# SMART INTEGRATION OF ELECTRICITY GRID, MICRO GRIDS AND DATA CENTER

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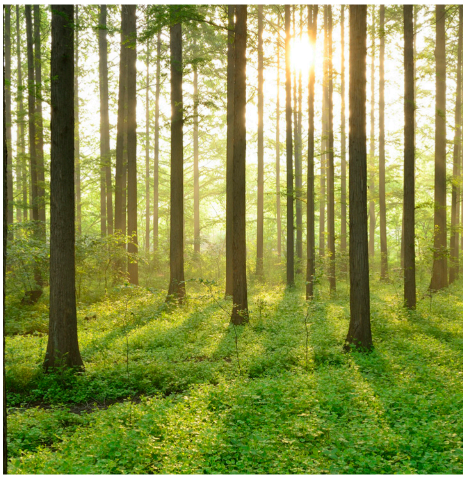

ELNÄTENS DIGITALISERING
OCH IT-SÄKERHET

Energiforsk

# Smart Integration of Electricity Grid, Micro Grids and Data Center


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# Förord

**Projektet *Smart integration av elnät, mikronät och datacenter* tillhör programmet Elnätens digitalisering och IT-säkerhet och syftar till att studera hur olika abonnemang och tariffer påverkar driften av ett AI-kontrollerat mikronät där lasten utgörs av ett datacenter. Projekt har studerat optimering av datacenter genom styrning av el, last och kyla. Tariffer är framtagna genom AI som gynnar datacenter-, mikro- och elnätsägare.**

Vid RISE ICE anläggning för datacenterforskning i Luleå bedrivs ett flertal projekt i nära samarbete med både industri och akademi. Genom att använda verkliga anläggningar kan empirisk forskning både på industriell användning och kontrollerad belastning göras. Mikko Siltala, Tina Stark och Mattias Vesterlund på RISE har varit engagerade i projektet.

Energiforsk vill framföra varmt tack till referensgruppen som bidragit till projektet:

- Adam Nilsson, Jämtkraft
- Petra Josefsson, Vattenfall
- Emil Rehnstedt, Gävle energi

Stort tack också till programstyrelsen för programmet som består av ledamöterna:

- Kristina Nilsson, Ellevio (ordförande)
- Arne Berlin, Vattenfall Eldistribution
- Hampus Bergquist, Svenska kraftnät
- Ferruccio Vuinovich, Göteborg Energi
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Stockholm i augusti 2022
*Susanne Stjernfeldt*

# Summary


**With machine learning and Artificial Intelligence, it is possible to reduce the operation cost of a data center microgrid and with a variable electricity pricing the use of renewable electricity could be encouraged.**

The increasing growth of the ICT-sector when introducing IoT and 5G has made data center a part of the industrial ecology. Data center is a power demanding industry and is using about 1-2% of the global electricity production, where this project aims to study how the electricity pricing could affect the data center operation. To do that a data center at RISE ICE is studied containing a microgrid with a controller for the solar panels and battery storage, a chiller with free cooling possibility and a cold thermal storage. This is done by first creating a model of the data center microgrid which is the base for operation optimization and self-optimization by using "reinforcement learning", as a final step the model is used for evaluation of different power and energy tariffs.

The data center microgrid was modelled in MATLAB and Simulink with a resolution of 1 hour. The microgrid operation was optimized by using linear programing, grid search, brute force, and system identification. To analyze the pricing of electricity different tariffs are applied, simple tariff, time tariff, power tariff and time and power tariff.

The results shows that tariffs are a good way to affect the operation of the data center to make use of both grid and self-produced renewable power, by this a microgrid would influence the power grid and increase its utilization. With a variable electricity price, the use of batteries could be encouraged. A combination of a variable energy fee and power fee is good in order to make operation optimization feasible and still reduce peak power load. The optimization shows that it is possible to reduce the data center operation cost and by that recoup some of the investments without reducing the battery lifetime. A self-optimization algorithm can succeed in finding the optimal control plan for reducing the operational costs within a specified time horizon.


# Keywords

*Data center, microgrid, machine learning, tariffs, energy arbitrage, optimization.*

# Sammanfattning

**Med hjälp av machine learning och artificiell intelligens är det möjligt att reducera driftkostnaden av ett datacentermikronät och med ett variabelt elpris främjas användning av förnyelsebar energi.**

Den ökade utbyggnaden av ICT-sektorn och med introduceringen av IoT samt 5G har gjort datacenter till en del av den industriella ekologin. Datacenter är en energikrävande industri och använder cirka 1 – 2% av den globala elproduktionen, där detta projekt syftar till att studera hur elprissättningen kan påverka datacenterdriften. För att göra det studeras ett datacentermikronät på RISE ICE innehållande ett mikronät med en styrenhet för solpaneler och batterilagring, en kylare med möjlighet till fri kylning och ett kyl-lager. Detta görs genom att först skapa en modell av datacentrets mikronät som är basen för driftoptimering och självoptimering genom att använda ”reinforcement learning”. Som ett sista steg används modellen för utvärdering av olika effekt- och energitariffer.

Datacentermikronätet modellerades i MATLAB och Simulink med en upplösning på 1 timme. Mikronätsdriften optimerades genom att använda linjär programmering, rutnätssökning, brute force och systemidentifiering. För att analysera prissättningen av el tillämpas olika tariffer, enkel tariff, tidstariff, effekttariff samt tid- och effekttariff.

Resultaten visar att tariffer är ett bra sätt att påverka driften av datacentret för att ta tillvara både på nät- och egenproducerad förnybar kraft. Genom detta skulle ett mikronät påverka elnätet och öka dess utnyttjande. Med ett rörligt elpris skulle användningen av batterier kunna uppmuntras. En kombination av en rörlig energiavgift och effektavgift är bra för att göra driftoptimering möjlig och samtidigt minska toppeffektbelastningen. Optimeringen visar att det är möjligt att minska driftkostnaden för datacentret och på så sätt få tillbaka en del av investeringarna utan att förkorta batteritiden. En självoptimeringsalgoritm kan lyckas hitta den optimala styrplanen för att minska driftskostnaderna inom en angiven tidshorisont.

# List of content

# 1 Introduction

The global number of data centers and their use of electricity is growing fast because of the increasing need of data processing, today the ICT sector stands for about 1 – 2% of the total global power consumption (van Heddeghem, o.a., 2014) and is estimated to increase to 8 – 21% until 2030 (Jones, 2018). With the growing trend of IoT and introduction of 5G more compute power will be needed closer to the end user, by this the data center development is estimated in the direction of more small, distributed data centers as Edge nodes.

As Edge data centers are installed close to the user there is still a need of methods for making them sustainability friendly by using as much renewable energy and free cooling as possible. It would also be possible to use the Edge data center as grid stabilator if it has battery backup, which means that during periods when the grid has high load level the Edge data center could reduce its need of grid power and by that increase the grid utilization rate. With machine learning methods, operations can be optimized to both reduce the operations cost and support the grid. By combining renewable energy sources and both thermal and electrical storage to an Edge data center it could contribute to a more sustainable society and power grid that is better used.

## 1.1 MICROGRID

Many different things can be included in the word microgrid. Within this document and the scope of this project we have used the following definition: "An independent energy system with local electricity production and energy storage, that can be disconnected from the distribution grid and be run in island mode of operation." (Energiforsk, 2021) The microgrid can for example consist of batteries, solar panels, thermal storage etc.

### 1.1.1 Data center Microgrid Integration test bed

At RISE ICE Data center facility in Luleå there is a data center microgrid integration (DMI) test bed that the models in this project are based on. In addition to the 10kW of IT, the DMI test bed is equipped with a thermal energy storage (TES) tank and a microgrid with photovoltaic cells and batteries allowing for experimentation on using alternative energy sources, reliability and partial self-sufficiency for micro-grid connected data centers. The test bed has been reported earlier (Brännvall, o.a., 2020) and can be seen in figure 1 but is briefly summarized below.

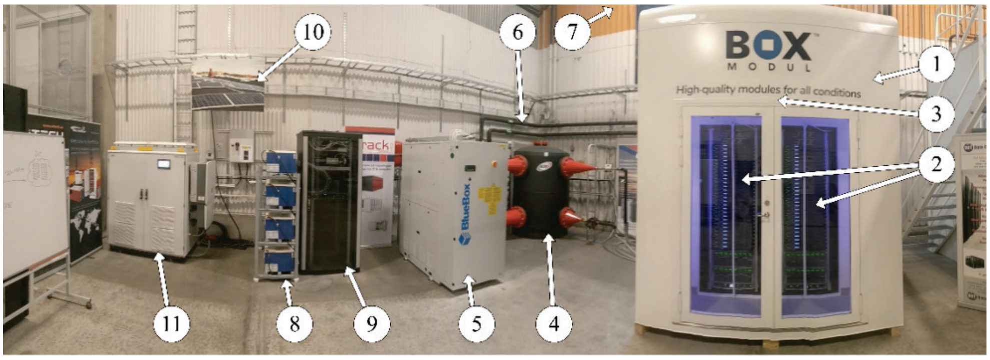


**Figure 1. DMI test bed: (1) The data center module. (2) Two server racks. (3) CRAH (mounted above the racks). (4) The coolant water storage tank. (5) Chiller. (6) Coolant pipes going to the roof. (7) Cooling tower (on the roof). (8) Batteries. (9) The measurement and control system. (10) Picture of the solar panels (on the roof). (11) Microgrid inverter.**

1. Data center module. A sheet metal container, which is separated into a cold and hot aisle (full containment).

2. Two server racks are positioned between the aisles with 38 Dell PowerEdge R430 servers each. The servers have a total idle load of about 6 kW, and a maximum load of around 12 kW.

3. An air-to-water heat exchanger (CRAH) sits above the racks providing cooling air in the closed loop between the hot and the cold aisle.

4. The storage tank has a capacity of 2000 liters and is filled with water that is circulated through the module heat exchanger and chiller. Flow diffusers and nozzles (red cones in picture) helps to create a laminar flow in the tank.

5. The chiller unit has three modes of operation: chiller mode of 23 kW at 4,5 electrical power usage, free cooling mode, and a partial free cooling mode. The first two modes cool the incoming water by vapor-compression technology or liquid-to-liquid heat-exchange technology, respectively, and the third mode uses both methods. The free cooling mode is used when the outside temperature is low, and vapor-compressor is not required to increase the temperature difference between the water and glycol.

6. Cooling tower pipes carry the glycol-mixture from the chiller to the dry cooler and back again.

7. The cooling tower is an air-liquid dry-cooler of 28 kW at 2,1 kW of electrical power usage, where outside air is forced through the heat exchanger, removing some of the heat in the liquid received from the chiller.

8. Lead-acid batteries with capacity to hold 30 kWh of electrical energy.

9. A measurement and control system collects sensor data and sends it downstream for storage, visualization, analysis, and input to control algorithms.

10. The solar panels on the roof of the facility have a maximum capacity of 10 kW.
11. The microgrid inverter connects the data center system with the nominal external load power of 20 kW, a maximum solar panels power of 24 kW, and a maximum battery charging power of 12 kW.

The inputs used to control the system are:

- IT load setpoint determines the synthetic load placed on servers by the stress-ng software.
- Chiller output setpoint is the temperature of the water the chiller outputs to the storage tank.
- Pump setpoint controls the pump between the storage tank and module heat exchanger.
- Fan setpoint for the module heat exchanger fan.

## 1.2 ELECTRICITY TARIFFS

In Sweden we have a deregulated electricity market. As a customer you can decide who you want to buy electricity from, but the electricity distribution takes place via the electricity network monopoly. So, to get electricity in Sweden you need two contracts. One with the electricity network operator who owns and operates the power grid where one is located and one with an electricity supplier who sell the electricity. (Swedish Energy Markets Inspectorate, 2022) In addition to the fees from these two contracts, energy taxes also need to be paid.

Sweden is divided in four electricity areas from area Luleå (SE1) in the north to area Malmö (SE4) in the south. The price can vary between these areas since there are an electricity surplus in the north and a shortfall in the south. Therefore, a huge amount of electricity is transported from the north to the south and the boarders between the different areas are located where limitation in the electric grid is situated. The electricity price in each electricity areas is decides by supply and demand on the electricity market and the transmission capacity between the areas. (Svenska kraftnät, 2021)

### 1.2.1 Electricity price

For the electricity supplier contract the customer can usually choose from fixed or variable rate. For fixed price agreement one sign a fixed price per kilowatt hours for usually, one, two or three years. The fee for electricity certificate is usually included in the price.

The contract form variable price will follow the development on the electricity market Nord pool and the price per day will fluctuate. The customer can often choose to have a variable monthly price or an hourly price, so called "time-of-use-pricing" (TOU). With a TOU agreement the user can affect their cost by using electricity when the price is cheaper, and demand is lower. (Konsumenternas Energimarknadsbyrå, 2022)

In this project two electricity price has been considered, a variable hourly rated price (TOU) and a fixed price. More about that in chapter 2.4.

### 1.2.2 Electricity network tariffs

In Sweden there are around 170 electricity grid operators who's responsible for different parts of the electricity network in the country. (Swedish Energy Markets Inspectorate, 2021) Each grid operator decides their own design of the tariff but is usually divided into a variable and a fixed part. The fixed part (subscription fee) varies with the fuse size or the subscripted power. The variable part (electricity transmission fee) changes with the customers electricity consumption.

In this project four different tariffs used in Sweden has been examined and below, the variable rate for the tariffs will be explained.

- **Simple** – a fixed electricity transmission fee per kWh.
- **Time** – the electricity transmission fee varies depending on the season and time of day, divided in two different fees (SEK/kWh), "high load time" and "low load time". High load time is defined as Monday to Friday, 6am to 22pm during the months of November, December, January, February, and March. All other hours of the year are low load time.
- **Power** – the electricity transmission fee is based on the average peak power. Each company calculates the average peak power a bit different, but in this tariff the power value is the measured mean hour value for the highest power peak of one month (SEK/kW per month).
- **Time and power** – the electricity transmission fee consist of both the time and power tariff fees. One fee for high load/low load time (SEK/kWh) and one power fee for the average highest peak (SEK/kW per month).

## 1.3 MACHINE LEARNING AND OPTIMISATION METHODS

Machine learning is a branch within artificial intelligence and computer science that uses algorithms and data to imitate how the human mind learn. The algorithm uses sample data, called training data, to learn from and identify patterns. (Tamir, 2020) describes that a typical machine learning algorithm consist of three components:

- **A decision process:** Based on some input data, the algorithm will make a "guess" about a pattern in the data the algorithm is trying to find.
- **An error function:** It evaluates the guess of the model by comparing it to known examples (if available). It assesses how good (or bad) the guess was.
- **An updating or optimization process:** The weights of the model are adjusted to decrease the discrepancy between the known example and the guess. This so that the next guess will be more accurate.

The model uses this iterative process to learn from itself and the data it analyses and improve the accuracy for each run.

Optimization is the finding of the best solution for a set of possible alternatives, with regards to some criteria. There are many different methods used, but the simplest case is finding the correct input values to a function that maximize or minimize the result of computing that equation.

### 1.3.1 Grid search / Brute force

Grid search is a method for parameter optimization where a grid is created with the dimension of the number of adjustable parameters. The case for a three-dimensional problem produces a grid which can be seen in figure 2. For each parameter a range of possible values is defined, and the result for all possible parameter combinations are computed to minimize identify the minimum of the objective function.

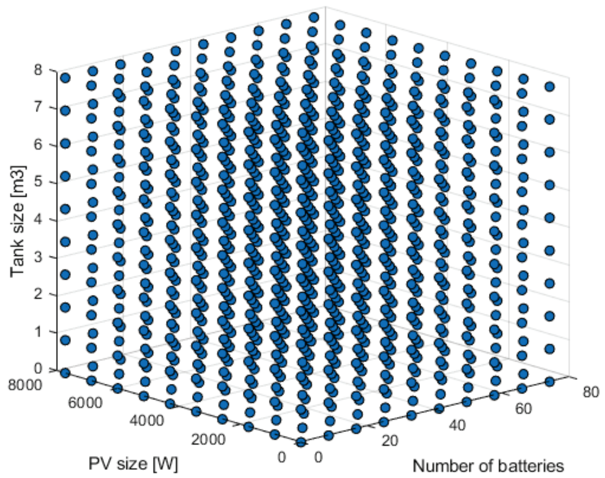


**Figure 2. Example graph of the 3-dimensional grid search for identifying optimal dimensions of microgrid components.**

### 1.3.2 Linear programming

Linear programming is a method for finding an optimal solution to an objective function that obeys linear limitations. The method is guaranteed to find the optimal solution, given that there exists one, that satisfies all the given limitations.

The linear program is commonly expressed in the form

Find a vector $x$

that maximizes $c^T x$

subject to $Ax \leq b$

and $x \geq 0$

Which can be read as; find a vector $x$ of the adjustable parameters that maximizes the objective function $c^T x$, which is subject to the linear inequalities $Ax \leq b$ and $x \geq 0$.

Not all systems are inherently linear, but by carefully linearizing a nonlinear system it may be represented with linear relationships without affecting the solution too much.

### 1.3.3 System identification

System identification is the act of building mathematical models from input-output data. It is a powerful method of creating models which relies on real measurements instead of expert knowledge on a system. Some of the benefits include the lack of need for human understanding of a system, the accuracy of the resulting model and speed of implementation. There exist multiple solvers for this problem, but they all attempt to minimize the error of the model response to input data, and the actual output data.

The concept of system identification may be utilized with equations of multiple formats, such as with a polynomial equation or a state space model.

A state space model is a mathematical modelling method for representing a system which is often used in control theory. In simple terms a state space model uses the inputs and current state of a system to compute the system outputs.

A state space model is generally written as:

$$\dot{x}(t) = Ax(t) + Bu(t)$$
$$y(t) = Cx(t) + Du(t)$$

Where the x(t) represents the state vector of the system, u(t) the input vector and $y(t)$ the output vector.

## 1.4 AIM AND OBJECTIVE

On today’s electricity market the electricity price varies over the day and season with the supply of intermittent renewable energy sources. In addition, the IT load in data centers also varies. For electricity intensive industries, such as data centers with microgrids, there is a lack of knowledge of the most effective operating strategy for the micro grid with the tariffs that are available today. The aim of the project is to find benefits for the data center, microgrid and electrical grid owners through innovative tariffs and optimization. By doing this the benefit for the microgrid owner is maximized, and the benefit for the electrical grid owner can be adjusted by the setting of the tariff.

The division to tasks proposed in the application was followed as the ‘red thread’ through this project. The project was envisioned as having 4 separate activities, each with their own specific goals. The activities also built on the work and successes of the previous activities in a linear manner, where task 1 and 2 builds the system and models that is being used in task 3 and 4. The original description was written in Swedish, but the activities are summarized in English here, and described in more detail in their respective chapters under methodology.

### 1.4.1 Task 1, Machine learning for microgrid optimization

A microgrid with energy storage has a great potential of optimization for reducing the operation cost and help stabilize the electricity grid.

By building a machine learning model for the Data center Microgrid Integration (DMI) test bed at RISE ICE Data center in Luleå, methods for optimized operations can be developed for different operation conditions and price levels. By analyzing the models, the data center and microgrid owners get knowledge about operation strategies and how they can optimize design and operation of the microgrid.

### 1.4.2 Task 2, Machine learning for optimizing data center operations integration

With the help of methods based on machine learning, optimization for the data center and integration with the electricity grid is done. Models based on load, weather and other external circumstances can be developed for the DMI test bed and be optimized with respect to cost, energy efficiency or data processing performance. By analyzing integrations and environment parameters, the data center owner will get knowledge for making optimization possible.

### 1.4.3 Task 3, Self-optimization of data center and microgrid integration

For smaller facilities or facilities located far away the human interaction wants to be minimized to lower the operation costs. For this, self-regulated and self-optimization methods are needed. It is called "lights-out" or "zero-touch" operation and can result in an increased flexibility and lower costs.

With the help of methods based on so called "reinforcement learning", continuous self-optimization is done for the data center, microgrid and its integration with the electricity grid. Models are developed for the DMI test bed and can be used to achieve optimized operation without human interaction.

By letting the system itself analyses the integration and environment parameters to achieve operation optimum, the data center owner gets knowledge about how the self-optimization can be used.

### 1.4.4 Task 4, Business models and tariffs for industrial symbiosis

There is a possibility to use a data center as an active customer on the electricity market. If there also are storage options and own production of renewable electricity on the site, the possibility increases.

By using the machine learning model for the DMI test bed, the most favorable pricing can be obtained for the most advantageous integration for all parties. By analyzing different pricing to finding the optimal for a more stable grid in symbiosis with all parties, the electricity grid owner will get knowledge about how they can encourage customers to install small-scale renewable electricity production.

## 1.5 SCOPE

In this project the focus is on Edge data centers i.e., small data centers. The scope is an individual microgrid with only a data center as its customer. The models that are being developed is based on the DMI test bed at RISE ICE test and demo facility in Luleå. One can change the price area within Sweden but not change where the facility physically is located in the model. Due to this, for example the solar power model uses the GPS coordinates of Luleå as input data.

The only source of electricity production for the microgrid is solar panels. A wind turbine model was previously implemented to the microgrid simulation environment (see section 2.1.1 for more information) but was not used in this project due to that the wind turbines in the model were too big for placement by an edge data center.

The data center model has a constant load profile implemented since no verification of an edge data center load profile could be find. No IT load balancing is within this scope. Nor have we looked at load balancing or utilization rate of the electricity grid but has only focus on the pricing.

## 1.6 PROJECT TEAM

This project is done by researchers at RISE, consisting of project manager Mattias Vesterlund, research and development engineers Tina Stark, Mikko Siltala, and Rickard Brännvall.

During the project we have had help from a reference group consisting of Adam Nilsson (Jämtkraft), Petra Josefsson (Vattenfall Eldistribution AB) and Emil Rehnstedt (Gävle energi). We would like to thank the reference group for their input during the project.

# 2 Methodology

In this chapter the methodology used in the project is described. It is divided in the four tasks that has been summarized in the introduction chapter earlier and is here described in more detail.

## 2.1 TASK 1 - MACHINE LEARNING METHODS FOR OPTIMIZATION OF MICROGRIDS

As we can read from the description for this task in the section 1.4.1, the aim of this task was to find optimal methods to help in the design and operation of microgrids with renewable energy production, energy storage and a data center which represents the load. The way we chose to proceed was to first develop models for representing microgrids, and then to develop the required methods for optimizing both the design and component dimensioning, as well as operating the system optimally. Due to the synergies with task 2, work on these two activities progressed largely simultaneously to allow work with similar tasks (modelling/optimization) to occur at the same time.

### 2.1.1 Microgrid model

The initial model of a microgrid was based on the DMI test bed, described in section 1.4.1, as it contains the three components, we deemed necessary for a microgrid: electrical consumption, electricity production and energy storage. The electrical load in the system is in the form of a data center and cooling system with ~10 kW + ~5 kW power requirement for the IT and cooling system respectively. In addition to the load, the microgrid is partially self-sustaining with power production from a solar array, with 10 kWp of power production. The test bed can store both electrical and thermal energy, but only the batteries within the 20 kWh uninterruptible power source (UPS) were considered a part of the microgrid-section of the test bed.

For the modelling environment MATLAB and Simulink were chosen as they are easily approachable and they support a plethora of useful tools that aid in model creation and evaluation, and to not deviate from the work environment used in the other tasks.

To optimize for the simulation runtime a large time resolution was preferred, and since the weather prediction values from most sources and the varying component of the electricity price change hourly, a resolution of 1 hour was chosen. Any resolution smaller than this would not necessarily provide us better results as the input data resolution does not increase. The resolution for electricity prices will however increase to a 15-minute resolution during 2023, which means that the model must be updated then.

A simple model structure was pursued to allow the simulations to be run efficiently in later tasks. This means that only the major dynamics of the system were modelled as can be seen from figure 3, which summarizes the main components and their respective directions of power flow, and from figure 4, which shows the resulting model within the Simulink simulation environment. Modelled are the electrical grid, the power generation of the solar cells, the power consumption by the load and the energy stored to the batteries. These components are connected to each other through the microgrid controller, and these connections are assumed to be lossless.

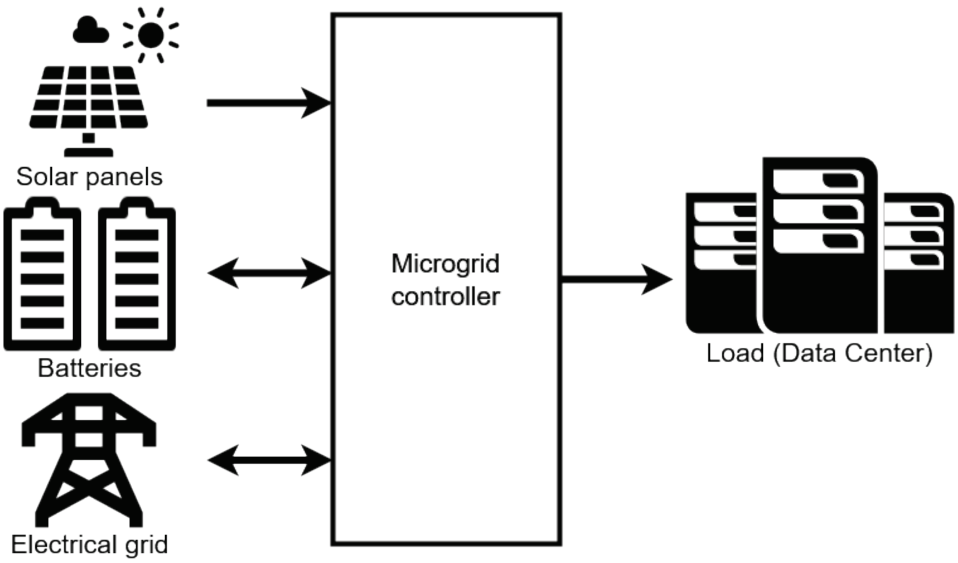


**Figure 3. Microgrid block diagram.**

The connection to the electrical grid was modelled as an infinite energy supply, where the power flow is limited by a chosen circuit breaker size. Any circuit breaker size is allowed, but sizes matching the common circuit breaker sizes are used.

For estimating the solar power generation, a mathematical model was developed. This model estimates the location of the sun in reference to any point and time on the globe and calculates the incident solar radiation based on the orientation and size of the solar array. The photovoltaic panel efficiency and predicted cloudiness are utilized to calculate the resulting power generation. The prediction of weather events was delegated to meteorologists, and we implemented ways to import weather predictions from the Swedish meteorological and hydrological institute (SMHI) to the model.

The uninterruptible power supply (UPS) or the battery system was modelled as an energy storage system with the appropriate charging and discharging efficiencies. A self-discharge component and battery degradation were also included, where some of the stored energy is lost with time, and each charge cycle of the batteries decreases the total capacity of the battery.

The connected load, the data center and cooling system, consists of multiple subcomponents within that system, which are discussed further under section 2.2 where the data center model is described. The power consumption for each component was modelled by finding the connection between the utilization and power consumption of each component. The data center model in turn calculates the utilization of each component which is required for the IT and cooling systems to function as designed.

The microgrid controller balances the power inflows and outflows to always provide sufficient power for the load, inverts the direct current from the batteries and solar, as well as rectifies the AC power from the grid while charging the batteries. These interactions were modelled by calculating the net consumption/production of the load + solar array, and sourcing/distributing the remainder power from/to the grid or batteries according to the currently chosen operation regime. A simple backup power controller always prioritizes sourcing power from the grid and charging up the battery for maximal reserve power and sells any extra production to the grid if the local production exceeds local consumption. A more advanced control scheme is described later in Section 2.1.2.

An addition to the DMI model which only exists in the simulated environment is the wind turbine model. This model was created by Riitta Rankinen from the University of Oulu, as her master's thesis within the project Arctiq-DC. The model was integrated to the microgrid simulation environment but was later decided not to be used in following tasks in this project due to a difference in scales (The wind turbines within that model were much too large for placement by edge data centers.).

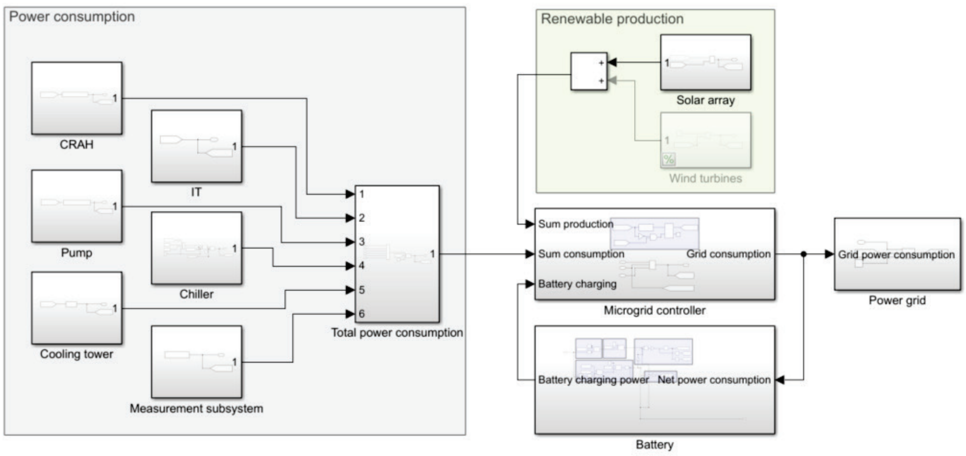


**Figure 4. Screengrab of the microgrid model in Simulink.**

### 2.1.2 Microgrid optimizer algorithm

As the modelling task was divided in two, so was the optimization task. By the quite broad name 'microgrid optimization' we mean that we attempt to optimize the operation of those microgrid components which may be influenced. If we assume the DC to be a customer within the microgrid which we may not control, the only remaining piece of equipment with flexibility are the batteries. Optimization of the data center operation is considered in chapter 2.2.2.

It is possible to influence the charging and discharging of the batteries while the grid connection is functional to reduce or increase the energy purchased from the electrical grid. It is also possible to back feed power to the electrical grid. Some reasons to do this might be to avoid paying for expensive electricity during peak hours, or to utilize excess solar production when the local production exceeds the local consumption.

An optimal solution guarantees to provide the absolute best solution given the currently available knowledge. Multiple methods exist for searching an optimal solution, and which ones can be utilized depends on the problem to be optimized. One of the most well-known and common methods is called linear optimization or linear programming, and this method was utilized. The method is introduced in Section 1.3.2.. Linear programming requires that the optimization problem consists of linear relationships. Not all systems are inherently linear, but by carefully linearizing a nonlinear system the nonlinear optimization problem can be represented with linear relationships without sacrificing the optimality of the solution.

For optimizing the battery operation, the optimizable costs are assumed to consist of the cost of purchasing electricity for the loads within the microgrid. By exploiting the variability in price through the flexibility provided by the batteries the total purchase price can be lowered without negatively affecting the operation of the loads. The optimized state vector $x$ within the linear optimization equation is therefore a vector with the amounts of purchased energy within the time horizon. The values of vector x can be further described as the initial predicted load plus or minus the charges or discharges from the battery.

The total cost over the optimization horizon is represented by the linear programming objective function $c^T x$, which simply is the cost of purchasing electricity (vector $c$) during a time interval times the amount purchased (vector x), summed for all time intervals within the horizon. The initial and final battery state of charge is also given some value, as otherwise the battery would always be encouraged to sell its contents. We did it by allocating its value according to the mean price for the time horizon. The resulting objective function is thus:

$$c^T x = \sum (c_i(P_i + P_i^+ + P_i^-)) + \bar{c}(Q_0 - Q_n)$$

Where $c_i$ are the costs of purchasing one kWh during an hour, $P_i$ are the predicted loads of the data center per hour, $P_i^+$ and $P_i^-$ are the charges and discharges to the battery per hour, and the $Q_i$ represents the battery state of charge for each hour ($Q_0$ for the initial state, $Q_n$ for the final state).

The battery dynamics should be written with linear constraints in a way where they fit the functions $Ax \leq b$ and $x \geq 0$ as linear equalities of inequalities. The constraints of the system are directly derivable from the physical limitations of the system. For the power flow of charging and discharging the battery ($P_{min}^+, P_{max}^+, P_{min}^-, P_{max}^-$) the limits are derived from all system limitations such as circuit breaker sizes, battery design limitations, available power, etc. The battery capacity limits ($Q_{min}, Q_{max}$) can be represented using nameplate capacity values, same for the round trip efficiency $\eta$, or alternatively by running an experimental charge cycle on the battery like we did. The self-discharge rate $P_{loss}$ is often defined as loss of capacity as % per month, which was also found from the battery documentation.

The battery dynamics were represented as an energy storage unit, where the charges and discharges increase and decrease the battery state of charge respectively, with the addition of a round trip efficiency value for the losses occurring during a battery charge cycle, and a self-discharge of the batteries. An option for allowing and disallowing back flow of electricity to the grid was also implemented to allow for experimenting with both types of setups.

The equalities and inequalities can therefore be expressed with the following equations.

Hard limits:

$$P_{min}^{+} \leq P_i^{+} \leq P_{max}^{+}$$

$$P_{max}^{-} \leq P_i^{-} \leq P_{min}^{-}$$

$$Q_{min} \leq Q_i \leq Q_{max}$$

Initial state:

$$Q_0 = Q_{actual}$$

Battery dynamics:

$$D\ Q_i = \eta\ P_i^{+} + P_i^{-} + P_{loss} \tag{1}$$

Where the matrix *D* is of size n × n+1, where n is the number of hours within the time horizon and has the following form:

$$D = \begin{bmatrix} -1 & 1 & 0 & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & 0 & -1 & 1 \end{bmatrix}$$

And if back feeding of electricity is disallowed:

$$P_i + P_i^{+} + P_i^{-} \geq 0$$

Solving this linear optimization problem for the prediction horizon of the following day (considering the day ahead prices are published the day before) produces a result for how much the battery should be charged and discharged during each time interval of one hour, and what the corresponding state of charge will be that minimizes the cost of purchasing electricity during the following day. Solving this linear program is left for the MATLAB linear programming function *linprog*. This solution is produced in under a second when solving it on a normal laptop. The solution is valid for as long as the assumptions for the prediction horizon remain unchanged, but the optimization should be redone at the latest when the prediction horizon may be lengthened when new price data comes available for the following day. In case something changes during the day, for example the actual loads differ from the predicted loads, a rerun of the optimization is also in place.

To leverage these mathematically proven results this optimized control regime must be utilized by a battery management system to control and fit the real loads as close to the optimal values as possible, but the integration of this optimizer with a physical setup was beyond this project.

### 2.1.3 Dimensioning algorithm

To see which dimension of components of the microgrid are most profitable for a set CAPEX, we investigated the optimal dimensioning of grid components. The size of solar array, tank and batteries was considered for the dimensioning algorithm.

Different algorithms were considered and studied but due to complexity and implementation the chosen method became grid search, described in section 1.3.1. The grid consists of battery, solar panels, and tank size. The range of the component size is calculated as the maximum size for the set CAPEX. In this case, the lowest operational cost is searched.

A year was simulated by doing the calculation for one day every other month and then multiplied for a year. The result for a full year was then multiplied to show 10 years as a payback period.

## 2.2 TASK 2 – MACHINE LEARNING METHODS FOR OPERATIONAL OPTIMIZATION OF DATA CENTER INTEGRATION

Task 2 is similar to task 1 in the sense that we developed a model and optimal control algorithms for the data center contained within the microgrid. The development process of the data center model was begun even before this project, but necessary modifications and improvements were done to the previous model to allow it to be used within this project.

### 2.2.1 Data center model

The data center model used in this project has its roots in a master's thesis (Siltala, Simulating data center cooling systems: data-driven and physical modeling methods, 2020) and is also shortly described in an article (Siltala, Brännvall, Gustafsson, & Zhou, 2020) where a model for a data center cooling system was developed. The model is based on the setup described in Section 1.1.1, but the parameters for any component can be scaled to represent a data center of any size following the same architecture, which is visualized with a block diagram in figure 5. The diagram includes the microgrid diagram from figure 3, but the data center section has been expanded to show the individual components within that system. The model includes the data center with the IT equipment, but also the cooling system which in many ways is the more complex system of the two. As heat is generated by the servers, it must be transported outside of the data center structure in real-time and depending on the equipment used the power consumption of this cooling system might be as high as that of the IT equipment. Therefore, we have also modelled the cooling system in high detail. A screen capture of the resulting model is presented in figure 6.

For simulating the IT load, we prepared models for estimating the characteristic load profile of different types of data centers. Some computation tasks require more constant utilization of the equipment, while others are highly variable and intermittent. The estimated utilization is used to calculate the actual utilization grade of the equipment, which rarely is higher than 50% for the more variable loads but can be 95% for the constant loads. In the end we preferred the use of constant loads with a lower utilization level within the simulations as the load profile for an edge data center could not be verified. (The edge data center industry is still finding its place in the market and no service providers were found to publicize their operational data.) Most server manufacturers provide the idle and peak power consumption values for their equipment, but we conducted experiments with real hardware to produce a mapping of the utilization grade and power consumption, which was then used as a basis for calculating the IT equipment power consumption for a certain utilization.

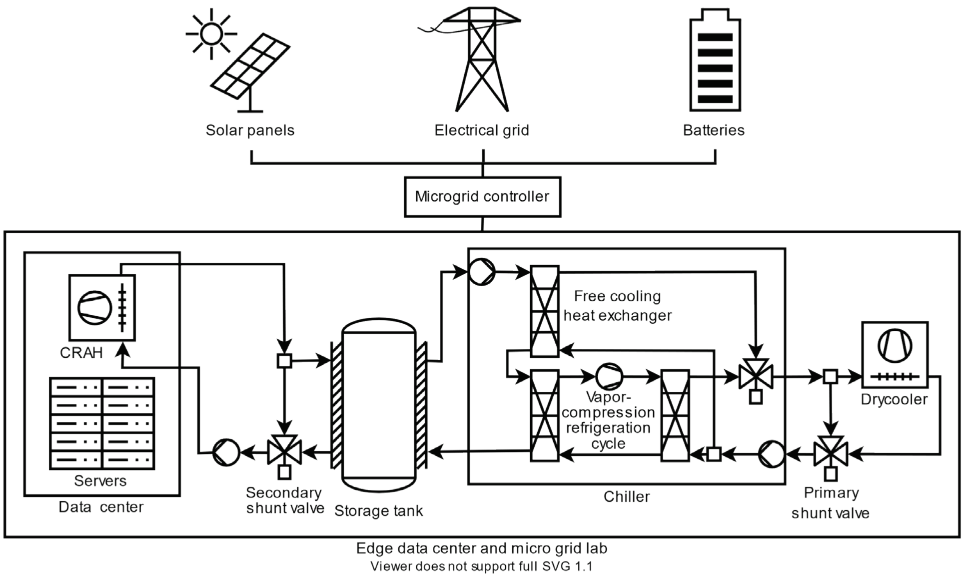


**Figure 5. Block diagram of the data center model.**

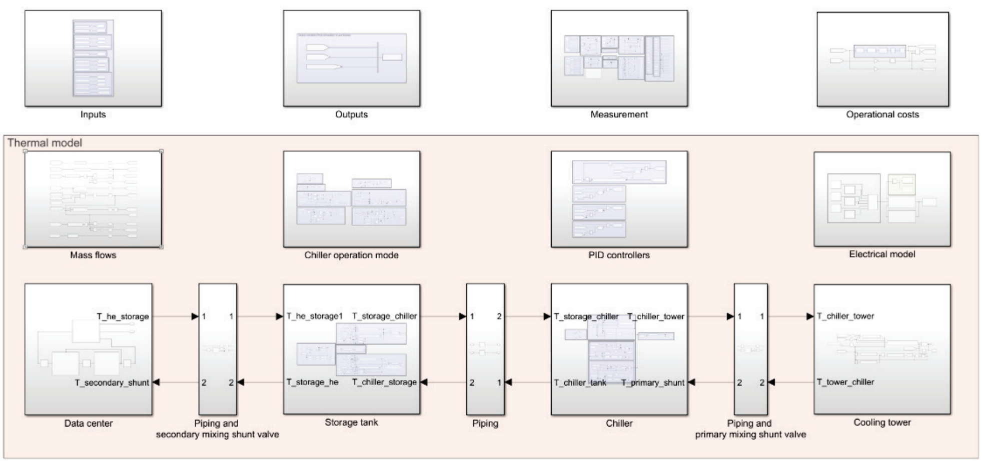


**Figure 6. Screen grab of the data center model in Simulink.**

The first step in cooling the data center is achieved using the closed air-cooling loop, where the computer room air handler (CRAH) is used to extract heat from the DC air to the water within the coolant system. Models for a heat exchanger, fan and pump were developed to represent the CRAH. The fan and pump are controlled to regulate for the pressure and temperature of the data center, similarly to what is done with the real data center. In addition, some heat is lost through the walls of the data center structure, which was also modelled.

Heat from the data center is deposited to the coolant storage tank, where cold water is stored. This was represented by modelling the tank as a thermally insulated storage where the cold water is separated from the hot by a thermocline layer which moves vertically in the tank according to the incoming and outgoing water flows. The flows are deposited/withdrawn from the top/bottom of the tank according to the direction of flow in the system which keeps the hot and cold water separate. The thermal losses through the insulated walls and the thermocline were modelled as they become major sources of heat loss in the system as the temperature gradients increase.

The chiller is used to cool the water with a one of the two available modes which were both modelled. The control logic of the chiller was also represented as accurately as possible within the model to be able to estimate which mode would be used and how much of the available capacity would be utilized given the current conditions. The free cooling method relies on a heat exchanger model between the water and glycol loops, whereas the chiller model utilizes an additional model for a vapor-compression refrigeration cycle machine. This model represents the use of a vaporizer valve and a compressor to decrease and then increase the temperature of the refrigerant so that heat can be extracted from the water and then deposited to the glycol loop even if the temperature difference between the water and glycol is low or negative. This was done by using the coefficient of performance of the machine, as provided by the manufacturer, and calibrated by experimentation, to represent the cooling effectiveness. The system is controlled by duty-cycling the machine on and off according to the control scheme employed also by the real system.

The dry cooler model is fairly similar to the CRAH model but in reverse, as heat is rejected from glycol to the outside air. This model therefore also consists of a heat exchanger and fan models, and the pump action is calculated by the chiller model. As this section of the model is in contact with the “outside” world, the temperature value for the air is required to calculate the effectiveness of the heat rejection. A module for using the weather predictions from the Swedish Meteorological and Hydrological Institute (SMHI) was implemented for assuring high quality predictions for the temperature.

The piping from the data center to the storage tank, as well as the other pipes within the system were modelled as having a length, which together with the liquid flowrate provides the model with the delays in the system. The pipes are mostly well insulated, and heat losses were assumed to be negligible. Within the piping there are two shunt valves. One is located between the data center and storage tank, where the water temperature to the CRAH is regulated to reduce the flowrate from the storage tank by mixing the returning warm water with the cold water from the tank. Something similar is done between the drycooler and chiller, where the glycol temperature is kept above 0 C to avoid freezing and condensing within the chiller by mixing warm and cold glycol.

In order to calculate the power consumption of these individual components a mapping of the utilization and power were done on the real equipment. For example, the fan speeds were mapped against their power consumption, as well as the resulting air flow rate. This allows us to link the calculated mass flow rate through the fan to the power consumption at that speed. These power consumption values were then joined with the microgrid model to integrate the two models together.

### 2.2.2 Data center operation optimizer algorithm

The concept of optimizing the data center operation is quite broad, as one can attempt to find for example methods to find the optimal utilization grade of a server, of the optimal temperature setpoint within the data center that achieves the lowest energy consumption. These are however well-known problems where some solutions and best practices already exist that produce good results. Instead, we wanted to leverage the unique characteristics of the edge data center which has a thermal storage component to it. The thermal storage allows for the data center operation to resume even in the case where the cooling capacity is unavailable, or together with the UPS to provide cooling with reduced power consumption in the event of a power outage. But in addition to these backup use cases the storage may be utilized flexibly to move a part of the cooling demand from a hot day to a cold night, which increases the efficiency of the cooling system but also allows the operator to take advantage of lower electricity prices during the night for a double benefit.

The optimal solution is therefore to utilize the cooling system and storage tank in a way which reduces the electricity costs of operating the data center. The algorithm should be able to choose during which hour it is most beneficial to cool the storage tank and during which hour the temperature within the storage tank can be allowed to increase in accordance with the two variables which affect this calculation.

The problem set up is therefore similar, although more complex, to the microgrid optimization task examined in Section 2.1.2, and can be solved using the same tools. The difference being that the storage tank is utilized continuously and the efficiency of charging the tank varies according to the outside temperature. As the requirement for solving an optimization problem using linear programming is that the problem must be represented with linear equalities and inequalities, we developed an approximation of the more complex simulation model for use with linear programming.

As both the outside temperature prediction by meteorologists and the electricity price for the following day have a time resolution of one hour, we can simplify the model to provide the system states only once per hour. In addition, the equations within the data center model must be transformed to linear equalities and inequalities for them to function with linear programming.

Due to the sheer number of equations present in the data center cooling system model we decided to utilize system identification, explained in Section 1.3.3, to describe the cooling system with a simpler equation. By leveraging the over 2 years of data from operating the DMI data center, and by increasing the time resolution to one hour, we could approximate the operation state with simpler equations that generalize the operation during a longer time step. For forwards compatibility the model was made compatible also with a 15-minute time resolution in case the model will be utilized with the 15-minute energy prices after year 2023.

The data set contains some gaps but provides us with enough data at a wide operating range covering the normal operational states but forces us to extrapolate the power consumption at the less well-known states. The dataset was cleaned of outliers and the data was aggregated using a mean sliding window with a 15-minute length in accordance with the proposed use case. After cleaning the dataset, a curve fitting algorithm was utilized to find the parameters that fit the proposed equation to the data. The data as well as the curve are visualized in figure 7. The resulting equation can be utilized to quickly find out a good approximation for the total power consumption for providing a specific amount of cooling at a certain outside temperature.

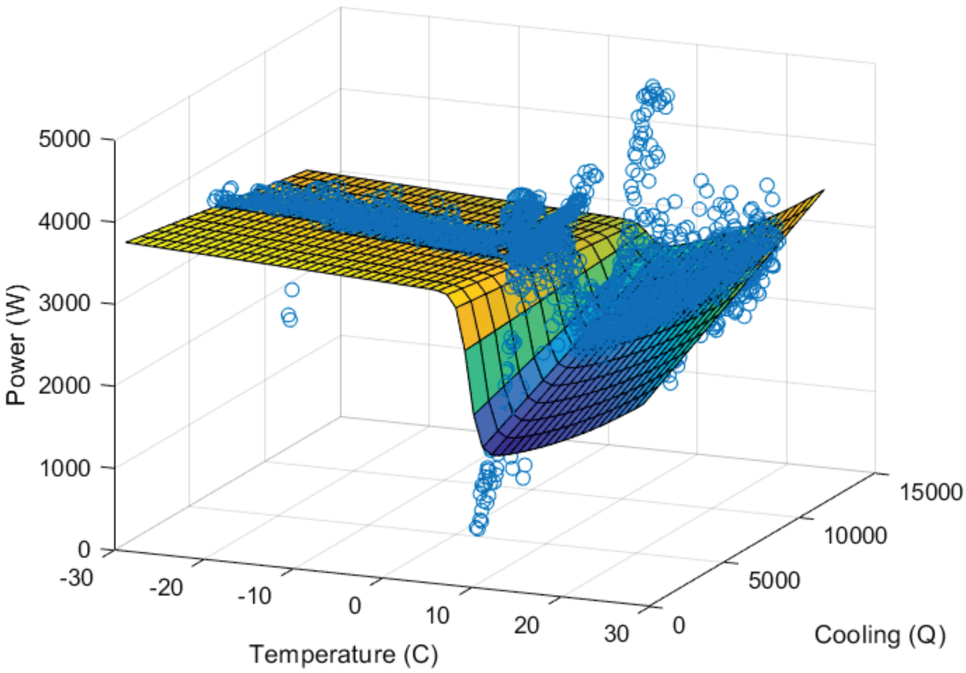


**Figure 7. The simplified cooling power curve along the cleaned data set.**

The equation in the figure 7 has been carefully chosen to represent the change between the two operation modes of the chiller at a specific temperature, as well as the linear increase resulting from increasing the duty cycle of running the equipment as well as the exponential increase from increasing the fan speeds. The equation consists therefore of two components, one for each of the two modes, as well as of the step-change between these modes. The equation is described in more detail below:

We knew that the cooling system operates in two distinct modes, which interchange relative to the outside temperature. The first component of the cooling model was therefore to identify a logistic function defined by the equation:

$$S(T) = \frac{1}{1 + e^{-k(T-T_0)}}$$

Where the state $S$ at a given temperature $T$ is defined using the crossover point from one state to the other, which is defined by the value of $T_0$, and the logistic growth rate, or the rate of change from state to the other, by the value of $k$. To find out the crossover point and change rate, the dataset was split to two according to the state utilized at each point, and the identified value was verified by comparing it against the control system setpoints.

The equation for the free cooling mode consists of a rather constant power consumption $P_{fc}$ regardless of the produced coolth $Q$ or the outside temperature $T_{out}$. This is because the system operates in a constant state, where the pumps and fans in the system have the same utilization. Linear programming requires that the equation must always be linearly increasing, so we fit a linear equation to the free cooling mode data, which produces an almost constant surface for operating in the free cooling mode.

$$P_{fc}(T_{out}, Q) = p_{00} + p_{10}T_{out} + p_{01}Q$$

During the chiller operation mode, the cooling effect for a given air temperature is regulated by regulating the duty cycle of activating the compressors. The relationship is therefore directly proportional. For a changing air temperature, the relationship is however a cubed one, as the air flow rate through the dry cooler must be increased to provide the same coolth, and according to the fan laws the volumetric air flow rate is directly proportional to the RMP of the fan, and the power required to increase the speed of a fan varies according to the cube of the ratio of the change in RPM. For the chiller mode a cubic-linear equation was therefore fit to the data.

$$P_{chiller}(T_{out}, Q) = p_{00} + p_{10}T_{out} + p_{01}Q + p_{11}T_{out}Q + p_{20}T_{out}^2 + p_{21}T_{out}^2Q + p_{30}T_{out}^3$$

The simplified cooling system is then assembled from these three equations, one for identifying the mode, and the one for calculating the power in each mode:

$$P(T_{out}, Q) = S(T_{out})(P_{fc}(T_{out}, Q) - P_{chiller}(T_{out}, Q)) + P_{chiller}(T_{out}, Q)$$

At the same time as the tank is cooled it is also warmed up as the heat generated by the IT equipment is put into the tank. The $P_{IT}$ is assumed to be injected into the storage tank without losses.

If we go back a few steps, we wished to optimize the cost of purchasing power for the cooling system. This is easily calculated as the price to purchase the energy we consume each hour. To encourage the algorithm to recharge the coolth at the end of the optimization horizon and to keep track of the worth of the stored coolth the initial and final coolth within the storage tank are given value according to the average cooling efficiency during the optimization horizon. The resulting objective function is therefore:

$$c^T x = \sum (c_i P_i) + \bar{c}\bar{\eta}(T_n - T_0)C$$

Where the $c_i$ are the costs of purchasing one kWh during an hour, $P_i$ are the cooling loads per hour as calculated by the simplified cooling model, the $\eta$ is the efficiency of the cooling system, $T_i$ represents the temperature in the thermal storage tank ($T_0$ for the initial state, $T_n$ for the final state), $C$ is the heat capacity of the thermal storage and $\frac{h}{s}$ is for the conversion from seconds to hours.

The equalities and inequalities of this optimization problem can therefore be expressed with the following equations.

Hard limits:

$$T_{min} \leq T_i \leq T_{max}$$

$$Q_{min} \leq Q_i \leq Q_{max}$$

$$P_{min} \leq P_i \leq P_{max}$$

Initial state:

$$T_0 = T_{actual}$$

The storage tank temperature can be calculated by dividing the incoming and outgoing heat flows with the heat capacity of the storage tank:

$$D\ T_i = \frac{P_{IT} + Q_i + Q_{loss}}{C}$$

Where the matrix $D$ is of size n × n+1, where n is the number of hours within the time horizon and has the following form:

$$D = \begin{bmatrix} -1 & 1 & 0 & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & 0 & -1 & 1 \end{bmatrix}$$

And the $Q_{loss}$ is the amount of heat lost from the storage tank during a time period, which can be identified using the overall heat transfer coefficient $U$, the surface area $A$ in question and the mean difference in temperature $\Delta\bar{T}$ between the tank and the surrounding air.

$$Q_{loss} = UA\Delta\bar{T}$$

The cooling power consumption can be calculated using the equation identified before:

$$P(T_{out}, Q) = S(T_{out})(P_{chiller}(T_{out}, Q) - P_{fc}(T_{out}, Q)) + P_{fc}(T_{out}, Q)$$

This linear programming problem was solved using the MATLAB function *linprog* which solves the problem in under a second on a normal laptop. In a similar manner as to how the microgrid operation optimization problem could be solved for the following day, this method is also subject to the same limitation of utilizing the day ahead prices for electricity. In order to be able to utilize this optimization result it would require to be interfaced to the cooling system control system, which should then control the equipment to produce coolth according to the rate recommended by the optimization solution.

## 2.3 TASK 3 – SELF OPTIMIZATION METHODS FOR DATA CENTER AND MICROGRID INTEGRATION

Many things can be understood by the words self-optimizing, but in general we describe it as that the agent responsible for optimizing can improve upon itself. The goal of this task is to find methods for both the data center and microgrid optimization, much like in tasks 1 and 2, but instead in a so-called *self-optimizing* way.

The logical conclusion we had at this point was to attempt to improve upon the optimization algorithms in the two previous tasks and make them more intelligent and able to improve their already optimal solutions. If there would be no room for improvement this would be impossible, but luckily, or should we say unluckily, the optimization solutions for the previous two tasks are not guaranteed to be optimal even if we have attempted to lead the reader to think so. The problem arises from the fact that even if the solution to the mathematical optimization problem is guaranteed to always be the optimal solution, there exists a high probability that the reality differs from the mathematical representation. There are at least two reasons why this might be the case. Firstly, the initial version of the model might already have a discrepancy, or the real system might diverge away even from a perfect model. The algorithms presented in tasks 1 and 2 build on nameplate values or data which was first gathered for multiple years before a model was created, after which the model would not be changed during the equipment lifetime. Static algorithms such as these fall victim to both reasons as to why the mathematical representation can differ from the reality.

Multiple methods of creating agents that may learn by themselves exist, and most recently the machine learning methods called reinforcement learning methods have seen lots of hype. These methods rely often on gradient descent to find the parameters within a neural network which produces a desirable reaction to the real world. This method is powerful and can be used to teach an AI basically anything, but the computational cost and training time are through the roof.

As an alternative to those methods, we wish to find a method which provides good results for a fraction of the effort needed and which can be explainable or understood by the owner of the system who might not have the capability to understand the complex AI networks. If the problem of creating a self-optimization algorithm is framed as finding the optimal parameters and equations that went into creating the optimization algorithm for any given operation state or even for a new system which might have a different configuration or equipment dimensions, we understand that we do not necessarily need a super AI to solve the problem.

Within control theory exists the concept of system identification, which we have already explored in task 2 where in creating the data center operation optimizer we used tools for fitting an equation to data. If we can leverage similar methods to find the parameter values that went into creating the optimization algorithms and can do it even after the algorithm has been deployed and thus correct for any mistakes within the algorithm, we can confidently call the new algorithm self-optimizing. Even if for example a major part of the battery capacity would be lost, or a piece of equipment were to be replaced with a different kind, the algorithm would be able to learn in a short time and provide more suitable control schemes than a static algorithm.

To do this the algorithms presented in tasks 1 or 2 do not need any changes other than that they should take the parameter values as inputs, which was easily organized. What must be done however is to collect the system states during operation and then use this data every time the optimization algorithm is to be used to find correct values for the parameters. For this purpose, we created a method where the system states are logged each hour, and then used to fit a state space model of the system, from which the parameter values may be extracted for the optimization algorithm. The state space model and system often used in control theory. In simple terms it takes the inputs given to a system, the current state of the system and computes the resulting outputs just like it is done in the optimization algorithm. The system identification method is presented in Section 1.3.3.

For example, within the microgrid model the battery dynamics are represented using the self-discharge, round trip efficiency, and capacity parameters as is shown in Equation (1). Therefore, it is enough if the state space model is also described with just these 3 parameters.

The battery dynamics can therefore be represented by assigning these values to the state space matrices A-D where the states $x(t)$ are the states of charge of the battery, the input vector $u(t)$ contains the charge and discharge powers for each timestep, and where the states of charge are the system outputs $y(t)$. The matrices thus get the values:

$$A = [1 + P_{loss}]$$
$$B = \begin{bmatrix} \frac{\eta}{Q_{max}} & \frac{1}{Q_{max}} \end{bmatrix}$$
$$C = [1]$$
$$D = [0 \quad 0]$$

The state space model parameters can be identified using the Matlab function *ssest*, which finds the parameters that best fit the input and output data to each other. Not necessarily all of the collected data should be used for parameter identification. In the instance of a stable system this would be allowed as the parameters should remain constant through time, but in the instance that the system changes/degrades with time, only the most recent data should be used for identification. Depending on the rate of change or wished sensitivity to change, the latest week or month could be a reasonable length of time.

We experimented with the self-optimization algorithm by utilizing the microgrid model developed earlier, changing its dynamics, and comparing the identified parameters with the actual parameters for each time step. Two methods were utilized: firstly, the battery capacity was degraded in accordance with the charge cycles, and secondly, by having part of the capacity be removed to simulate a fault.

## 2.4 TASK 4 – BUSINESS MODELS AND TARIFFS FOR INDUSTRY SYMBIOSIS

As described in section 1.4.4 the aim of this task was to investigate different tariffs and how the most favorable pricing can be obtained.

After investigating different grid operators, it was made clear that the pricing of the tariffs varies a lot from company to company. To get a good comparison between the different tariffs a standardized pricing was used from (Lindén, Helbrink, Nilsson, & Andersson, 2015) where the cost consists of 40% fixed and 60% variable, where both energy (SEK/kWh) and power fee (SEK/kW) are counted as variable costs.

In table 1 the electricity network tariffs are presented in detail for different circuit breaker sizes. For the Power and Time and Power tariffs a power fee is included. This is calculated as the measured average hourly power value for the highest extracted power during a month. The Time and Time and Power tariff have an energy fee that varies during the day and season. High load time is Monday to Friday at 6am to 22pm during the months of January, February, March, November, and December. Low load time is counted as the rest of the time.

**Table 1. Tariff fees from (Lindén, Helbrink, Nilsson, & Andersson, 2015).**

| | 16A | 20A | 25A | 35A | 50A | 63A |
|---|---|---|---|---|---|---|
| **Simple tariff** | | | | | | |
| Fixed fee (SEK/year) | 1056 | 1478 | 1846 | 2528 | 3632 | 4896 |
| Energy fee (SEK/kWh) | 0.23 | | | | | |
| **Time tariff** | | | | | | |
| Fixed fee (SEK/year) | 1056 | 1478 | 1846 | 2528 | 3632 | 4896 |
| Energy fee - low load time (SEK/kWh) | 0.14 | | | | | |
| Energy fee - high load time (SEK/kWh) | 0.51 | | | | | |
| **Power tariff** | | | | | | |
| Fixed fee (SEK/year) | 1550 | | | | | |
| Energy fee (SEK/kWh) | 0.15 | | | | | |
| Power fee (SEK/kW,month) | 0.15 | | | | | |
| **Time and power tariff** | | | | | | |
| Fixed fee (SEK/year) | 1550 | | | | | |
| Energy fee - low load time (SEK/kWh) | 0.09 | | | | | |
| Energy fee - high load time (SEK/kWh) | 0.26 | | | | | |
| Power fee (SEK/kW,month) | 0.20 | | | | | |

For the electricity price, day ahead prices from Nord pool were used in the model with an hourly resolution. This created a “time of use” pricing, described in the introduction, and allowed the model to optimize on the highest resolution possible. To have a “case” with fixed fees where optimization is non profitable, a “Fixed price” tariff was added. This tariff has a fixed electricity price for the year, taken as the average yearly price from (Nord Pool, 2022) and the network fees the same as the Simple tariff.

Since the electricity certificate fee usually is included in the electricity price contract this fee was added. The fee varies depending on the electricity supplier's cost when purchasing electricity certificates, what the year's quota is and the type of electricity contract that the electricity customer has. The average fee from (Energimyndigheten, 2021) was used for the model for the year 2020.

Another fee that is not included in the electricity price or the network tariff is the energy taxes, and thereby needs to be added. Historical values from the Swedish tax agency, (Skatteverket, 2021), was used. For some businesses in Sweden, you can apply for tax reductions and data center is one of them. The requirements for a data center today are:

- *"When a business that mainly (to at least 75 percentage) conducts information services, information processing or rental of server space and associated services and,*
- *Whose total installed capacity is at least 0.1 megawatt. You are not allowed to add the cooling and fan system to the installed capacity. What is meant with the term installed capacity is the equipment's rated power. That is the power that the equipment has been labelled with from the manufacturer."*

More information about the requirements can be read here (Skatteverket, 2022). Even though the IT power for the model in this project is lower than 0.1 MW we still wanted to investigate how this reduction will affect the operation cost since the taxes is a big part of the fixed cost for the electricity. There is also a big reduction, 0.006 SEK comparing to the ordinary tax of 0.356 SEK.

The models developed in task 1 and 2 was incorporated to this task's model. Each hour of a year was simulated for each tariff type and the operational cost was accumulated. To compare with a case with no optimization, a "fixed price" tariff was designed. It was combined with the "simple tariff" for the grid fees and a fixed electricity price for each hour of the year, composed of the average electricity price of the year.

# 3 Results

## 3.1 TASK 1 - MACHINE LEARNING METHODS FOR OPTIMIZATION OF MICROGRIDS

### 3.1.1 Microgrid model

The performance of the microgrid was examined by comparing the simulated results against the results measured on the real system for a typical day of operation. A summary of the results is presented in figure 8. The figure contains the total consumption of the loads and renewable production in the microgrid, as well as the battery power flows when running the system in island mode and the subsequent recharging that occurs soon after.

As can be seen from the figure, the estimated load follows the real load value with minor errors. Closer inspection of the major discrepancies revealed that the cyclic actions during the later stage of this simulation could not be reproduced by the simulated control system even when the measured states were used as controller inputs. Without access to the chiller firmware the simulated controller could be as good as the system documentation. Nevertheless, the simulation was accurate enough in all other aspects, which indicates that the system utilization is accurately estimated, as are the power consumptions of the individual components in the system.

In addition, there is a large possibility for error within the solar production estimate when compared to the real production in case the weather prediction ends up not being accurate. During this simulated day, completely clear skies were predicted for the area, but some clouds ended up appearing and shading the array throughout the day, which resulted in lower production than initially estimated.

During the hour when the system was in island mode the power flows from the battery can be seen to closely match the measured values, and during the recharge period the estimated charge current matches the real one, but after some time the higher charging current is decreased to a lower top-off charge, while the estimate does not do this for simplicity’s sake.

All things considered; this model is an accurate representation of the major dynamics that affect the microgrid operation and can act as a trustworthy environment to test out any optimization scripts.

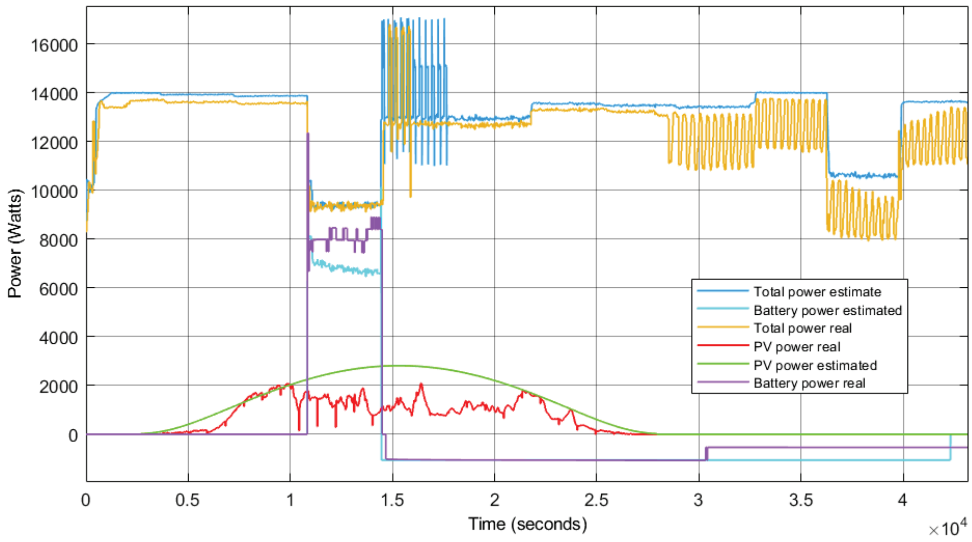


**Figure 8. Microgrid model accuracy validation results.**

### 3.1.2 Microgrid optimization algorithm

In figure 9 below the microgrid optimization is shown for each hour during a day. Presented are the grid power price for each hour, and the power consumption for each hour. The sum of their hourly products is the basis for the optimization, and as we can see, the optimized power consumption aims to decrease consumption when prices are high and balances this out by increasing consumption (charging of batteries) when the prices are low. The limit to this energy arbitrage comes from the installed battery capacity, and so the resulting battery state of charge is also shown for each hour. During the last hour the battery is also recharged in anticipation of the following day. This result shows that the algorithm works as intended. The potential savings from operating the microgrid using this method during this individual day amount to 8.50 SEK and 2.19 %.

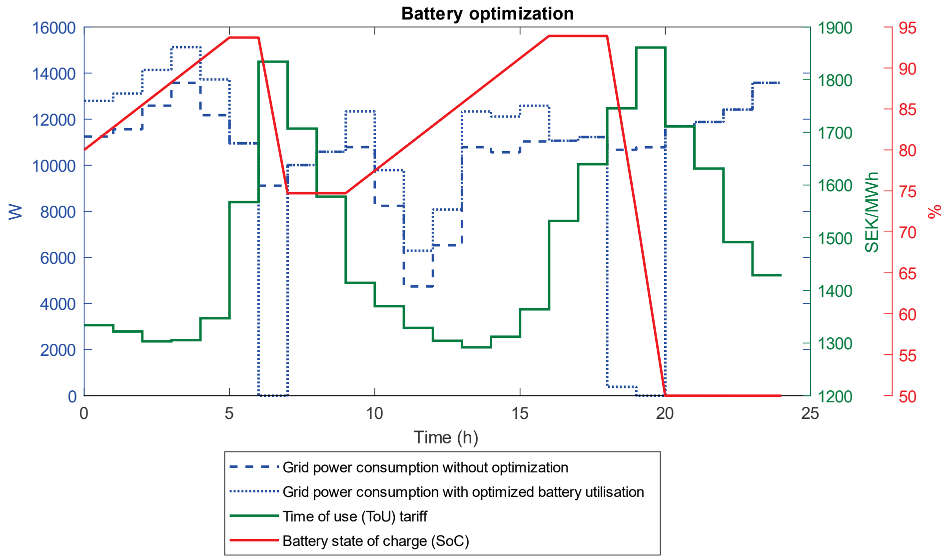


**Figure 9. Microgrid optimization result for August 11th, 2021, for price area SE4.**

### 3.1.3 Dimensioning algorithm

The result of the dimension algorithm can be seen in figure 10 below. The algorithm was run for SE3 price area and with a *Time and Power* tariff, where the sizing of the PV, battery and storage tank was optimized. The left y-axis, named as OPEX, shows the saved OPEX, which are the original operation costs without the microgrid components compared to operation costs with a given dimension of components. The size of the tank is missing in the graph, since according to the result, it was never more beneficial within the system with any CAPEX amount.

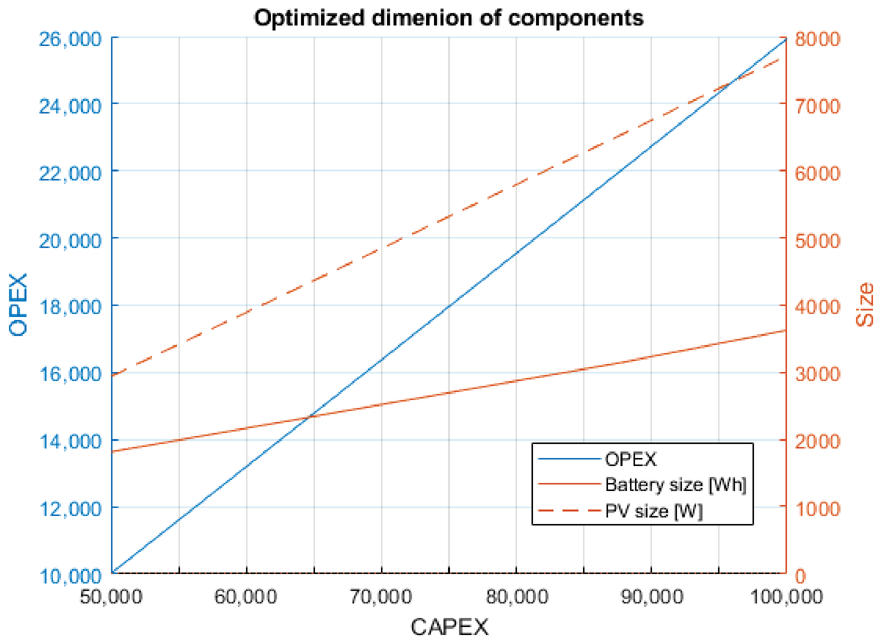


**Figure 10. Optimized dimension of components on the right y-axis and saved OPEX on the left y-axis. All for a given set of CAPEX.**

## 3.2 TASK 2 – MACHINE LEARNING METHODS FOR OPERATIONAL OPTIMIZATION OF DATA CENTER INTEGRATION

### 3.2.1 Data center model

The performance of the data center model was verified by comparing the estimated temperature at different components within the system to real measurements of the system. The most critical one of them, the air temperature at the intake to the servers which must abide by the temperature recommendations and limits as specified by the equipment manufacturers, codes and best practices have been compared in the figure 11. The results show that the estimated temperature reacts accurately to the hourly changes in IT load experienced by the system during this period, where the data center was stress tested for 12 hours. The model was therefore accepted for use in later stages of this project.

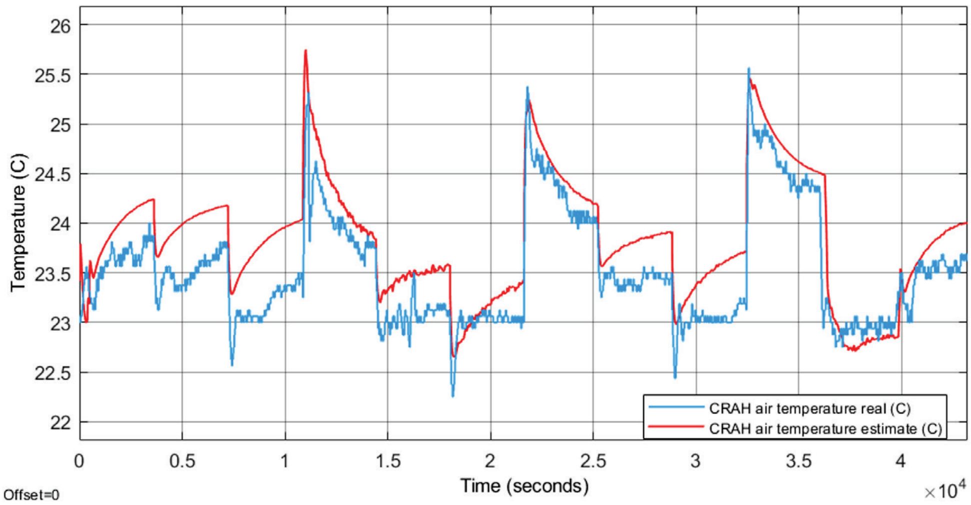


**Figure 11. Data center model verification results for the cold aisle temperature.**

### 3.2.2 Data center optimization algorithm

The cooling system optimization result using a system such as the DMI-testbed is presented in figure 12. The optimization is based on the changes in the outside temperature and the changes on the electricity price, as well as the hourly cooling system energy consumption. In addition, the optimized energy consumption and the resulting temperatures within the storage tank are represented in the figure. The algorithm can be seen to move cooling demand away from either expensive or hot hours and onto the cheap and/or cooler hours. The resulting savings for this individual day amount to 1.48 SEK and 1.37 %.

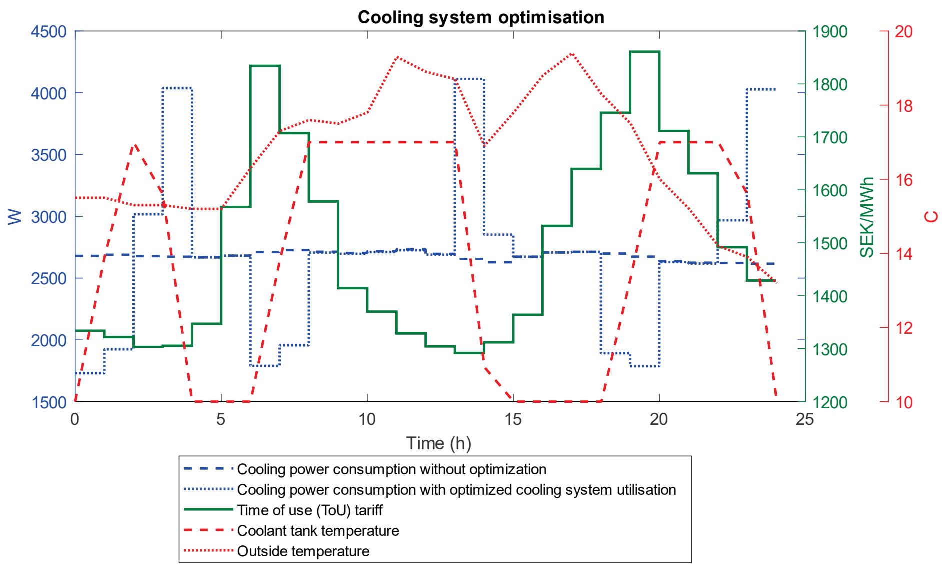


**Figure 12. DMI testbed data center optimization result for August 11th, 2021, within price area SE4.**

### 3.2.3 Total optimization results

#### 3.2.3.1 Changes in power profile

After optimizing the cooling operation or the microgrid operation the load profile can be seen to change. The cooling optimization is run first to optimize the data center load, after which the microgrid optimization is run. The total savings for the day were 9.98 SEK or 2.51 %. As we can identify from figure 13, the effect of the cooling optimizer has a lesser effect on the total grid load, but the effects of the two types of optimizations tend to be cumulative, i.e., occurring on the same hours. The optimized grid load is therefore much more varied than the original load.

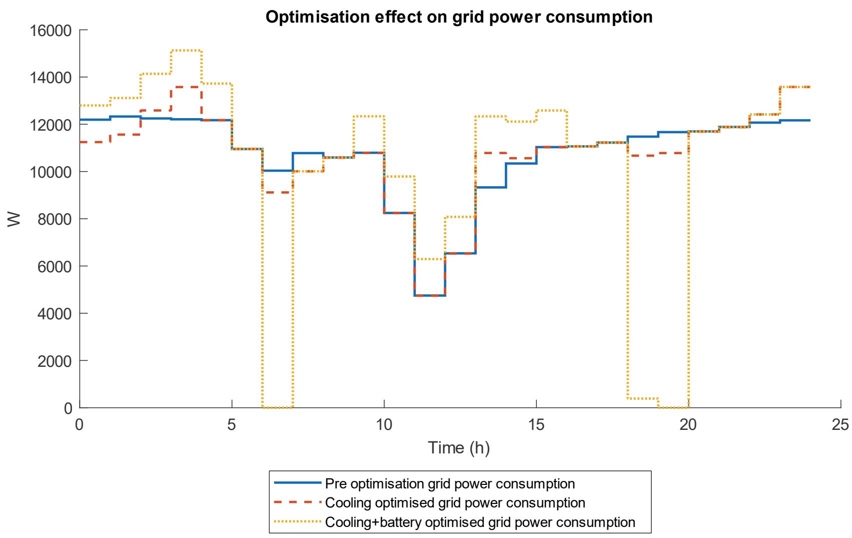


**Figure 13. Effect of the operation optimizers on the grid power profile for the August 11th, 2021, in price area SE4.**

#### 3.2.3.2 Cumulative optimization results over a year

While optimizing for an individual day might be interesting, the system will be operated for longer periods of time and therefore also the cumulative results over a year have been identified. In figure 14 the cumulative operation costs can be seen to increase through the year, and in figure 15 the cumulative savings can be seen. The accumulated savings rate is proportional to the variability in the energy price. As the last months of the year experienced record variations in price through the day, the optimization algorithm also achieved the highest savings per day towards the end of the year. The total savings during the year amount to 1690.05 SEK, or 4.19 %, and accounting for the charge cycles the battery lifetime would be 12.6 years. The savings therefore do not cover the cost of battery purchase during their lifetime for the lead-acid batteries of the DMI testbed as the payback time would be 34.5 years.

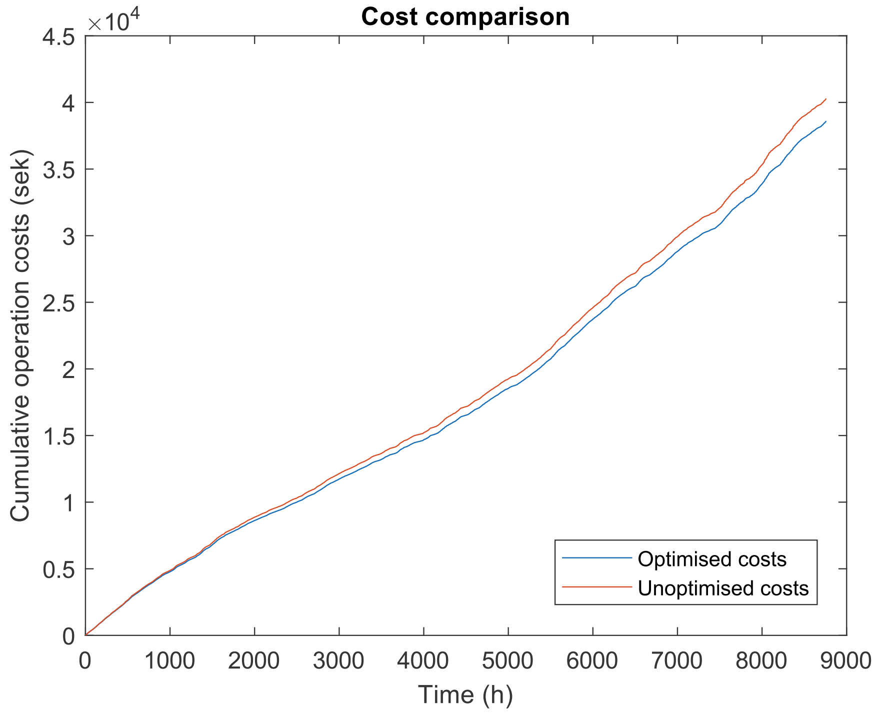


**Figure 14. Cumulative cost comparison for the DMI testbed for 2020 using price area SE4.**

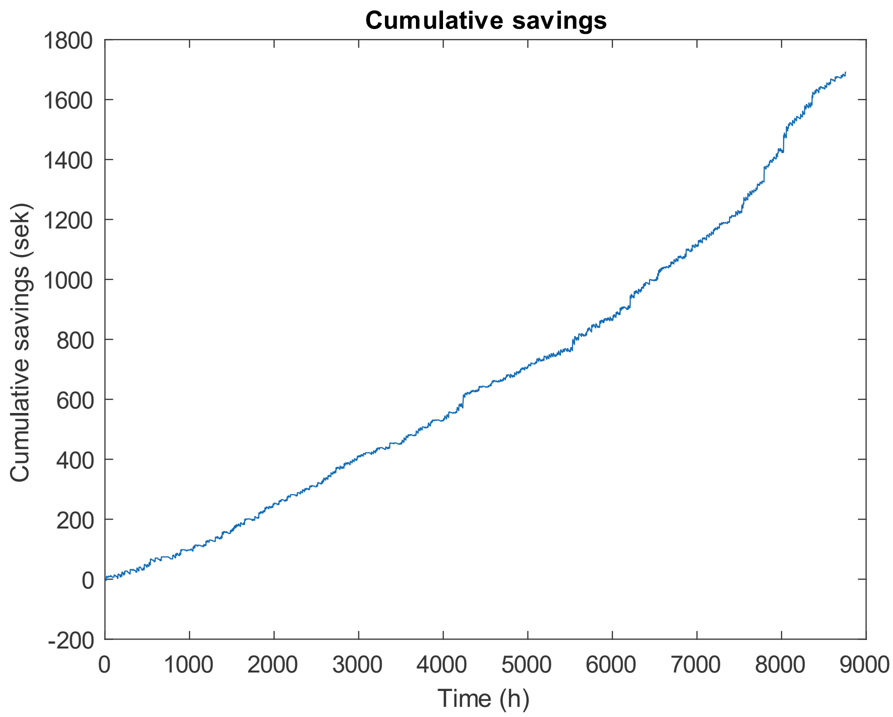


**Figure 15. Cumulative savings for operating the DMI testbed for 2020 using price area SE4.**

However, if lithium batteries would be used instead, which may reach up to 6000 cycles through their life and have a better efficiency, the economical calculation should be more beneficial. Similarly, additional savings can be achieved by allowing power backfeeding to the grid. For a similarly sized battery setup using Lithium NMC batteries which have a higher efficiency (95% instead of 85% for the lead acid batteries), the higher cycle life, appropriate higher charge and discharge limits, and a higher allowed degree of discharge, the savings for the year are 4613.91 SEK and 11.45 %, with a payback period of 12.7 years and a battery lifetime of 10.4 years. By allowing the power back-feeding option, the savings increase to 5525.60 SEK and 13.72 %, with a payback time of 10.6 years and a lifetime of 9.4 years.

Even if the capital investment is not recouped within the equipment lifetime, this proposed method may be utilized to regain some of the operational costs. In other words, this algorithm reduces the costs for owning the UPS system by 1/3 if using lead acid batteries, or nearly 90% for the lithium batteries. The lithium batteries however must be replaced roughly twice as often as normal, as the lifespan for a lead-acid battery may otherwise be up to 12 years and for a lithium battery up to 20 years.

## 3.3 TASK 3 – SELP OPTIMIZATION METHODS FOR DATA CENTER AND MICROGRID INTEGRATION

For identifying potential performance boosts from utilizing the self-optimization algorithm in comparison to the static algorithm an experiment was conducted where a complete year was simulated. Within this experiment two types of errors were examined; while setting up the initial model, a small error of 5% in the parameter values was given to simulate initial steady state errors, and during the operation of the system, halfway through the simulation at the start of July, half of the battery capacity was assumed to malfunction without it getting repaired before year end.

As the result in figure 16 shows, the self-optimization algorithm performed better than the static algorithm and achieved a further 128.12 SEK or 8.58 % more savings than the static algorithm. The simulated system is the actual DMI setup, as also examined in Section 3.2.3.2. The self-optimization algorithm is therefore successful in capturing the initial error, as well as the fault occurring during operation.

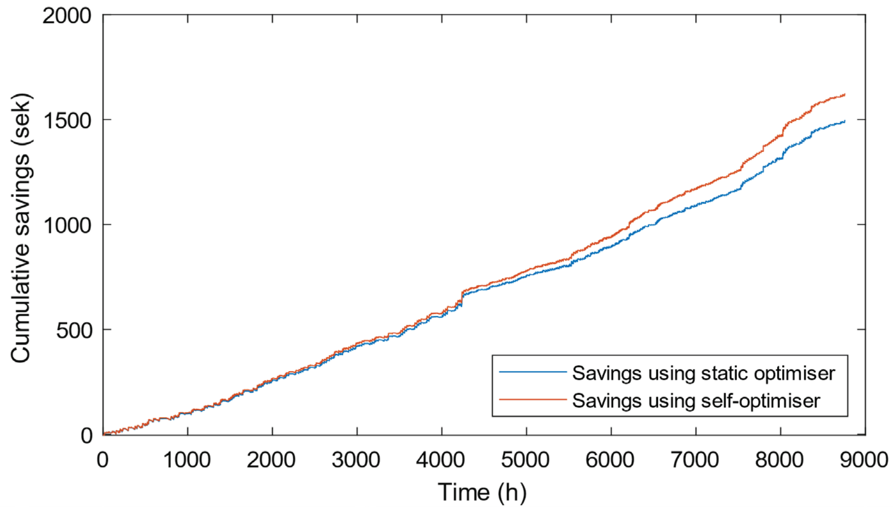


**Figure 16. Comparison of the savings results of the self-optimization version to the static operation optimization algorithms in the presence of initial model errors of just 5%.**

## 3.4 TASK 4 – BUSINESS MODELS AND TARIFFS FOR INDUSTRY SYMBIOSIS

The different tariffs influence the hourly energy consumption from the power grid, but also on the overall cost of operation during longer time scales. The two different views are examined here.

### 3.4.1 Effect on individual days

In figure 17 to 19 below the effect of different tariffs for a 24-hour period is presented. The simulation was done for the 5$^{th}$ of November in 2020. In figure 17, the variable cost (SEK/Wh) for the tariffs is presented over 24 hours. It consists of electricity price, electricity certificate fee, taxes, and energy fee. For the Fixed price tariff, that has a fixed electricity price over the day and a fixed energy fee, the variable cost is constant for every hour.

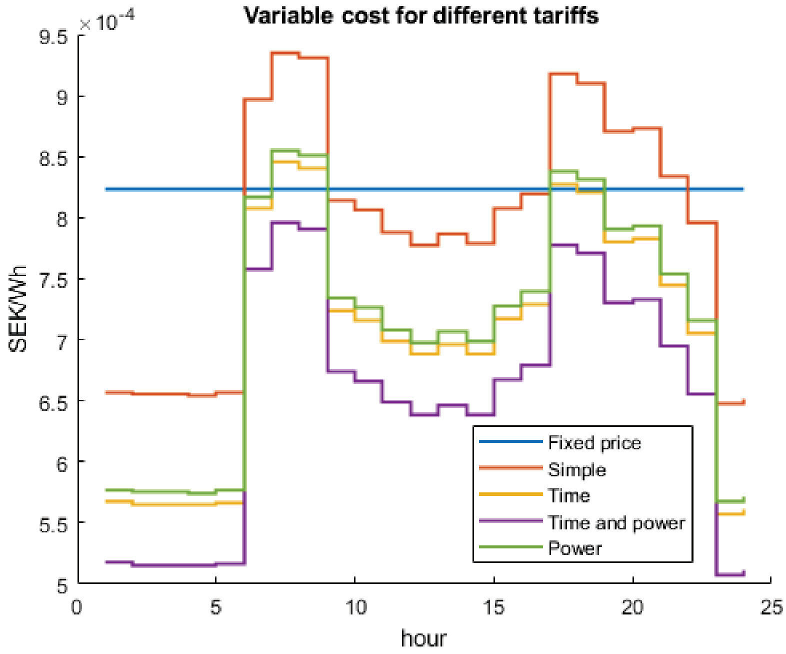


**Figure 17. Variability of the variable cost per hour.**

The cost per hour for the different tariffs can be seen in figure 18. This cost includes both the variable and fixed part of the tariff cost. The fixed part consists of the subscription fee and, depending on the tariff, the power fee. The net power consumption in shown in figure 19. In these two figures, the tariffs effect of the optimization during a day can be seen. For example, during the morning hours and the afternoon, when the cost is high (see figure 17), the model chooses to use the battery so that the cost become zero for these hours. The pattern of the optimized operation is similar for most of the tariffs, where Fixed and Simple tariff are the one that deviates the most from it.

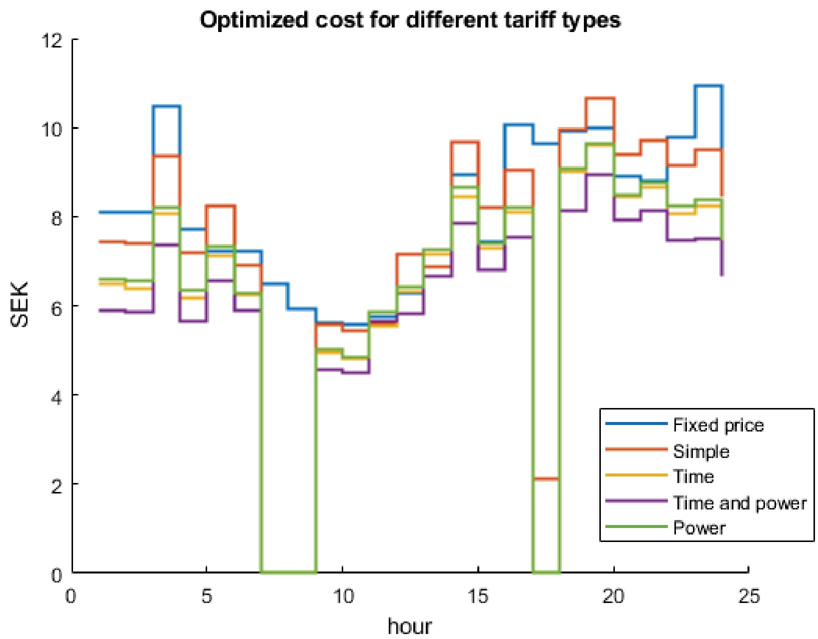


**Figure 18. Cost of operation per hour using different tariffs.**

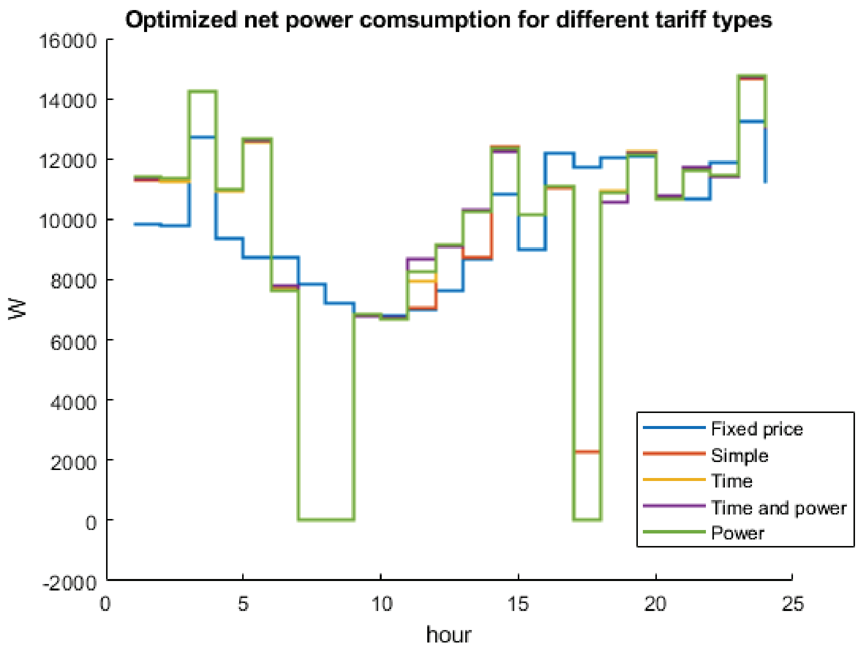


**Figure 19. Resulting grid load after optimizing operation using different tariffs.**

### 3.4.2 Cumulative results

In figure 20 and figure 21, graphs of the cumulative operation cost for each hour over the year of 2020 are presented for the price areas SE1 and SE4 in Sweden. The trend of the operation costs for the different tariffs are the same regardless of price area. The time and power tariff has the lowest operational cost over a year for both price areas. The total operation costs are presented in numbers in table 2 for each tariff and all price areas.

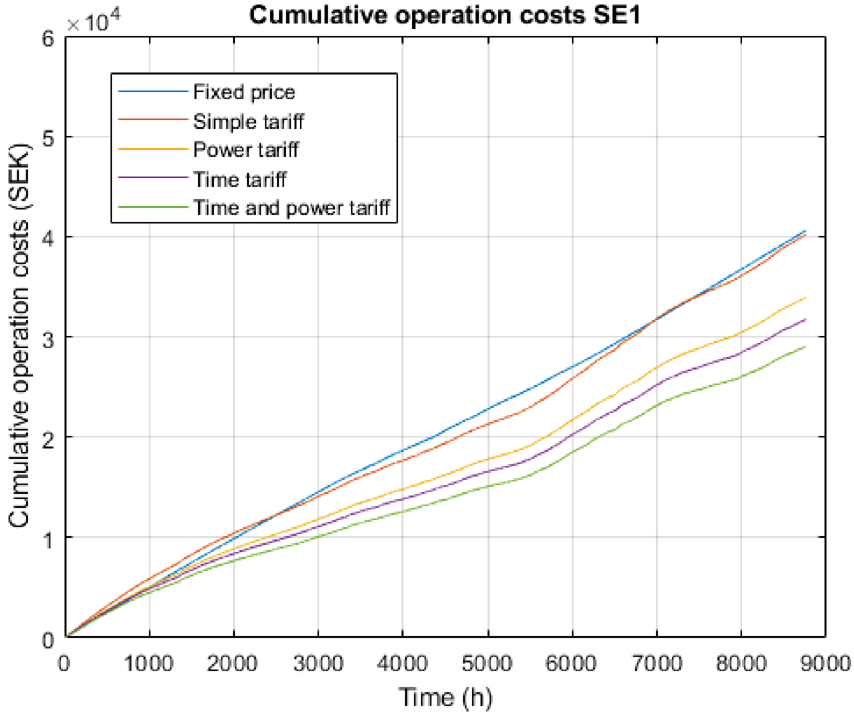


**Figure 20. Cumulative operation costs over the year of 2020 and different tariffs for the price area SE1.**

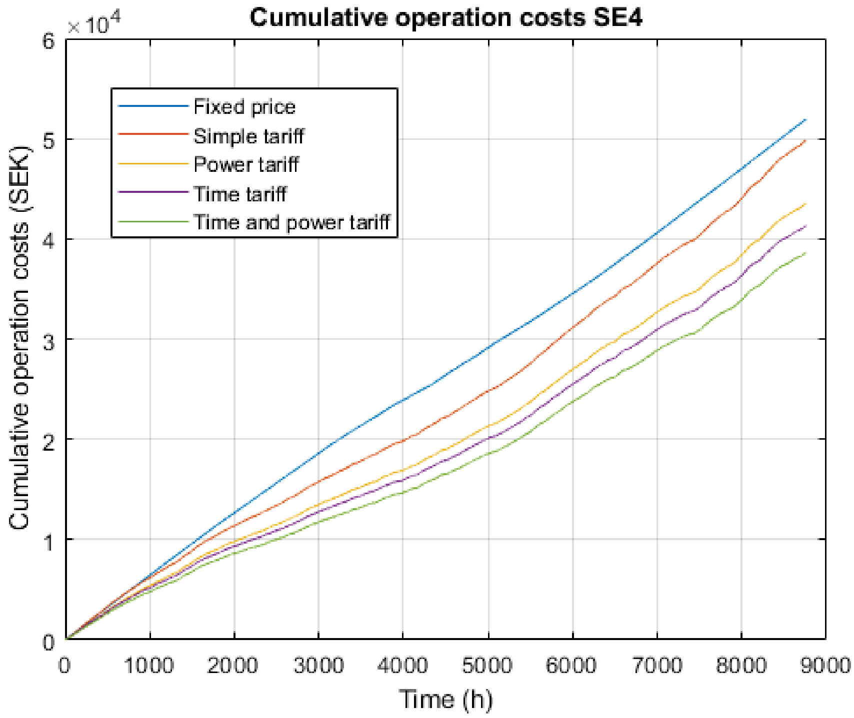


**Figure 21. Cumulative operation costs over the year of 2020 and different tariffs for price area SE4.**

**Table 2. Cumulative operation costs over a year in SEK for different tariffs and price area.**

| Tariff | SE1 | SE2 | SE3 | SE4 |
|---|---|---|---|---|
| **Fixed price** | 73 397 | 73 397 | 80 119 | 84 736 |
| **Simple** | 73 110 | 73 110 | 78 585 | 83 005 |
| **Power** | 66 884 | 66 885 | 72 320 | 76 717 |
| **Time** | 64 665 | 64 674 | 70 099 | 74 499 |
| **Time and power** | 62 009 | 62 009 | 67 410 | 71 804 |

In figure 22 the cumulative operation costs for different tariffs with and without tax reduction are presented. For both the cases the time and power tariff have the lowest operational cost. With tax reduction, the operational costs almost halves.

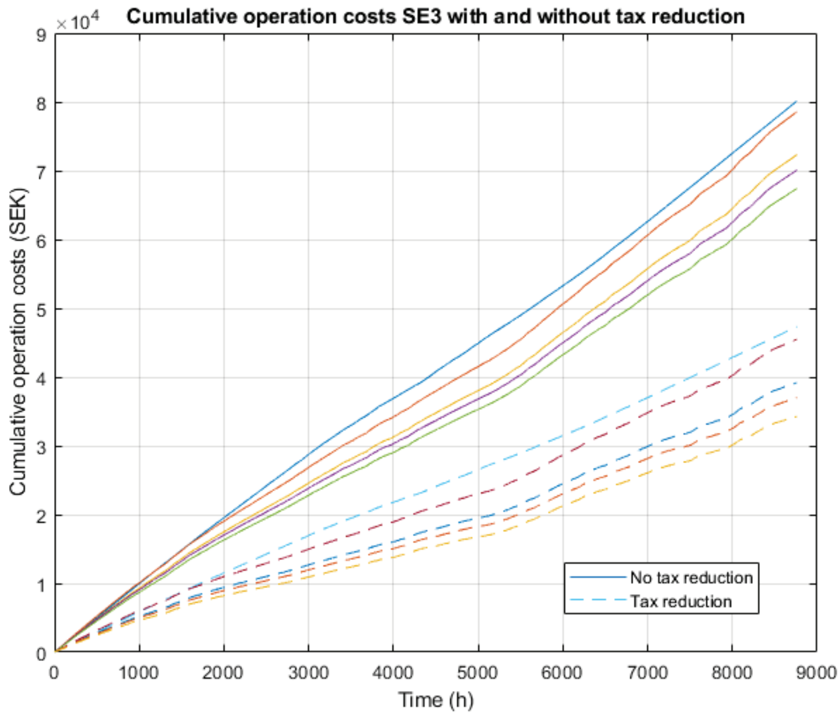


**Figure 22. Cumulative operation costs for different tariffs with ordinary tax and tax reduction.**

# 4 Discussion

The result from our models shows that with a variability in price the use of batteries is encouraged. It gives a higher flexibility and therefore a bigger potential for savings of operation costs. Solar panels do not give higher flexibility in the same meaning as for the batteries, but still lowers the costs seen over the full day since the electricity produced can either be used for IT, cooling, charging the batteries or sold back to the grid. All of this lowers the operation cost. In the case of decreased variability in price this then encourages the use of solar rather than batteries since the solar will produce electricity that lowers the operation cost.

Our results point towards that, batteries provide more flexibility for the money than thermal storages. The dimensioning algorithm showed that the optimized size of components did not contain a thermal storage, only batteries and solar panels.

## 4.1 TARIFFS

The results from the simulation with different network tariffs shows that with more variable parameters the cost gets lower since there is a bigger potential energy arbitrage to gain. The reason that the *Time and Power* tariff has the lowest cost might not only depend on the more variability, but also the pricing of the fees. If you compare the energy fee for the *Time and Power* and *Time* tariffs it is lower for both low and high load time with almost the half. The fixed fee is also significant lower for *Time and Power* tariff compared to *Time*.

The *Power* and *Time and Power* tariffs have the same fixed fee, but *Power* tariff has a lower power fee. Since *Power* tariff has the highest cost of the three mentioned above, this indicates that the power fee has a lower potential for optimization compared to the "time of use" energy fee. With this said, the power fee has however an important role with lowering the peak load to get a more stable electricity grid.

As mentioned in the beginning of this chapter, the conclusion is that the future tariffs should contain as much variable parameters as possible, to encourage microgrid owner. The "standard" time of use network tariff has two different fees today, high, and low load. Perhaps the energy use over a year could be reinvestigated to find patterns of use that could lead to an even more variable energy fee.

## 4.2 TAX SUBSIDIES

Reduction of the energy tax subsidy limit from 100kW would allow for smaller edge data centers to benefit from the reduced energy cost. This would increase the variability of the energy price, and as we have seen from the previous results, increased variability and flexibility encourage the use of batteries for load shifting.

Another of the requirements is that the IT equipment is on the same geographical location and is accommodated in the same or adjacent facility. If this requirement would be taken away, a company with a potential cluster of different edge data centers in for example, a city could be granted the lower tax.

### 4.3 ALGORITHMS

The simulation models and linear programming algorithms presented in this report have been proven to succeed in generating accurate estimates of the future and optimal results for the optimization problem they set out to solve. They utilize data such as system characteristics and weather predictions to estimate the local power consumption and generation, and additionally the day-ahead electricity prices to find the optimal solution to controlling the cooling system and batteries to reduce the cooling and microgrid energy costs. Using another method than linear programming for solving the optimization problem would not result in better results as the solution is the best one that can be made considering what we know of the future. The resulting profitability thereby depends on the inputs to the algorithm and not on the algorithm used.

However, one potential improvement to the algorithm would be to extend the optimization horizon. This would require the estimation of the electricity prices beyond the day-ahead prices which are conveniently known one day prior. Another possibility for improvement is by improving the system model. The models for the data center are already quite complex and only marginal improvements could be made in that aspect, but more accuracy could be added for the battery and solar array models, where quite simple models have been utilized.

The dimensioning problem could be solved more elegantly, as our solution utilizes a brute force approach to check all possible solutions to find the best one. Multiple methods exist which could find an optimal answer with fewer computations, for example gradient-based approaches or genetic algorithms, but these solutions may settle on a solution other than the global optimum. Depending on the number of parameter combinations to be examined the brute force search might become unfeasible, and other solutions should be considered.

System identification was utilized for the self-optimization algorithm to find and calibrate the system parameters. This method was successful but was only as good as the measurement data from the system itself. If the input data had a discrepancy the calibration could degrade, and in the worst case provide impossible results such as change the battery capacity to a negative value. To combat this the proposed calibrations were disregarded for recognized misjudgments, but a more robust methods such as Kalman filtering could be utilized to better keep track of the true system state and not rely on the raw measurement data alone.

# 5 Conclusion

We have seen that tariffs are a good instrument to help the symbiosis of grid and microgrid owners. The electricity grid owners can regulate with the help of tariffs and, with a microgrid the facility owner gets lower operation costs.

- With a variable electricity price, the use of batteries is encouraged and gives a higher flexibility with potential to lower the operation costs.
- The future tariffs should have as much variability as possible to encourage microgrid owners. The combination of an energy fee and a power fee is a good combination since it makes it flexible for optimization while keeping down the peak load for a more stable electricity grid.
- The simulated results show that the payback period of building and operating the DMI battery system using the proposed method would not make economic sense on their own, however the proposed optimization method can be used to recoup part of the initial investment of a data center UPS without reducing the battery lifetime.
- The operation optimization and self-optimization algorithms can succeed in finding the optimal control plans for reducing operational costs within the optimization horizon even in the presence of initial or transitory errors and faults.

There is a big potential to use microgrids and price regulations to affect and support the electricity grid. But to achieve good results it demands accurate models and computing power.

# 6 Next steps: looking into further methods of grid-microgrid-DC symbiosis

A further step of the symbiosis could be to look at ancillary services for a microgrid to stabilize the frequency of the electricity grid. A data center has a good potential for both up and down regulation of the frequency since it quickly can shut off or change its IT load. Except helping in keeping the electricity grid stable, this is a source of income which could lower the operation cost or even perhaps make a profit of it.

This project could be scaled up to cover a bigger data center or a cluster of edge data centers. The load could also be altered to consider residences, industries, and a mix of load.

The models could be integrated with a physical system to test them in live conditions. In this project, Matlab and Simulink was considered. To have a more commercial value and easier implementation in industry the models could be rewritten in another programming language, such as C/C++.

# 7 References


Brännvall, R., Siltala, M., Gustafsson, J., Sarkinen, J., Vesterlund, M., & Summers, J. (2020). Edge: Microgrid data center with mixed energy storage. *proceedings of the Eleventh ACM International Conference on Future Energy Systems* (pp. 466-473). Australia: Association for Computing Machinery.

Energiforsk. (2021, November 9). *Mikronät kan spela en viktig roll i energiomställningen*. Retrieved from Energiforsk: https://energiforsk.se/nyhetsarkiv/mikronat-kan-spela-en-viktig-roll-i-energiomstallningen/

Energimyndigheten. (2021, 12 27). *Elkundens bidrag till förnybar elproduktion*. Retrieved from Energimyndigheten: http://www.energimyndigheten.se/fornybart/elcertifikatsystemet/om-elcertifikatsystemet/elkundens-bidrag-till-fornybar-elproduktion/

Jones, N. (2018, September 13). The Information Factories. *Nature, 561*, pp. 163-166.

Konsumenternas Energimarknadsbyrå. (2022, March 11). Retrieved from Konsumenternas Energimarknadsbyrå: https://www.energimarknadsbyran.se/el/dina-avtal-och-kostnader/valja-elavtal/jamfora-elpriser/valja-fast-eller-rorligt-elpris/

Lindén, M., Helbrink, J., Nilsson, M., & Andersson, M. (2015). *Simulering och analys av ett flertal tariffmodeller ur ett kostnadsperspektiv.* Stockholm: Energiforsk.

Nord Pool. (2022, April 11). *Day-ahead prices*. Retrieved from Nord Pool: https://www.nordpoolgroup.com/en/Market-data1/Dayahead/Area-Prices/ALL1/Yearly/?view=table

Siltala, M. (2020). *Simulating data center cooling systems: data-driven and physical modeling methods.* Espoo: Aalto University. doi:http://urn.fi/URN:NBN:fi:aalto-202003222561

Siltala, M., Brännvall, R., Gustafsson, J., & Zhou, Q. (2020). Physical and Data-Driven Models for Edge Data Center Cooling System. *2020 Swedish Workshop on Data Science (SweDS)* (pp. 1-7). Luleå: IEEE. doi:https://doi.org/10.1109/SweDS51247.2020.9275588

Skatteverket. (2021). *Energiskatt på elektrisk kraft*. Retrieved from Skatteverket: https://skatteverket.se/download/18.339cd9fe17d1714c07739ac/1639754819253/skattesatser%20el%20t.o.m.%202021-12-31.pdf

Skatteverket. (2022, 04 04). *Energiskatter*. Retrieved from Skatteverket: https://skatteverket.se/foretag/skatterochavdrag/punktskatter/energiskatter.4.18e1b10334ebe8bc8000843.html

Svenska kraftnät. (2021, March 9). *Översikt av kraftsystemet*. Retrieved from Svenska kraftnät: https://www.svk.se/om-kraftsystemet/oversikt-av-kraftsystemet/

Swedish Energy Markets Inspectorate. (2021, March 4). *The electricity market*. Retrieved from Swedish Energy Markets Inspectorate: https://ei.se/ei-in-english/electricity/the-electricity-market

Swedish Energy Markets Inspectorate. (2022, January 4). *Electricity*. Retrieved from Energimarknadsinspektionen: https://ei.se/ei-in-english/electricity

Tamir, D. M. (2020, June 26). *What is Machine Learning (ML)?* Retrieved from Berkeley school of information: https://ischoolonline.berkeley.edu/blog/what-is-machine-learning/

van Heddeghem, W., Lambert, S., Lannoo, B., Colle, D., Pickavet, M., & Demeester, P. (2014). Trends in worldwide ICT electricity consumption from 2007 to 2012. *Computer Communications*, 64-76.

# SMART INTEGRATION OF ELECTRICITY GRID, MICRO GRIDS AND DATA CENTER

The increasing growth of the ICT-sector when introducing IoT and 5G has made data center a part of the industrial ecology. Data center is a power demanding industry and is using about 1-2% of the global electricity production, in this project the aim has been to study how the electricity pricing could affect the data center operation.

With machine learning and Artificial Intelligence, it is possible to reduce the operation cost of a data center microgrid and with a variable electricity pricing the use of renewable electricity could be encouraged.