Day-Ahead Optimization Algorithm for Demand Side Management in Microgrids

Tiba Feizi[1], Lennart von der Heiden[1], Raisa Popova[1], Mauricio Rojas[2] and Jean-Marie Gerbaulet[1]
[1]*Deutsche Bahn Energie GmbH, Europaplatz 2, 10557, Berlin, Germany*
[2]*Schneider Electric GmbH, EUREF-Campus 12-13, 10829 , Berlin, Germany*

Keywords: Demand Side Management, Electric Vehicles, Microgrid, Smart Grid.

Abstract: Germany has the political vision of reducing carbon emissions and becoming environmentally sound. According to this vision, the number of electric vehicles (EVs), charging stations and renewable power generators being installed in low voltage grids would increase. The uncontrolled charging of a large number of EVs can generate additional load peaks and lead to the violation of utilization limits in distribution grids. However, the charging of EVs can be controlled, providing the opportunity to relieve the grid and reduce the peak load. This control strategy is called Demand Side Management (DSM). This paper presents a day-ahead optimization algorithm for DSM in a microgrid. The developed algorithm focuses on minimizing the load peaks of a microgrid. Two scenarios, with and without stationary battery storage, have been developed and tested with various historical load profiles of the Micro Smart Grid (MSG) on the European Energy Forum (EUREF) campus in Berlin. The optimization results have shown that using the algorithm offers the possibility to reduce microgrid load peaks.

1 INTRODUCTION

The German federal government promotes the selling of new electric vehicles with the help of an environmental bonus. This funding supports the rapid spread of electric vehicles in the market (Bafa, 2017). By 2025, 40 to 45 percent of the electricity consumed in Germany has to derive from renewable energy sources (BMWi, 2017).

The coupling of energy production from renewable sources with EVs helps to reduce CO_2 emissions, and making the transition to a larger share of renewable energy (Link, 2011). The increase of the simultaneity of EV charging processes in the future could lead to load peaks and utilization limit violations (Nobis, 2015).

Controlled EV charging is used to avoid additional load peaks and improve renewable energy integration into the power grid (Agricola, 2011). The function of charging management is to ensure that charging takes place at times with excessive generation from renewable sources, to improve the integration of fluctuating renewable energies (Link, 2011).

Both load management and energy saving are important elements of DSM. The approach DSM is defined as load control, with the goal of smoothing the load (Haasz, 2017).

By means of DSM, for example, by shifting load peaks during off-peak periods, negative grid perturbations could be significantly reduced (Friedle, 2018). There are different forms of DSM, as shown in Table 1. The first form of DSM, shifting peak consumption, has been used in the optimization algorithm which is presented in this paper. In this case, it is realized by load management of EVs. The second form, reduction of peak consumption, is used to minimize load peaks without shifting of the loads, and the third form would be critical in the grid due to increasing consumption. The fourth form has no effect on load smoothing (Agricola, 2011).

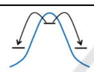
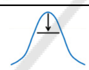
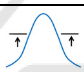
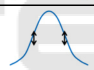
EVs, especially when used in car sharing, can be used for DSM because of their flexible load profile (Seddig, 2015). A number of studies have discussed the DSM of EVs in order to reduce the peak power. Reference (Shao, 2011) presents a load shaping tool to avoid the overloading of the transformer by using a sensor at the transformer for load monitoring. Paper (Pournaras, 2017) presents an optimization of EVs

Feizi, T., von der Heiden, L., Popova, R., Rojas, M. and Gerbaulet, J.
Day-Ahead Optimization Algorithm for Demand Side Management in Microgrids.
DOI: 10.5220/0007686600510057
In *Proceedings of the 8th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS 2019)*, pages 51-57
ISBN: 978-989-758-373-5

charging by using a software application controlling the battery charging in each EV to reduce the power peaks and energy costs. Jaiswahl (Jaiswahl, 2017) proposes an optimization algorithm to reduce both demand and energy cost by integrating the system in a smart metering. To implement the proposed algorithms, bi-directional communication infrastructure is required. The focus of this paper is on a day-ahead optimization algorithm using forecast data, which does not necessarily require bi-directional communication.

EVs can also be used to reduce CO_2 emissions, they must be charged with electric energy from renewable sources. Otherwise, the CO_2 emissions related to charging can be equal to or greater than those of vehicles with combustion engines (Bräuninger, 2017).

Table 1: Different forms of DSM (Agricola, 2011).

Shift of consumption to off-peak hours	
Reduction of consumption at peak load times	
Increase in consumption during off-peak hours	
Short-term change of the load curve	

The integration of EVs into microgrids using renewable energy systems is the prime objective of the research project Mobility2Grid (Karohs, 2018). This integration is practically tested in the laboratory on the EUREF Campus.

The requirements for practical implementation of DSM include forecasting and optimization of load profiles of the EVs. The presented optimization algorithm is based on the structure of a microgrid on the EUREF Campus in Berlin, called MSG, as shown in Figure 1.

Three PV systems with a total power of 82.5 kWp, and a stationary Li-ion battery storage with a capacity of 78 kWh, are connected to the MSG on the EUREF campus. The maximum transformer power in this MSG is 630 kVA. The transformer connects the low voltage MSG to the medium voltage grid. The car sharing station on the EUREF Campus has 33 charging stations, each with a maximum charging power of 22 kW AC and a DC quick charger with a power of 50 kW. In addition, there are also three inductive charging stations, two of which with a maximum power of 3.7 kW and one with a maximum power of 7.4 kW.

2 PROPOSED MODELS

The proposed DSM method, specifically of a load peak shaving on the EUREF MSG, is based on a day-ahead data optimization. Figure 2 shows the modules of the program used to implement the method of an optimized DSM. The optimization tool is also used to create day-ahead load profiles of EVs.

The aims of the controlled charging are minimization of grid load and reduction of the extent of grid expansion, which is taken into account by the day-ahead optimization algorithm. The minimization of the grid load of the MSG has been realized with a linear optimization algorithm.

The constraints of the optimization algorithm are defined by characteristics and limits of the charging process of EVs and the battery storage. This includes for example State of Charge (SoC) of batteries.

The used input data are the PV generation forecasts and the load profiles of EVs. The output data are the predicted load profiles of the following day for stationary battery storage, and EVs.

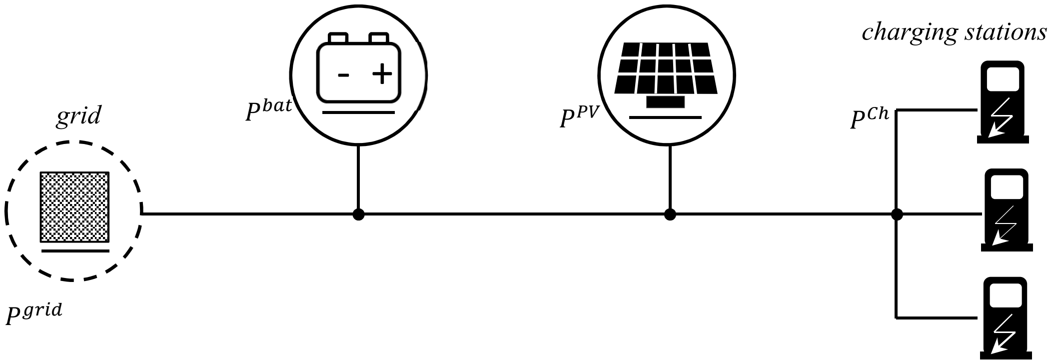


Figure 1: Structure of the MSG on the EUREF Campus.

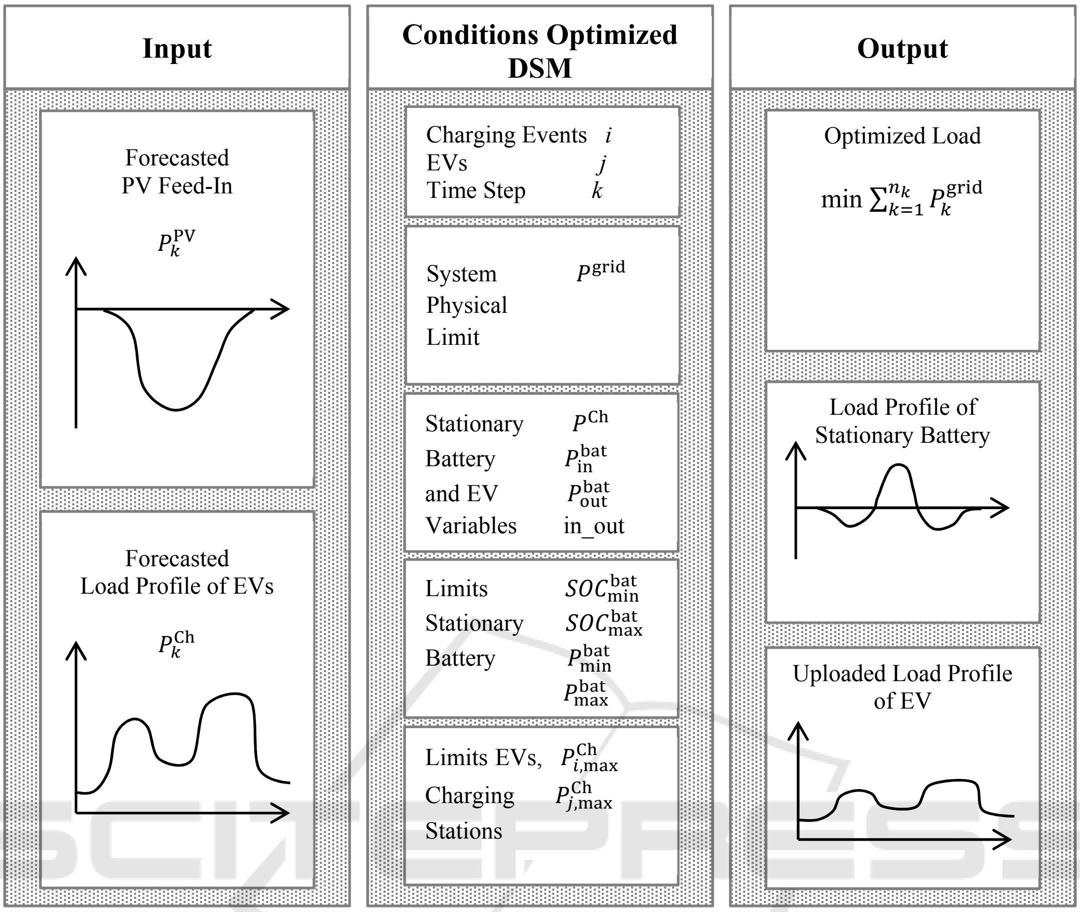


Figure 2: Modules of the program for implementing the suggested DSM method.

2.1 Mathematical Models

The objective function minimizes the power from the grid P_k^{grid}, on the condition that the EVs achieve the required SoC ($SoC_{\mathrm{max}}^{\mathrm{Ch}}$), cf. Formula 1. The linear optimization is conducted based on equations 1 and 2. Set H_j defines the number of electric vehicles and set $H_{\text{time step}}$ defines 15-minute time steps in the 24-hour period ($\Delta t = 0.25$ h). The penalty parameter ρ is multiplied by the difference between the desired and actual States of Charge of EV ($SoC_{j,\mathrm{max}}^{\mathrm{Ch}}$,$SoC_{j,k_{\mathrm{end}}}^{\mathrm{Ch}}$). Formula 2 is necessary to achieve the goal of peak load reduction despite the sum based objective function. For example, a charging power of 22 kW is demanded in the first hour and charging power of 0 kW in the second hour. The application of Formula 2 would result in an averaging over both hours, with the result of a charging power of 11 kW in the first and second hour. Table 2 summarizes the mathematical symbols of the paper.

Table 2: An overview of the mathematical symbols.

Symbol	Definition
P_k^{grid}	Power from the grid at the *k*th time step
$P_{\mathrm{max}}^{\mathrm{grid}}$	Maximum power of the transformer
P_k^{PV}	PV feed-in power at the *k*th time step
$P_{k,\mathrm{in}}^{\mathrm{bat}}$	Charging power of the stationary battery storage at the *k*th time step
$P_{k,\mathrm{out}}^{\mathrm{bat}}$	Discharging power of the stationary battery storage at the *k*th time step
$P_{i,\mathrm{max}}^{\mathrm{Ch}}$	Maximum charging power of the *i*th charging event
$P_{j,\mathrm{max}}^{\mathrm{Ch}}$	Maximum charging power of the *j*th EV
SoC_k^{bat}	SoC of the stationary battery storage at the *k*th time step
$SoC_{\mathrm{max}}^{\mathrm{bat}}$	Maximum SoC of the stationary battery storage
SoC_{min}^{bat}	Minimum SoC of the stationary battery storage

Table 2: An overview of the mathematical symbols (cont.).

$SoC_{k,j}^{\mathrm{Ch}}$	SoC of the *j*th EV at the *k*th time step
Cap_{j}^{Ch}	Battery capacity of the *j*th EV
Cap^{bat}	Capacity of the stationary battery storage
η_{j}^{Ch}	Charging efficiency of the *j*th EV
$\eta_{\mathrm{in}}^{\mathrm{bat}}$	Charging efficiency of the stationary battery storage
$\eta_{\mathrm{out}}^{\mathrm{bat}}$	Discharging efficiency of the stationary battery storage

$$\min\left(\sum_{k=1}^{n_{\mathrm{k}}} P_{k}^{\mathrm{grid}} + \sum_{j=1}^{n_{\mathrm{Ch}}} \rho \cdot \left(SoC_{j,\max}^{\mathrm{Ch}} - SoC_{j,k_{\mathrm{end}}}^{\mathrm{Ch}} \right)\right) \quad \forall k \in H_{\text{time step}},\ \forall j \in H_j \tag{1}$$

$$P_{k}^{\mathrm{grid}} \leq \left(\sum_{k=1}^{n_{\mathrm{k}}} P_{k}^{\mathrm{grid}}\right) / \left(\frac{24}{\Delta t}\right) \tag{2}$$

The power balance requires that electrical power fed into the grid ($\sum P_{\mathrm{in}}$) equals consumed electrical power ($\sum P_{\mathrm{out}}$) (Frohe, 2011). The MSGs power balance for the EUREF campus is represented by Formula 3. Set H_i defines the number of load events.

$$0 = \left(\sum_{j}\sum_{i} P_{i,j,\max}^{\mathrm{Ch}}\right) + P_{k,\mathrm{in}}^{\mathrm{bat}} - P_{k,\mathrm{out}}^{\mathrm{bat}} - P_{k}^{\mathrm{PV}} + P_{k,\mathrm{in}}^{\mathrm{grid}} - P_{k,\mathrm{out}}^{\mathrm{grid}} \quad \forall k \in H_{\text{time step}},\ \forall i \in H_i,\ \forall j \in H_j \tag{3}$$

The maximum power of the MSG $P_{\max}^{\mathrm{grid}}$ is expressed by Formula 4. This parameter is determined from the maximum capacity of the transformer.

$$0 \leq P_{k,\mathrm{in}}^{\mathrm{grid}} - P_{k,\mathrm{out}}^{\mathrm{grid}} \leq P_{\max}^{\mathrm{grid}} \quad \forall k \in H_{\text{time step}} \tag{4}$$

The stationary battery storage of the MSG is represented by the power $P_{k,\mathrm{in}}^{\mathrm{bat}}$ and $P_{k,\mathrm{out}}^{\mathrm{bat}}$, the efficiencies $\eta_{\mathrm{in}}^{\mathrm{bat}}$ and $\eta_{\mathrm{out}}^{\mathrm{bat}}$, the capacity Cap^{bat} and the SoC. The SoC of the stationary battery storage SoC_{k}^{bat} is calculated at time k with Formula 5.

$$SoC_{k}^{\mathrm{bat}} = SoC_{k-1}^{\mathrm{bat}} + \eta_{\mathrm{in}}^{\mathrm{bat}} \cdot P_{k,\mathrm{in}}^{\mathrm{bat}} \cdot \Delta t \cdot \frac{1}{Cap^{\mathrm{bat}}} - \eta_{\mathrm{out}}^{\mathrm{bat}} \cdot P_{k,\mathrm{out}}^{\mathrm{bat}} \cdot \Delta t \cdot \frac{1}{Cap^{\mathrm{bat}}} \quad \forall k \in H_{\text{time step}} \tag{5}$$

The SoC of the stationary battery SoC_{k}^{bat} must not drop below or increase above fixed limits, expressed in Formula 6.

$$SoC_{\min}^{\mathrm{bat}} \leq SoC_{k}^{\mathrm{bat}} \leq SoC_{\max}^{\mathrm{bat}} \quad \forall k \in H_{\text{time step}} \tag{6}$$

The variable in_out is defined to avoid the stationary battery storage being charged and discharged at the same time. This variable is used in Formulas 7 and 8 to limit the feed-in power and output power of the battery. These formulas are also used for the EVs at the MSG charging stations.

$$P_{k,\mathrm{out}}^{\mathrm{bat}} \leq P_{\max,\mathrm{out}}^{\mathrm{bat}} \cdot in\_out \quad in\_out \in [0,1],\ \forall k \in H_{\text{time step}} \tag{7}$$

$$P_{k,in}^{bat} \leq P_{\max,\mathrm{in}}^{\mathrm{bat}} \cdot (1 - in\_out) \quad in\_out \in [0,1],\ \forall k \in H_{\text{time step}} \tag{8}$$

The actual charging time is a result of the optimization of $P_{k,i,j}^{\mathrm{Ch}}$ for each time step k and each EV j for the individual load events i. If the EV is not connected to the charging station, $P_{k,i,j}^{\mathrm{Ch}}$ is limited to 0. If the EV is connected to the charging station and the time is within the charging time, $P_{k,i,j}^{\mathrm{Ch}}$ is limited by the maximum possible charging power, as seen in Formula 9.

$$P_{k,i,j}^{\mathrm{Ch}} = \min\left(P_{i,\max}^{\mathrm{Ch}}, P_{j,\max}^{\mathrm{Ch}}\right) \quad \forall k \in H_{\text{time step}} \tag{9}$$

To calculate the SoC of the EV $SoC_{k,j}^{\mathrm{Ch}}$, Formula 10 is used. It is analogous to Formula 5 for calculating the SoC of the stationary battery storage.

$$SoC_{k,j}^{\mathrm{Ch}} = SoC_{k-1,j}^{\mathrm{Ch}} + \sum_{j=1}^{n_j} P_{k,j}^{\mathrm{Ch}} \cdot \eta_{j}^{\mathrm{Ch}} \cdot \Delta t \cdot \frac{1}{Cap_{j}^{\mathrm{Ch}}} \quad \forall k \in H_{\text{time step}},\ \forall j \in H_j \tag{10}$$

The value of the SoC of the EV $SoC_{k,j}^{\mathrm{Ch}}$ is limited by Formula 11.

$$\mathrm{SoC}_{\min}^{\mathrm{Ch}} \leq SoC_{k,j}^{\mathrm{Ch}} \leq \mathrm{SoC}_{\max}^{\mathrm{Ch}} \quad \forall k \in H_{\text{time step}},\ \forall j \in H_j \tag{11}$$

The mathematical problem was transformed into an algorithm using Python programming language.

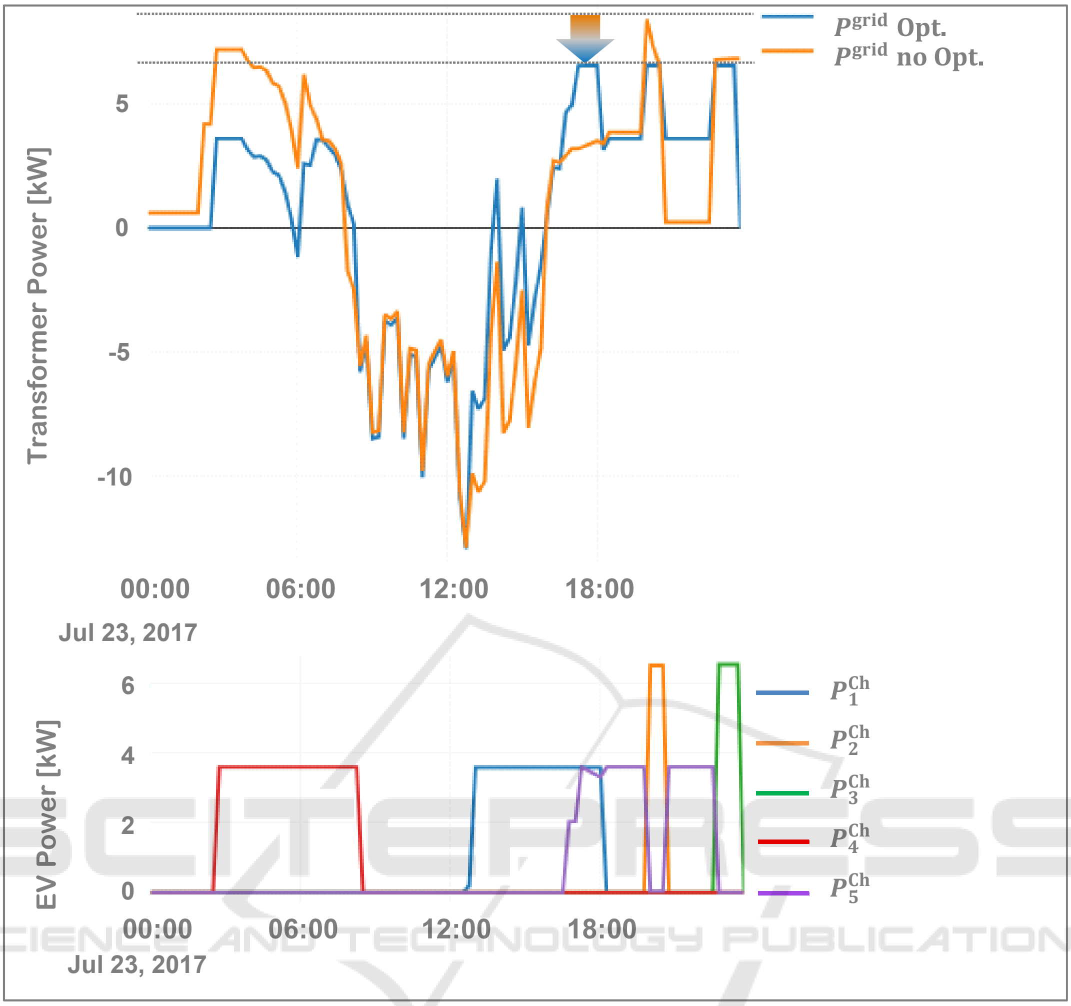


Figure 3: Scenario 1 – Power from the grid measured at the transformer with / without optimization (top) and charging cycles of the EVs (bottom).

The optimization models were implemented with the python software package Pyomo (Python Optimization Modeling Objects). The implementation is based on algebraic modelling languages (AMLs), which support the analysis of the previously constructed mathematical model (Hart, 2012). The open source mixed integer programming solver "CBC" (COIN-OR Branch and Cut) was used as the solver of the optimization algorithm.

2.2 Validation Scenario

The proposed algorithm is validated with two scenarios. In scenario 1, the charging cycle and charging power of the EVs are optimized on the basis of the MSG conditions. At the departure time, all EVs should be as fully charged as they would be without optimization. For scenario 2, the conditions of the first scenario are considered, and the stationary battery storage is added as a flexible load.

3 OPTIMIZATION RESULTS

The optimization algorithm was validated with historical data from the EUREF campus MSG. The results of the optimization algorithm are shown, for the 23rd of July 2017 in Figure 3.The upper section of the figure, shows the transformer load with and without optimization in scenario 1 (P^{grid} Opt., P^{grid} no Opt.). The lower section shows the charge cycles of the EVs. In the upper section, it can be observed that the maximum power of the day in question can be reduced from 8.8 kW to 6.5 kW. Further reduction of power is not possible, under the constraint that the EVs must obtain the same SoC they would have

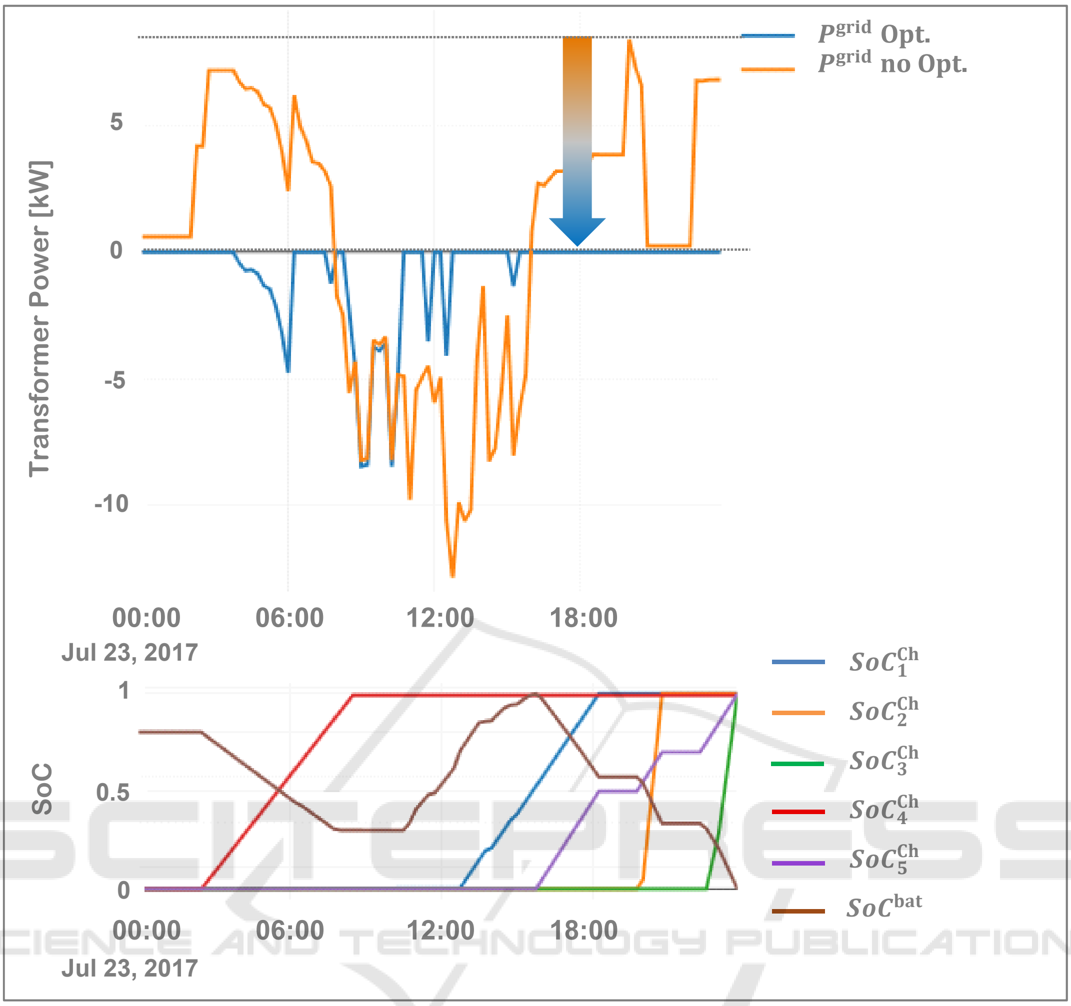


Figure 4: Scenario 2 - Power from the grid measured at the transformer with / without optimization (top) and SoC of the battery of the EVs and Stationary battery Storage (bottom).

without optimization. The EVs (orange and green curve) must be charged during parking time, with the maximum available power.

In scenario 2, with the flexibility of the stationary battery, the maximum grid load can be reduced to 0 kW (blue curve), see the upper part of Figure 4. In the same figure, the lower section shows the SoC of the EVs batteries and the stationary battery storage. The electric vehicles are charged completely within the given time, despite the load shift. It can be observed that the stationary battery storage SoC^{bat} (brown curve) is discharged during the morning and in the evening, and is charged at noon by the PV feed-in. The energy for the EVs comes either directly from the PV system (the blue curve) or from the stationary battery (the purple curve), as can be seen in the lower part of Figure 4.

4 CONCLUSIONS

In this paper, an optimization algorithm for DSM has been presented and its functionality was validated with the historic load profile of the MSG on the EUREF Campus. Two scenarios were outlined. The optimization results have shown that the use of the DSM operating strategy in the MSG allows to postpone the load to off-peak hours and to reduce load peaks. On the EUREF Campus, maximum load was reduced up to 30% in the first scenario by using the EVs as a flexible load. In the second scenario, the load was reduced up to 100% by adding the flexible stationary battery storage. Consequently, the presented method can help minimize the need for reinforcements of the grid.

This day-ahead optimization algorithm requires either forecast data or data provided by charging protocol ISO 15118 as input parameters. The protocol allows accessing the SoC and capacity of the EV battery. There is currently no EV on the market, which supports this standard protocol. When forecasting is used, the forecast errors are quite high (around 2.5 hours) (Renner, 2018). To reduce the forecast errors, more application data is needed. The Mobility2Grid project is working on that subject (Voß, 2018). The optimization algorithm can also be used for electric vehicle or bus fleets with known data, such as the timetables of EVs and load profiles. In that case, the problem of forecast errors or inaccessible data of the vehicles does not apply.

ACKNOWLEDGEMENTS

The work in this paper is part of the Mobility2Grid research project, which is funded by the German Ministry for Research and Education and supported by the Deutsche Bahn Energie GmbH.

REFERENCES

Agricola, A., 2011. Demand Side Management in Deutschland Potenziale und Märkte. Deutsche Energie Agentur.

Bafa, 2017. Bundesamt für Wirtschaft und Ausfuhrkontrolle, Förderung von elektrisch betriebenen Fahrzeugen.

BMWi, 2017. Bundesministerium für Wirtschaft und Energie, Die nächste Phase der Energiewende, Erneuerbare Energie-Gesetzt- EEG 2017.

Bräuninger, M., Schnaars, Ph., Teuber, M., 2017. Implications of Electromobility for the Electricity Market and CO2 Levels, Volume 97, Issue 10, pp 752–754.

Friedle, G., Walcher, F., Sträglich, J., Fritz, T., Manteufeufell, D., 2018. Blackout E-Mobilität setzt

Netzbetreiber unter Druck. Available at https://www.oliverwyman.de.

Frohe, H., Löcherer, K., Müller, H., Harriehausen, T., Schwarzarzenau, D., 2011. Moeller Grundlagen der Elektrotechnik, 22. Auflage, Page 59.

Haasz, T., 2017. Entwicklung von Methoden zur Abbildung von Demand Side Management in einem optimierenden Energiesystemmodell, University of Stuttgart.

Hart, W., Watson, J., Woodruff, D., 2012. Pyomo - Optimization Modelling in Python. Bd. 67. Springer Science Business Media.

Jaiswahl, S. Ballal, M., 2017. Optimal Load Management of Plug-in Electric Vehicles with Demand Side Management in Vehicle to Grid Application, IEEE Transportation Electrification Conference, India.

Karohs, K., Göhlich, D., Lauth, E., 2018. Research Campus Mobility2Grid, In 2nd E-Mobility Power System Integration Symposium.

Link, J., 2011. Elektromobilität und erneuerbare Energie: lokal optimierter Einsatz von netzgekoppelten Fahrzeugen, Technical University of Dortmund.

Nobis, Ph., Fischhaber, S., 2015. Belastung der Stromnetze durch Elektromobilität, Forschungsstelle für Energiewirtschaft e.V.

Pournaras, E., Jung, S., Zhang, H., Fang X., Sanders L., 2017. Socio-technical Smart Grid Optimization via Decentralized Charge Control of Electric Vehicles, Journal of Latex Class Files, Vol. 14, No. 8.

Renner, M., et al., 2018. Electric Vehicle Intraday Forecasting with Artificial Intelligence, In Mobility2Grid Lab2Reality Conference.

Seddig, K., Salah, F., Schnug, S., Frank, M., 2015 Dezentrales Lastmanagement von E-Flotten unter Berücksichtigung der Erzeugungs- und Netzverfügbarkeit, In ETG- Fachbericht 145, Von Smart Grid zu Smart Markets, Kassel.

Shao, S., Pipattanasomporn M., Rahman S., 2011. Demand Response as a Load Shaping Tool in an Intelligent Grid with Electric Vehicles, IEEE Transactions on Smart Grid, Vol. 2 No. 4.

Voß, M., Wilhelm, M., Albayrak, S., 2018. Application Independent Flexibility Assessment and Forecasting for Controlled EV Charging, In 7th International Conference on Smart Cities and Green ICT System (SMARTGREENS).