# AUTONOMOUS AND COST-EFFICIENT OPERATION OF A STATIONARY BATTERY ENERGY STORAGE IN LOW VOLTAGE NETWORKS

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## *ABSTRACT*

*This project assessed the use of stationary energy storages operated by intelligent software to find optimal operation modes and to adapt it to the changing load conditions in low voltage networks. The goal is to develop an autonomous energy storage controlling software that creates revenues of price ranges of the daily day-ahead market while also considering and assessing load peaks in low voltage networks. Furthermore, installation of this software should be as easy as possible with only minor knowledge of the respecting grid and the need for external commands should be as little as possible.*

*During the project it has been shown that the proposed algorithm performs very well under computer simulated circumstances. In addition, hardware experiments by using a 30kW/100Wh Vanadium Redox Flow Battery (VRFB) and an adjusted low-voltage grid shows the capability of the control software under realistic conditions.*

## INTRODUCTION

Usually when installing new components in low voltage networks they will remain unmodified, without any special optimization or reconfiguration, until the end of its service time (“fit-and-forget” approach). This is true, even if every low voltage network has its unique behaviour. However, the environment of the energy sector is changing faster than before and manual maintenance of increasingly complex devices becomes more difficult. That is why, components should be capable to adapt to new conditions and to find optimal operating modes on their own.

Especially transformers face new challenges such as higher load peaks through electric vehicles or in contrary a back-feeding of electric energy due to an increasing decentral generation of photovoltaic power generators. These challenges can lead to a shortened lifetime of transformers. [1, 2]

Stationary energy storages are becoming interesting solutions to increase the hosting capacity of low voltage networks in multiple ways. Computational techniques have the potential to bring the operation of a battery energy storage to another level in a way that allows to minimize the operational costs without the need of manpower in day-to-day operation. On one hand, an algorithm could forecast the future loading conditions of the particular network and their associated thermal and voltage restrictions and, on the other hand, gather information of the forecasted market prices of the electricity. Based on these information, the battery can be charged from the network during the least expensive hours without hampering the network operation and can be discharged during price peaks. This would result in lower energy costs which, in turn, would lead to an increased value generated by the battery.

For this purpose, an algorithm based on machine learning techniques and linear optimization was developed in Java aiming to create an open and non-restricted software. The principal focus of the algorithm is threefold. Firstly, the practicality, meaning an easy installation without the knowledge of programming skills. Secondly, the robustness resulting from the ability to automatically adapt to changing price-, load-, and thermal circumstances. Thirdly, a decentralization that eliminates the need to directly control the battery with centralized charge/discharge commands as all data will be processed locally. Only external electricity prices will be needed.

For a better understanding of the chosen programs design, the main steps involved in the algorithm are described following. Starting with the reading of electricity prices, followed by the process of load anticipation and combining both in an optimization process to find the best charging schedule.

After, simulations in a more realistic environment are carried out and discussed. Finally, a brief analysis regarding monetary benefits is presented and discussed.

Additionally, as the concept aims at creating an economic benefit, theoretical possible earnings are examined as well comparing Redox Flow Batteries with Lithium Ion Batteries.

## DAY-AHEAD ELECTRICITY PRICES

In the European electricity markets, large parts of the trading takes place in Over-The-Counter (OTC) transactions, but there is also a growing trade via official electricity stock exchanges like EPEX SPOT, Nord Pool and others. In contrast to OTC trades, the official stock exchanges offer high amounts of transparency referring to products and their respective prices and, thus, provide valuable information for the software. Nowadays, there are many electricity products that are traded via the stock exchanges such as long-term, short-term, day-ahead, intraday-trades and single hour or block contracts. While the long- and short-term prices certainly affect the overall price, an energy supplier has to pay for electricity in the respective timeframe, it is the prices shortly before energy delivery that define the possible costs or earnings that can be facilitated. In this context, the intraday market seems to be the most interesting as it is very short-termed with times of only 30 min between deal and delivery, and also offers prices for each of the 96 quarter hours each day. The problem with intraday trading is its “Pay-As-Bid”-method to create electricity prices which means prices can change quickly during the day and there is no standard price. The day-ahead market, on the other hand, uses a standard-price-method where the prices for each hour of the next day are released on 12:40 p.m. of the current day. These prices offer beneficious conditions to plan the charging and discharging of the battery. Price data, used in the designed algorithm, were automatically acquired by the website of the EPEX SPOT.

## METHOD OF LOAD-ANTICIPATION

Distribution transformers are expensive components that are built to last for many years, without the need for repairs or replacements. High grid loads can lead to a heating of the transformer components that in turn can damage its insulation and thus, decrease its lifetime. A battery connected to the grid alongside the transformer could support it during load peaks. Reserve capacities enable a battery to support grid devices during load peaks or load dips. To achieve an optimal and beneficial mode of operation, it is important that the reserve capacities are not defined as this would lower the potential benefits generated by the battery. That is why the created software aims at anticipating the future load curve, so that the amount and time spans of the reserve capacities can be adapted to the respective need.

There are multiple ways to generate a future load curve, for instance, standard load profiles, registered power measurements or probabilistic load models. Using these methods often requires lots of work and only produces static load models that are not updated automatically.

The load curve of low voltage networks can differ from the standard load profile according to the respective amount and characteristics of the networks consumers, as well as the amount of installed decentral renewable energies. Especially for small networks with less than 150 households, standard load profiles are not sufficient for a precise load prediction. [3] Machine learning (ML) or artificial neural network (ANN) techniques could be advantageous in terms of efficiency and their ability to automatically recognize and assess a multitude of external influences on the load curve. Their potential is assessed in this paper.

### Artificial Neural Networks

With a sufficient amount of data, an ANN can read repeating patterns that would otherwise need an extensive manual evaluation. As the name states, an ANN consists of a number of interconnected artificial neurons. Each neuron has its own weights for incoming data that represent the relative importance of each input. Following, a summation function adds up all weights to define the neurons internal activation level, which will further be processed in a transfer function to create an output that will either being forwarded to following neurons or state the final output.

The neurons are ordered in several layers, with always one input and one output layer and hidden layers in between. An ANN has to be built according to necessary and available inputs and the desired output data. While the amount of input- and output-neurons is fixed according to the data, the number of hidden layers and their respective neurons can be flexible.

After creating the ANN, it needs to be trained with respective data. In a supervised neural network, as it is used in this project, each set of training data with input values has assigned output values. While training, the neural network adapts its weights to reach the given output.

### Used Artificial Neural Network

The software of this project uses an ANN with three layers. The input layer consists of three neurons, the hidden layer of six neurons and the output layer of one neuron. The design bases on the following three criteria.

Firstly, the respective day has to be described. When using standard load profiles, there are three day-types that must be differentiated between due to their distinct load profiles: weekday, Saturday and Sunday. As low voltage networks can be very small with just a couple of customers or only an electric vehicle parking lot, they might also have their own characteristics for each day. To acquire load information as precise as possible, the software treats every day of the week separately so that the input neuron *day* can get values between one and seven. Secondly, the respective hour of each day must be defined which leads to values between one and 24 for the input neuron *hour*. Thirdly, the load of the previous hour is given to the input neuron *load* to get some orientation on how the load curve currently looks like. There are further information that can be considered for creating a neural network. For example, weather data like cloudiness and temperature, holidays or even special events like important sports finals. The main reason they are not implemented in the program, is due to the lack of appropriate data. Also, it was chosen to use only load data of the past seven days, as more data would increase the time needed for training a ANN. However, this leads to the necessity to train the ANN every week. Also, the shortened time period of only seven days for load anticipation lessens the ANNs possibility to differentiate effects of whether or special events from random differences in the load curve.

The forecasted load values are set to hourly time steps to fit the read energy price-data, so they can be used in the following linear optimization without further adaption.

With this in mind, for future improvement of this concept it should be analysed if longer timeframes of historical data can be implemented and how they would actually influence the computing time and the accuracy of load predictions. Additionally, predicting the load curve in smaller timesteps would increase the precision of appearing load peaks and back feedings as well.

## CHARGING AND DISCHARGING STRATEGY

The acquired energy-prices and the forecasted load-values can be used to operate the battery in an optimized way. To do so, it is necessary to create a schedule for charging and discharging taking into account beneficial price margins, as well as the limitations of the transformer. One way to generate an optimal schedule is to use linear optimization techniques such as the SIMPLEX algorithm, which is fast and easy to apply. This algorithm bases on an objective function that can either be minimized or maximized, while also respecting the given constraints. In the studied case, the function to be maximized is the sum of the energy-price multiplied by the amount of charged or discharged energy of each respective hour during the defined timeframe.

$$MAX \sum_{1}^{n} x_i * y_i$$

What also has to be respected is that this formula underlies several restrictions. The restrictions on the battery side contain the minimal and maximal battery capacity range as well as its maximal charging and discharging power. Whereas, the restrictions on the grid/transformer side include the spread between the forecasted grid-load values and the transformer specifications if these are violated. Another important part of the optimization process is the battery efficiency in economic terms.

A complete charge and discharge schedule based on simulated values is shown in Figure 1. Graph A displays the forecasted daily load of an exemplary low voltage network comparing it with the maximal load that the local transformer can provide. It can be seen that thermal violations can be expected between 5:00 p.m. and 9:00 p.m. These must be handled by the battery. Graph B shows the charging schedule according to the grid load, the electricity prices and responding State-of-Charge (SoC) levels of the battery. As the number of possible charging-cycles of batteries can be highly dependent on the minimal and maximal SoC, [4] it was chosen to set the SoC-borders between 20 % and 80 %. At every time step, the load restrictions of the transformer and the given SoC limits are respected. Simultaneously, a monetary benefit can be created resulting from the automatically determined price margins.

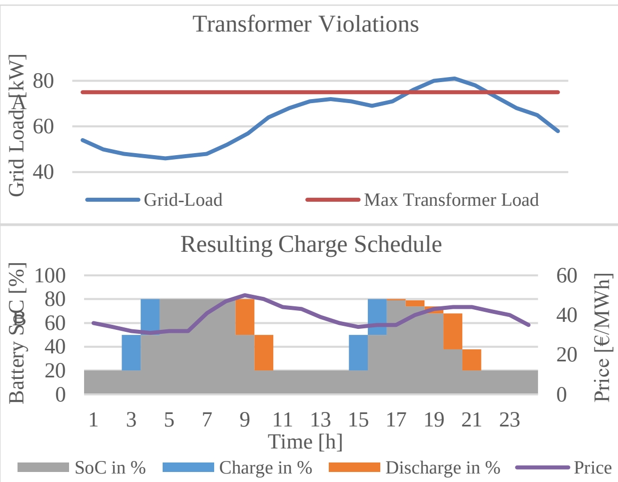


*Figure 1 – A: An example load curve and the maximum load of the transformer; B: The charging and discharging schedule resulting from both the load and electricity prices*

## TEST ON HARDWARE

After the performance of the program is demonstrated under a simulation, it is important to test the program on a commercial hardware. Therefore, various experiments are carried out at TU Dortmund University. The testing setup includes a 30kW/100kWh Vanadium Redox Flow Battery (VRFB) as shown in Figure 2, a power amplifier and measurement devices. For the simulation, the minimum SoC of the battery was set to 20 % and the maximum SoC to 80 %. Data reading and command input was done via Modbus.


*Figure 2 - Picture of the used 30kW/100kWh Vanadium-Redox-Flow-Battery*

The procedure is to simulate the load of a low voltage network during one week, to read out resulting data and implement them into the ANN to forecast the load of the next day. The day-ahead prices are acquired from epexspot.com and both data are combined to create a charging and discharging schedule. Finally, this schedule is executed on the VRFB.

Due to a limited time frame, the simulation time was shortened to 42 steps within one week, with six steps each day, resulting in a load forecast of six steps. Each time step was simulated for 30 seconds. The generated forecast shows two thermal violations at transformers at 8:00 a.m. and 4:00 p.m. with 8,12 kW and 20 kW above the maximal load that had to be met by the battery. From the price curve and the determined charging and discharging schedule (Figure 3), it can be seen that during charging (12:00 a.m., 12:00 p.m., 8:00 p.m.) the battery did not reach the pre-set power due to technical issues on the day of the simulation. While the two discharging commands on 8:00 a.m. and 4:00 p.m. were only given to meet the transformer violations, the command on 4:00 a.m. is carried out to create a revenue. All charging commands take into account the maximum and the minimum capacity of the battery.

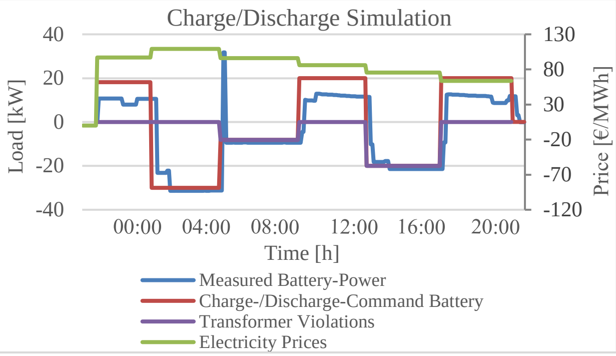


*Figure 3 - Real charging and discharging of the VRFB according to load and price signals.*

However, due to the short time frame of the simulation, only minor changes of the SoC can be seen. Load data management is an important part of the algorithm, as the accuracy of the forecasted load in the low voltage network increases the more data the ANN can use for it. During the simulation, it appeared that the load data management strategy has room for improvement.

## ECONOMIC ANALYSIS

The presented concept serves two purposes: (1) to keep the transformer load from exceeding the limitations and (2) to create a monetary benefit of the margins of the day-ahead energy prices. As an example for the possible earnings of a 30kW/100 kWh battery, the hourly whole sale electricity prices in Germany of the years 2015 – 2018 are used. Charging schedules are created for every day of each year and their resulting revenues are added up, independent from the load violations of the transformer. The performed calculations reveal that a battery with 85 % system efficiency and defined SoC borders of 20 % and 80 % could generate earnings of 595.51 € in the time frame between August 2017 and September 2018. In contrast, a lithium-ion battery with the same specifications but a system efficiency of 93 % could reach 732.98 € in the same year. Furthermore, an increase in theoretical yearly revenues from 2015 until 2018 of 16 % per year has been detected for both battery types.

Although, this calculation indicates higher revenues from lithium-ion batteries, there are other aspects why redox flow batteries could be more advantageous. One advantage of redox flow batteries over lithium-ion batteries is their stability even at deep discharges, allowing a wider use of SoC range without losing their long-term stability. If, for example, a VRFB with 85 % system efficiency and SoC borders of 5 % and 95 % would run that simulation, the possible earnings would rise to 801.18 €. In addition to that, VRFBs allow for up to 14000 complete charge cycles compared to lithium-ion batteries with only up to 7000. [5] To date, possible economic incomes only cannot justify the installation of such energy storages.

However, as this concept creates a higher monetary benefit the more volatile are the electricity prices. With the current plan of development of renewable energies, it seems likely that both the amount and intensity of volatilities will grow in the future. [6] Additionally, it seems likely that prices for lithium-ion batteries as well as redox flow batteries will decline.

## CONCLUSIONS

The presented concept shows a possibility to establish batteries in electricity grids that have multiple benefits. Firstly, there is the economic benefit created by using margins in electricity prices. Admittedly, these are relatively low compared to the investment costs of batteries today. However, with increasing price volatilities and decreasing battery costs this fact could change in the future. It was observed that redox flow batterie could serve for this task very well, as they provide the ability of deep discharging while simultaneously allowing a high number of lifecycles. Secondly, the battery could support the respective transformer which is an expensive grid component that faces increasing challenges. A prolongation of its lifetime and peak shaving will result in non-negligible economic benefit.

The simulation shows the general functionality of the program under real conditions. However, room for improvement were identified before the implementations in real networks. Overall it can be said, that the project's goals of a battery that is easy to install and to maintain with low costs while generating revenues and supporting the transformer can be achieved with this concept.

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