Optimising BESS Control Strategies for Congestion and Price Arbitrage

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TUDelft

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by

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to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on Monday July 11, 2022 at 11:00 AM.

Student number:	4486528	
Project duration:	November 1, 2021 – July 11, 2022	
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An electronic version of this thesis is available at http://repository.tudelft.nl/.

Abstract

Renewable energy generation projects are often measured by their peak capacity. A wind farm rated at 25 MW will generate 25 MW of power under the right circumstances. This peak capacity is reached very little in practice. However, these generators are forced to purchase grid operation infrastructure that can handle this peak generation event. The high voltage grid connections are expensive and increasingly difficult to receive permits for. This work presents a solution in which the high voltage grid connection is undersized in comparison to the renewable energy generator. A battery energy storage system is installed in the local grid to solve the issue of excess energy generation (congestion).

A simulation of the local network has been built that models a battery energy storage system (BESS), the network and uses data from a solar park. A case study in which a 19 MW solar park is connected to the high voltage grid with a transformer of only 14 MW as well as a 14 MW | 30 MWh BESS on the network is investigated in the rest of the work. Furthermore a BESS control strategy for price arbitrage on the TenneT imbalance market is presented and encoded such that it can be optimised.

Four heuristics are presented that time and size the congestion issue in a manner the control strategy of the BESS can prepare for and solve congestion when necessary. These heuristics are tested against strategies optimized for revenue maximisation through price arbitrage. While the most aggressive strategies did not solve all the congestion events in these simulations, we found that the heuristic that takes the average generation of the solar park into account performs the best while remaining appropriately conservative.

A basic evolutionary algorithm is presented that optimizes a BESS control strategy for price arbitrage when the BESS is not needed on the local network to solve congestion. Although the strategies earn $\sim 33\%$ less revenue due to the congestion related limitations, the optimisation surrounding congestion does improve revenue by 2.58%.

The results presented in this work suggest that this setup of a local grid can be economically viable and that the BESS can solve the congestion issue when steered with an appropriate control strategy. We hope to inspire parties that battery energy storage systems can earn substantial revenue aside from solving issues on a (local) grid.

Preface

BESS control strategies steer energy storage systems smartly and earn revenue in the process. This thesis has been a combination of the business world in which a real problem is expected to be solved as well as an academic contribution to a field in which energy storage systems are still sometimes seen as systems that can only serve a single purpose. I hope this work can inspire parties from both sides of the spectrum to see energy storage systems as the flexible, powerful asset I have come to know them as in the past year.

I heard of GIGA Storage for the first time 2 years ago in the summer of 2020 when I was looking for an internship to help with the slur that studying during the COVID-19 pandemic had become. Without any prior knowledge on anything energy related the interview compromised more of me learning about the energy market than me selling my skill set to them. During that initial internship the CEO Ruud came to me one lunch break and said: *“Jip, promise me you will finish your masters degree.”* as by that time I was in awe of the energy world and making full time weeks building the IT platform that was going to steer the GIGA Rhino BESS.

Working on my thesis has been an educational journey which started when I came to the TU Delft in 2015 with 3 partners in crime Dieuwer, Jaap en Rolf. I want to thank them for the sheer amount of fun we had together as well as the harsh code reviews they could give me during group projects. A special thank you is in place for Jan, a housemate of over 6 years with whom I could discuss any issue I was encountering. I also want to thank my other housemates in Delft and Rotterdam whom I’ve bored most often with my stories on computer science and for the past years the tales about energy markets.

I want to thank my supervisors Dr Valentin Robu from CWI and Jeroen Buis from GIGA Storage. Their sharp feedback and guidance during this thesis have elevated this work. I am curious to see what the future will bring but know for certain that there will be times at which I will hear your voices in my head with advice I have received from you at some point in the past year. I want to also thank Dr Mathijs de Weerdt and Dr Jochen Cremer for being part of my thesis committee.

Céline my partner deserves a very special thank you as all of the above applies to her three-fold. I hope I can bore you with stories about energy markets and count on your love and support for many years to come. My last thank you goes out to my family, other unmentioned friends and colleagues at GIGA Storage for their support during this thesis.

Jip Rietveld
Rotterdam, June 2022

Glossary, Acronyms and Nomenclature

Glossary

TenneT Transmission System Operator of The Netherlands

Imbalance Market The quarterly priced, real-time market to solve imbalance on the grid

TenneT Balans Delta The minutely message that communicates an indication of the current imbalance market price

Acronyms

BESS Battery Energy Storage System

ESS Energy Storage System

FCR Frequency Control Reserve

PPA Power Purchasing Agreement

REG Renewable Energy Generator

SoC State of Charge

TSO Transmission System Operator

Nomenclature

ES_{max} The maximum amount of energy stored in the BESS

$ES(t)$ The amount of energy stored in the BESS at timestep t

P_{max}^{BESS} The maximum power of the BESS

$P^{BESS}(t)$ The power of the BESS at timestep t

η_{rt} The round trip efficiency of the BESS

ES_{lower} The lower limit of the capacity before the BESS would be derated

ES_{upper} The upper limit of the capacity before the BESS would be derated

cycle(t) The cycle made at timestep t

$P^{REG}(t)$ The power of the REG at timestep t

$P^{transformer}$ The power of the transformer

$NetworkPower(t)$ The amount of power being supplied to the transformer from the network

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1 Introduction

The Dutch high voltage network is reaching the limits of its transport capacity. For this reason TenneT, the Transmission System Operator (TSO) of The Netherlands, has sometimes been forced to limit access to the grid [1]. Consumers or generators looking for room to install a connection to the high voltage grid suffer from enormous waiting times or downright denial of service [2]. In part, this is due to the large investments in renewable energy generation (REG) of the past years. Due to the small size of The Netherlands as a country, when the sun is shining, all solar parks will generate a lot of energy; a similar situation occurs for wind farms. This peak generation capacity can only just be handled by the currently installed grid. Classically speaking the TSO looks towards the installation of additional transformers and cables to solve these issues [3]. However these investments are expensive and take many years to implement.

Energy storage systems (ESSs) have been investigated by the scientific community due to their flexible capabilities to solve local and larger-scale energy network related problems (Luo et al., 2015). This work presents an additional solution that can help solve the issue of an overfull high voltage grid. Before exploring the solution this work will present, let's first explain what issues are encountered by parties wanting to connect to the high voltage grid.

Renewable energy generation projects are often measured by their peak capacity. A wind farm rated at 25MW for example will generate 25MW of power if the wind is coming from the right direction at the right speed. As this energy production is dependent on the renewable energy source (wind in this example), this peak capacity will only rarely be reached. Far more often less energy will be generated by the wind farm.

However, the renewable energy project is expected to have grid operation infrastructure large enough that can handle these peak generation events. As discussed above, these large grid connections can be excessively expensive, or permit applications can limit the realisation of the project. This grid connection that poses all these issues is only fully utilised in high renewable generation situations, which means they are utilised very little.

Energy storage systems can offer a solution to these issues, which could help realise the renewable energy generation project. In the same example, the wind farm rated at 25MW could add a 10MW energy storage system to their local network. The ESS can charge 10MW when the wind farm produces 25MW. Thereby ensuring the need for a network connection to the high voltage grid of only 15MW. This smaller grid connection could be easier to realise than the previous network connection of 25MW.

This implementation raises interesting issues and research questions for the ESS. How should the energy storage system be steered during these congestion events? The energy storage system should also be prepared correctly for these congestion events and finally, can the energy storage system be utilised to earn additional revenue when not necessary tasked with solving congestion.

[1]https://www.tennet.eu/nl/tinyurl-storage/nieuws/voorlopige-stop-voor-nieuwe-grootverbruikers-van-elektriciteit-in-noord-brabant-en-limburg/

[2]https://nos.nl/artikel/2431946-stroomnetwerk-limburg-en-n-brabant-vol-nieuwe-bedrijven-niet-aangesloten

[3]https://www.nu.nl/290603/video/waarom-het-stroomnetwerk-in-nederland-overvol-raakt.html

1.1. GIGA Storage

This thesis has been created in a partnership with GIGA Storage, a Dutch-based company in the industry of large-scale sustainable energy storage[4]. They currently own the GIGA Rhino battery, a lithium-ion based battery project set in Lelystad. It is the most powerful battery project in The Netherlands with a power of 12 MW and a capacity of 7.5 MWh. They have recently signed an agreement with Eneco to build their next battery project, the GIGA Buffalo, which is expected to come online in January of 2023.

The business case of the GIGA Rhino battery lies in its power to earn money in multiple energy markets. The battery can be used to earn money on the imbalance market with price arbitrage. On that market the battery can be charged at low prices and discharged later at high prices. However the system can also be bid into the Frequency Control Reserve (FCR) market. In that market the battery is tasked with charging and discharging small amounts to ensure the frequency of the network remains a stable 50Hz. During that time the system is compensated by the bid amount.

It is important to take into account battery degradation when considering what strategy to apply for price arbitrage in the imbalance market. When a battery is supplied, it has an expected lifetime in accordance to how the battery is utilised. Similarly to the battery found in your smartphone, when you charge and discharge it often, the quality of the battery degrades (Stroe et al., 2017). Suddenly it doesn't last you the entire day, or starts working less efficiently. Large-scale energy storage projects encounter the same issues and therefore they often have clear guarantees surrounding usage of the system to ensure the battery has an elongated lifetime.

1.2. Research Questions

This thesis will answer three research questions. The first one is proof of concept that an appropriately sized battery energy storage system (BESS) is able to solve congestion for the network. Furthermore the performance of the BESS on additional energy markets is to be considered. When there is no congestion management necessary on the network, the BESS is free to trade and earn additional revenue. Research question 2 will explore the possibility of optimising the BESS control strategies and compare their performance to a baseline offered by GIGA Storage. Research question 3 will additionally investigate the effectiveness of this optimisation method by combining it with the findings of RQ1 to solve the congestion issue while earning additional revenue.

RQ1: Can the battery energy storage system solve the issue of congestion when a renewable energy generator is operated with a limited connection to the transmission network?

RQ2: To what extent can a battery energy storage system control strategy for price arbitrage be optimised (with an evolutionary algorithm).

RQ3: How much additional revenue can the battery energy storage system earn aside from solving the issue presented in RQ1.

Additional revenue within this work will be considered to be earned on the imbalance market. Actions taken on the FCR market are defined by irregularities in the network frequency. Furthermore the FCR market is met with many physical restrictions the asset must follow when it participates in this market. This work therefore focuses on the strategy that is executed by the BESS for price arbitrage on the imbalance market. Executing different strategies on the BESS can have a lot of impact on the generated revenue as well as usage of the system. An aggressive strategy could charge and discharge often and generate revenue through smaller margins. A more passive strategy could bide its time and wait for large margins before deciding to charge or discharge.

[4] https://giga-storage.com/?lang=en

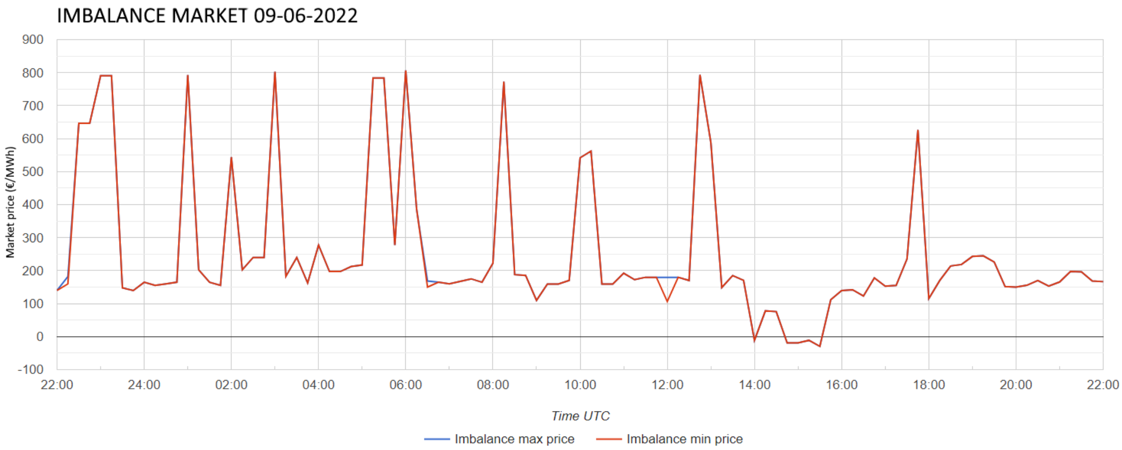


Figure 1.1: TenneT imbalance market prices for 09-06-2022

1.3. Contributions

The contribution of this work will be three-fold.

1. A model for a control strategy for battery energy storage systems will be presented.
2. Heuristics will be used to determine control strategy constraints regarding congestion issues on the local smart grid.
3. An evolutionary algorithm is presented to optimise the control strategy of the BESS in a case study.

1.4. TenneT Imbalance Market

In this thesis all actions taken on the network are considered to be priced based on the imbalance market. This market is managed by TenneT. When unscheduled actions are taken by energy parties TenneT offers them the current imbalance market price. This price is set every 15 minutes and an indication of this quarterly price is communicated every minute, albeit with a 2-minute delay.

These price signals are designed to solve the imbalance on the high voltage grid. In times of excess energy, the price is set lower (or negative) to promote usage of this excess energy. In times of limited energy, the price is set higher to dissuade parties from using energy or promote generation of additional power.

The price offered is in €/MWh. An example day of the imbalance market can be seen in Figure 1.1. The difference in high and low prices represents an earning opportunity for a flexible asset such as a battery energy storage system. When prices are low, the BESS can be charged. When prices are high, the BESS can be discharged. The margin between these prices is considered profit for the BESS.

1.5. Overview of the document

The rest of this document is structured as follows. In chapter 2 related work on the topic of energy storage systems and control strategies is investigated. Chapter 3 describes the simulation built in this thesis, including but not limited to the model of the BESS, assumptions regarding energy markets and the chosen case study. In chapter 4 we discuss the methodology used to solve congestion and optimize BESS control strategies. In chapter 5 we describe the executed experiments and present their results. Then in chapter 6 we discuss the results of the experiments and their significance to the case study. Finally in chapter 7 we make recommendations for future work and conclude our findings.

2
Related Work

2.1. (Battery) Energy Storage Systems

Energy Storage Systems have been researched due to their flexible capabilities for local- and larger-scale energy-related problems. An ESS can solve many issues including voltage control, peak shaving, frequency regulation, reliability improvement, and reduction of the fluctuating nature of wind (Luo et al., 2015).

Although accidents such as the *Fire at 20MW UK battery storage plant in Liverpool* (Colthorpe, 2020) cause distrust in the eyes of the public, more and more ESSs are being installed around the globe. In varying sizes these systems either solve issues for local micro grids (Romero-Ruiz et al., 2016) but can also be utilised in larger-scale grid issues (Ke et al., 2015).

To the list of effective solutions this thesis proposes a system to undercut high voltage grid network sizing in favour of solving the locally caused congestion problems through an ESS. However the main contribution of this work is the consideration that the possibilities of an ESS do not end at the solution of an offered problem. The flexibility of the ESS can ensure the system is used elsewhere to solve additional issues or earn additional revenue for the network when the original problem has been solved.

Many works simply consider the ESS as a solution to a presented problem Root et al., 2017. Although all of these papers show the effectiveness and capabilities of an ESS, often when considering the cost of installing an ESS they find that the technology is too expensive to realise. To that extent this thesis hopes to show that by utilising the ESS in downtime of the problem it has to solve, the business case of the asset can be improved. This could improve it in such a manner that the ESS project can be realised rather than considered hypothetically.

2.2. Battery Degradation

The current GIGA Storage projects, GIGA Rhino and GIGA Buffalo, are both based on lithium-ion technology. Chosen due to their competitive pricing (Curry, 2017) and high round-trip efficiency as well as low self discharge rates (Luo et al., 2015) this currently seems to be the most competitive option when realising large scale energy storage. However no matter what the application is, lithium-ion batteries degrade with time.

There has been extensive research in the field of measuring battery health. Roman et al., 2021 investigated a machine learning pipeline to estimate battery capacity fade, a metric used for battery health. It is important to keep track of the battery health and often when purchasing large-scale energy storage from a party, they deliver the product with certain usage guidelines that when broken will have the warranty on the battery performance expire.

Such usage guidelines can be very extensive as a lot of factors influence the lifetime of the BESS. Stroe et al., 2017 investigate the influence of depth of cycles, the resting state of charge as well as temperature on the lifetime of a lithium-ion based BESS. All of these heavily influence the battery health but often battery suppliers choose for a simpler model of battery usage. Such a model is easier to implement and can be used to clearly define battery usage in a contract. Furthermore re-evaluations of the battery health take place at fixed intervals (e.g. yearly) which can adjust usage guidelines and guarantees dynamically if the system is degrading faster or slower than initially expected.

2.3. Congestion Management

There has been extensive research in the field of energy management and -systems to investigate and solve congestion. However the scope of the congestion issue as well as the definition of congestion is sometimes varying.

Smaller networks such as neighbourhoods, that contain distributed renewable energy generation as well as electric vehicles, have been investigated in the work by Romero-Ruiz et al., 2016. A probabilistic model of the neighbourhood is created in which congestion can be caused and solved by steering the batteries contained in electrical vehicles. The model of the neighbourhood network is far more comprehensive than that of the case study discussed in this work. The batteries contained in EVs are of course distributed between the different housing estates of the neighbourhood. Similarly to this work, it is considered that when steering the batteries there is knowledge over the power (or probability of an amount of power) on a line connected to the battery system. To that extent, it is trivial to determine if the battery is within its physical capabilities to solve the issue by either charging or discharging the required power.

In the work by Root et al., 2017, a case study of Northern Vermont is presented in which similar issues to the Dutch grid are encountered. *”At present, a large amount of renewable energy generation, both wind and solar, is connected to the power transmission system in northern Vermont. At times and under certain conditions, limitations of capacity or operation of the transmission system in New England force curtailment in the operation of that renewable generation, so it produces less power than it could.” ”Electrical energy storage can potentially improve this situation by allowing the renewable energy to be stored rather than curtailed”* (Root et al., 2017). In their work the renewable energy generation is forced to curtail due to the grid being too small.

However they encounter curtailment situations 35% of the time. The average length of a congestion issue is 27 hours. This issue is far larger than the presented case study in this thesis. The work investigates a hypothetical scenario in which a 104MW, 2000MWh battery energy storage system could solve the presented issue. Following that, they investigate more realistic battery sizing. The findings of that investigation are not presented clearly, which leaves the question of how many curtailment issues are left. Besides that, Root et al., 2017 mention price arbitrage briefly but do not mention the strategy employed by the BESS to maximise profit using it.

The conclusion presented in section three of the work by Root et al., 2017 is short-sighted. They mention that a BESS can be utilised in different energy markets for further profits. They then shortly mention a simulation in which the BESS is used in a frequency reserve market which brings the initial 407-year payback period down to 14 years. My research strives to elaborate on this work and present the additional profits of the BESS in an explicit and realistic manner. This further defends the position of batteries as part of a future energy grid.

Pillay et al., 2015 outline different reasons for power system congestion. Violations of system operating limits, overloading transmission lines on thermal or capacity bounds and finally when power flows are higher than the operating reliability limits. The congestion encountered in this work falls into the final reason for congestion. Other forms of congestion which involve voltage and frequency stability are left outside of the scope of modelling the network.

In the work they discuss multiple different technical and non-technical solutions to solve congestion within networks. Different pricing methods are also discussed to incentivise parties to solve congestion within their grid. However most of these methods are either too extensive for use within this work or cannot be applied.

2.4. BESS Control Strategies

Controlling an ESS is a modern issue presented in many smart grid-related works. Xu and Singh, 2014 investigated a control strategy for a ESS connected to local network that needs to consume a lot of energy. In this network the renewable energy generation on site is lacking at which point in time the external grid, or ESS, should be steered to keep the grid online. A clearly defined cost minimisation function is solved in this work to determine if and when the ESS should charge or discharge to fulfil demand on the local grid. This considers current and forecasted energy prices.

Within the work they define so-called *Modes of Operation*, these are defined moments at which the local grid is fully connected, not connected or coordinating with the external grid. This coordination with the external grid in this paper could be translated to this work by considering reserve and capacity markets. An ESS as large as the one presented in this work could competitively bid and offer capacity services to TenneT. The FCR and aFRR markets are examples of those. However currently this work disregards these options and focuses on the price arbitrage optimisation of the imbalance market.

The Modes of Operation however inspire the modes of operation coined within subsection 3.2.2 to determine explicit moments in which the strategy is adjusted according to preparation of congestion for example.

The work by Esmaeili et al., 2021 investigates optimising an expected output of renewable energy generation as a optimisation problem. They take a day-ahead forecasted schedule for the renewable energy generation and ensure the ESS is steered in such a way the schedule is fulfilled optimally regarding energy prices between day-ahead and real-time (imbalance) energy markets. This work serves a similar technique as presented in this thesis. According to the generated power of renewable energy generators the ESS is steered accordingly.

In the context of a renewable energy generator this approach is logical. An ESS on your network is there to serve your needs. It allows the intermittency of solar or wind power to be flattened to a curve that energy companies recognise from traditional energy generators. The methods used to model future expected energy prices and energy production are interesting. However such a strategy is currently deemed to difficult to implement and model for an algorithm to optimise.

So although this thesis will not explore those options and utilise them to improve the performance of the presented algorithm. In this work the ESS is not limited to only aiding the renewable energy generator. The ESS has down-time from these mandatory actions in which profits can be earned. This viewpoint, where the renewable energy generator is seen as only one of many clients of the ESS, instead of the only client, is the research gap we fulfil. The optimisations around this assumption is where my work differs from that of Esmaeili et al., 2021. A simple example is that Esmaeil et al. consider wind farm revenue as a key metric of a successful ESS strategy. This thesis considers ESS revenue as the metric of a successful ESS strategy.

Finally Teo et al., 2018 investigated a very similar problem setting to what this work looks at. However simarlarly to the first work here by Xu and Singh, 2014 it focusses on balancing a local grid fully. Aside from balancing the local grid however they optimise price arbitrage.

2.5. Price Arbitrage

Bradbury et al., 2014 have researched different energy storage system technologies and optimised their earnings in an hourly-based real-time market. Considering installation costs of different systems a sizing- and revenue technique was developed and offered to the reader. This work is from 2008, which means that cost estimations of the different ESS technologies have shifted significantly compared to today. The research done on price arbitrage however is still relevant.

They assess the performance of the ESSs in seven different wholesale electricity markets. The year 2008 was simulated due to its high volatility and high average electricity prices. From the 7 different markets, the markets with the highest price volatility (measured by the standard deviation) proved to earn the highest revenue.

Similarly to this work, revenue is calculated by using foresight of past price data. However, Bradbury et al., 2014 optimise these earnings perfectly considering prior known best charge and discharge prices. This thesis however simplifies the price arbitrage strategy to a design which could be used in real time by battery operators. This step worsens the predicted earnings on the wholesale market as a non-optimal approach to the market is taken. However, this does improve the real-life application of the methods discussed in this thesis.

Krishnamurthy et al., 2018 make similar observations in their work considering day-ahead market optimisation prior to real-time market optimisation. With extensive 24-hour ahead forecasts a strategy is calculated for the ESS to follow during the day. A 25 MW|50 MWh as well as a 50 MW|50 MWh system are investigated. However, instead of verifying these schedules based on real market data, their performance is measured based on 1000 different real price scenarios which are matched to the proposed strategy.

This method offers concrete analysis on measuring battery usage and performance in many different scenarios. Their findings show a one hour system heavily out performs the two hour system in both revenue total as well as battery usage. Within GIGA Storage often the earnings per MW are calculated as the investment for additional power are more expensive than that of installing more capacity. So a real comparison between a single hour and two hour system would be more fair when comparing a 25 MW|25 MWh and a 25 MW|50 MWh system. It seems natural that the system with more power can make use of more diverse prices to earn additional revenue where the other system is only half as powerful.

Although the authors consider some limitations to their comparison between a one- and two hour system, this point is not listed. They consider the additional revenue through different ancillary services to be more indicative of different earning model for differently sized systems.

Barbour et al., 2012 have investigated an objective method to determine the maximum value of earnings through price arbitrage for a certain time series. They disregard issues considering forecasts and purely view the energy prices of a certain time series to determine a schedule for an ESS. This schedule assumes the ESS starts and ends empty at the start and end of the time series. Using a Monte Carlo optimisation algorithm they keep track of SoC, round trip efficiency and power limitations of the system. This method shows how the system will charge cheaply and discharge for a profit during high price hours.

Although this method is not applicable as a real world scenario, knowing the upper limit of your price arbitrage strategy can help determine the performance of your own. With that being stated, this exact system is hard to apply to the work done in this thesis as the method does disregard all network capacity constraints.

The work by Lin et al., 2019 arrive closest to the GIGA Storage way of determining a real-time market strategy. Based on a certain time series (varying from 12 to 6 hour prognostic forecasts or 24 hour historical price data) a charge price and discharge price are determined. Please note that these hours reference the real-time market of the United Kingdom where the market is priced every half hour instead of quarter hour as it is done in The Netherlands. Given the time series, an expected marginal charge and marginal discharge price is calculated. This is based on the expected energy the system wants to discharge and at what price it expects to be able to charge that power. Those prices determine the charge and discharge thresholds applied by the ESS when considering its decision in the real-time market.

Once those prices are determined, this strategy is similar to that of GIGA Storage. If the energy price is equal to or better than P_{low}, charge the system. If it is higher than or equal to P_{high}, then discharge the system. As stated, this approach is similar to that of GIGA Storage, however instead of adjusting these prices every hour based on a forecast or 24 hour historical data, GIGA Storage sets the prices for an entire month. Aside from that GIGA Storage also considers different pricing set points according to the current state of charge of the ESS. Although the price numbers are adjusted each hour, it does not seem to take into account the fullness of the battery when charging or discharging more greedily. To that extent this approach is noted but not considered when modelling the ESS control strategy.

3
Description of Simulation

3.1. Datasets

3.1.1. TenneT Balans Delta

The Tennet Balans Delta is the minutely message TenneT sends out to inform energy parties of the imbalance market price. This is public information[1] offered at a minutely basis. In a live setting it is communicated 2 minutes after the given time. By combining the messages sent in a quarter an expected quarterly price can be derived. This quarterly price is used as input for the price arbitrage strategy utilised by GIGA Storage.

In this work the TenneT Balans Delta has been moved forward by 2 minutes to offset the original 2-minute delay. It is assumed that when an asset is expected to maximise earnings on the imbalance market that an imbalance price forecaster would be used. Dexter [2] and Recoy [3] are known parties that offer such forecasts. These forecasts use weather, day-ahead price and other indicators to create a forecast that is available from minute 0 in a quarter. In this work, I assume this is a decent forecast and do not consider forecasting error. Furthermore TenneT has already improved the delay of the TenneT Balans Delta from 3 to 2 minutes since March 14th 2022 [4] which suggests further decrease of this delay to be a work in progress. Therefore, this work simply assumes the TenneT Balans Delta is reported without the 2 minute delay.

Similar to the work by Barbour et al., 2012 it is assumed that the actions taken by the BESS in this simulation do not influence the imbalance market price. The BESS will act as a price taker. However, as the number of energy storage projects increases on the grid, it is expected that these would have a smoothing effect on the market prices. These flexible assets are capable of charging and discharging according to the current energy price rather than being dependant on the amount of sun or wind. However, this smoothing effect is not expected within the short term.

The data of the Tennet Balans Delta has been retrieved for the year 2021.

3.1.2. Solarvation Solar Farm

Solarvation has offered the data of two solar farms, internally identified as $lelystad1$ and $lelystad2$. Information as modelled generation (kW) and irradiance (kW/m^2) is contained, but the most important information it contains is the measured generation (kW) at 5 minute intervals. The measured generation is the real value of generated power from the solar farm at that specific point in time. Through linear interpolation this data has been made to match the 1m interval of the TenneT Balans Delta.

The measured solar farm data has been retrieved for the year 2021.

[1] https://www.tennet.org/bedrijfsvoering/Systeemgegevens_uitvoering/Systeembalans_informatie/BalansDeltaplusPrijzen.aspx
[2] https://dexterenergy.ai/
[3] https://www.recoy.com/oplossingen/optimize/
[4] https://www.linkedin.com/feed/update/urn:li:activity:6904078676854419456/

3.2. Local Energy Network Components

3.2.1. Battery Energy Storage System Object

The battery energy storage system object is defined by the following parameters.

- Capacity → ES_{max} (kWh)
- Power → P^{BESS}_{max} (kW)
- Round trip efficiency → η_{rt} (%)
- Derating limits → ES_{lower} and ES_{upper} (kWh)

The following equations hold for the BESS object during the simulation.
Let $ES(t)$ be the energy stored in the BESS at time t.

$$0 <= ES(t) <= ES_{max} \tag{3.1}$$

Let $P^{BESS}(t)$ be the power offered by the BESS at time t.

$$|P^{BESS}(t)| <= P^{BESS}_{max} \tag{3.2}$$

When $P^{BESS}(t)$ is negative, the BESS is considered to be discharging. When $P^{BESS}(t)$ is positive, the BESS is considered to be charging. These actions define $ES(t+1)$. In principle the round trip efficiency (η_{rt}) is the combination of efficiency when charging and discharging the system. This work approaches this by only taking into account a loss of efficiency when charging the system. The value for η_{rt} is adjusted accordingly. This simplification approaches the actual situation because there is hardly any energy loss when discharging the system. However, when charging the system often excess heat is generated and most of the round trip efficiency is lost. To convert the power to capacity in the BESS, you divide the power by the chosen time step. In this simulation a timestep of 1 minute has been taken.

$$ES(t+1) = ES(t) + \frac{\begin{cases} P^{BESS}(t) * \eta_{rt} & \text{if } P^{BESS}(t) \geq 0 \\ P^{BESS}(t), & \text{otherwise} \end{cases}}{t} \tag{3.3}$$

However $ES(t+1)$ has to be held to the following equations.

$$0 <= ES_{lower} <= ES(t+1) <= ES_{upper} <= ES_{max} \tag{3.4}$$

If $ES(t+1)$ would exceed its acceptable bounds at any point in the simulation, then instead $P^{BESS}(t)$ is adjusted before calculating the updated state of charge. To this end we apply the following update to $P^{BESS}(t)$:

$$P^{BESS}(t) = \begin{cases} (ES_{upper} - ES(t)) * \eta_{rt} * t & \text{if } ES(t+1) > ES_{upper} \\ (ES(t) - ES_{lower}) * t & \text{elif } ES(t+1) < ES_{lower} \end{cases} \tag{3.5}$$

The new value for $P^{BESS}(t)$ will then be used to determine $ES(t+1)$ in accordance with Equation 3.3. The new value for $P^{BESS}(t)$ will ensure Equation 3.4 is not violated.

Usage metrics

BESS objects have limitations to their usage. These limitations are defined in accordance with the guarantees a battery provider might offer in their contract. These guarantees in turn ensure the BESS can perform sufficiently during its life cycle. Therefore two usage metrics have been added to the BESS object to measure the usage of the system. Both of these measurements heavily simplify work by Roman et al., 2021 and Stroe et al., 2017 but do so in a manner often seen from battery suppliers from the industry.

State of Charge From (%)	State of Charge Until (%)	Price From	Price Until	Action
0	5	-9999	9999	CHARGE
5	50	-9999	50	CHARGE
50	70	-9999	30	CHARGE
70	95	-9999	0	CHARGE
5	40	100	9999	DISCHARGE
40	70	80	9999	DISCHARGE
70	95	65	9999	DISCHARGE
95	100	-9999	9999	DISCHARGE

Table 3.1: Rhino Strategy 1. A Q4 2020 price arbitrage strategy. Represented with strategy lines.

Cycle counter A simple cycle counting system has been implemented in which 1 cycle is defined as the BESS going from empty to full and back to empty again. However, the system does not have to be charged fully as soon as the charge action is taken. The power of a BESS lies in its ability to be flexible. So a cycle is simply counted according to the physical energy entering or leaving the system.

$$\text{cycle}(t) = \frac{|ES(t+1) - ES(t)|}{ES_{max}}/2 \tag{3.6}$$

Average State of Charge At each timestep t the energy stored in the system is measured ($ES(t)$). At the end of the simulation this is used to determine the average value of $ES(t)$ during the simulation.

3.2.2. BESS Control Strategy

GIGA Storage has supplied this work with *Rhino Strategy 1*, a real imbalance market control strategy used in the last quarter of 2020. The so-called strategy lines that make up this strategy can be found in Table 3.1. The input necessary is the state of charge of the BESS and the current charging- and discharging prices of the imbalance market. These strategy lines can be read as followed. If the state of charge of the BESS is between the SoC from, and the SoC until, and the current imbalance price is between the price from and price until take the action specified by that strategy line.

The action taken by these strategy lines will always be at 100% of the available power of the BESS. So if you have a 10MW system, it will charge or discharge with the full 10MW. This translates to the strategy being content with the price it is being offered, meaning it wants to make full use of the current price. In reality a BESS can often be steered at many different powers to charge or discharge less aggressively.

The strategy can be intuitively explained. When the battery energy storage system is almost full, the system wants an *even lower* price when charging this final part of its SoC. However when almost empty, a lower price could already be sufficient as it allows more room in the battery to be utilised flexibly. The same holds vice-versa, when the battery is nearly empty, it expects a very high price when discharging and a lower price when discharging when the BESS is more full.

This strategy is designed in such a way it respects the derating limits ES_{lower} and ES_{upper} of the GIGA Rhino BESS. The strategy takes any price for charging the battery between 0 and 5% SoC similarly each price is accepted for discharging the system between 95 and 100 % SoC.

Although the strategy lines are sufficient to execute and explain the price arbitrage strategy, this work presents a different method to visualise the strategy. By visualising the different SoC % and imbalance prices in a 2d grid, the margin earned by the BESS is visualised effectively. This margin should at least accommodate the lost energy when charging the system due to η_{rt}. The visualisation can be found in Figure 3.1. Please note that imbalance prices can vary between -500 and 3000 €/MWh but the figure can be extended in the y-direction to accommodate these prices.

3.2.3. Encoding the control strategy

The visualisation in Figure 3.1 is the basis of the encoding method presented in this work. The BESS control strategy will be encoded such that a computer system will be able to represent such a strategy effectively. Furthermore, this allows this thesis to explore the possibility of an optimisation of the offered

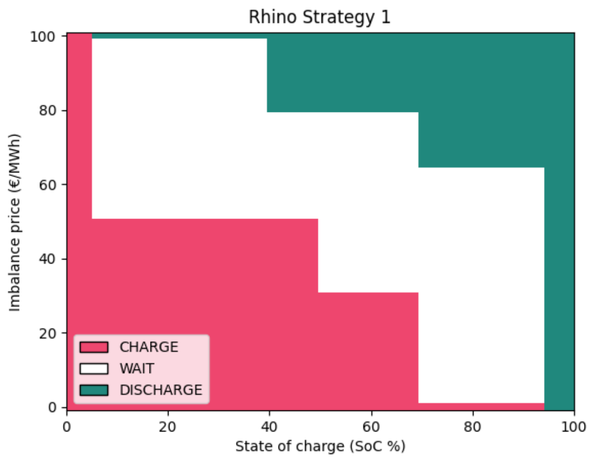


Figure 3.1: Rhino Strategy 1. A Q4 2020 price arbitrage strategy. Represented as a figure that can be extended to accommodate all imbalance prices.

control strategy. The strategy lines of Table 3.1 could be simplified to encode the same strategy in the following manner:

- (SoC%, €/MWh, ACTION)
- (50, 50, CHARGE)
- (70, 30, CHARGE)
- (95, 0, CHARGE)
- (40, 100, DISCHARGE)
- (70, 80, DISCHARGE)
- (95, 65, DISCHARGE)

These points coincide with the corners of the surfaces as seen in Figure 3.1. To complete a strategy, the ES_{lower} and ES_{upper} values are converted to a percentage through ES_{lower}/ES_{max} and ES_{upper}/ES_{max}. These coincide with the width of the charge- and discharge only lines on the left and right side of the figure.

To convert this point encoding of a BESS control strategy into the strategy lines presented in Table 3.1, Algorithm 1 is offered to the reader.

Imbalance prices are real monetary values with two decimal points. However the strategy implementation converts these prices to a value it can work with. This value is defined as the $price\_step\_size$ and when it is not explicitly defined, the reader can assume it is set as $price\_step\_size = 2$. In regards to charge decisions, the price is rounded up. In regards to discharge decisions, the price is rounded down. Therefore this adjusted scale will never make a decision outside the bounds defined by the given points.

3.2.4. Preparing for and solving congestion

Based on a single BESS control strategy, a preparing for and solving congestion strategy can be generated. In the worst-case scenario in which the BESS is expected to be fully empty, this strategy will only ever discharge.

When the strategy is set to only discharge, then the BESS will be trying to empty itself in time for congestion that takes place. Aside from that, as soon as it is possible, the asset will be emptied further. This ensures that the most room is generated in the asset in case of additional for congestion occurring later that day.

Such a *discharge only* strategy raises questions in regards to solving congestion. As is clear in section 3.4, the BESS can solve congestion by **charging** away excess power of the network. In the

Algorithm 1 Converting a BESS control strategy point encoding to strategy lines

$chargePoints.sort$(SoC%)
$dischargePoints.sort$(SoC%)
$maxPrice = 9999$
$minPrice = -9999$
$lowerStrategyLine = (0, ES_{lower}, minPrice, maxPrice,$'CHARGE')
$strategyLines = \emptyset$
$strategyLines = strategyLines \cup lowerStrategyLine$
$lastSoC = ES_{lower}$
for each $point$ in $chargePoints$ **do**
  $strategyLine = (lastSoC, point$(SoC%)$, minPrice, point$(price), 'CHARGE')
  $strategyLines = strategyLines \cup strategyLine$
  $lastSoC = point$(SoC%)
end for
$lastSoC = ES_{lower}$
for each $point$ in $dischargePoints$ **do**
  $strategyLine = (lastSoC, point$(SoC%)$, point$(price)$, maxPrice,$ 'DISCHARGE')
  $strategyLines = strategyLines \cup strategyLine$
  $lastSoC = point$(SoC%)
end for
$upperStrategyLine = (ES_{upper}, 100, minPrice, maxPrice,$'DISCHARGE')
$strategyLines = strategyLines \cup upperStrategyLine$

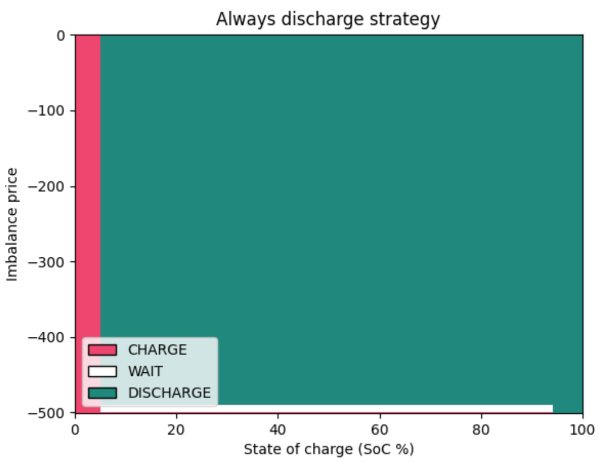


Figure 3.2: Always discharge strategy. Represented as a figure that can be extended to accommodate all imbalance prices.

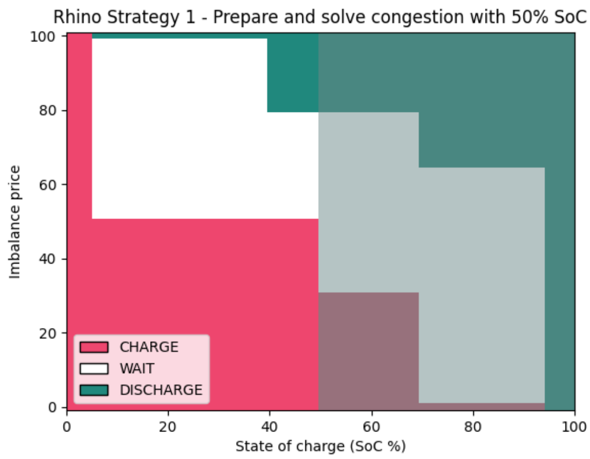


Figure 3.3: Rhino Strategy 1, set to solve congestion above 50% SoC. Represented as a figure that can be extended to accommodate all imbalance prices.

built simulation environment, this discharge only strategy is overwritten as soon as the BESS is forced to charge due to congestion. This is reflected in Equation 3.7 which will overwrite any chosen action by the BESS control strategy.

$$P^{BESS}(t) = max(|P^{transformer} + P^{REG}(t)|, 0) \tag{3.7}$$

Furthermore, subsection 3.2.2 explains that the control strategy of the BESS makes full use of the power of the BESS. It will charge or discharge at 100% of the power available. However, the 100% discharge action will be overwritten so as not to cause congestion on the network when discharging the BESS. This is enforced by Equation 3.8.

$$P^{BESS}(t) = min(P^{BESS}(t), NetworkPower(t) - P^{transformer}) \tag{3.8}$$

For both of the above equations, the BESS object will adjust $P^{transformer}$ slightly as a safety margin for the network:
$P^{transformer} = P^{transformer} \cdot 0.99$.

Although the BESS is forced to charge to solve congestion (Equation 3.7) in the simulation, congestion can still occur. This is due to the physical limitations of the system and the lack of preparation for the congestion event. If the congestion event is large enough, the BESS will forcibly charge itself full until the BESS is overfull and can no longer charge away the excess power.

Equation 3.8 will also ensure that the BESS does not **cause** congestion by discharging at full power when the solar park is generating energy. The BESS will smartly use the available power of the transformer to ensure it does not cause congestion itself.

However, in the case that the BESS is not necessary to be fully empty, but for instance 50 % SoC is enough to solve expected congestion events. Then a discharge only surface can be placed over the same control strategy. This allows the BESS to earn money with price arbitrage at lower SoC levels of the BESS while remaining on standby for the possibility of solving congestion.

At what times the strategy is placed to prepare and solve congestion is discussed in subsection 4.1.1.

3.2.5. Network Environment

Let the network be defined as an array of network objects N. All objects in N are considered to be safely interconnected according to their own power limitations. However all objects are connected to the same transformer with a size of $P^{transformer}$.

$$NetworkPower(t) = \sum_{i=0}^{n} N[i] \rightarrow P^{i}(t) \tag{3.9}$$

Equation 3.9 correctly cancels actions in which the BESS charges energy directly from the renewable energy generator and therefore less energy is exported through the network. For example, if $P^{REG}(t) = -4000$ and $P^{BESS}(t) = 5000$, the summation of Equation 3.9 will become $NetworkPower(t) = 1000$. In this example 4000 kW will be charged that is generated by the REG, and 1000 kW will be imported from the high voltage grid through the transformer.

The network environment is initialised with a network connection size. Let this be $P^{transformer}$. In that case the following must hold

$$P^{transformer} >= |NetworkPower(t)| \tag{3.10}$$

When this equation is overwritten, the simulation is allowed to continue, the amount of timesteps t in which this occurs is tracked.

Although transformers can handle importing and exporting energy at the same power, importing energy from the high voltage grid incurs so-called transportation costs. The cost of importing energy is calculated based on the peak amount of energy imported as well as the number of hours in which energy has been imported.

Renewable energy generators use very little energy and therefore do not incur high transportation costs by themselves. To that extent, in line with current GIGA Storage practices, the simulation has limited importing from the grid to 2MW.

$$NetworkPower(t) <= 2000\text{kW} \tag{3.11}$$

This means that when there is no additional power being generated, the BESS can only be charged at a rate of 2MW. When there is power being generated, the BESS can charge this additional power.

3.2.6. Renewable Energy Generation

Often in research the generation of a renewable energy generator must be modelled according to weather data or theoretical values of a system. However, for this work we have been supplied with the measured generation data of a solar farm. Therefore, no modelling of this generation is needed and simply the measured values have been taken.

To ensure the network is modelled correctly, the same sign is taken as the BESS for 'charging' energy from the grid or 'discharging' energy. So when the renewable energy generation generates power it is seen as 'discharging' the solar park or wind farm and is given a **negative** sign.

3.3. Measurements

TenneT high voltage grid connections are measured in Megavolt-ampere (MVA). The network object which is able to convert low- or medium voltage to the high voltage necessary to transport energy is the transformer. By transforming the power to a high voltage, it can be transported through The Netherlands through the TenneT high voltage network.

In this work 'congestion' is defined as when the lines leading up to the high voltage transformer exceed the rated capacity of the transformer. For example if 22 MVA is being supplied to a 20 MVA transformer, there is congestion. If only 19 MVA is being supplied, then the transformer does not encounter any problem.

Although transformers and the lines connecting the transformer to the rest of the local grid have their capacity measured in MVA, other network objects often utilise the measurement for real power, Megawatt (MW). The difference between these is as follows. MVA is defined as apparent power.

$$MVA = V \cdot I \tag{3.12}$$

This equation uses voltage (V) and current (I) to calculate the (apparent) power in a system. However, in actuality there is a power factor that reduces the real power supplied to the line. Multiply MVA by the power factor and you receive the MW, or real power that is supplied to the line.

$$MW = V \cdot I \cdot pf \tag{3.13}$$

For this work we assume that $pf = 1$ which ensures that MVA and MW can be used interchangeably. A 70 MVA transformer can therefore also be referenced as a 70 MW transformer. In reality however $pf <= 1$. If the pf is smaller than 1, then the problem discussed in this work will only be reduced. Therefore this assumption can be treated as a certain safety factor in the calculations.

	19 MW	14 MW	10 MW
Maximum excess capacity (MWh)	0.0	28.5	64.4
Maximum excess power (MW)	0	4.9	8.9

Table 3.2: Size of the congestion issue with different transformer sizes

3.4. Determining Congestion

Congestion is determined according to the size of the transformer. Let the capacity of the transformer be given by $P^{transformer}$. During the simulation congestion is measured as soon as $NetworkPower(t) > P^{transformer}$.

$$\begin{aligned} &\text{if } NetworkPower(t) > P^{transformer}: \\ &time\_steps\_with\_congestion += 1 \end{aligned} \tag{3.14}$$

3.5. Case Study

To determine a case study that has a feasible solution and consists of realistic-sized network components, analysis was done on the Solarvation data of solar farm $lelystad1$. This solar farm with rated capacity of 19MW is currently connected to the high voltage grid with a large enough transformer that would never encounter congestion. This was confirmed and then challenged by investigating the congestion issue under 3 different transformer sizes: 19, 14 and 10 MW.

Two values were measured when evaluating the performance of this network: capacity and power. Capacity of the network congestion was measured by the amount of MWh that was in excess of the provided grid connection summed on a day basis. Power was measured by taking the maximum amount of MW in excess of the provided grid connection. The results of this analysis can be found in Table 3.2.

The measured values in Table 3.2 can be matched to the sizing of a energy storage system to solve the presented issue. E.g. a 4.9MW|28.5MWh BESS connected to the transformer of 14MW could physically solve the problem.

Both the 14MW and 10MW transformer sizes point towards a BESS of similar size to the new project of GIGA Storage, the GIGA Buffalo, a 25 MW|48 MWh system[5], at least in terms of capacity. The network connection with a smaller congestion issue was chosen with the reason being that a smaller congestion issue allows the BESS more freedom to earn revenue through price arbitrage.

The ESS was not sized entirely to the problem but was adjusted slightly for three reasons. The capacity of the system was adjusted to fulfil realistic numbers that have previously been supplied by battery suppliers. The power of the system was upgraded to have a similar ratio to the capacity as the GIGA Buffalo system. However that power was then limited by the power of the network connection e.g. 14MW. If the ESS had more power than the size of the network connection, the ESS itself would already cause congestion when discharging the system at 100% power. With these things taken into account an ESS of 14MW|30MWh was taken for the case study.

To conclude, the network will consist of:

1. A solar farm with rated capacity of 19 MW
2. A battery energy storage system with 14 MW power and 30 MWh capacity
3. A transformer of size 14 MW

Further assumptions in regards to the battery energy storage system will be that it is a lithium ion based system with limitations similar to the current GIGA Storage Rhino project. Therefore the following values have been set:

[5]https://giga-storage.com/the-buffalo-battery/?lang=en

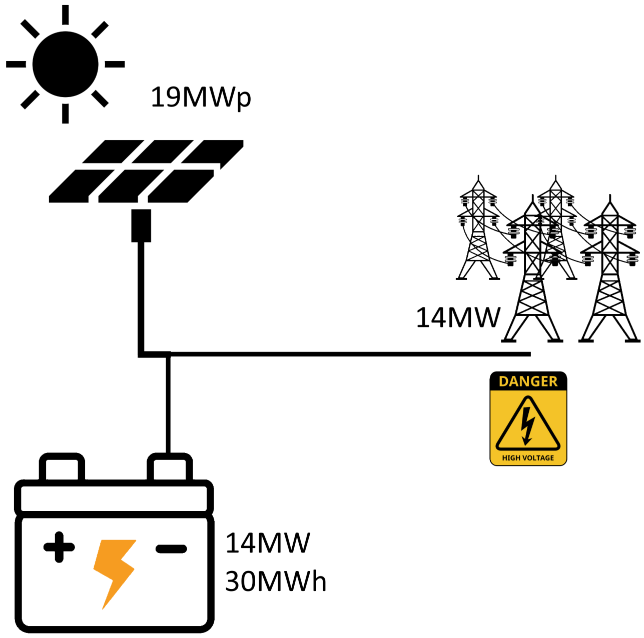


Figure 3.4: Proposed network topology of the case study

- $\eta_{rt} = 90\%$
- $ES_{lower} = 1500$kWh
- $ES_{upper} = 28500$kWh

The values for ES_{lower} and ES_{upper} coincide with a 5 % margin of state of charge at both the lower and upper bracket of the BESS.

3.5.1. Network Schematic

The network topology can be found in Figure 3.4.

3.6. Validation of implementation

As a proof of concept as well as a sanity check, three simple network topologies or battery control strategies were designed and simulated. These different designs offer context for the problem statement as well as an insight into the capabilities of a BESS that is unencumbered by aiding the local network. The three scenarios are as follows:

1. No Battery
2. Battery ignoring congestion
3. Battery only solving congestion

The first simulation baseline taken is the simulation in which there is no BESS connected to the network. The solar farm will simply generate power and the network connection will report how much congestion was encountered.

The second simulation is a baseline in which the BESS object is introduced to the network. However, the control strategy of the BESS object disregards the network connection limitations. Therefore no preparation in regards to congestion or congestion management is executed. For this baseline the Rhino Strategy 1 control strategy offered by GIGA Storage will be executed.

The final baseline simulation this work offers the reader is the situation in which the BESS is only ever utilised to solve congestion. The BESS is only charged when the network would otherwise encounter congestion. The BESS is discharged as soon as the price is 'above average', a price point of 60

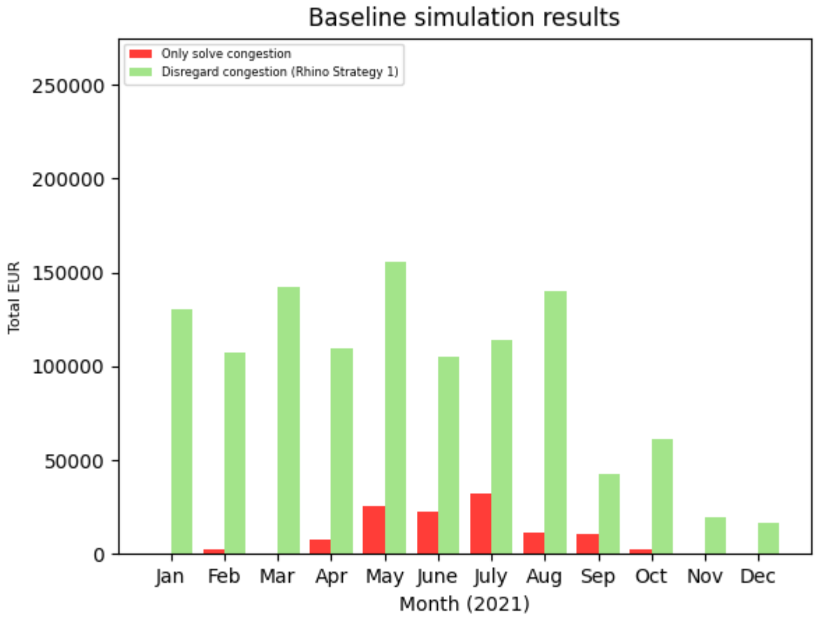


Figure 3.5: Baseline simulation results with Rhino Strategy 1

	No battery	Battery ignoring congestion (Rhino Strategy 1)	Battery ignoring congestion (GIGA Baseline)	Battery only solving congestion
# minutes with congestion	29640	40421	53423	0
% of time with congestion	5.64%	7.69%	10.17%	0.0%
Total battery earnings (€)	n/a	1,143,900.50	2,013,845.38	113,778.59
Total number of cycles	n/a	186.29	362.86	41.25
Daily average earnings (€)	n/a	3,135.32	5,519.75	311.86
Daily average cycles	n/a	0.51	0.99	0.11

Table 3.3: Baseline simulation results

€/MWh has been used. The BESS is urged to discharge at this price simply to utilise space on the network connection as soon as congestion allows it. Thereby allowing more space in the system to solve upcoming congestion.

2021 has been simulated in 1 minute timesteps for a total of 525375 timesteps in the simulation. The findings of these simulations are presented in Table 3.3. The performance of the BESS measured in revenue is visualised per month in Figure 3.5.

When viewing the results of the baseline simulations in Figure 3.5, it seems clear the Rhino Strategy 1 is outdated. Its performance in the first months of 2021 seems okay but drops off heavily towards the end of 2021. Please recall that this strategy was designed for use in Q4 of 2020 with knowledge of energy prices of 2020. Since that time, there have been significant changes to the energy market. The situation in Ukraine[6] and rising gas prices have had a huge influence on the imbalance market. Therefore Rhino Strategy 1 and its performance on 2021 imbalance market data cannot be considered as a good representation of a BESS price arbitrage control strategy.

[6]https://www.bbc.com/news/world-europe-60506682

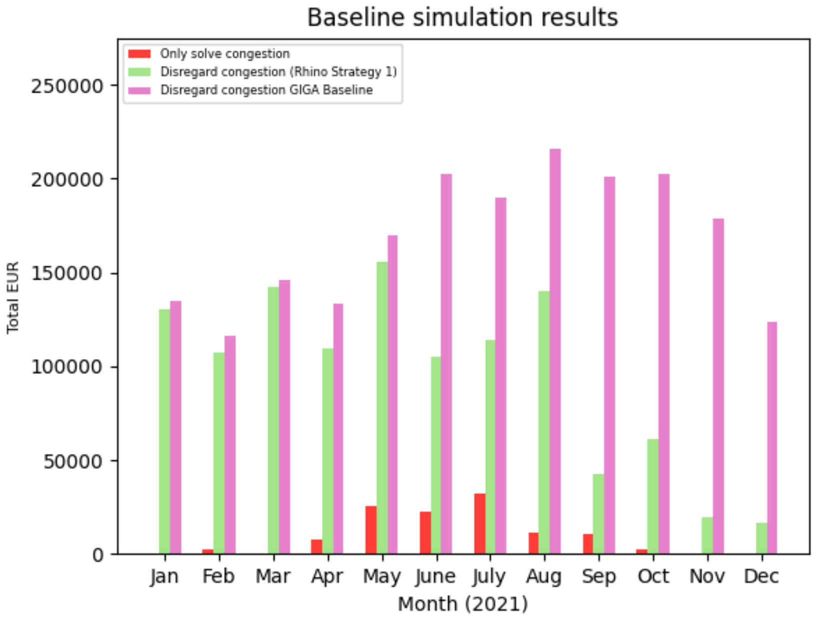


Figure 3.6: Baseline simulation results

3.6.1. GIGA Baseline

To approach a baseline earning that *is* representative of the performance of GIGA Storage during 2021 Rhino Strategy 1 will not be used. Furthermore the difference in the size of the GIGA Rhino BESS in comparison to the BESS presented in the case study (12 MW|7.5 MWh vs 14 MW|30 MWh) means that considering real-time revenues is also not the best baseline value.

Furthermore the GIGA Rhino BESS is a very fast system (its power is larger than its capacity) which means an optimal control strategy would be very different from that of a slower system (where power is nearly two times smaller than its capacity) presented in this case study. Finally the methods used by GIGA Storage are not all applicable to the built simulation, for example one of the GIGA Storage strategies take into account the day-ahead energy market price when determining the charge and discharge points of the price arbitrage strategy. These day-ahead prices are not part of the presented simulation.

To that extent this thesis has tried to approximate the GIGA Storage method of generating a price arbitrage strategy around the differences between the real-life energy markets and the created simulation. In discussion with traders from GIGA Storage, a method was devised to generate a BESS control strategy pseudo-randomly in a manner that GIGA Storage expects price arbitrage strategies to be structured. Using this method 100 strategies were generated per month and the best performing was chosen. Following that process, the strategy was investigated by hand and tuned further in discussion with the same traders.

This method has generated 12 BESS control strategies for the twelve months of 2021 similarly to the optimisation that will be executed. From here on out, this will be referenced as the GIGA Baseline. The performance of the strategy can be seen in Figure 3.6. The exact results can be found in Table 3.3.

3.6.2. Lessons learnt from validating the simulation

As the performance of Rhino Strategy 1 on the imbalance market of 2021 was under-performing, this work considers the new GIGA Baseline when referencing the performance of the baseline simulation when ignoring congestion.

In the first baseline simulation without a BESS to solve congestion, we find that congestion occurs 5% of the time. This coincides with the findings of Root et al., 2017. Adding a BESS system that disregards congestion issues worsens the congestion issue. In this simulation (Battery ignoring congestion) the actions taken by the solar farm and BESS combine to cause even more congestion, nearly 10% of the time. The only baseline simulation that solves congestion is when the BESS is set to purely solve congestion. That baseline shows that this setup can solve the issue at hand.

When viewing the usage of the BESS (measured in cycles) and the earnings, it is obvious that the ‘Battery only solving congestion’ baseline is under-utilising the BESS. It is interesting to note when comparing the only solve congestion scenario to the GIGA Baseline that only 5.6% of the earnings have been earned however the BESS was used 10.9% of the time. This points towards the forced action of congestion management in which the BESS is forced to accept a price which is perhaps worse than the GIGA Baseline strategy would dictate.

The fact that the congestion management actions taken by the only solve congestion strategy do earn money for the BESS coincides with the intuitive explanation that during congestion there is excess energy in the total market, therefore prices are expected to be lower. The moment congestion is solved on this site, it seems that prices also rise on the imbalance market allowing this strategy to then discharge the excess power at a profit.

The earnings presented by the GIGA Baseline coincide with expected earnings of GIGA Storage. The same holds for the number of cycles the system made in the year. These baselines serve as a manner to present the size of the issue as well as the capability of the system to solve the issue. The rest of the work will focus upon the further utilisation of the BESS surrounding the forced actions to solve congestion.

4

Methodology for BESS control strategy optimisation

4.1. Solving Congestion

To enable the BESS to prepare for and solve congestion, the system must have some information on the congestion problem it is expecting. However, this work has not been supplied with a forecast that estimates the expected generation of the 19MW $lelystad1$ solar farm. Therefore, this work will assume only historical data of the generation of the solar farm is available to the BESS control strategy.

Due to the high costs associated with congestion-induced network damage, the model is required to deal with the worst case scenario for congestion, only adjusting for hourly and monthly variations. While better forecasting methods might give a lower upper bound on the worst case scenario for congestion, such forecasting models require a high degree of confidence to be used in practice. The assumption that a large safety factor would be applied to the forecast, such as the worst-case days of the month of last year, is assumed to not be too conservative. This is due to the sheer amount of (monetary) damage that can occur on the network if congestion does occur.

4.1.1. Sizing and Timing Congestion

When sizing and timing congestion, a safety margin has been taken. Instead of using $P^{transformer} = 14MW$ as it is defined in the case study, the power of the transformer is adjusted according to Equation 4.1.

In addition, the cable usage for any point in time was averaged over a rolling window of 30 minutes. Each point in time for which the average generation exceeded the maximal cable capacity was also considered to be congested. This models a state of alert for the network in which the transformer is close to congestion occurring.

$$AdjustedTransformerPower = 0.95 \cdot P^{transformer} \tag{4.1}$$

$$CableUsage(t) = P^{REG}(t)/AdjustedTransformerPower \tag{4.2}$$

$$AverageCableUsage(t) = \frac{\sum_{i=t-30}^{t+30} CabelUsage(i)}{60} \tag{4.3}$$

$$CongestionChance(t) = max(CableUsage(t), AverageCableUsage(t)) \tag{4.4}$$

$$Congestion(t) = \begin{cases} True & \text{if } CongestionChance(t) > 1.0 \\ False & \text{otherwise} \end{cases} \tag{4.5}$$

When there is congestion, this formula will announce true. When there is no congestion, it could announce true if the network is encountering a lot of energy either before or after the timestep t.

4.1.2. Heuristics

Four heuristics are used to determine the time periods in which congestion management is required, and the size of the energy storage capacity required to solve potential issues.

Earliest starting time Consider a set of timestamps $Congestion$; the timestamp with the earliest time of day where $Congestion(t)$ holds True is considered the earliest starting time of the set.

Latest end time Consider a set of timestamps $Congestion$; the timestamp with the latest time of day where $Congestion(t)$ holds True is considered the latest end time of the set.

SoC level preparation Two approaches are taken when considering the SoC level for preparation of a congestion event. The first one assumes the BESS should be entirely empty and defines SoC level preparation as ES_{lower}.

The second approach to define the SoC level for preparation considers a set of timestamps $Congestion$ and defines the following value:

$$ExcessPower(t) = CableUsage(t) - P^{transformer} \tag{4.6}$$

The value of $ExcessPower$ is summed on a day to day basis. The value is then taken with a safety margin of 20%. Following that value the SoC level for preparation is defined as.

$$\text{SoC level preparation} = max(ES_{lower}, ExcessPower) \tag{4.7}$$

Preparation time Preparing the BESS for congestion has a lot to take into consideration. The specific congestion case presented in this work expects the BESS to be able to *charge* excess generated energy from a solar farm. Therefore the BESS must *discharge* itself in preparation for congestion. For a 14 MW|30 MWh BESS, a time frame of 2 hours and 8 minutes ($30MWh/14MW = 2:08$) should be enough to empty a fully charged system.

However, this assumes the system is able to discharge 14MW fully during this 2-hour period. Due to the network topology, as soon as solar power is being generated, the BESS can only discharge less than the expected 14MW.

Taking a fixed 2-hour time frame also assumes the battery has to be entirely discharged to be considered prepared. In accordance with the SoC level preparation discussed in the previous paragraph, the battery could sometimes only have to be half empty to solve congestion.

3 different methods were considered.

1. Fixed 2:08 timeframe
2. Fixed timeframe according to SoC level preparation
3. Average generation of the solar farm in preparation timeframe considered for placing start of preparation time

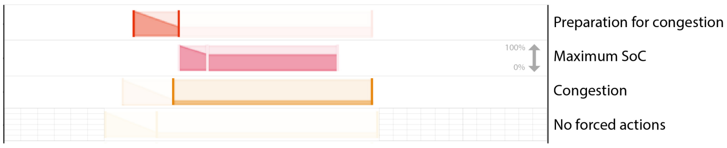
The final method tracks the average generation of the solar farm during the offered $Congestion$ period and will take into account leftover space on the transformer when calculating how fast the system can discharge to the desired SoC level preparation at the offered earliest starting time.

4.1.3. Solving congestion with different heuristics

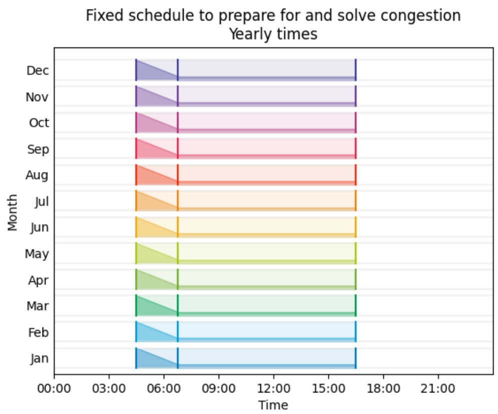
4 different heuristics were investigated that worked in a iterative manner.

1. Yearly times
2. Monthly times
3. Smart sizing
4. Average generation considered

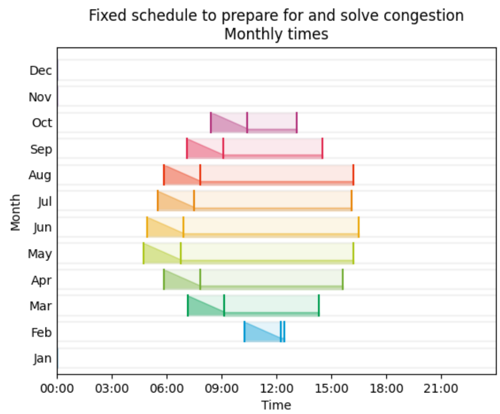
With the yearly times method, the set $Congestion$ is simply the entire dataset of the year 2021. The improvement in monthly times splits up this method to find values relative to the single month. The smart sizing method ensures the SoC level preparation is adjusted according to the expected size of the congestion issue. Finally, the average generation considered makes the preparation time slightly more conservative to account for the solar park generating power.



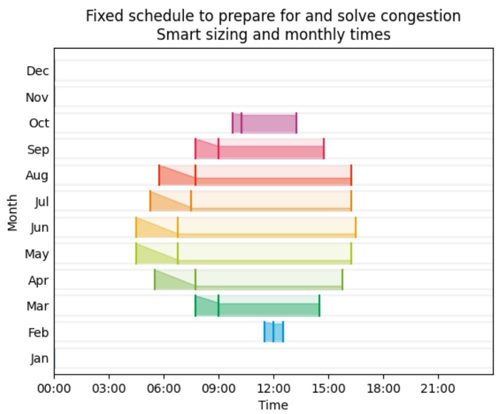
(a) Legend for figures b-e



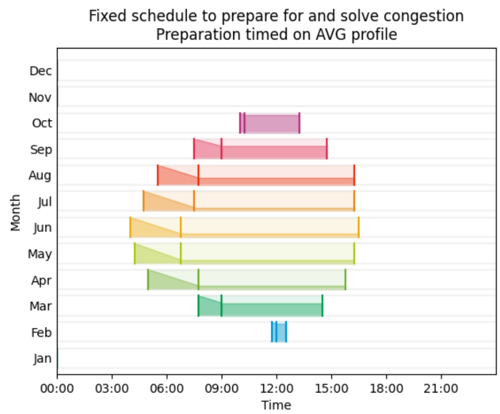
(b) Yearly times, a fixed 2:08 preparation period and the BESS should be empty for congestion



(c) Monthly times, a fixed 2:08 preparation period and the BESS should be empty for congestion



(d) Smart sizing, a preparation period relative to how empty the BESS should be for congestion



(e) Average generation considered, the preparation period is adjusted according to the average generation of the solar park at that time

Figure 4.1: 4 different congestion timing and sizing methods

In Figure 4.1 the earliest start times, latest end times and SoC level for each month are visualised. The white space surrounding these labels can be utilised by the BESS to earn additional revenue.

4.2. Evolutionary Algorithm Optimisation

4.2.1. Why use an evolutionary algorithm?

This thesis has decided to focus on optimising a BESS control strategy through use of an evolutionary algorithm. Although methods such as machine learning, neural networks or simple gradient descent can be considered, this work has decided to implement an evolutionary algorithm (EA).

The main reason an evolutionary algorithm has been considered is due to the match between the evolutionary algorithm and the proposed model of a BESS control strategy. The model is defined by the different charge- and discharge points. Each point has a relation to the other points in the strategy. For example the 'opposite' points that decide the margin between the charge- and discharge decisions is the essential part that allows the BESS to earn revenue in the imbalance market.

The singular points of the model lend themselves well to be approached as a single gene that together with all other genes form an individual that will be the BESS control strategy. The evolutionary algorithm can optimise each individual through operators inspired by the biological concepts of reproduction, mutation and selection.

When considering pairing and mutation methods that will be discussed in subsection 4.2.3 the evolutionary algorithm approach fell into place. The fact that the best parts of two well-performing individuals could be combined to generate a better-performing control strategy felt intuitive. Although an individual still consists of the charge and discharge points, the evolutionary algorithm has the power to combine parts of individuals in search of the best performing solution.

4.2.2. Evolutionary algorithm implementation

This work presents a basic evolutionary algorithm designed to optimise a control strategy for the BESS. The implementation of the algorithm can be found Algorithm 2.

Algorithm 2 Basic evolutionary algorithm to optimize a BESS control strategy

$offspringPerCouple = 4$
$tournamentSize = 4$
$I =$ a set of $popSize$ individuals
while not $earlyStop$ **do**
    $numOfParents = numOfOffspring/offspringPerCouple$
    parents_1, parents_2 = $tournamentSelect(I, numOfParents, tournamentSize)$
    $O = \emptyset$
    for each parent_1, parent_2 in zip(parents_1, parents_2) **do**
        for $offspringPerCouple$ **do**
            offspring = parent_1.$pair$(parent_2)
            offspring = offspring.$mutate$()
            $O = O \cup$ offspring
        end for
    end for
    for each individual in I **do**
        if $chance > mutationProbability$ **then**
            mutatedIndividual = individual.$mutate$()
            $O = O \cup$ mutatedIndividual
        end if
    end for
    $I = I \cup O$
    $I =$ Select best $popSize$ individuals from I
end while

4.2.3. Individual

An individual within the evolutionary algorithm is defined as a single control strategy specified by 8 points. Each point consists of a market price in €/MWh and a percentage describing a state of charge percentage level. Finally, each point specifies if it is a 'CHARGE' or 'DISCHARGE' point. However, this has been fixed as 4 points connected to charge prices and 4 points related to discharge prices. Please refer to subsection 3.2.2 that further describes how these points construct a market strategy and how it relates to solving congestion or earning revenue.

The 8 points decided upon here coincide with the similar amount of points used to encode the GIGA Storage Rhino Strategy 1.

The random initialisation for an individual follows the structure of 4 CHARGE and 4 DISCHARGE points. The market price and SoC percentage are randomly generated as follows:

- market price $\leftarrow randint(-100, 400)$
- SoC % $\leftarrow randint(6, 95)$

Please note, to construct the individual correctly, the points are sorted by ascending state of charge. The random values for SoC % are limited by the derating limits ES_{lower} and ES_{upper}. Aside from this, market price is generated in step sizes according to $price\_step\_size = 2$.

4.2.4. Adjusting the individual to a sensical strategy

Rhino Strategy 1 (subsection 3.2.2) when encoded with the proposed method holds true to its original definition through strategy lines. However when allowing the evolutionary algorithm free rein over charge and discharge prices as well as SoC levels some parts of the encoding may break. E.g. there is overlap between strategy lines defining charge prices and those defining discharge prices. Some steps are taken to ensure the strategy utilised on the BESS is sensical.

Take for example the following encoding:

1. (30, 200, 'CHARGE')
2. (70, 24, 'CHARGE)
3. (50, 50, 'CHARGE')
4. (95, 0, 'CHARGE')
5. (30, 100, 'DISCHARGE)
6. (80, 58, 'DISCHARGE)
7. (60, 98, 'DISCHARGE)
8. (95, -150, 'DISCHARGE)

The first step taken will be to order the charge and discharge points by SoC % respectively. In this example, points 3 and 2 as well as points 6 and 7 will be interchanged. As the SoC % rounds down to the last highest value this ensures each point explicitly defines at least some part of the strategy and is not overwritten by a previous point.

Furthermore, the charge surface is placed over that of the discharge surface. So if the strategy is content with the charging price, it will not search further if it was also content with the discharging price. This means the higher price of point 1 will overwrite the price of point 5. So at 30% SoC and a price of 200 €/MWh the system will charge. The same holds for points 4 and 8. At 90% SoC and a price of -50€/MWh the system will charge.

However the prices of the charge points define an upper limit while the discharge points define a lower limit. Therefore, once the price is outside of the upper limit defined by the charging points 1 and 4 the strategy will discharge. E.g. at 30% SoC and a price of 202€/MWh the strategy will decide to discharge.

The difference of 2 euros here is not a coincidence. The prices set by these points are defined in steps of $price\_step\_size = 2$. To round the real imbalance price to this price step size, the imbalance price for charge will be rounded up while the imbalance price for discharge will be rounded down. An example of this can be found in Table 4.1.

This naturally enforces a margin between the charging- and discharging surfaces of $price\_step\_size$. Therefore the touching surfaces in Figure 4.2 actually have a margin of $price\_step\_size = 2$.

Real imbalance price (€/MWh)	Charge price	Discharge price
201.25	202	200
0.75	2	0
64.37	66	64

Table 4.1: Real imbalance price conversion to $price\_step\_size = 2$

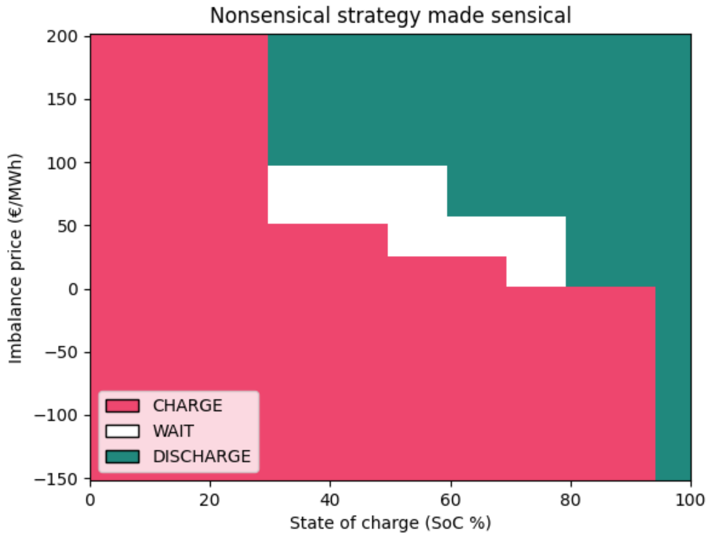


Figure 4.2: Sensical interpretation of nonsensical strategy points

Pairing methods
Different pairing methods for individuals have been investigated. Each offspring is generated from the 8 points of parent *one* and 8 points of parent *two*. Sorted by the SoC% and whether they are charge or discharge points these 16 points are matched. For the 8 pairs of points, two different pairing methods have been explored: multi-axes gaussian distribution and single-axis gaussian distribution. The two different pairing methods are visualised in Figure 4.3.

Multi-axes gaussian distribution The multi-axes gaussian distribution generates two random values according to a gaussian distribution. One on the axis of SoC % and the other on the axis of market price. The mean of the distribution is placed in the middle of the two parent points and 1 sigma is defined as the first parent and -1 sigma as the other. Because 2 different axes are used, the eventual position of the point for the child generated by this pair can be visualised as a circle around the mean.

Single-axis gaussian distribution For the single-axis gaussian distribution implementation, a single value is generated from a gaussian distribution. This value is scaled according to both SoC % and market price. Because only a single value is generated from a distribution, the child point can be visualised as a line between the two parent values.

Mutation methods
Three different mutation methods have been explored. For each point in an individual the SoC % can change as well as the market price. The SoC % change is changed according to a value generated between soc_lower and soc_upper. The market price is changed according to a value generated between price_lower and price_upper $\cdot$ $price\_step\_size$. This ensures the new market price value is scaled correctly to $price\_step\_size$. Additionally, the SoC % has been limited to the same derating limits as during random initialisation of the individual.

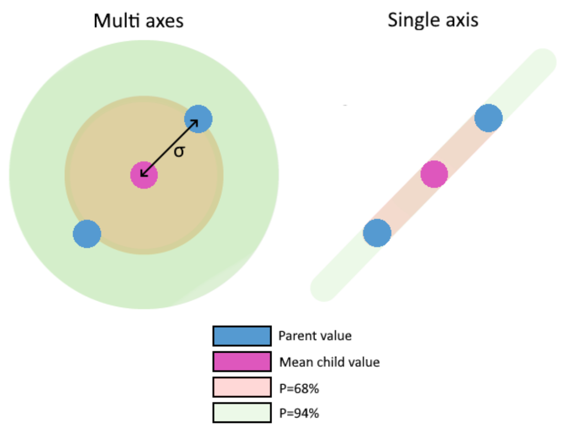


Figure 4.3: Two different pairing methods

	random_mutation	big_random_mutation	big_sided_mutation
soc_lower	-3	-5	-5
soc_upper	4	5	5
charge_price_lower	-3	-6	-6
charge_price_upper	3	6	3
discharge_price_lower	-3	-6	-3
discharge_price_upper	3	6	6

Table 4.2: Overview of the mutation parameters

The values are generated on a uniform distribution. The 'sided' mutation method will therefore more often mutate the individual in search of cheaper charging or better-discharging prices. Table 4.2 displays the three different mutation parameters explored and the values they contain.

Both pairing methods base their offspring on a gaussian distribution between the two parents. However due to the possibility of a single individual being both parent *one* and parent *two* in offspring generation, mutating each generated offspring ensures there is a higher chance of exploration rather than recreating an individual.

Mutation possibility

Three different mutation possibilities have been investigated during the experiments. The mutation possibility represents the chance that a single individual from the population is mutated. This mutated individual is added to set O as if it was an offspring that has been generated. Please note that this does not influence the number of offspring generated determined by the offspring ratio parameter.

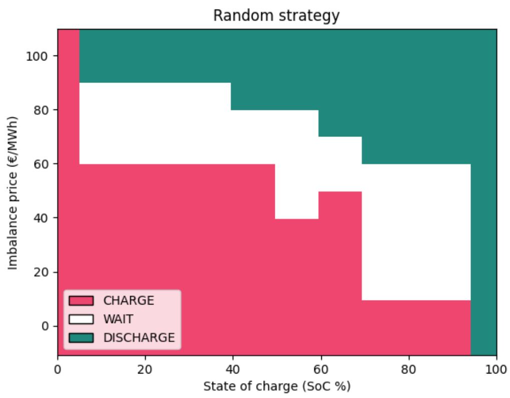
The mutation possibilities that have been explored are $[25\%, 50\%, 75\%]$.

Guidance methods

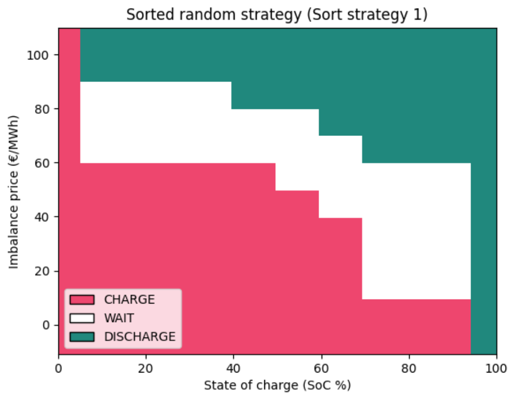
Subsection 3.2.2 discusses the intuitive measure that prices should decline for both charging and discharging as the BESS becomes more charged. This coincides with a requirement setout by GIGA Storage. The individuals and offspring generated by this algorithm do not enforce this intuition in one way or another. However adding this aspect could either increase performance of the individual or increase the chance of GIGA Storage actually accepting and utilising the offered strategy generated by the optimisation.

To that extent 3 different sorting methods were investigated. Figure 4.4 visualises the sorting methods.

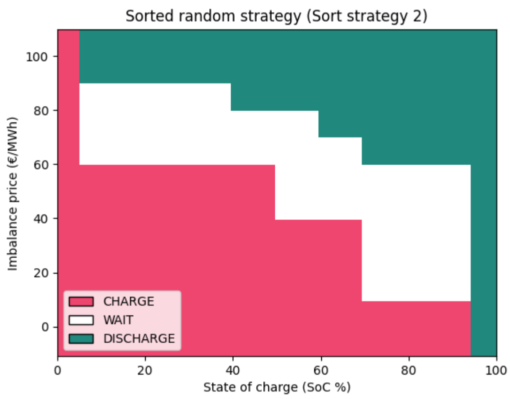
Sort 1 - Interchange prices In the case where a lower SoC % has a higher price than the previous point the prices of these two prices are interchanged.



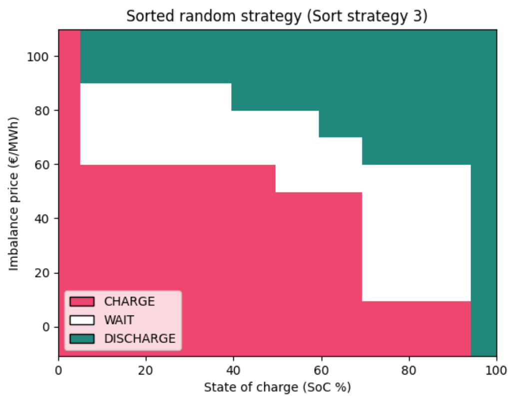
(a) Original strategy, where a higher charge price is present at a higher SoC%



(b) Sorting strategy 1, the two prices are inverted



(c) Sorting strategy 2, the cheaper charging price is taken



(d) Sorting strategy 3, the 'worse', or higher charging price is taken

Figure 4.4: 3 different sorting strategies

Sort 2 - Take best price In the case where a lower SoC % has a higher price than the previous point, the best of the two prices is chosen. For discharge points this is considered the higher of the two points. For charge points this is the lower of the two points. These higher or lower prices will enforce larger margins.

Sort 3 - Take worst price In the case where a lower SoC % has a higher price than the previous point the worst of the two prices is chosen. For discharge points this is considered the lower of the two points. For charge points this is the higher of the two points. These higher or lower prices will enforce smaller margins and utilise the BESS more.

Population size
The parameter $popSize$ determines the size of the generation. From the population the parents will be determined that generate offspring. The different population sizes that have been explored are $[20, 40, 100, 200]$.

Offspring ratio
The evolutionary algorithm proposed generates 4 offspring per paired individual. This allows the amount of generated offspring to be adjusted to many different values. The work explores the influence of generating more or less offspring per generation. The different offspring ratios that have been explored are $[40\%, 80\%, 160\%]$.

4.2.5. Early stopping criteria

Two early stopping criteria have been implemented to ensure run times of the optimisation are limited.

The first early stopping mechanism is in regards to variation in the population. If the worst performing individual and best-performing individual differ less than 99 %, a strike is incremented.

The second early stopping mechanism is in regards to improvement of the population. If the average performance of the population does not increase by at least 99.99 % then a strike is incremented. Such a strict value is often only hit when the population does not improve at all.

Both of these early stopping mechanisms increase the strike counter. The strike counter can only be increased by one during each generation. Once 5 strikes have passed, the early stopping mechanism will ensure the optimisation is ended.

An additional stopping mechanism limits the total number of generations to 200 during any and all runs of the evolutionary algorithm.

4.2.6. Fitness function

The fitness of an individual is measured by running a simulation for the month in which the strategy will be utilised. In accordance with the network topology presented, either the congestion heuristic smart sizing will be used or no congestion will be considered when optimising the BESS control strategy. Furthermore the BESS will be initialised with little energy: $ES(0) = 1600$kWh. The revenue of the BESS for that month will be the fitness and expect to be maximised.

Furthermore, when an individual causes congestion, the income generated by that individual will be fined by 50%. This allows the evolutionary algorithm to consider very well-performing but congestion-causing individuals and hopefully optimises the best performing individuals away from causing congestion due to the heavy fine.

It is also important to note that the fitness function is measuring the performance of the strategy on the month it is being optimised for. In this sense the strategy can be seen as a hind-cast method of approaching the performance that could be achieved with the knowledge of that month after the fact. To apply this method to the real world, one would use historical or forecasted market price data to optimise a strategy and then apply the generated strategy in real time.

5

Experimental Results

5.1. RQ1 - Solving congestion

The GIGA Baseline strategies will be applied to the 4 different heuristics presented in subsection 4.1.3 to investigate if these heuristics are capable of solving the presented congestion problem.

Figure 5.1 shows the results of this experiment. The first line presented in the same figure is the only solve congestion method discussed in section 3.6. This method would only ever charge the BESS when congestion occurs.

It is important to note that the hatched bars in this graph portray that congestion occurred in that month. This automatically means that this strategy is unable to be executed, as damage to the network would occur. The yearly timing method causes congestion, while all other heuristics successfully solve congestion.

The exact values can be found in Table 5.1.

5.2. RQ2 - Optimising strategies while disregarding congestion

5.2.1. Description of experiment

This experiment will explore the best performing BESS control strategy in a network topology which has no congestion issues. This was done by adjusting the network topology such that the transformer power was set to 34MW. This ensures the solar farm as well as the BESS are both capable of fully discharging/generating power through the transformer and onto the high voltage grid.

In a business case in which there are no network limitations, this optimisation would generate strategies relevant to the BESS operator. However for the case study presented earlier, this method generates strategies that cannot be implemented, as they cause congestion. Therefore these control strategies will be applied to the methods discussed in subsection 4.1.3. This further tests the presented heuristics and the extent to which they are able to solve congestion for other control strategies than the presented GIGA Baseline.

The optimisation was run 4 times to account for randomness contained in the initialisation-, pairing- and mutation methods.

5.2.2. Result of experiment

Figure 5.2 demonstrates the performance of the evolutionary algorithm optimisation of a BESS control strategy without any congestion issues. During optimisation, the transformer power has been set to 34MW which allows both the solar farm as well as the BESS to discharge/generate power without causing congestion. The generated strategies were then applied to the case study to correctly measure congestion.

The results of applying these strategies to the same 4 congestion heuristics are visualised in Figure 5.3. The performance of these methods were compared to the performance of the average generation considered heuristic applied to the GIGA Baseline.

Similarly to the graphs above, hatched bars indicate congestion occurred.

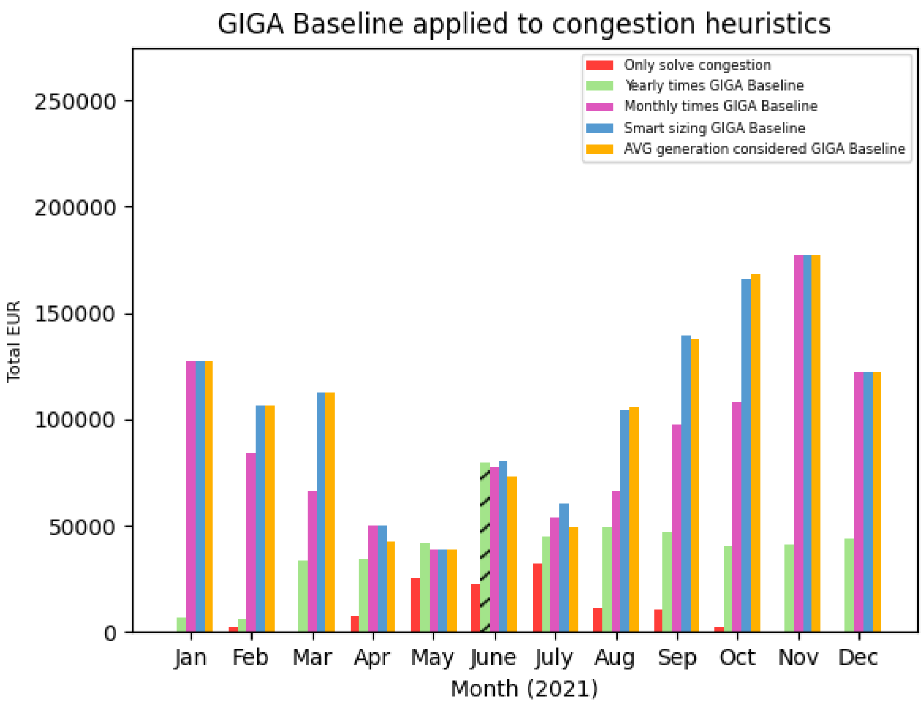


Figure 5.1: Results for Research Question 1

(Battery revenue €)	January	February	March	April	May	June
Only solve congestion	0.00	2626.06	0.23	7393.81	25450.34	22709.67
Yearly timing GIGA Baseline	6516.91	5796.20	33622.37	34692.71	42113.85	79804.65
Monthly timing GIGA Baseline	127407.68	83928.33	66094.07	50022.41	38975.25	77247.98
Smart sizing GIGA Baseline	127407.68	106705.74	112169.32	50087.45	38658.21	80588.04
Average generation considered GIGA Baseline	127407.68	106424.41	112169.32	42228.67	38975.25	73310.27
	July	August	September	October	November	December
Only solve congestion	31802.70	11115.82	10432.11	2246.32	1.52	0.00
Yearly timing GIGA Baseline	44885.82	48985.33	47129.71	40431.83	40725.59	44175.17
Monthly timing GIGA Baseline	53966.51	66700.40	97736.78	108392.03	177481.86	122251.55
Smart sizing GIGA Baseline	60736.50	103996.84	139020.69	165870.45	177481.86	122251.55
Average generation considered GIGA Baseline	49233.09	105512.17	137765.15	168309.74	177481.86	122251.55

Table 5.1: GIGA Baseline performance with different congestion heuristics

	GIGA Baseline disregard congestion	Disregard congestion optimisation	
Total battery earnings (€)	2,013,845.38	2,363,724.08	±7685.96
Total number of cycles	362.86	607.90	±48.79
Average SoC (kWh)	14657	16747.25	±90.97
Daily average earnings (€)	5519.75	6495.75	±21.07
Daily average cycles	0.99	1.67	±0.13

Table 5.2: Overview of battery usage and performance when disregarding congestion

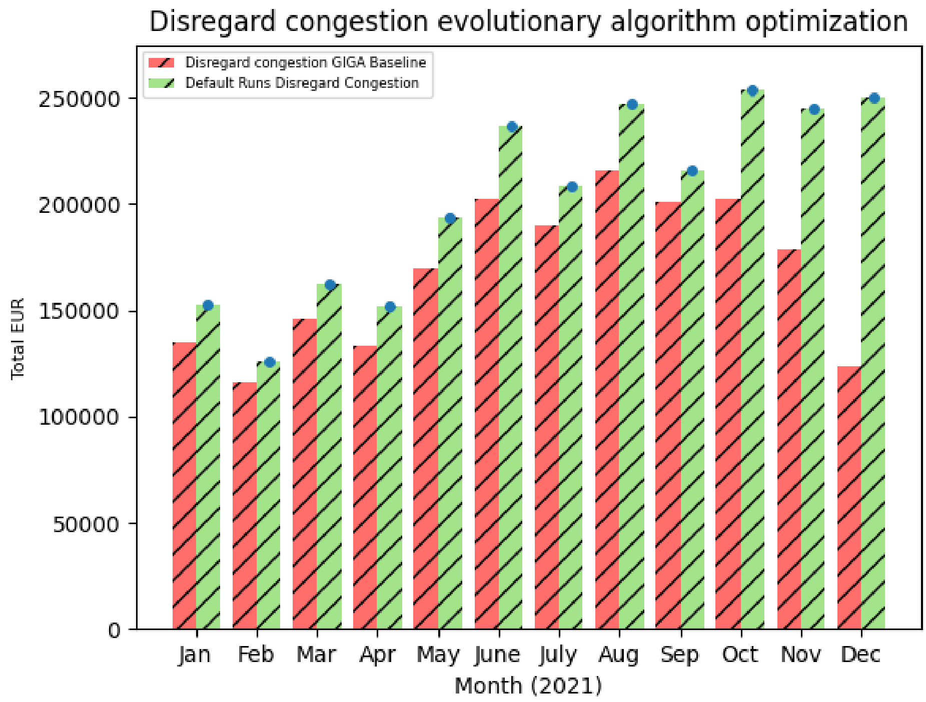


Figure 5.2: Disregard congestion evolutionary algorithm optimisation compared to the GIGA Baseline

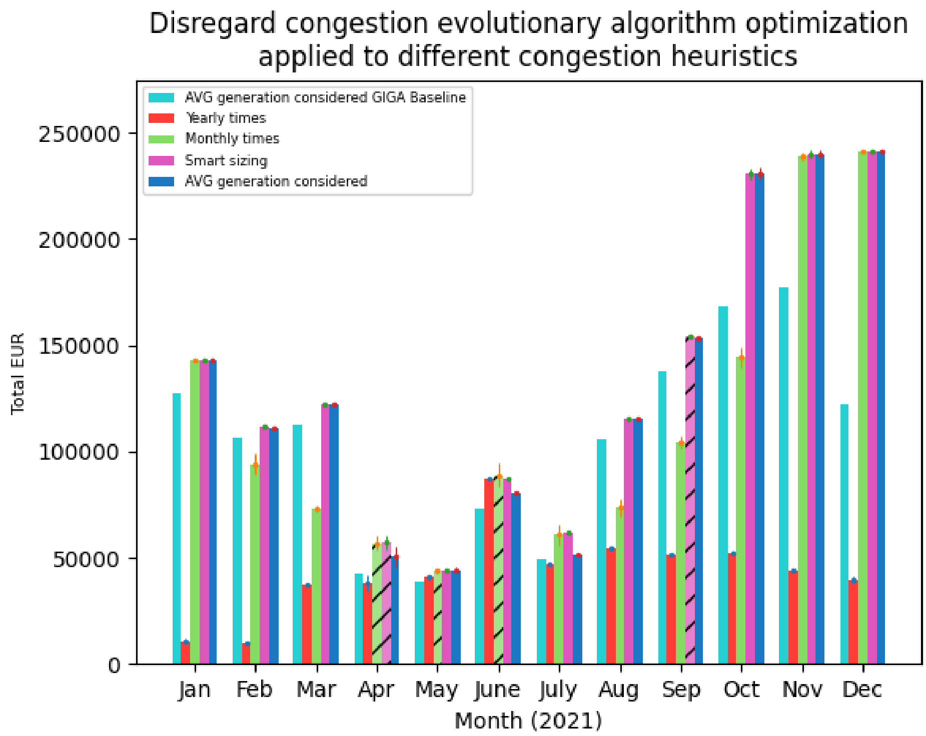


Figure 5.3: Disregard congestion evolutionary algorithm optimisation applied to congestion heuristics, compared to the GIGA Baseline

5.3. RQ3 - Optimising strategies while solving congestion

5.3.1. Description of experiment

The next evolutionary algorithm optimisation will be executed with the network topology defined as it is stated in the case study, with a transformer power set to 14MW. This method will generate strategies that can immediately be utilised in the proposed smart grid as they are tuned to function around the presented congestion times. For all these optimisations the smart sizing congestion heuristic was used.

The optimisation was run 4 times to account for randomness contained in the initialisation, pairing and mutation methods.

Hyperparameter optimisation Exploration of hyperparameters was done with the same optimisation in which congestion was solved. The experiments are run on three months, March, April and November. A slight congestion month, heavy congestion month and finally a month without congestion. Each run has been done 3 times to account for randomness contained in initialisation, pairing and mutation methods. The explored parameters can be found in Table 5.3.

	Pairing method	Mutation method	Mutation possibility
Default value	Multi axes	random_mutation	50%
Additional explored values	Single axis	big_random_mutation	25%
		big_sided_mutation	75%
	Guidance method	**Offspring ratio**	**Population size**
Default value	Sort 1	80%	100
Additional explored values	No Sort	40%	20
	Sort 2	160%	40
	Sort 3		200

Table 5.3: Explored parameters

5.3.2. Results of experiment

The performance of the generated strategies are laid out in Figure 5.4 in comparison to the GIGA Baseline of RQ1 and the best performing non-congestion causing method from RQ2.

The optimisation finds an average increase of revenue of 2.69% in comparison to the disregard congestion optimisation. A T-test confirms that this improvement is statistically significant with a P-value of 0.0004.

5.3.3. Hyperparameter optimisation

In the interest of limiting the length of the results section, only the statistically significant parameters are shown in figures 5.5, 5.6 and 5.7. Please note in these graphs the dashed lines portray the average average fitness of the population and the solid lines portray the average best performing individual of that generation.

None of the hyperparameters improved the performance of the evolutionary algorithm optimisation significantly. However with analysis of the number of fitness function calls for each optimisation some parameters did show a significant difference with a 95% certainty.

For the congestion-heavy month April the single-axis pairing method found a similar performing control strategy in statistically significant less fitness function evaluations than the multi-axes method. A T-test calculated a P-value of 0.0479.

Similarly to above, in the congestion-heavy month April, a mutation probability of 50% found a similar performing control strategy in statistically significant more fitness function evaluations than both the 25% and 75% mutation probabilities. T-tests calculated P-values of 0.0184 and 0.02998 respectively.

Finally in the congestion heavy month April, an offspring ratio of 80% spent significantly more fitness function evaluations to find a similar performing strategy to an offspring ratio if 40%. A T-test calculated a P-value of 0.03348. The final Figure 5.7c shows the similar performance of the different offspring ratios. Similar graphs can be found for the other parameters in Appendix A.

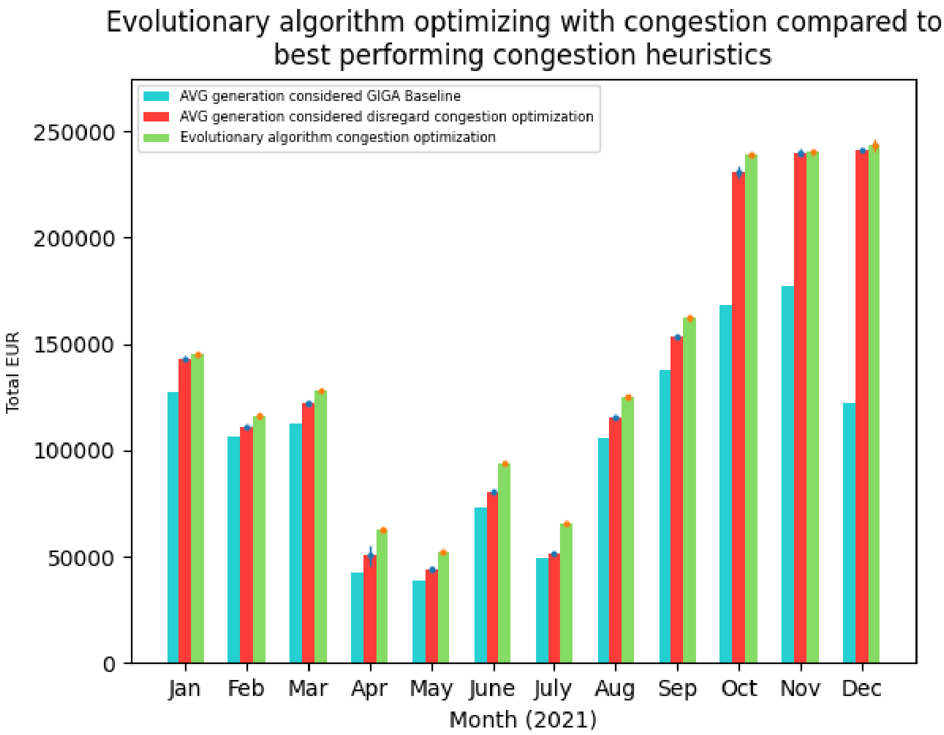


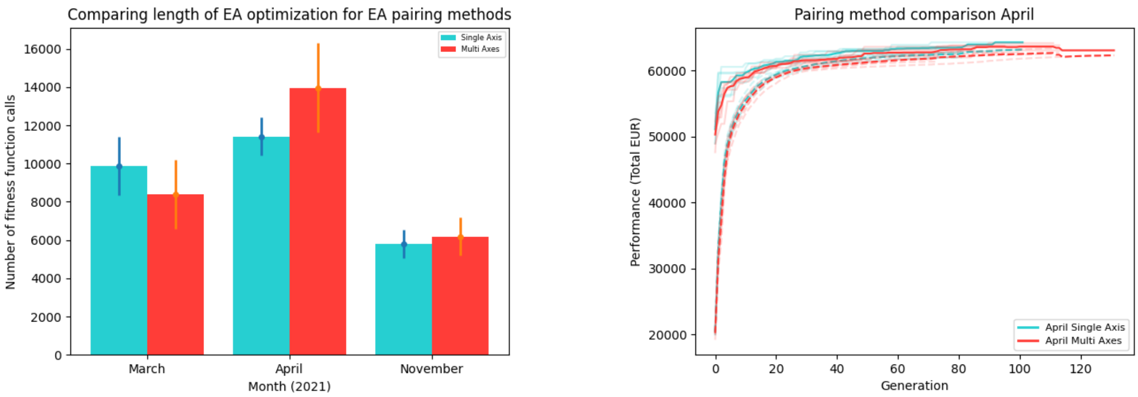
Figure 5.4: Congestion evolutionary algorithm optimisation, compared to the GIGA Baseline and previous best performing heuristic

Earnings (€mean ±€std)	Disregard congestion EA optimisation		Congestion EA optimisation		Difference (%)	Unpaired T-Test (N=4)
January	142653.39	±456	145132.41	±490	+1.71%	P=0.0003
February	111351.05	±532	116336.41	±1551	+4.29%	P=0.0009
March	122352.0	±679	128289.81	±397	+4.63%	P=0.0001
April	50439.49	±4836	62872.47	±923	+19.77%	P=0.0023
May	44248.74	±1154	51920.43	±261	+14.78%	P=0.0001
June	80660.69	±645	93618.89	±424	+13.84%	P=0.0001
July	51475.73	±333	65456.73	±455	+21.39%	P=0.0001
August	115239.44	±868	125015.26	±1027	+7.82%	P=0.0001
September	153540.73	±569	162369.07	±1840	+5.44%	P=0.0001
October	230935.66	±2745	239014.19	±432	+3.38%	P=0.0011
November	239815.56	±1785	240264.53	±1252	+0.19%	P=0.6948
December	241091.57	±444	243676.09	±3067	+1.06%	P=0.1464
Year 2021	1,595,169.57 ±10,987		1,637,439.78 ±4,271.41		+2.58%	P=0.0004

Table 5.4: Congestion evolutionary algorithm optimisation, compared to the GIGA Baseline and previous best performing heuristic.

	GIGA Baseline Average disregard congestion	Disregard congestion optimisation		Congestion optimisation	
Total battery earnings (€)	1,261,033.37	1,595,169.57±10987.42		1,637,439.78±4271.41	
Total number of cycles	307.31	425.18	±9.94	439.35	±9.4
Average SoC (kWh)	10895	13820.50	±95.77	13511	±137
Daily average earnings (€)	3456.37	4372.20	±30.11	4488.27	±11.56
Daily average cycles	0.84	1.17	±0.03	1.21	±0.03

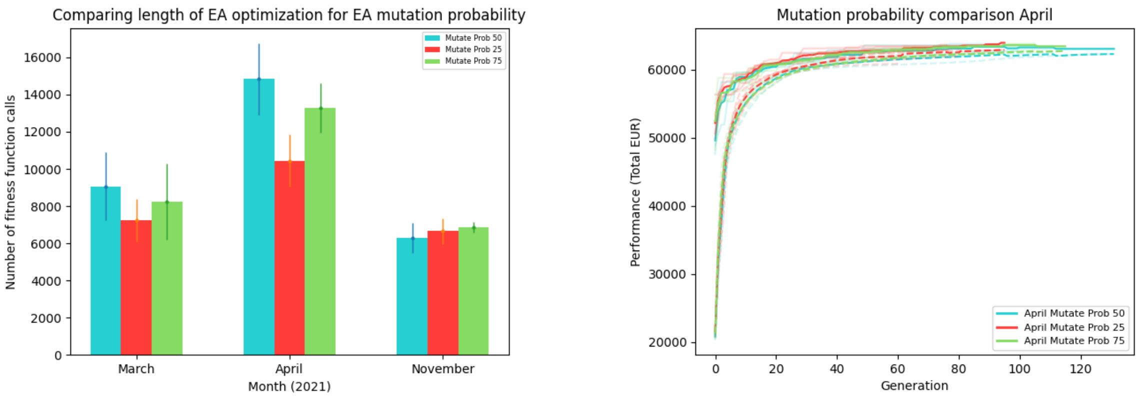
Table 5.5: Overview of battery usage and performance when solving congestion



(a) Length of EA optimisation with different pairing methods

(b) EA optimisation for April with different pairing methods

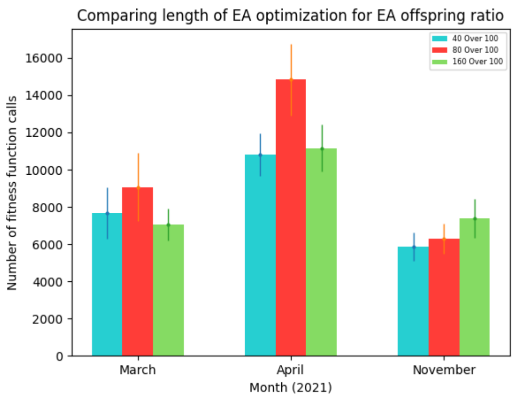
Figure 5.5: Investigating hyperparameter of different pairing methods



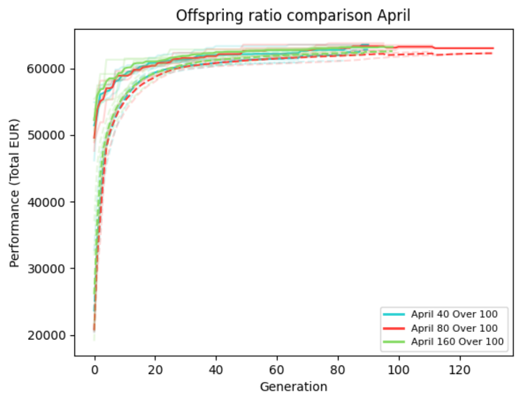
(a) Length of EA optimisation with different mutation probabilities

(b) EA optimisation for April with different possibilities of mutation

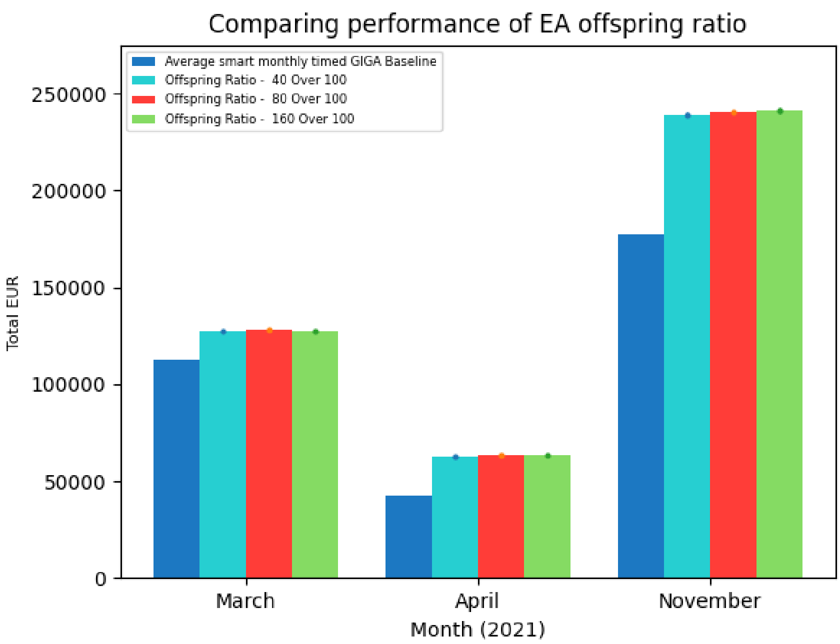
Figure 5.6: Investigating hyperparameter of different mutation probabilities



(a) Length of EA optimisation with different offspring ratios



(b) EA optimisation for April with different offspring ratios



(c) Performance of EA optimisation with different offspring ratios

Figure 5.7: Investigating hyperparameter of different offspring ratios

6 Discussion

6.1. RQ1 - Solving congestion

The investigation of different congestion heuristics make clear that conservative approaches such as only solving congestion or using yearly times heavily under-utilise the BESS to earn additional revenue through price arbitrage. The difference in performance of the yearly timings in comparison to the other monthly timings is smallest during the months in which congestion is most prevalent, May, June and July. The revenue of these months differs $\sim 4\%$ on average when comparing the yearly timing to the other 3 methods. That is due to the similarity of the yearly and monthly timings for those specific months.

The difference between the monthly timed, smart monthly timed and average generation considered methods is 0% in months where there is no congestion, e.g. January, November and December. As for these months there is no difference between these methods.

In months in which congestion occasionally happens, the difference between the monthly timed and smarter methods is most prevalent e.g. March, September and October. In those months an average revenue increase of $\sim 53\%$ is achieved. This increase is expected as even though congestion is occurring, the BESS still has room at the lower state of charge levels to earn additional revenue through price arbitrage.

It is important to note that the yearly timing method still causes congestion in June. Seemingly the approach this heuristic takes is insufficient to account for all congestion scenarios contained within the simulation.

Investigation by hand of the congestion that occurred confirms that it occurs due to the battery energy storage system being unable to prepare itself sufficiently for the congestion event. During the preparation for congestion phase, the BESS is unable to discharge sufficient power due to the solar park generation limiting available space on the transformer. This means that by the start of the congestion period there is excess power still contained within the BESS. Once that is the case, a certain day in which the congestion event causes enough congestion will cause the BESS to be limited by its physical capabilities and unable to solve the congestion on the network.

The average generation considered heuristic takes into account this issue by measuring the average generation of the solar park to adjust the preparation period accordingly. This allows this method to effectively solve congestion. That being said it is important to note that less aggressive strategies will still be able to solve congestion with the other congestion heuristics. Less aggressive strategies might ensure the BESS is less full at the start of the preparation phase which means there is sufficient space on the transformer to fully prepare for the oncoming congestion event.

6.2. RQ2 - Optimising strategies for earning money

Setting the power of the transformer to 34MW allows both the solar park as the energy storage system to simultaneously generate/discharge power to the high voltage grid. Although the strategies that are generated through this optimisation are unable to be applied to the presented case study they show the potential of this optimisation method.

In all months the optimised strategy outperforms the GIGA Baseline. The GIGA Baseline was not an exact approximation of the earnings GIGA Storage. However this does show that this optimisation method produces well-performing price arbitrage strategies.

It is interesting to note the very small standard deviation of the optimisation method. A mean revenue of $2,363,724.08$ and standard deviation of ± 7685.96 is only 0.3%. Although the standard deviation is small the strategies generated by this method are still quite different. Seemingly the same market data and proposed model for a control strategy allow multiple methods to converge to similar revenues. Manual investigation of daily performance of the different strategies could show how one strategy optimised a certain set of days with particular price patterns in comparison to another strategy. That would suggest this similar performance is only achieved when averaging the performance of the strategies over the particular month.

When applied to the same congestion heuristics used in RQ1 comparisons between the yearly, monthly, smart monthly and average generation considered heuristics to that of RQ1 are confirmed.

Similarly to the GIGA Baseline when applied to the congestion heuristics some strategies still cause congestion. These heuristics are not the same ones as the heuristics that still caused congestion for the GIGA Baseline. Within the different runs of optimised strategies different heuristics did cause and solve congestion differently, the hatched bars in Figure 5.3 represent the congestion moments still present of a single run.

This coincides with the previous discussion that some more aggressive strategies can still cause congestion on some of the most conservative heuristics. One of the optimised strategies even caused congestion when utilising the average generation considered heuristic. Perhaps an even more conservative approach such as considering the largest generation (instead of average) would be a fool-proof heuristic that would make the most aggressive strategy still solve congestion.

6.3. RQ3 - Optimising strategies while accounting for congestion

Setting the power of the transformer to 14MW enables the evolutionary algorithm to tune price arbitrage strategies to the congestion heuristics.

For example the forced discharge action when preparing for congestion can either be embraced by having a higher SoC or dodged entirely by discharging earlier when prices might be more profitable than when the action is forced. Furthermore the strategy can utilise lower SoCs of the asset during congestion in months such as March, September and October where the SoC is only forced below ~ 15 MWh.

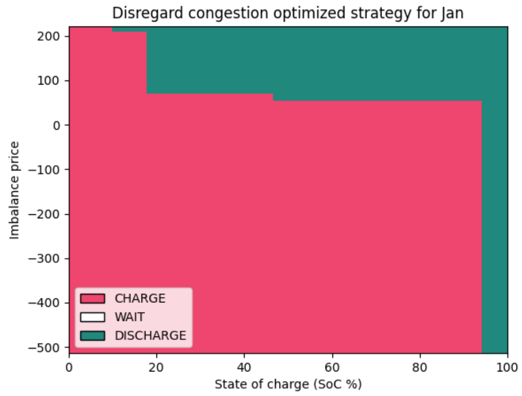
The optimisation successfully finds a more optimal control strategy than the strategies presented by the optimisation without considering congestion. These perform better with a statically significantly P-value of 0.0004. On average the performance is 2.58 % better. The highest increase of performance is achieved in the months April through July, this is expected as these months encounter the largest issues of congestion. Seemingly the EA optimisation that takes congestion into account effectively steers the asset around the congestion event and increase revenue by on average $\sim 17\%$.

A small increase in the earnings in slight-congestion months March, September and October has been found to be statistically significant. An average increase of revenue of $\sim 4.48\%$ was found which shows that optimisation around small congestion events or in lower SoC brackets has been made. Manual investigation of the performance of the strategies could show if the additional revenue is generated in lower SoC brackets or in moments surrounding congestion events.

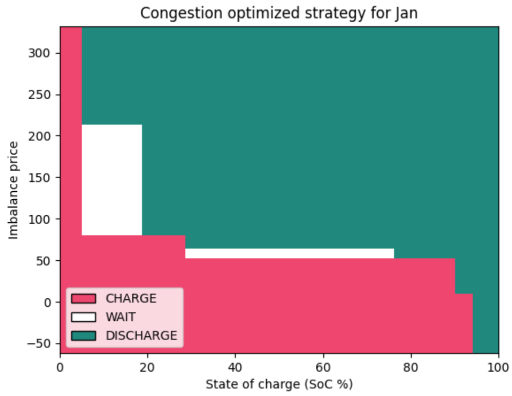
As expected in November and December, months in which there are no congestion events, there is no statistical significant improvement between the two optimisation methods. However in January, where there are also no congestion events, there is a statistical significant improvement of 1.71%. Investigation of the strategies by hand might help explain this improvement. Perhaps the limitation of discharge (to not cause congestion) that is taken into account in the optimisation that considers congestion manages to find better prices surrounding energy prices when discharge might be limited.

6.3.1. Hyperparameter optimisation

Not a single explored hyperparameter ensured a statistically significant difference in performance of the evolutionary algorithm was achieved. However a statistically significant difference in number of fitness evaluations was found. For optimisations ran on high-congestion month April, an offspring ratio of 40%, mutation possibility of 25% and the single-axis pairing method all outperformed their counterparts in



(a) Disregard congestion optimised strategy for January



(b) Congestion optimised strategy earning for January

Figure 6.1: Investigation of two January individuals

generating a similar performing strategy in statistically significant less number of fitness evaluations.

It is difficult to pinpoint the reason why these parameters caused a significant difference in number of fitness function evaluations. A lower offspring ratio suggests that converging to the current best-performing strategies works best, however if that is the case a higher mutation possibility is expected to be an improvement but the higher mutation possibility was outperformed by the 25% value. Perhaps however the better performance of a lower mutation possibility suggests that the mutation method chosen simply does not perform well for high-congestion months.

During all runs it was clear that the evolutionary algorithm took the most fitness function evaluations to optimise a strategy for the high-congestion month April. Therefore any significant speedup to this method could ensure lower run times for the algorithm during other high congestion months.

Finally, it seems that the basic evolutionary algorithm implemented in this thesis cannot further optimize the proposed model of a BESS control strategy. Because no hyperparameters were able to improve the performance of the algorithm. The best effort to improve the performance of the evolutionary algorithm would be to explore related work in the context of evolutionary algorithms.

6.4. General

6.4.1. Manual investigation of optimised strategies

Besides investigating the performance of the strategies through the measurement of generated revenue it is interesting to compare the generated strategy points and if they coincide with realistic strategies generated and utilised by GIGA Storage.

The intuitive approach that when the BESS is nearly full, a better charge and cheaper discharge price are expected and that when the BESS is almost empty, a cheaper charge price and better discharge price are expected is enforced by the hyperparameter Sort 1. For that reason the generated strategies by the optimization show this structure.

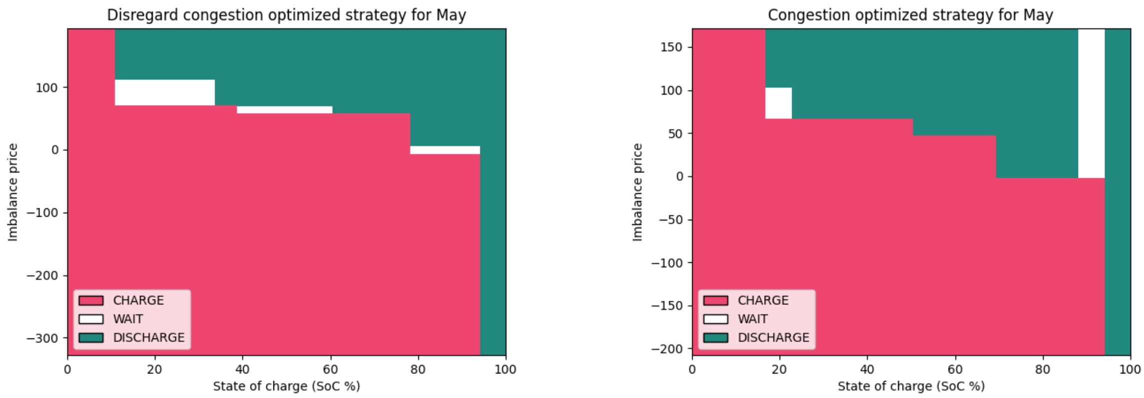
Furthermore two design choices of the structure of a control strategy ensure certain odd-looking strategies do perform well. The first is that charge takes priority over discharge presented positions. Therefore discharge prices that lay below the charge price are disregarded and seen as charge actions. The discharge action will only be taken at a price above the charge price.

The second design choice to recall is that the strategy is always sorted by the SoC% of the point. Therefore the different points seem to naturally follow each other.

Design choice one of placing the charging surface over that of the discharge surface ensures that both of the presented strategies for January in Figure 6.1 have similar performance. Even though the disregard congestion strategy wants to discharge from prices of -176 €/MWh it is limited by the charge price of 68 €/MWh at the same SoC. Therefore the actual discharge price will be set at 70 €/MWh.

Seemingly the large margins the congestion optimised strategy strives for at lower SoCs do not make a significant impact on the performance of this strategy in comparison to the other.

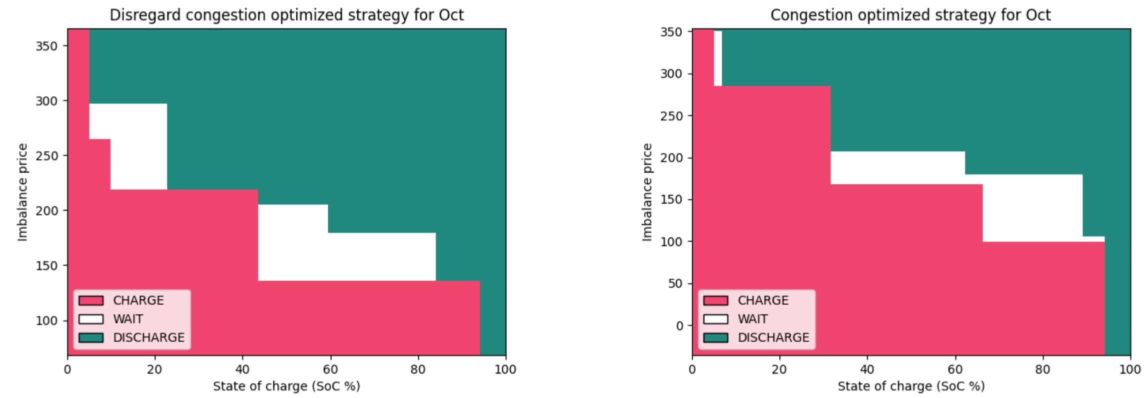
Figure 6.2 presents two different strategies optimised for the month of May, a month with a lot of



(a) Disregard congestion optimised strategy for May

(b) Congestion optimised strategy for May

Figure 6.2: Investigation of two May individuals



(a) Disregard congestion optimised strategy for October

(b) Congestion optimised strategy for October

Figure 6.3: Investigation of two October individuals

congestion. The strategy that was optimised for congestion has a white band leading upwards between 89-95 SoC%. Such a structure in the strategy means that once the ESS has been charged to such a high SoC that there is not a single price at which it will discharge and the asset would be 'stuck' at that SoC%. However due to May being a high-congestion month, forced discharge actions during and in preparation for congestion will still ensure the SoC is brought down out of this white band by a congestion-related discharge.

All strategies that were optimised while disregarding congestion have found this structure in their strategy and placed one of their points at an SoC level of ES_{upper}. This ensures that the strategy does not generate such a white band.

Furthermore for these May strategies we can see that extreme discharge prices are being overwritten by charge prices. These structures can be seen in both the optimisation with and without considering congestion. It seems the difference in performance between these strategies stems from the higher charge price at an average level SoC in the congestion optimised strategy.

In months in which there are few congestion events (e.g. October) we can theorise why certain differences in strategies have been generated. Especially months in which the BESS is not forced to discharge fully in preparation of congestion allows for the BESS to optimise a strategy at lower SoC levels. The vastly different charge prices presented in Figure 6.3 at 20 SoC% are an example of this.

Although the presented strategies all perform well especially in comparison to the GIGA Baseline it remains a question if these strategies would be applied in the real world. Such overlapping structures as presented in Figure 6.2 do not instil trust in the knowledge of the system and raise the question that a larger margin might vastly improve the presented strategy.

Furthermore once the evolutionary algorithm started converging around very low discharge prices they might as well have been discarded due to the charge prices simply overwriting them. It raises the question what would happen if the evolutionary algorithm was able to act upon such findings. Perhaps if an optimization was ran where the discharge command took priority over the charge command, the found discharge prices would be able to be matched to that of the current model to improve the overall strategy. Other improvements to the BESS control strategy could consider time (different strategies at different times), power (not all actions have to be executed at 100%) or day-ahead prices.

However the generated strategies for October (Figure 6.3) do show the capabilities of the algorithm to generate strategies more in line with strategies previously utilised by GIGA Storage. This suggests that by improving the model for a BESS control strategy that maybe a far better performance can be reached.

6.4.2. Battery Usage

Table 5.2 not only presents results regarding revenue of the BESS but also displays battery usage statistics of the different strategies. Regarding the strategies optimised while disregarding congestion it is good to inform the reader that these usage statistics are well in line with battery manufacturer guarantees of that of the GIGA Rhino BESS. The average SoC % is below 60% and the average cycles per day are below 1.8.

It is interesting to note that the optimised strategy is far less efficient with its battery cycles when compared to the performance of the GIGA Baseline. Although the optimised strategy (on average) outperforms the baseline by 17% they are using 60% more cycles to earn this additional revenue. This suggests that allowing the evolutionary algorithm to optimise for minimising the number of cycles could perhaps improve battery usage while still out performing the baseline method.

The same findings can be found in Table 5.5. Although the earnings of the base model are lower than that of the other two methods it is the most efficient strategy with its cycles. All methods that solve congestion make fewer cycles than their earn money counterparts. Even though these strategies contain many forced actions, e.g. discharging to prepare for congestion and charging when congestion occurs. Seemingly the prepared state of the BESS ensures that little to no actions are taken when congestion does not occur even though it was prepared. For example when it is a cloudy day or a thunder-storm passes over during the prognosed congestion period. That the prepared state of the BESS remains underutilised when congestion does not occur is in line with the lower average state of charge found when comparing those values to that of the results of Table 5.2.

6.4.3. Significance to the case study

The results of this research show that to solve congestion for the case study the price arbitrage strategy generates $\sim 33\%$ less revenue than a situation in which the same price arbitrage strategy could be free to take actions when it wanted to. Further tuning the strategy to account for the congestion can improve the earnings by $\sim 2.5\%$.

Due to the fixed timing scheme created by the congestion-based heuristics presented in this work it is easy for GIGA Storage or other parties to present their congestion encountering clients with a fixed cost per hour for preparation of and solving the congestion issue. If such a system would be priced in a way to make up for all lost revenues this would be approximately 320 €per hour (€$720,000/2254h \approx 320$). However considering the earnings of the BESS could inspire a more competitive offer.

Further, the strategy presented here could be optimised with a generation forecast of for example 24 hours. This could heavily reduce the number of hours the system was waiting for congestion to occur while it was perhaps a cloudy day. To that extent profits would rise and hours spent expecting forced actions would be minimised, further realising the business case of a BESS in combination with a renewable energy generator.

Other points to consider when discussing a potential contract between the BESS and the renewable energy project would be to consider energy prices other than the imbalance market prices. If for example the REG has a power purchasing agreement (PPA) with a fixed energy price perhaps the BESS can use that price when taking a forced charge action to solve congestion than a worse imbalance price. The same goes for a discharge action taken by the BESS when discharging to prepare for congestion. In the current simulation the BESS simply takes the imbalance price while other options can be taken into account.

If the case study would want to be installed to the current grid TenneT restrictions define that the grid would have to apply for a 34MW grid connection which is capable of handling the full load of the solar park as well as the discharging BESS. Applying for such a large grid connection is a complicated process that is becoming more difficult when considering the current state of the grid. Furthermore the investment necessary for a larger transformer can also be mentioned.

This research shows how it is possible to utilise the grid more efficiently and bring the size of the transformer down to 14MW. The monetary savings made on the investment of installing a smaller transformer are not expected to be significant when considering the entire lifetime of the project. These savings would be a smaller one-time saving of investment costs in comparison to yearly or hourly costs incurred by having a BESS on the local grid to solve congestion. Furthermore the installation of a BESS cannot be considered a small investment so the impact of this research on the feasibility of the cost and benefits of the project as a whole is minimal. However the smaller transformer could ease the application process for actually realising the grid connection and thereby the instalment of additional renewable energy to the grid.

Finally transport costs should also be mentioned, subsection 3.2.5 mentioned limitations the BESS encounters when the system wants to charge when there is no power being generated by the solar park (e.g. every night). This ensures the control strategy is also limited during those hours to earn additional revenue. Although it is physically possible for the BESS to charge from the high voltage grid, the transport costs TenneT bills grow very fast with the peak capacity charged from the grid. The ironic part is that the next consumer, e.g. the utility that buys power once the BESS is discharging, is also paying for transportation costs. The novel nature of battery energy storage systems on the grid means these high costs which are effectively paid twice are limiting actions and revenue of the BESS. If steps are made to change these things Equation 3.11 can be adjusted and changes are expected in the performance of all presented methods.

7 Conclusion and Future Work

This thesis concludes that it is possible for an appropriately sized battery energy storage system to solve congestion in a smart grid where the transformer has been undersized when considering the size of the renewable energy generator. The BESS will earn $\sim 30\%$ less revenue when forced to solve congestion on the grid. This revenue could be accounted for by charging a fee for the congestion services. But before such an offer is made other pricing points such as energy prices and saving on investment costs should be considered.

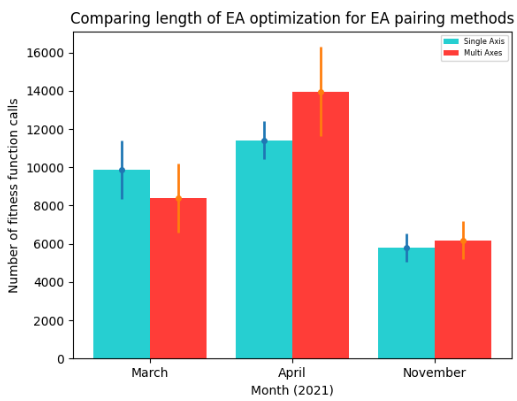
Four different heuristics were presented and if the control strategy is tuned towards the heuristic all four can be utilised to solve the congestion issue. However when considering a revenue maximisation control strategy the safest choice of heuristic would be the average generation considered method. Within this work these heuristics were applied to monthly historical data of a solar park however future work could consider the uncertainty and performance of a generation forecast of the renewable energy generator to improve performance.

The implemented evolutionary algorithm to optimise the control strategy of the BESS during, in preparation of and in downtime of congestion was able to outperform the offered baseline as well as the pure revenue-based optimised strategies. Although the generated strategies were limited by the offered model of the BESS control strategy this work hopes to inspire the community to consider BESS strategies outside of solving single problems on a (local) network.

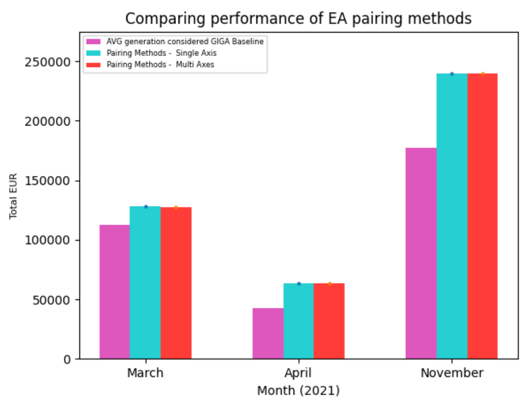
Hyperparameter optimisation of the evolutionary algorithm improved the runtime of the algorithm when considering high-congestion months but did not statistically significantly improve performance. Once an improved model of the BESS strategy has been implemented future work is urged to consider proven well-performing evolutionary algorithms such as GOMEA and NSGA-II to improve the optimisation.

This thesis has proved that the proposed case study can be realised. Although the costs saved on investing in a smaller transformer do not weigh up to the investment costs of the BESS this work hopes to inspire parties to help realise renewable energy generation projects in an overfull grid.

A
Hyperparameter optimization

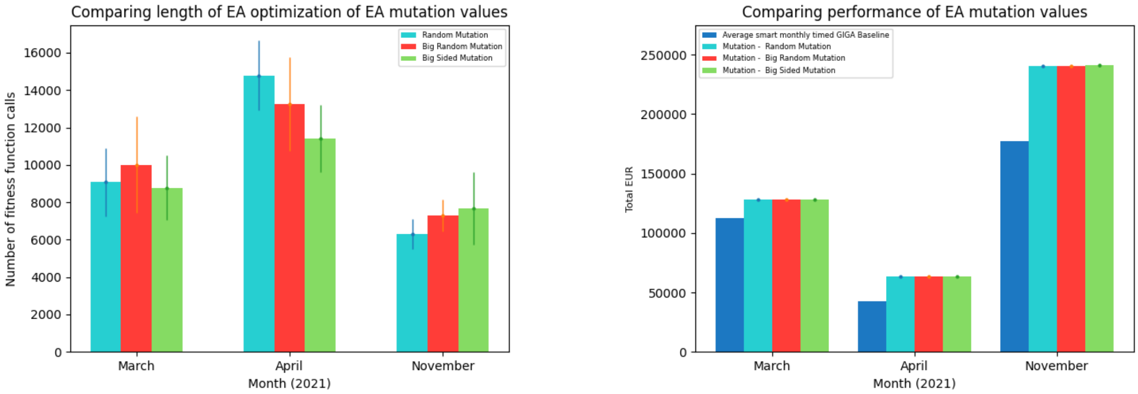


(a) Length of EA optimization with different pairing methods



(b) EA performance with different pairing methods

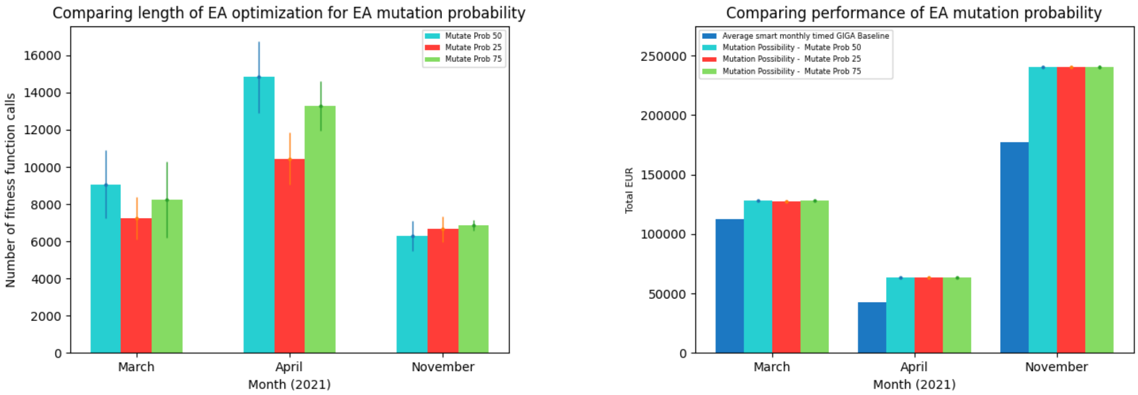
Figure A.1: Investigating hyperparameter of different pairing methods



(a) Length of EA optimization with different mutation values

(b) EA performance with different mutation values

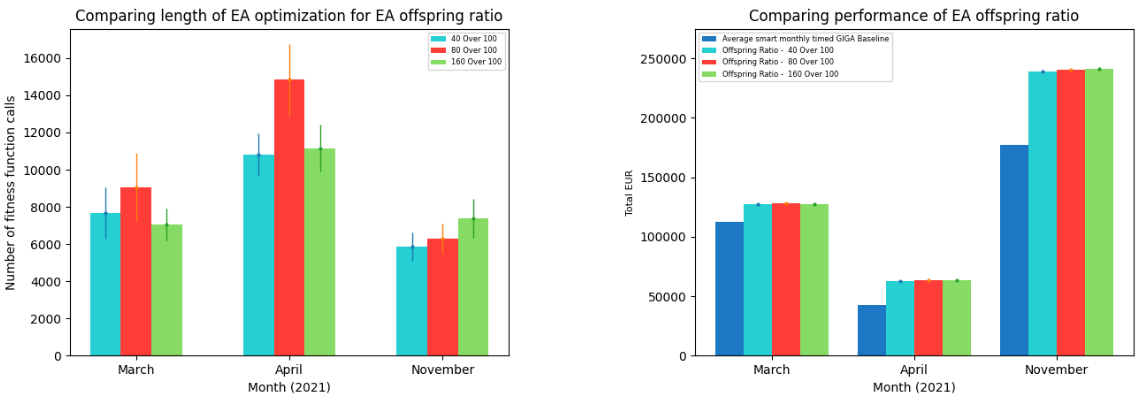
Figure A.2: Investigating hyperparameter of different mutation values



(a) Length of EA optimization with different mutation probabilities

(b) EA performance with different mutation probabilities

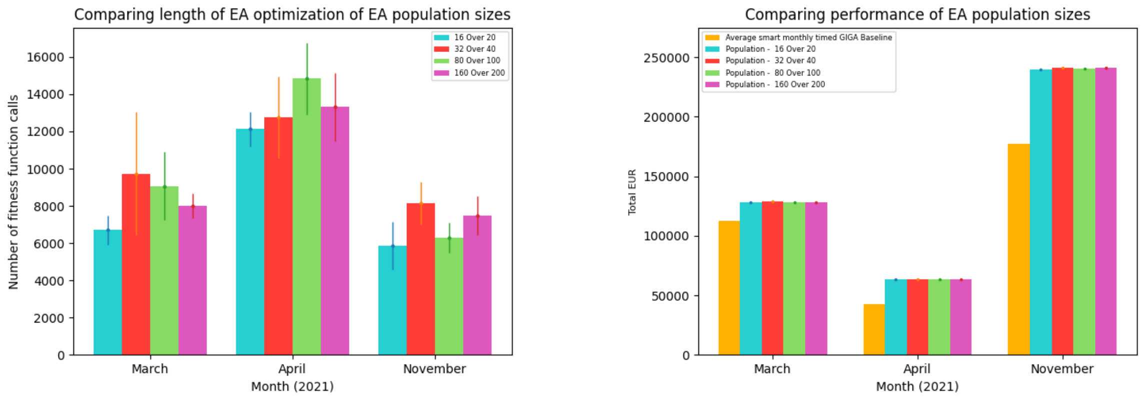
Figure A.3: Investigating hyperparameter of different mutation probabilities



(a) Length of EA optimization with different offspring ratios

(b) EA performance with different offspring ratios

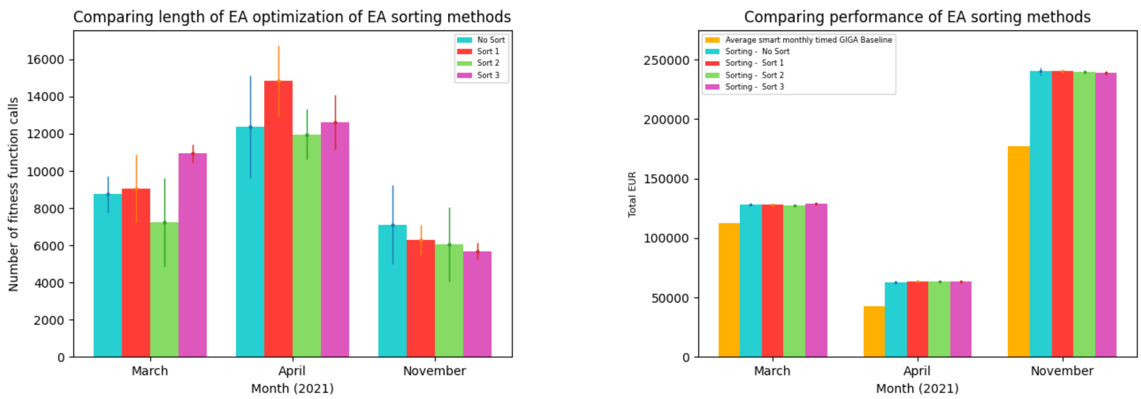
Figure A.4: Investigating hyperparameter of different offspring ratios



(a) Length of EA optimization with different population sizes

(b) EA performance with different population sizes

Figure A.5: Investigating hyperparameter of different population sizes



(a) Length of EA optimization with different guidance methods

(b) EA performance with different guidance methods

Figure A.6: Investigating hyperparameter of different guidance methods

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