TECHNICAL UNIVERSITY OF LIBEREC
Faculty of Mechatronics, Informatics
and Interdisciplinary Studies

# Modeling and real-time optimization exploitation of battery pack included in Smart Microgrid

## Master Thesis

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Liberec 2020

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**Master Thesis Assignment Form**

# Modeling and real-time optimization exploitation of battery pack included in Smart Microgrid

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| *Academic year:* | **2019/2020** |

**Rules for Elaboration:**

1. Conduct a literature review in the field of modeling and operation optimization of microgrid with batteries energy storage. Focus on the relation between lifetime power capacity and type of operation (state of charge).
2. Using Matlab or Python modeling environment create a simulation model (or script) of a microgrid including an uncontrolled load as a consumer (end-user) and energy storage in the form of batteries. This microgrid is connected to the main grid where prices of the electricity vary with time (real-time pricing).
3. Develop a real-time optimizing control that will minimize the cost of operation of this microgrid, considering the smart use of battery packs based on increasing their lifetime. It is recommended to use the economic model predictive control and dependence between the depth of discharge and expected average cycles of life.
4. Test the model with the controller. If the performance is satisfactory, explore the model with different battery configurations.

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|---|---|
| *Scope of Graphic Work:* | by appropriate documentation |
| *Scope of Report:* | 40-50 pages |
| *Thesis Form:* | printed/electronic |
| *Thesis Language:* | English |

**List of Specialised Literature:**

[1] WIKNER, Evelina and Torbjörn THIRINGER. Extending Battery Lifetime by Avoiding High SOC. Applied Sciences [online]. 2018, 8(10) [cit. 2019-11-26]. DOI: 10.3390/app8101825. ISSN 2076-3417. Downloadable from: http://www.mdpi.com/2076-3417/8/10/1825.
[2] SMITH, Kandler, Aron SAXON, Matthew KEYSER, Blake LUNDSTROM, ZIWEI CAO and Albert ROC. Life prediction model for grid-connected Li-ion battery energy storage system. In: 2017 American Control Conference (ACC) [online]. IEEE, 2017, 2017, s. 4062-4068 [cit. 2019-11-26]. DOI: 10.23919/ACC.2017.7963578. ISBN 978-1-5090-5992-8. Downloadable from: http://ieeexplore.ieee.org/document/7963578/.
[3] RENIERS, Jorn M., Grietus MULDER, Sina OBER-BLÖBAUM and David A. HOWEY. Improving optimal control of grid-connected lithium-ion batteries through more accurate battery and degradation modelling. Journal of Power Sources [online]. 2018, 379, 91-102 [cit. 2019-11-26]. DOI: 10.1016/j.jpowsour.2018.01.004. ISSN 03787753. Downloadable from: https://linkinghub.elsevier.com/retrieve/pii/S0378775318300041.
[4] ELLIS, Matthew, LIU, Jinfeng, and Panagiotis, D. CHRISTOFIDES. Economic model predictive control. New York, NY: Springer Berlin Heidelberg, 2016. 292 p. ISBN 978-3-319-41107-1.

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| *Date of Thesis Assignment:* | November 8, 2019 |
| *Date of Thesis Submission:* | May 18, 2020 |

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Liberec November 8, 2019

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# Modeling and real-time optimization exploitation of battery pack included in Smart Microgrid

## Abstract

Currently, renewable energy sources such as solar panels, wind turbines, tidal stations etc. occupy an increasing share in the energy market. Since the activity of the sun and wind cannot be controlled by humans, new approaches are necessary to keep the production consumption balance. The relationship between current electricity production and electricity demand is reflected in price fluctuations in short-term electricity markets. This makes us think about the idea that the entire electricity system can win if consumer prices also change in real time, respectively. In this case, consumers can help maintain the balance of the energy system by minimizing their energy costs locally and transferring consumption at a time when renewable energy is plentiful and its price is low. This thesis is focused on the consumer side of this price based control, and also on smart use of battery in such systems. Its goal is to develop an economic model predictive controller that minimizes the cost of operating a microgrid. For this reason was create simulation of consumer, was chosen battery and model of capacity fade of this battery. Also an economic model predictive controller based on mixed integer optimization is developed. It performs real time coordination and optimization of the microgrid operation. It was tested in Matlab environment.

**Keywords:** Smart grid, Economic MPC, Real time pricing, battery lifetime

# Modeling and real-time optimization exploitation of battery pack included in Smart Microgrid


## Abstrakt

V současné době mají na trhu s energií rostoucí podíl obnovitelné zdroje energie, jako jsou solární panely, větrné turbíny, přílivové stanice atd. Protože činnost slunce a větru nemůže být ovládána lidmi, jsou nezbytné nové přístupy k udržení rovnováhy spotřeby produkce. Vztah mezi současnou výrobou elektřiny a poptávkou po elektřině se odráží v kolísání cen na krátkodobých trzích s elektřinou. To nás nutí přemýšlet o myšlence, že celý elektrický systém může vyhrát, pokud se spotřebitelské ceny změní také v reálném čase, resp. V tomto případě mohou spotřebitelé pomoci udržovat rovnováhu energetického systému tím, že minimalizují své náklady na energii na místní úrovni a přenášejí spotřebu v době, kdy je obnovitelná energie dostatečná a její cena je nízká. Tato práce je zaměřena na spotřebitelskou stránku této cenově orientované kontroly a také na inteligentní využití baterie v takových systémech. Jeho cílem je vyvinout prediktivní ekonomický model, který minimalizuje náklady na provozování mikrosítě. Z tohoto důvodu byla vytvořena simulace spotřebitele, byla vybrána baterie a model vybití této baterie. Je také vyvinut prediktivní ekonomický model založený na smíšené celočíselné optimalizaci. Provádí koordinaci v reálném čase a optimalizaci mikrogridní operace. Byl testován v prostředí Matlab.



**Klíčová slova:** Inteligentní mřížka, ekonomické MPC, stanovení ceny v reálném čase, životnost baterie

# Acknowledgements

I thank everyone who participated in this work. Many thanks to Pavel Vedal and Lukas Hubka for helping. And also many thanks to the people who made my stay here possible: Mr. Zmud, Mr. Nosek. Ms. Frantsuzova and Erasmus program

# Contents

# List of abbreviations

| | |
|---|---|
| **TUL** | Technická univerzita v Liberci |
| **FM** | Fakulta mechatroniky, informatiky a mezioborových studií Technické univerzity v Liberci |
| Li | Lithium |
| **DOD** | Depth of discharge |
| **SOC** | State of charge |
| **BOL** | Beginning of life |
| **EOL** | End of life |
| **SEI** | Solid-electrolyte interface |
| **MPC** | Model Predictive Controller |
| **EMS** | Energy Manage System |
| **IEA** | International Energy Agency |
| **ILP** | Integer Linear Programming |
| **MG** | MicroGrid |
| **MILP** | Mixed Integer Linear Programming |
| **ILP** | Integer Linear Programming |
| **ILP** | Integer Linear Programming |

# 1 Modern energy system

## 1.1 Reason of transition to renewable source of energy

Now, the issue of energy is one of the most pressing issues of mankind. World energy system is developed and evolved during the time. Energy demand is growing and, thus, growing the energy supply. Most of the energy comes from the combustion of non-renewable sources, such as coal, gas, oil, nuclear fuel. All these sources are not only endless, but also, uncontrollable usage of traditional (primary) energy sources leads to the world's ecological problems. Greenhouse gas emissions (carbon dioxide $CO_2$, methane $CH_4$, nitrogen oxides $NO_x$, chlorofluorohydrocarbons (freons)), depletion of energy sources and global warming – all of them will negatively influence the life on the Earth in the long-term outlook.

By the aforementioned reasons, the agreement of synergies of all world powers for containment climate changes was developed in Paris in 2015. The main figures of the agreement are the following:

- Holding the global average temperature well below 2 $\circ$C above pre-industrial levels and to make an effort to limit the increase of temperature to 1.5 $\circ$C above pre-industrial level.

- In order to reach the long-term global temperature goal, all sides strive for achieving the peak of greenhouse gas emissions in order to then achieve well-balanced level between anthropogenic emissions from sources and absorption by absorbents of greenhouse gases in the second half of 21 century.

Thus, it is possible to achieve the requirements of the agreement, if the consumption of fossil fuel would be significantly reduced and the complex transition to renewable energy would be started.

It is necessarily to introduce the sufficient number of solar panels, wind turbines and hydro turbines to cover all consumers' needs; petroleum cars should be replaced with electrocars; space heating should be done with the help of heat pumps.

To store electricity is much more difficult than fossil fuel, the huge production share of stochastic electricity requires intellectual energy supply system – so called SmartGrid. Such system balances energy consumption and production all the time. SmartGrid requires flexible energy producers and consumers, which can actively help the energy system. Such paradigm means active usage of heat and electricity storages, replenishment of capacity of the storages during the periods of cheap electricity and smart discharging during the periods of expensive electrical energy. Additional advantages include higher system reliability, cheaper price of energy supply (by saving fuel and delayed investments in additional generation capacities) and reducing the impact on the environment[1].

However, since the number of charge-discharge cycles of batteries is not unlimited, and the batteries themselves are not free, and they must be disposed of after use, it may not always be beneficial to use batteries. Typically, end-of-life (EOL) is defined when the battery degrades to a point where only 70-80% of beginning-of-life (BOL) capacity is remaining under nameplate conditions. The idea of this work is to optimize the use of batteries not only regarding the price of electricity, but also regarding the degradation of the battery itself.

1.1 shows the Sustainable Development Scenario (SDS), which is provided by International Energy Agency [1]. The Figure depicts an integrated approach to achieve internationally agreed objectives on climate change, air quality and universal access to modern energy.

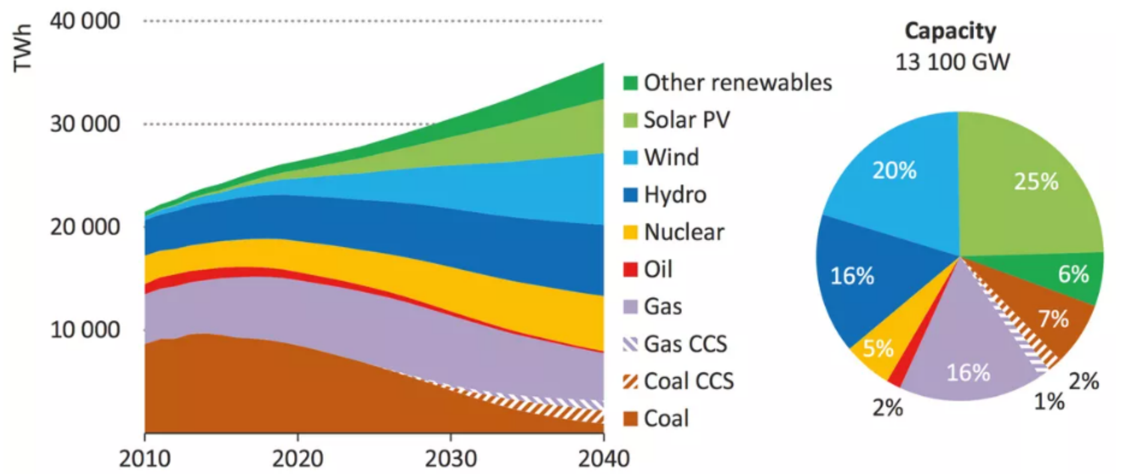


Figure 1.1: BPower generation all but decarbonises in the Sustainable Development Scenario[2].

## 1.2 Optimization types used in energy management problem

The problem of energy management in microgrids solved by different optimization techniques by researches. In firure4.3 the various methods demonstrate, which are used to solve the problem of energy management. Each method is utilizedin different microgrid strategies, where each is tuned to reach specified goal. For this work methods linear programming were consider the main idea submitted at 1.1, non-linear programming methods at 1.2.

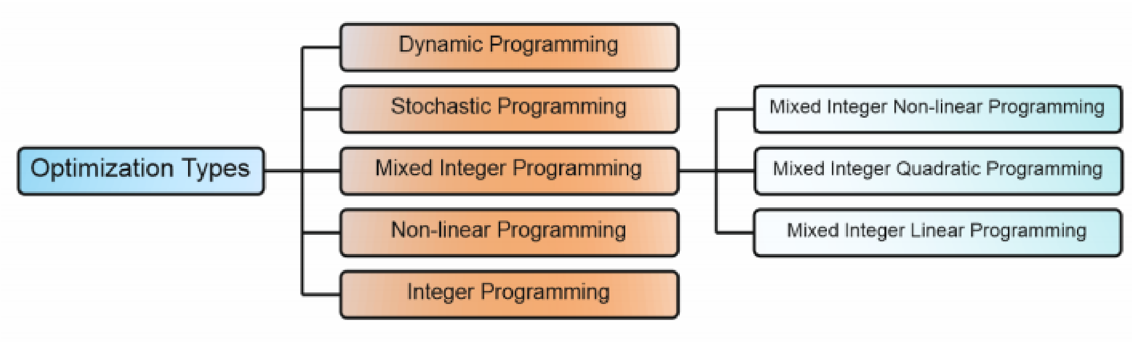


Figure 1.2: Optimization types.

## 1.3 Solution techniques of energy management problem

Different researchers used different solution techniques to solve the optimization framework that is concerned with energy management in microgrids. There are types of solution techniques, which are used to solve the energy management problem in1.3. The solutions based on Model Predictive Control and the relevant works are discussed below. Here 1.3 we briefly introduce main trends, approaches and features of MPC solutions. It can be noticed that it is possible to solve (or distinguish) a wide range of problems of energy management control, which are currently implemented, just using introduced approaches.

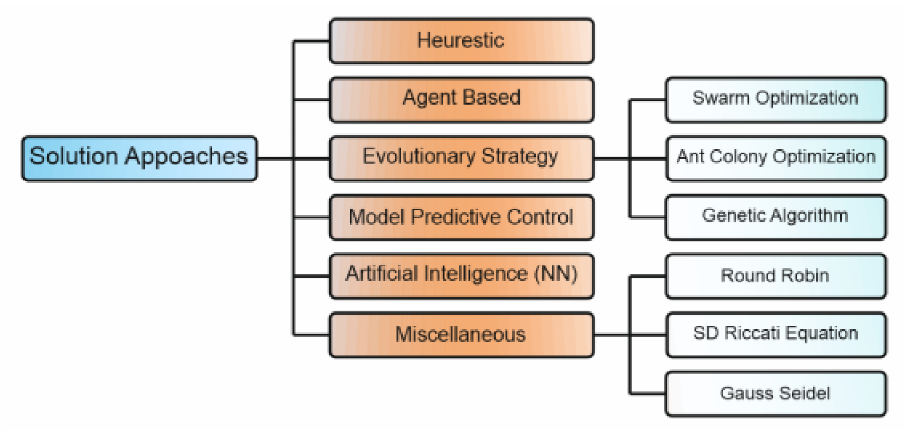


Figure 1.3: Solution types.

Table 1.1: Critical analysis MG EMSs based on linear programming methods

| **Ref.** | **Main stream** | **Innovation, features or approach** |
|---|---|---|
| [3] | Reducing demand fluctuations and improving economic balance | Annual decrease of demand fluctuations up to 19% |
| [4] | Minimizing total annual cost by optimally selecting various system components and renewable resources for a smartgrid. | Mixed Integer Linear Programming (MILP). |
| [5] | Solution of the problem of optimal generation distribution by dividing it into two phases, namely, the site planning model and the capacity planning model. | Mixed Integer Linear Programming (MILP). The authors argue that the model they proposed was computationally efficient with the best optimal solution, taking into account the current state of the system and the predictions for the future. |
| [6] | An economical smart microgrid network (CoSMoNet), which facilitates economic operations on the microgrid network. | A scheme based on integer linear programming (ILP) matches the excess energy in the storage elements of a microgrid network with the requirements of another microgrid network, the load of which cannot be compensated by their local power source. |

Table 1.2: Critical analysis MG EMSs based on non-linear programming methods

| Ref. | **Main stream** | **Innovation, features or approach** |
|---|---|---|
| [7] | System optimization with the objective function of maximizing income through the exchange of electricity between the microgrid and the main power grid | Non-linear function. |
| [8] | Performance evaluation of a hybrid renewable energy system<br>The optimal controller for tracking the trajectory of | Computing structure based on mixed integer non-linear programming |
| [9] | non-linear systems. The presented scheme is used to ensure the efficient exchange of energy flows between various sources in the micronet using energy converters. | This task was formulated as a non-linear quadratic program that minimizes the quadratic cost function. |
| [10] | The task of planning operations for microgrids with renewable energy sources. This problem is associated with the allocation of the lowest cost per unit commitment (UC). | Integer non-linear programming. There are requirements for loads, the environment and system performance. A new concept of probability of self-sufficiency (PSS), which indicates the probability that the microgrid |
| [11] [12] | The task of optimizing long-term planning with a net of renewable energy microgrid with a hybrid energy storage device in the form of a mixed quadratic program | will satisfy local demand in a self-sufficient manner<br>Take into account the lifetime, degradation, start-up / shutdown, operating costs of the hybrid system and energy storage system. |

Table 1.3: Critical analysis MG EMSs based on the model-based prediction approach (MPC)

| **Ref** | **Results or suggestions** | **Methods or features** |
|---|---|---|
| [13] [14] [15] | A multipurpose structure for modeling energy management in microgrids is considered. The proposed model believes that the microgrid consists of distributed generation, network connection, energy storage elements and various loads. | The Model Predictive Control (MPC) approach is used to minimize energy costs and increase battery life at the same time. For these purposes, the central controller of the microgrid must find the best charging and discharging circuit for the battery. The MPC approach is used to solve the optimization |
| [11] | Energy management is solved by MPC, in order to maximize economic benefits microgrids while minimizing the use of each storage system costs. | problem, which is to maximize the economic benefits and minimize the causes of degradation of each storage system |
| [16] | Represent a predictive control method for a stochastic model for microgrid control. | The input data of the stochastic disturbance and the various restrictions imposed by the distribution lines and the battery level are taken into account. |
| [17] | They propose a predictive model management approach that gives better performance and overcomes the technical limitations associated with the rate of linear change. | Emphasis is placed on optimal control of dynamic dispatch and formulations of dynamic economic dispatch. |

# 2 Degradation of batteries

Most of these systems use lithium-ion batteries because, thanks to significant developments in the mobile electronics and automotive industry, Li-ion batteries at present hold cost, performance, energy/power density and lifetime advantages over other electrochemical battery chemistries [18].

Like all battery chemistries, Li-ion degrades with each charge and discharge cycle. Cycle life can be maximized by maintaining battery temperature near room temperature but drops significantly at high and low temperature extremes. Cycle life is also dependent on depth-of-discharge (DOD) and current, or C-rate. While it is common to discuss Li-ion lifetime in terms of number of cycles, often the calendar life of the cell is more limiting than cycle life. Detrimental side reactions occur within the cell even during storage. The rate of these deleterious side reactions increases with high temperature and high SOC. The electrochemical literature provides theoretical models of some individual mechanisms including side reactions impacting calendar life [19], cycling driven electrode stress [20] and fracture [21], as well as coupling of calendar and cycling mechanisms [22]. The physics models are complex however, and not all degradation mechanisms are fully understood. As a result, the industry mainly uses semi-empirical lifetime models with varying range of complexity and accuracy [23, 24, 25, 26]. These models extrapolate component-level accelerated aging test data to real-world lifetime scenarios [18].

In work [18] was developed a life model including reversible thermal effects on performance is developed describing the cell's capacity as measured at the 0.2 C-rate as it varies with temperature, state-of-charge (SOC), depth-of-discharge (DOD), calendar time, and number of cycles. The approach follows previous battery life modeling framework [9] where capacity is controlled by the limiting of several competing degradation mechanisms. Amp-hour capacity directly relates to the number of moles of lithium (Li) that are shuttled between the negative and positive electrodes during discharge or charge of the battery. In rough order of importance, capacity changes over lifetime for the Kokam cell are due to three mechanisms:

1. Cyclable Li is consumed due to a solid-electrolyte interface (SEI) growth side reaction with time, coupled with electrode mechanical damage due to cycling

2. Negative electrode active sites that store cyclable Li are lost due to mechanical damage with cycling

3. Positive electrode active sites that store cyclable Li are gained due to increased surface area/electrolyte wetting during initial cycles, increasing the capacity

that the positive electrode can hold with initial cycling. (Note that this phenomenon is much smaller than the other two and is only evident at BOL.) [18]

Provided the battery is not severely cycled, the first mechanism, SEI growth, generally dominates in real-world aging conditions. Growth of the SEI accelerates with high average temperature and high average SOC. Generally the second mechanism, loss of electrode sites, outpaces the first mechanism under low temperatures, high DODs, C-rates, and/or frequent cycling greater than, e.g., 4 cycles per day. Cycle life aging tests, particularly at low temperature, follow this limiting mechanism [18].

Development of the model from capacity and resistance aging data follows previous work [8]. Measured Amp-hour capacity, $Q$, is taken to be the minimum of Li-limited capacity $Q_{Li}$, negative electrode-site-limited capacity $Q_{neg}$, or positive electrode-site-limited capacity $Q_{pos}$ [18].

$$Q = min\ (Q_{Li}, Q_{neg}, Q_{pos}) \tag{2.1}$$

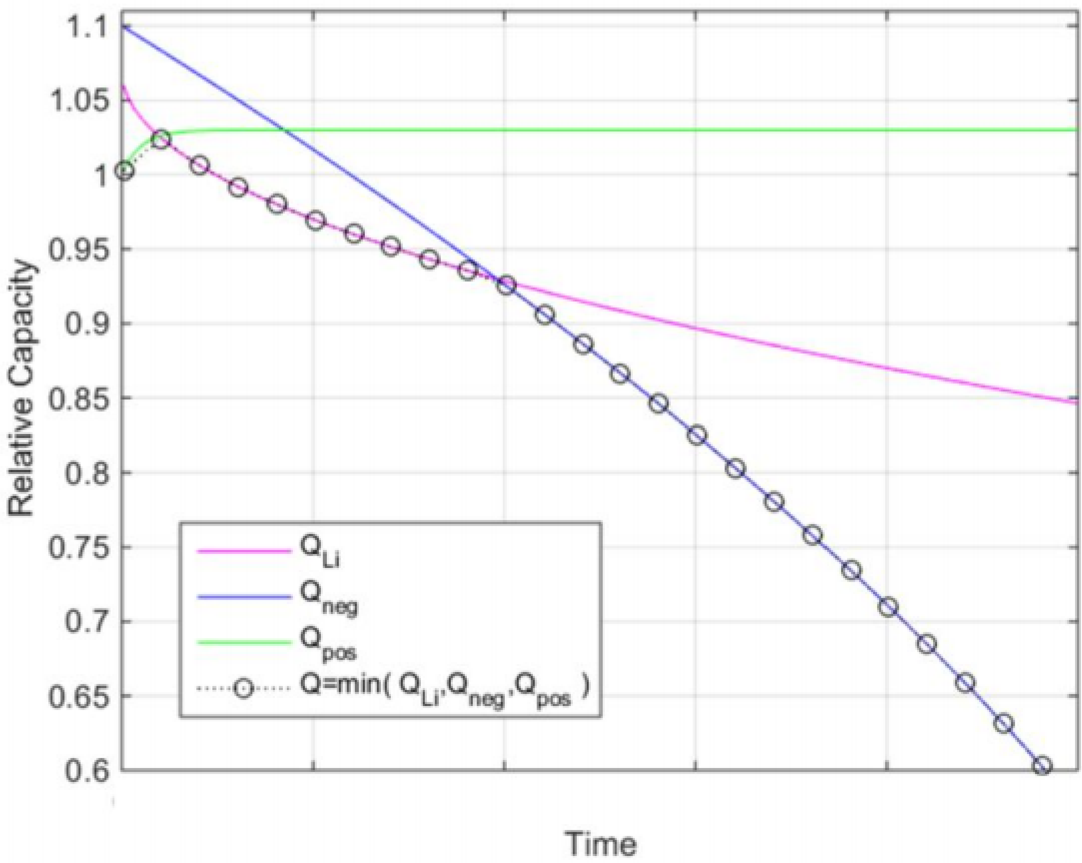


Figure 2.1: Battery capacity as the minimum of three limiting mechanisms [18].

2.1 shows an example how these three separate mechanisms can interact to each separately control capacity. Capacity on the y-axis is relative to BOL nameplate.

during different portions of the battery's life. Many other combinations of these mechanisms and thus fade patterns are also possible depending on the aging condition. Model equations below use common reference constants $T_{ref} = 298.15\ K$, $V_{ref} = 3.7\ V$, and $U_{-,ref} = 0.08\ V$, Faraday constant $F = 96485\ A/mol^{-1}$ , and universal gas constant $R_{ug} = 8.314\ JK^{-1}mol^{-1}$ [18].

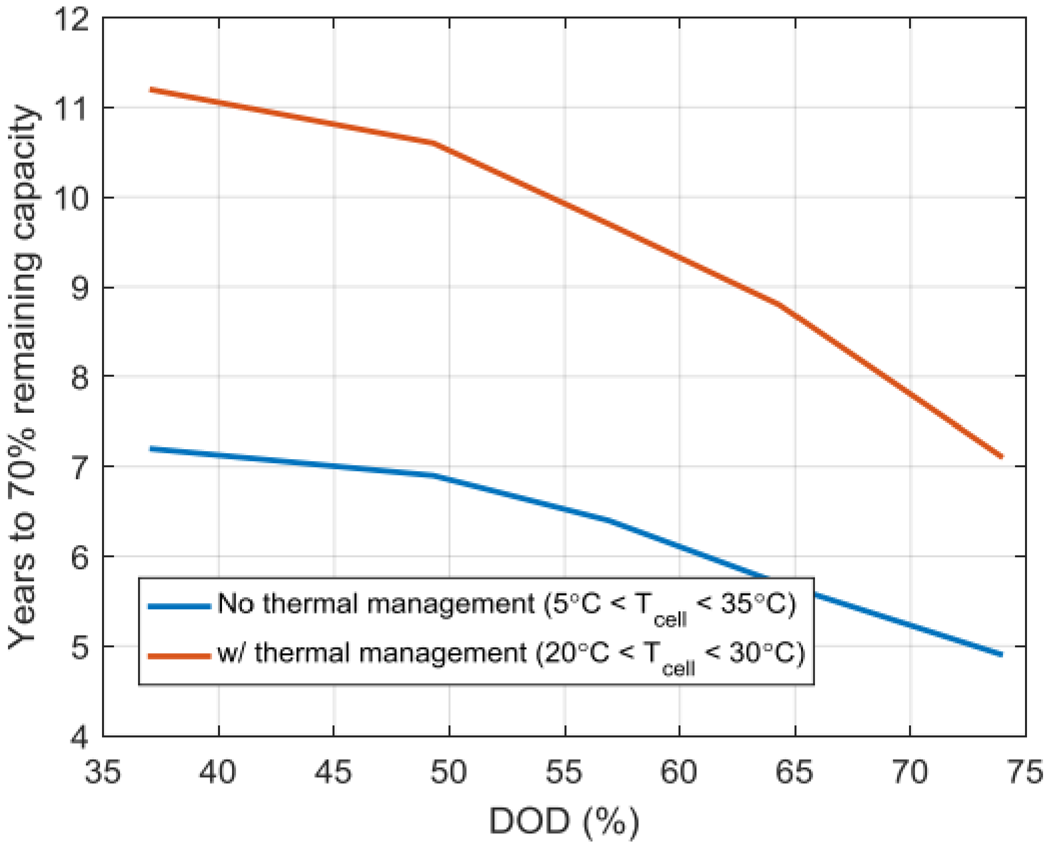


Figure 2.2: Impact of battery over sizing and thermal management on lifetime [18].

2.2 shows a simulated aging result with seasonal ambient temperature variation of 18/28/12/5°C representing spring, summer, fall and winter seasons, respectively, together with modest cell temperature rise. The cold temperatures impose additional degradation compared to the constant 28°C ambient temperature. In this case, the battery lasts 4.9 years until it degrades to 70% of nameplate capacity. The battery first falls below this performance threshold during a winter season [18].

The utility of the simulation model is that it enables rapid exploration of multiple system design and control scenarios. Two methods to extend lifetime include (2.1) over sizing the battery and thereby restricting its maximum daily DOD and (2.2) adding battery thermal management. These trade offs are shown in 2.3.

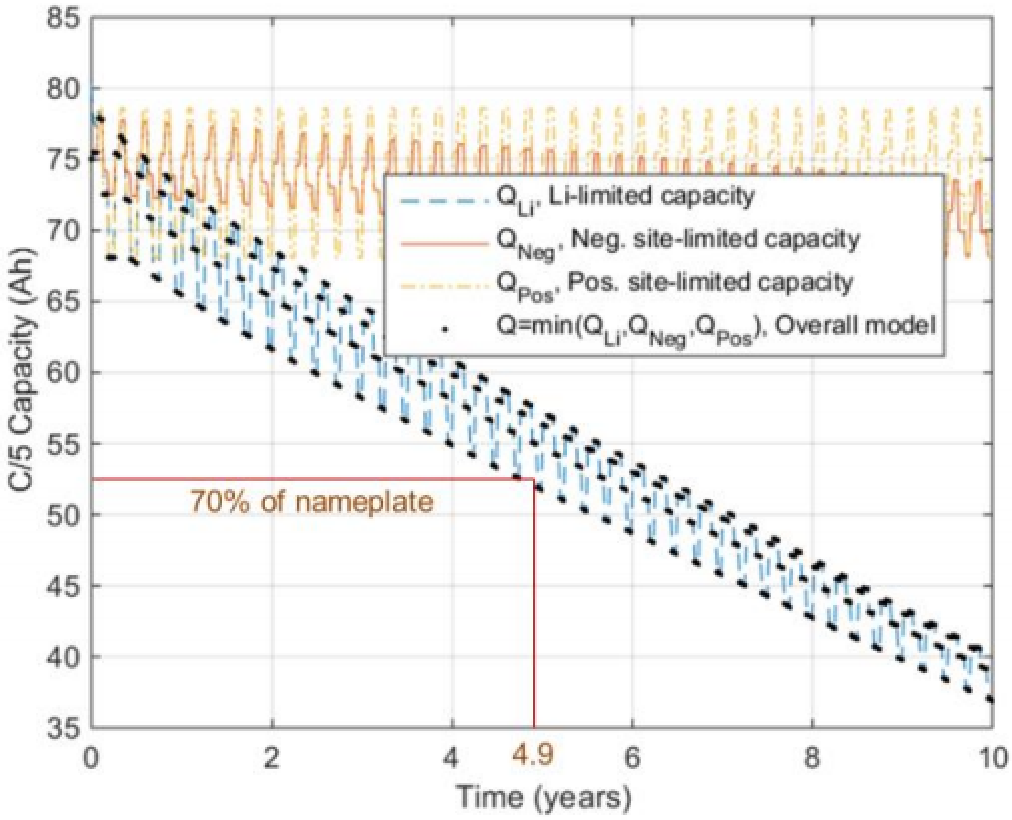


Figure 2.3: Simulated battery capacity fade under self-consumption mode operation with seasonal ambient temperature variation of 18/28/12/5°C for spring/summer/fall/winter seasons, respectively [18].

## 2.1 Beginning-of-Life Capacity Increase Temperature Dependence

In work [1] they consider battery capacity at BOL, assumed to be controlled by positive electrode-site-limited capacity, $Q_{pos}$. 2.4 shows data for the first several cycles of the aging test. Temperature is the main factor controlling capacity at BOL. Capacity increases a small amount, on the order of 0.5%, over the first cycles. These two effects are captured mathematically as:

$$Q_{pos} = d_0 + \underbrace{d_3(1 - exp(-Ah_{dis}/228))}_{Increase\ in\ capacity\ at\ BOL} \tag{2.2}$$

$$d_0 = d_{0,ref}\left(exp\left(\frac{-E_{a,d_0,1}}{R_{ug}}\left(\frac{1}{T(t)} - \frac{1}{T_{ref}}\right) - \left(\frac{E_{a,d_0,2}}{R_{ug}}\right)^2\left(\frac{1}{T(t)} - \frac{1}{T_{ref}}\right)^2\right)\right) \tag{2.3}$$

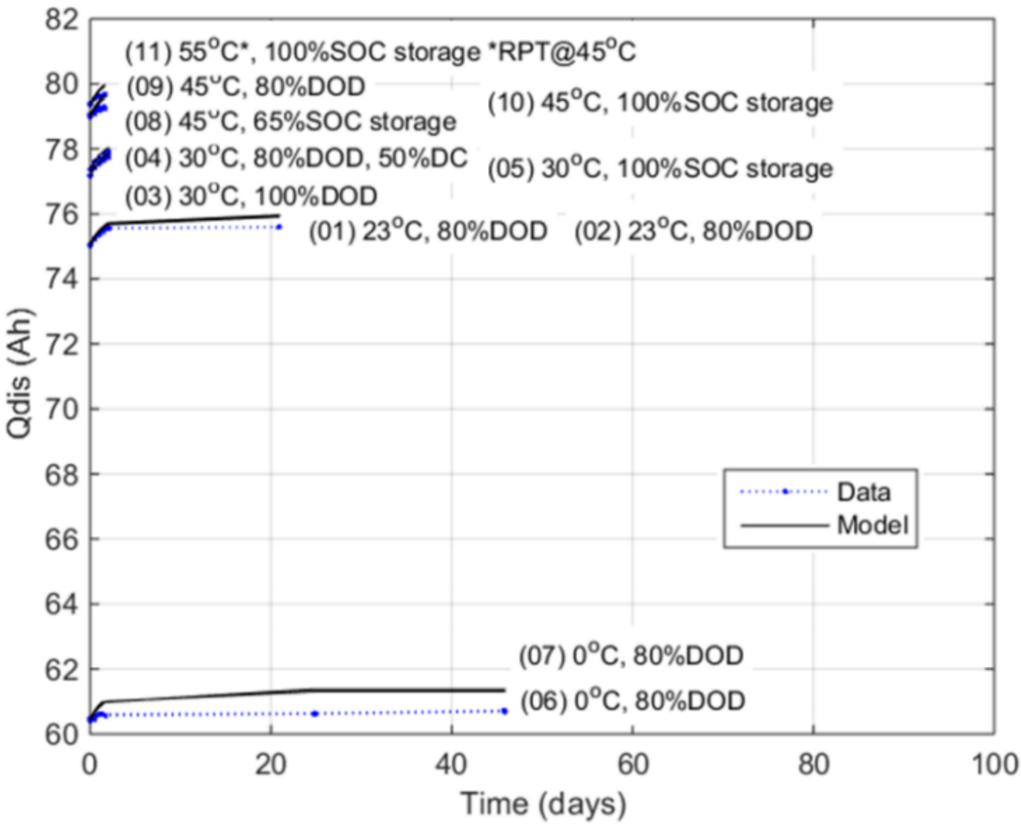


Figure 2.4: Initial capacity described by positive electrode-site-limited capacity model [18].

where $Ah_{dis}$ is the cumulative Amp-hours discharged from the cell. The remaining parameters are fit using the nonlinear least-squares function nlinfit in Matlab©, with values of $d_3 = 0.46\ Ah$, $d_{0,ref} = 75.10\ Ah$, $E_{a,d_0,1}$=34300 $Jmol^{-1}$ , and $E_{a,d_0,2}$ = 74860 $Jmol^{-1}$ providing the best fit [18].

## 2.2 Calendar Life Capacity Fade with Mild Dependence on Cycling

Next, in work [18] they consider the Li-limited capacity, $Q_{Li}$, generally exhibited under storage aging conditions, but also for mild-to-moderate cycling conditions where capacity fade rate decelerates with time and does not experience sudden fade. All Li-ion batteries with graphite or carbon negative electrodes lose Li due to a SEI growth side reaction. The side reaction is generally diffusion limited and therefore proceeds with the square root of time. Individual storage capacity fade test conditions dominated by this diffusion limited side reaction can be described using a model of the form $b_0 + b_1 t^{1/2}$. For the present cell, two additional terms must also be included to account for Li loss proportional to cycling and a small loss of Li at BOL as the cell is broken in. With these three Li loss mechanisms, the model is

$$Q_{Li} = d_0\Big(b_0 - \underbrace{(b_1 t^{(1/2)})}_{calendar} - \underbrace{b_2 N}_{cycling} - \underbrace{b_3(1 - exp\ (-t/_{b3}))}_{Break\ at\ BOL}\Big) \tag{2.4}$$

In this Li loss model, $d_0$ captures temperature dependence of initial capacity as previously described. Coefficients $b_1$, $b_2$, and $b_3$ are dependent on the aging condition as follows:

$$b_1 = b_{1,ref} exp\left(\frac{-E_{a,b_1}}{R_{ug}}\left(\frac{1}{T(t)} - \frac{1}{T_{ref}}\right)\right)$$
$$exp\left(\frac{\alpha_{b1} F}{R_{ug}}\left(\frac{U\_(t)}{T(t)} - \frac{U_{ref}}{T)ref}\right)\right) exp(\gamma_{b1}(DOD_{max})^{b1}) \tag{2.5}$$

$$b_2 = b_{2,ref} exp\left(\frac{-E_{a,b_2}}{R_{ug}}\left(\frac{1}{T(t)} - \frac{1}{T_{ref}}\right)\right) \tag{2.6}$$

$$b_3 = b_{3,ref} exp\left(\frac{-E_{a,b_3}}{R_{ug}}\left(\frac{1}{T(t)} - \frac{1}{T_{ref}}\right)\right)$$
$$exp\left(\frac{\alpha_{b3} F}{R_{ug}}\left(\frac{V_{OG}(t)}{T(t)} - \frac{V_{ref}}{T)ref}\right)\right)(1 +_P max) \tag{2.7}$$

The data show that high or low average temperature, high average SOC and high maximum DOD all accelerate Li-loss capacity fade. High temperature and SOC both accelerate the SEI growth side reaction. Deep cycling mechanically disturbs the SEI, creating fresh electrode surface area where new SEI can form. This mechanical damage can also be accelerated by low temperature [18].

Li-loss model parameters are fit mostly in a sequential fashion following dominant trends in the data as described below. However, small iterative adjustments are made along the way to improve overall quality of fit [18].

1. First, a simple model1 $y = y_0 - b_1 t^{1/2}$ is fit only to storage aging data ($DODmax = 0$) for data after 50 days of aging, providing parameters $b_{1,ref}$ = 3.503e-3 day$^{-0.5}$,E$_{a,b1}$ = 35392 $Jmol^{-1}$ and $_b1 = 1.0$.

2. Next, the simple model is also fit to moderate cycling conditions that follow the square root of time fade trajectory, providing parameters = 2.472 and $_{b1}$ = 2.157.

3. Fitting the simple model $y = y_0 - b_1 t^{1/2}$ to data beyond the first 50 days showed that the y-intercept, y0, varied with temperature and DOD. This motivated the inclusion of the break-in mechanism model. Fitted parameters are $b_0$ = 1.07, $b_{3,ref}$ = 2.805e-2, $E_{a,b3}$ = 42800 $Jmol^{-1}$, $_{b3}$ = 0.0066, $_{b3}$ = 5, and = 0.135.

4. Initially neglecting the $b_2$ term, model error increased proportionally with number of cycles, motivating the inclusion of the cycling dependent term. Including this term in the model with parameters $b_{2,ref}$ = 1.541e-5 and $E_{a,b2}$ = –42800 $Jmol^{-1}$ improved the quality of fit [18].

2.5 shows a comparison of the model with data. The model matches all cases well except 0°C cycling conditions for which the model under predicts capacity fade after 200 days. (In the following section, those under-predicted aging conditions are captured by including an additional negative electrode site loss mechanism.) Excluding the 0°C test cases, the model has a quality of fit of $R^2 = 0.97androotmeansquareerror, RMSE = 0.77Ah, oranaverageerrorof1.0\%relativetothecell's75 - Ahnameplatecapacity.$

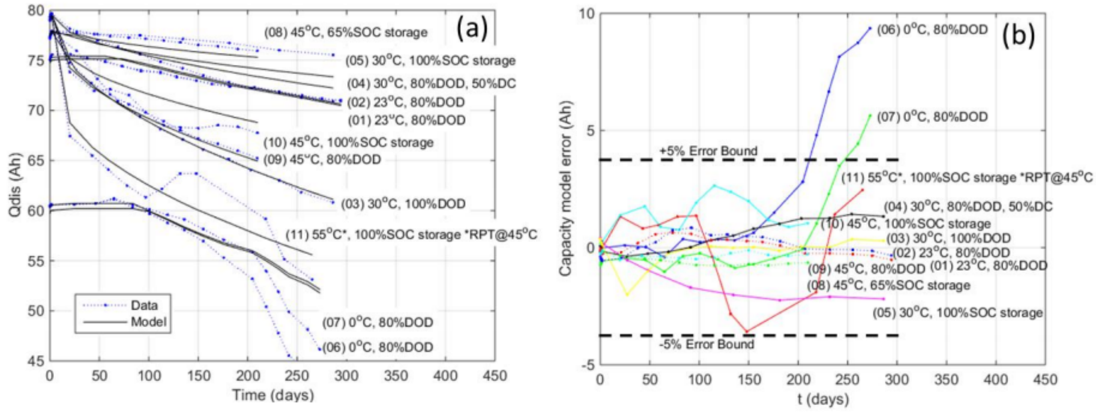


Figure 2.5: Positive- and Li-limited capacity fade model. (a) Model versus data. (b) Model error [18].

## 2.3 Cycle Life Model

Active sites may be lost from both electrodes due to expansion and contraction of the Li host materials during charge and discharge cycling causing mechanical stress and fatigue. The graphite negative electrode expands up to 8% during a full discharge. The NMC positive electrode expands on the order of 2%; hence, the loss of negative electrode active sites is assumed to outpace the positive [18].

The negative electrode site-loss model assumes that the site capacity lost with each cycle, N, is inversely proportional to the amount of remaining sites. In other words, as sites are lost, the remaining sites are stressed more and more in order to maintain the same duty cycle[18],

$$\frac{dQ)neg}{dN} = -\left(\frac{c_2}{Q_{neg}}\right). \tag{2.8}$$

The analytical solution to this ordinary differential equation is:

$$Q_{neg} = ({c_0}^2 - 2c_2c_0N)^{1/2} \tag{2.9}$$

Coefficient $c_0$ represents the initial negative electrode site capacity. Rate of capacity loss per cycle, $c_2$, is dependent on temperature, DOD, and C-rate. Too little data are available here to separately characterize C-rate and DOD effects, however based on previous experience, DOD is the dominant effect. The present rate model captures temperature and DOD dependence

$$c_2 = c_{2,ref} exp \left( -\frac{E_{a,c_2}}{R_{ug}} \left( \frac{1}{T(t)} - \frac{1}{T_{ref}} \right) \right) (DOD)^{\beta_{c2}} \tag{2.10}$$

Data beyond 170 days for 0°C and 23°C are used to fit the negative electrode site loss model, providing $c_{2,ref}$=3.9193e-3 $Ah\ cycle^{-1}$, $\beta_{c_2} = 4.54$, and $E_{a,c_2} = -48260\ J\ mol^{-1}$. The initial negative site capacity, $c_0$ also shows slight temperature dependence fitted with parameters $c_{0,ref} = 75.64\ Ah$ and $E_{a,c_0} = 2224\ J\ mol^{-1}$.

$$c_0 = c_{0,ref} exp \left( -\frac{E_{a,c_0}}{R_{ug}} \left( \frac{1}{T(t)} - \frac{1}{T_{ref}} \right) \right) \tag{2.11}$$

2.6 shows the final capacity fade model, with $R^2$ =0.99 and RMSE of 1.05 Ah, or 1.4% of nameplate. The cases with largest model error are those with the most fade. For cell 11 aged under storage at 55°C, the model slightly under-predicts fade. For 0°C cycling, cells 6 and 7, the model falls between the fade experienced by the two replicate cells. Cell 6 fade is slightly under-predicted; Cell 7 is slightly over-predicted. Fade is predicted within ±5% error bounds for all cells [18].

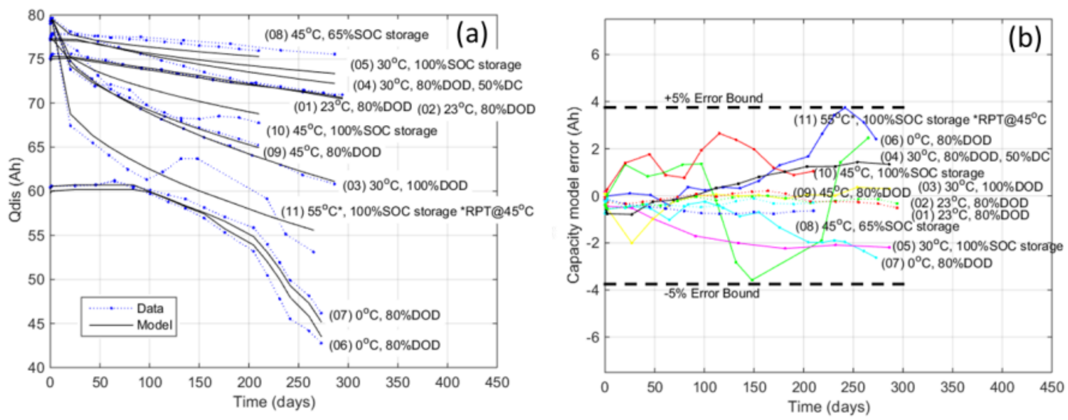


Figure 2.6: Final capacity fade model, incorporating positive-, negative-, and Li limiting mechanisms. (a) Model versus data. (b) Model error [18].

# 3 Main part

As mentioned in introduction, the main idea of work is minimization of electricity price by smart using batteries. For solution of this main problem we have to solve next tasks

1. Create a simulation of consumer
2. Chose battery for system
3. Create model of degradation of battery
4. Develop optimization system

## 3.1 Simulation of consumer

As simulated consumer was chosen a family of four person. Such families consume on average about 8 kWh per day. On this site [27] there are report of consume electricity in 2013 - 2019 year, which consist of date, hour, load, price. Load in this report normalized by unit. For our use, we re-normalize it so that the average daily load is 4 kWh.

In 3.1 graphs of tariff versus, re-normalized consumption versus time time and cost versus time on a randomly selected day September 17, 2018. In that day family consume 6.23 kWh of energy and payed for this 1.344 Euro. The same date we can easily obtain for any day in the interim 2013 - 2019 year.

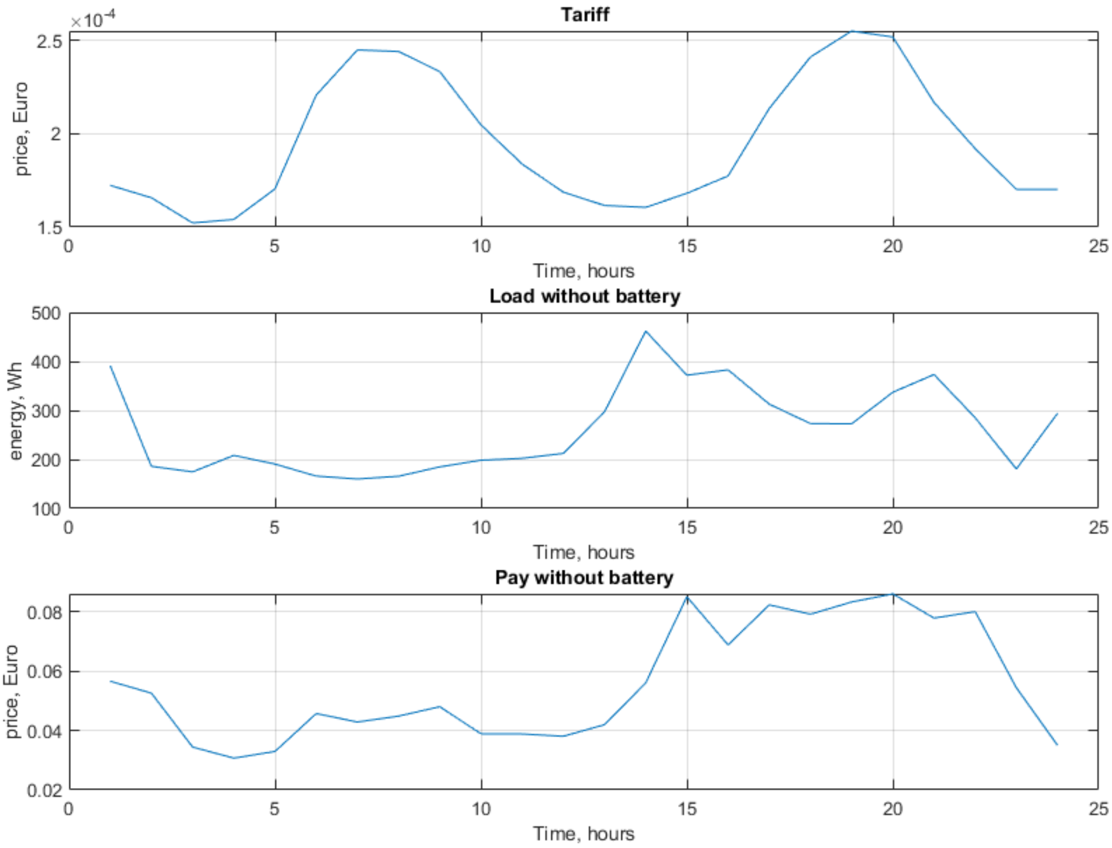


Figure 3.1: The electricity tariff, load and electricity price on September 17, 2018

## 3.2 Chose battery

As storage of energy in our system was chosen Li-ion batteries, as was mentioned above, Li-ion batteries at present hold cost, performance, energy/power density and lifetime advantages over other electrochemical battery chemistries [18]. But there are a lot of Li-ion batteries in the world. We chosen battery from this site [28], because this shop provide a lot of information about batteries in form of data sheets.

On this site there are also a lot of different batteries. So we imposed some conditions, namely the price is less than \$ 1000, and the weight is less than 15kg. And from this batteries we chose the one with the lowest price for 1Ah of using energy by cycling. All of these batteries have a limited number of discharge cycles. And this number of discharge depends on the DOD. But all of them have the same number at the same DOD, if we can trust data from site. 3.2 shows this dependence of remaining capacity on DOD levels 50/80/100%, T = 25°C (77°F or 302K), and C-rate = 0.2 . As we can see, for 50% DOD the number of cycles before capacity higher then 70% of BOL is equal to 13000, for 80% is equal to 7000, for 100% is equal to 3800.

At 3.2 you can see the some data of 10 batteries. 3.3 show us comparison of price of discharge 1 Ah of these batteries at different DOD. As we can see RB100 have

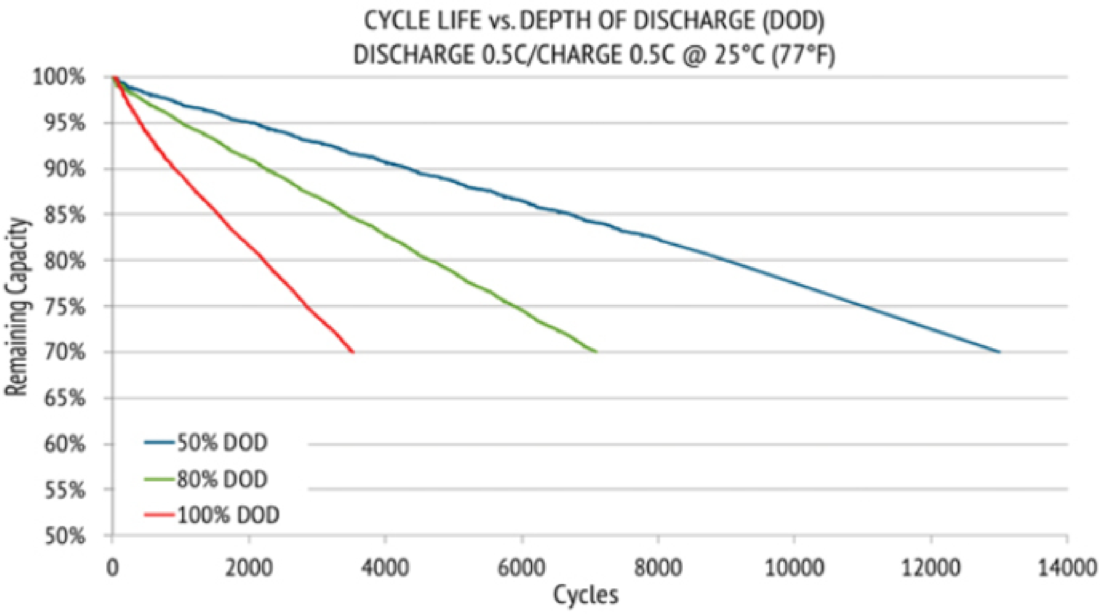


Figure 3.2: Remaining capacity dependence on DOD [29]

cheapest 1 Ah of discharge-charge. And energy capacity is equal to 1280 Wh, which is approximately twenty percent of the average electricity consumption by a family of three people per day, and therefore not too large for battery to stand idle.

Table 3.1: Comparison of different batteries

| | | | | Price of 1 Ah | | |
|---|---|---|---|---|---|---|
| Name | price, $ | Voltage, V | Capacity, Ah | 50% DOD | 80% DOD | 100% DOD |
| RB20 | 276,95 | 12.8 | 20 | 0,00213038 | 0,00247277 | 0,00364408 |
| RB20 lt | 332,95 | 12.8 | 20 | 0,00256115 | 0,00297277 | 0,00438092 |
| RB35 | 489,95 | 12.8 | 35 | 0,00215363 | 0,00249974 | 0,00368383 |
| RB35 lt | 530,95 | 12.8 | 35 | 0,00233385 | 0,00270893 | 0,00399211 |
| RB40 | 514,95 | 12.8 | 40 | 0,00198058 | 0,00229888 | 0,00338783 |
| RB50 | 625,95 | 12.8 | 50 | 0,001926 | 0,00223554 | 0,00329447 |
| RB75 | 862,95 | 12.8 | 75 | 0,00177015 | 0,00205464 | 0,00302789 |
| RB80 | 920,95 | 12.8 | 80 | 0,00177106 | 0,00205569 | 0,00302944 |
| RB100 | 1050 | 12.8 | 100 | 0,00161538 | 0,001875 | 0,00276316 |

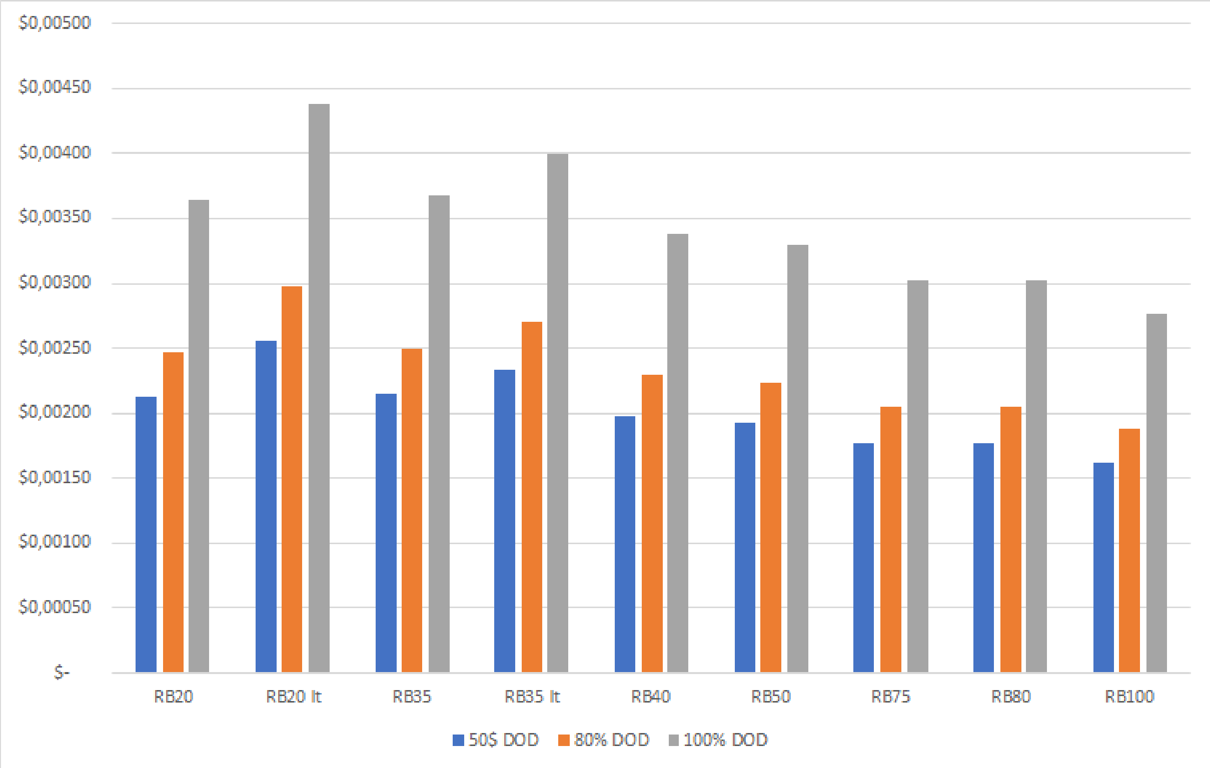


Figure 3.3: Price of using 1 Ah of charge.

## 3.3 Model of degradation

For further work we have to develop the model of degradation of battery. Our model will consist of calendar life capacity fade and cycle life capacity fade model. According to the final capacity fade of battery is the maximum of two of this capacity fade mechanisms.

For calendar capacity fade we used simple model. On the battery distributor website [28] expiration date is 20 year. So we can assume that after the twenty year of idle stay, the capacity of battery have to be at 70% of BOL capacity. And according to [18] the dominant part of calendar fade mechanism is loosing of Lithium ions by this diffusion limited side reaction which occurs in proportion to the square root of time. In 3.4 the graph received by us remaining capacity versus time. After the 20 years of idle stay the capacity level is equal to 70% of BOL capacity.

For cycling capacity fade we are used simple enough model too. As we can see at 3.2 the remaining capacity is linear depends of number of cycles. Which means we can easily obtain a fade of 1 cycle. And if we know. that we decide to use the battery sparingly, which mean on C rate equal to 0.2C, the one hour of use battery charge or discharge mean use 20% of energy of battery, which mean 10% of discharge cycle. But as we can see, with different DOD levels the fade of 1 cycle is different. For rough approximation we decide to use such model as. If SOC more then 60%, the one hour of use battery at the tariff 50% DOD, if SOC less than 60% but more

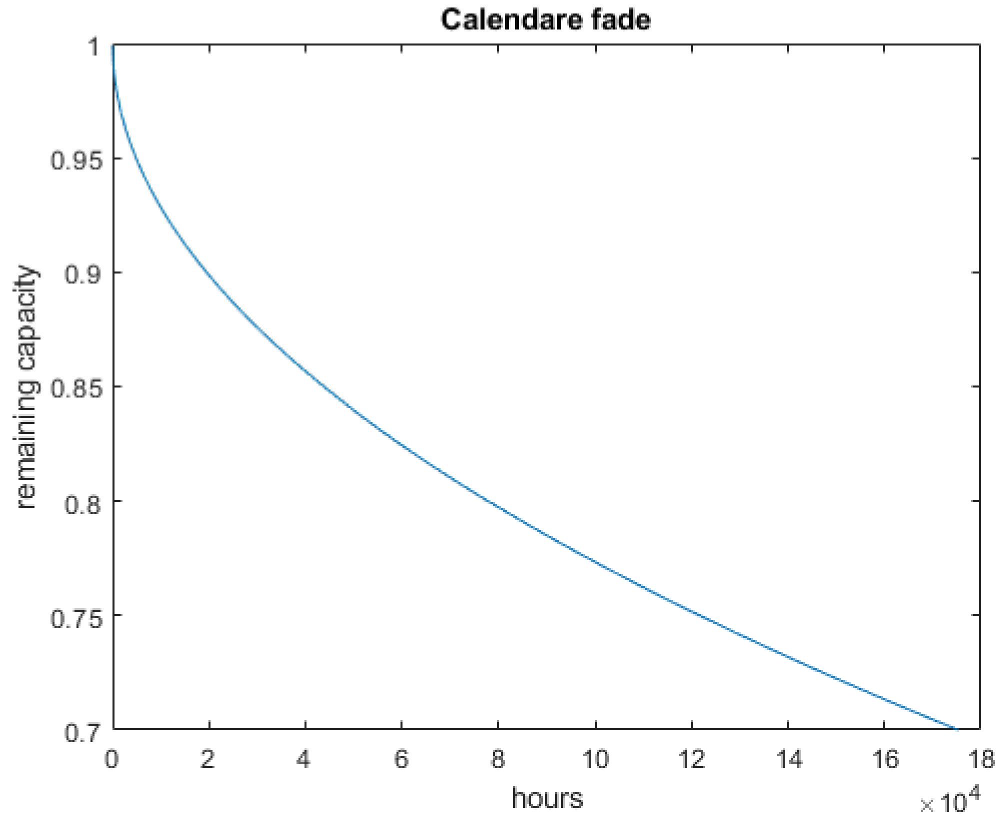


Figure 3.4: Calendar capacity fade model.

then 40% , at the tariff 80% DOD, and if SOC less then 40%, at the tariff for 100% DOD

In 3.5, **??** we can see discharge and charge characteristics of battery in different conditions. which interest for us, C-rate 0.2C, temperature 25°C. As we can see, and discharge and charge have almost the same values at interval from 10 to 90% mean value at this interval is 13.4 V for discharge and 12.9 for charge. At the ends of the interval, the voltage value takes on uncomfortable values. For this reason we will use battery at exactly this interval.

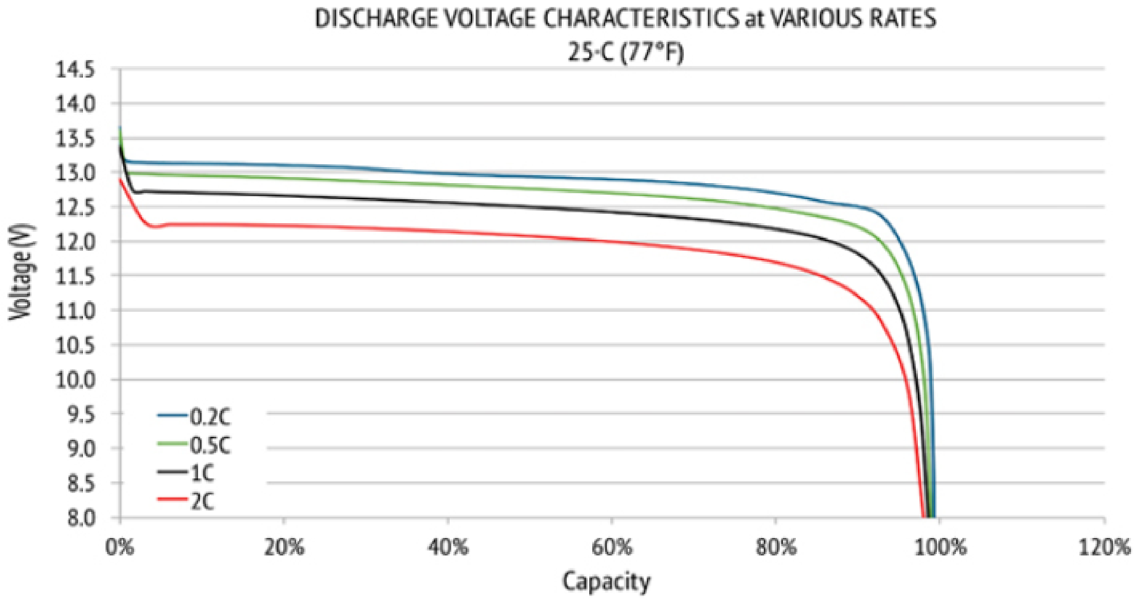


Figure 3.5: Discharge characteristic. Voltage versus SOC [29]

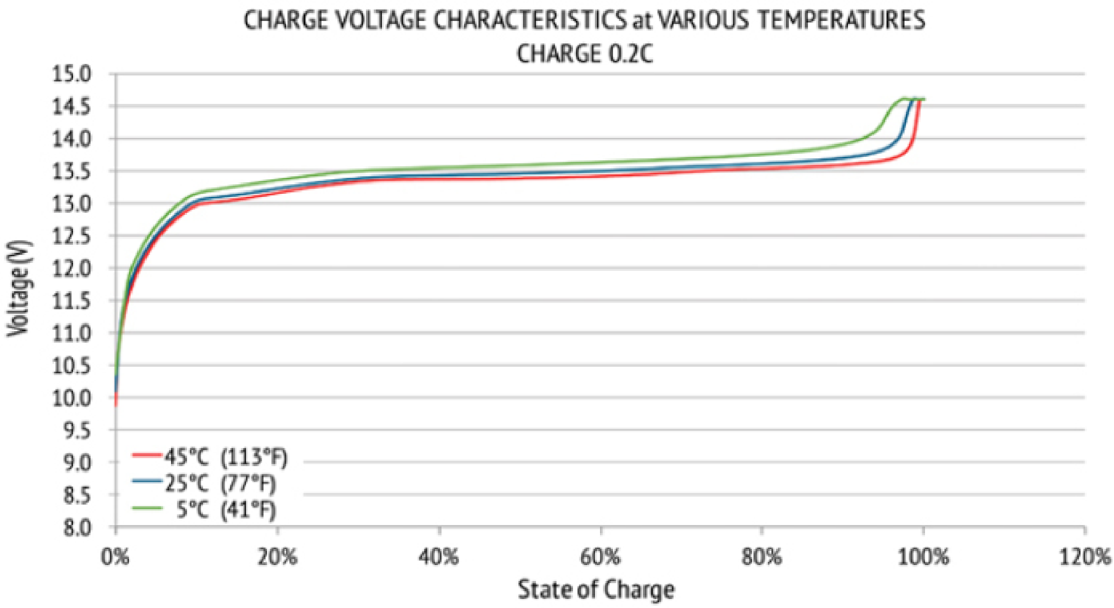


Figure 3.6: Charge characteristic. Voltage versus SOC [29]

## 3.4 Optimization

The aim of this work is economical optimization of microgrid in the environment where energy price and power consumption correlate in time. In order to obtain it we need to complicate our microgrid with energy controller by creating smartgrid. For this reason was chosen Model Predictive Control. Because only when we use

MPC we achieve cost minimization not only for the current moment of time, but for the whole assumed final event horizon taking into account dynamic of the system. At its core is iterative optimization model that tries to minimize cost function $Total\_Cost$ (3.1) every time moment. Sampling time of the controller and horizons is 3600 second (1 hour). Control horizon equal to the length of input horizons. Controller will use linear programming. All functions, which are connected with energy generation/consumption in microgrid, are described with linear control law. Linear minimization function. Controller must minimize (3.1) on the interval [t;t + horizon].

$$Total\_Cost = \sum_{h=t}^{t+horizon} (Consumption(h) * Price(h) + ...$$
$$.. + Cost\_Of\_Battery(h). + Consumption(h) * Price_{Distr}) \tag{3.1}$$

Where $t$ - time of final horizon in hours, Price(h) price of electricity, $Price_{Distr}$= 20 Euro/MWh price of destribution electricity, $Consumption(h)$ is array of optimize variables with length equal to number of hours in our horizon $horizon$ = 24.

$$Cost\_Of\_Battery(h) = max(Calendar\_Cost, Cycle\_Cost(h)) \tag{3.2}$$

$$Calendar\_Cost = Cost\_Of\_Battery/Time\_Of\_Life \tag{3.3}$$

$$Cycle\_Cost(h) = Battery_{Charge\_\_Use}(h) * Cost_{One\_\_Charge}(DOD) + ...$$
$$...Battery_{Discharge\_\_Use}(t) * Cost_{One\_\_Discharge}(DOD) \tag{3.4}$$

$$Cost_{One\_\_Charge}(DOD) = Cost\_Of\_Battery/N_C(DOD) * ...$$
$$... * Battery_{Charge}/Capacity \tag{3.5}$$

$$Cost_{One\_\_Discharge}(DOD) = Cost\_Of\_Battery/N_C(DOD) * ...$$
$$... * Battery_{Discharge}/Capacity \tag{3.6}$$

$$Consumption(h) = Load(h) + Battery_{Charge} * Battery_{Charge\_\_Use}(h) - ...$$
$$... - Battery_{Discharge} * Battery_{Discharge\_\_Use}(h) \tag{3.7}$$

Where Charge of Battery $Battery_{Charge}$ = 269 Wh, Discharge of Battery $Battery_{Discharge}$ = 258 Wh, $N_C(DOD)$ is number of cycles was obtained from 3.2,

$Capacity = 1280$ Wh it is the conduct energy of battery, $Battery_{Charge\_Use}(h)$ and $Battery_{Discharge\_Use}(h)$ is arrays of optimize variables with length equal to $horizon$ lower boundaries equal to 0, upper equal to 1.

Also we have to create the array of variables to control current charge of battery

$$\begin{aligned} Charge\_Battery(h+1) = Charge\_Battery(h) + ... \\ ... + Battery_{Charge} * Battery_{Charge\_Use}(h) - ... \\ ... - Battery_{Discharge} * Battery_{Discharge\_Use}(h) \end{aligned} \tag{3.8}$$

And according to us model of degradation we have to include capacity fade of battery. It will be next function

$$Capacity_{Current\_Max}(h) = min(Capacity_{Cal}(h), Capacity_{Cycl}(h)) \tag{3.9}$$

$$Capacity_{Cal}(h) = Capacity\left(1 - 0.3\left(\frac{h}{t\_Life}\right)^{1/2}\right) \tag{3.10}$$

$$\begin{aligned} Capacity_{Cycl}(h+1) = Capacity_{Cycle}(h) - ... \\ ... - Fade\_One\_Dis(DOD) * Battery_{Discharge\_Use}(h) - ... \\ ... - Fade\_One\_Charge(DOD) * Battery_{Charge\_Use}(h) \end{aligned} \tag{3.11}$$

$$Fade\_One\_Charge(DOD) = 0.3/N_C(DOD) * Battery_{Charge} \tag{3.12}$$

$$Cost\_One\_Discharge(DOD) = 0.3/N_C(DOD) * Battery_{Discharge} \tag{3.13}$$

If we want that function (3.1) works correctly under the system conditions, we need to impose functional limits. Limits can be:

- Strict-value equality (A · x = B)
- Non-equality constraints of possible values (A · x B and lb x ub).

X is a vector of $[N_{gen} \cdot horizon]$ element dimension. Vector x is a minimization decision in the form of supplied power for each system element, battery state and supplementary variable for each hour of event horizon. $N_{gen}$ – number of minimized system parameters for each hour. Equals 4 to this system. For (3.1) there are the next limits

$$CON_1 == Charge\_Battery >= 10\% Capacity_{Current\_Max} \tag{3.14}$$

$$CON_2 == Charge\_Battery <= 90\% Capacity_{Current\_Max} \tag{3.15}$$

$$\begin{aligned} CON_3 == Consumption(h) = Load(h) + ... \\ ... + Battery_{Charge} * Battery_{Charge\_Use}(h) - ... \\ ... - Battery_{Discharge} * Battery_{Discharge\_Use}(h) \end{aligned} \tag{3.16}$$

To prevent simultaneous charge and discharge was create integer optimize variable array $\alpha$ with the same horizon, lower boundaries equal to 0 upper to 1, and with constraints bellow was achieved this prevent

$$CON\_dis == Battery_{Discharge} <= \alpha \tag{3.17}$$

$$CON\_ch == Battery_{Charge} <= 1 - \alpha \tag{3.18}$$

# 4 Analysis of the results

In chapter 3 we optimized microgrid which consist of consumption and battery by MPC controller. Let us now demonstrate that our system and controller perform correctly.

At start lets look what will with the previous family from four people at 17.09.2018 4.1. We can see, that with that tariff the electricity price for this day equal to 1.206 Euro, which less then 1.334 Euro without system, but the deprecation equal to 0.1526 and more than that, the battery have lower charge level then at start, so it wasn't good enough to have our system in that day.

Main model parameters with MPC controller during one-week (from 25.06.2018 to 31.07.2018 on this graphics) with one-day horizon are depicted in 4.2.

As we can see almost at all interval price with battery are higher than without this is consequence that a lot of time battery stayed idle. On this submitted week prices next

- The electricity price without battery was equal to 8.4177 Euro
- The electricity price with battery and MPC equal to 8.2296 Euro
- The deprecation of battery equal to 0.9631 Euro
- The total price with system 9.1927 Euro

Which mean, that our system not useless the price on electricity per month almost on 1 Euro cheaper than without it, and if we will look close we can find that yes, system work correctly, but the price on battery almost at five time higher than this benefit.

Does it mean, that this system useless? No we think this isn't useless, because price on electricity grows up year by year and as we can see at 4.3 if the cost of electricity will be higher than 129 Euro/MWh in 3 times, the usage of battery will grow with the same load and the same tariff.

In this situation prices next

- The electricity price without battery was equal to 23.3610 Euro
- The electricity price with battery and MPC equal to 22.034 Euro
- The deprecation of battery equal to 1.4801 Euro
- The total price with system 23.5104 Euro

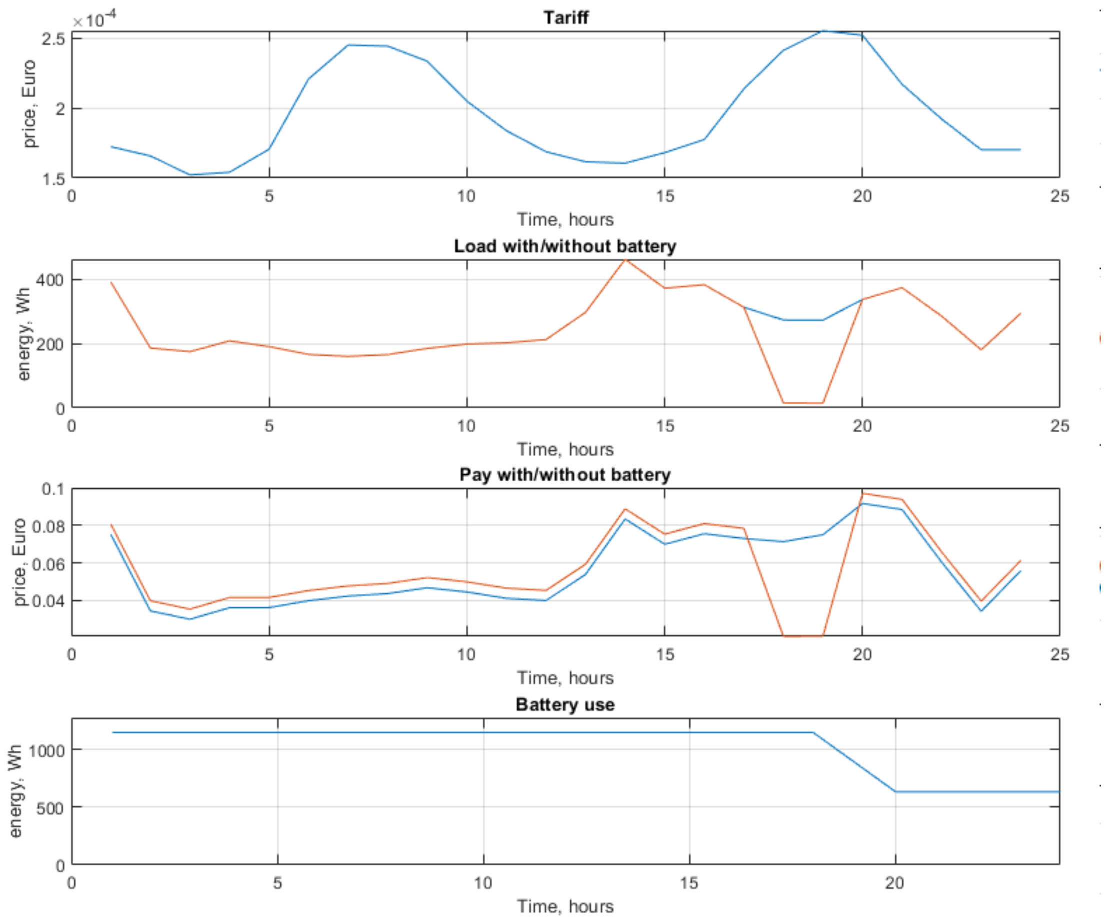


Figure 4.1: Tariff. Load with battery (red) without battery (blue). Final price which contains both electricity and depreciation of battery. Battery use.

Which almost the same and if the price on electricity will continue to grow up, or if the price of batteries decreases. The usefulness of this system will grow.

Also we try to optimize system with two-days horizon. But result was the same at almost every week which we used. And almost the same with insignificant benefit at some weeks, but time of optimization grows significant, so we are stopped at one-day horizon.

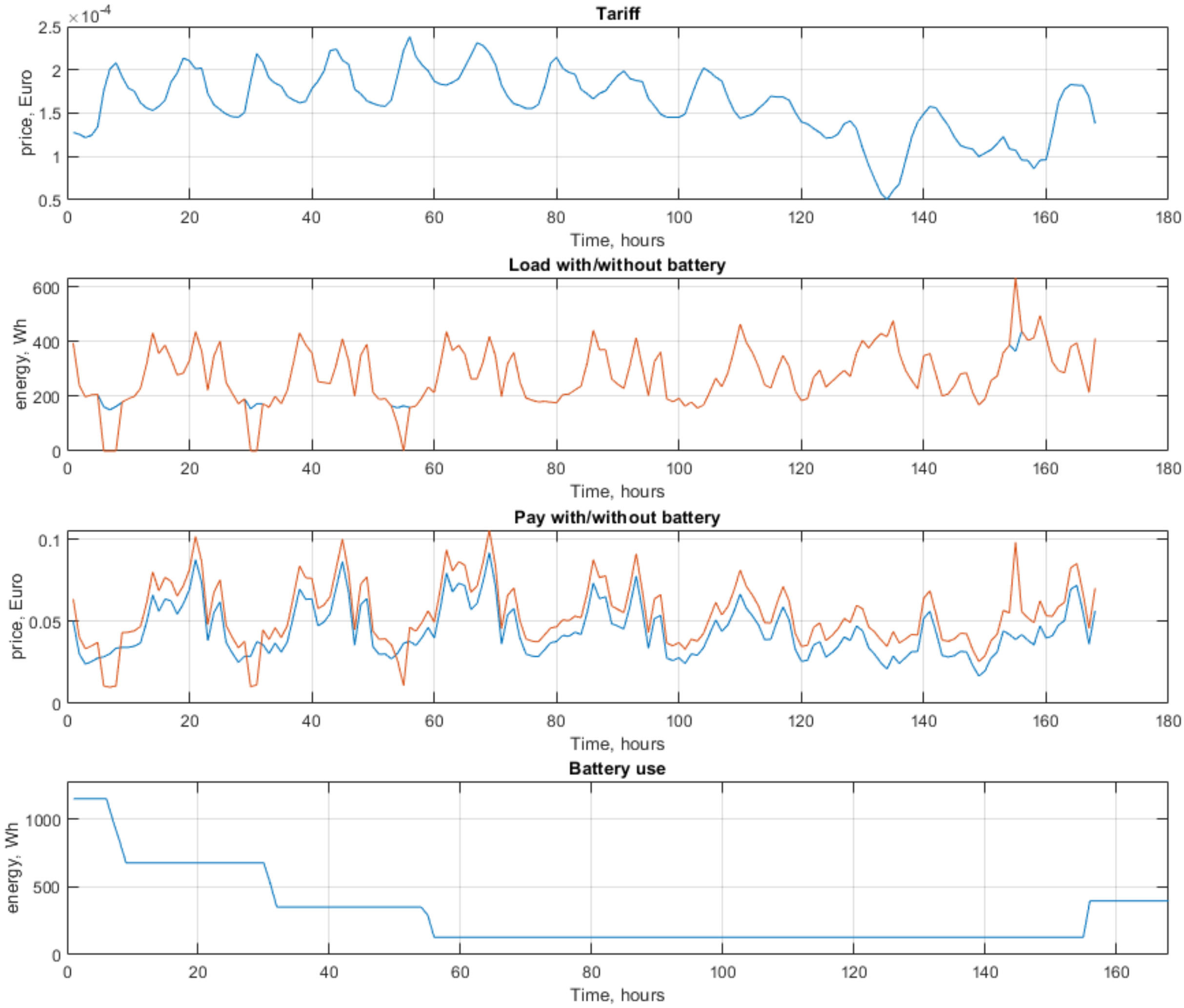


Figure 4.2: Tariff. Load with battery (red) without battery (blue). Final price which contains both electricity and depreciation of battery. Battery use.

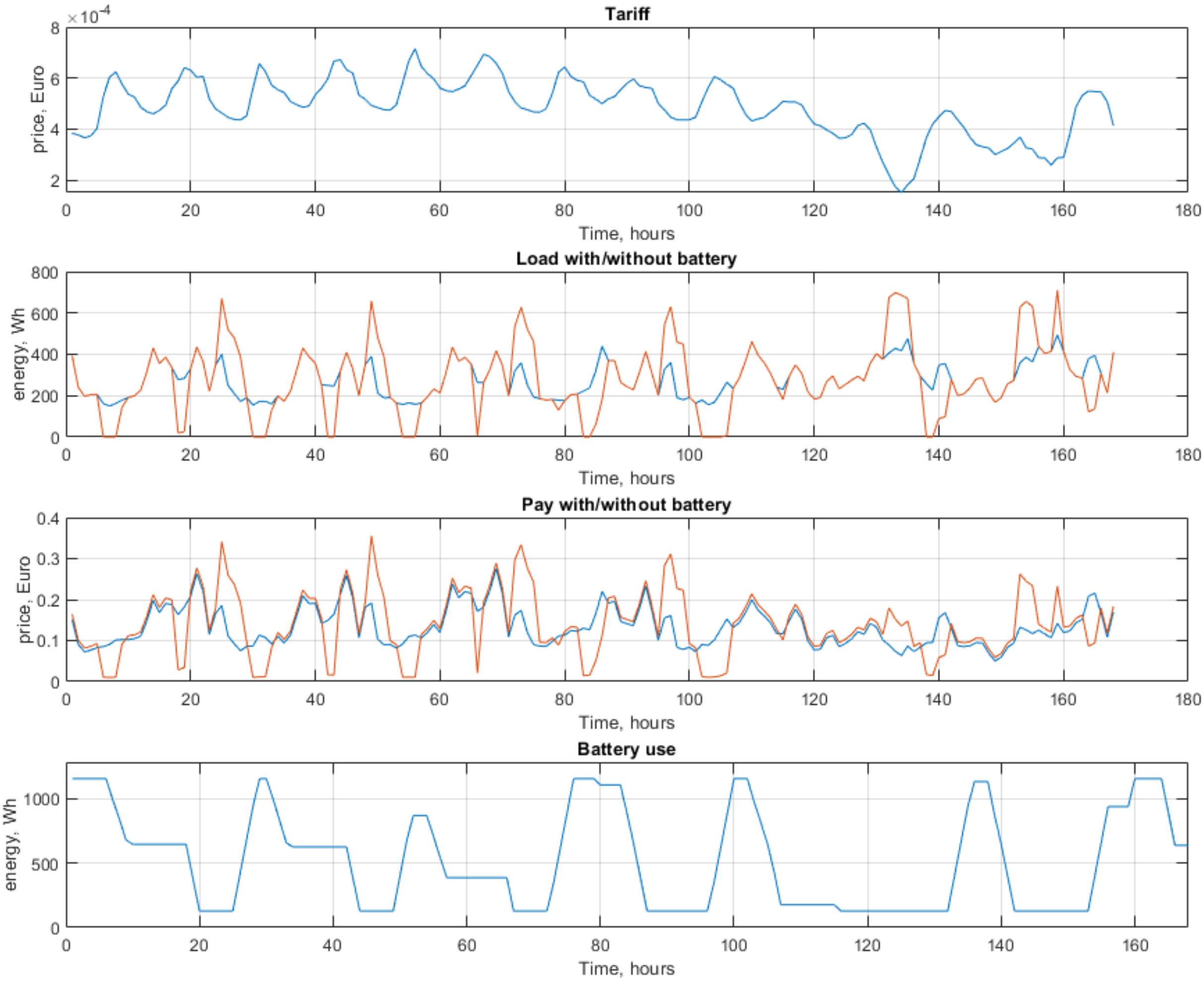


Figure 4.3: Tariff x3. Load with battery (red) without battery (blue). Final price which contains both electricity and depreciation of battery. Battery use.

# 5 Conclusion

In this diploma thesis we consider introduction to the smart microgrid conception: their purpose, structure and possible variants of mathematical realization, which are presented in the work as literature review.Conclusion of advantage of the method based on MPC is made, with condition that system profiles (load, cost) of the method have predictable behavior.

We choose an abstract object of residential community of northern part of Czech Republic, which is connected to the main electricity grid and have average consumption equal to 8000kWh per day.

Some analysis was carried out and a battery suitable for the criteria set by us was selected. Also based on a model from [18] a battery degradation model was developed.

The next step is to choose the method of solving optimization task of MPC controller: mixed-integer linear programming (MILP). Weight function and restriction matrices are created based on the method. Weight function describes possible minimum cost for object electrification during the whole horizon. Restriction matrices are used to describe power requirements and functional limits of objects.

Afterwards we verify adequacy of smart microgrid performance for chosen object and made conclusion about controller solutions at certain time moments. System work correctly, and we can achieve benefit in electricity price, but battery wear more then that benefit. But may be in future, even not so faraway future, it can be usefulness.

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