Comprehensive Study of Metahueristc Algorithms for Optimal Sizing of Multiservice BESS or Comprehensive Study of Metahueristc Algorithms for Optimal Sizing of BESS in Multi-energy system

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Abstract

The question of finding optimal size for battery energy storage systems (BESS) to be used for energy arbitrage and peak shaving have gained more and more interest in recent years. This due to the increase in variability of electricity prices caused by the increase of renewable but also variable electricity production units in the electricity grid. The problem of finding the optimal size for BESS is a of high complexity and includes many factors that affect the usefulness and the economic value of a BESS. This study includes a thorough literature study regarding different methods and techniques used for the problem of finding optimal size for a BESS. From the literature study two meta-heuristic algorithms were found to have been used with success for similar problems. The two algorithms were Genetic algorithm (GA) and Firefly algorithm (FF). These algorithms have been tested in a case study optimizing the BESS capacity and power to either maximising the net present value (NPV) of investing in a Li-ion BESS of the LPF type or minimizing the levelized cost of storage (LCOS) for the BESS, with a project lifetime of 10 years. For the case study a simplified charge and discharge schedule was implemented with the focus of maximising the value of energy arbitrage. The case study was divided into 3 different cases, the base case where no installment of a BESS were done. Case 2 included the installment of the BESS whilst case 3 included installing both a BESS and an electrical heater. The electrical heater in case 3 was implemented to shift the heating load to an electrical load, as well as reduce CO_2 emissions from a preinstalled gas heater, compared to the base case.

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The results showed that overall GA was a better optimization algorithm for the stated problem, having lower optimization time overall between 60%-70% depending on the case. For case 2 GA achieves the best LCOS with a value of 0.225 €/kWh compared to FF at 0.254 €/kWh. Regarding NPV for case 2, FF achieve the best solutions at the lowest possible value in the search space for the capacity and power (i.e 0.1 kWh for capacity and 0.1 kW for power), with an NPV at -51.5€, showing that for case 2 when optimizing for NPV an investment in a BESS is undesirable. GA finds better solutions for case 3 for both NPV and LCOS at 954,982€ and 0.2305 €/kWh respectively. For case 3 it was shown that the savings from installing the ELH stands for a large portion of the profits, leading to a positive NPV compared to case 2 when it is not implemented. The results also showed that there exist different combinations of solutions of capacity and power that results in similar results regarding NPV and LCOS. Finally, it was found that both the algorithms can be useful tools for finding optimal power and capacity for BESS installments, where it was seen as GA were able to give better results. However, is was seen that the charge and discharge schedule plays an important role regarding the effectiveness of installing a BESS. As for some cases the BESS was only used 17% of all hours during a year (case 2, when optimizing for NPV). Therefore, further research is of interest into the schedule function and its role regarding finding the optimal BESS size.

*Achieves

*Is this not specific to the case?

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*Since the focus of the thesis is the performance and comparison of the algorithms, it could be better to mention the % differences or scale differences rather than exact values.

* Defining that the basis for the case more clearly would help clarify the basis of the cases. For example, mentioning that the arbitrage is done for demand values from a residential building, the sizes, etc

Sammanfattning

Acknowledgments

Felipe, Nordpool...

Abbreviation

BES	battery energy storage
BESS	battery energy storage system
CAPEX	capital Expenditures
DoD	depth of discharge
ELH	electrical heater
ESS	energy storage system
FF	firefly algorithm
GA	genetic algorithm
IEA	international energy agency
LCOS	levelized cost of storage
LFP	lithium ferrophosphate
NPV	net present value
OPEX	operating expenditure
PSO	particle swarm optimization
STD	standard deviation

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1 Introduction

Today more and more variable renewable energy production units as solar and wind are *such as
introduced into the energy systems to reduce the amount of greenhouse gases emitted from the energy sector [1]. The international energy agency (IEA) has forecasted that per year between 2021-2026, 300 GW capacity of renewable sources for energy production will be installed [2]. With these large penetration levels of variable energy production units into the energy grids, problems with variable energy sources become more important, such as grid stability and power quality [3]. Energy storage has been acknowledge as a method to prevent *acknowledged
these problems [4], but energy storage can also be used as as a tool for energy services such as load shifting and peak shaving for demand side management [5]. The problem that then arises is to pick the optimal size in regards of capacity and power output from the energy storage to maximize net present value (NPV) or minimize levelized cost of storage (LCOS) from implementing an energy storage.

This thesis will investigate by looking ~~at~~ from a~~n~~ third-party developers perspective of installing a~~n~~ Li-ion battery either to maximise profits, by specifically looking to maximize the NPV for installing and operating a battery energy storage system (BESS) or to minimize the LCOS. To solve this problem a literature study is firstly done to find state of the art methods. Meta-heuristic optimization algorithms have been found to be a powerful tool in many different research areas. In the last years especially in the field of energy engineering *research areas especially in the last few years in the field of energy
as they are able to provide close to optimal results in computationally heavy optimization problems [6]. Therefore, two different meta-heuristic algorithms are used to find the optimal sizing of an Li-ion battery of the lithium ferrophosphate (LFP) type and compared their usefulness for this type of optimization problem. This is done using a simple function for scheduling the charge and discharge of the BESS with focus on energy arbitrage and peak shaving.

2 Background and Literature review

This section starts of with introducing two common areas of use for energy storage, energy arbitrage and peak shaving. Thereafter optimization algorithms and meta-heuristic algorithms are introduced followed by a literature review regarding the development of different techniques used for finding the optimal size in capacity and/or power for different energy storage technologies.

2.1 Energy Arbitrage and Peak Shaving

Energy arbitrage is a method to obtain monetary value from the use of an energy storage system (ESS), by buying and storing energy in an ESS at times of low market price for the energy and then selling it back at times when the price of energy is higher. [7]. Peak shaving is a method to reduce the peak load demand for a user (in kW). The reason is to reduce the extra cost that comes with specifically high load demands at short intervals at times of peak demand in the energy grid, also known as demand charges. The possibility for peak shavings depend on the user as well as on the energy market it is operating in, as different energy markets have different system for peak demand charges. Demand charges is usually only applied to commercial customers of the utility company. The demand is *are based on the peak demand in kW per billing period, where the cost is based on the highest average demand over a predefined time interval that occurs during the billing period of the consumer [8]. Peak shaving can and have been done using on site generators (diesel or gas turbines) often owned by the consumer itself. The installment of on-site BESS for peak shaving have been seen as a usable emission free option, but the problem with optimal size then arise [9].

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2.2 Optimization Algorithms

Optimization algorithms are used to solve optimization problems. These problems focus on computing an objective function and trying to minimize or maximize the results by systematical testing different input variables within a set of values (the search space). There are three important factors that go into an effective and viable optimization algorithm, it has to be *efficient* (Meaning it shouldn't demand an disproportionate amount of processing time or storage), *accurate* (It should have high precision in the results it obtains and not be sensitive to rounding errors as well as errors in the data) and *robust* (Meaning that the algorithm should be able to work on many different problems, when using sensible starting values). Usually, trade-offs between these three factors have to be made when choosing which algorithm to use. Two powerful type of optimization algorithms is *heuristic* or *meta-heuristic* algorithms. These algorithms are not assured to find the best solution, as for example linear programming usually is. However, they are useful as they can find close to optimal solutions in big search spaces with low computational load. These algorithms use randomization and local search functions to find the most optimal solution globally in the search space. Therefore, two fundamental components for these optimization algorithms are firstly the function used to find the optimal solution locally in a search space. Secondly is a randomization function for the algorithm to prevent the possibility to get stuck in local optimums and find the optimal solution globally whilst looking at the whole search space [10].

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2.3 Heuristic and Meta-Heuristic Optimization Algorithms

The word Meta-heuristic can be divided into its two parts Meta, which derives from Greek meaning *"after"*, *"beyond"* or *"along with"* [11]. Whilst Heuristic coming from Greek meaning *"to discover"* [12]. The field of heuristic optimization started in 1945 by G. Polya [13], but it would take time until these algorithms were starting to be used more frequently. It was not until conventional optimization techniques that found an exact solution to optimization problem were facing the problem unreasonable high computational times. Heuristic algorithms trade computational performance for lower accuracy in order to solve problems that previously would have taken upwards of years with conventional optimization techniques. What is important to note is that heuristic optimization algorithms are very specifically designed for the problem at hand. Meta-heuristic optimization algorithms were first used in the 80s where several general heuristic algorithms were put together to create a set of algorithms to be able to solve many complex optimization problems [14]. A definition of meta-heuristic was given by Sörensen et.al. [15] in 2013 as:

*the problem of

> "A meta-heuristic is a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms."

The difference between a meta-heuristic algorithm and a heuristic one is the meta-heuristic algorithm is problem independent and can therefore be used for many different problems but with varying success. The defining and interesting feature of meta-heuristics algorithms are how they are applicable to optimization problems where no expert knowledge of the problem at hand is required beforehand, that said most meta-heuristic optimization algorithms are approximation algorithms, and therefore cannot guarantee to find the global optimal solution [14].

2.4 Optimization of Energy Storage

The problem of finding the optimal size and capacity of energy storage as a use for energy service (Load shifting, Energy arbitrage, peak shaving, frequency control, etc) has existed for some time. Many different methods have been tried in solving this question, depending how one limits the complexity of the question different methods have been used and different techniques have developed over the years.

2.4.1 Multi-pass Dynamic Programming

A multi-pass program is defined by it going through the program multiple times when compiled. It uses the results from the previous run as input for the next run and therefore improves the result by each pass. This compared to a single-pass program that only goes through the program one time to then give the final result [16]. Lee and Chen [17] looked into the problem of optimizing energy storage size already in 1995. The objective function in the study was designed to find the optimal battery size (capacity and power). The objective function also optimized for the optimal time of use contract capacity (if energy used is above the predefined capacities a penalty bill was added to the cost of energy) over a battery's life cycle~~, this~~ in order to reduce the cost of electricity. To solve this problem, an advanced multi-pass dynamic program was used in conjunction with an expert knowledge base system. The expert knowledge system was designed to give the optimal operation of the energy storage, to maximize the saved energy. The study did however not implement any capacity degradation of the battery during its lifetime. D.K Maly and K.S Kwan [18] used multi-pass dynamic programming to solve a similar problem in 1995. The objective function was to find the optimal charge and discharge rate of a battery energy storage (BES) in order to minimize the electricity bill. This was done by load shifting and peak shaving. The study only investigated optimizing the power capacity output of the batteries and not the energy storage capacity and had that variable at different fixed sizes. It was found that the method of "shaving the peaks, fill the troughs" is in practice not an optimal charge/discharge schedule for the battery storage, and to maximize energy efficiency or minimizing peaks in kW the proposed method could be applied. In 1999 Lo and Anderson [19] also used multi-pass dynamic programming to find the optimal size of a BES whilst also finding the optimal dispatch in a power system, to maximize for fuel-cost savings. A time shifting technique where a week of hours (168 hours) ~~where~~ split into 7 different time segments of 24 hours was implemented to reduce the calculations time. Thus this study did not either implement degradation of the battery storage capacity, as it did not look at its whole lifespan.

What is it referring to?

Are you saying that the proposed method could only be applied to max. efficiency/ min peaks?

*Furthermore, this study did not implement

2.4.2 Genetic Algorithm, and other non Meta-Heuristic Methods

In 2005 Chacra et.al. [20] investigated in a multi scenario study to find optimal size and power of a BES, comparing different battery types in economic performance such as NPV in a grid connected setting. This was done using a meta-heuristic non-dominant sorting genetic algorithm (GA) with tournament selection as the randomizer in the GA. The reason to use GA was due to the stated problem was multi-variable and non-linear. The study found the methodology to be effective and showed how PSB batteries were more cost effective than VRB, but further development of including the technical constraints of the batteries (lifetime, battery degradation, etc.) were needed in order to evaluate the BES to real world circumstances. Oudalov et.al. [9] found the optimal size for capacity and power for peak shaving from a predefined load profile with the use of linear function. Thereafter, dynamic programming was used to find optimal operation strategy (charging schedule for the BESS). This method was found to be sound but focused only to optimize the BESS size for the economic benefits of peak shaving and not for energy arbitrage, even though that was included in the economic model. In 2009 Abbey and Joos [21] investigated using a stochastic optimization approach to solve for the optimal size and power of a BES. The BES was connected to a wind farm with a diesel generator to stabilise the stream of electricity produced to meet a demand load. Both the winds and loads stochastic nature were included to optimize the energy storage for those unknowns. The study only looked at a 24-hour period and found that most economical savings were made with a combination of installing the ESS and different diesel operating schemes. Chen et.al. [22] investigated in 2011 into using a matrix coded GA to find the optimal number of distributed generation and energy storage units in a micro grid, as well as the optimal allocation of these units in the system to maximising NPV. The results showed that the method was viable in order to maximise NPV and could be used for both operational planning and optimal sizing of ESS. However, the case study only optimized over 1 year and ESS degradation was not included in the model. In 2012 Chen et.al [23] investigated optimal size of an ESS in an micro grid by focusing on the unit commitment problem in both grid connected and island mode. To solve this a mixed integer linear solver was used and compared to a commercial software (KNITRO). It was found that integrating an ESS increased the daily profits, but the difference in size in grid connected and island mode was quite big at 400 and 1400 kWh respectively. This study only optimized over a 24-hour span and therefore did not include the degradation of the ESS. Mohammadi et.al. [24] used a GA in 2012 to find an optimal solution for sizing distributed generators and storage units in a grid-connected micro grid but focused on how pool and hybrid markets effected the optimal solution. In a hybrid market the inclusion of energy storage was extra valuable due to the possibility to use it for energy arbitrage. In 2015 Fossati et.al. [25] investigated optimal size of an ESS to minimize the operational cost of a micro grid. To solve this a GA was used to find the knowledge base for a fuzzy expert system to solve the optimal dispatch problem for the micro grid. This was tested for both a grid connected and island mode and the results were that the total operational cost was lowered with 3.2% and 14.1% respectively. However, in order to find the optimal ESS the study optimized varied the power and capacity separately.

2.4.3 Comparison between different Meta-Heuristic Algorithms

As more and more research has been done into this area of research more and more optimization algorithms have been developed in order to improve the possibility to find the optimal solution for an ESS. Bahmani and Azizpanah [26] investigated in 2014 into using an improved bat algorithm (meta-heuristic) to find the optimal size for an ESS to reduce the operational cost in a micro grid. The improved bat algorithm was first tested on three well used test function to see that it worked as intended (Rastrigin, Griewank and Ackley functions). The algorithm was also tested against 3 different meta-heuristic algorithms (Teacher-Learners based optimization, Artificial Bee Colony, and a regular bat algorithm) to prove its superiority in finding the best solution for the defined objective function. The results showed that the improved bat algorithm could solve the three test functions and also found the optimal solution compared to the three other meta-heuristic algorithms when tested in a case study. The study did however only optimize over a 24 hour span and disregarded the degradation of the ESS. In 2017, Khan and Singh [27] compared 6 different meta-heuristic optimization algorithms. It focused on operational cost minimization with the use of an optimally sized energy storage unit in grid connected micro grid. These algorithms were tested on 19 different test function where the Teacher-Learners based optimization algorithm was found to be overall best. It was also tested on two case-studies of the operations of a smart micro grid where the swarm intelligence algorithm firefly algorithm (FF) was found to give the most optimal result (minimized operational cost). The other four algorithms that was used where GA, Whale Optimization, Differential Evaluation and particle swarm optimization (PSO). One conclusion from the study were that PSO algorithms were more suited in solving the case study of optimal ESS size and operation in the micro grid. Shivaie et.al [28] developed a modified discrete bat search algorithm in 2019. This was used to solve for an optimal size of a hybrid renewable system with an ESS to minimize the total operational cost whilst securing an stable grid frequency. Here an additional Monte Carlo simulation was applied to the stochastic factors such as load demand, and power generation from renewable sources. The improved bat algorithm was compared to 3 other meta-heuristic algorithms (PSO, GA and harmony search algorithm) where the most optimal results came from the new improved bat algorithm. Diab et.al [29] also investigated comparing different meta-heuristic algorithms to find the optimal size of a micro grid hybrid system with hydroelectric pumped storage system as a case study. Here Whale optimization, Water cycle algorithm, Grey wolf optimizer and Salp swarm algorithm was compared. The results showed that Whale optimization gave the most optimal results regarding lowest cost of energy. However, as the study only compared the algorithms to each other and not to other more common methods such as GA, the usefulness of the algorithms for optimizing for energy might be satisfactory but not as effective as the more common methods.

2.4.4 Optimization time steps

A problem regarding finding the optimal size is looking into the time step used for optimizing the operation of an ESS. Most studies in this research field uses 1 hour time step and look into different lengths of periods depending on the energy service provided by the energy storage. Xiang et.al. [30] investigate in 2018 the use of Fourier-Legendre series to change the discreet time step of 1 hour into a continuous curve. The main reason for this was to find a more optimal size for the energy storage size, as it might sometime be between two discreet points. For this a GA was used to solve for the state of energy of a BES that then could be used to calculate the optimal size of the energy storage. The results showed that a more optimal solution for the size could be found between two discreet points, showing that the time-step length is of importance.

*What are the features that the discreet points referring to?

2.4.5 Current day research

In 2021 Emrani-Rahagi et.al. [31] investigated the optimal operation in a renewable energy hub system with energy storage installed (both thermal storage and BES). To find the optimal solution for minimizing the operational cost a GA was used. The study also compared the differences between having thermal or BES installed individually or together in a hybrid mode. The results showed that with a hybrid system for the case study a lower operational cost could be achieved using the GA. Monforti Ferrario et.al [32] investigated in 2021 optimal storage size in an island micro grid while using hydrogen storage, BES and an hybrid system. For the dispatch, four different energy management strategies were used from Simulink (which is a MATLAB tool for simulating dynamic systems) [33]. To find the optimal size of the system a PSO algorithm was used. In parallel a multi-dimensional sensitivity analysis was implemented to get both the optimal results and how trends in the design variables affect the performance parameters. The results showed that the BES where better for short term, whilst the hydrogen storage would be more efficient for long term. It also showed that letting the percentage of allowed load loss to go from 1% to 5%, lead to that the total cost of the energy storage could be reduced by 30% - 45%.

3 Knowledge Gap and Objective

From the literature review found in section 2 many different techniques has been found for finding optimal size for ESS. A knowledge gap have been found regarding the optimal sizing for energy storage. Most previous literature chose to only focus on the storage capacity of the ESS, and not investigate the combination of power output and energy storage capacity at the same time. Therefore this thesis will contribute to this field of research by comparing how well two optimization techniques used in previous literature perform when implemented to optimize for both the capacity and power of an Li-ion BESS in a multi-energy system. Regarding the two techniques, meta-heuristic algorithms have been found very useful in this research area, but other techniques such as linear or multi-pass dynamic programming have been used as well. The two techniques chosen is firstly GA as it is a method that have been tried and used multiple times and are still used in the research today. The second method is a PSO algorithm as it has been seen as one of the more suited algorithms to be used in this research field from the literature study. One of the main reasons why PSO are effective is that share common information between different agents in the population (swarm), and they have also been seen as good tools to solve real world problems [6]. When it comes to what type of PSO algorithm to be used many can be chosen but as Khan and Singh [27] found, the FF (which is a modified version of PSO algorithm) gave the best result regarding reducing cost for optimizing operations of a micro grid with an ESS, it has been chosen for this thesis as well.

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3.1 Objective and research questions

The objective of this thesis is to investigate with a literature study what the current state of the art techniques for finding optimal sizing for energy storage is. Thereafter, then apply *are
the top techniques to a case study with focus on a Li-ion BESS in a multi-energy system, to *, the tope techniques are applied to a case
compare the techniques and find which is most useful for the given case study. The research questions that are to be answered is therefore: *are

- What methodologies, techniques and good practices are there for optimal sizing of energy storage in multi-energy systems?
- What difference and similarities can be found comparing GA and FF when applied to the case study?
  - Which is most effective in finding converging results?
  - Which is overall best for the given case study?
  - Which is most time effective?

3.2 Limitations

This thesis is limited firstly by time constraint to only focus on two different techniques for finding optimal size of ESS, when in this field of research there is other effective methods that also could have been of interest to investigate. For example, other optimization algorithms such as Teacher-Learners based optimization, bat search algorithm or many other PSO type algorithms that the FF algorithm are derived from have been successfully used for optimal energy storage capacity optimization [26][28][29]. These techniques could have be implemented and used for comparison. The schedule function used in the optimization is of a simple nature due to time constraints. More complex functions could have been used to compare its effect on the result. The use of Python libraries for both optimization algorithms are used in the thesis due to time and programming knowledge constraints of the author. This thesis is only focusing on Li-ion BESS as the choice of ESS due to time constraints, but as the focus of the thesis is on a multi-energy system the investigation of optimizing for thermal ESS as well as electrical BESS is of great interest for the result regarding the effectiveness of the optimization algorithms. Lastly the time step used in the thesis is of one-hour steps as going lower would require a huge computational load, but would lead to more accurate results.

4 Methodology

This section starts with going over the system model for the case study that the optimization techniques are going to be used on. Thereafter an explanation of the charge and discharge schedule for the BESS is presented, with accompanying equations. After that the objective functions are presented and laid out. A short subsection is included regarding the capacity loss of the BESS during the case study's lifetime. Lastly the meta-heuristic algorithms used for optimizing is presented and their inner workings explained.

4.1 System model

The system model that is used for testing and comparing the two different algorithms is from a third-party perspective looking to install a Li-ion BESS in order to gain a profit by the use of energy arbitrage and peak shaving. A simplified overview of the system model can be seen in figure 1 The system consists of a Li-ion BESS, an electrical heater (depending on the case), a load demand from the user (electrical and thermal). From figure 2 and 3 the system is shown depending on if the optimization is done for LCOS or NPV respectively. The load demand comes from one large residential building in Iran [34].

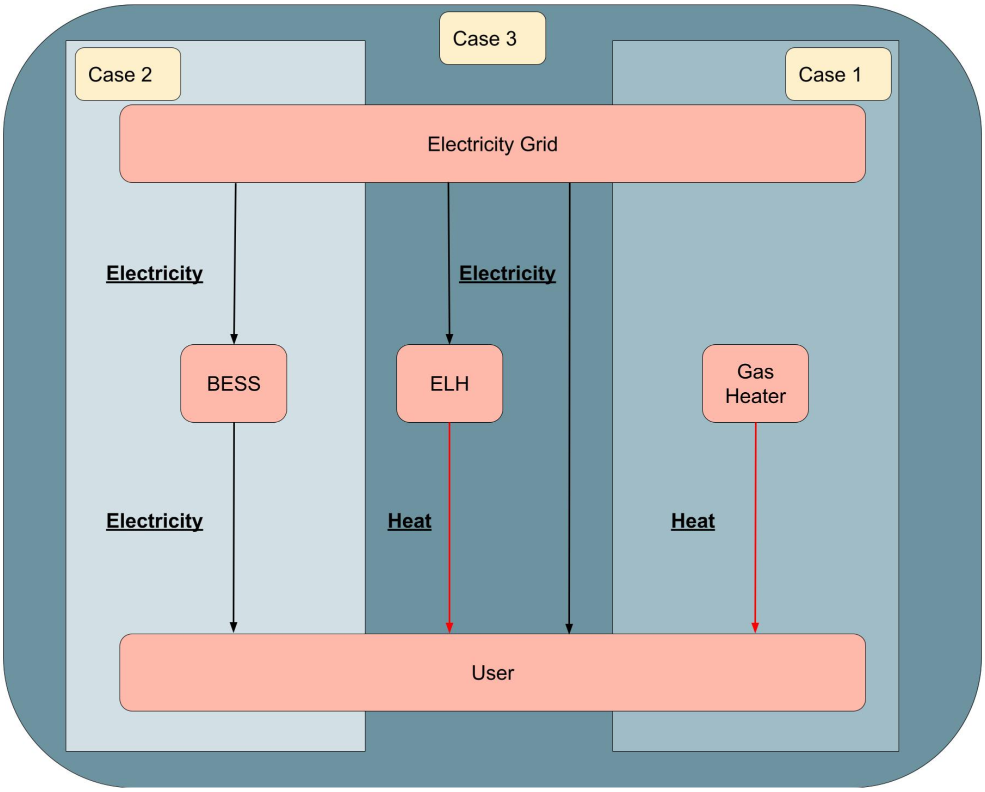

Figure 1: LCOS for Case 2 and 3

4.2 BESS charge/discharge schedule

For each different power characteristics for the BESS, a specific hourly schedule must be design for energy shifting and peak shaving. For this thesis this is done by comparing the average cost of energy for a 24-hour day period to each hour in that day. To simplify this schedule a limitation has been set that the BESS storage only can charge/discharge its maximum power constantly for each hour, or at hours when the BESS is nearly at full or empty capacity but below the maximum power of the BESS the remaining will be discharge/charged. The mathematical expressions for the discharge/charge schedule can be found in section 4.3. The charge and discharge efficiency are accounted for in the calculations on how much energy gets charged and discharge from the BESS. The efficiency of a Li-ion battery depends on the dynamics of its operation, but in this thesis a simplification has been made as BES with Li-ion batteries have very similar (between 95-80%) efficiency depending on the c-rate, and an average 90% charge and discharge rate has therefore been

Does this sentence refer to the fact that the battery is only charged when the power is at its max? What is max power defined as? Max power wrt. the hours in a day or is it above a certain limit? Define it as the sentence seems to refer to the power output of the battery

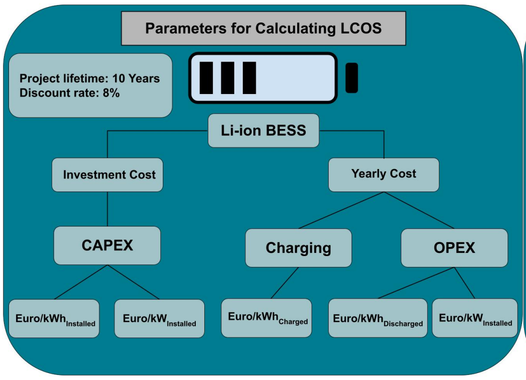

Figure 2: LCOS for Case 2 and 3

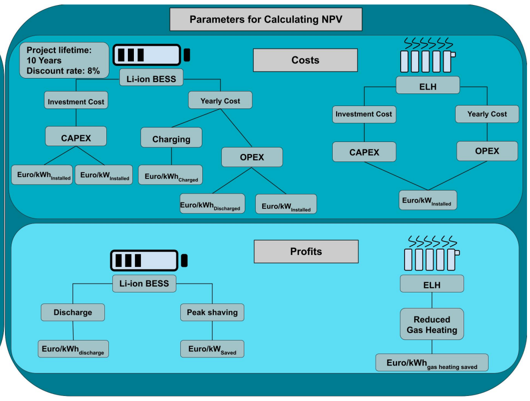

Figure 3: NPV for Case 2 and 3

used [35]. The round-trip efficiency for Li-ion batteries is around 90% and therefore by using 90% as the efficiency for both charge and discharge the overall round trip efficiency becomes 81%, and this is used in order to get the results as the worst case scenario. The life cycle of a battery is an important factor and is important to take into account in order for the battery to work well during it whole lifetime. The life cycle depends on the depth of discharge (DoD). For Li-ion batteries of LFP type a recommended DoD is around 80% [36]. The schedule is designed for energy arbitrage, by only discharging the BESS when the prices are higher than the average. Therefore, the charge/discharge schedule might not be the most cost effective way to use the battery. It could exist a schedule were buying and selling electricity at points where the average price is higher or lower than average in order to gain a higher yearly profit. See Appendix A for a flowchart of how the schedule function is structured.

4.3 Li-ion Battery Charge/Discharge Equations

The Li-ion battery used in the thesis is of the LFP type. For the Li-ion battery some constraints are used in the algorithm to ensure that it stays in its desired operation. Firstly the state of charge of the battery, and how much energy that is stored at time-step t in the battery is given by $BESSc(t)$, where t is the time-step in hours. In equation 1 and 2 down below the equations used to charge and discharge energy from/to the battery between each time-step is given. η_d and η_c is the discharge and charge efficiency respectively, whilst $P^d(t)$ and $P^c(t)$ is the discharge and charge power at time t. In figure 4 a simplified flowchart of the charge and discharge is shown were the charge and discharge efficiencies are implemented.

Figure 4: Charge/Discharge flowchart

$$Charge : BESSc(t+1) = ESSc(t) + P_c(t) * \eta_c \quad (1)$$

$$Discharge : BESSc(t+1) = ESSc(t) - P_d(t) * \eta_d \quad (2)$$

Define ESSc(t), is it equivalent to BESSc(t) here?

*Mention the exact criteria for charge/discharge as it is part of the algorithm

With the charge and discharge equations above some restrictions and limitation are also active during the optimization for the battery. Firstly, are the power limits for the charge and discharge of the battery given in equation 3 and 4 respectively. Secondly, the stored energy limit given in equation 5 states the max and minimum state of charge for the battery. Lastly is the starting value for the energy stored in the battery given in equation 6 (the BESS capacity starts empty in all optimizations). *limitations

$$0 \leq P^c(t) \leq P_{c,max} \tag{3}$$

$$0 \leq P^d(t) \leq P_{d,max} \tag{4}$$

$$BESS_{min} \leq BESS(t) \leq BESS_{max} \tag{5}$$

$$BESS(t=0) = 0 \tag{6}$$

4.4 Objective function

An objective function is the function used in an optimization to maximise or minimize a specific objective value that is of interest [10]. The objective function for the optimization problem in this thesis is to either minimize the LCOS or maximizing the NPV of the installed BESS unit.

4.4.1 Net present value (NPV) calculations

NPV is a measure to calculate the return of an investment. This is done by taking into account the investment cost, all the future cashflows from the investment and the discount rate that implements the lower value of future money due to inflation into the equation. Equation 7 down below shows the mathematical formula to calculate NPV [37].

$$NPV = CAPEX + \sum_{t=1}^{M} \frac{V_t}{(1+i)^t} \tag{7}$$

Where:
CAPEX = Capital expenditure
M = The number of periods (years)
t = Time period (year)
V_t = Total cash inflow - outflow at year t
i = Discount rate

To calculate the NPV in this thesis the Python library "NumPy Financial" is used. NumPy financial has an inbuilt function to calculate the NPV by using two different inputs. The first input is the discount rate (i), and the second one is an array of the net cash inflow - outflows (V_t) during each time period (t) [38]. V_t is the net profit from each year calculated by taking all profits minus the annual cost, equation 8 down below shows all different part included in V_t.

$$V_t = DISCHR_t + PeakShv_t - (OPEX_t + CHRC_t) + (GasSaved_t - ElHeating_t) \tag{8}$$

Where:
$DISCHR_t$ = Profit from discharge of energy from BESS at year t

$PeakShv_t$ = Profit from monthly peak shaving using BESS at year t
$OPEX_t$ = Operational expenditure at year t
$CHRC_t$ = Cost of charging BESS at year t
$GasSaved_t$ = Profit from saved money for not buying gas for heating
$ElHeating_t$ = Cost of using electricity for heating instead of gas using electrical heater (ELH)

The capital Expenditures (CAPEX) depends on the case, where for case 2 with only the installment of an BESS, it is depending on the BESS's capacity and power. For case 3 when both the BESS and the ELH are installed both these are included into the CAPEX cost, Where the cost for the ELH is depending on its power. Regarding the annual cost it depends on the operating expenditure (OPEX) which is either the size in kW or how much kWh has gone through the BESS during a year. And the OPEX for the ELH is depending on its size i kW. *both of these *in

Regarding peak shaving profits this is calculated by finding the monthly max usage before the BESS is installed (peak kW) and comparing this to the max monthly power usage after the BESS is installed. When the BESS is installed a new electrical consumption array will be made, where for some hours due to discharging from the BESS a lower peak power is seen by the electricity provider from the user. This also means that for some hours it might be higher than before as the charging of the BESS will affect this as well. The schedule function is not designed for optimizing for peak shaving, but this profit is included but can for some months be a cost depending on when the charging/discharging for the BESS occurs. As a monthly peak usage each month depends on the max kW, each month the reduction in peak kW is seen as a profit, and vice versa a cost of the peak power becomes higher due to the BESS. See equation 9 down below for the mathematical expression used to calculate the yearly profits/cost from peak power. *the

$$PeakShv_t = \sum_{M=1}^{12} PeakPowPre_M - PeakPowAft_M \tag{9}$$

Where:
$PeakShv_t$ = Profit from discharge of energy from BESS at year t
$PeakPowPre_M$ = Monthly max power used before BESS installment at month M
$PeakPowAft_M$ = Monthly max power used after BESS installment at month M

4.4.2 Levelized cost of storage (LCOS) calculations

The LCOS method was derived from the widely used levelized cost of energy (LCOE) method by Jülch [39]. The difference is that the LCOS focuses how much the lifetime cost is compared to the cumulative delivered energy from the BESS, whilst LCOE focuses on the cost of energy produced. The LCOS is therefore used as a measure to compare different energy storage technologies and their life cycle cost [40]. In equation 10 below the mathematical formula from Jülch on LCOS and its parameters described.

$$LCOS[\frac{€}{kWh}] = \frac{CAPEX + \sum_{t=1}^{M} \frac{C_t}{(1+i)^t}}{\sum_{t=1}^{M} \frac{W_{out}}{(1+i)^t}} \tag{10}$$

Where:
CAPEX = Capital expenditure
M = The number of periods (years)
t = time period (year)
C_t = Annual cost at year t
W_{out} = Annual energy output
i = Discount rate

The CAPEX is only regarding the CAPEX for the BESS for both cases and excludes the cost of installing the ELH for case 3. The annual cost for each year C_t is given by equation 11 below.

$$C_t = OPEX_t + CHRC_t \tag{11}$$

Where:
$OPEX_t$ = Operational expenditure at year t
$CHRC_t$ = Cost of charging BESS at year t

For $OPEX_t$ it includes both the fixed and variable operational cost, and for case 3 it includes the OPEX for both the BESS and ELH, whilst for case 2 it only include the OPEX for BESS.

4.5 Fitness function

A fitness function is a function which gives a value (fitness) from different solutions to compare them to each other to know which one is the best. The better the value of the fitness function the higher the feasibility that the solution is closer to the optimal solution to the problem at hand [41]. The fitness function can be the same as the objective function depending on the problem but have to be scaled sometimes from the objective function in order for the fitness function to have positive values. This is sometimes required for the genetic algorithm depending on what selection methods is used [42]. For a flowchart explaining the fitness function see figure 5, this flowchart is used for both case 3 and 2 with the only difference being for case 2 the ELH power is excluded.

4.6 BESS capacity loss over lifetime

There are many different factors that affect the BESS capacity. For the Li-ion battery, cell degradation is what effects the total capacity degradation. A cell can degrade by two different aspects, firstly during operation (i.e. cycling ageing) and secondly during stationary time, (i.e. calendar ageing) when no charge or discharge is occurring. Both types of ageing are dependent on temperature, but the calendar ageing is also dependent on the storage state of charge whilst the cycling ageing is dependent on depth of discharge, state of charge and lastly the charge and discharge current rate. These two types of ageing are independent of each other and have therefore to be model by themselves and combined later on [43]. Mongird et al. [36] found that LFP Li-ion batteries with 80% DoD would result in around 2000 full equivalent cycles and used this value for economical calculations. As the economical parameters used in this thesis comes from Mongird et.al the same DoD is also used in the optimizations. Using this data, a linear degradation between each years totaling in 15% after the total lifetime of the BESS (10 years) is used. The higher value of 15% was chosen

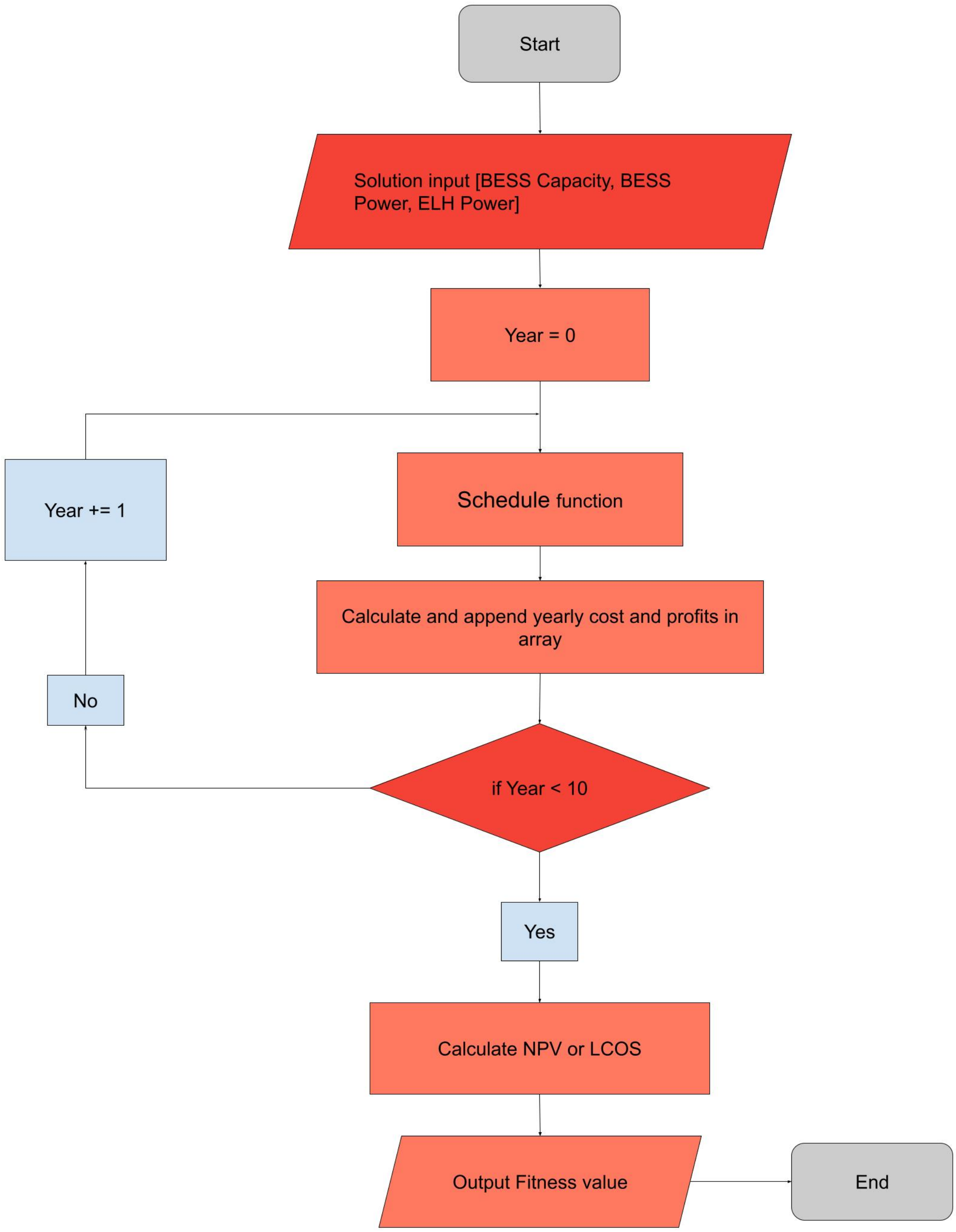

Figure 5: Flowchart over fitness function

as the uncertainty regarding the numbers, as to optimize for worst case scenario is preferred over the best case. This resulted in a yearly linear degradation of 1.612% each year that is implemented into the optimization.

*is this for the cycling and calendar aging together?

4.7 Genetic algorithm

A GA is an optimization algorithm based on evolutionary theory. It goes under the category of meta-heuristic algorithms. It was firstly developed in the 60s and 70s by J. Holland and his team [44]. A GA have three genetic operators it takes advantages of: crossover, mutation and selection. Each solution is represented by a chromosome, which is a string (typically binary or decimal) with the solution encoded onto it. By switching sections or "genes" of the chromosomes, the crossover of two parents' strings generates children (new solutions). Crossover has a high chance of occurring, usually between 0.8-0.95%. Mutation, on the *do you mean 80-95% other hand, is for example accomplished by flipping some digits of a string, resulting in new solutions. The probability of a mutation is normally low, ranging from 1-5%. Each generation's new solutions are then evaluated based on their fitness, which is linked to the optimization problem's objective function. The new solutions are chosen (selected) based on their fitness, where the fittest solution/s are selected. One can introduce elitism into the algorithm by making sure that the best solution always remains in the population by always passing down the best solution to the next generation without changing it [45].

In this thesis, the Python library "PyGAD" is used to implement the GA [46]. A flowchart for the GA with the different steps can be seen in figure 6. The first step is to generate a population of solutions, randomly assigning a power and capacity for the BESS for each solution. Thereafter the fitness function is applied to each solution in the population and then the list with solutions is sorted with the best solution (highest fitness value) at the first index. This is done to set up the GA with a starting population of different solutions. Thereafter the crossover, mutation and surviving selection operations are run in corresponding order to generate the next generation of solutions. This repeats until the optimization have run through the assigned number of generations. A detailed explanation on each step in the GA is given down below in this section, and a Pseudo-code can be found from Yang [47].

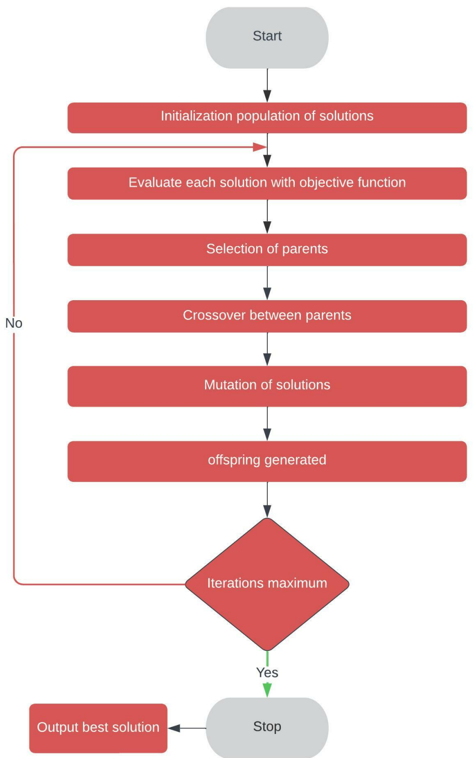

Figure 6: Genetic Algorithm Flowchart

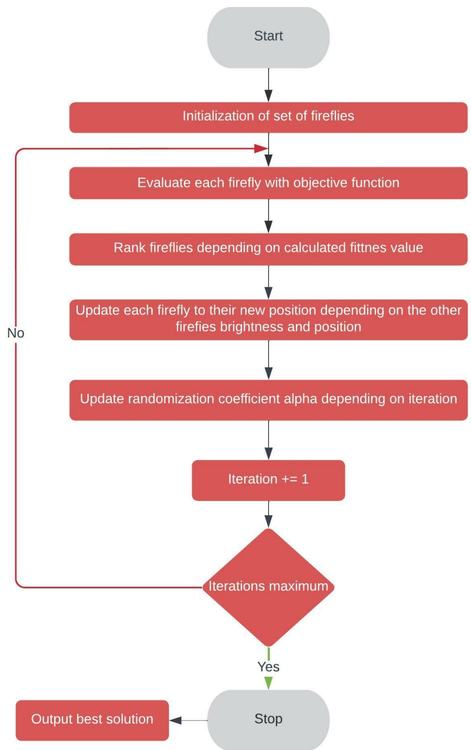

Figure 7: Firefly Algorithm Flowchart

4.7.1 Parent Selection

One important part in a GA is the method to select the parents for the next generation. One would not like the best solutions (highest fitness value) to always be chosen as it might be stuck in a local optimum. Different methods are used for this, some commons ones used are explained below, but for this thesis the rank selection method is used [48]. For this thesis half of the starting population is picked as parents for the next generation, and the remaining half gets updated with new random solutions for the next generation.

Roulette wheel selection: Roulette wheel selection or also know as *Fitness proportionate selection*, uses a uniform distribution to randomly select the parents for the crossover stage. this is done by normalizing the fitness value of each solution dividing by the sum of all the solutions giving each solution a probability to be picked, where the higher fitness value gives higher probability to be picked as a parent for the next generation [48]. Important to note with this method is that the fitness value cannot be negative for any solution [49].

Tournament selection: This selection methods instead selects a random set of solutions from the generation and from that subset the best solutions are picked as parents for the next generation. This method allows all solutions to be able to survive which helps the algorithm not get stuck in a local optimum [48].

Random selection: This method randomly chooses what solutions to be kept as parents for the crossover stage. This method then has no way to guarantee that better solutions are picked to be parents.

Rank selection: This method ranks the solutions depending on their fitness value with the best as rank 1, this allows the chromosomes to have negative fitness values. It is also used when the fitness values are very similar as then roulette wheel selection would grant similar probabilities to the different solutions, this would make it hard to pick the fitter solutions over others more unfit solutions [49].

4.7.2 Crossover

The first part of the Genetic algorithm after the fitness value for the population have been calculated, is to apply the crossover function. If by a random input the crossover rate is achieved the crossover operation will begin. The crossover function is an operator that combines two solutions genetic material to create one or more offspring (new solutions). If elitism is used in the algorithm the two best solutions are paired with each other to emphasise the best results. Depending on the structure of a solution, i.e. vector, matrix, size etc, the way a crossover is done is very different. One common way is splitting a vector array of n bits at a specific point/s and save the bits before the point into one parent and take the specific point for the second solution into the last part for the for the first solution, and vice versa for the other solution in the crossover, this is known as single or one point crossover. Another common solution is taking the arithmetic average of each point in the solutions list between the two parents to generate one new solution, this is known as arithmetic crossover [48]. For this thesis, as there is only two or three different variables (depending on the case), a uniform crossover is applied. This method gets a value for each gene by randomly selecting one of the parents and taking the value at that gene from that parent. *has

4.7.3 Mutation

A mutation in a genetic algorithm is a change in a solution due to a random factor (the mutation rate is usually lower compared to the crossover rate). For mutation operators, there are three primary needs. The first criterion is reachability. An arbitrary point in solution space must be able to reach each point in solution space. Every part of the solution space must have a reasonable chance to be reached. Otherwise, the possibility to find the optimal solution disappears. The un-biasedness principle is the second good design guideline for mutation operators. The mutation operator should not cause the search to drift in one specific direction. Scalability is the third design principle for mutation operators. It means that each mutation operator should provide a degree of flexibility that allows its strength to be adjusted. For mutation operators that are based on a probability distribution, this is usually doable. An example is the Gaussian mutation operator that is based on the Gaussian distribution [48]. As the number of genes in the problem of ESS sizing is low, methods such as swap which works by swapping two different gene's values become unusable, especially as the search space for the genes are different as well. Therefore, the random operator is used where it assigns a random value to each gene of a solution if the mutation threshold is reached, where it gets the random value for the genes search space.

4.7.4 Termination

When deciding the best option to end the algorithm different methods can be used. The first one and used in this thesis is that a maximum set of generation is defined beforehand and the best solution after that is given as the result. The other method is to compare the fitness value between the previous and current generation, and if the difference is low enough the algorithm stops. In order to compare how the effect different numbers of iteration/generation have on the result, the method of termination by similar fitness values between generations is disregarded in this thesis.

4.7.5 Parameters used in GA

Below in table 1 the parameters for the GA are given. In table 2 the minimum and maximum values for the search space are given. This search space is the same for both the GA and FF. For the BESS capacity 8,000 kWh was chosen as an arbitrary high number after an iterative process of testing the algorithms for the case study. For BESS power and ELH power the maximum values are depending on the load demand used in the optimization, taken the highest hourly value in the data set as there will never be a need of a higher output than that. For the minimum values of 0.1 this was chosen instead of 0 for the reason of being able to see that the data points are given values and not zero. As some of the values generated by the optimization are able to be 0 when at least a capacity or power is present but is always 0 if the power and capacity is zero. As 0.1 is the lowest value it is probable that if an optimization converges at this value, it tends converge to 0 instead.

4.8 Fire Fly algorithm

In 2007 Yang et.al. [45] developed the FF algorithm. It is similar to the well used PSO algorithm but takes inspiration from the behavior of fireflies and their flashing patterns. The core principle is that a firefly is attracted to (and moves towards) a more attractive

Type/data:	Value
Parent Selection Type	Rank
Crossover Type	Uniform
Crossover Probability	80%
Mutation Type	Random
Mutation Probability	10%
Solutions per Population	50
Number of Generation	[5, 10, 25, 50, 100, 200]

Table 1: Parameters used in GA

Solution search Space:	Minimum	Maximum
BESS capacity [kWh]	0.1	8,000
BESS power [kW]	0.1	Max(Electricity load)
ELH power [kW]	0.1	Max(Heating load)

Table 2: Minimum and maximum values for solution search space

or brighter firefly, where the attractiveness also varies with the distance between each two fireflies that is in focus. Here each firefly represents a solution with the brightness of the firefly is proportional on the final value from the objective function. In the end the brightest firefly can be chosen as the optimal solution. A pseudo-code can be found from Yang [50], and the FF used in this thesis coming from the Python library "Opytimizer" is based on that method [51]. It is simplified by three rules in order to capture the behavior of the flashing fireflies.

- The sex of a firefly is unisex. Meaning that all fireflies are attracted to all other fireflies.
- A firefly's attractiveness is proportional to their brightness/light intensity, whereas for a pair of firefly the one with inferior brightness moves in the direction of the brighter one.
- A firefly's brightness/light intensity is directly determined and affected by the landscape of the fitness function.

An simplified flowchart is given in figure 7, showing in what order the different steps are taken for each iteration.

4.8.1 Attractiveness and movement of fireflies

The firefly's attractiveness and movement toward another firefly are the two main aspects of the firefly algorithm [52]. The attractiveness of a firefly is dependent on its brightness (light insensitivity) which in turn is proportional to the value of the fitness function. A firefly algorithm can be designed to both solve minimization and maximization problems. It is only a matter to decide that the firefly with the lowest brightness to be the most attractive in a minimization problem, and vice versa for a maximization problem. For a solution $\mathbf{x}$ a fitness value for the solution is given by the fitness function $f(\boldsymbol{x})$. The brightness I of a firefly for a solution $\mathbf{x}$ is as said before proportional to the fitness value $I(\boldsymbol{x}) \propto f(\boldsymbol{x})$. But between two fireflies the attractiveness β is subjective; it should be evaluated as seen from the eyes of the beholder i.e., the other firefly. As a result, β will change depending on the distance r_{ij} between firefly i and firefly j. Furthermore, because brightness diminishes with distance from its source and light is absorbed in the media around the two fireflies, the attractiveness should be permitted to fluctuate depending on the absorption of light into the surrounding media [53].

Following Yang's [50] design of the FF the equations used in the firefly algorithm are laid out below. Firstly, the light intensity of what one firefly observe of another firefly can be written depending on the distance between the two fireflies as:

$$I(r) = \frac{I_0}{r^2} \tag{12}$$

where I_0 is the light intensity at its source and r is the distance between the fireflies. To add the absorption effect an approximation can be made using the Gaussian form as:

$$I(r) = I_0 \cdot e^{-\gamma \cdot r^2} \tag{13}$$

where γ is the fixed light absorption coefficient. As explained before the light intensity and the attractiveness of a firefly as seen by the other fireflies is proportional to each other, the equation for the attractiveness of a firefly is therefore written as:

$$\beta(r) = \beta_0 \cdot e^{-\gamma \cdot r^2} \tag{14}$$

where β_0 is the firefly's attractiveness at distance r = 0 and is usually set to be equal to 1. It is recommended to rewrite this equation as:

$$\beta(r) = \frac{\beta_0}{1 + \gamma r^2} \tag{15}$$

as the calculation time of equation 15 is faster than that of solving a exponential function. r_{ij} is the distance between two fireflies i and j at x_i and x_j in the solution space, it is calculated by taking the Cartesian distance between as seen below in equation 16:

$$r_{ij} = ||x_i - x_j|| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{16}$$

where d is the dimensions of the solution space, $x_{i,k}$ is the kth component of the spatial coordinate x_i of the ith firefly.

The movement of a firefly is the second important factor, this is dependent on three terms as can be seen below in equation 17. Where the movement of a firefly i is attracted to a brighter and thus more attractive firefly j. The first term is the firefly at the current time step (t) denoted x_i^t. The second term contains the attractiveness parameter β and is multiplied with the difference between the spatial coordinates of the firefly x_i and x_j. Lastly the third term is a randomization parameter to help the algorithm not get stuck in local optimums, where α is a randomization parameter, usually in the range $[0,1]$. ε_i^t is a vector of random number from either a normal or Gaussian distribution, for this thesis the Gaussian distribution is used in the optimization.

$$x_i^{t+1} = x_i^t + \beta \cdot \exp^{-\gamma r_{ij}^2} \cdot (x_j^t - x_i^t) + \alpha \cdot \varepsilon_i^t \tag{17}$$

Different methods can be used to control the randomization factor α in order to reduce its influence on the solution as an constant dependent on the current iteration. The Optimizer library [51] used for the FF algorithm in this thesis uses the model of Xin-she, Yang [54]. The randomization coefficient is dependent on the starting value α_0 and how many iterations the optimization goes through. Where α_0 is the value for α at the first iteration. The change in α follows equation 18 as shown down below. Where α depends on the current iteration *below,where and the previous iterations value for α. As can be seen at a high number of iterations the lower the value *alpha* will take.

$$\alpha = \alpha \cdot (1 - \delta) \tag{18}$$

Where δ is given as equation 19:

$$\delta = 1 - (\frac{10^{-4}}{0.9})^{\frac{1}{iterations}} \tag{19}$$

The values for the parameters that are used in the firefly optimization is given in table 3 below. For the FF search space, it is the same as for the GA, see table 2 for a detailed values of the search space used for the FF.

Variable	Value
Agents	10
Light absorption coefficient (γ)	1.0
Attractiveness coefficient (β)	0.5
randomization parameter (α_0)	1
Numbers of iterations	[5, 10, 25, 50, 100, 200]

Table 3: Input data Firefly algorithm for the case study

5 Case Study

The case study in this thesis is used to compare the GA and FF to each other on their effectiveness in finding the optimal capacity and power for a BESS. The BESS is to be used for peak shaving and energy arbitrage for a large residential building, for maximising NPV (or minimizing LCOS). It also investigates how the installment of an ELH to shift thermal load to electrical load together with the BESS affects the result.

5.1 Different Cases

The study looks at three different cases, the first is when no BESS or ELH is installed and is a base case for how much CO_2 emissions comes from using a gas heater to supply the heating demand. The second case is the optimal size for installment of a BESS, and lastly the third case is for the optimal installment of both a BESS and an ELH. All cases and the data used are explained in more detailed in their respective subsection below.

5.1.1 Case 1 - Base case

The base case focuses on the CO_2 emissions coming from using a gas heater to supply the heat demand for the resident building. This is used later to compare with Case 3 when the ELH is installed to compare how much CO_2 emissions that can be saved. The calculations for this part are done in Excel.

5.1.2 Case 2 - Optimal BESS installment

For the second case a Li-ion BESS (of the LFP type) is installed in order to profit from energy arbitrage and peak shaving the residential buildings electrical load. This is done by charging (buying) the battery at times when the price of electricity is low, and discharging (selling) it to the residential building during times when electricity prices are high. It is also making a profit by peak shaving the maximum power used by the residential building at any one hour in monthly time steps. The optimization is focusing on two different values to optimize the power and capacity to maximize NPV or minimize LCOS. Important to note is that the NPV and LCOS are optimized separately as two different optimization runs.

5.1.3 Case 3 - Optimal BESS and ELH installment

For the last and third case both a Li-ion BESS (of the LFP type) and an ELH are implemented. The ELH is used to reduce the thermal demand of the user and instead turn it into an extra electrical demand. For this case, 3 different values are used for the optimization. Capacity (kWh) and power (kW) for the BESS and power(kW) for the ELH. This case have an additional way to make a profit by including the saved cost for heating *has
using the ELH instead of the gas heater, compared to the base case. This case as in case *case, as with case 2, also
2 also looks to maximise either the NPV for the whole system of installment of both the BESS and ELH or to minimize the LCOS looking only at the BESS and its parameters. As in case 2 when optimizing for LCOS and NPV these are separate optimization runs. *with

5.1.4 Value of reduced gas usage from heating load in case 3

For Case 3 two positive values of using ELH instead of a gas heater are achieved, first~~ly~~ from the reduction in burning of natural gas leading to less CO_2 emissions. The second value is the saved monetary value from using electricity for heating instead of natural gas. This is implemented by first calculating depending on the size of the ELH how much more *Add , before and after highlight
electricity is needed each hour from the ELH. With a part or all the heating demand now being taken care of by the ELH the difference between the base case with no ELH and with ELH gives the monetary saving by using the cost of gas explained in section 5.1.1. This saved heating load from gas heating is added to the profits of the system during each year for the NPV calculations. The extra electricity needed due to the usage of the ELH is also added as a cost into the optimization. This cost is divided into the hourly electricity usage of the ELH and applied to the hourly cost data. Important to note here is that an *a
simplification is made, and this electricity comes directly from the grid and is never taken from the battery.

5.2 Data used in case study

In table 4 below the data used in the simulation is given for the Li-ion LFP battery. Data for the BESS are from Brinsmead et.al. [55], the study investigated current and future trends for energy storage and their cost, compiling data from many different sources. The study also included performance parameters for different batteries, such as DoD, lifetime and round-trip efficiency. The DoD is the depth of discharge for the energy storage and refers to the quantity of energy in a battery that it can actually use. Although the DoD is not a rigid limit, if a battery is used past its DoD, its performance will suffer, and its lifetime can then be reduced. As a result, in this thesis the Li-ion BESS will not be discharged past its recommended DoD.

The electricity cost data used in the thesis comes from Nordpool ~~and are using~~ Stockholm's day-ahead hourly prices for 2017. In the data set each one of the 8,760 data points represent the electricity cost in €/MWh for that hour. The maximum and minimum value of the 8,760 hours was 130 and 1.7 €/MWh. One of the 8,760 values was missing. This value was filled in by taking the average cost for that day [56]. For the base case calculations regarding the CO_2 emissions and cost the data comes from IEA where the gas cost and emissions are 0.09125 €/kWh and 0.442 kg-CO_2-eq/kWh respectively [57][58]. The gas heater efficiency is chosen to be 95% [59]. Comparably the average CO_2 emissions from electricity in Sweden are set to be 0.0029 kg-CO_2-eq/kWh [60]. The discount rate has been set to 8% for all calculations regarding NPV and LCOS in the thesis. *considering

5.2.1 Cost of BESS storage

Mongird et.al. [36] investigated the cost for 2020 and 2030 projections for different energy storage types for the US department of energy. For Li-ion batteries (LFP) the cost was divided into three different parts. The first "Storage system" includes cost of "Storage Block ($/kWh)" and cost of "Storage Balance of System ($/kW)". The second, "Energy Storage system" includes cost for "Power Equipment ($/kW)", "Controls & Communication ($/kW)" and "System Integration ($/kWh)". Lastly is the "ESS Installed Cost" which includes the cost of "Engineering, Procurement, and Construction ($/kW)", "Project Development ($/kWh)" and lastly "Grid Integration ($/kW)". These values are summed upped depending on kWh or kW and used in the optimization. The cost of warranty, insurance and decommissioning of the Li-ion BES was not included into these values and therefore is not included in the optimization. For the operational cost of the BESS two different parameters are included, fixed O&M cost in $/kW-year, and variable O&M cost at $/MWh-year. Where the "MWh" is not about the capacity size but about how much energy throughput in MWh that goes through the BESS in a year. Important to note about the variable O&M cost is as the research field in this area is fairly new and the research is ongoing, ~~and this cost~~ comes from an average from different ESS technologies variable O&M costs. All these costs have been recalculated to the 2022 value of € and can be found in table 4. *the cost

5.2.2 Cost and Residual cost of Electrical heater system

The cost for the ELH is divided into its CAPEX depending on the size in kW and the fixed OPEX also depending on kW- The data is from NERA, where the efficiency for the ELH

*CAPEX, depending on the size in kW, and the fixed OPEX, which also varies with size

[1]See section 4.2 for a detailed explanation of charge and discharge efficiency

Type/data:	Li-Ion
Capital cost capacity (€/kWh)	389.2 [36]
Capital cost power (€/kW)	148.8 [36]
Fixed O&M cost (€/kW-year)	4.4 [36]
Variable O&M cost (€/MWh-year)	0.5125 [36]
Depth of discharge (%)	80 [55]
Charge efficiency (%)	90[1]
Discharge efficiency (%)	90[1]
Lifetime (years)	10 [55]

Table 4: BESS data for the case study

also is also taken from [61]. As the lifetime of the ELH is longer than that of the project lifetime (10 years). The residual value for the last years is implemented as a positive cash flow at the last year of the project. To calculate the residual value the Numpy financial library using the "pmt" method [62]. The numerical values for the ELH and the residual values calculations used in the optimization can be seen in table 5 down below, these values have been adjusted to 2022 values in €.

*the Numpy financial library utilizing the " pmt" method is used

Type/data:	Electrical Heater
Capital cost power (€/kW)	331.2
Fixed O&M cost (€/kW-year)	1.5
Interest rate (%)	8
ELH efficiency (%)	95
ELH Lifetime (years)	15
Project Lifetime (years)	10

Table 5: Input data for the Electrical Heater in case 3

5.2.3 Inflation change of different sources cost

As different monetary values in this thesis comes from different sources published during different years and in different currencies, a basis has to be set where all cost are rewritten to a base value. As the cost of energy is crucial part of the optimization that has been set as the basis, it comes from 2017 and is in €, but as other sources are newer all cost are rewritten to € and 2022 values by including inflation. This is done by firstly changing the cost to € applying the exchange rate at that time of the sources (using the first of January at the year of the published source), then the value is changed due to inflation of the value of € to its 2022 value in €.

5.2.4 Load demand and temperature

The load demand used for the case study comes from a large residential building in Iran [34]. It includes both electricity and heat demand for the whole building. The data set includes a data point for each hour during a year. The year of focus for the data is 2017. In figure 8 the heating demand of the building are plotted with the outside temperature during 2017 for Theran, Iran. As can be expected the heat demand is coupled to the outside temperature. During the summer months the outside temperature is high and then the heating demand for the residential building is small. The electricity and heating demand have a total yearly electrical and heating demand of 3.45 TWh and 2.3 TWh respectively. The temperature data is from 2017 and are from NSRDB [63].

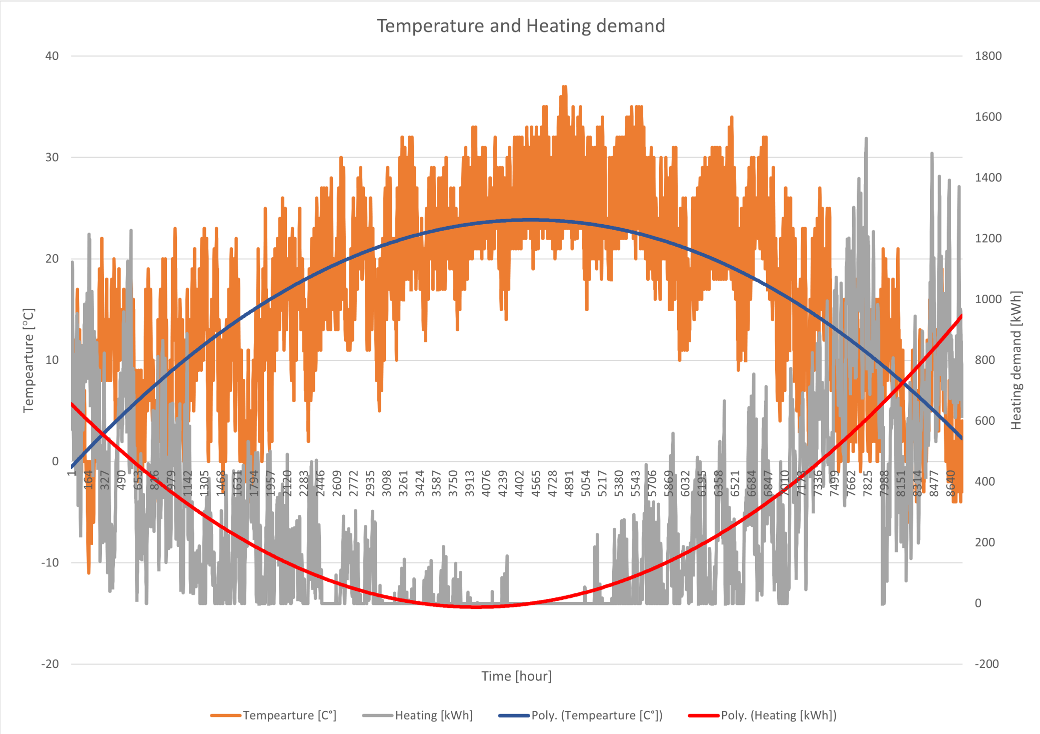

Figure 8: Heating load [kWh] and temperature[C^o]

5.2.5 Increase energy demand or Energy cost increase

As no planned work regarding energy efficiency for the residential building in this thesis is made, an assumption is made that the change in energy demand of the residential building is zero during the span of the project (10 years). For the change in energy cost during the lifetime of the project the assumptions is also here made to be zero. The reasoning behind this is the unpredictability of energy prices ~~and as~~ the focus of this thesis is to compare the optimization algorithms and therefore is not of significant importance to that result.

*.Since the focus of this thesis is to compare the optimization algorithms, the assumption is not of significant importance.

5.3 Sensitivity analysis

A sensitivity analysis is implemented regarding the effects of CAPEX of the BESS on the results and effectiveness of the case study and algorithms respectively. The analysis investigates how the price difference in steps of 10% of the original price [-20%, -10%, +10%, +20%] will affect the results (NPV and LCOS). The sensitivity analysis is done on case 2 rather case 3 as to more clearly see the effects that CAPEX will have on the final results regarding the BESS optimal size. The analysis is only done for 200 iterations as the most optimal solutions are found for the high iterations and is compared to the results from the basic optimization at 200 iterations.

6 Results and analysis

In this section the results are presented from the case study. As a significant volume of data were outputted from the optimization, only the most interesting and useful data is brought up in the thesis. The remaining data and plots can be found at the GitHub repository together with the code for the optimization used for this thesis [64]. This section goes into the three different cases and what the results from those were. Lastly the results for the sensitivity analysis is presented and analyzed. All values for NPV are in 2022 € and LCOS in €/kWh. The optimization was implemented in a Python environment running on personal computer with a Core i5-8250U clocked at 1.6GHz with 8GB of ram memory. *was *are

6.1 Case 1: Base case

For the base case the results are shown in table 6. These are the resulting cost for the user and emissions from supplying the heating demand of 2.3 TWh of the residential building with the natural gas heater. The cost of supplying the electricity demand of 3.45 TWh is also presented here. *were *costs

Type/data:	Case 1
Yearly heating demand supplied by natural Gas [MWh]	2,455.4
Yearly cost of gas [Million €]	0.224
Yearly cost of electricity [Million €]	0.114
Yearly CO_2 emissions from gas heating [tons CO_2-Eq]	1,085
Yearly CO_2 emissions electricity usage [tons CO_2-Eq]	9.86

Table 6: Case 1: Gas cost and CO_2 emissions

6.2 Case 2: NPV and LCOS with BESS installed

From figure 9 the average NPV and LCOS with its accompanying STD is shown, in appendix B, table 10 shows the numerical values. As can be seen for case 2, a positive NPV can not be found for either GA or FF. However, FF can find a better solution in maximizing the NPV. Comparing instead the LCOS for GA and FF ~~a~~ completely opposite results can be seen. The GA can minimize the LCOS more efficiently compared to FF. What can be seen is that the FF finds and optimum quite fast (by 25 iterations ~~already~~) and gets stuck in that local optimum. Looking at table 11 in appendix B shows the average capacity and power for the different optimization in case 2 as well its standard deviation (STD). For the BESS the FF finds the optimal at 0.1 for both the capacity and power. This is the smallest value allowed for the optimization. The FF finds these values for capacity and power when both optimizing for NPV and LCOS. Comparably GA finds a better solution in minimizing LCOS by having ~~a lot~~ higher values for the capacity and power. This then shows that the best solution for minimizing LCOS is not at 0.1 (i.e., not installing the BESS), showing that there is value in investing in the BESS if the main objective is to minimize the LCOS. This is possible due to the larger capacity and power the more energy can be charged and discharge from the BESS during the project's lifetime. But only up until a specific point, as it can not discharge more each hour then what the user are demanding. Therefore, the optimal solution found is one where the cost of investing in it is minimal compared to how *are *while in appendix B *much *power, allowing more energy for charging and discharging much energy discharge from it. This optimal solution then lies somewhere between not installing the BESS and the biggest power and capacity combo that is equal or lower to the maximum electricity usage form the user. What is interesting to note is that the STD for the capacity and power of the BESS is quite high compared to the average value even for 200 iterations, but as the STD for the NPV and LCOS is getting smaller it would mean that there exist a lot of different solutions (capacity, power) that results in similar NPV or LCOS.

*discharges
*than
*from

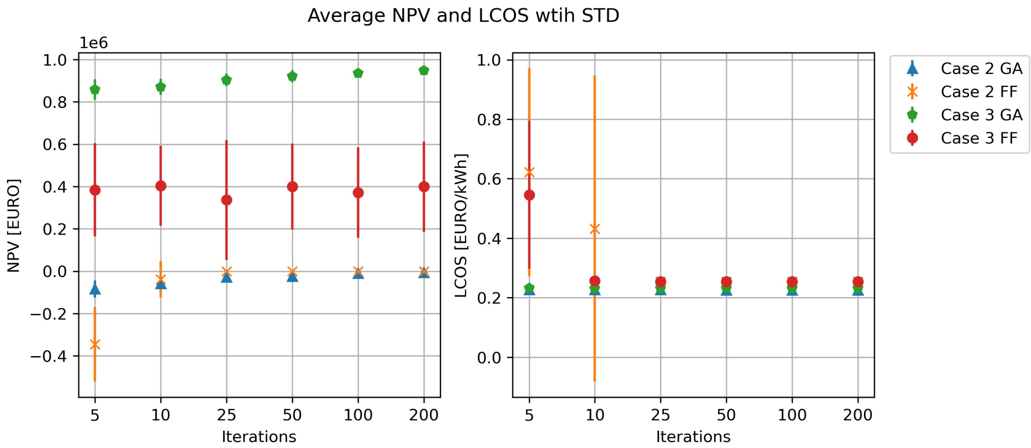

Figure 9: Average LCOS and NPV, with error bars showing STD

In figure 10 an 3D plots showing the result of each of the ten runs in capacity and power for the BESS and the corresponding NPV to each solution using the GA. Each dot represents a solution for a specific number of iterations (gen). As can be seen for higher iterations the solutions converge to similar and better fitness values. This can also be seen in table 10 where the STD is lower for the optimization using higher number of iterations. See appendix C for 3D plots when optimizing for LCOS as well as using FF for optimizing both LCOS and NPV.

*3D plots show the

Table 7 presents the best solution from the 10 runs when using 200 iterations for both GA and LCOS. As could be seen with the average result the best result shows the same thing, that both GA and FF only find negative NPV. GA finds the best value for LCOS compared to FF. The power and capacity when optimizing for LCOS is at quite large values compared to the results when optimizing for NPV. The best solution when optimizing using FF is 0.1 for both the capacity and power, meaning that it found the best solution at the lowest possible value in the search space. As GA could find better values for LCOS at other solutions show it is more viable when optimizing for this parameter.

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*when compared
*is much larger when compared
add unit to 0.1

6.3 Case 3: NPV and LCOS with BESS and ELH installed

The average results for case 3 with all ten runs with their respective STD for LCOS and NPV for both the GA and FF can be found in table 8. Comparing the average results for case 3 and case 2 some similarities can be seen, first is the solution to LCOS for FF is the same, it gets zero STD as the solution converges to the same results (0.1 for all the solution parameters, that will say BESS capacity, power and ELH power). Comparing GA and FF for case 3 the STD of the NPV for FF is not reducing, in other words, it is not

*First, the solution
*does not reduce
*does not converge

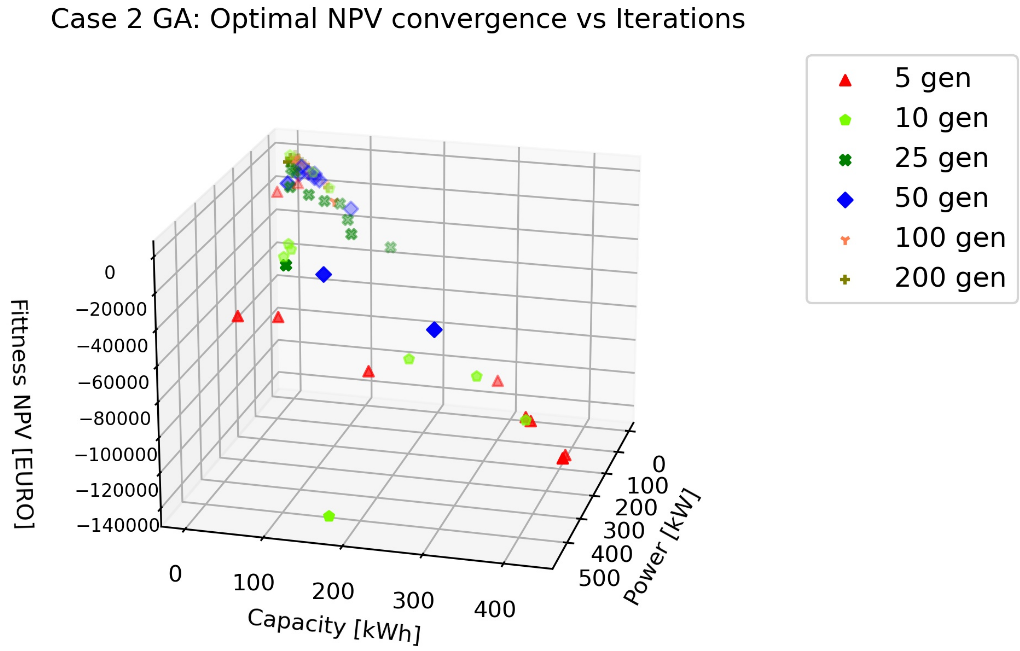

Figure 10: GA NPV convergence vs iterations

Case 2 Best NPV and LCOS results 200 iterations					
Algorithm	GA			FF	
Optimize for:	NPV	LCOS		NPV	LCOS
Fitness Value [€][€/kWh]	-2187.98	0.2253955		-51.51	0.253808
BESS Capacity [kWh]	5.72	440.79		0.1	0.1
Bess Power [kW]	0.94	133.15		0.1	0.1

Table 7: Result from case 3: BEST NPV and LCOS

converging with an increase of iterations. comparably the STD of NPV for the GA have a steady decrease. Comparing the results, it can also be seen the superiority of GA over FF for both the results of NPV or LCOS. For all number of iterations GA finds better solutions in both NPV and LCOS. Regarding the convergence of the solution parameters figure 11 shows an 3D graph of the different solutions depending on number of iterations for GA when optimizing for NPV. It shows how higher iterations converges NPV to similar solutions, as it did in case 2. For 3D plots using FF and optimizing for LCOS ~~as well~~ see appendix D. From these plots even for high number of iterations FF have trouble converging to a specific solution for NPV optimizing. FF convergence well when optimizing for LCOS but these results are at 0.1 i.e. the smallest allowed value, and as could be seen GA found better values for LCOS. Therefore, it seems that the FF converges to a local optimum.

*Comparably

*the superiority of GA can also been seen over FF

*plots, even for a high number of iterations, FF has

*converges

The results regarding saved CO_2 emissions due to the installment of the ELH is presented in table 9. Here the best solution is presented when running the simulations for 200 iterations. As can be seen when optimizing for NPV both FF and GA find solutions with a high power installment for the ELH. What is interesting is that the difference in size is quite large but the amount of heating supplied by the ELH is all above 95% or more except for the

*are

Case 3 NPV and LCOS average								
Algorithm	GA				FF			
Iteration/Data	NPV	STD_{NPV}	LCOS	STD_{LCOS}	NPV	STD_{NPV}	LCOS	STD_{LCOS}
5	858811	48443	0.232441	0.0014966	384572	220482	0.253808	0.248568
10	870681	38314	0.231725	0.0010973	403325	188363	0.546243	0.012908
25	903779	30080	0.231491	0.0008542	336185	283371	0.253808	0
50	921129	28328	0.231016	0.0004857	400167	202601	0.253808	0
100	936223	21850	0.230856	0.0002974	370941	213428	0.253808	0
200	948055	7450	0.230812	0.0003096	399116	212844	0.253808	0

Table 8: Result from case 3: Average NPV and LCOS

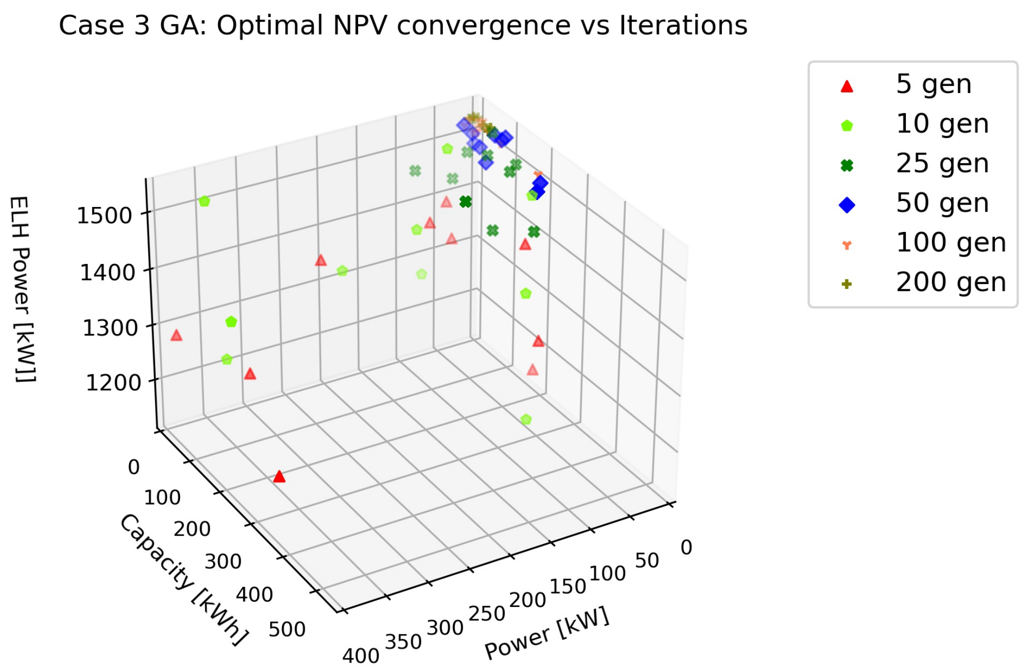

Figure 11: Case 3 GA: Optimal NPV vs Iterations

LCOS case when using FF. This case finds the optimal ELH power to be 0.1, in other word the smallest allowed value in the search space, and if it would be allowed would possibly have gone down to 0, i.e. having not installed the ELH at all. When optimizing for NPV with GA the ELH power is close to its maximum and therefore have nearly 100% of the heating demand supplied by the ELH. But ~~what~~ when optimizing for LCOS the ELH size is around 60% of the maximum size and still achieves 96.7% of the yearly heating demand to be supplied by the ELH. The yearly saved CO_2 emissions is from comparing to case 1 when no ELH is installed, and all heating demand is supplied by the gas heater. *has

6.4 Breakdown of cost and earnings for case 2 and 3

From figure 12 the breakdown of cost and earnings for the best solution for each case when optimizing for NPV is shown. Important to note is that for case 2 (both GA and FF) the value for NPV is negative but have been reversed in order to plot it on a log-scale. For case 3 the results shows that the savings by switching to the ELH is where a huge part of all earnings comes from (99.99% and 87.76% when optimizing for GA and FF respectively), *has

Case 3 Best NPV and LCOS results 200 iterations				
Algorithm	GA		FF	
Optimize for:	NPV	LCOS	NPV	LCOS
Fitness Value [€][€/kWh]	954982	0.230494	703491	0.253808
BESS Capacity [kWh]	0.383872	435.19	382.15	0.1
Bess Power [kW]	4.12	130.47	291.56	0.1
ELH Power [kW]	1528.21	898.32	1018.59	0.1
Yearly heating by ELH [MWh]	2429.51	2349.17	2391.82	122.05
Yearly heating by ELH [%]	99.9	96.7	98.4	0.5
Yearly saved CO_2 emissions [tons]	1073.84	1038.34	1057.18	53.94
Yearly saved CO_2 emissions [%]	99.9	96.7	98.4	0.5

Table 9: Result from case 3: BEST NPV and LCOS

leading to a positive NPV. In all cases the earnings from discharging from the BESS is very similar to the cost of charging, giving a small profit margin from using the BESS for energy arbitrage. However, for case 3 when using FF, the result shows a huge portion of the earnings coming from peak shaving, indicating there might be value in optimizing for that instead of energy arbitrage. In figure 13 the breakdown of the parameters involved for the calculation of LCOS is shown for the best run. The biggest cost involved over the ten year project lifespan for each case is the investment cost (At a lowest of 52.75% of the total combined cost, for case 3, when optimizing for FF), thereafter comes the charging cost and lastly the OPEX.

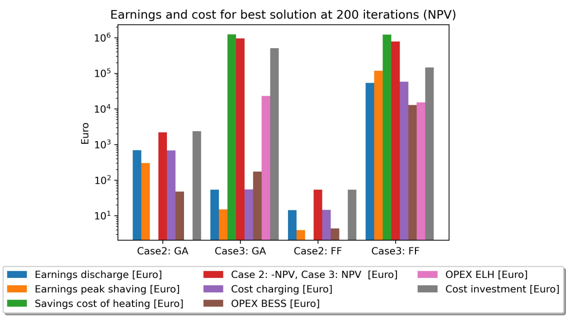

Figure 12: Best result breakdown (NPV)

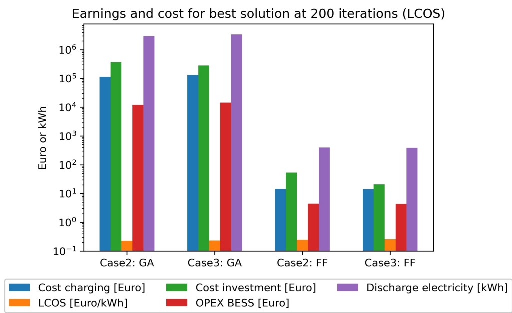

Figure 13: Best result breakdown (LCOS)

6.5 Optimization time and STD

From figure 14 the average time from the ten runs and STD of the time for the different *From figure 14,
cases/algorithm can be seen respectively. As can be expected the time to run an optimization is increasing with the number of iterations. Comparing GA to FF, the results shows that FF *increases
take overall longer time to run the optimization for all cases compared to the GA, ranging *FF overall takes longer to run
between 60%-70% lower overall time depending on the case for GA. Looking at the right plot in figure 14 the STD is increasing for all cases/algorithms for both FF and GA, but the STD for FF is increasing more than for GA. This difference is likely due to the higher complexity of the algorithm residing in the FF compared to the GA. Important to notice is

that in this figure a log scale for the y-axis is used whilst for the left plot have a regular scale for its y-axis. *has

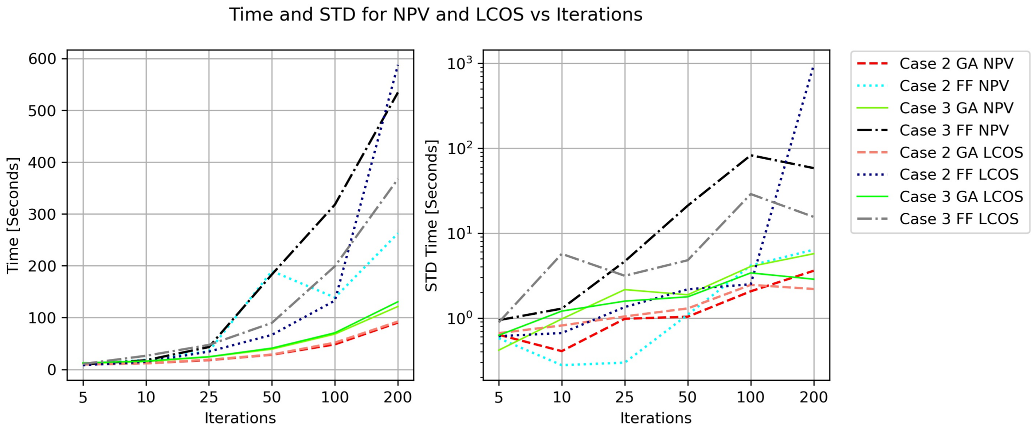

Figure 14: Optimization time for all cases with STD

6.6 Schedule function

Figure 15 shows the usage of the BESS during the last year of the optimization when using the GA, for the ~~the~~ different cases and objective function to optimize for. As can be *functions
seen when optimizing for NPV, low values for the capacity and power is found. Using the schedule function using these low values the BESS is only used for about 14% evenly split low values, the
for charging and discharging for both case 3 and case 2. The remaining 86% of the time the BESS is passive and not in use. When optimizing for LCOS higher values for power and capacity is found, and with that applied to the schedule function the BESS is used more then twice as compared for the case when using NPV. Even with more then twice the usage *to
the BESS is still passive and staying idle for around 65% of the year. In figure 12 and 13 the charging cost compared to the profits from discharge and peak shaving using the BESS is shown. As can be seen the cost of charging is sometimes even higher then the profits from discharging the BESS. This is due to the loss of electricity charged and discharged from the BESS due to its efficiency, and combined with the low usage during the operation could be why negative NPV values are shown for case 2 as shown in section 6.2. Therefore the main monetary value gained is from the peak shaving in case 2.

6.7 Sensitivity analysis of case 2

The results for the sensitivity analysis of case 2 can be seen in figure 16. The analysis looked at the effect that a positive or negative change in CAPEX for both the power and capacity of the BESS would have on the results of NPV or LCOS. These results come from using the capacity and power that resulted in the best fitness value from the 10 runs, while doing 200 iterations (see table 7). As can be expected and seen in figure 16 both the NPV and LCOS have a linear relationship with the change in CAPEX, however they are not directly linked. That will say a change in +20% of the CAPEX does not lead to a direct change of *that is to say
+20% in NPV or LCOS as firstly CAPEX is just on part of the economical factors but also *first the *one
the discount rate applied over the project lifetime of 10 years effect this result as well. *affects

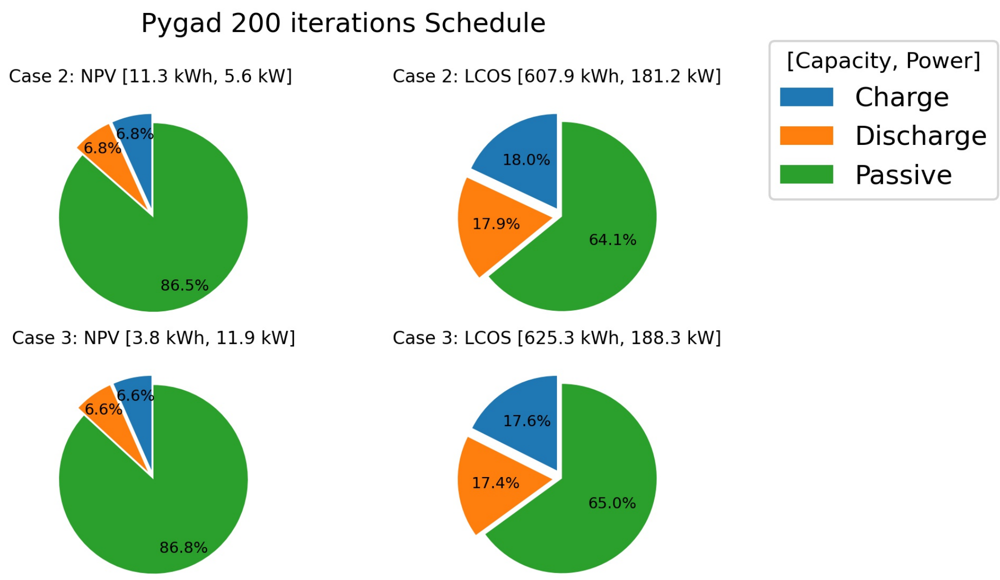

Figure 15: Usage of BESS during the last year (10th) of optimization

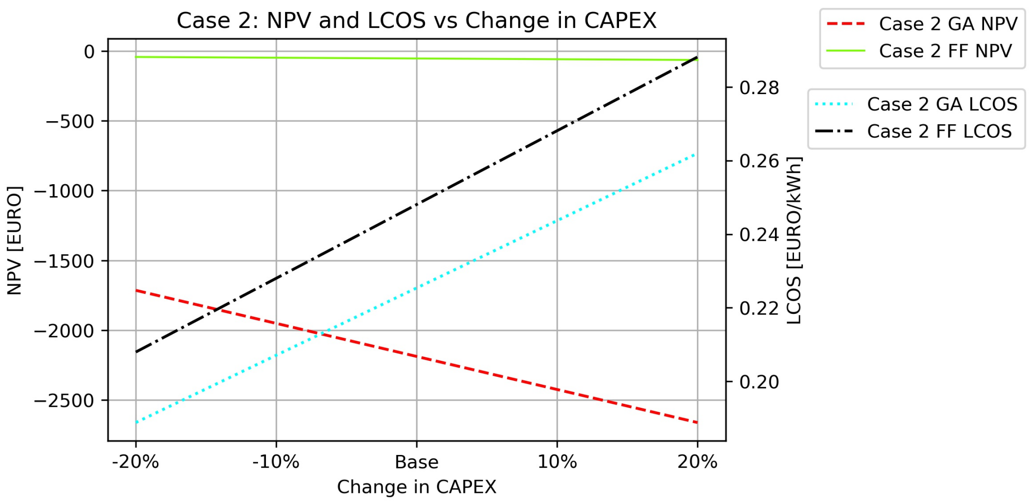

Figure 16: Case 2: Sensitivity analysis of NPV and LCOS dependence on CAPEX

7 Discussion

7.1 Main findings

For case 2 NPV was negative for all cases showing that for the case study energy arbitrage *, the NPV
and peak shaving is not enough with the implemented schedule function to make enough profits to compensate for the CAPEX, OPEX costs and the discounted value of money of the system. As could be seen in the sensitivity analysis even a lower CAPEX did not effect this result, further showing the ineffectiveness of the schedule function. Regarding the LCOS the best and smallest results for case 2 it was found to be 0.2256 €/kWh and 0.2308 €/kWh for Case 3, both with the use of GA at 200 iterations. This is in the same range as LAZARD's found in 2018 for Li-ion batteries LCOS between 0.204 \$/kWh - 0.298 \$/kWh (0.185 €/kWh - 0.2704 €/kWh in 2022 values) [65]. Which would mean that GA can find *this

solutions for LCOS that are reasonable compared to the real-world values. Therefore, GA can be a useful tool in the choice of size for a BESS when optimizing for LCOS.

The schedule function used in this thesis is using a simple methodology, as could be seen on *uses the results this leads to a low usage of the BESS during a year. The main methodology of *as this the schedule function is to charge at low prices and discharge at high prices with the daily average cost as the divider between high and low electricity prices. It could be seen that the monetary value from energy arbitrage was slim from the results and that peak shaving stands for a bigger part of the earnings for increasing the NPV in case 2. As the schedule function is only focused on scheduling the charge and discharge for energy arbitrage there is a possibility that more value can be gained by instead focusing on peak shaving using the BESS. However, finding a methodology that considers both energy arbitrage and peak *Hence shaving for the charge and discharge schedule would also be of great interest.

For case 3 when optimizing for NPV the FF showed its inability to converge even with *an higher iterations. A reason for this is due to the objective functions high dependence on the ELH power for good results. As the ELH power is of great importance to achieve high NPV for case 3 it allows the BESS capacity and power to take on many different values that would lead to similar results. And as the FF change the solution of an agent depending *changes on the best solution of the all the active agents (fireflies), the best of the starting random solutions (especially the ELH power) have a great impact on what the resulting solution of the algorithm is going to be.

7.2 Comparative analysis between FF and GA

Comparing the results between FF and GA it could be seen that GA required less time to finish the optimization. This gives it an upper hand if it was to be used for a more complex optimization problems where more steps are required to find the fitness value of the objective function. For case 3 which is a more complex optimization compared to case 2 GA showed its superiority again in finding better solutions compared to FF when optimizing for both NPV and LCOS. These results follow the characteristics of GA and FF that Khan and Singh [66] found that FF have a high optimization time whilst the results from GA *has can be unpredictable, as well as it sometimes find sub-optimal solutions. The sub-optimal solutions could be seen in the results for case 2 when optimizing for NPV where FF finds its best solutions with zero STD for 25+ iterations. Comparably the unpredictability of the GA is seen on the STD that is never zero and often quite large compared to the average value (For case 2 the STD for NPV can be seen to be around 50% of the average value of the ten runs in table 10, for all iterations). The sensitivity analysis showed that both that no difference could be seen between the algorithms when a change in CAPEX was introduce, as both showed the same linear dependence on the CAPEX. *introduced

As can be seen form the results of the breakdown regarding the earnings and cost for each *from case in section 6.4, the earnings made by installing the ELH is a significant reason ~~in order to get~~ *for positive NPV. As this is not done in case 2 It would not be worth for a third-party developer to invest in the BESS, without the investment of the ELH. If the focus is just incomplete sentence looking at the LCOS as the factor to invest. The BESS gets in a competitive range for using the best solution when using GA. Therefore, be valid to invest in the BESS even *it is valid without the ELH. Regarding the third-party developer and how to choose what parameter incomplete sentence to optimize for, either NPV or LCOS. It depends on the reason for investing in the BESS, for economical gain, it would be better to optimize for the NPV, but it would only be worth *BESS. If its for if the developer also invested in the ELH as in case 3. As the results showed it would be most profitable to use the GA for optimizing. If instead the goal of the developer is to use the BESS for securing electricity stability to their customers, it would be more valuable to optimize for minimized LCOS. For that the results for both case 2 and 3 shows that it would be preferable to use GA for optimizing as it gives the best (minimal) value for LCOS. The results showed that for minimizing LCOS the capacity and power of the system to be quite large compared to the optimal size that was found when optimizing for NPV. Therefore, it is of great importance for the developer to choose beforehand which parameter is of most importance to optimize for, as the resulting optimal solution differ a lot.

7.3 Sources of errors

The variable O&M cost for the Li-ion BESS is from different energy storage technologies and could therefore be very far off. As the cost is low compared to the fixed O&M cost as well to the CAPEX of the BESS storage this should have a small effect on the final results. Another source of error for the case study results is the battery capacity degradation is a *that linear function, but is in fact non-linear and depends on factors such as~~,~~ state of charge, *while depth of discharge, C-rate, and temperature to name a few [67].

8 Conclusion

From the Literature review two meta-heuristic algorithms were found to be of interest as methods to find the optimal capacity and power for a BESS, GA and FF. Applying the selected algorithms on a case study from a third-party developers viewpoint, it was found for case 2 at 200 iterations that GA finds the best solution for LCOS at 0.2254 €/kWh (with a capacity and power of 440.79 kWh, and 133.15 respectively), but FF finds the best solution for NPV at -51.51€ (with a capacity and power of 0.1 kWh and 0.1 kW respectively, implying that no BESS should be installed). For case 3 with the ELH also included as a changeable parameter, GA gave superior results for both NPV at 954,982€ (with a capacity and power of 0.384 kWh, and 4.12 kW respectively for the BESS and an ELH power of 1528.21 kW), and LCOS at 0.2305 €/kWh (with a capacity and power of 435.19 kWh, and 130.47 kW respectively, and an ELH power of 898.32 kW) at 200 iterations. From an *the breakdown of cost and earnings it could be seen for case 3 that the saving in gas heating cost from installing the ELH was a major part of all the earnings (at 99.99% and 87.76% for GA and FF respectively). For all cases and iterations, GA had a lower optimization time than FF at around 60%-70% depending on the case. From the results it could also be seen that for higher iterations both GA and FF converge to more optimal solutions, with smaller STD for higher iterations except for FF case 3 when optimizing for LCOS. Therefore from the results of the case study both GA and FF appear to be useful tool to optimize the capacity and power of a BESS but GA is faster and finds better results overall. It is also shown that depending on the objective parameter the resulting solutions differs widely. Showing the importance for a third-party developer to choose which objective parameter (NPV or LCOS) to optimize for. From the case study it is also seen that the charge/discharge schedule functions are of importance for the effectiveness of energy arbitrage and peak shaving as for some cases the BESS was only used 17% of all hours during the projects lifetime.

8.1 Future work

The charge/discharge schedule functions for the BESS seems to have great importance for the results of the NPV and LCOS when using BESS for peak shaving and energy arbitrage. Therefore, trying different functions and methods for the schedule of the charge and discharge of the BESS would be of great interest. Many studies before having used different meta-heuristic algorithms to find specific sizes of BESS capacity and power as shown in the literature study in section 2. Therefore, it could be of interest to investigate using a meta-heuristic algorithm to find the optimal schedule that is then used in the optimization and from that also using meta-heuristic algorithms to find optimal capacity and power for the BESS. Another area to investigate is the model for battery capacity degradation, as it is a linear function in this thesis, it could be investigated and implemented in the optimization a more real-life capacity loss and how that would effect the results. The ELH installment seems to be a big part of the positive NPV values for case 3 and therefore an optimal size of this would be interesting. As for this thesis the objective function has been to maximise the NPV or minimize the LCOS of the BESS. But as the ELH can achieve high values of yearly heating with the ELH for lower than the max allowed value for the ELH, optimizing for the optimal ELH size could be of interest, or investigate for optimal reduction in CO_2 emissions.

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*and then from

*.It

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Appendices

A Schedule flowchart

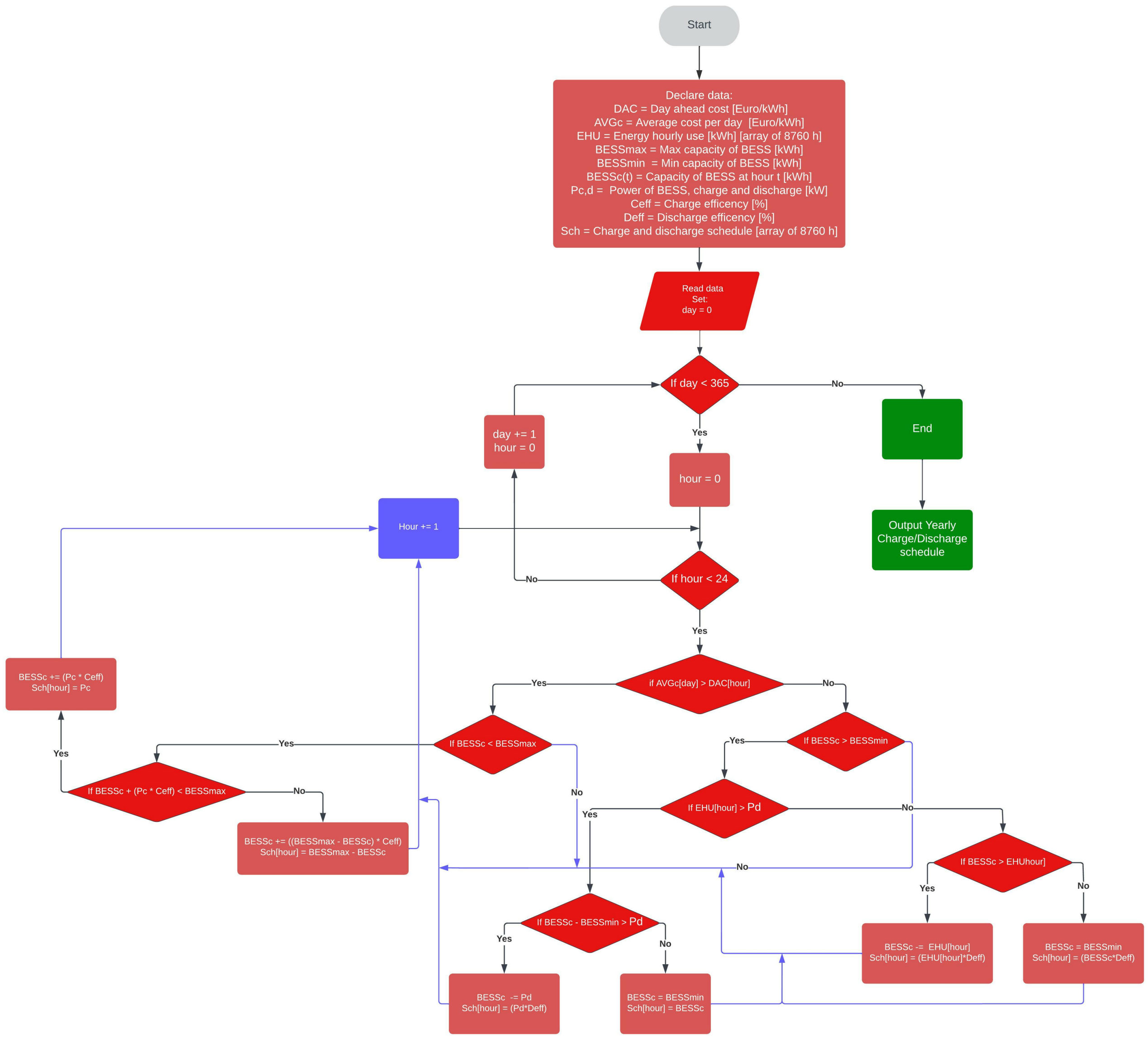

Figure 17: Charge/Discharge schedule Flowchart

B Case 2 Results: Tables

Case 2 NPV and LCOS average								
Algorithm	GA				FF			
Iteration/Data	NPV	NPV_{STD}	LCOS	$LCOS_{STD}$	NPV	NPV_{STD}	LCOS	$LCOS_{STD}$
5	-84,239	41,020	0.227633	0.0017242	-346,009	175,789	0.621763	0.349083
10	-59,018	44,211	0.226897	0.00127705	-37,761	201	0.432304	0.514233
25	-27,720	14,511	0.226745	0.00089996	-51.5	0	0.253808	0
50	-24,993	22,720	0.226068	0.00040577	-51.5	0	0.253808	0
100	-10,614	6,623	0.225877	0.00025301	-51.5	0	0.253808	0
200	-6,316	4,756	0.225656	0.00025179	-51.5	0	0.253808	0

Table 10: Result from case 2: Average NPV and LCOS

Case 2 Capacity and Power average								
Algorithm	GA				FF			
Objective function	NPV		LCOS		NPV		LCOS	
Iteration/Data	Capacity	Power	Capacity	Power	Capacity	Power	Capacity	Power
5	213	234	937	326	91.8	149	364	279
10	124	186	791	270	0.1	2.6	146	88
25	54	50	804	278	0.1	0.1	0.1	0.1
50	56	45	746	238	0.1	0.1	0.1	0.1
100	25	10	746	230	0.1	0.1	0.1	0.1
200	14	8	648	193	0.1	0.1	0.1	0.1
Iteration/Data	$Capacity_{STD}$	$Power_{STD}$	$Capacity_{STD}$	$Power_{STD}$	$Capacity_{STD}$	$Power_{STD}$	$Capacity_{STD}$	$Power_{STD}$
5	173.8	101.4	272.2	89.3	175.7	93.6	245.2	131.9
10	124.8	162.4	270.2	92.9	0	7.4	244.2	244.2
25	40.1	50.1	226.5	82.5	0	0	0	0
50	120.1	59.9	164.4	53.1	0	0	0	0
100	17.8	7	120.1	38	0	0	0	0
200	14.4	6.9	163.4	49.5	0	0	0	0.

Table 11: Result from case 2: Average Capacity and Power

C Case 2 Results: 3D Plots

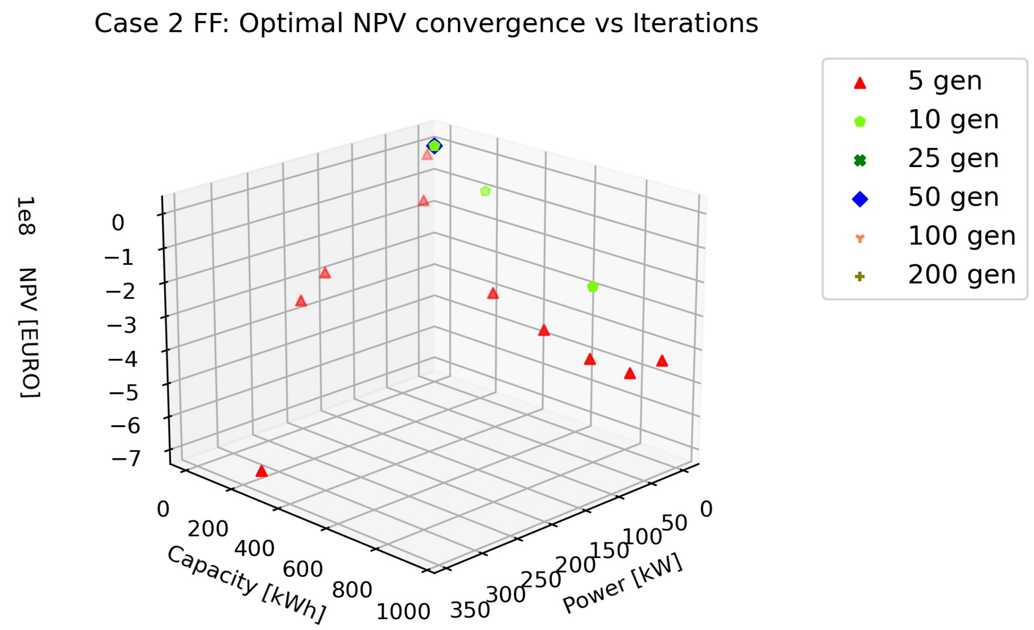

Figure 18: Case 2: FF NPV convergence vs iterations

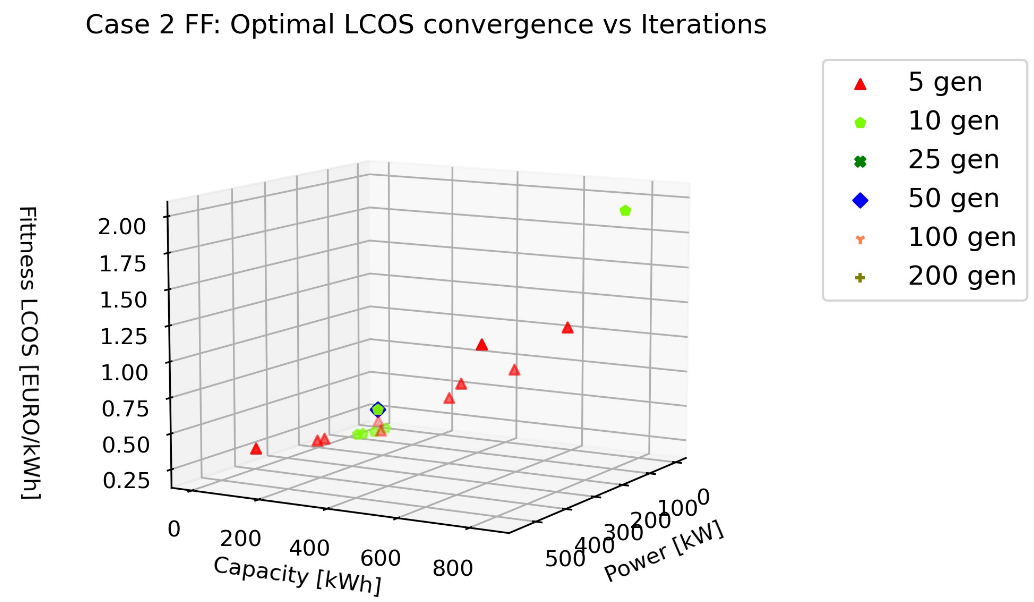

Figure 19: Case 2: FF LCOS convergence vs iterations

D Case 3 Results: 3D Plots

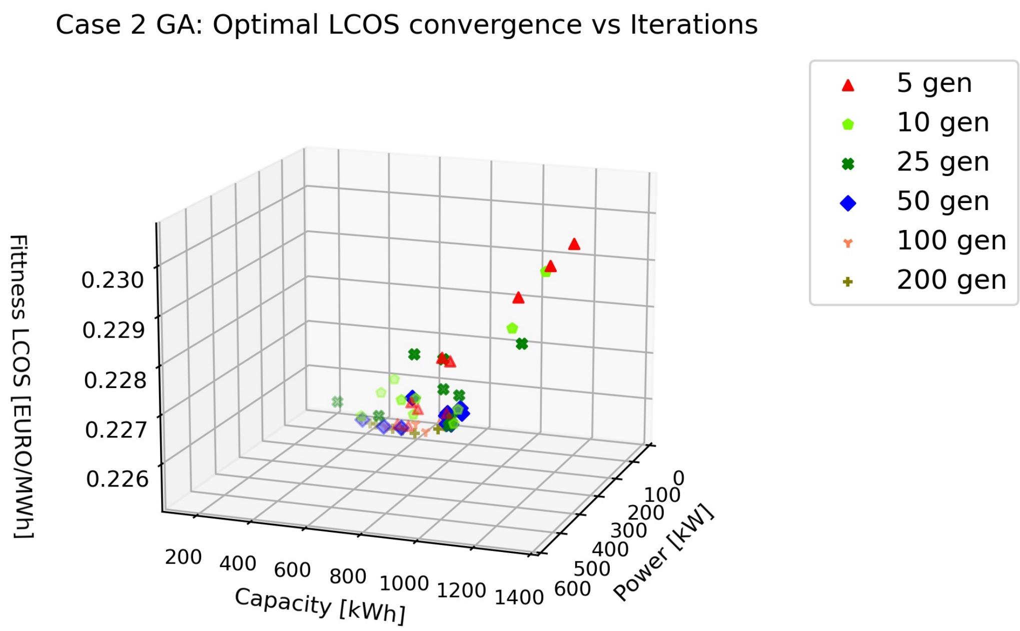

Figure 20: Case 2: GA LCOS convergence vs iterations

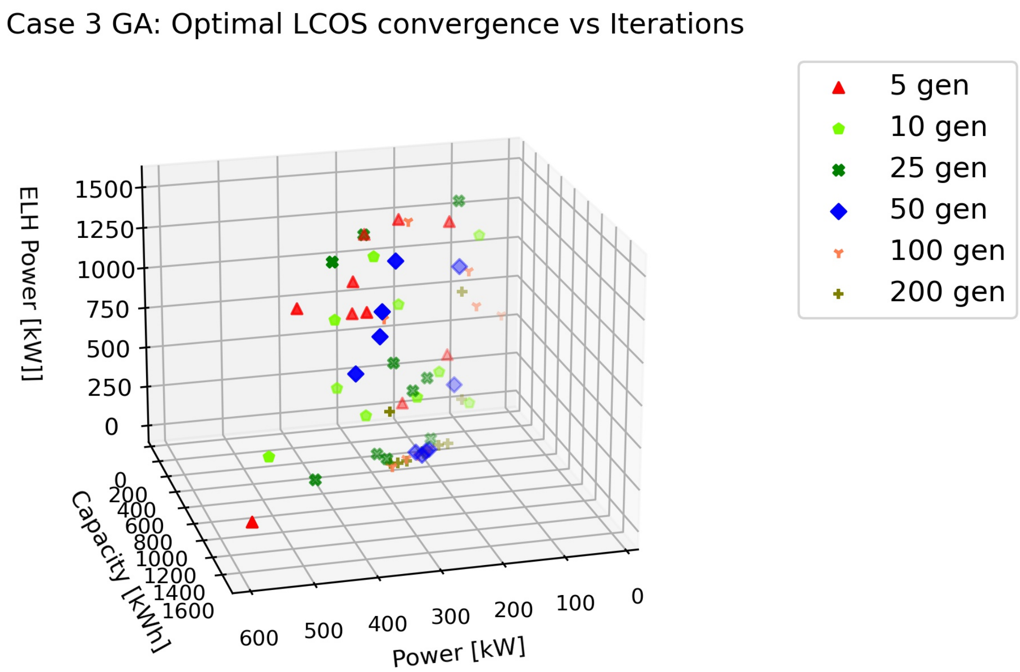

Figure 21: Case 3: GA LCOS convergence vs iterations

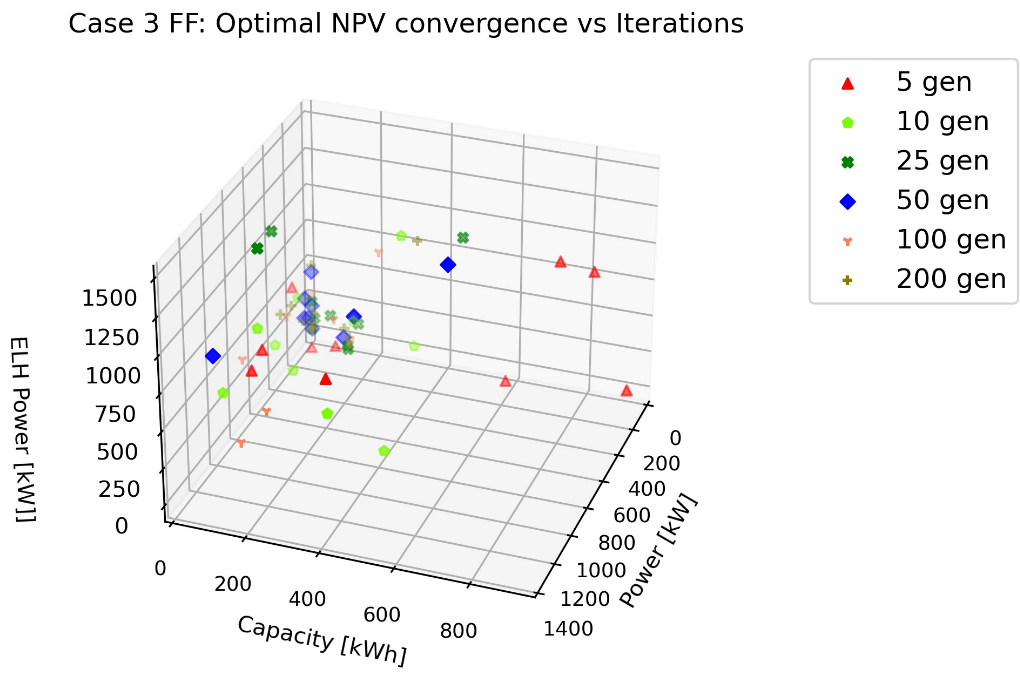

Figure 22: Case 3: FF NPV convergence vs iterations

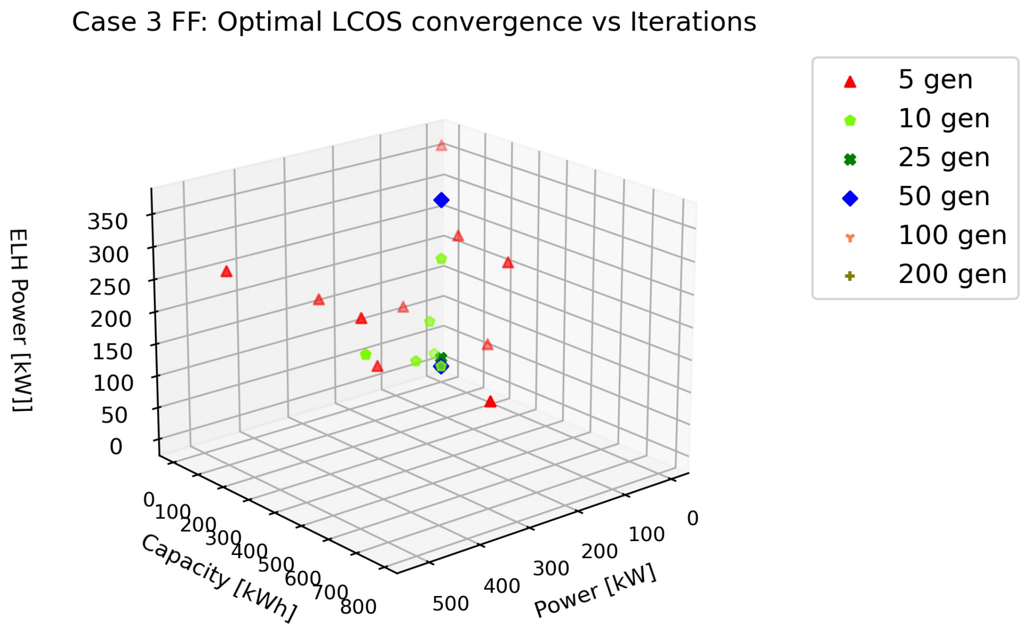

Figure 23: Case 3: FF LCOS convergence vs iterations