Lappeenranta University of Technology
School of Engineering Science
Master's Program in Electrical Engineering
Electrical Engineering Major

Master's Thesis

Denis Vorotyntsev

ENERGY MANAGEMENT OPTIMIZATION WITH BATTERY AND SOLAR PANELS IN FINNISH ELECTRICITY MARKET

Examiners: Professor Samuli Honkapuro
Professor Lasse Lensu

Supervisors: Professor Samuli Honkapuro
Professor Lasse Lensu

ABSTRACT

Lappeenranta University of Technology
School of Engineering Science
Master's Program in Electrical Engineering
Electrical Engineering Major

Denis Vorotyntsev

ENERGY MANAGEMENT OPTIMIZATION WITH BATTERY AND SOLAR PANELS IN FINNISH ELECTRICITY MARKET

Master's Thesis

2019

43 pages, 12 figures, 3 table.

Examiners: Professor Samuli Honkapuro
Professor Lasse Lensu

Keywords: energy management, demand-side management, Finland electricity markets, linear optimization, photovoltaics (PV), battery storage

Energy management is an important topic in modern smart grids. Energy management strategies allow to reduce the electrical consumption of microgrid from macrogrid and smooth the graphic of electricity consumption and thus reduce overall costs of electrical energy. This work provides the pipeline for energy management and evaluation metrics for the goodness of energy management strategies based on the overall savings from applying the strategy. Several modern strategies for solving energy management optimization task were described and compared on the historical data of Lappeenranta University of Technology Smart Campus.

PREFACE

To my beloved parents, whose perseverance made me finish this monument of procrastination.

Lappeenranta, June 9, 2019

Denis Vorotyntsev

CONTENTS

LIST OF ABBREVIATIONS

CET	Central European Time
DER	Distributed Energy Resources
DR	Demand Response
DSM	Demand-Side Management
DSMS	Demand-Side Management Strategies
FCR	Frequency Containment Reserves
FCR-D	Frequency Containment Reserves disturbance
FCR-N	Frequency Containment Reserves normal operation
FRR	Frequency Restoration Reserves
FRR-A	Automatic Frequency Restoration Reserve
FRR-M	Frequency Containment Reserves manual
LUT	Lappeenranta University of Technology
PV	Photovoltaics
RH	Rolling Horizon
SQP	Sequential Quadratic Programming
TSO	Transmission System Operators

1 INTRODUCTION

1.1 Background

Rapid exhaustion of fossil fuels and increased greenhouse gas emissions of conventional generators is a consequence of the exponential increase in global energy demand [1]. To reduce the problem of greenhouse gases emissions and achieve sustainable development, the world is aimed to install renewable energy resources, such as solar, wind, biomass, hydro and tidal power on a large scale. In literature distributed energy resources (DERs) are described as renewable energy power plants which works in microgrids [2, 3]. DERs are often combined with energy storage systems. With DERs generation, no transmission losses are accrued as far as generation is done on-site. In DERs solar and wind energy are mostly used. Those sources are highly intermittent throughout the day. Thus, DERs are required to deal with those changes. Several approaches are used to overcome this problem. One of them is the usage of an energy storage system near the end-user side. The most frequently used however is integrating DERs into power grid (macrogrid) with the possibility to operate during grid failure or periods with low renewable generation.

Microgrid is defined as a low-voltage distribution network of interconnected DERs, controllable loads, and critical loads. It can operate in either grid-connected or island mode subject to operational characteristics of the main grid [4]. They have several advantages over macrogrid such as greenhouse gases emission reduction, demand response, voltage level improvement, line losses reduction. However, microgrids have drawbacks such as high integration costs and control management issues [5]. To reduce the impact of those problems energy management strategies (EMS) are used [6]. The International Electrotechnical Commission in the standard IEC 61970, related to EMS application program interface in power systems management, defines an EMS as “a computer system comprising a software platform providing basic support services and a set of applications providing the functionality needed for the effective operation of electrical generation and transmission facilities so as to assure adequate security of energy supply at minimum cost” [7]. EMS is aimed to operate microgrids in the most economically, sustainable and reliable way. EMS operates demand and supply with respect to the system constraints.

The mathematical approach of energy management strategy for Lappeenranta University of Technology (LUT) Green Campus microgrid is presented in this thesis. The obtained results are based on historical data of microgrid generation and load.

1.2 Objectives and delimitations

The objective of this thesis is to determine the most economically efficient strategy for using photovoltaics (PV) systems with battery storage for the on-site use. The strategy is aimed to provide an optimized solution that is in compliance with the technical requirements of the system and meets the needs of the end-user. The results of this work provide an overview for the battery owner to choose the most economically efficient way to use a PV array with an energy storage system. The scope of the thesis is to develop a methodology for optimizing the exploitation of a PV array and battery capacity for optimizing the cost of energy for the end-user.

The problem is formulated as a profit maximization problem with a number of constraints related to the technical requirements of the battery storage system, the PV system, and user requirements. The possible ways of solving this task, such as linear programming, reinforcement learning, and heuristics will be shown. Comparing several approaches for solving the problem will be discussed. The advantages and limitations of each approach will be provided. The most important variables for the model will be determined.

1.3 Structure of the thesis

This thesis is organized in chapters as follows:

Chapter 1 of the thesis includes an introduction to the topic and objective and scope of the thesis.

Chapter 2 provides an overview of the electricity markets in Finland including Nord Pool Spot market that has places for day-ahead and intra-day trading and Fingrid that holds ancillary service markets.

Chapter 3 is focused on the importance of demand-side management in modern microgrids. Description and examples of several energy management approaches are provided in this chapter, including their advantages and disadvantages.

Chapter 4 describes the proposed pipeline for linear optimization for solving energy management task. This chapter provides both a description of the simulation engine, which then will be used in experiments and a description of the linear optimization approach.

Chapter 5 gives an overview of conducted experiments and their results. In this chapter, the compassion between rule-based algorithm (simplest one) and the linear optimization algorithm is made. Also, this chapter illustrates the importance of battery capacity and solar radiance in demand side management.

Chapter 6 is the summary of the thesis and provides a discussion on the key results. The main outcomes of the thesis are presented in this chapter.

Chapter 7 is the final conclusion and the important outcomes.

2 CURRENT STATUS OF ELECTRICITY MARKET IN FINLAND

Open electricity market allows to deregulate the conventional electrical power industry and establish a competitive environment. Obstacles to competition in electricity generation and sales was removed by the Finnish electricity market reform in 1995 in sectors where competition is possible. From than on, end-users can consider tenders from different electricity suppliers. While earlier, local electricity company operating in an area had certainly been becoming an electricity supplier, now the market opened new possibilities in electricity purchasing [8].

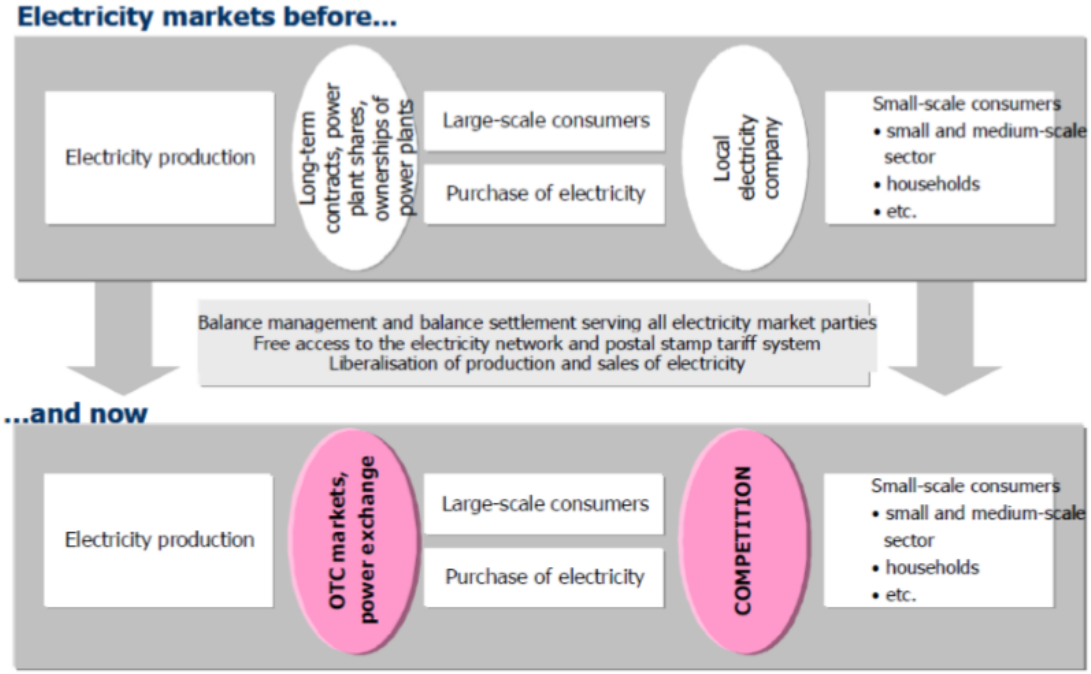


Figure 1. Illustration of deregulating of the Finnish electricity market

Electricity trading marketplaces in Finland are organized by Nord Pool spot which offers both intraday and day-ahead energy markets, and Fingrid which runs secondary service markets. Market participants should observe trading rules and regulations. Bids must be placed according to bidding rules within specified time limits (different time-scales for different markets are shown in Figure 2).

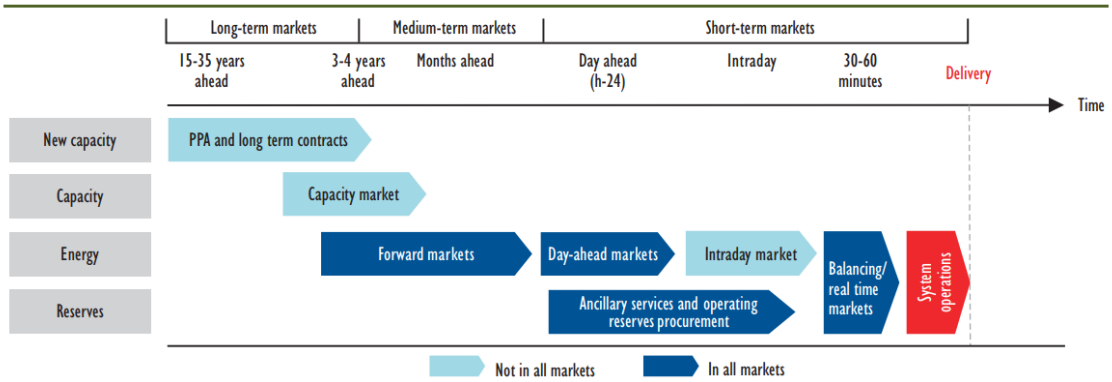


Figure 2. Overview of different building blocks of electricity markets [9]

2.1 Nord Pool markets

The Finnish electrical power system includes power plants, national transmission grid, regional and distribution networks and electricity consumers, and it is included to the inter-Nordic power system. In Finland, as well as in other Nordic countries, electricity generation and retail allow competition. Distribution and transmission are natural monopolies due to the natural characteristics of this components of the system.

Over the years, with extended power production and transmissions capacity and with increasing number of lines, power pools, a new framework for the competition was required and developed. These pools provide a market allowing to buy or sell power more easily across areas and countries. Such a dynamic market induce the generating companies to compete for the customers, developing their own trading strategy to increase their income while acting accordingly to the market.

Nord Pool, owned by the Nordic operators of transmission system, is the leading power market in Europe offering services associated with trading, clearing, and settlement in intraday and day-ahead markets across nine European countries, including Finland. Thanks to the highest supply security level, Nord Pool has become the one of the world‘s most efficient electricity markets [10]. To take part in any physical markets, entities must be defined as counteragent under the Clearing Rules, and sign with Nord Pool a Participant Agreement.

2.2 Elspot market

Elspot market is the main day-ahead market of Nord Pool spot where power hourly contracts and block contracts are traded. Also, it is possible to buy and sell and flexible contracts for the following day. Elspot day-ahead market has a special part in the electricity market of Nordic countries. This market trades by means of day-ahead auction for the following day. It takes into account all orders, which were sent and received before completion of trade. Nord Pool requires all participants to submit their offers with desired price and energy volume (MWh) to be purchased or sold hourly in the following day.

After submitting the bids by all members, for all areas of bidding balance between the total demand and supply is determined to calculate and publish the system and area prices. Supply and demand balance determines the price of power. Some factors can impact the prices changing (like weather). The calculated price is used as a reference price for Nordic electricity market [11].

By 12:00 CET, market participants are submitting their bids for the following day. Based on all submitted bids selling and buying curves are formed, and an algorithm calculates the price by equilibrium point trading method. The system price for each hour is determined by the intersection point of these curves. The system price calculation is made without taking into account grid capacities and congestion problems. However, most of the time the area price differ from system price due to exceeding the network limits. Transmission between areas exceeds the transmission capacity, which lead to changes in prices: in area, with excess supply, the price drops; in area with short supply the price rises. The illustration of this principle is shown in Figure 3.

Hourly prices are announced to the market around 12:45 CET and trades are settled. Hourly prices and energy capacity that are delivered by sellers or needed by buyers, are entered into the day-ahead trading system of the Nord Pool and power delivery from seller to buyer for the following day is agreed. According to the agreement, the actual delivery of power starts from midnight CET of the next day.

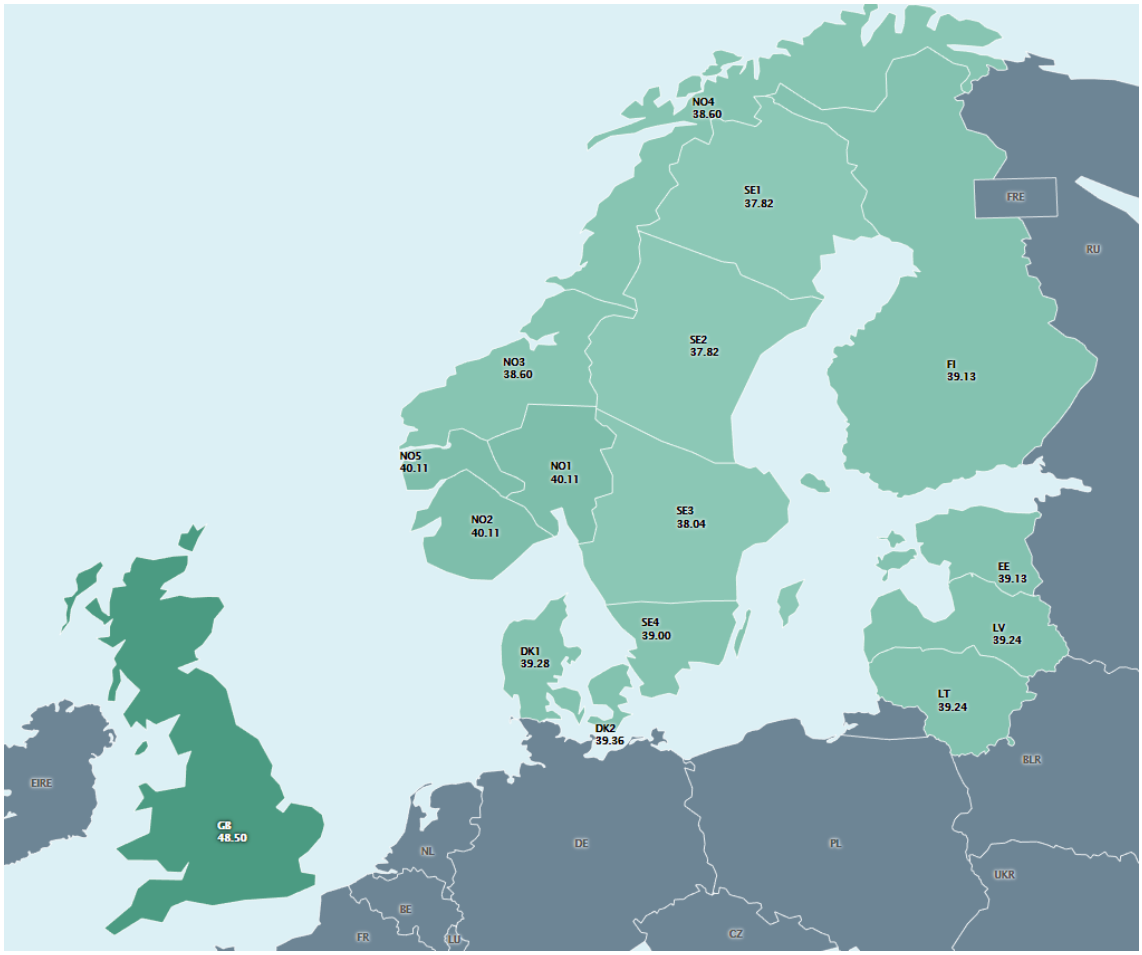


Figure 3. The map of area prices of Nord Pool on the First April 2019. The system price is 39.42 $\frac{euro}{MW}$ [12]

2.3 Elbas market

Elbas is an intraday market of Nord Pool which supports day-ahead market and is a following market after Elspot for non-stopping trading before the time of power delivery. Intraday market allows participants to correct their physical electricity balance to reduce imbalances between volume of day-ahead contracts and actual produced energy. It might happen because actual power delivery happens with a delay to Elspot trading closing.

Capacities available for intraday trading are published after the Elspot market is closed at 14:00 CET. Elbas offers continuous trading up to one hour to physical delivery time. Price and volume for each particular hour must be specified in the bids. Day-ahead electricity prices could not be changed after agreement. Intraday prices, on the other hand, are often changing. Prices are determined with a following principle: the first lower sell or higher

buy proposal is fulfill, the second best is fulfilled second, etc [13]. It is called: first-come - first-served principle.

Various reasons may cause imbalance in power market, such as incidents which may take place between the closing of the day-ahead market and the next day delivery. For instance, a problem in a power plant operation can change the balance of the power or unpredictable nature of wind power. Indetermination should always be taken into account, especially in the markets with high amount of renewable generation. Nord Pool with a lot of wind generation is one example of such markets. Increasing in the amount of wind and solar generation makes the intraday market extrmely important to keep the balance.

2.4 Fingrid balancing market

Fingrid balancing power market provides power balance regulating capacity. All producers can submit power regulation bids in the balancing power market. There are two bidding categories: Up-regulation bids and Down-regulation bids [14].

To reduce electrical consumption or to increase power generation, up-regulation is used. On the other hand, down-regulation bids are used for the opposite: to decrease generation or to increase consumption. In both cases, bids must contain the price for an additional volume, which participant should be payed in case of up-regulation (or pay in case of down-regulation). Regulating power proposals should be submitted to Fingrid 45 minutes before the operating hour. The current minimum balancing power bids capacity is 10 MW and the bidder should be able to activate the resource in 15 minutes [15].

2.5 Fingrid ancillary service markets

Fingrid controls electricity transmission system in Finland planning and monitoring its operation. Fingrid is in charge for the system robustness. It also should maintain and develop the grid. To insure the security of the grid, supply and demand should be also maintained by Fingrid. This is reached by the means of its balancing power market. Fingrid also organizes markets for ancillary services such as frequency control, voltage control, spinning and standing reserve.

2.5.1 Frequency control

The most important part of the power system is a balance between production and consumption. It should be insured all the time and Fingrid is responsible for it. It is achieved by applying non-stop managing and controlling. If consumption exceeds production (or vice verse) grid frequency start to change. If the frequency goes beyond predefined minimum and maximum values, regulation of the consumption and production is trying to return frequency to normal values. Maintained reserves can be activated or regulating bids from the balancing power markets can be initiated to achieve the consumption and production balance [16].

Nordic Transmission System Operators (TSOs) bear the reserves maintaining obligations. There are two types of reserves in Fingrid:

- Frequency Containment Reserves (FCR)
- Frequency Restoration Reserves (FRR).

Frequency Containment Reserves (FCR) are used for constant frequency control while Frequency Restoration Reserves (FRR) are used during abnormal conditions when frequency exceed normal values, and it is aimed to balance the production and consumption, so frequency could go back to normal values. All FCR could be grouped into two groups: FCR-N are used for normal operation: these resources are used when the frequency is more than 50.05 Hz or lower than 49.95 Hz. If the frequency falls down below 49.9 Hz or exceed 50.1 FCR-D are activated. The activation time depends on the type of power resource.

Fingrid has two separate markets for FCR-N and FCR-D. There are two types of agreements on these markets: long-term for year and short-terms for hours. Before 18:00 all participants must submit their bids to Frequency Containment Reserve (FCR) hourly markets. All bids are proceeded before 22:00. Frequency Restoration Reserves (FRR) is divided into Automatic Frequency Restoration Reserve (FRR-A) aimed to turn back the frequency to 50 Hz automatically and manual (FRR-M) designed for power balancing control in normal situation and disturbance with manual activation from Main Grid Control Centre. Bids for the FRR-A market must be submitted by 17:00 o'clock. Accepted bids are announced by 18:05 o'clock. Frequency reserve obligations for Finland:

- Normal operation (FCR-N) - 140 MW

- Disturbances (FCR-D) - 220-265 MW
- Automatic restoration (FRR-A) (only morning and evening hours) - 70 M
- Manual restoration (FRR-M) - 880-1100 MW

To meet the requirements of FRR-M Fingrid has its own reserve power plants. Fingrid's own power plants and leasing power plants are not used for commercial electricity production.

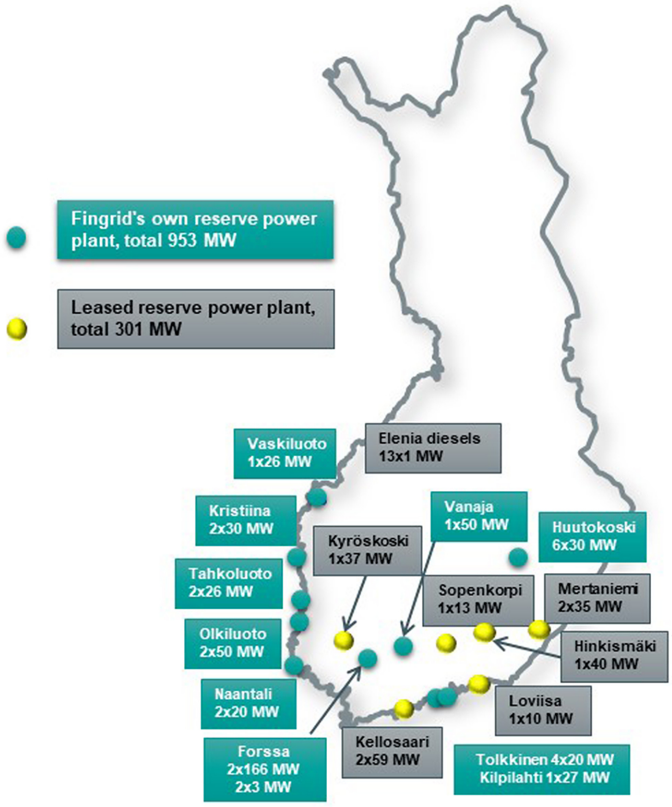


Figure 4. Reserve power plants of Finland [17]

3 DEMAND SIDE MANAGEMENT

The traditional approach of electrical system operation is unidirectional and top-down oriented. The idea of such an approach is that the generation of electrical energy is done mainly by a number of big electrical generators, such as steam power plants, nuclear power plants, hydropower plants, and others. However, an increasing amount of renewable energy and the introduction of smartgrid are changing this approach towards open market systems [18, 19].

The main changes involved in the understanding of the load. Nowadays load is becoming "smart", i.e. load could be influenced in order to achieve additional technical and economic efficiency. Electrical and thermal load are used as additional degrees of freedom [20], i.e. modification of consumer demand for energy through various methods. This modification is achieved by various methods, which is called demand-side management (DSM) (Figure 5).

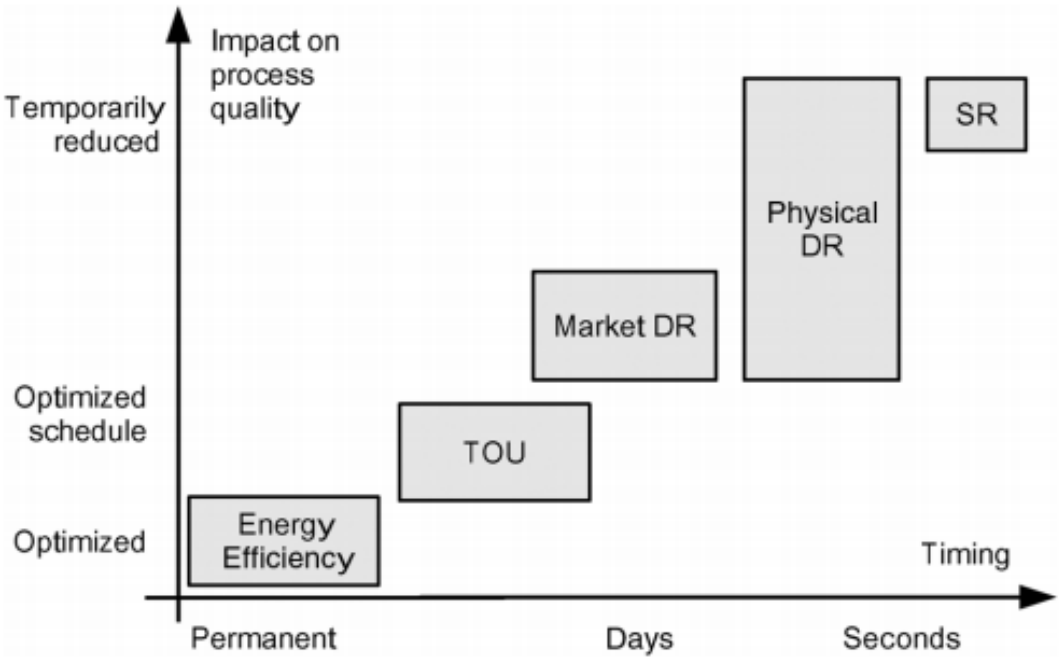


Figure 5. Illustration of the methods of Demand Side Management. TOU - time of use, DR - demand response, SR - spinning reserve [20].

Demand response (DR) is one example of such methods. DR is changing electric usage by end-user from their normal consumption patterns in response to changes in the price of electricity or other control sign over time [21]. Demand response could be achieved in

various ways: reducing the consumption in peak hours, when prices for electrical energy are high (which involves loosing of some comfort to the customer); shifting some load from peak hours to off-peak hours (for example doing laundry or dishwashing during the night); using onsite generation. Demand respond is beneficial both for the customer, due to cost savings in peak hours; and for market, because DR increases technical efficiency of available system. DR could increase short-term capacity, which would lead to avoiding deferred capacity costs. Also, DR increases the reliability of the system by decreasing the risk of outages. With DR operator will have more options and resources to maintain the system in optimal level [22].

Working as a standing reserve, DSM could increase the amount of wind and solar power that could be absorbed, which is relevant in a period of low consumption and high wind or solar power plant generation. Thus DSM replaces fuel-based generation units and allows to decrease carbon-dioxide emissions. In the end, it increases the performances of the system. Authors mentioned another benefits of DSM [23]:

- Replace aging assets of the electricity infrastructure
- Reducing the generation margin
- Improving transmission grid investment
- Improving operation efficiency
- Improving distribution network
- Improving investment efficiency
- Balancing intermittent renewable

The idea of DSM is not new and the key technologies for its implementation have already been developed. However, the implementation of DSM has been slow because of a number of challenges of inducing DSM in current power systems:

- Lack of information and communication technology infrastructure
- Lack of understanding of the benefits of DSM solutions
- DSM-based solutions are often not competitive when compared with traditional approaches

- DSM-based solutions tend to increase the complexity of the system

To conclude: demand side management is a promising research field, which could become widely used in many product applications in smart grids and smart houses. Today demand side management is represented by a number of strategies for controlling energy flow (energy management strategies, EMS).

Strategies could be groped by their complexity (complexity of solving the task, number of changing parameters), calculation speed, the cost and complexity of implementation. The most frequently used strategies include rule-based approach, linear optimization, reinforcement learning approach. Rule-based approach and reinforcement learning approach will be discussed in the details later. Linear programming approach will be demonstrated in the next chapter.

3.1 Energy management strategies based on rule-based method

Rule-based methods are the simplest ones in all fields. They do not require computational power and they are the fastest ones comparing with other methods. Rule-based methods could be used in simple systems, where a complex solution is not needed. For example, rule-based methods were used in conditioning [24, 25]. Despite their simplicity, rule-based methods prove their efficiency in a number of cases, such as systems of energy buildings controls.

Doukas et al. [26] proposed intelligent decision support model using rule sets based on a typical building energy management system. Authors concluded that the performance of the model could be evaluated as satisfactory. Also, the system could be adjusted to any given building in a short time, which makes the system robust to changes. Trovão et al. [27] used a rule-based system, which was aimed to deal with a multilevel energy management system for a multi-source electric vehicle. The proposed system fulfills the requested performance.

A rule-based method is a naive approach for an energy management strategy. They are often used as a baseline approach for solving the task. The idea is based on the assumption that simple rules are enough for energy management. The rules are based on conditional statements and should be adjusted to each user. The best set of rules could be obtained from tests on historical data. A possible set of rules might include:

- Charge battery at specific hours and discharge when it is needed;
- Charge battery if electricity prices are lower than a daily mean prices and discharge when prices are higher than a daily mean prices;
- Charge battery if electricity prices are lower than a daily median prices and discharge when prices are higher than a daily median prices;
- Charge battery if electricity prices are lower than a daily 5th percentile prices and discharge when prices are higher than a daily 95th percentile prices;
- Charge battery if PV generation is higher than a user consumption and discharge when PV generation is lower than a user consumption;
- Charge battery if PV generation is higher than a user consumption and discharge when PV generation is lower than a user consumption and prices are higher than a daily mean prices.

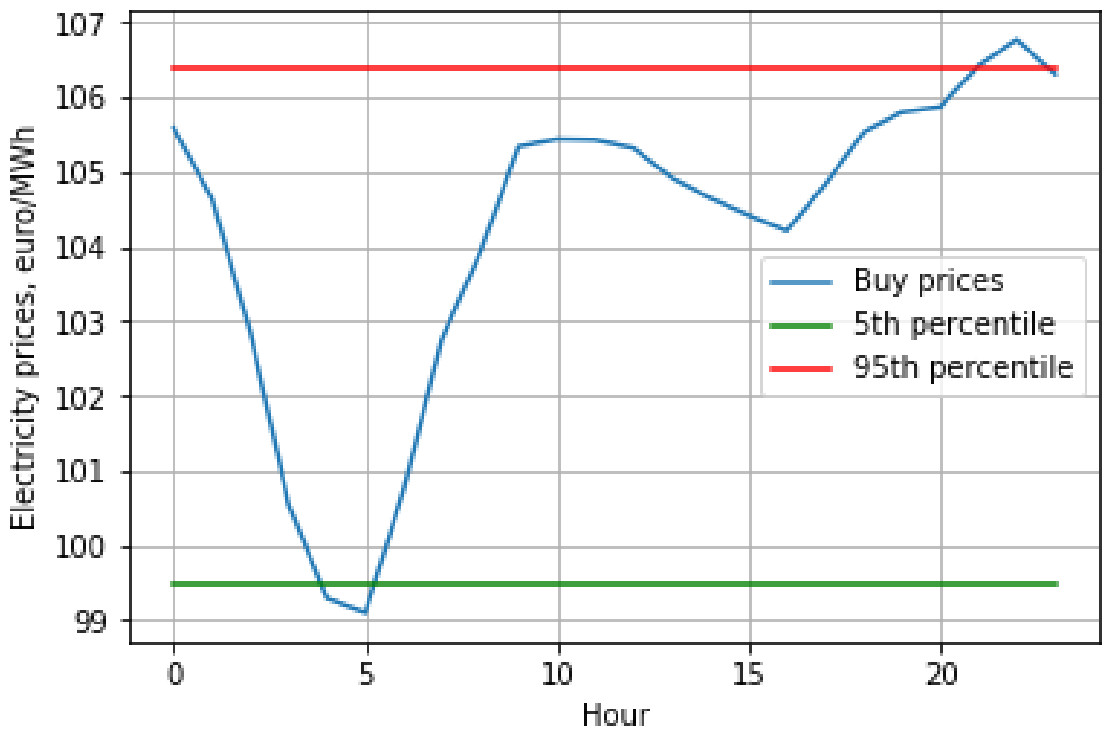


Figure 6. Example of a percentile rule-based strategy. Based on this strategy, battery charging during a time, when electricity prices are lower than the green line and discharging during a time when prices are above the red line.

A number of authors concluded that rule-based strategy, despite their simplicity, could be useful in energy management strategies. Teleke et al. [28] described rule-based control

strategy for optimizing battery energy storage system (BESS) with the PV array. The effectiveness of this control strategy has been tested by using an actual PV system and wind farm data. It was shown that the BESS can indeed help to cope with variability in wind and solar generation. Choudar A. et al. [29] proposed a state of charge-based (SOC) structure for a microgrid energy management to smooth operation of a microgrid.

3.2 Energy management strategies based on reinforcement learning

Reinforcement learning is a new field of machine learning inspired by behaviorist psychology [30]. The idea of reinforcement learning could be defined as follows: an agent is interacting with the environment in order to gain maximum reward from agent's actions (Figure 7). Currently, reinforcement learning is mostly used for various fields of robotics [31–33], but it also has shown its efficiency in a number of fields.

Dalamagkidis et al. [34] used agent-based approach to improve the thermal comfort of buildings, energy quality, and energy consumption. They concluded that the reinforcement learning model could outperform fuzzy controllers. Henze et al. [35] evaluated the performance of the reinforcement learning approach in controlling thermal storage in building. The proposed system is simple, easy and fast in terms of operation. Also, it is comparable in terms of increased efficiency to current state of art systems. O'Neill et al. [36] proposed an energy management system for residential demand response. In a number of simulations, they showed the increase in cost savings from 16% up to 40% with using of a deep reinforcement learning system.

The reinforcement learning could be explained using a Markov process. The Markov process is a random process whose evolution after any given time parameter t does not depend on the evolution preceding t, provided that the value of the process at that moment is fixed (the "future" of the process does not depend on the "past" with the known "present"). Basic models are modeled as a Markov process:

- A number of environments and agents states: S
- A number of agent's possible actions: A
- The probability of transition from state s to state $s^{'}$ under action a: $P_a(s, s^{'}) = Pr(s_{t+1} = s^{'}|s_t = s, a_t = a)$
- Reward after transition from s to $s^{'}$ with action a: r

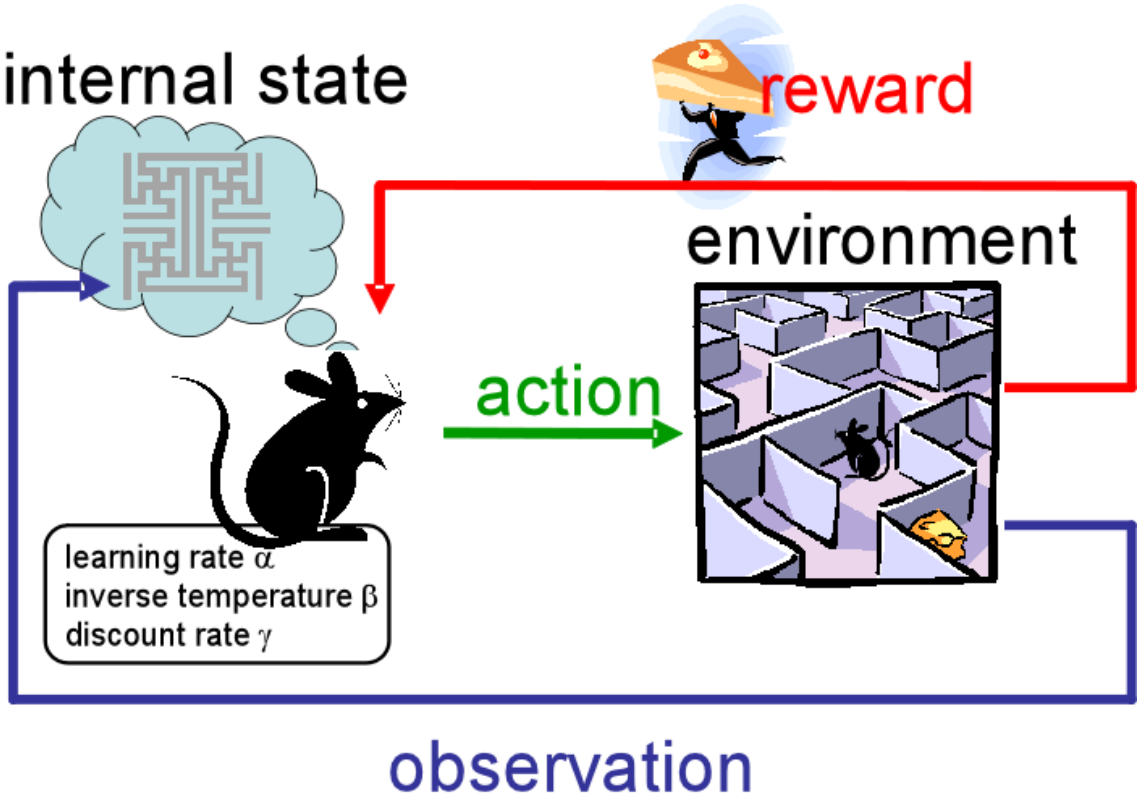


Figure 7. The illustration of reinforcement learning basics [37].

- Set of rules that describe what information is available for agent

In most cases the agent could observe the whole environmental states and a set of available actions is restricted. A learning agent interacts with the environment in discrete time steps. At each time step t, the agent observe o_t. Then agent pick action a_t from available actions A. The action made in the environment and the environment transfers to the new state s_{t+1}. The agent receives reward associated with a such transition (s_t, a_t, s_{t+1}). The agent is aimed to collect as much reward as possible.

Today Q-learning is the most commonly used reinforcement learning method, where Q stands for the long-term value of an action. Q-learning is about learning Q-values through observations [38]. A number of authors prove the efficiency of Q-learning in the various tasks of energy systems optimization [39, 40]. Also, it could be combined with other approaches such as linear programming and fuzzy optimization [41, 42].

Q-learning consists of several steps. In the beginning, the agent initializes Q-values to 0 for every state-action pair. More precisely, $Q(s, a) = 0$ for all states s and actions a. This is essentially saying we have no information on the long-term reward for each state-action pair. After the agent starts learning, it takes an action in a state s and receives reward r. It

also observes that the state has changed to a new state $s^{'}$. The agent will update $Q(s, a)$ with this formula [43]:

$$Q(s^{'}, a^{'}) = Q(s^{'}, a^{'}) + LF * (r + DF * \max(Q, s) - Q(s^{'}, a^{'})) \tag{1}$$

where LF - is a learning factor. The higher it is, the stronger the agent trusts in new information; DF - is a discount factor. The smaller it is, the less agent thinks about the benefits of future actions.

3.3 Energy management strategies based on other approaches

Logenthiran et al. [44] proposed a demand-side strategy that could be used in the smart grids. The proposed strategy was formulated as a minimization problem solved by a heuristic evolutionary algorithm. Authors concluded that the proposed algorithm could be used in smart grids in order to achieve substantial savings and reducing peak load demand of smart grids.

Atzeni et al. [45] formulated the resulting demand-side optimization problem as a non-cooperative game and analyzed the possibility of the existence of an optimal solution. The proposed distributed and iterative algorithm based on the proximal decomposition. Authors tested the day-ahead optimization algorithm in a realistic situation.

Wu et al. [46] described optimal energy management for a grid-connected photo-voltaic-battery hybrid system. The proposed algorithm was aimed to minimize cost for end-user with respect to the number of constraints. They concluded that disturbance in the predictions of solar generation could affect the optimization results significantly.

Matallanas et al. [47] described the development of a control system for demand-side management in the residential sector with distributed generation. The distributed control system was composed of two modules: a scheduler and a coordinator, both implemented with neural networks. Results showed that Artificial Neural Networks were able to be implemented as an active demand-side management system that meets the user requirements and schedules the tasks for the next day to improve the electrical local behavior.

Chaabene et al. [48] proposed a fuzzy-logic based algorithm for DSM, which was implemented and tested. Authors concluded that the described system could reduce the energy costs by 10-20%.

Palma-Behnke et al. [49] described DSM system for energy and water usage using rolling horizon (RH) strategy and linear optimization. The overall pipeline of DMS included Neural Networks for predicting generation and consumption and linear optimization engine. They reported an increase in the economic efficiency of such system.

4 PROPOSED METHODS

In the previous section, several algorithms for energy management were described. For further work, two algorithms were selected - linear optimization and heuristics. Linear optimization approach showed great potential for this type of task in the recent "Power Laws: Optimizing Demand-side Strategies" competition hosted on the DrivenData platform. In terms of score, it outperformed both Reinforcement Learning, fuzzy-logic and other algorithms. Teams, who managed to get the first three places were using linear optimization as their main model [50]. On the other hand, approach with predefined rules took is the simplest approach, which was used in this work as a baseline solution of this task.

4.1 Algorithms

In this section, the linear programming optimization algorithm will be discussed. As it was mentioned before, the aim of demand-side management in the case of this thesis is to decrease the overall cost of electrical energy for LUT Green Campus. Green Campus microgrid consists of a number of elements: 6 PV arrays, battery storage system, 5 buildings (consumption). The microgrid is connected to the macrogrid. The overall scheme of LUT Green Campus is presented on Figure 8 (used symbols are presented in table 1). The aim of the demand-side strategy is to minimize electricity cost.

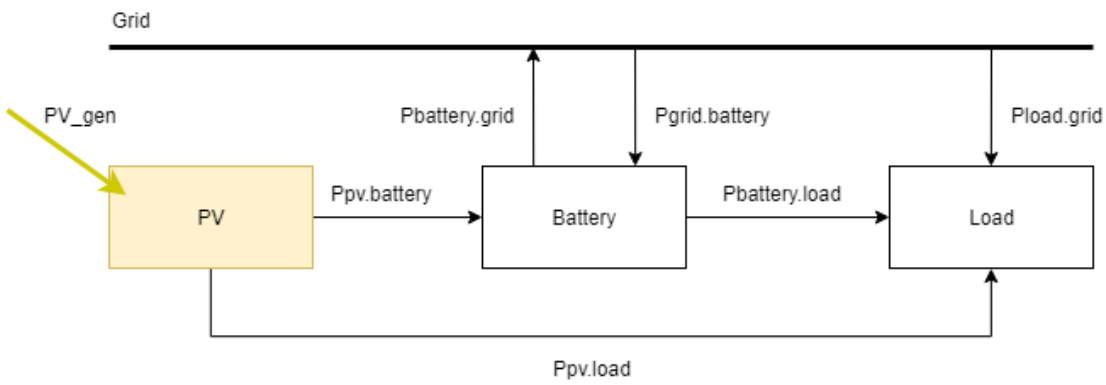


Figure 8. Design scheme

Table 1. Used symbols

Symbol	Meaning	Dimension
P_{gen}	Power output of PV array	kWh
$P_{\text{pv.battery}}$	Power flow from PV array to battery	kWh
$P_{\text{pv.load}}$	Power flow from PV array to load	kWh
$P_{\text{battery.grid}}$	Power flow from battery to grid	kWh
$P_{\text{grid.battery}}$	Power flow from grid to battery	kWh
$P_{\text{battery.load}}$	Power flow from battery to load	kWh
$P_{\text{grid.load}}$	Power flow from grid to load	kWh
P_{load}	Power consumption	kWh
SOC	Battery charge state	%

Macrogrid plays an important role in the EMS strategy. During hours with high PV generation, not utilized energy could be accumulated in a battery storage system or it could be sold in macrogrid. In the end, in this case, most of the electrical energy is coming from macrogrid. Battery storage, however, lowering consumption from macrogrid during peak and half-peak hours, hours with the highest electricity price.

This aim could be transformed into minimization task. The objective function could be defined as follows:

$$J = \sum_{t=1}^{T} (P_{\text{grid.load,t}} + P_{\text{grid.battery,t}}) * r_{\text{buy,t}} - P_{\text{battery.grid,t}} * r_{\text{sell,t}} \rightarrow \min \tag{2}$$

$$J = \max(P_{\text{grid.load,t}} + P_{\text{grid.battery,t}}) * r_{\max} +$$
$$\sum_{t=1}^{T} (P_{\text{grid.load,t}} + P_{\text{grid.battery,t}}) * r_{\text{buy,t}} - P_{\text{battery.grid,t}} * r_{\text{sell,t}} \rightarrow \min \tag{3}$$

$$J = \max(P_{\text{grid.load,t}} + P_{\text{grid.battery,t}}) * r_{\max} \tag{4}$$

where T - length of optimization horizon; $r_{\max}$ - price for maximum consumption. This price is based on the network fee. It depends on the maximum consumption of the grid for a calculating period (i.e. month). $r_{\max} = f(P_{\max})$; $r_{\text{buy,t}}$ and $r_{\text{sell,t}}$ - electricity buying and selling prices for the time t. Price for selling electricity was taken equal to the NordPool price. Price for buying electricity was calculated as follows:

$$r_{\text{buy,t}} = r_{\text{sell,t}} + r_{\text{tax}} + r_{\text{distribution}} \tag{5}$$

where $r_{\text{buy,t}}$ and $r_{\text{sell,t}}$ - price for buying and selling electricity at time t; $r_{\text{tax,t}}$ - additional buying tax, $r_{\text{distribution,t}}$ - electricity distribution costs. We assumed that, $r_{\text{tax}} = 2.79\frac{cent}{kWh}$, $r_{\text{distribution}} = 5.28\frac{cent}{kWh}$.

During optimization, we charge and discharge battery, thus induce a state of battery charge, which could be calculated as follows:

$$SOC_{\text{t}} = SOC_{\text{t}-1} + \big[(P_{\text{pv.battery}} + P_{\text{grid.battery}}) * \eta_{\text{charging}}$$

$$-(P_{\text{battery.grid}} + P_{\text{battery.load}}) * \eta_{\text{discharging}}\big] * \frac{1}{BC} \tag{6}$$

where $\eta_{\text{chargning}}$ and $\eta_{\text{discharging}}$ - battery charging and discharging efficiencies which are specified by manufacturer; BC - maximum battery capacity, kWh.

Following constraints must be fulfilled during the optimization process:

1. Sum of power flows for PV array in any given time t must be equal to zero (PV constraint):

$$P_{\text{gen}} - P_{\text{pv.battery,t}} - P_{\text{pv.load,t}} = 0 \tag{7}$$

2. Sum of power flows for load in any given time t must be equal to zero (power balance constraint):

$$P_{\text{load}} - P_{\text{pv.load,t}} - P_{\text{battery.load,t}} - P_{\text{grid.load,t}} = 0 \tag{8}$$

3. Battery charge state must be higher than S_{min} and lower than S_{max} - minimum affordable value for battery according to the manufacturer restrictions and maximum value according to the battery capacity limit (battery state constraint):

$$SOC_{\text{t}} - S_{\text{min}} \geq 0 \tag{9}$$

$$S_{\text{max}} - SOC_{\text{t}} \geq 0 \tag{10}$$

The defined minimization task could be solved as linear programming task with prior

known parameters: P_{gen}, P_{load}, S_{min}, S_{max}, $r_{\text{buy,t}}$, $r_{\text{sell,t}}$, η_{charging}, $\eta_{\text{discharging}}$ and unknown variables: $P_{\text{pv.battery}}$, $P_{\text{pv.load}}$, $P_{\text{battery.grid}}$, $P_{\text{grid.battery}}$, $P_{\text{battery.load}}$, $P_{\text{grid.load}}$, SOC_{t}. The most common way of solving linear programming task is sequential quadratic programming (SQP) [51], [52].

Schittkowski [53] presented a method that has higher efficiency and lower computation time over a large number of test problems. The general idea of SQP method is to transform the problem into easier subproblem that can then be solved and used as the basis of an iterative process. At each major iteration, an approximation is made of the Hessian of the Lagrangian function using a quasi-Newton updating method. This is then used to generate a QP subproblem whose solution is used to form a search direction for a line search procedure. The algorithm of solving such task is presented at Algorithm 1.

Currently, number of programming languages have libraries of implementation of SQP methods. For the scope of this work, $ortools$ library (Python) was used [54].

Algorithm 1 Sequential Quadratic Programming

Input: $f(x) \to \min, b(x) \geq 0, c(x) = 0$
Output: x

1. Calculate Lagrangian for this problem: $\mathcal{L}(x, \lambda, \sigma) = f(x) - \lambda^T * b(x) - \sigma^T * c(x)$, where λ and σ - are Lagrange multipliers.
2. Solving quadratic programming (QP) subproblem:
   $\frac{1}{2} * d^T * H_k d + \nabla * f(x_k)^T * d, d \in R$
   $\nabla g_i * (x_k)^T d + g_i(x_k) = 0, i = 1, ..., m_e$
   $\nabla g_i * (x_k)^T d + g_i(x_k) \leq 0, i = m_e, ..., m$
3. $x_{k+1} = x_k + a_k * d_k$

The optimization process will be performed using a moving window approach. At time $t = t_i, SOC = SOC_{\text{t}_\text{i}}$ optimization task is done for optimization horizon T (starting in t_i, ending in $t_i + T$) and than optimized values are used to evaluate $SOC_{\text{t}_{\text{i+1}}}$. The system moves in time $t = t_{i+1}$ and the the algorithm repeats. The simulation run until the end of time steps. The illustration of moving window approach is shown on Figure 9.

The proposed approach is used for similar types of tasks. By updating the charging and discharging rules every timestep t, the uncertainty of the dataset, i.e. the accuracy of measurements and predictions might be neglected. Thus the overall goodness of the pipeline

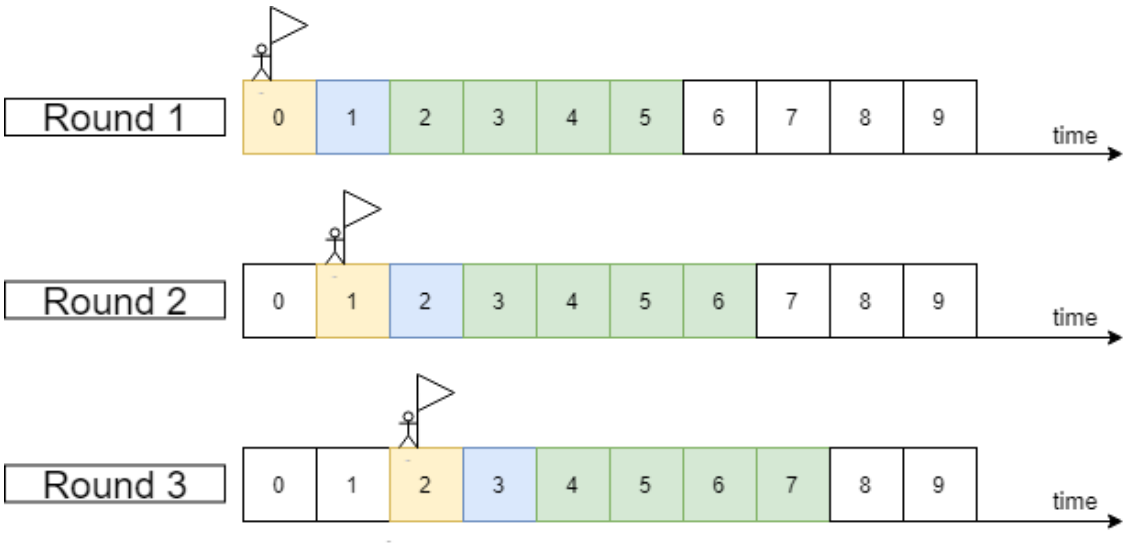


Figure 9. Moving window illustration. The initial state is $t = 0$, optimization is run for time steps $t_{\text{start}} = 1$ up to $t_{\text{end}} = 5$. The optimized values of $t = 1$ is used as initial state for the next optimization Round 2. The optimization run until the end of time steps.

would be higher. On the other hand, frequent updates require more computational power.

5 EXPERIMENTS AND RESULTS

In the previous chapters, several ways to deal with energy management optimization were discussed. To insure that the proposed method of linear optimization is viable in a real-world scenario, several experiments were conducted. Also, the compassion of linear optimization to a rule-based method is shown. The scope of this chapter is aimed to show used data in experiments, evaluation criteria and experimental conditions.

5.1 Data

The dataset which was used in the experiments contained the information about LUT Green Campus consumption and PV generation for the period from January 2016 up to January 2017. The dataset consisted of several time-series observations of active power consumption of LUT Campus buildings. To increase the speed of calculations, only four months were used in experiments. Selected months represents the tendency in consumption and solar generation of the seasons: January (winter), April (spring), July (summer), October (autumn).

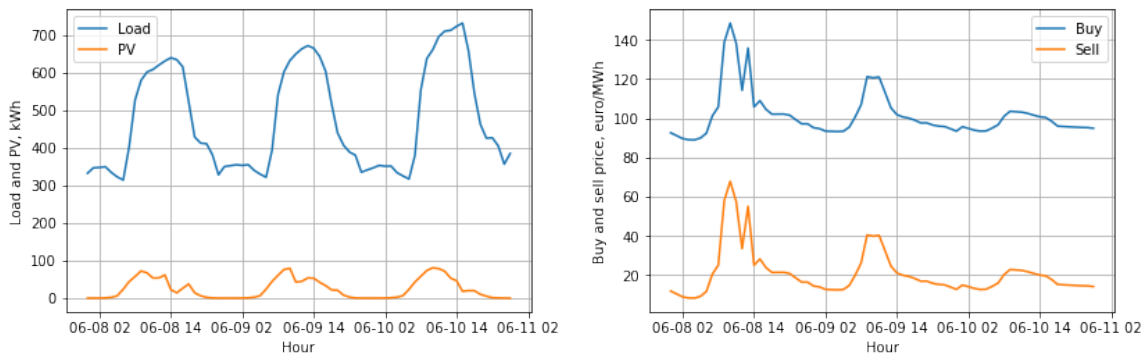
Information about electricity prices for were taken from NordPool web-site [55]. In the scope of experiments, it was assumed that price for selling electricity was taken equal to the NordPool price and price for buying electricity was calculated as follows:

$$r_{\text{buying}} = r_{\text{selling}} + r_{\text{max}} + r_{\text{tax}} + r_{\text{distribution}} \tag{11}$$

where r_{buying} and r_{selling} - price for buying and selling electricity; r_{max} - price for maximum consumption. This price is based on the network fee. It depends on the maximum consumption of the grid for a calculating period (i.e. month). $r_{\text{max}} = f(P_{\text{max}})$; r_{tax} - additional buying tax; $r_{\text{distribution}}$ - electricity distribution costs; $r_{\text{tax}} = 2.79\ \frac{cent}{kWh}$, $r_{\text{distribution}} = 5.28\ \frac{cent}{kWh}$

During the following experiments, the ground-truth knowledge about PV generation, consumption, selling and buying prices for the next n periods were used. However, in the real-case scenario this information is not available beforehand. Thus it is necessary to predict it.

A number of studies of prediction electricity consumption and PV generation were con-



(a) (b)

Figure 10. Data example: (a) PV and load of LUT Green Campus; (b) prices for selling and buying electricity.

ducted. The trend of research is the usage of modern data-driven models and approaches. Popular approaches include linear models (AR, ARMA, ARIMA, SARIMA) [56–58], Support Vector Machines [59, 60], Neural Nets approaches (perceptron, Feed-Forward and Long Short Term Memory Neural Nets) [61–64], tree-based approaches (Random Forest and Gradient Boosting) [65, 66].

In most cases prediction is based on available to researcher historical data, which might include the information about the following variables:

- Time: year, month, day, hour, minute;
- Weather-related variables: temperature, wind speed, humidity, cloud cover;
- Condition of PV array: time in exploitation, dust cover, the temperature of an array;
- Parameters of consumers;

5.2 Evaluation metric

For each hour in the historical dataset, we calculate the spent money on the electricity with and without the proposed algorithm. Then, the total spends are calculated. The relative difference in the total sum of spent money was used as a metric. The metrics could be calculated as follows:

$$M = \frac{M_2 - M_1}{M_2} * 100\% \tag{12}$$

where M_1 and M_2 - spent money with and without DSM.

5.3 Description of experiments

To compare the performance of proposed approaches, two experiments were performed. In the first experiment, comparison between the heuristics approach and the linear optimization approach were made. As it is discussed in Section 3, there are several approaches for solving energy management optimization. The simplest one is based on a predefined set of rules. In this work, this method is used as a baseline solution for DMS. The set of charging and discharging rules for a battery was defined:

- Charge battery with constant speed of charging during hours with low tariff (night hours, i.e. from 10 PM to 7 AM, 10 hours total);
- Discharge battery with constant speed of discharging during hours with high tariff (day hours, i.e. from 7 AM to 10 PM, 14 hours total);

The speed of charging and discharging were calculated with following formulas:

$$S_{\text{charging}} = \frac{\text{BC}}{10}; S_{\text{discharging}} = \frac{\text{BC}}{14} \tag{13}$$

where BC - maximum battery capacity, kWh. These rules were used due to the significant difference between prices in a day and night periods of a day.

The aim of the second experiment is to determine the influence of the amount of PV generation, battery capacity on the metrics. We run simulations with changing initial parameters: PV generation is multiplied by the factor of 3, 6, 9 and 12. The second set of experiments - battery capacity is multiplied by the factor of 3, 6, 9 and 12.

Both experiments were performed on 4 months data, as it was discussed in 5.1.

5.4 Results of experiments

5.4.1 Comparison between rule-based approach and linear optimization approach

In this section, the comparison between the rule-based approach and linear optimization approach is presented. As it was discussed in Section 5.3, the scope of the first experiment is to compare the performance of rule-based approach and linear optimization approach. This was done by running several simulations on the dataset, which was introduced in 5.1. The results of the experiment are presented in Table 2.

Table 2. Rule-based approach and linear optimization approach results

Month	**PV multiplier**	$M, \%$
January	Rule-based	0.313
	Linear optimization	0.922
April	Rule-based	0.520
	Linear optimization	1.542
July	Rule-based	0.578
	Linear optimization	1.596
October	Rule-based	0.402
	Linear optimization	1.366

From the results of this experiment, we may see that both rule-based and linear optimization algorithms are suitable for solving energy management optimization task. Both approaches showed a positive value of the metric, but the performance of linear optimization was 2.94 times better on average.

The consumption from a grid for several cases is shown in Figure 11 and a battery charge for a given time is presented in Figure 12. The consumption from the grid in a rule-based approach is similar to the consumption without any energy management optimization strategy at all. In the same time, linear optimization consumption has several spikes in the consumption. These spikes might be a result of a sudden difference between buying and selling prices in the electricity market.

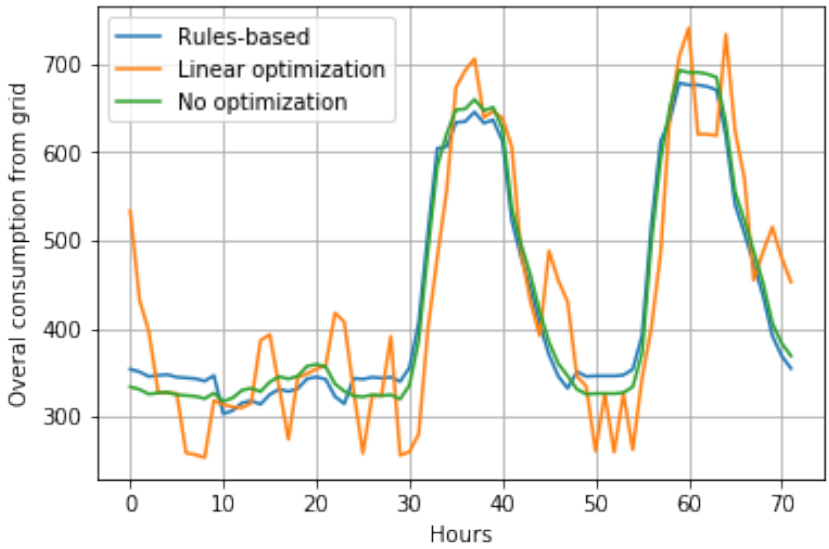


Figure 11. The illustration of overall consumption from a grid for tree cases: rule-based optimization, linear optimization, no optimization (1st-3rd January, 2016).

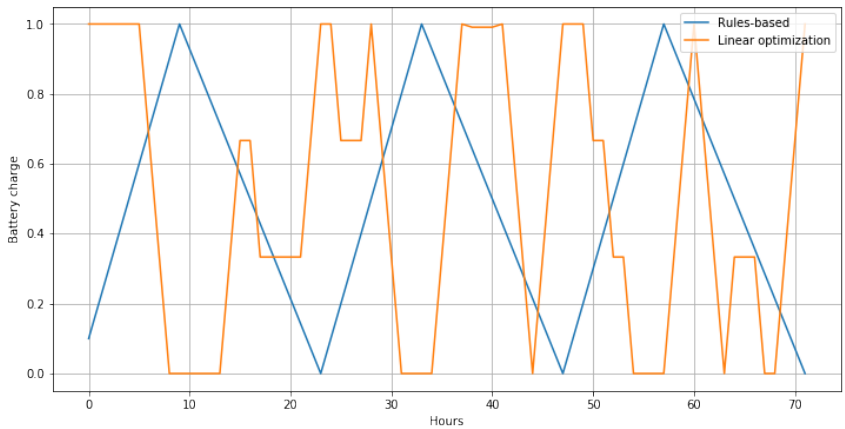


Figure 12. Battery charge for the two cases: rule-based optimization and linear optimization (1st-3rd January, 2016).

5.4.2 Comparison between the rule-based approach and linear optimization approach

The scope of the second experiment was aimed to determine the influence of battery capacity and the amount of solar radiation on the performance of the proposed linear optimization approach. The results of second experiment is presented in Table 3 and shown in Figures 13 and 14.

Table 3. Results of battery capacity experiment.

Month	Battery capacity multiplier	$M, \%$	Solar radiance multiplier	$M, \%$
January	1	0.922	1	0.922
	3	2.736	3	3.648
	6	3.612	6	4.093
	9	4.362	9	5.097
	12	4.964	12	5.603
April	1	1.542	1	1.542
	3	5.394	3	5.252
	6	8.285	6	7.064
	9	9.821	9	7.328
	12	10.777	12	7.750
July	1	1.596	1	1.596
	3	4.142	3	6.554
	6	8.654	6	7.236
	9	11.640	9	7.876
	12	11.900	12	8.922
October	1	0.402	1	1.366
	3	5.239	3	3.401
	6	7.873	6	5.482
	9	9.612	9	6.857
	12	10.634	12	7.245

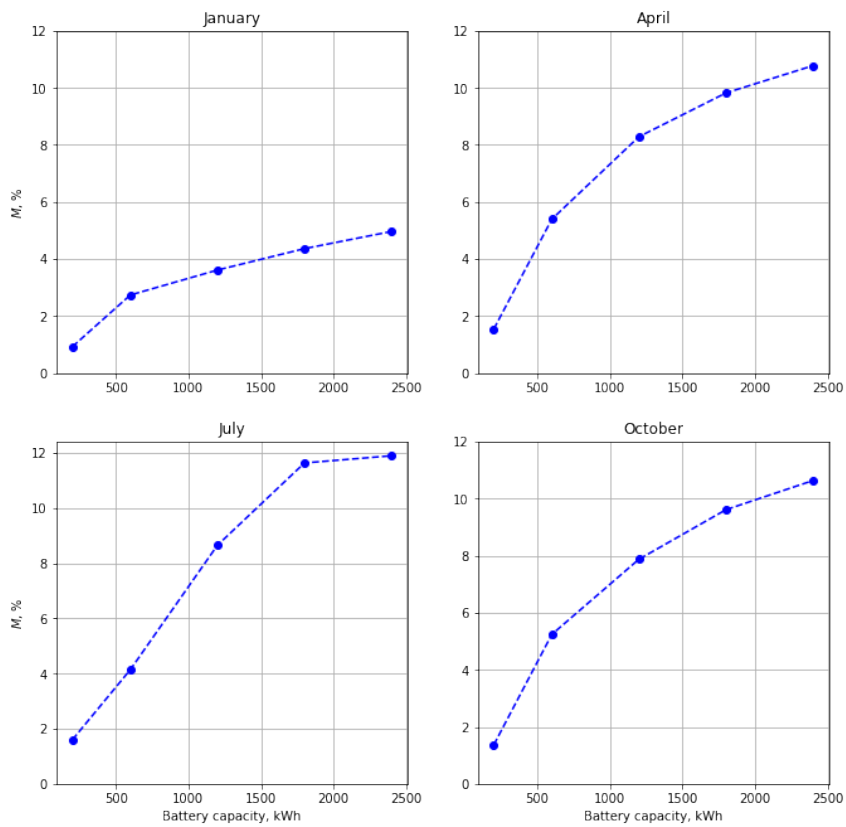


Figure 13. The value of optimization metric as a function of battery capacity.

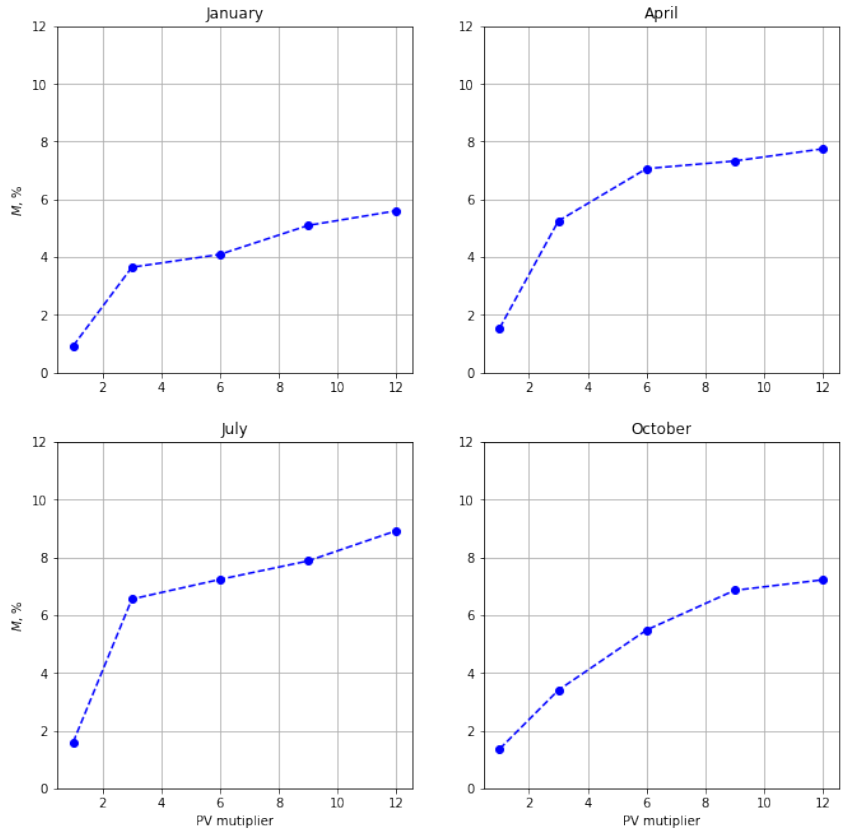


Figure 14. The value of optimization metric as a function of radiance multiplier.

From the conducted experiment, it is possible to conclude, that the relative difference between spent money with and without proposed approach (M) is close to a power function of battery capacity and radiance multiplier, where the power of function is equal to 2. The influence of battery capacity is bigger than the influence of total radiance, which could be caused by a relatively big capacity of batteries to the available solar radiance in Finland.

Also, we may see the saturation of M for bigger values of battery capacity and solar radiance multiplier. This could be a result of constraints of technical capabilities of battery: the speed of charge and discharge is limited. However, the saturation of function might become an aim of further research.

6 RESULTS AND DISCUSSION

The purpose of this thesis was to provide an overview of existing methods of energy management optimization and compare several most popular approaches for solving this task in a real-world scenario; determine influencing variables on the goodness of energy management.

Firstly, the comparison of several existing methods for energy management optimization was made. Advantages and disadvantages of such approaches were listed and compared. This part allowed selecting two algorithms because of their relatively good performance in similar tasks and ease of use and implementation for further research - rule-based and linear optimization.

Secondly, the metric of the goodness of energy management optimization was proposed along with the pipeline of linear optimization and simulation engine. The created engine allowed to test optimization algorithm on the historical data as it was performed in the real world. It took into account the physical limitations of battery, photovoltaic panels and the electrical grid, which made it a reliable replicate of the real world.

Thirdly, several experiments were conducted in the created simulation engine. The results of simulations showed that the proposed pipeline of energy management optimization could overcome the case without any energy management strategy and case with rule-based strategies. In the first experiment, the value of the metric was positive, but in the case of linear optimization, it was greater than in the case of the rule-based approach. Also, the influence of battery capacity and the amount of solar radiance were shown. The second experiment clearly showed that the value of metric is close to a power function of battery capacity, where $p = 2$ and to a power function of the amount of solar radiance, where $p = 2$.

6.1 Future work

In the conducted experiments, the cost of the energy system (batteries and solar panels) nor additional bonuses for a battery owners were not taken into account in the calculation of the profitability of the proposed algorithm. It might be the case, that the total savings from electricity bills would be much lower than even the cost of amortization of such system in Finland. On the other hand, participants of FCR markets have additional bene-

fits from batteries, which could be increased with the proposed method. These additional circumstances are the scope of further research.

7 CONCLUSION

This work provides an overview of the electricity markets in Finland including Nord Pool Spot market that has places for day-ahead and intra-day trading and Fingrid that hold ancillary service markets and importance of demand-side management in modern micro-grids. The description and examples of several energy management approaches were provided in this work, including their advantages and disadvantages. The linear optimization approach and heuristics approach were tested based on the historical data of electrical consumption of Lappeenranta University of Technology Green Campus. The importance of battery storage and the sum of solar radiance on the goodness of energy management strategy was shown during the conducted experiments. To ensure the viability of the proposed approaches, economic calculations are required. However, due to low values of absolute savings and relatively high cost of batteries, the proposed algorithm might not be the best choice in the Finnish electricity market.

REFERENCES

[1] Renewables REN21. Global Status Report. REN21 Secretariat. Paris. France. 2017.

[2] B Keith Hodge. Alternative energy systems and applications. 2017.

[3] Sina Parhizi, Hossein Lotfi, Amin Khodaei, and Shay Bahramirad. State of the art in research on microgrids: A review. *Ieee Access*, 3:890–925, 2015.

[4] N Hatziargyriou, H Asano, R Iravani, and C Microgrids Marnay. Ieee power energy mag., 2007; 5 (4): 78–94. 2007.

[5] Yao Zhang, Wei Chen, and Weijun Gao. A survey on the development status and challenges of smart grids in main driver countries. *Renewable and Sustainable Energy Reviews*, 79:137–147, 2017.

[6] Faisal A Mohamed and Heikki N Koivo. Online management of microgrid with battery storage using multiobjective optimization. pages 231–236, 2007.

[7] IEC. *IEC 61970: Energy management system application program interface*, 2005.

[8] Jukka Lassila Samuli Honkapuro Kaisa Salovaara Hanna Niemelä Salla Annala Mari Makkonen Jarmo Partanen, Satu Viljainen. Electricity markets-lecture notes. 2017.

[9] IEA. Re-powering markets: Market design and regulation during the transition to low-carbon power systems. 2016.

[10] Nord pool spot, about us, [online], www.nordpoolgroup.com/About-us. 2019.

[11] Nord pool spot, day-ahead market, [online], www.nordpoolgroup.com/the-power-market/Day-ahead-market. 2019.

[12] Nord pool, market data, [online], www.nordpoolgroup.com/Market-data1/nordic/map. 2019.

[13] Nord pool spot, intraday market, [online], www.nordpoolgroup.com/the-power-market/Intraday-market. 2019.

[14] Marjan Alizadeh et al. Multi-objective optimisation of community battery energy storage capacity exploitation. 2017.

[15] Fingrid, balancing power market, [online], www.fingrid.fi/en/electricity-market/reserves-and-balancing. 2019.

[16] Fingrid, maintenance of power balance, [online], www.fingrid.fi/en/grid/electricity-system-of-finland/maintenance-of-power-balance. 2019.

[17] Fingrid, reserve power plants, [online], www.fingrid.fi/en/electricity-market/reserves-and-balancing/reserve-power-plants. 2019.

[18] Vincenzo Giordano and Gianluca Fulli. A business case for smart grid technologies: A systemic perspective. *Energy Policy*, 40:252–259, 2012.

[19] Kankar Bhattacharya, Math HJ Bollen, and Jaap E Daalder. Operation of restructured power systems. 2012.

[20] Peter Palensky and Dietmar Dietrich. Demand side management: Demand response, intelligent energy systems, and smart loads. *IEEE transactions on industrial informatics*, 7(3):381–388, 2011.

[21] Mohamed H Albadi and Ehab F El-Saadany. Demand response in electricity markets: An overview. pages 1–5, 2007.

[22] S Braithwait and Kelly Eakin. The role of demand response in electric power market design. *Edison Electric Institute*, 2002.

[23] Goran Strbac. Demand side management: Benefits and challenges. *Energy policy*, 36(12):4419–4426, 2008.

[24] Keith J Holyoak, Kyunghee Koh, and Richard E Nisbett. A theory of conditioning: Inductive learning within rule-based default hierarchies. *Psychological Review*, 96(2):315, 1989.

[25] Plamen P Angelov. Evolving rule-based models: a tool for design of flexible adaptive systems. 92, 2013.

[26] Haris Doukas, Konstantinos D Patlitzianas, Konstantinos Iatropoulos, and John Psarras. Intelligent building energy management system using rule sets. *Building and environment*, 42(10):3562–3569, 2007.

[27] João P Trovão, Paulo G Pereirinha, Humberto M Jorge, and Carlos Henggeler Antunes. A multi-level energy management system for multi-source electric vehicles–an integrated rule-based meta-heuristic approach. *Applied Energy*, 105:304–318, 2013.

[28] Sercan Teleke, Mesut E Baran, Subhashish Bhattacharya, and Alex Q Huang. Rule-based control of battery energy storage for dispatching intermittent renewable sources. *IEEE Transactions on Sustainable Energy*, 1(3):117–124, 2010.

[29] Adel Choudar, Djamel Boukhetala, Said Barkat, and Jean-Michel Brucker. A local energy management of a hybrid pv-storage based distributed generation for microgrids. *Energy Conversion and Management*, 90:21–33, 2015.

[30] Richard S Sutton and Andrew G Barto. Reinforcement learning: An introduction. 1(1), 1998.

[31] Jens Kober, J Andrew Bagnell, and Jan Peters. Reinforcement learning in robotics: A survey. *The International Journal of Robotics Research*, 32(11):1238–1274, 2013.

[32] Marco Wiering and Martijn Van Otterlo. Reinforcement learning. *Adaptation, learning, and optimization*, 12, 2012.

[33] Jan Peters, Sethu Vijayakumar, and Stefan Schaal. Reinforcement learning for humanoid robotics. pages 1–20, 2003.

[34] Konstantinos Dalamagkidis, Denia Kolokotsa, Konstantinos Kalaitzakis, and George S Stavrakakis. Reinforcement learning for energy conservation and comfort in buildings. *Building and environment*, 42(7):2686–2698, 2007.

[35] Gregor P Henze and Jobst Schoenmann. Evaluation of reinforcement learning control for thermal energy storage systems. *HVAC&R Research*, 9(3):259–275, 2003.

[36] Daniel O'Neill, Marco Levorato, Andrea Goldsmith, and Urbashi Mitra. Residential demand response using reinforcement learning. pages 409–414, 2010.

[37] Aneek Das. The very basics of reinforcement learning. 2017.

[38] Junling Hu. Reinforcement learning explained. 2016.

[39] Viswanathan Lakshmi Prabha and Elwin Chandra Monie. Hardware architecture of reinforcement learning scheme for dynamic power management in embedded systems. *EURASIP Journal on Embedded Systems*, 2007(1):065478, 2007.

[40] Ying Tan, Wei Liu, and Qinru Qiu. Adaptive power management using reinforcement learning. pages 461–467, 2009.

[41] Li Xin, Zang Chuanzhi, Zeng Peng, and Yu Haibin. Genetic based fuzzy q-learning energy management for smart grid. pages 6924–6927, 2012.

[42] Xin Li, Chuanzhi Zang, Wenwei Liu, Peng Zeng, and Haibin Yu. Metropolis criterion based fuzzy q-learning energy management for smart grids. *Indonesian Journal of Electrical Engineering and Computer Science*, 10(8):1956–1962, 2012.

[43] Christopher JCH Watkins and Peter Dayan. Q-learning. *Machine learning*, 8(3-4):279–292, 1992.

[44] Thillainathan Logenthiran, Dipti Srinivasan, and Tan Zong Shun. Demand side management in smart grid using heuristic optimization. *IEEE transactions on smart grid*, 3(3):1244–1252, 2012.

[45] Italo Atzeni, Luis G Ordóñez, Gesualdo Scutari, Daniel P Palomar, and Javier Rodríguez Fonollosa. Demand-side management via distributed energy generation and storage optimization. *IEEE Transactions on Smart Grid*, 4(2):866–876, 2013.

[46] Zhou Wu, Henerica Tazvinga, and Xiaohua Xia. Demand side management of photovoltaic-battery hybrid system. *Applied Energy*, 148:294–304, 2015.

[47] E Matallanas, Manuel Castillo-Cagigal, A Gutiérrez, F Monasterio-Huelin, Estefanía Caamaño-Martín, D Masa, and J Jiménez-Leube. Neural network controller for active demand-side management with pv energy in the residential sector. *Applied Energy*, 91(1):90–97, 2012.

[48] Maher Chaabene, Mohsen Ben Ammar, and Ahmed Elhajjaji. Fuzzy approach for optimal energy-management of a domestic photovoltaic panel. *Applied energy*, 84(10):992–1001, 2007.

[49] Rodrigo Palma-Behnke, Carlos Benavides, Fernando Lanas, Bernardo Severino, Lorenzo Reyes, Jacqueline Llanos, and Doris Sáez. A microgrid energy management system based on the rolling horizon strategy. *IEEE Transactions on Smart Grid*, 4(2):996–1006, 2013.

[50] Meet the winners of power laws: Optimizing demand-side strategies, [online], http://drivendata.co/blog/power-laws-optimization-winners/. 2019.

[51] Joseph-Frédéric Bonnans, Jean Charles Gilbert, Claude Lemaréchal, and Claudia A Sagastizábal. Numerical optimization: theoretical and practical aspects. 2013.

[52] Jorge Nocedal and Stephen J Wright. Sequential quadratic programming. 2006.

[53] Klaus Schittkowski. Nlpql: A fortran subroutine solving constrained nonlinear programming problems. *Annals of operations research*, 5(2):485–500, 1986.

[54] Or-tools - google optimization tools, [online], www.github.com/google/or-tools. 2019.

[55] Nord pool, market data, [online], www.nordpoolgroup.com/Market-data1//nordic/table. 2019.

[56] Nesreen K Ahmed, Amir F Atiya, Neamat El Gayar, and Hisham El-Shishiny. An empirical comparison of machine learning models for time series forecasting. *Econometric Reviews*, 29(5-6):594–621, 2010.

[57] Michael J Kane, Natalie Price, Matthew Scotch, and Peter Rabinowitz. Comparison of arima and random forest time series models for prediction of avian influenza h5n1 outbreaks. *BMC bioinformatics*, 15(1):276, 2014.

[58] Durdu Ömer Faruk. A hybrid neural network and arima model for water quality time series prediction. *Engineering Applications of Artificial Intelligence*, 23(4):586–594, 2010.

[59] Nicholas I Sapankevych and Ravi Sankar. Time series prediction using support vector machines: a survey. *IEEE Computational Intelligence Magazine*, 4(2), 2009.

[60] Ping-Feng Pai and Wei-Chiang Hong. Support vector machines with simulated annealing algorithms in electricity load forecasting. *Energy Conversion and Management*, 46(17):2669–2688, 2005.

[61] Atsushi Yona, Tomonobu Senjyu, T FunabaShi, et al. Application of neural network to one-day—ahead 24 hours generating power forecasting for photovoltaic system [j]. *Intelligent Systems Applications to Power Systems*, 2007.

[62] EG Kardakos, MC Alexiadis, SI Vagropoulos, CK Simoglou, PN Biskas, and AG Bakirtzis. Application of time series and artificial neural network models in short-term forecasting of pv power generation. pages 1–6, 2013.

[63] Prasis Poudel and Bongseog Jang. Solar power prediction using deep learning. 2017.

[64] Xiangyun Qing and Yugang Niu. Hourly day-ahead solar irradiance prediction using weather forecasts by lstm. *Energy*, 148:461–468, 2018.

[65] Jing Huang and Matthew Perry. A semi-empirical approach using gradient boosting and k-nearest neighbors regression for gefcom2014 probabilistic solar power forecasting. *International Journal of Forecasting*, 32(3):1081–1086, 2016.

[66] Marco Cococcioni, Eleonora D'Andrea, and Beatrice Lazzerini. 24-hour-ahead forecasting of energy production in solar pv systems. pages 1276–1281, 2011.