Comprehensive Study of Optimization Techniques for Energy Storage Technologies in Circular Multi-Energy-Systems

OR

Comprehensive Study of Optimization for Optimal BESS Size for Energy Arbitrage Usage

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1 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 due to the increase of variable electricity production units such as solar and wind in the electricity system in order to reduce CO_2 emissions from the energy sector. The problem of finding the optimal size for BESS is a of high complexity and includes many factors that effects the usefulness of the 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 or minimizing the levelized cost of storage (LCOS) for the Li-ion BESS over a ten year lifespan of the BESS. For the case study a simplified charge and discharge schedule were implemented with the focus of maximising the value of energy arbitrage. The case study is divided into two different cases, one only including installing the BESS (case 2) and another one which includes the installment of an electrical heater as well (case 3) in order to shift a heating load demand to electricity load demand, to reduce CO_2 emissions from a gas heater as well as increasing the electricity demand. The results showed that overall GA was a better optimization algorithm, having lower optimization time and finding better solutions for case 3 for both NPV and LCOS at 948055 Euro and 0.23 Euro/kWh respectively. For case 2 GA finds a the best LCOS with a value of 0.226 Euro/kWh compared to FF at 0.254 Euro/kWh. Regarding NPV for case 2 FF finds the best solutions at the lowest possible value in the search space for the capacity and power, with an NPV at -51.5 Euro compared to GA at -6316 Euro, showing that for case 2 an investment in a BESS is not worth it. The results also showed that there exist different combinations of solutions for 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, but it was shown that the charge and discharge schedule plays an important role regarding the effectiveness of the BESS as for some cases the BESS was only used 17% of all hours during a year for case 2 when optimizing for NPV, which could explain the negative values for NPV. Therefore further research is needed into the schedule function and its role regarding finding the optimal BESS size.

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6 Introduction

Today more and more variable renewable energy production units as solar and wind are introduced into the energy systems as a way to reduce the amount of greenhouse gases emitted from the energy sector [1]. The IEA have a forecast that it will be installed around 300 GW of capacity per year between 2021-2026 of renewable sources for energy production [2]. With large penetration levels into energy grids and their unpredictability, problems with variable energy sources emerges such as ~~lack of~~ grid stability and power quality ~~as an example~~ [3]. Energy storage has seen as a method to prevent these problems [4], but energy storage ~~has also seen~~ 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 battery ~~to minimize investment cost whilst~~ maximizing the profits gained from using the energy storage. This thesis will investigate by looking at from an investors perspective of installing an Li-ion battery either to maximise profits specifically looking to maximize the net present value (NPV) for installing the storage or to minimize the levelized cost of storage (LCOS). To solve this problem ~~with finding the optimal size for the Li-ion battery storage,~~ a literature study is firstly made to find ~~what type of~~ methods to solve this optimizing problem ~~is currently state of the art.~~ Meta-heuristic optimization algorithms have been found a powerful tool in many different research areas and in the last years especially in the field of energy engineering as they are able to provide close to optimal results in computationally heavy optimization problems [6]. Therefor two different meta-heuristic algorithms are used to find the optimal Li-ion battery size and compared their usefulness for this type of problem, when using a simple function for scheduling the charge and discharge of the BESS with focus on energy arbitrage and peak shaving.

7 Literature review

This section~~s~~ introduces optimization algorithms and meta heuristic algorithms followed by a literature review of the development of different techniques used for finding optimal energy storage size.

7.1 Optimization Algorithms

Optimization algorithms are used to solve optimization problems. These problem focuses on computing a objective function and trying to minimize or maximise the final results by systematical testing different input variables within a set of values. There is three important factors that go~~es~~ into an effective and viable optimization algorithm, it has to be *efficient*, *accurate* and *robust*, but usually trade-offs between these three factors have to be made when choosing which algorithm to use. One powerful type of optimization algorithms are *heuristic* or *meta-heuristic* algorithms, these algorithms are not assured to find the best solution, as linear programming usually is, but are useful at they can find close to optimal solutions in big search spaces with low computational load. These algorithms ~~have a~~ use randomization and local search functions in order to find the most optimal solution globally in the search space. Therefore two fundamental components are the function used to find the optimal solution locally in a search space and a~~n~~ randomization function in order for the algorithm not to get stuck in local optimums and find the optimal solution globally whilst looking at the whole search space [7].

7.2 Heuristic and Meta-Heuristic Optimization Algorithms

The word Meta-heuristic can be divided into its two part Meta, which ~~today have many different meanings, but~~ derives from Greek meaning *"after"*, *"beyond"* or *"along with"* [8]. Whilst heuristic coming from Greek meaning *"to discover"* [9]. The field of heuristic started in 1945 by G. Polya [10], but it would take time until they were starting to be used more, not until conventional optimization techniques that found an exact solution to a problem were facing problems with not being able to solve optimization problems in a reasonable amount of time. The 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. Regarding meta-heuristic optimization algorithms they were first used in the 80s were several general heuristic algorithms were put together to create a set in order to be able to solve many complex optimization problems [11]. An definition of meta-heuristic was given by Sörensen et.al. [12] in 2013 as:

> "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 an meta-heuristic algorithm and an heuristic one is the meta-heuristic algorithm is problem independent and can therefor be used for many different problems but with varying success. The defining and interesting feature of meta-heuristics algorithms are how they are applicably 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 [11].

7.3 Optimization of energy storage

The problem ~~regarding~~ finding the optimal size and capacity of energy storage as a use for energy service (Load shifting, Energy arbitrage, peak shaving, frequency control, etc) have 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 methods have developed over the years. This section goes through a timeline of used methods for finding the optimal energy storage starting at 1995 until today's research.

Lee and Chen [13] looked into the problem of optimizing energy storage size already in 1995, where the objective function was to find the optimal battery size (capacity and power) as well as the optimal time of use (TOU) contract capacity (if energy used is above the predefined capacities a penalty bill is added to the cost of energy) over a battery's life cycle in order to reduce the cost of electricity. In order to solve this problem, an advanced multi-pass dynamic program was used as well as an expert knowledge base system for the optimal operation of the energy storage to maximize the saved energy. D.K Maly and K.S Kwan [14] also used multi-pass dynamic programming to solve a similar problem in 1995, where instead the optimal charge and discharge rate of an battery energy storage was looked at in order to minimize the electricity bill, this was done by load shifting as well as peak shaving. That work only looked into optimizing the power capacity output of the batteries and not the energy storage and had them at different fixed sizes. It was also seen that the method of "shaving the peaks, fill the troughs" is in practice not an optimal charge schedule for the battery storage, and to maximize energy efficiency or minimizing peaks in kw their method could be applied. In 1999 Lo and Anderson [15] also used multi-pass dynamic programming to firstly find the optimal size of an battery energy storage whilst also finding the optimal dispatch in a power system in a regard of the economic aspect. Here a~~n~~ time shifting technique were a week of hours where split into 7 different time segments of 24 hours was used to reduce the calculations time.

In 2005 Chacra et.al. [16] looked into an multi scenario study to find optimal size and power of a~~n~~ battery energy storage, comparing different battery types in economical performance and its NPV in a grid connected setting, this was done using a meta-heuristic non-dominant sorting GA with tournament selection as the randomizer in the GA. The reason to use GA was due to the problem stated was multi-variable and non-linear. In 2009 Abbey and Joos [17] looked into using an Stochastic optimization approach to solve for the optimal size and power of an battery storage connected to a wind farm in order to stabilise stream of electricity produced to meet an demand load. Both the winds and loads stochastic nature was included to optimize the energy storage for those unknowns. Chen et.al. [18] looked 2011 into using a matrix coded GA to find 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 by while maximising NPV. In 2012 Chen et.al [19] investigated to optimal size of an ESS (energy storage system) in an micro grid by focusing on the unit commitment problem in both grid connected and island mode. To solve this an mixed integer linear solver ~~was~~ 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 for the case study. Mohammadi et.al. [20] used an GA in 2012 to find an optimal solution for sizing distributed generators (DG) and storage units in a grid-connected micro grid but focused on the 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 buy and sell energy from the grid and store it in the energy storage units.

Continuing on the problem regarding finding optimal size for energy storage for operation management in a grid connected micro grid, Bahmani and Azizpanah [21] looked 2014 into using an improved bat algorithm (Meta heuristic) to find the optimal size for the ESS to reduce the operational cost in an micro grid. The new improved bat algorithm that was used was first tested on three 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 (TLBO), Artificial Bee Colony (ABC) and a regular bat algorithm (BA)) to prove its superiority in finding the best solution for the defined objective function. The results where that the improved bat algorithm could solve the three test functions and also found the optimal solution compared to the 3 other meta heuristic algorithms when tested in a case study. In 2015 Fossati et.al. [22] investigated optimal size of ESS in order to minimize the operational cost of an micro grid. To solve this an 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 an grid connected and island mode and the results where that the total operational cost was lowered with 3.2% and 14.1% respectively.

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. In 2017, Khan and Singh [23] looked into comparing 6 different meta heuristic optimization algorithm regarding operational cost minimization with the use of an optimally sized energy storage unit in grid connected micro grids. These algorithms were tested on 19 different test function where TLBO was found to overall be best. It was also tested on 2 case studies of the operations of a smart micro grid where the swarm intelligence algorithm Fire fly (FF) algorithm was found to give the most optimal result (minimized operational cost). The other four algorithms that was used where

Genetic Algorithm, Whale Optimization, Differential Evaluation and Particle Swarm Optimization. One conclusion from these test were that particle swarm optimization algorithms were more suited in solving the case study of optimal ESS size and operation in the micro grid. Another problem regarding finding the optimal size is looking into the time step used for simulating the operation of an micro grid.

Most studies uses 1 hour time step and look into different lengths of periods depending on the use case for the energy storage (energy service). Xiang et.al. [24] investigate in 2018 the use of Fourier-Legendre series to change the discreet time step of 1 hour into an continuous curve in order to find a more optimal size for the energy storage size, as it might sometime be between two discreet points. For this an GA was used to solve for the state of energy of an battery energy storage that then could be used to calculate the optimal size of the energy storage. The results showed that an more optimal solution for the size could be found between two discreet points resulting in an more optimal size in an test case.

Shivaie et.al [25] developed an modified discrete bat search algorithm in 2019, this was used to solve for an optimal size of an hybrid renewable system with energy storage 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 (Particle swarm optimization, genetic algorithm and harmony search algorithm) where the most optimal results came from the new improved bat algorithm. Diab et.al [26] also looked into comparing different meta heuristic algorithms to find the optimal size of an 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 where the results showed that Whale optimization gave the most optimal results in regards lowest cost of energy.

In 2021 Emrani-Rahagi et.al. [27] investigated the optimal operation in an renewable energy hub system with energy storage installed (both heat energy storage and battery energy storage). To find the optimal solution for minimizing the operational cost and an GA was used. It also compared the differences between having heat storage or battery energy storage installed individually or together in a hybrid mode. The results showed that with an hybrid system for the case study an lower operational cost could be achieved using the GA. Monforti Ferrario et.al [28] investigated in 2021 optimal storage size in an island micro grid while using hydrogen storage, battery storage and an hybrid system. For the dispatch four different energy management strategies were used from Simulink (which is an MATLAB tool for simulating dynamic systems) [29]. To find the optimal size of the system an particle swarm optimization algorithm was used, in parallel with an multi-dimensional sensitivity analysis to get both the optimal results both also how trends in how the design variables affect the performance parameters. The results showed that the battery energy storage where better for short term, whilst the hydrogen would work better for long term. It also showed that letting the percentage of allowed load loss to go from 1% to 5% the total cost of the energy storage could be reduced by 30% - 45%.

As can be seen the uses of meta heuristic algorithms in this field of research are great, for some edge cases more linear problem solving method have been used, or the use of multi-pass dynamic programming. Regarding the solving the optimization problem in this thesis two different methods have been chosen. Firstly Genetic algorithm as it is a~~n~~ method that have been tried and used multiple times and are still used in the research today. The second method is the particle swarm optimization algorithm as it have 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 they 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 particle swarm optimization algorithm to be used many can be chosen but as Khan and Singh [23] found ~~that~~ the Fire Fly algorithm (which is a modified version of PSO) gave the best result regarding reducing cost for optimizing operations of a micro grid with an ESS, it have been chosen for this thesis as well.

7.3.1 Genetic Algorithms

A~~n~~ genetic algorithm (GA) is an optimization algorithm based on evolutionary theory, and goes under the category of meta-heuristic algorithms. It was firstly developed in the 60s and 70s by J. Holland and his team [30]. 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 encodes onto it. By switching sections or genes of the chromosomes, the crossover of two parent strings generates children (new solutions). Crossover has a hig~~her~~ chance of happening, usually between 0.8 and 0.95 percent. Mutation, on the 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 0.001 to 0.05 percent. Each generation's new solutions is 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 remain ~~the~~ the population by always passing down the best solution to the next generation without changing it [31]. A detailed explanation on each step in GA and the implantation of the GA algorithm for this thesis problem can be found in section 8.7, and a Pseudo-code can be found from Yang [32].

7.3.2 Fire Fly

In 2007 Yang et.al. [31] developed the FireFly (FF) algorithm. It is quite 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~~n~~ firefly is attracted to (and moves towards) a~~n~~ ~~most~~ attractive or brighter firefly, where the attractiveness also varies with the distance between each two fireflies that is in focus. Here each firefly represent an solution with the brightness of the firefly is proportional on the final value from the objective function, and in the end the brightest firefly can be chosen in order to find the optimal solution. A detailed explanation on implantation of the firefly algorithm for this thesis problem can be found in section 8.8, and a Pseudo-code can be found from Yang [33].

8 Methodology

8.1 System model

The system model that is used for testing and comparing the two different algorithms is from a 3rd party perspective looking to install an Li-ion BESS in order to gain a profit by the use of energy arbitrage and peak shaving. 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 1 and 2 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].

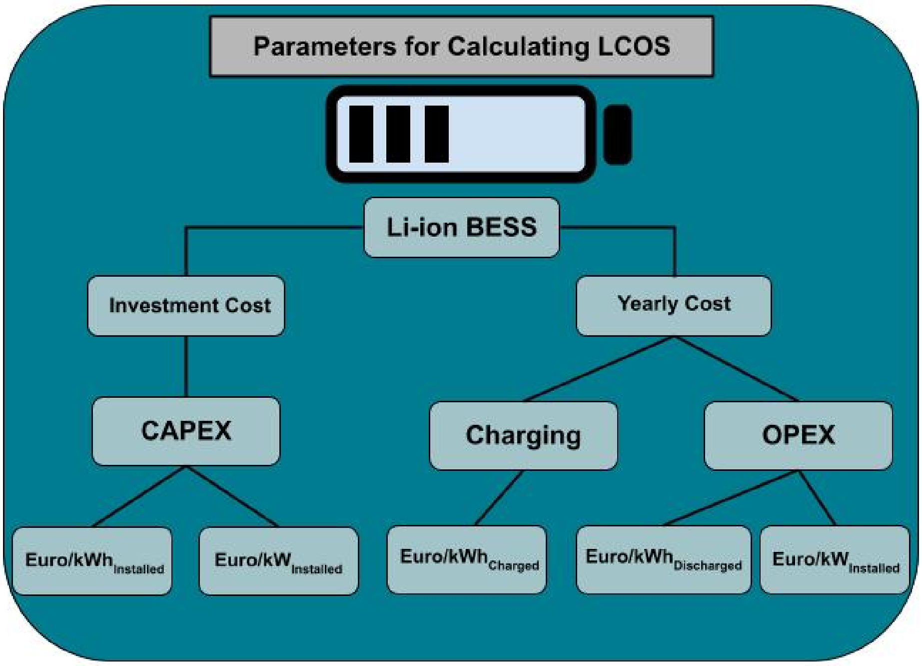

Figure 1: LCOS for Case 2 and 3

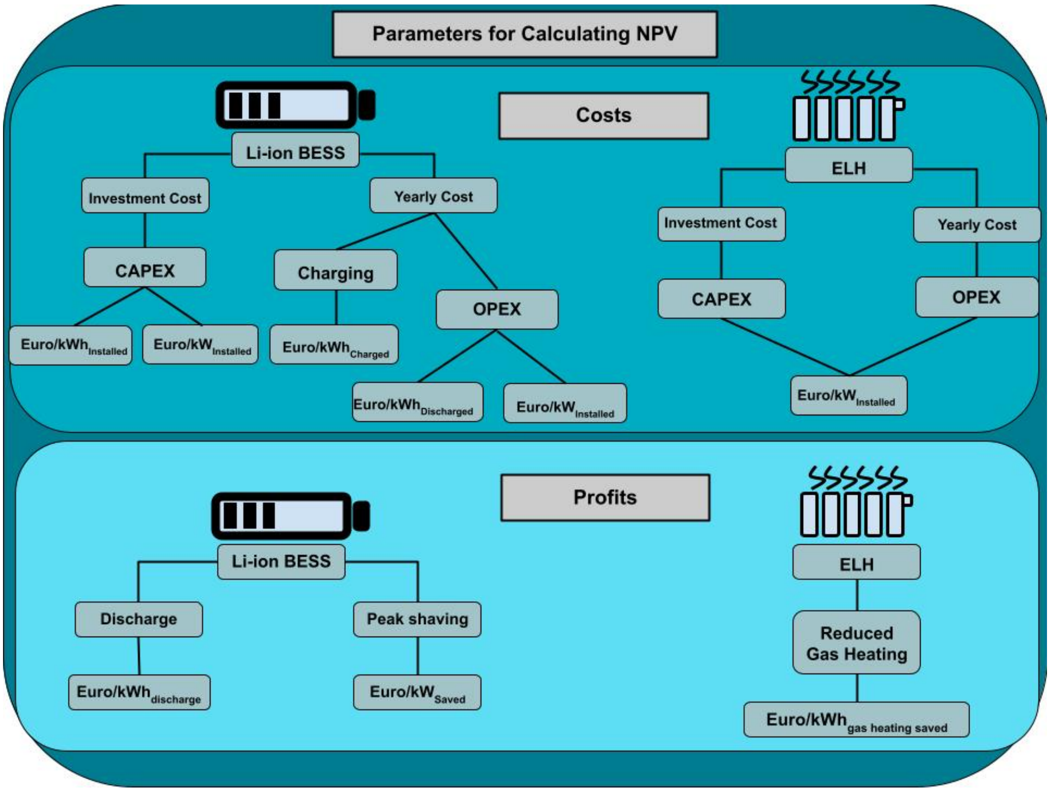

Figure 2: NPV for Case 2 and 3

8.2 BSS charge/discharge schedule

For each different power characteristics for the BESS a specific hourly schedule has to 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 ~~an~~ limitation have 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 8.3. The charge and discharge efficiency are ~~included into the~~ calculations on how much energy ~~that~~ gets charged and discharge from the BESS, but are not included when getting how much energy that has been drawn from the grid or the storage. The efficiency of a Li-ion battery depends on the ~~c-rate,~~ but in this thesis an simplification has been made as battery energy storage with Li-ion batteries have very similar (between ~~100~~-80%) efficiency depending on the c-rate, and an average 90% charge and discharge rate has therefore been used [35]. The round trip efficiency for Li-ion batteries are around 90% so by using this we get somewhat worse round trip efficiency but for realistic sake a lower round trip efficiency have been used in order for the results to give a worst case scenario instead of a best case. The cycle life 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 cycle life depends on the Depth of discharge (DoD), depending on the DoD the life cycle of a battery will be worse or better. For Li-ion batteries 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. Therefor the charge/discharge schedule might not the most cost effective way to use the battery. It could exist a schedule where 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.

8.3 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 in order to ensure that it stays in its desired operation. Firstly the current capacity of the battery, and how much energy that is stored in the battery is given by $ESSc(t)$, where t is the time-step in hours. In equation 1 and 2 down below the equation used to change the stored energy in 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.

$$Charge : ESSc(t+1) = ESSc(t) + P_c(t)/\eta_d \tag{1}$$

$$Discharge : ESSc(t+1) = ESSc(t) - P_d(t)/\eta_c \tag{2}$$

With the charge and discharge equations above some restrictions and limitation are also active during the optimization for the battery. These are the power limits for the charge and discharge of the battery given in equation 3 and 4, 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).

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

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

$$ESS_{min} \leq ESS(t) \leq ESS_{max} \tag{5}$$

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

8.4 Objective function

An objective function is the function used in an optimization in order to ~~usually~~ maximise or minimize a specific objective value that is of interest [7]. 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.

8.4.1 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 ~~returns~~ from the investment and the discount rate that translate to lower value of future money due to inflation into the equation. Equation 7 down below shows 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 on not buying gas for heating
$ElHeating_t$ = Cost of using electricity for heating instead of gas using ELH

The capital expenditure depends on the case, where for case 2 with only the installment of an BESS, that is depending on the BESS's capacity and power. For case 3 when both the BESS and the ELH is 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 depend on the OPEX which is either the size or how much kWh have gone through the BESS during a year.

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 the 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 of the user. This also means that for some hours it might be higher than before as the charging of the BESS will effect this as well. The schedule function does not have as focus on optimizing for this but this profit is included but can for some months be a profit or 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.

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

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

8.4.2 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. The LCOS is therefore used as a~~n~~ 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 are described.

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

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 capital expenditure for the BESS for both cases and excludeds 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.

8.5 Fitness function

A fitness function are used in both meta heuristic algorithms in this thesis, it is a function which gives a value to compare different solutions to each other in order to know which one is the best. The better the value of the fitness function the ~~higher is the feasibility that the solution is close~~ to the optimal solution to a problem [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 as it is sometimes required for the genetic algorithm depending on what selection methods is used [42]. For a~~n~~ flowchart explaining ~~the~~ the fitness function see figure 3, this flowchart is used for both case 3 and 2 with the only difference being the for case 2 the ELH power is also excluded.

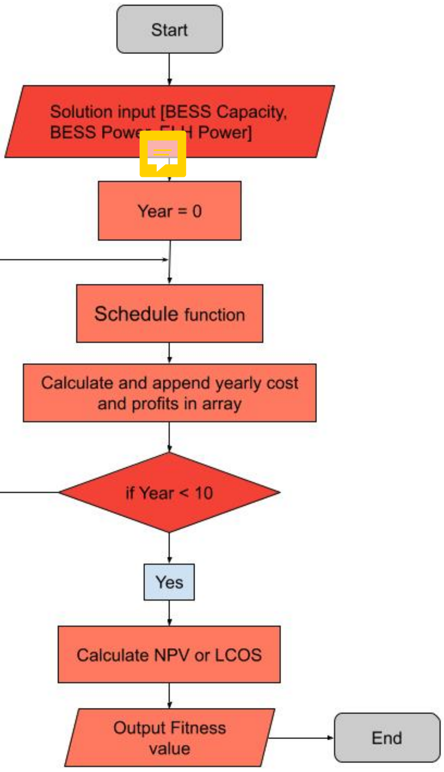

Figure 3: Flowchart over fitness function

8.6 BESS capacity loss over lifetime

There are many different factors that effect the BESS capacity. For the Li-ion battery, cell degradation is what effects the total capacity degradation. A~~n~~ cell can degrade~~d~~ by two different ~~main~~ 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 is 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]. Timmermans et.al [43] et.al. investigated the ageing of Li-ion batteries and found that both high DoD and long storage times at high state of charge have negative effect on the lifetime of a battery. This was done with different temperatures and DoD compared to number of Full equivalent cycles (FEC). At 25°C and a DoD of 80%, with 3000 FEC the degradation is around 15% and around 10% at 2000 FEC. Mongird et.al [36] found that LFP Li-ion batteries with 80% DoD would result in around 2000 FEC and used thi 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 a Li-ion battery (10 years) is used. The higher value of 15% was chosen as the uncertainty regarding the numbers, to optimize for worst case scenario is better then best case. This resulted in a yearly linear degradation of 1.612% each year that is implemented into the optimization.

8.7 Genetic algorithm

As describe before in the section 7.3.1 an GA is a meta heuristic algorithm designed to mimic evolution in order to find optimal solution to a defined problem. In this thesis the Python library "PyGAD" is used to implement the GA [44]. There exist many different selection method with different properties which gives different possibilities for the best solutions to have the highest chance of being the parents for the next generation. The chosen parents offspring get~~s~~ put into the next generation and the rest of the genes in the population are filled with random solutions. The step by step guide can be seen in the flowchart down below in figure 4. The first step is to generate a population of solutions, randomly assigning a power and capacity for the BESS storage for each solution. Thereafter the fitness function is run for 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 that order to generate the next generation of solutions.

8.7.1 Parent Selection

One important part in an 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 [45].

Roulette wheel selection: Roulette wheel method or also know as Fitness proportionate selection, uses a uniform distribution to randomly select the parents for the crossover stage. this is done by normalize the fitness value of each solution ~~by~~ 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 [45]. Important to note with this method is that the fitness value cannot be negative for any solution [46].

Tournament selection: This selection methods instead selects a~~n~~ random set of solutions from the generation and from that subset the best solutions are picked as parents for the next generation. This methods allows all solutions to be able to survive witch helps the algorithm not get stuck in a local optimum [45].

Random selection: This method used randomly choose what solutions to be kept as parents for the crossover stage. This method then ha~~ve~~ no way to guarantee that better solutions are picked to be parents ~~the worse ones~~.

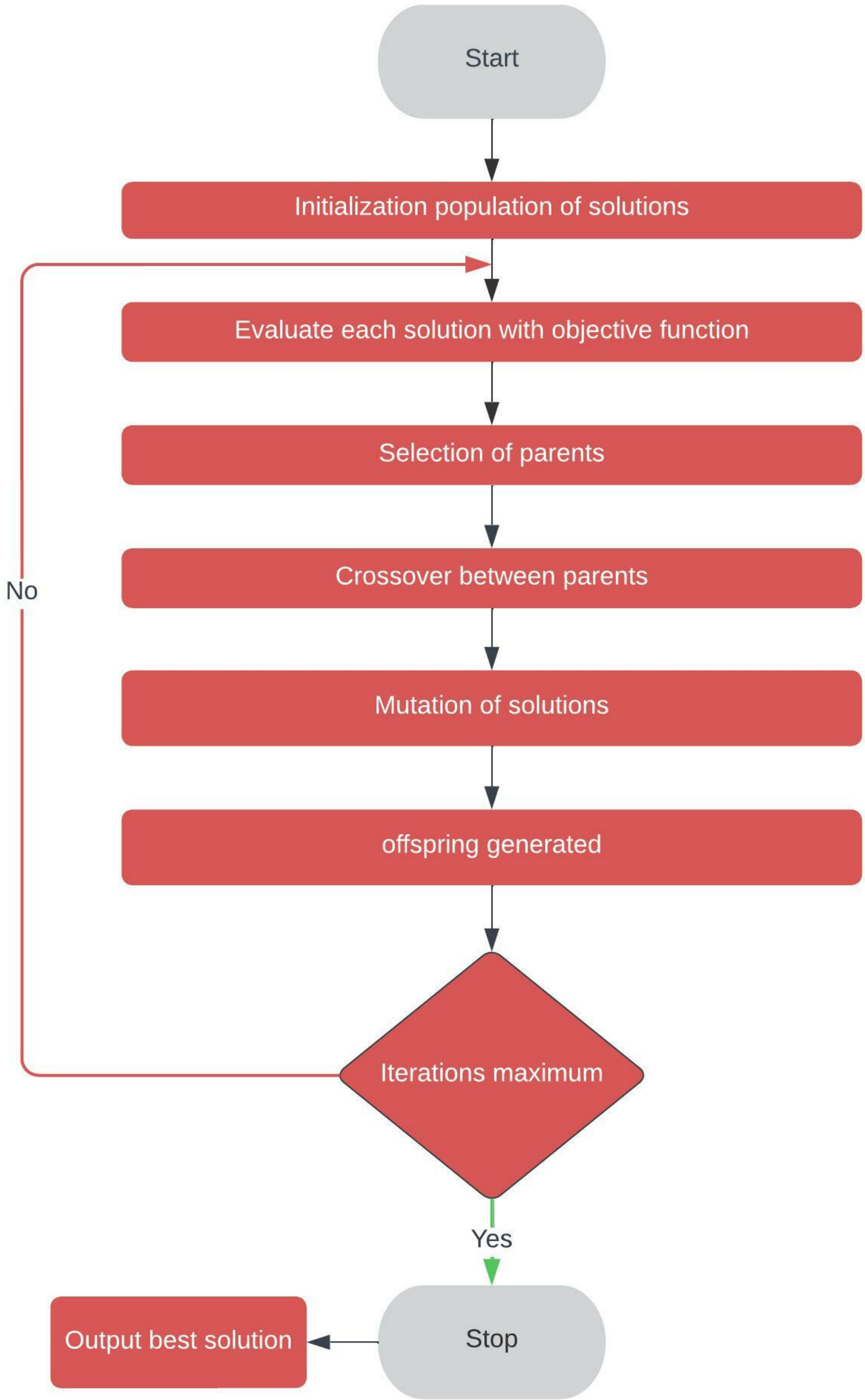

Figure 4: Genetic Algorithm Flowchart

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 with the for example 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 [46].

8.7.2 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 combine two solutions genetic material in order to create one or more offspring (new solutions). If elitism is used in the algorithm the two best solutions are paired with each other in order to emphasise the best results. Depending on the structure of a solution, ie. vector, matrix, size etc, the way a crossover is done is very different, one common way is splitting ~~an~~ vector array of n bits at a specific points and saves the bits before the point into one parent and takes the specific points 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 know 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 in order to generate one new solution, this is known as arithmetic crossover [45]. For this thesis, as there is only two or three different variable (depending on the case), ~~and therefor~~ a uniform crossover is applied. This method gets a value for each gene by randomly selecting one of the parent and taking the value at that gene from that parent.

8.7.3 Mutation

A mutation in a genetic algorithm is ~~when a solution is changed~~ due to a random factor (the mutation rate which usually is a lot lower then 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, there's a 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 [45]. As the number of genes in this type of problem 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.

8.7.4 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 have on the result the method of termination by similar fitness values between generations is disregarded in this thesis.

8.7.5 Parameters used in GA

Below in table 1 the parameters for the genetic algorithm is given. ~~And~~ in table 2 ~~the~~ the minimum and maximum values for the search space is given. This search space is the same for both the GA and FF. For the BESS capacity 8000 kWh was chosen as an arbitrary high number after a iterative process testing of 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. ~~But~~ as 0.1 is the lowest value it is probable that if a optimization converges at this value it want to converge to 0 instead.

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	8000
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

8.8 Fire Fly algorithm

The firefly algorithm used in this thesis is based on Xing-She Yang proposed method that is based on an idealized firefly's flashing behavior [33]. It is simplified by three rules in order to capture the behavior of the flashing fireflies.

- The sex of a fireflies is unisex. Meaning that all fireflies are attracted to all other fireflies.
- A fireflies 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 fireflies brightness/light intensity is directly determined and affected by the landscape of the fitness function.

An simplified flowchart is given in figure 5, showing in what order the different steps are taken for each iteration.

8.8.1 Attractiveness and movement of fireflies

The firefly's attractiveness and movement toward the attractive firefly are two important aspects of the firefly algorithm [47]. 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 minimisation and maximisation problems. It is only a matter to decide that the firefly with the smallest amount of brightness to be the most attractive in a minimization problem, and vice versa for a maximization problem. For an solution **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 **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 ~~by~~ as seen from the eyes of the beholder ie. the other firefly. As a result, it 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 [48].

Following Yang's [33] design of the FF the equations used in the firefly algorithm is laid out below. Firstly the light intensity of what one firefly observe the other 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 8.8.1 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:

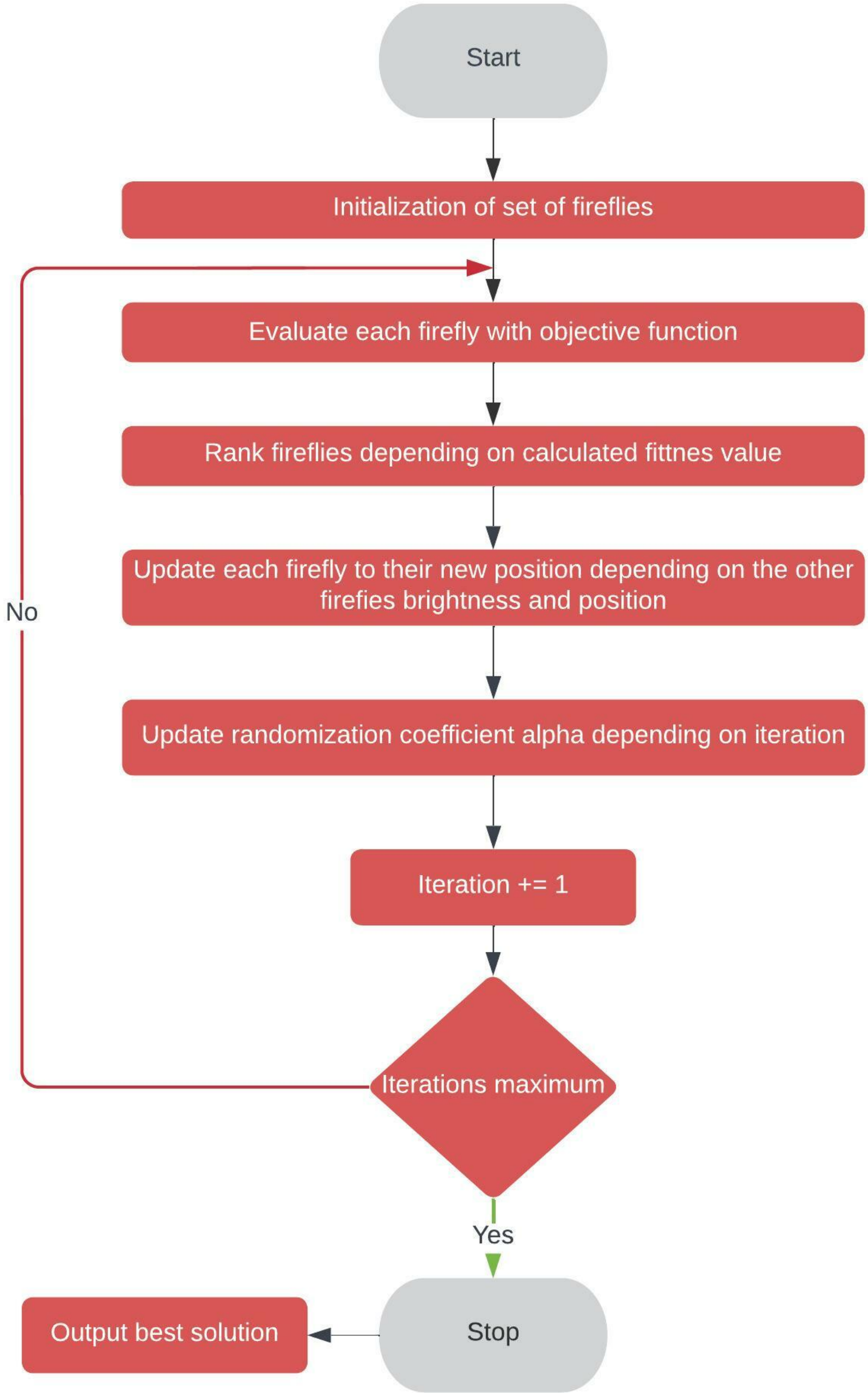

Figure 5: Firefly Algorithm Flowchart

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

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 an 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 more brighter and thus more attractive firefly j. The first on 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 spacial 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 [49] used for the FF algorithm in this thesis uses the model of Xin-she, Yang [50]. 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 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:

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

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

9 Case Study

The case study for this study is used in order to compare the GA and FF to each other on their effectiveness in finding the optimal capacity and power for a BESS and ELH when installed to be used for peak shaving and energy arbitrage for a large residential building. This section focus on the data used for the case study.

9.1 Different Cases

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

9.1.1 Case 1 - Base case

The base case focuses on what 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 is done in Excel.

9.1.2 Case 2 - Optimal BESS installment

For the second case a~~n~~ Li-ion LFP BESS is installed in order to profit from energy arbitrage and peak shaving the residential buildings electrical load. This is done by charging 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.

9.1.3 Case 3 - Optimal BESS and ELH installment

For the last and third case both a~~n~~ Li-ion LFP BESS and an ELH is implemented. The ELH is used to reduce the thermal demand of the gas heater and instead turn it into an extra electrical demand. For this case, 3 different values are used for the optimization. Capacity and power for the BESS and only power for the ELH. This case have an additional way to make a profit by including the saved cost for heating using the ELH instead of a gas heater, compared to the base case. This case as in case 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.

9.1.4 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 is achieved, firstly 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 electricity is needed each hour from the ELH. With a part or all of 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 9.1.1. 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 need due to the ELH is also added as a cost into the model. 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 this cost comes directly from the grid cost and is never taken from the battery.

9.2 Data used in case study

In the table 4 below the data used in the simulation is given for the Li-ion LFP battery. Data for the battery energy storage unit (Li-ion) are from Brinsmead et.al. [51], the study looked into 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 energy 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 the 8760 data points represent the electricity cost in EUR/MWh for that hour. The maximum and minimum value of the 8760 hours was 130 and 1.7 Euro/MWh. One of the 8760 values was missing. This value was filled in by taking the average cost for that day [52]. 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 Euro/kWh and 0.442 kg-CO_2-eq/kWh respectively [53][54]. The gas heater efficiency is chosen to be 95% [55]. The discount rate have been set to 8% for all calculations regarding NPV and LCOS in the thesis.

9.2.1 Cost of BESS storage

Mongird et.al. [36] investigated cost for 2020 and 2030 projections for the cost 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)". The cost of warranty, insurance and decommissioning of the Li-ion battery energy storage 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 in MWh that has gone through the BESS throughout 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 BESS technologies variable O&M costs. All these cost have been recalculated to Euro 2022 values and can be found in table 4.

[1] See section 8.2 for a detailed explanation of charge and discharge efficiency

Type/data:	Li-Ion
Capital cost capacity (Euro/kWh)	389.2 [36]
Capital cost power (Euro/kW)	148.8 [36]
Fixed O&M cost (Euro/kW-year)	4.4 [36]
Variable O&M cost (Euro/MWh-year)	0.5125 [36]
Depth of discharge (%)	80 [51]
Charge efficiency (%)	90[1]
Discharge efficiency (%)	90[1]
Lifetime (years)	10 [51]

Table 4: BESS data for the case study

9.2.2 Cost and Residual cost of Electrical heater system

The cost for the electrical heater 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 also is taken from [56]. As the lifetime of the electrical heater is longer then 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 was used [57]. The numerical values for the electrical heater 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 Euro:

Type/data:	Electrical Heater
Capital cost power (Euro/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

9.2.3 Inflation change of different sources cost

As the different monetary values in the thesis comes from different sources published during different years and in different currencies a basis has to be set were all cost are rewritten to an 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 euro, but as other sources are newer all cost are rewritten to Euro and 2022 values by including inflation. This is done by firstly changing the cost to euro 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 Euro to its 2022 value in Euro.

9.2.4 Load demand and temperature

The load demand used for the case study comes from a residential building in Iran [34]. It include 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 6 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 data comes from a large residential building with a total yearly electrical and heating demand 2017 of 34.5 TWh and 23 TWh respectively. The temperature data is also from 2017 and are from NSRDB [58].

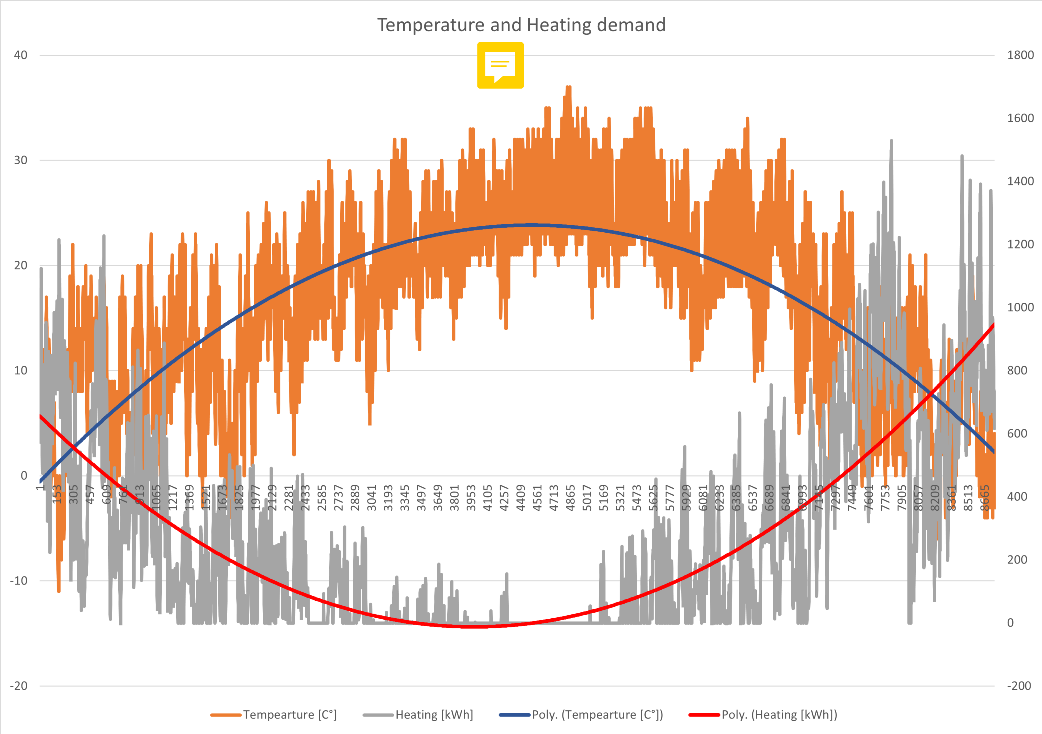

Figure 6: Heating load [kWh] and temperature[C^o]

9.2.5 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 important to that result.

9.3 Sensitivity analysis

A sensitivity analysis regarding the effects of CAPEX ~~price~~ of the BESS on the results and effectiveness of the case study and algorithms respectively. The analysis check how the price difference in steps of 10% of the original price [-20%, -10%, +10%, +20%] will effect the results (NPV and LCOS). The sensitivity analysis are 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.

10 Results and analysis

In this section the results are presented from the case study. As a significant number data points were outputted from the optimization only the most interesting and useful data is brought up in the thesis and its appendix. The remaining data and plots ~~of data~~ can be found at the GitHub repository together with the code ~~used~~ for the optimization used for this thesis [59]. 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 is in 2022 Euro and LCOS in Euro/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.

10.1 Case 1: Base case

For the base case the results are shown in table 6. These are the resulting cost and emissions from supplying the heating demand of the residential building with the natural gas heater.

Type/data:	Case 1
Yearly heating demand supplied by natural Gas [MWh]	2455.4
Yearly cost of gas [M Euro]	0.224
Yearly CO_2 emissions [tons CO_2-Eq]	1085

Table 6: Case 1: Gas cost and CO_2 emissions

10.2 Case 2: NPV and LCOS with BESS installed

The main results for case 2 can be found in in table 7. The LCOS and NPV is the average from the ten runs whilst the STD is the standard deviation from 10 runs for each iteration. As can be seen for case 2, a positive NPV can not be found for either GA or FF. but FF is able to 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 is able to minimize the LCOS better compared to FF. What can be seen is that the FF finds and optimum quite fast (by 25 iterations already) and gets stuck there. Looking at table 8 showing the average capacity and power for the different optimization in case 2 as well its STD for the BESS it can be seen that 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 with GA who finds a better solution in minimizing LCOS by having a lot higher values for the capacity and power. 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.

In figure 7 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 represent a solution for a specific number of iterations (gen). As can be seen for higher iterations the solutions converge.

This can also be seen in table 7 where the STD is lower for the optimization using higher number of iterations. See appendix B for 3D plots when optimizing for LCOS as well as using FF for optimizing both LCOS and NPV.

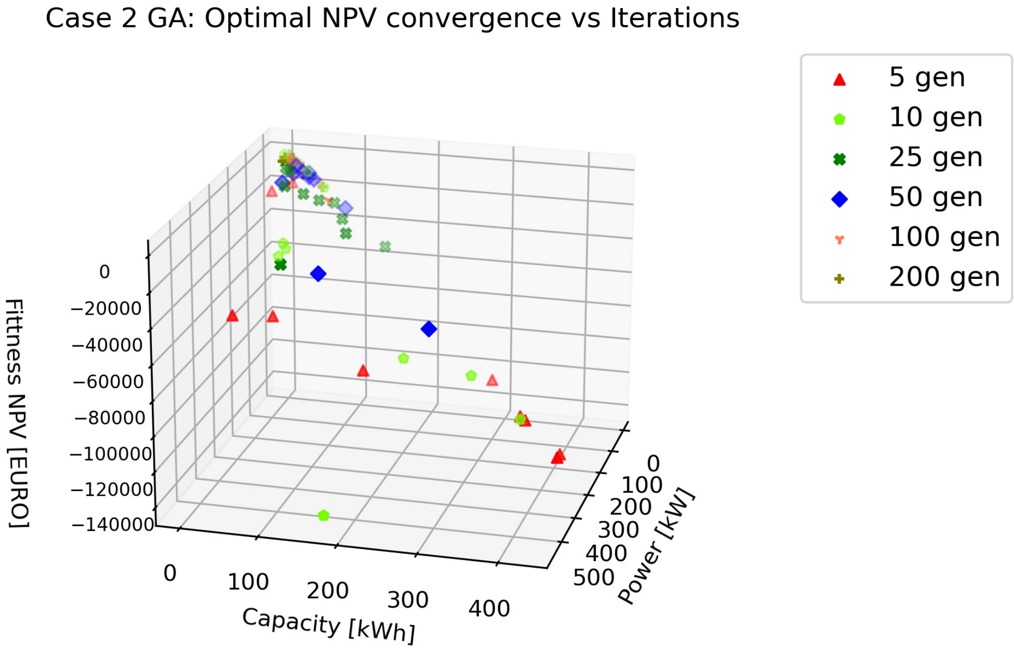

Figure 7: GA NPV convergence vs iterations

Case 2 NPV and LCOS average								
Algorithm	GA				FF			
Iteration/Data	NPV	NPV_{STD}	LCOS	$LCOS_{STD}$	NPV	NPV_{STD}	LCOS	$LCOS_{STD}$
5	-84239	41020	0.227633	0.0017242	-346009	175789	0.621763	0.349083
10	-59018	44211	0.226897	0.00127705	-37761	201	0.432304	0.514233
25	-27720	14511	0.226745	0.00089996	-51.5	0	0.253808	0
50	-24993	22720	0.226068	0.00040577	-51.5	0	0.253808	0
100	-10614	6623	0.225877	0.00025301	-51.5	0	0.253808	0
200	-6316	4756	0.225656	0.00025179	-51.5	0	0.253808	0

Table 7: Result from case 2: Average NPV and LCOS

Case 2 Capacity and Power average								
Algorithm	GA				FF			
Iteration/Data	NPV: Capacity	NPV: Power	LCOS: Capacity	LCOS: Power	NPV: Capacity	NPV: Power	LCOS: Capacity	LCOS: 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	NPV: $Capacity_{STD}$	NPV: $Power_{STD}$	LCOS: $Capacity_{STD}$	LCOS: $Power_{STD}$	NPV: $Capacity_{STD}$	NPV: $Power_{STD}$	LCOS: $Capacity_{STD}$	LCOS: $Power_{STD}$
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 8: Result from case 2: Average Capacity and Power

10.3 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 9. 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 that will say the minimum value of 0.1 for all the solution parameters (BESS capacity, power and ELH power). Comparing GA and FF for case 3 it can be seen that the STD of the NPV for FF is not reducing, in other words, it is not converging with an increase of iterations. Which can be seen for the STD of NPV for the GA, which 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 8 shows an 3D graph of the different solutions depending on number of iterations for GA when optimizing for NPV. It can be seen how higher iterations converges NPV to similar solutions, as it did it case 2. For 3D plots using FF and optimizing for LCOS as well see appendix C. From these plots it can be seen that 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, FF seems to get stuck at 0.1 and therefore converges at a local optimum.

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 9: Result from case 3: Average NPV and LCOS

The results regarding saved CO_2 emissions due to the installment of the ELH is presented in table 10. These results are for 200 iterations, meaning the optimization when the solution have had most steps to converge. These values are the best result from the 10 runs. As can be seen when optimizing for NPV both FF and GA finds solution with a high power installment for the ELH. What is interesting to see that the difference in size is quite different but the amount of heating supplied by the ELH is all above 95% or more except for the the LCOS case when using FF. This case find 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, that will say not having installed the ELH at all. It can be seen that 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 is more interesting is that 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.

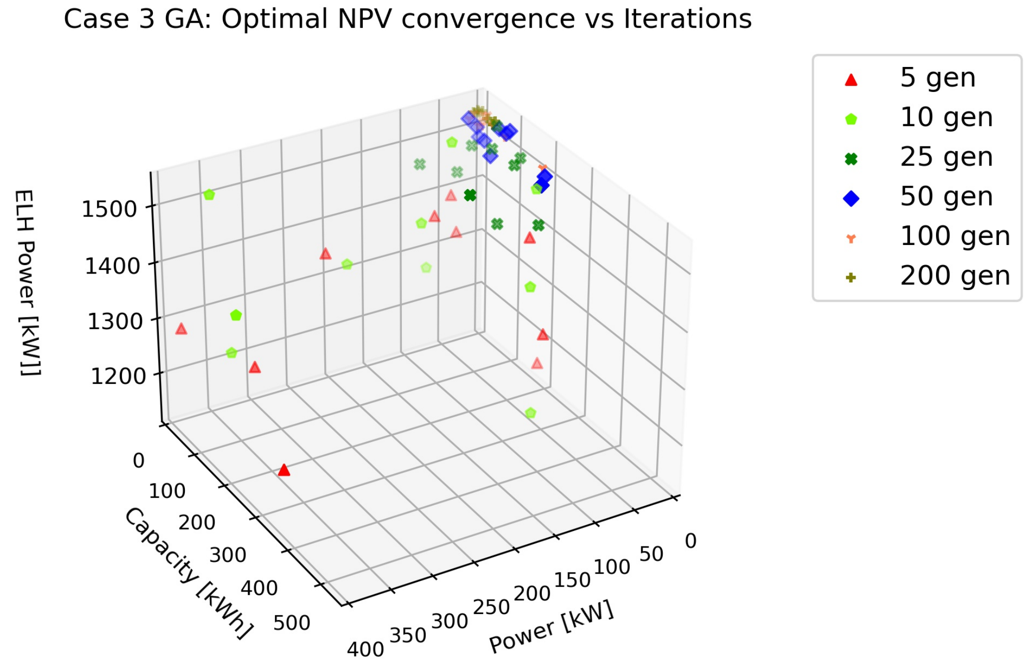

Figure 8: Case 3 GA: Optimal NPV vs Iterations

Case 3 Best NPV and LCOS results 200 iterations				
Algorithm	GA		FF	
Optimize for:	NPV	LCOS	NPV	LCOS
Fitness Value [Euro][Euro/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 10: Result from case 3: BEST NPV and LCOS

10.4 Optimizing time and STD

From figure 9 the average time from the ten runs and STD of the time for the different 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 it can be seen that FF take overall longer time to run the optimization for all cases compared to the GA. Looking at the right plot in figure 9 the STD is increasing for all cases/algorithms for both FF and GA, but as can be seen here also is that 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 compare to the GA. Important to notice is that in this figure a log scale for the y axis i used whilst for the left plot have a regular scale for its y axis.

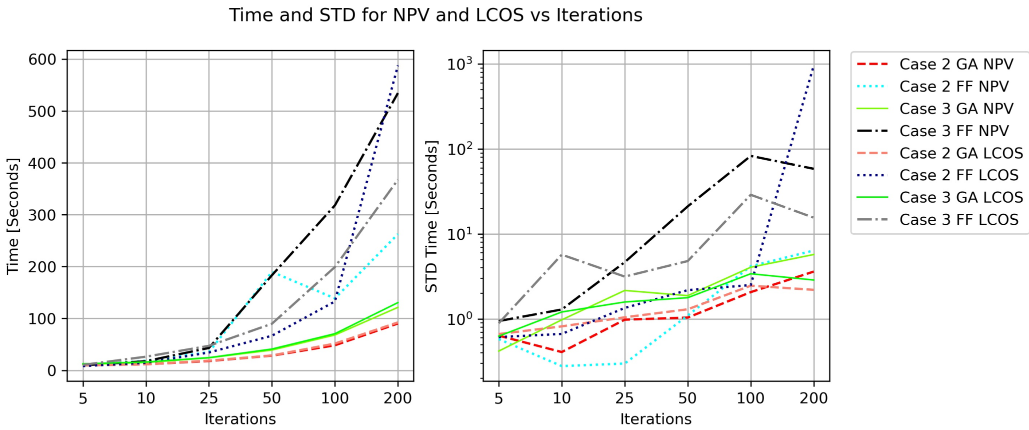

Figure 9: Optimization time for all cases with STD

10.5 Schedule function

Figure 10 shows the usage of the BESS during the last year of the optimization when using the GA, for the the different cases and value to optimize for. As can be seen when optimizing for NPV, low values for the capacity and power is found. Using the schedule function using these low values it can be seen that the BESS is only used for about 14% evenly split 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 the BESS is still passive and staying idle for around 65% of the year. Figure 19 in appendix D shows the average charging cost compared to the average profits from discharge and peak shaving using the BESS when optimizing for NPV. As can be seen the cost of charging is sometimes even higher then the profits from discharging the BESS. This probably 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 10.2. Therefore the main monetary value gained is from the peak shaving.

10.6 Sensitivity analysis of case 2

The results for the sensitivity analysis of case 2 can be seen in figure 11. The analysis looked at the effect that a positive or negative change in CAPEX for both the power and capacity of the battery would have on the final results of NPV or LCOS. These results are the average from 10 and compared to the base optimization results. It can be seen that the LCOS is linearly dependent on the CAPEX, which is expected as the LCOS is only dependent on the CAPEX, OPEX and the charging cost, and the other two variables stays unchanged. For the NPV the sensitivity analysis shows the expected trend that the higher the CAPEX the lower the value for the NPV. For GA it can be seen that it even gets a lower NPV at lower CAPEX (-10%) which is counter intuitive but shows the randomness of the GA and how it can't get the global optimum value each time due to its heuristic nature. The NPV for FF is barely noticeable the difference between CAPEX, this is due to finding an optimum solution at the lowest possible value for the capacity and power (at 0.1 kWh and 0.1 kW for the capacity and power respectively) for all different values for the CAPEX, but follows a linear trend.

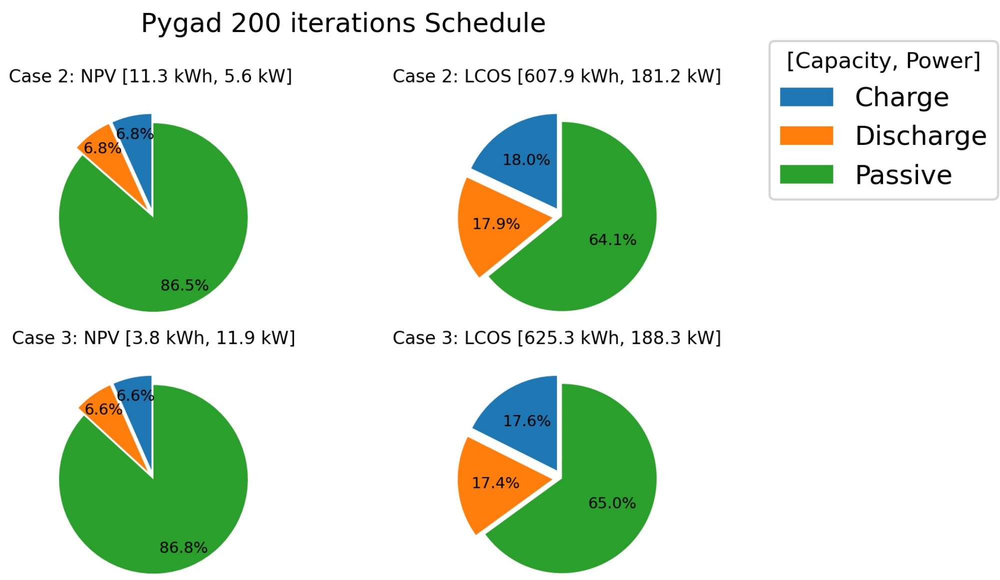

Figure 10: Usage of BESS during the last year (10th) of optimization

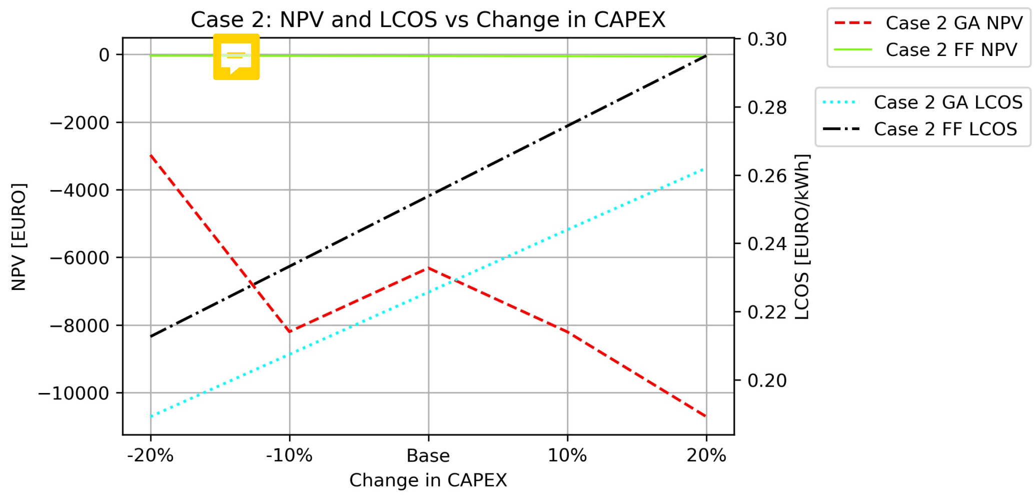

Figure 11: Case 2: NPV and LCOS dependence on CAPEX

11 Discussion

For case 2 NPV was negative for all cases showing that for the case study energy arbitrage 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 Euro/kWh and 0.2308 Euro/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 Euro/kWh - 0.2704 Euro/kWh in 2022 Euro values) [60]. Which would mean that the algorithm (GA) can find solutions for LCOS that are reasonable compared to the real world values, and therefor can be a useful tool in the choice of size for battery energy storage when optimizing for LCOS.

The schedule function used in this thesis is using a simple methodology, as could be seen on the results this leads to a low usage of the BESS during a year. The main methodology of 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 the monetary value increasing the NPV is therefore not from energy arbitrage but from the peak shaving. As the schedule function is only focused on scheduling the charge and discharge for energy arbitrage their is a possibility that more value can be gained by instead focusing on peak shaving using the BESS or finding a methodology that takes into account both energy arbitrage and peak shaving for the charge and discharge schedule.

11.1 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, which gives it a 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. The sensitivity analysis analysis showed how GA even with lower CAPEX then the base optimization got worse results for NPV showing the unpredictability of the GA. These results follows the characteristics of GA and FF that Khan and Singh [61] found that FF have a high optimization time whilst the results from GA 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 the best solutions with zero STD for 25+ iterations, whilst 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 7, for all iterations).

11.2 Future work

The schedule functions 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 have used different meta heuristic algorithms to find that for specific sizes of BESS capacity and power as shown in the literature study in section 7. Therefore it could be of interest to look into 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 look into is the model for battery capacity degradation, as it is a linear function, 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 have 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 then the max allowed value for the ELH, optimizing for the optimal ELH size could be of interest, or looking at optimal reduction in CO_2 emissions as the fitness value.

11.3 Sources of errors

The variable O&M cost for Li-ion batter is energy storage is from different ESS technologies and could therefore be very far off. but as the cost is fairly low compared to the fixed O&M cost as well to the CAPEX of the BESS storage this should have fairly small effect on the final results. Another source of error for the case study results is the battery capacity degradation is a linear function, but is in fact non-linear and depends on factors such as, state of charge, depth of discharge, C-rate and temperature to name a few [62].

12 Conclusion

From the Literature review two meta heuristic algorithms was found to be of interest as methods to find the optimal Capacity and Power for a BESS, GA and FF. Using these algorithms on the case study it was found that for case 2 GA was able to find better LCOS at 0.225656 Euro/kWh at 200 iterations compared to 0.253808 Euro/kWh for FF. For the NPV for case 2 FF found the better value at -51.5 Euro at 200 iterations with an STD of 0, whilst GA found an average value -6316 Euro ~~with~~ and STD of 4756. For case 3 with the ELH also included as a changeable parameter, GA gave superior results for both NPV at 948055 EURO with an STD of 7450, and LCOS at 0.230812 Euro/kWh with an STD of 0.0003096 at 200 iterations. Compared this to FF with an NPV of 399116 Euro and an STD of 212844, and LCOS of 0.253808 Euro/kWh with an STD of zero. GA had for all cases and iterations lower optimization time then FF. From the results it could also be seen that for higher iterations both GA and FF converges 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. From the case study it is also seen that the charge/discharge schedule functions is of importance for the effectiveness of energy arbitrage and peak shaving.

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14 Appendix

A Schedule flowchart

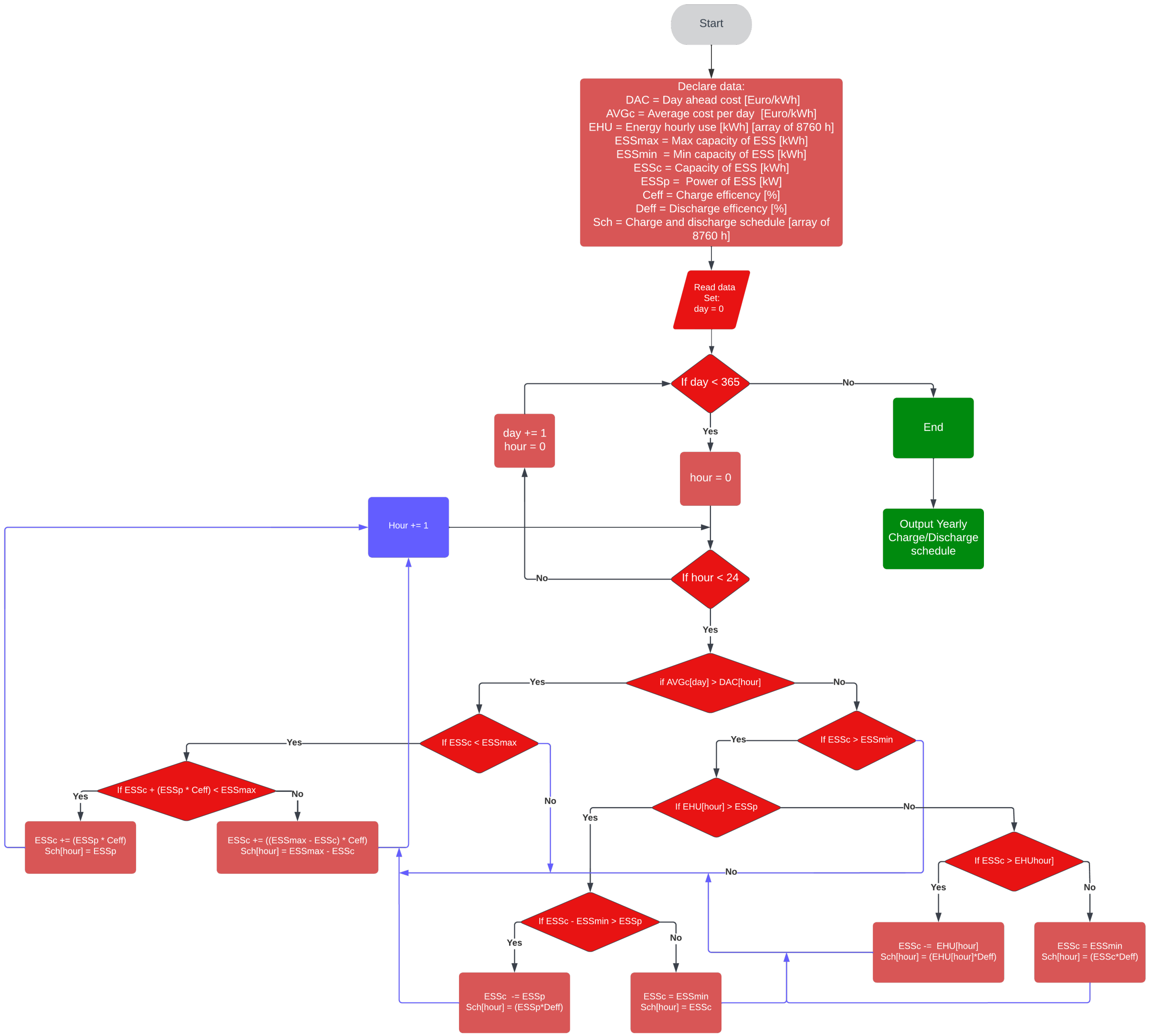

Figure 12: Charge/Discharge schedule Flowchart

B Case 2 Results: 3D Plots

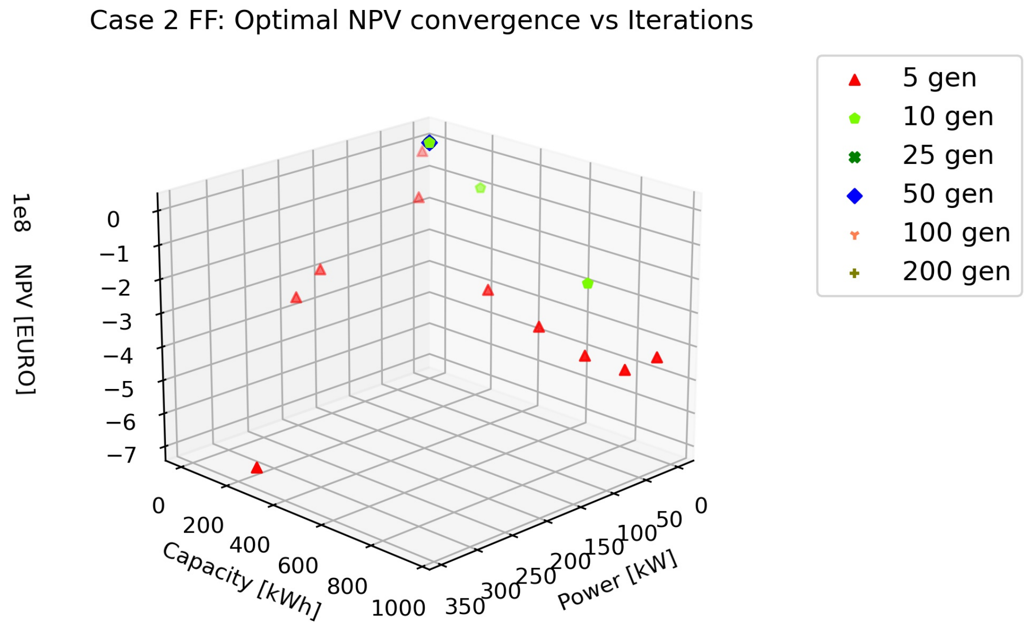

Figure 13: Case 2: FF NPV convergence vs iterations

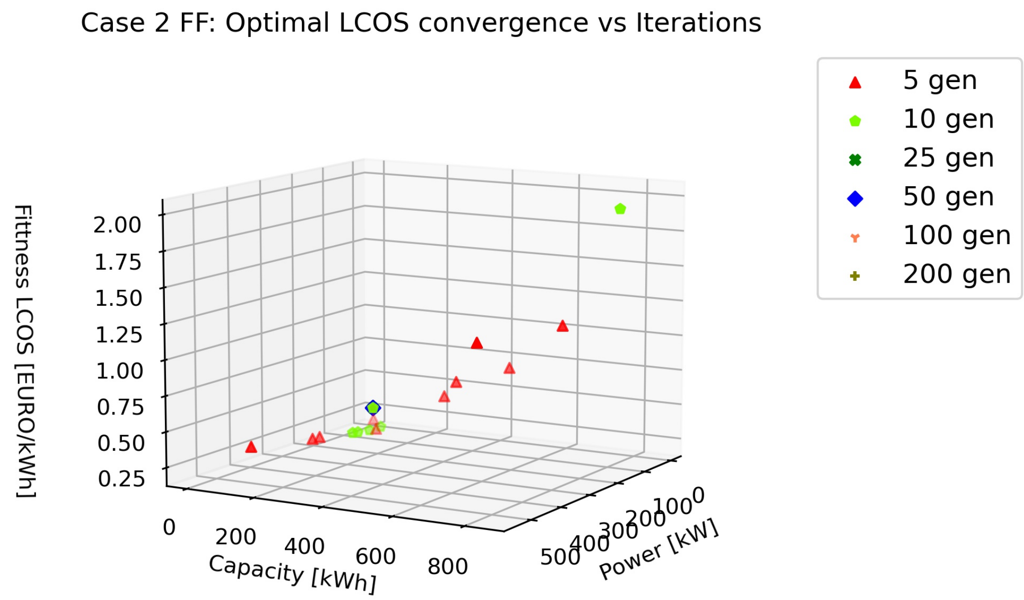

Figure 14: Case 2: FF LCOS convergence vs iterations

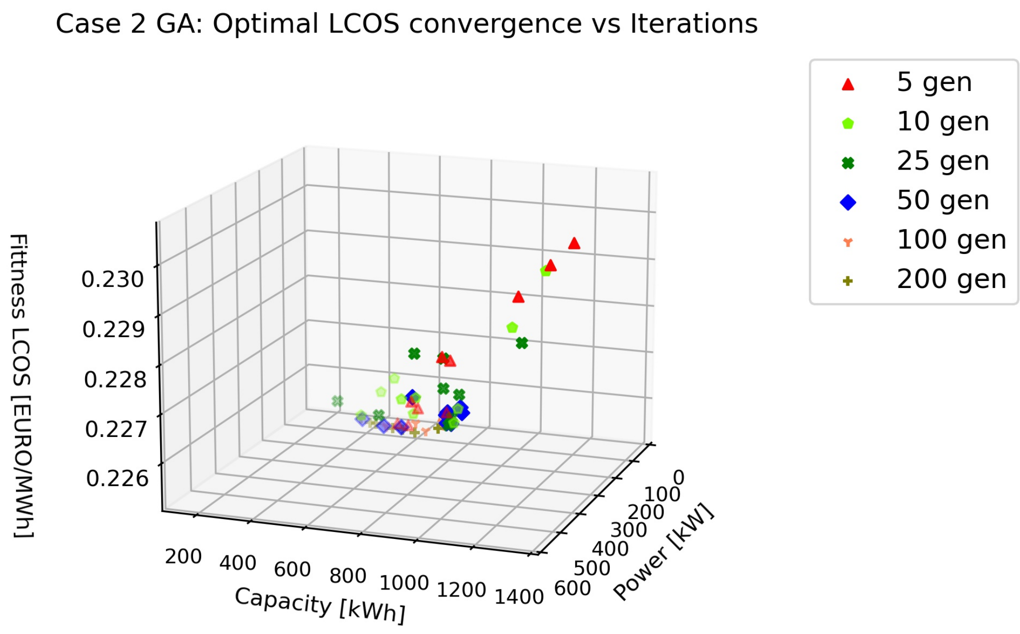

Figure 15: Case 2: GA LCOS convergence vs iterations

C Case 3 Results: 3D Plots

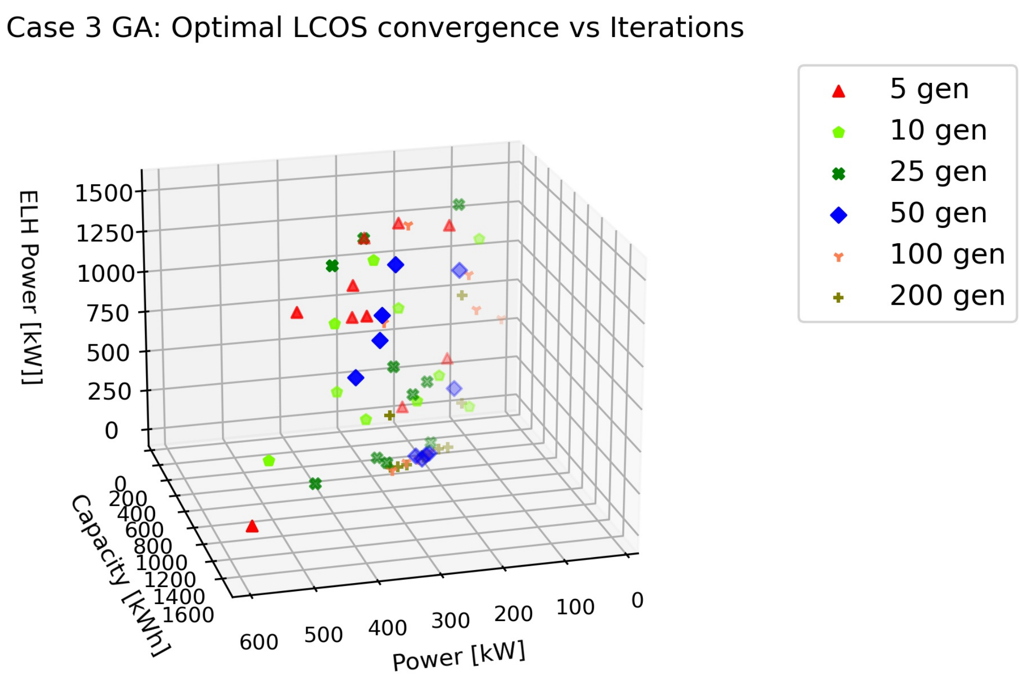

Figure 16: Case 3: GA LCOS convergence vs iterations

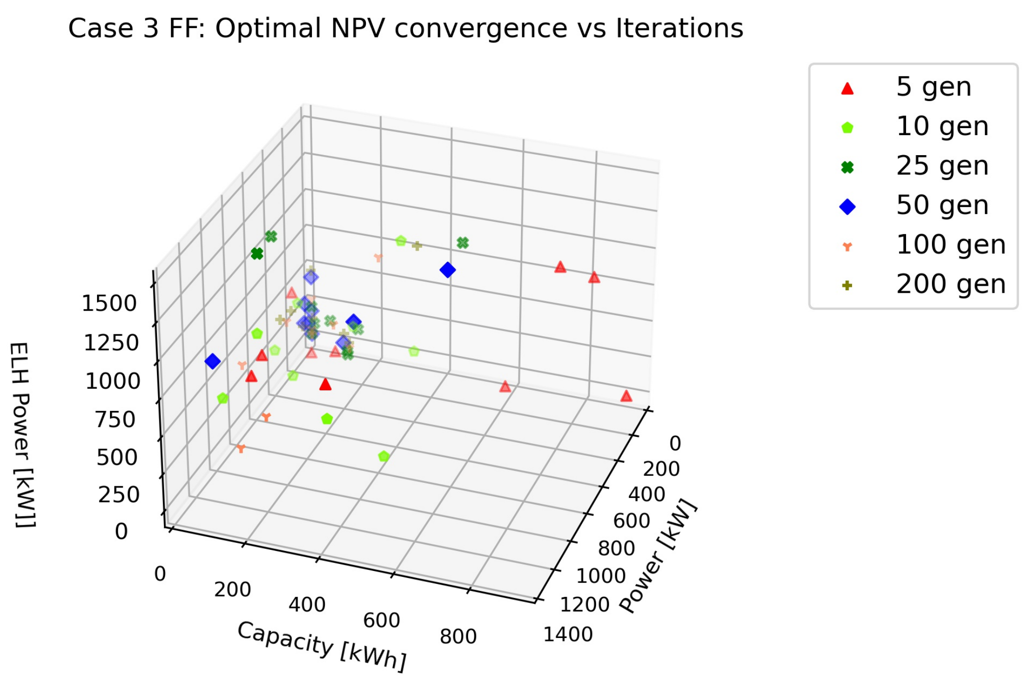

Figure 17: Case 3: FF NPV convergence vs iterations

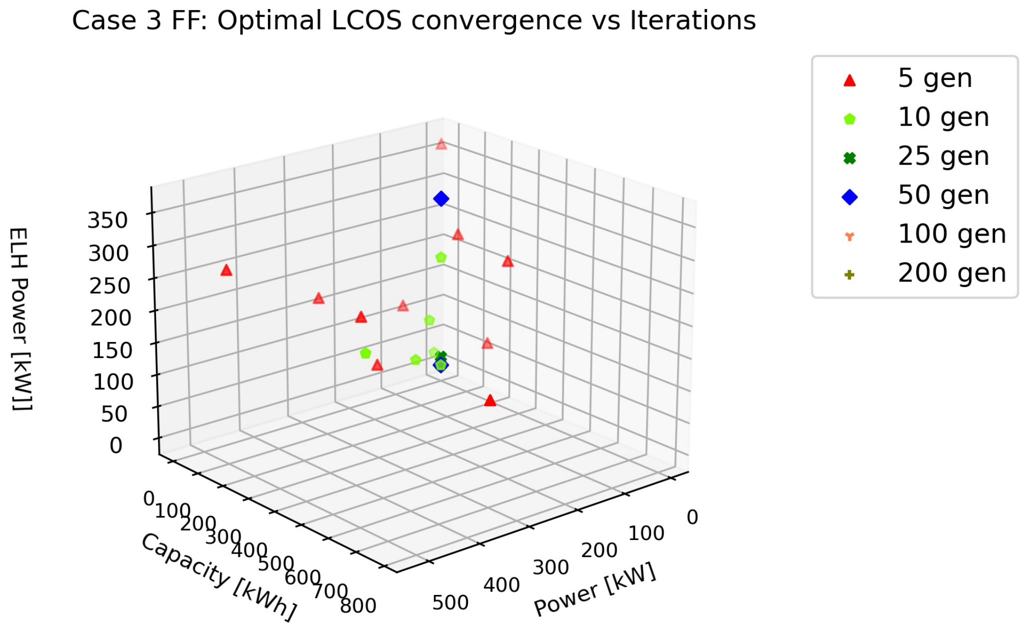

Figure 18: Case 3: FF LCOS convergence vs iterations

D Cost and profit

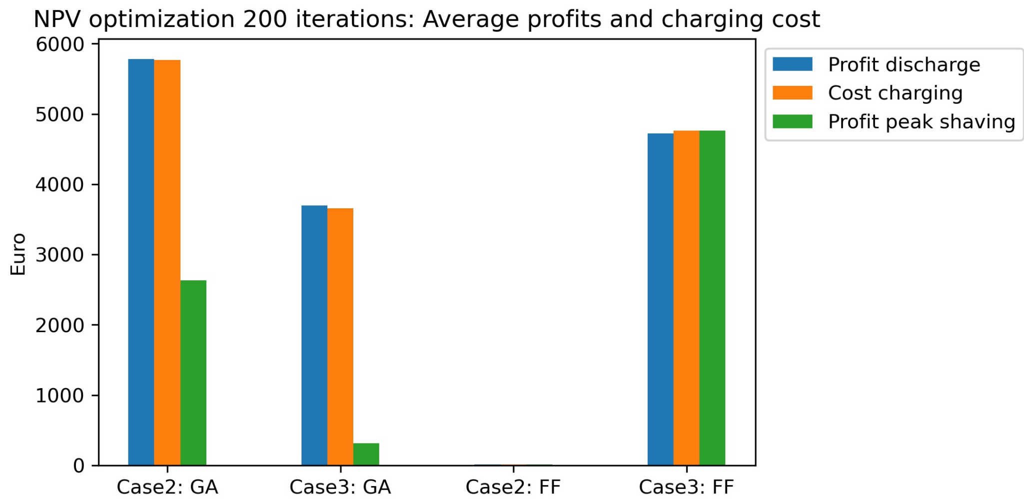

Figure 19: NPV 200 iterations: Charging cost and profits