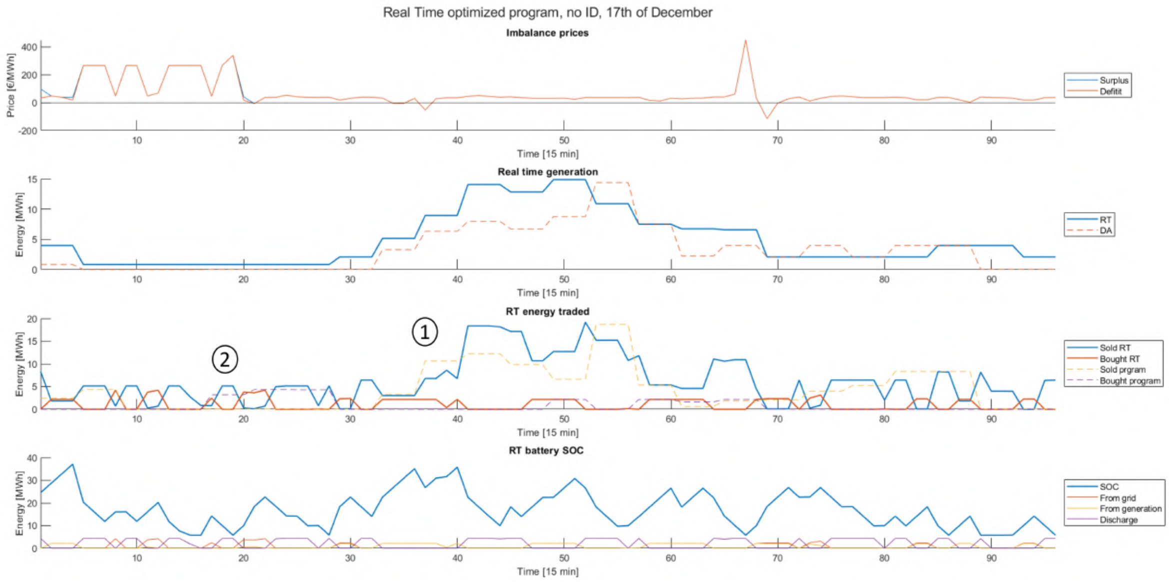


Figure 8.19: Optimized Real time dispatch, without participation in the ID market for the 17^{th} of December.

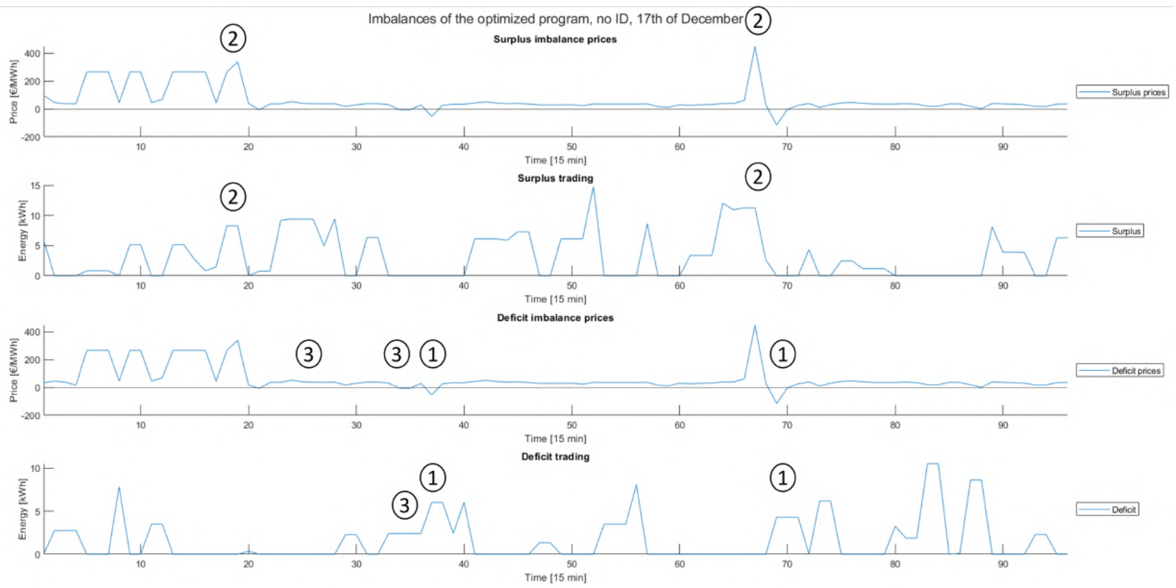


Figure 8.20: Optimized imbalances between the energy delivered and the energy programmed, and their corresponding imbalance settlement prices for the 17^{th} of December.

1. During negative settlement prices, which reward deficit imbalances, a deficit is generated through an energy purchasing excess and all generation is charged to the battery.
2. All generation is sold, the battery is discharged, and purchasing bids are waived to take advantage of the peaks in the surplus imbalance prices.
3. The battery is recharged from both generation and grid during periods of low imbalance

settlement prices. Since there is a constant excess of energy, by waiving purchasing bids it is ensure that deficit imbalances (and this penalization) are minimal.

Optimized, Day Ahead dispatch- full market participation

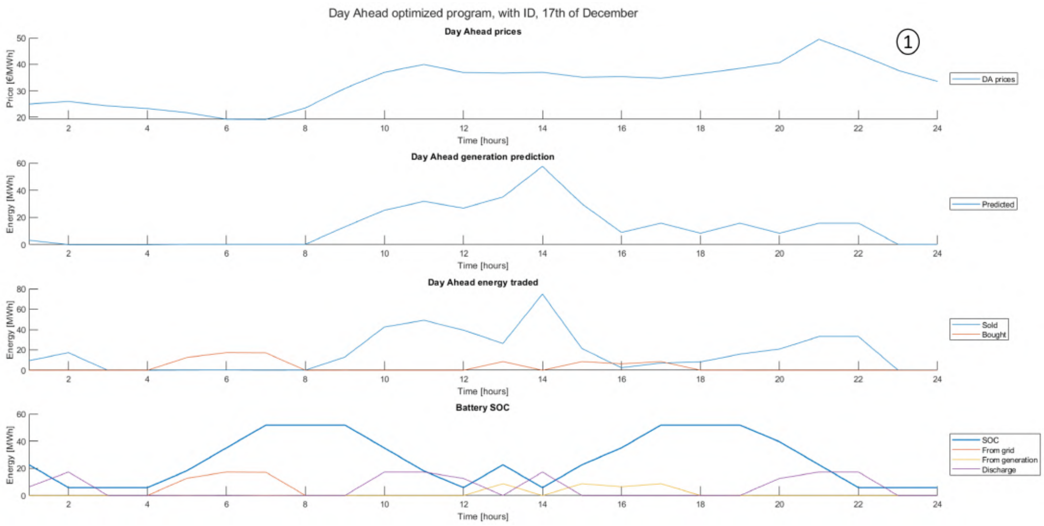


Figure 8.21: Optimized Day Ahead dispatch, with participation in the ID market for the 17th of December.

1. The battery is used following the same strategy seen in Figure 8.18, with discharges at the local price maxima and charges during the minima that are sourced either from the grid or the generation indistinctively. The CVaR also has no tangible effect in this case.

Optimized, ID dispatch - Full market participation

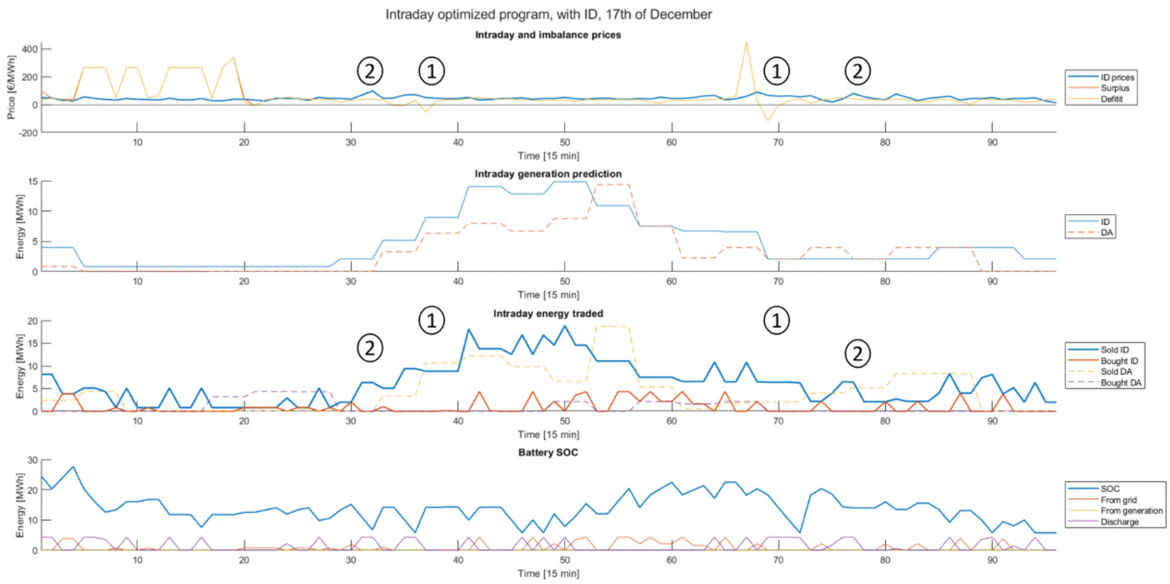


Figure 8.22: Optimized ID dispatch, for participating in the ID market for the 17th of December.

1. Even though these points coincide with local ID prices minima, no energy is purchased to ensure a beneficial deficit in the settlement period.

2. All energy is sold and the battery is discharged during local maxima in prices, and energy is either purchased or charged from the generation during local prices minima.

Optimized, Real Time dispatch - full market participation

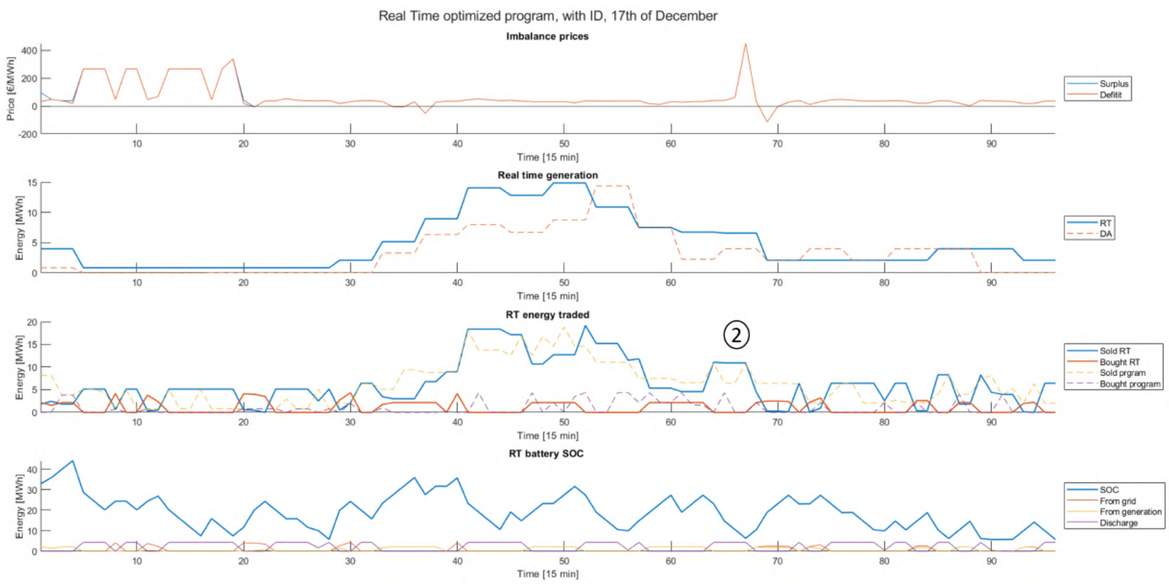


Figure 8.23: Optimized Real time dispatch, with participation in the ID market for the 17th of December.

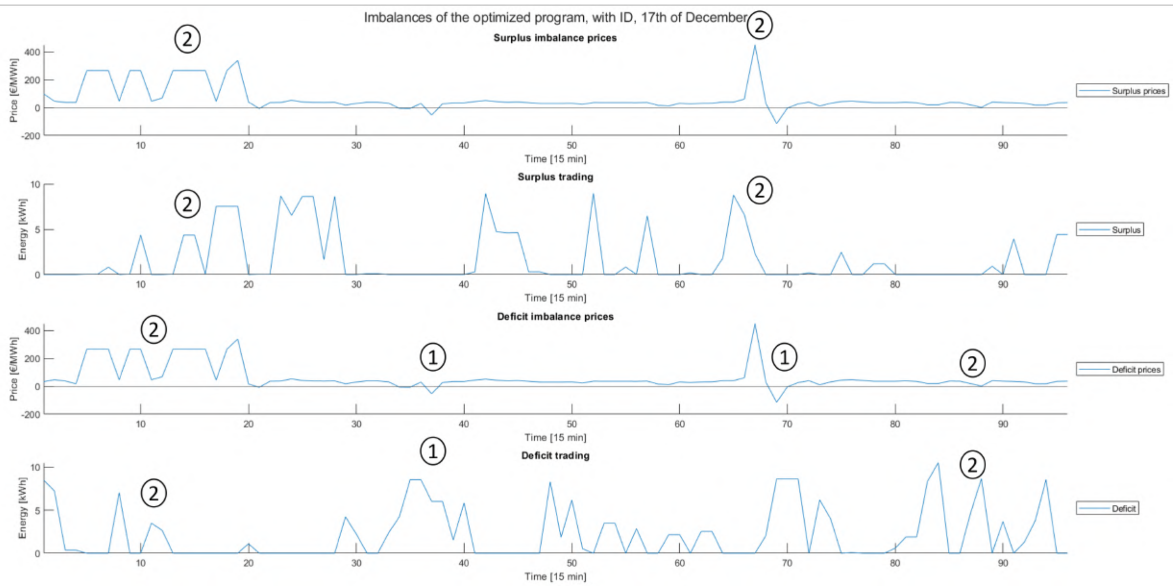


Figure 8.24: Optimized imbalances between the energy delivered and the energy programmed, and their corresponding imbalance settlement prices for the 17th of December.

1. The negative imbalance prices are exploited by an increase in the purchased energy with respect to the ID program, ensuring a deficit.

2. Punctual deficits are created to recharge the battery on low imbalance price periods, and discharge it during the following peaks in the imbalance prices.

   Imbalance price peaks which did not coincide with local maxima of the ID prices are exploited by creating excess in the energy delivered by discharging the battery. Much like for the dispatch shown in Figure 8.4, the fines for deficit imbalances are accepted during low price periods in order to ensure there is enough energy available in the battery to either exploit or cancel the imbalances at the points of peak imbalance prices.

8.2.2. Non-optimized dispatch

Non optimized, Day Ahead dispatch - No ID participation

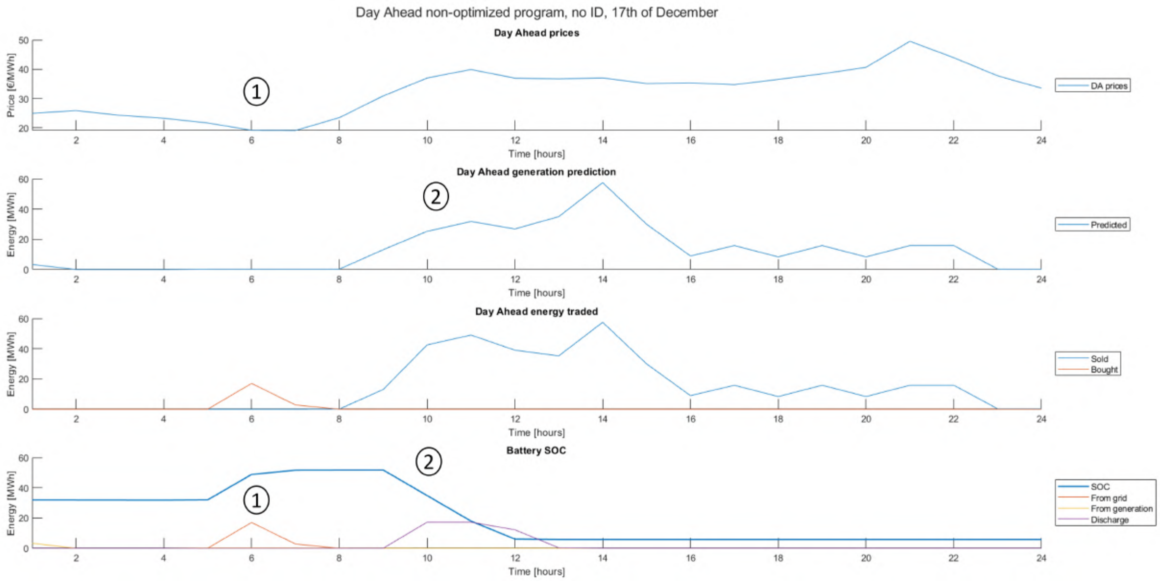


Figure 8.25: Non-optimized Day Ahead dispatch, without participation in the ID market for the 17th of December.

1. The purchase signal is triggered once, but this strategy still fails to take advantage of purchasing at the actual lowest minimum price point. Since the prices never dip below the purchasing signal again, the battery is never recharged after this one instance.

2. The battery is discharged when the discharge signal is triggered. The discharge does not take place over an optimal time span, and although it manages to cover the local price maxima it also discharges on a local minima region in which the optimized dispatch purchases energy. Since the battery is never charged after this, it remains effectively useless for the rest of the day.

Non optimized, Real Time dispatch - No ID participation

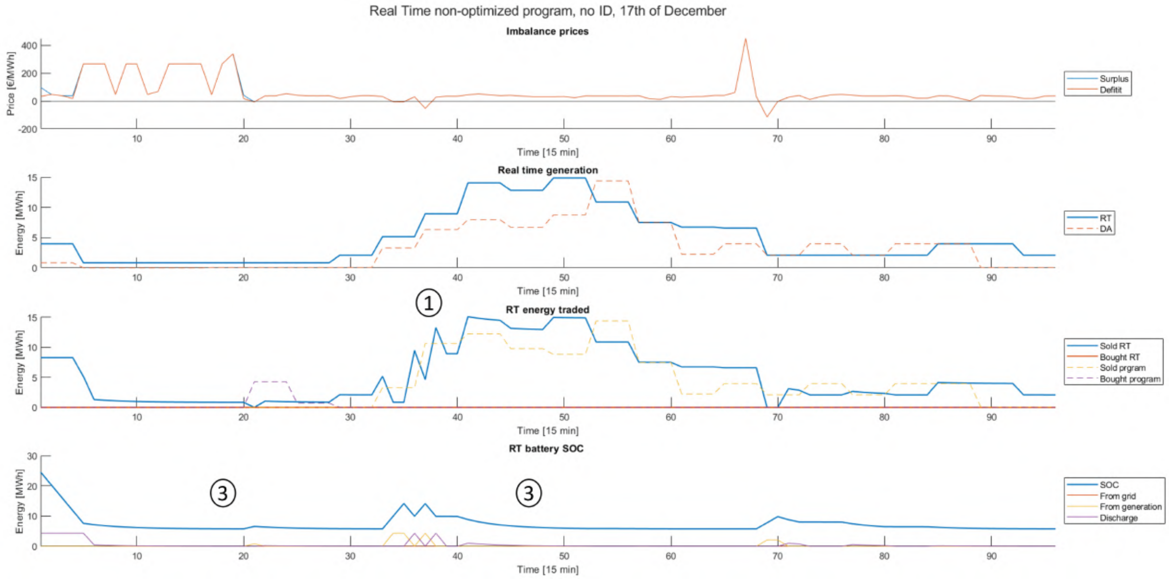


Figure 8.26: Non-optimized Real time dispatch, without participation in the ID market for the 17th of December.

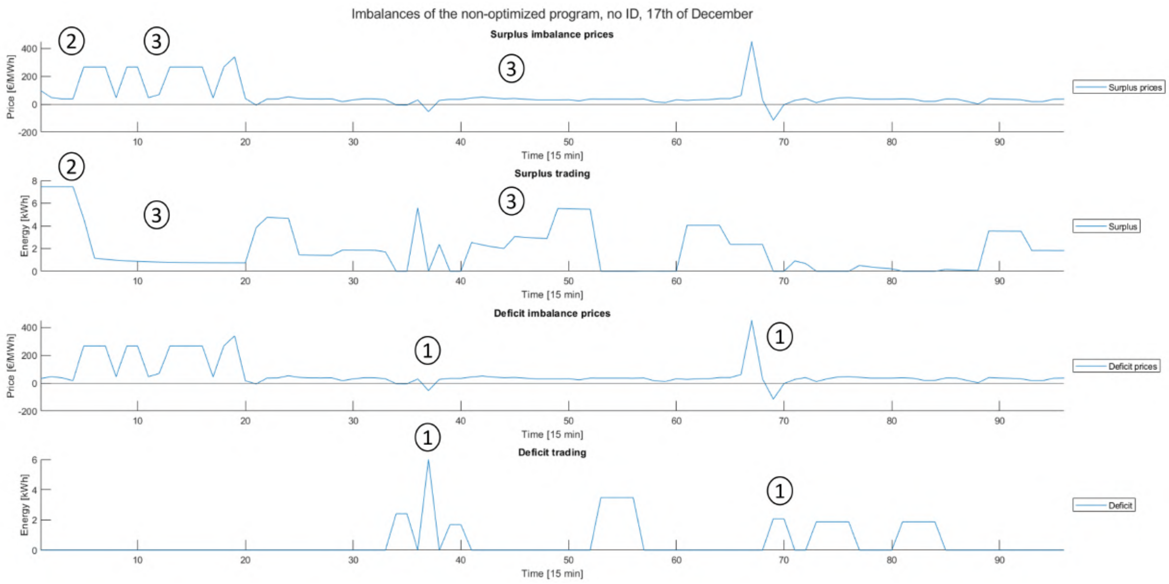


Figure 8.27: Non-optimized imbalances between the energy delivered and the energy programmed, and their corresponding imbalance settlement prices for the 17th of December.

1. These points of beneficial negative surplus prices are correctly identified, and since there is enough capacity available, the battery is charged to create a deficit.
2. The battery is discharged at this initial point to benefit from favorable surplus imbalance prices.
3. However, once the battery has been discharged, the non-optimized strategy is unable to trade-off between taking small fines for deficits and charge the battery and taking

full advantage of imbalance price peaks. Therefore the battery is never charged, and the rest of the program has a default surplus inherent to the excess of generation at delivery.

Non optimized, Day Ahead dispatch - with ID participation

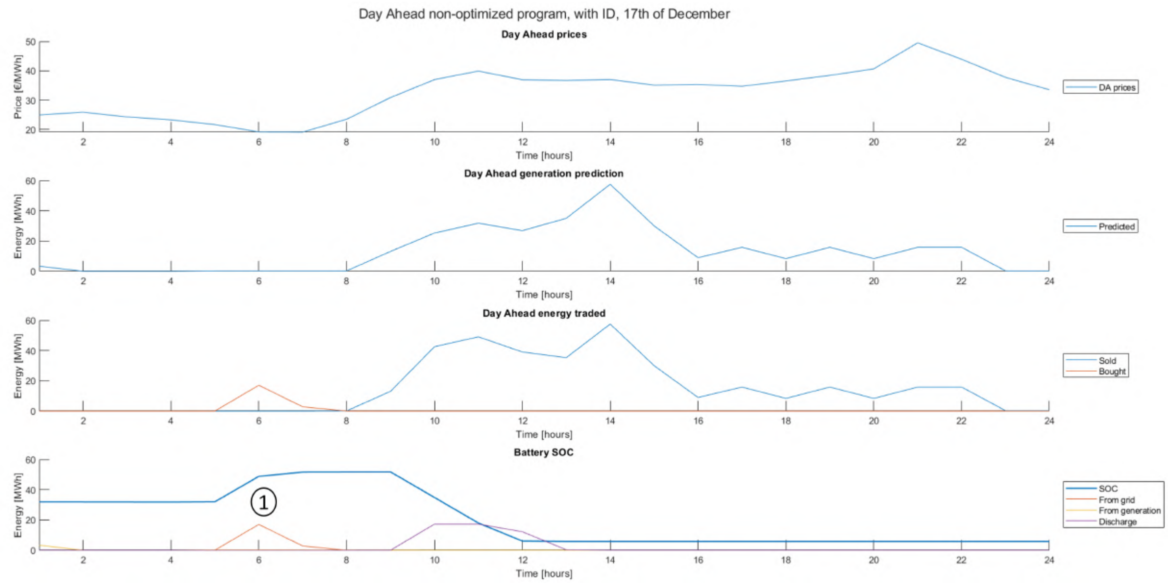


Figure 8.28: Non-optimized Day Ahead dispatch, with participation in the ID market for the 17th of December.

1. The same charge and discharge patterns can be observed here as in Figure 8.25.

Non optimized, ID dispatch

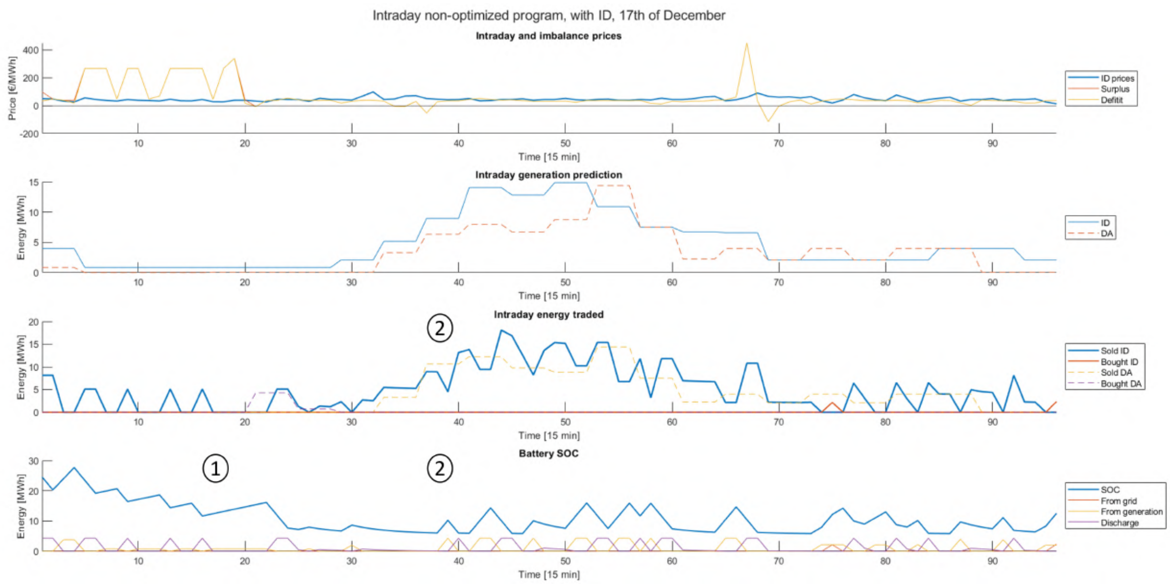


Figure 8.29: Non-optimized ID dispatch, for participating in the ID market for the 17th of December.

1. The discharge price benchmark falls very close to the average ID price of this period, and gets triggered from small fluctuations in prices.
2. The purchase and discharge signals are triggered at several points during the dispatch. The battery is mostly charged from the generation.

Non optimized, Real Time dispatch - with ID participation

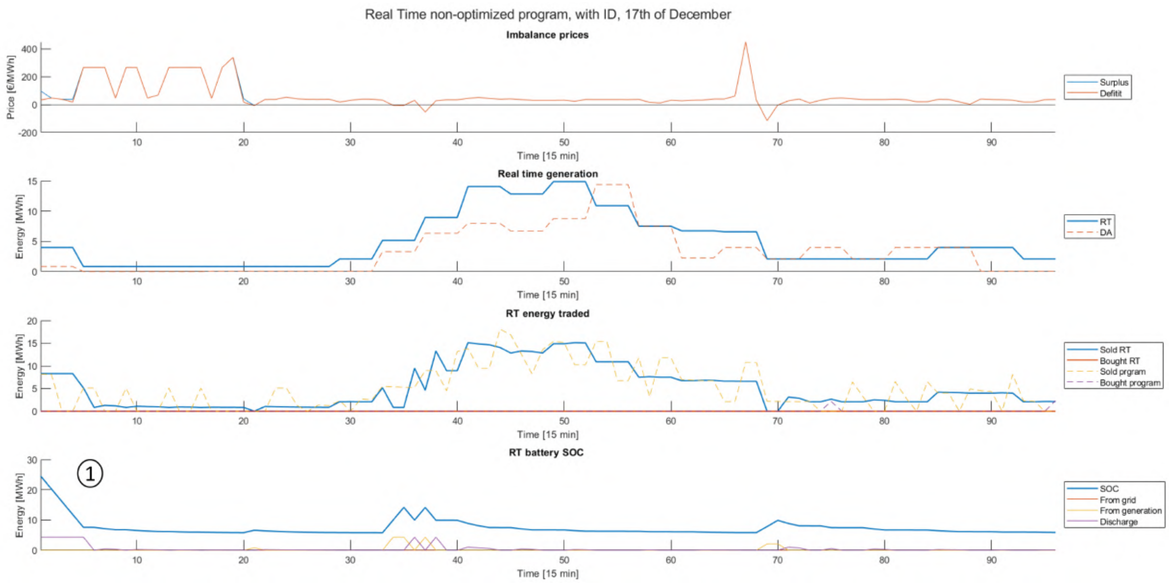


Figure 8.30: Non-optimized Real time dispatch, with participation in the ID market for the 17th of December.

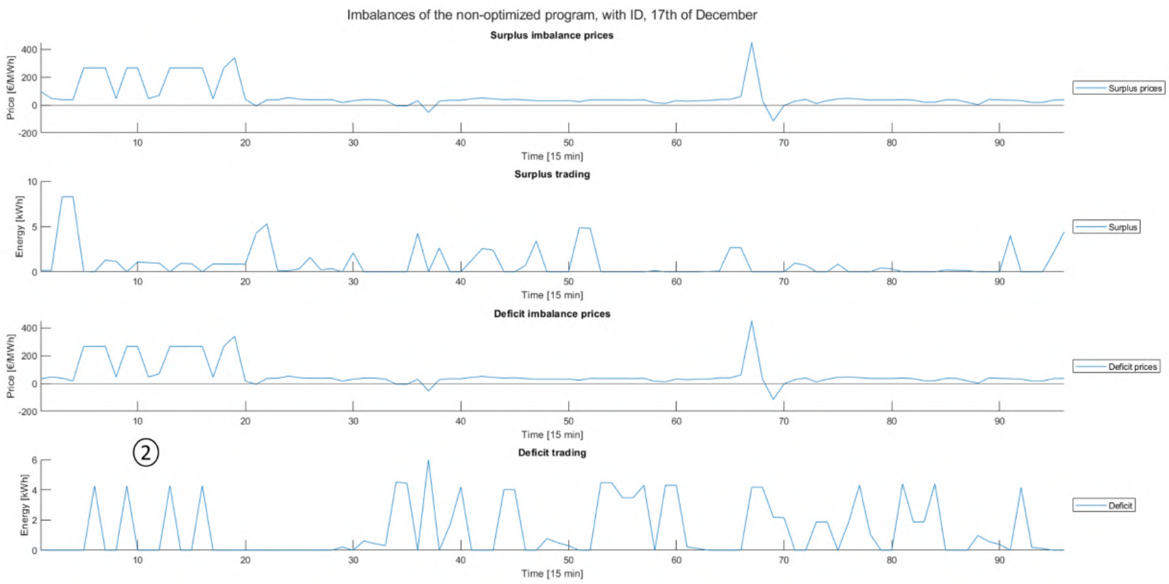


Figure 8.31: Non-optimized imbalances between the energy delivered and the energy programmed, and their corresponding imbalance settlement prices for the 17th of December.

1. Much like with Figure 8.30, the non-optimized strategy has a strong initial discharge to

try to take advantage of this first positive imbalance prices. However, the battery is never charged again except during negative imbalance prices.

2. Unlike in Figure 8.30, the default state of the dispatch is no longer being in a surplus due to excess generation. The ID bids make it such that the optimizer is actually in a deficit on numerous points, since the ID strategy triggered the battery discharge on several points but on the RT dispatch there is no capacity to deliver this energy.

8.2.3. Revenue table

Table 8.3: Revenue breakdown for the 17th of December.

Battery	Optimized	Market closings	DA rev. [€]	ID rev. [€]	Imb. rev. [€]	Total rev. [€]
Yes	Yes	With ID	137.08	114.42	111.39	362.90
Yes	Yes	No ID	137.08	-	241.59	378.67
Yes	No	With ID	131.00	97.35	-38.63	189.72
Yes	No	No ID	131.00	-	116.52	247.52
No	-	With ID	117.93	78.76	-5.08	191.61
No	-	No ID	117.93	-	85.87	203.80

As it can be seen in Table 8.3, the optimized strategy manages again to turn the highest profits regardless of market configuration, with a revenue 90.0 % higher than the no-battery case with participation in the ID market, and 85.8 % higher than the no-battery case without participation in the ID market.

Conversely, the non-optimized dispatch turns a revenue quite close to that of the case without battery, with a revenue 1.0 % lower for the case with participation in the ID market and 21.45 % higher for the case without participation in the ID market.

Similarly to the previous case presented in section 8.1, participating in the ID market did not yield any gains for any of the plant configurations. The optimized dispatch with ID participation had a revenue 4.1 % lower than without ID participation, the non-optimized dispatch had a revenue 23.3 % lower, and the generation-only plant had a revenue 6.0 % lower.

In the case of the generation-only plant, the accurate ID prediction and punctual deficit of generation at 2 PM and 7 PM meant that the overall delivery was in a slight deficit compared to the ID program, since all surpluses with respect to the DA program were passed as trade bids in the ID market. The case of the non-optimized dispatch is very notable: the erratic use of the battery on the non-optimized dispatch provided an ID dispatch with an intensive use of the battery, but this program could not be followed during the RT dispatch. This results in an effective deficit of the energy delivered with respect to the last program submitted, and a subsequent loss in the imbalance settlement in spite of the favorable market and generation conditions.

Taking the revenue of the generation-alone plant as a baseline, the extra profit generated by having a hybrid power plant can be calculated by subtracting this generation-only to the revenue of the hybrid power plant, resulting in Table 8.4.

Table 8.4: Increase in revenue of the hybrid plant compared to generation-only plant for the 17th of December.

Battery	Optimized	Market closings	Increase in revenue [€]
Yes	Yes	With ID	171.29
Yes	Yes	No ID	174.87
Yes	No	With ID	-1.89
Yes	No	No ID	43.72

Subtracting the baseline revenue earned with generation alone, the optimized dispatch had an increase of 8962.9 % compared to the non-optimized dispatch for the case with participation in the ID market; and the revenue for the optimized case without participation in the ID market was 300.1 % higher than the non-optimized dispatch.

8.3. A note of the use of the Conditional Value at Risk

A sensitivity analysis on the risk acceptance parameters for the Conditional Value at Risk revealed that there was a negligible difference ($\leq 1\%$) between the parameters for full risk acceptance ($\beta = 0$, $\alpha = 0.99$) and no risk acceptance ($\beta = 1$, $\alpha = 0$), for both study case days.

These results are consistent with the applied definition of the CVaR, which was used to maximize a profit-based objective function by accounting for the Conditional Revenue obtained for a set of stochastic scenarios. This would, in theory, allow for the consideration of potential losses (or negative profits) that could happen in said scenarios. However, the local CVaR ζ is calculated by evaluating the magnitude of the profit/losses obtained/lost on each scenario relative to the rest of scenarios. Since both selected study days have a generation profile relatively low compared to the battery capacity, the projected scenarios for the selected test case days are projected to turn a similar profit through the use of the battery. Therefore, the CVaR has virtually no effect on the dispatch of the first-stage optimization, since every second-stage projection is able to turn a profit for the original first-stage program.

This, however, does not mean that using the CVaR provides no value for the production of stochastic program. It should be understood that, by definition, the inclusion of the CVaR is not done in order to promote revenue, but to protect against potential losses, a factor that was lacking from the non-stochastic formulation of the problem. Furthermore, the CVaR provides leverage between loss acceptance and the inherent uncertainty of working with stochastic scenarios. Not using the CVaR would potentially lead to overly conservative estimates that over-account for the probability of scenarios with losses but low probability of taking place. By using the CVaR, the risks presented by all scenarios are unified in the representation of a single loss factor that accounts for the average of the worst potential losses among all of them.

Ultimately, the CVaR is a financial analysis tool, and like any other tool its use is decided by its perceived usefulness for a certain context. Hence, power plant operators with a high risk acceptance strategy or highly accurate prediction methods could decide to forego using this tool; while operators with a conservative approach to investment risk or with lower confidence in their generation prediction methods could chose to maintain this factor to have an added safety factor for their trade programs. This consideration is of particular importance if prices are also treated as a stochastic input, since the uncertainty (and its inherent risk of losses) would become even more prominent than in a deterministic price optimization like the one presented in this research.

9

Economic analysis

This chapter presents an overview of some fundamental indicators of the economic viability of operating a hybrid power plant with the same configuration as the SWITCH lab described in chapter 6, and under the different dispatch generation strategies proposed. The goal is not to provide an comprehensive analysis of the economic performance of the power plant, but rather to compare the differences in the financial outlook between managing the trading under the optimized versus the non-optimized and generation-only dispatch strategies.

The capital and operational investments are presented in section 9.1. The economic analysis is done through a study of the Net Present Value (NPV) in section 9.2, Internal Rate of Return (IRR) in section 9.3, and the payback time in section 9.4.

The following assumptions were used:

1. The days studied in section 8.1 and section 8.2 were taken to be representative of the lower and upper bounds, respectively, of the revenue that can be expected to be earned daily in a year.
2. An all-market trading strategy is followed for the entire year
3. The energy wholesale prices have a yearly increase proportional to the country's inflation, with a subsequent yearly increase in the revenue obtained that year.

For the purposes of this analysis, the assumed inflation rates per year are based on the predictions form the European Commission [104], shown in Table 9.1:

Table 9.1: Assumed inflation rates per year.

	2020	**2021**	**2022**	**2023-2030**
r	1.1	2.8	9.4	3.3

9.1. Capital and operational costs

This section presents a high-level estimation of the investment costs for building a plant with wind turbines, PV panels and a Lithium-Iron battery system following the same configuration as the SWITCH lab.

Note: these values were obtained through independent research of the author, and must not be taken as real values for the economic investment carried by TNO or any of its partners in regards to the construction of the SWITCH laboratory.

Wind turbines

The wind turbine model used in the SWITCH lab is the Aircon 10S, with a rated capacity of 10 kW. This model is listed for a selling price of 21,500.0 € per turbine [105]. The operational cost of a wind turbine is highly dependent on the model, geographical and weather conditions, and management of the assets, but the National Renewable Energy Laboratory uses a representative figure of 0.007 €/kWh/year to evaluate the expected costs for its projects [106]. Based on some calculations done by a student research team from TU Delft in collaboration with TNO, the costs associated with the degradation of the equipment would be 0.0015 €/kWh [107].

PV panels

The PV panel model used in the SWITCH lab is the Trina335, which is listed with a cost of 118.53 € per panel [108]. Much like with wind turbines, the operational costs per PV panel depend on their environmental conditions, use, and plant management, but they can be averaged to an estimate 0.002 €/kWh/year [109]. The degradation costs cited by the student research team for the PV panel are of 0.0019 €/kWh/year [107].

Battery

The battery model used in the SWITCH lab is the RE-Volt Lithium-iron Battery from Iron Edison, which is listed at a price of 7,910 € per unit. Calculating the operational and degradation costs of batteries is contingent on the model and use, but the operational costs can be estimated to be of 4.5 €/kWh/year for Lithium-iron batteries [110].

Cost summary table

The total capital and operational costs of the components is summarized in Table 9.2

Table 9.2: Summary of the capital and operational costs for the SWITCH lab.

	Capital expenditure [€]	**Operational costs [€/year]**
Wind turbine	129,000.0	510.0
PV panels	14,223.6	225.4
Battery	47,460.0	270.0

9.2. Net present value

The Net Present Value (NPV) is a measure of the value of a project at the present moment versus the value of the project in the future, by evaluating the ratio between the initial investment versus the future cash flow value at the required rate of return. Projects with a higher NPV have better economic prospects, since it means that the initial will be neutralized earlier and the future cash flows are more valuable.

The NPV can be calculated using Equation 9.1 [111], with N being the total number of periods, R_t being the net cash flow at time t, (R_0 is then the initial investment), and r is the discount rate. In this case, the discount rate was assumed to match the country's inflation, following the predictions of the European Commission for the inflation rates between 2020-2023, and assuming the same inflation rate as 2023 for the period between 2023-2030.

$$NPV = R_0 + \sum_{t=1}^{N} \frac{R_t}{(1+r)^t} \tag{9.1}$$

For a 10-year period, the NPV's per dispatch strategy are shown in Figure 9.1:

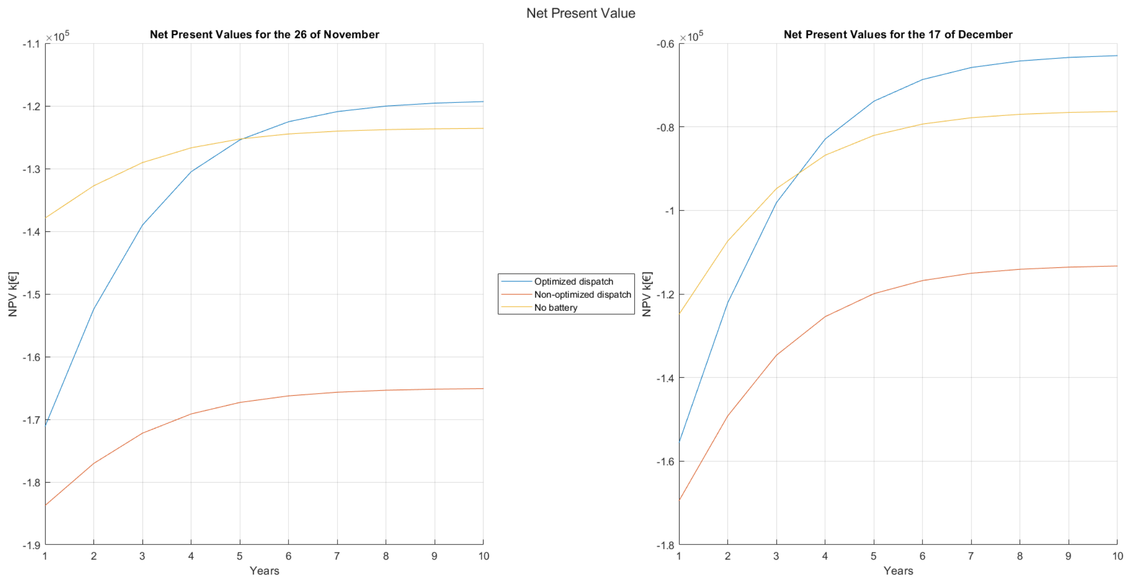


Figure 9.1: NPV for a 10-year period, for revenue projections based on the two study days, for the different dispatch strategies.

The optimized dispatch has the best performance compared to the non-optimized and generation-only dispatches, with the projections for the 17$^{\text{th}}$ of December being the only one to break positive numbers. The non-optimized dispatch actually has a NPV below the NPV for the generation-only configuration, which is consistent with the revenue projections from chapter 8. Both revenues fall very close together, but the non-optimized case has an extra investment expense for the battery assets. Consequently, the investment for the non-optimized case will take longer to be returned than for the generation-only case.

9.3. Internal rate of return

The Internal Rate of Return (IRR), is defined as the discount rate r in Equation 9.1 that delivers an NPV=0 [112]. Much like with the NPV, a higher IRR indiates more substantial future cash flows, and thus a better return on the investment.

The IRR for the project using the different dispatch strategies is presented in Table 9.3:

Table 9.3: Internal Rate of Return of the project for revenue projections based on the two study days, for the different dispatch strategies.

	Internal Rate of Return [-]	
	26th November	17th December
Optimized	0.9318	1.3717
Non-optimized	0.5014	1.0209
No battery	0.4750	1.0855

As it can be seen, although all IRR for these projections are negative for a 10-year span, the optimized dispatch provides the best IRR value for both days; and, most notably, the non-optimized dispatch provides a worse IRR than the generation-only dispatch. The implications of this is that a poorly managed storage system has a high risk of becoming a liability instead of an asset, and that non-optimal dispatch strategies not only worsen the market participation of the power plant, but can threaten the economic viability of hybrid generation-storage plants.

9.4. Payback period

The payback period is defined as the time it takes to recuperate the initial investment in a project [113], and it is calculated using Equation 9.2

$$Payback\ time = \frac{Initial\ investment}{Average\ yearly\ cash\ flow} \tag{9.2}$$

The payback time of the plant using the revenue projections for the different dispatch strategies on the days studied can be seen in Table 9.4:

Table 9.4: Payback time of the project for revenue projections based on the two study days, for the different dispatch strategies.

	Payback time [years]	
	26th November	17th December
Optimized	3.99	2.28
Non-optimized	10.03	3.5
No battery	10.80	3.19

Following the IRR factors from Table 9.3, the payback time for the optimized dispatch is substantially lower than for any of the other two configurations, being 60.2 % lower than the non-optimized dispatch and 63.1 % lower than the no battery configuration for the 26$^{\text{th}}$ of November; and 34.8 % lower than the non-optmized dispatch and 28.5 % lower than the no battery configuration for the 17$^{\text{th}}$ of December.

The non-optimized dispatch has the longest payback time of any configuration. It only has a 7.0 % improvement Compared to the generation-only dispatch for the 26$^{\text{th}}$, and it has a 9.8 % longer payback time for the 17$^{\text{th}}$ of December.

10

Conclusion and Recommendations

This chapter sumarizes the work done for this thesis, providing an answer to the main research question and its supporting sub-questions in section 10.1; and proposing recommendations for further research on the topic in section 10.2.

10.1. Conclusion and key insights

The main research question of this thesis was to propose a dispatch strategy with which the operator of a hybrid power plant with non-controllable production and energy storage resources can maximize its revenue by participating in the Dutch wholesale energy market.

The research was guided through the following questions:

1. *Are there any benefits to proposing the dispatch strategy as an optimization problem, if possible?*

   Under the condition that all energy production predicted has to be dispatched, the success of the dispatch strategy is therefore contingent on an effective management of the storage assets. This research has shown that in order to propose an effective dispatch strategy, it is fundamental to consider the long-term behavior of both generation and prices. This is only possible by formulating the dispatch strategy as an optimization problem, since here-and-now strategies that are based on the punctual behavior of either generation or prices fail to discharge the battery during price maxima and charge it during price minima.

   This is particularly important for unfavorable market conditions such as the one that can arise if the energy forecast is more than the energy generated and the imbalance settlement prices are largely positive. In such a circumstance in the imbalance period, the optimized strategy was able to turn in a profit while the non-optimized strategy stood at a loss. As a result, the final revenue for this adverse scenario was 189.2 % higher on the optimized case than the non-optimized case (with ID market participation).

The optimized dispatch was able to turn a revenue on all market closings for all study cases considered. By contrast, the non-optimized revenue turned a negative settlement revenue for 75 % of the cases that were considered, due to a deficient use of the battery that resulted in heavy imbalance penalization even under favorable market and generation conditions.

2. *How can the random nature of the weather inputs be accounted for and managed?*

   Random behavior of input variables necessitates converting the optimization into a stochastic one. If the probability and profile of possible generation scenarios are known, the original MILP stochastic optimization can be extended into a deterministic, scenario-based two-stage problem which can be solved using a modified Bender's cut. To account for the intrinsic financial risk of the stochastic generation, financial risk contingency measures such as the Conditional Value at Risk can be added. The Conditional Value at Risk provides a safety measure against prospective losses across all the predicted stochastic scenarios, while not hindering the revenue-maximizing objective of the basic optimization.

3. *What are the benefits of having a hybrid energy generation-and-storage plant, compared to traditional generation-only plants?*

   Having an energy storage system has a threefold benefit: it acts as an extra generation source for selling energy, adds flexibility by allowing the purchasing of energy, and provides a buffer to adapt the energy delivered to the best conditions of the settlement market based on the last submitted trade program. Without an energy storage system, the plant is exclusively dependent on weather forecasts for performing successful tradings, and has no resilience against unfavourable market conditions. Even though the capital expenditure is 33.15 % more for a hybrid power plant, the increase in revenue compared to a generation-only plant results in payback periods between 63.1 % and 28.5 % lower.

   However, these benefits only stand under a sensible battery management scheme. The non-optimized dispatch provided a worse economic outlook than the generation-only configuration, given that their revenues were similar (with an average 12.0 % increase for the non-optimized case) but the initial investment was higher for the hybrid plant. This was reflected in the economic performance of both configurations, since the non-optimized dispatch had lower NPV and IRR than the generation-only plants, and its average payback time was 1.4 % higher. Based on this, it can be concluded that it is most recommendable to have a generation-only plant than a hybrid plant with a poorly managed storage system.

To answer the main research question, the findings of this research indicate that formulating the dispatch as a Mixed Integer Linear optimization Problem (MILP) provides an effective and reliable strategy for trading in all markets, being able to turn a profit even in the case of a deficit at delivery compared to the predicted generation. It also has the benefit of being able to account for the marginal cost of the operation, and offers the flexibility of providing updated dispatches as improved weather forecasts are generated through the day.

For the case of known prices and highly accurate ID forecast, participating in the ID market was not found to be beneficial. This can be explained by the fact that a high-accuracy ID program in which all energy predicted must be dispatched will result in diminished opportunities for creating imbalances during the settlement period. However, this finding is contingent on deterministic prices and high forecast accuracy, and results of the benefits of participating in the ID market might vary under stochastic prices and lower forecast accuracy. The imbalance settlement market is highly volatile, and aiming to gain a revenue by exploiting the (predicted) imbalance prices is therefore a highly risky strategy. Under a more conservative risk strategy, such as aiming to minimize program imbalances, participating in the ID market would then yield a much better outlook that trading only on the DA and RT.

The use of the Conditional Value at Risk had a negligible impact on the trading program, regardless of the value of the risk acceptance parameters. This is explained by the effect of the battery, which for the days studied allowed to turn a potential profit regardless of the scenario projections. Although it is still a factor to curb potential losses in an optimization that otherwise only considers profit maximizing, this is indicative that the traditional formulation of the CVaR might not be the most useful tool to generate trading programs for maximum financial gain.

10.2. Recommendations for further research

The following topics are suggested for further research based on the work done for this thesis, either as an extension of the research or as add-ons to it:

- Extend the stochastic optimizations to include market price uncertainty. This might necessitate a revision of the stochastic optimization method used for solving the optimization and generating the uncertainty scenarios.
- Investigate other possible options of the objective function, such as optimizing the Conditional Value at Risk or minimizing losses.
- Investigate alternative applications of the Conditional Value at Risk, through its application of either alternative objective formulations or use with a non-scenario-based optimization. It would also be recommendable to study the performance of dual-objective functions in which the revenue is maximized while the Conditional Value at Risk is minimized, in order to have an increased impact of the Conditional Value at Risk in the final program
- Study the influence of forecast accuracy and stochastic prices in the advantages from participating in the ID market, and how optimizing for other objective functions (such as minimal imbalances) would benefit the dispatch programs.

- For the case of TNO in particular, it would be highly suggested to include the electrolyzer into the modeling and the hydrogen market in the optimizations.
- This research has a natural extension in options for service stacking, making use of the optimizations, stochastic methods, and addition of the Conditional Value at Risk laid down in this work.
- Include an analytical expression for the marginal costs of the system in the revenue equations.
- Extend the optimizations to include control parameters for the generation assets, in order to not only get an optimal revenue program but also the optimal use of the generation to achieve it.
- Include the effect of policy and contractual obligations in the program generation, particularly for the Real Time dispatch.
- Study the possibility of carrying the optimizations in other commercial solvers such as CPLEX and GAMS, in order to study whether the software selection has a significant effect in the speed and accuracy of the convergence.

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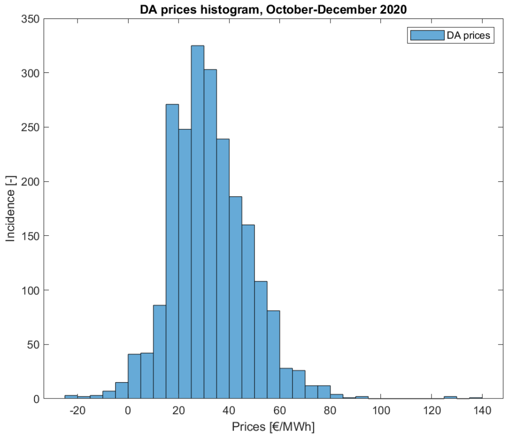
A

Historical Dutch energy market prices

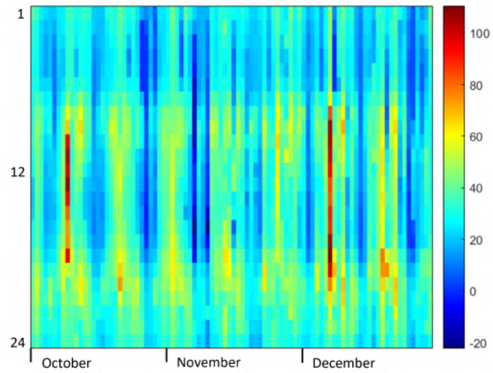
This appendix presents the Dutch energy market prices for the 2011-2020 period. Values for the historical Day-Ahead and Intraday prices were retrieved thanks to a collaboration between EPEX and TU Delft; and the imbalance settlement prices are publicly available through TenneT's own website [114]. The Day-Ahead and imbalance prices were available for the 2011-2020 period, but for the Intraday prices only data for the period of October-December 2020.

The analysis is presented using histograms, heat maps, a decomposition of the seasonal trends, and a plot of the prices with the dispersion and trends. The later two were obtained using the Prophet function in Python.

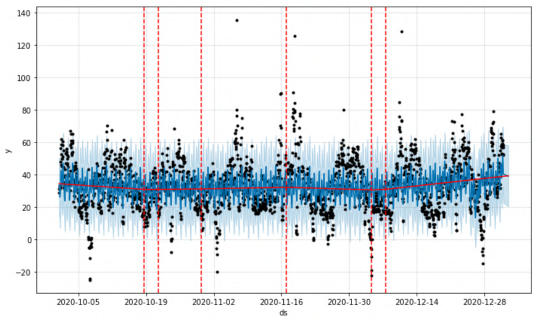
A.1. Day Ahead prices



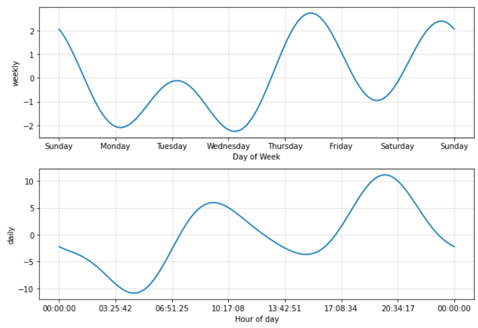
(a) Day-Ahead prices histogram



(b) Day-Ahead prices heat map



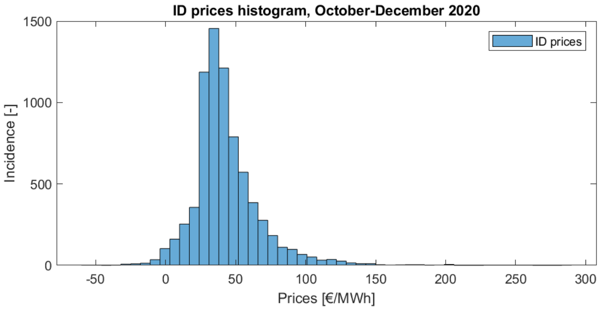
(c) Day-Ahead prices, showing the data dispersion and trends



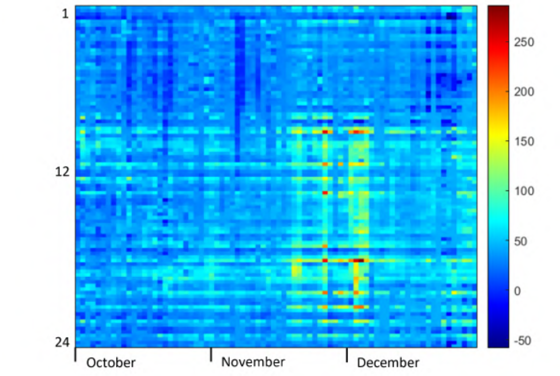
(d) Day-Ahead daily and weekly seasonality.

Figure A.1: Day-Ahead price analysis for the October-December 2020 period

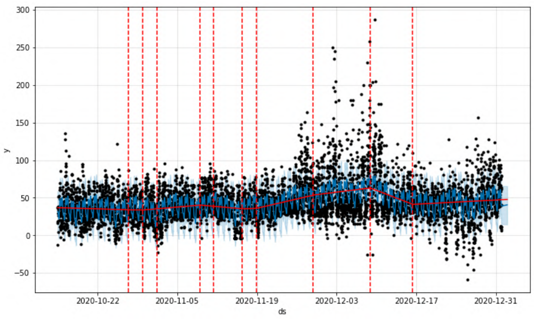
A.2. Intraday prices



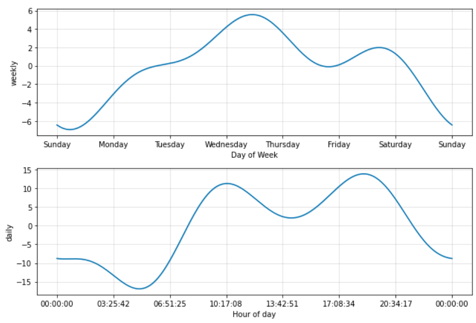
(a) Intraday prices histogram



(b) Intraday prices heat map



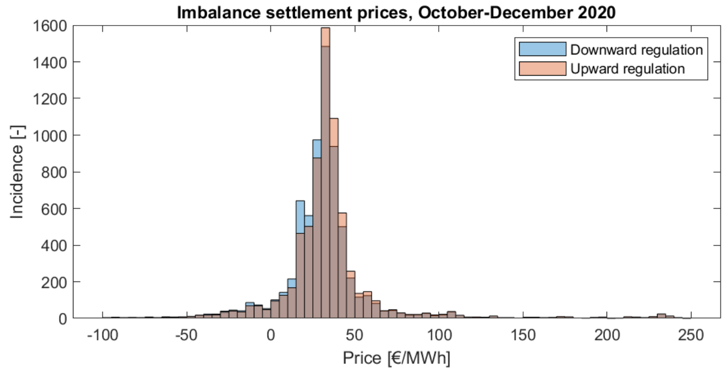
(c) Intraday prices, showing the data dispersion and trends



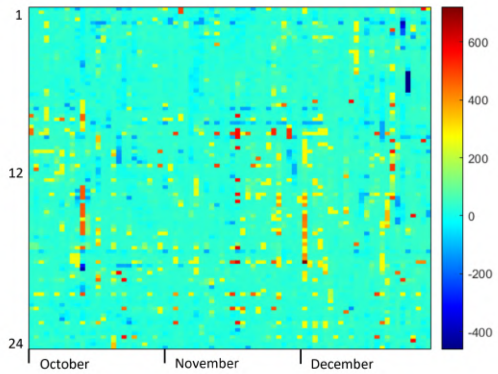
(d) Intraday daily and weekly seasonality.

Figure A.2: Intraday price analysis for the October-December 2020 period

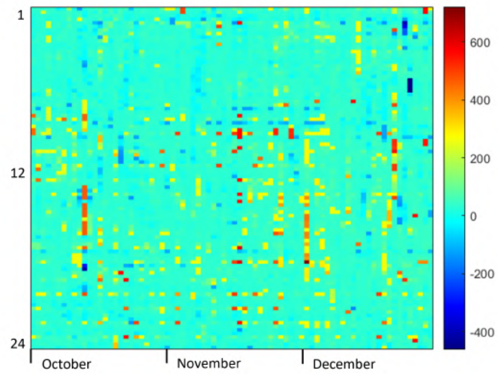
A.3. Imbalance prices



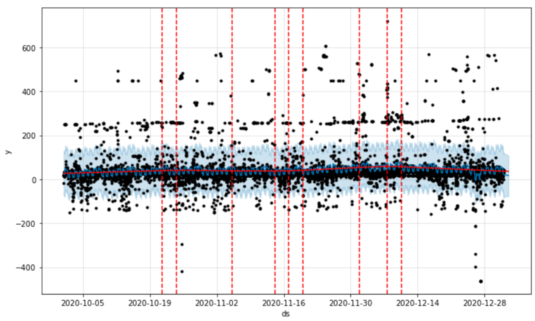
(a) Imbalance prices histogram



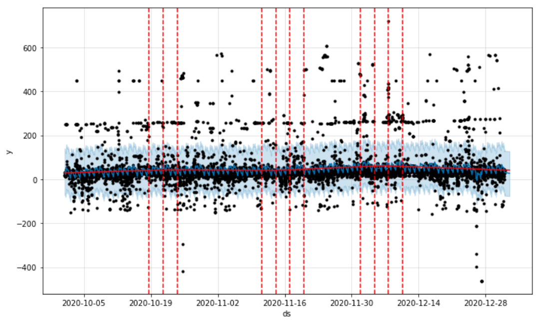
(b) Down regulation imbalance prices heat map



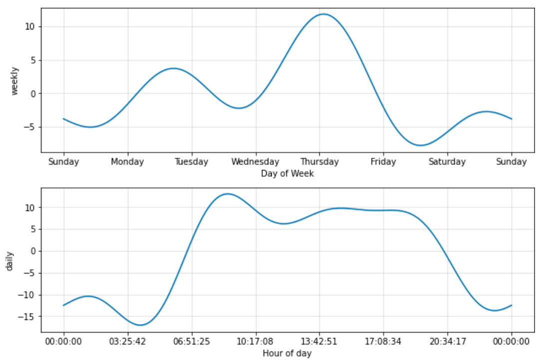
(c) Up regulation imbalance prices heat map



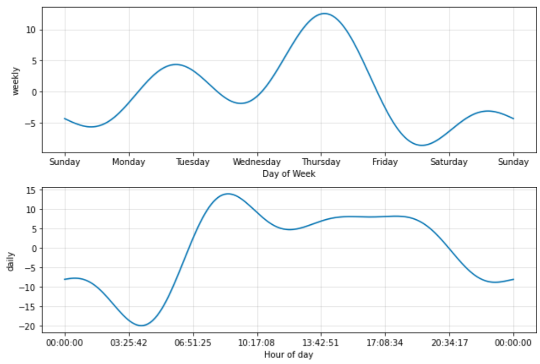
(d) Down regulation imbalance prices, showing the data dispersion and trends



(e) Up regulation imbalance prices, showing the data dispersion and trends



(f) Down regulation prices, daily and weekly seasonality.



(g) Up regulation prices daily and weekly seasonality.

Figure A.3: Imbalance prices analysis for the October-December 2020 period

B

Overview of optimization techniques in Matlab

Mathworks has developed a number of optimization toolboxes to be used in Matlab. The most basic - and widely used one - is the Optimization Toolbox [115], which includes solvers for *[...] linear programming (LP), mixed-integer linear programming (MILP), quadratic programming (QP), second-order cone programming (SOCP), nonlinear programming (NLP), constrained linear least squares, nonlinear least squares, and nonlinear equations*. The solvers form this toolbox serve as the basis for the Global Optimization Toolbox [116]. In addition two these optimization-focused toolboxes, the Statistics and Machine Learning Toolbox has algorithms for handling low-dimensional deterministic [117].

All of the solvers from these toolboxes use numerical methods to solve the optimizations, with each solver having a set of available algorithms to calculate the solution. These algorithms are based on a variety of methods published in peer-reviewed publications, such as dedicated journals and textbooks. Thus, selecting an appropriate solver is not a trivial issue, since the quality of the final solution (or whether a solution is found at all) will entirely depend on what method is used to find it. To select a fitting solver, the following points have to be considered:

- The nature of the optimization problem, as determined by the properties objective function and the constraints.
- The syntax of the problem, since most solvers only accept matrix-form constraints and objective functions.
- The algorithms available for each solver, and how they match the nature of the optimization.

The optimizations presented in chapter 3 have two key points to take into account:

1. The marginal cost term in the objective functions necessarily has to be input as a symbolic equation. In order to calculate the cost, it is necessary to select the linear terms also based on the depth of discharge; and to do a cycle count based on the depth of discharge and keep a memory of the total number of cycles.

2. Mutually exclusive terms (pairs of variables in which one must be zero if the other is nonzero, such as the battery charge/discharge and Δ^+/Δ^-) can be formulated in two ways:

   2.1. As a nonlinear constraint in which their product is zero:

$$var_1 \cdot var_2 = 0$$

   2.2. By introducing a binary variable and incorporating it as a "switch" constraint for the variables:

$$\delta \in 0, 1$$

$$var_1 \leq [...] \cdot \delta \qquad var_2 \leq [...] \cdot (1 - \delta)$$

Within the Optimization Toolbox, there are two solvers that present interesting properties:

- fmincon: it can handle non-linear equality or inequality constraints and symbolic formu□lation of the objective function. It has an available Sequential Quadratic Programming (SQP) designed specifically to solve nonlinear optimizations. The solver does not discriminate between local and global minimum by using fmincon alone, and it is also one of the costlier algorithms time-wise.

- intlinprog: it can handle Mixed Integer problems with equality and inequality constraints, but it only admits vector formulations for the objective function. It is set to use a branch-and-bound algorithm that generates successive cuts to reduce the feasible region of the relaxed problem.

The Global Optimization toolbox has the following solvers that present interesting properties:

- patternsearch: admits non-linear constraints and symbolic objective functions. The algorithms works by generating a mesh of objective function values around an initial point, and moving in the direction of the point with the best value.

- ga: admits admits non-linear constraints, integer variables, and symbolic objective functions. However, equality constraints and integer variables are not compatible on the same problem. It uses a genetic algorithm which randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population ”evolves” toward an optimal solution. It is thus an stochastic algorithm, and solutions might vary between runs.

- globalsearch: this uses a local solver from the Optimization toolbox to evaluate multiple viable starting points.

Documentation in the Mathworks' site includes a comparison between local solvers [117], guidance on how to select a global optimization method [116], and an overview of the local optimization algorithms [118].

One of the main factors in the optimizations is the definition of the marginal cost, which is a very computationally heavy formulation since each iteration of the solver requires recomputing the number of cycles and selecting the right cost expression based on the values for the battery state of charge variable. However, this term only represents the cost of actually using the battery, meaning that it is only enforced through the energy dispatch that is actually carried. In the stochastic optimizations, this dispatch that is actually enforced is the solution to the first stage problem. The purpose of the second second stage problems is to integrate the impact that possible realizations of the stochastic variables would cause on the first stage dispatch. Therefore, the marginal cost of the battery is only an indispensable element in the first stage optimizations, but not for the second stage. This allows to further narrow down the selection for the solver and algorithm:

- The first stage would include the battery Fractional Cost, and the only option to solve such problem would be by using Globalsearch with the fmincon solver and the SPQ algorithm. This necessitates that the mutually exclusive variables are written as nonlinear terms, as previously explained in this section.
- The second stage with the Fractional Cost term removed can be solved as a Mixed Integer problem, with the mutually exclusive variables being constrained through the introduction of extra binary variables. The resulting problem can be solved with intlinprog.