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# Development of a Charge Path Optimization Controller Block for a Battery Energy Storage System

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## 1. INTRODUCTION

As part of its efforts to progress and innovate in the field of Smart Grid technologies, Enexis[1] developed and currently operates a Battery Energy Storage System (BESS) called the Smart Storage Unit (SSU), part of the Smart Storage Project (SSP). The SSU is a 400 kVA, 232 kWh storage system, equipped with internet-connected control hardware in order to add "smartness" into the equation. The objective of the project is to enable field-testing and research on advanced electricity storage solutions in the LV distribution grid. It is installed in the LV grid to enable applications such as:

- The increase of local self-consumption of photovoltaic (PV) power,
- Improvement of reliability and flexibility,
- Reduction of losses and maximizing the utilization of existing infrastructure.

An elaborate system description of the SSP is given in [1]. This paper mainly focusses on the development of an addition to the controller system for minimizing grid losses and maximizing grid asset utilization. Its principles rely on using historic data for load prediction, in order to flatten the power demand at the transformer, through peak-reduction and valley-filling.

## 2. THE SMART STORAGE UNIT

The Smart Storage Unit (Fig. 1) consists of batteries, inverters and auxiliary hardware installed in a standard substation, which is depicted in the field in Fig 1. Schematically the SSU is indicated in Fig. 2 by the green box.

The inverter system consists of four separate inverters, each connected to one of four battery strings. The inverters convert the 696 $V_{DC}$ battery voltage into 230 $V_{AC}$ on the grid side. Each inverter is connected to the battery strings' battery management system (BMM) in order to monitor battery status and adjust current limits accordingly. In Fig. 3, two out of four inverters inside the SSU substation are depicted.

The four battery strings each consist of 29 battery modules. Each having a nominal voltage of 24 $V_{DC}$, adding up to a nominal voltage of around 696 $V_{DC}$. The maximum discharge power per string is 100 kW, adding up to 400 kW in total. The maximum charge power is limited to 25 kW per string, totalling to 100 kW of charging power. The batteries can operate normally in a temperature range between 20 and 50 degrees Celsius. An air-conditioning (AC) system ensures the batteries always operate in this temperature range. The BMM that is installed within each battery string ensures safe and prolonged battery operation by limiting (dis)charging currents when operational limits are about to be reached. Current limitations can be reached due to; a high state-of-charge (SoC), imbalance between individual battery modules within a string, high battery module temperatures, and very low or high SoC values.

Fig. 1. The Smart Storage unit installed in the field

## 3. CONTROL AND DATA COLLECTION SYSTEM

The SSP is equipped with a control and data collection (CDC) system, boxed in red in Fig. 2. It controls four separate inverters, each connected to one of the four battery strings. The CDC is built with off-the-shelve x86 hardware. It can run custom made applications in order to facilitate different control strategies. In Fig. 4 the interconnection between the novel charging path optimizer based on [2] proposed in this paper and the real-time controller is depicted. The real-time controller is currently fed by a static SoC table, with several charge-discharge cycles per week. The charge path optimizer will dynamically provide SoC reference data, based on real-time measurements and historical data. The CDC provides the historical data needed for the charge path optimizer.

[1] One of the largest DSOs in The Netherlands.

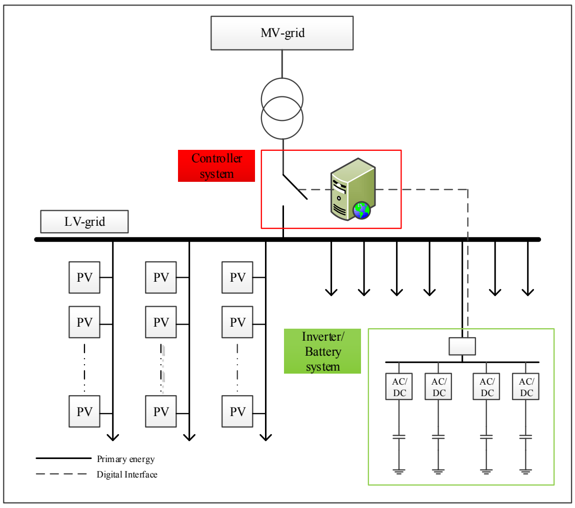


Fig. 2. Left: schematic overview of the Smart Storage Project

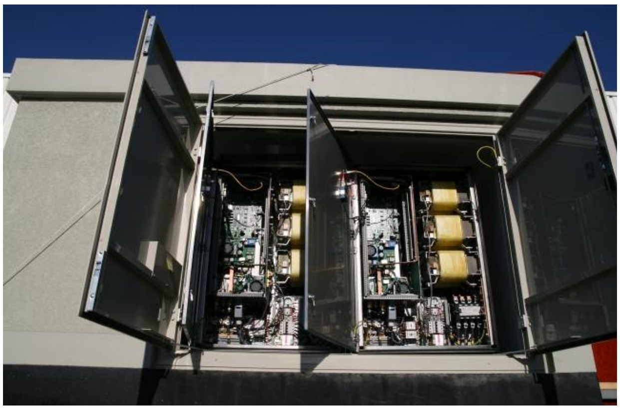

Fig. 3. The inverters inside the substation

## 4. CONTROL ALGORITHM

The objective of the newly developed controller is to minimize transformer peak-loading using historical power consumption data as input for future loading prediction. This single source of information has been chosen in order to demonstrate the performance of the controller algorithm with limited circumstantial information available. Future research will include assessments of the increase in performance when more information sources (such as weather forecasts) are available. The case considered in this paper can act as a base case control strategy for those assessments. The controller determines the optimal (dis)charging power for a 24 hour receding horizon, based on this historical data, real-time measurement data and current state-of-charge (SoC). Fig. 4 depicts the interconnection between the novel charging path optimizer and the real time controller. In Fig. 5 a graph of the energy envelope is depicted. This envelope determines the minimum and maximum values of the state of charge over time in the same way described by [2].

The controller algorithm proposed in this paper uses a load forecast, based on historical data, to determine the optimal charging strategy. In most cases the load will have a peak and valley in the period of a day which enables daily peak shaving with the help of the SSU. Therefore the horizon of the optimization algorithm is limited to the period of a day. It is assumed that daily load profiles are somewhat similar and that during a day the SSU has not enough energy storage capacity to completely flatten the load demand profile of the connected households. This leads to the proposition that at the moment of interest and twenty-four hours later the State of Charge (SoC) of the SSU should be the same.

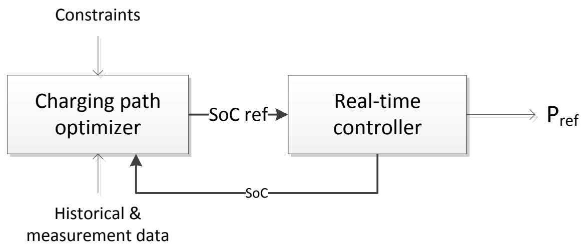


Fig. 4. Block diagram depicting the charging path optimizer within the control system

An optimal charge profile can be determined for this period. Therefore, an approach suggested by [2] is used, which assumes an envelope of possible states of energy between the two moments in time ($t=[0,t_{horizon}]$). The envelope is limited by the capacity of the battery ($E_{max}$), and a minimum energy state of the battery ($E_{min}$). This lower boundary increases the lifetime of the battery system. Furthermore, the envelope is formed by the maximum charge and discharge rates of the system, which are depicted in Fig. 5 by the rising and declining lines pieces representing respectively charging and discharging of the system at maximum rated powers. These power restrictions also apply inside the envelope, resulting in a limited range of energy states which can be reached in a certain period. In Fig. 5 this is visualised by points A, B & C. From point A only energy states between point B and C can be realised in the period $t_{res}$.

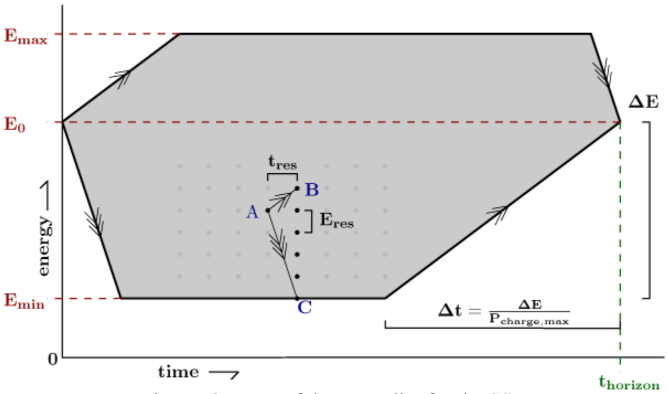


Fig. 5. Concept of the controller for the SSU

Within the envelope and regarding the power restrictions a backward induction algorithm is applied to determine the optimal (dis)charging path of the SSU for the time horizon. This enables non smooth cost functions to be applied for other strategies [2]. Therefore, the state (E) and action ($\Delta E$) space as well as time are quantized with respectively resolutions $E_{res}$ and $t_{res}$ (as depicted in Fig. 5). A positive and negative penalty of an action is associated with respectively charging and discharging actions. The series of actions with resulting in lowest penalty is regarded as the optimal (dis)charging path. Implementation with a backward induction algorithm enables additional modeling of detailed characteristics of the SSU. Also the reward function can be adapted to charge optimally regarding peak shaving, market price, matching renewable energy sources, etc.

## 5. SIMULATION MODEL

A simulation model is developed in MATLAB to simulate the SSU unit and the controller (Fig. 6). The SSU model describes he characteristics of the SSU and the controller model contains the concept described in section 4.

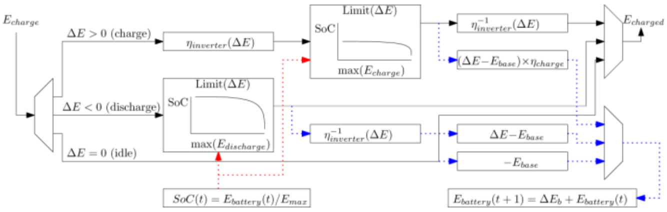

Fig. 6. Diagram of the SSU model

Fig. 6 shows a diagram of the SSU model with several function blocks (functions of ΔE). There are three modes within the model; charging, discharging and idle. The mode is dependent on the value of $E_{charge}$, the energy per time step from the grid into the SSU. In the idle mode, the SSU will only need energy ($E_{base}$) for a basic features such as AC, ICT, and control hardware. This energy comes from the SSU itself, since it also should work in island mode. In the charging mode, the charging rate of the SSU is limited by the Li-ion battery connected by the inverters, which also have losses. The remaining energy is partly used for the aforementioned base load and charging the battery. This charging has a certain efficiency, $\eta_{charge}$, which finally results in an effective charge energy, $\Delta E_b$. In case of discharging, the discharge rate is limited by the rated power of the inverters. The effective discharge energy of the battery, is based on the efficiency of the inverters and the base load.

The controller model first collects the forecast and the energy state of the SSU, and creates the envelope and optimizes the charging actions for the horizon of 24 hours regarding its penalty function. In this paper the objective is peak shaving and the corresponding penalty function that has to be minimised with $P_{action}(t)$ is therefore;

$$\sum_{t=1}^{24*4} (P_{demand}(t) + P_{action}(t))^2$$

Eq. 1: Penalty function

Secondly, the amount of energy to charge in the first time step is given to the SSU model. This will charge or discharge its battery and, finally, returns the new energy state to the controller. These steps, which represent 15 minutes, are repeated for the simulation period of a week.

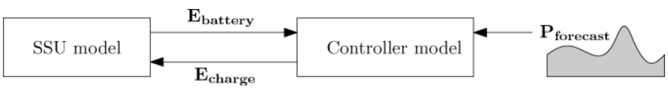


Fig. 7. Scheme of the simulation model

Since the SSU is fitted with Li-Ion cells, the maximum charge and discharge rates are related to the SoC of the system. This was modelled into the SSU model as well as into the penalty function of the controller model. Also the charge and discharge losses of the system were modelled in both sub-models.

The forecast of the demand which is needed for the controller model is based on actual measurements of the neighbourhood connected to the SSU. In Fig. 8 a screenshot is depicted of the resulting optimisation. The upper inset shows the envelope with the optimal charging state for the total time horizon, and the lower inset gives the associated power demand of the connected costumers, the transformer loading, and the power given by the SSU. It is clear to see that the concept of the optimal charging state will result in lower transformer loading as depicted in the lower inset, with the same power demand of the connected costumers.

## 6. CASE STUDIES

In order to assess the effectiveness of the charging path optimizer, several case studies have been performed through simulation. Three different scenarios are selected for simulation:

- Scenario 1: In this scenario the standardized profiles from the *Ecofys* [3] database are used. Day profiles vary over time, but due to the aggregation of a large number of consumers the profiles are smoother than generally seen at a MV/LV transformer. Only small deviations on load demand exist between days.
- Scenario 2: In the second scenario actual measurement data from the 'De Keen' neighbourhood have been used. A holiday is present in the middle of the week, showcasing its behaviour in case of unexpected load demand variations.
- Scenario 3: In the third scenario, two subsequent weeks, one sunny and one cloudy are simulated. This will show the algorithm's performance in case of strongly varying PV output in the neighbourhood.

In these three scenarios, a weeks' worth of historical data is used as the input for the charge path optimizer. From a practical perspective this simplifies operation of the controller, as this data is locally available through logging. Through these simulations it is assessed whether this practical approach can be effective in operation of the SSU.

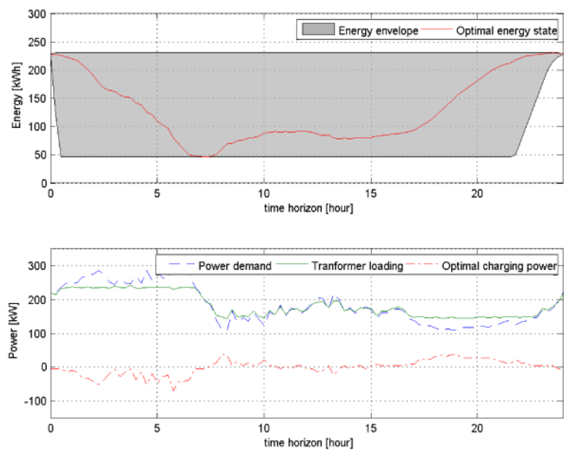


Fig. 8. A screenshot of the controller model variables during simulation

*Scenario 1*

As can be seen from Fig. 9, the profile is highly repetitive and therefore the controller is able to charge the SSU in the power demand valleys, using that same energy reducing peaks during highest demand. Peaks are reduced by 14.3% on average throughout the week.

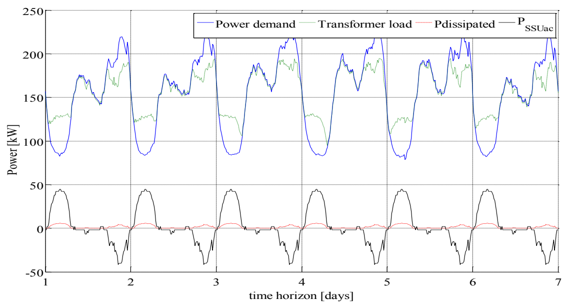


Fig. 9. Simulation results scenario 1

*Scenario 2*

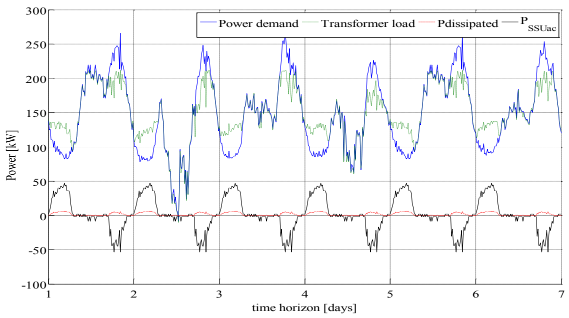


Fig. 10. Simulation results scenario 2

In scenario 2, reduced demand during day 2 (as can be seen from Fig. 10) and varying demand profiles during the rest of the week, showcase the controller's ability to adapt to varying circumstances. As load demand has spikier peaks than the Ecofys profiles, peak-shaving performance increases to 17.9%. Using this real-life data, we can conclude the algorithm's effectiveness in the field.

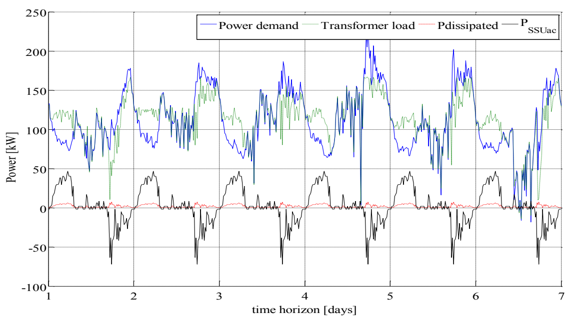


Fig. 11. Simulation results scenario 3

*Scenario 3*

In Fig. 11, the simulation results for scenario 3 are shown. In this case, load measurements of the summer months are used. In this case the preceding week had a lot of PV output, which has significantly dropped during the week depicted in Fig. 10. Nonetheless, the controller was able to reduce peak-loading with 13.7%, proving its effectiveness when handling historical data that significantly differs from week to week.

*Discussion*

From the scenarios described before, we can see that a single information source, historical load-demand data in this case, is suitable for determining (dis)charge paths in a BESS in the LV distribution grid. Only using a single data source, greatly reduces complexity of the controller, while providing sufficient performance. In all simulated scenarios, peak load at the transformer went down significantly.

In the first scenario, averaged, aggregated and therefore smooth, load profiles are used to test the controllers' capability to use historical data for the purpose of flattening the load profile seen at the transformer. Although the simulation turns out effective, its relevance to real life conditions is limited, since the used profiles are smoothed and daily variance is little.

The second scenario encompasses a simulation whereby field measured data taken from the SSU project is used. In this case, one deviating day is included in the simulation timeframe. This shows the controllers' capability to cope with unexpected changes in a more or less repeating pattern. As the resulting peak transformer load reduction does not vary significantly compared to scenario 1, it is shown that a deviation caused by for example a holiday, will not be of influence to the controllers' stability in flattening the transformer load profile.

In scenario 3, a different approach is taken; two subsequent weeks are simulated, first a sunny week with a lot of PV power generation, followed by a cloudy week with only little PV power generation. The historical data will result in a prediction expecting a lot of PV generation, resulting in low day-time power demand, or even net reverse power flow. Meanwhile, power demand will be a lot higher during daytime hours than predicted. Nonetheless, the controller is capable of reducing the transformer peak load under the uncertainty of weather circumstances. This shows that detailed weather information is not critical for sufficient controller performance.

## 7. CONCLUSIONS

This paper describes a charging path optimizing controller, based on [2], adapted for use with a BESS. As a study case the Smart Storage Project was selected, using power flow measurement data from the project the charging path optimizer was tested for robustness and effectiveness. As can been seen from section 6, the charging path optimizer is capable of reducing peak-loading of the transformer up to 17.9% in real-life field setting. When load demand significantly varies from week to week, the peak-load reduction drops down to 13.7%, which is. More robust control (against varying load profiles) can be achieved by improving the prediction accuracy. However, adding more accuracy will become increasingly more complicated as more external information sources will be needed. Nonetheless, the algorithm was proven to be effective, and robust even with rather simple prediction techniques, only utilizing historical data.

## FUTURE WORK

As a part of future work, we will proceed to make this controller system ready for field testing with the SSU. Furthermore, the addition of more information sources will be considered in order to achieve better load-prediction quality.

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## BIOGRAPHIES

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