Impact of Electric Vehicle Charging Infrastructure Expansion on Microgrid Economics: A Case Study

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Abstract—The operation of public and semi-public charging infrastructure is often not profitable yet. However, the integration of charging infrastructure in microgrids enables the introduction of innovative business models, e.g. by local renewable energy generation and storage units. Another driver to improve profitability is to adapt the charging infrastructure expansion according to its usage characteristics. This study presents a method to optimize the charging infrastructure expansion. Therefore, a mixed integer linear program with the aim to minimize costs is formulated and applied on real-world data. Via the optimization, different scenarios are developed and the microgrid integration is simulated in an operation optimization algorithm. Different business models such as PV and battery storage integration are computed and the economics of the business models in the different scenarios are evaluated. It can be concluded that microgrid integration can be a significant driver of charging infrastructure operation profitability. Integrating PV generation shortens the payback period in all scenarios. Also, PV generation and battery storage combined improve profitability, but not to the same extent than without storage unit. Furthermore, the optimization of the charging infrastructure expansion leads to a significant improvement of profitability. Combining both the microgrid integration, as well as the expansion optimization, the payback period can be decreased by up until 67%.

Index Terms—microgrid, electric vehicles, charging infrastructure, optimization, business models, infrastructure planning, data-driven decision support

I. INTRODUCTION

Despite the growing share of electric vehicles (EVs) worldwide [1], and therefore a growing charging demand, the operation of public and semi-public charging infrastructure (CI) is often not profitable yet [3], not even the operation of fast CI [4], [5]. However, the operation of CI within microgrids enables the introduction of innovative business models, thus creating a potential to improve profitability [6], [7].

Through its integration in microgrids, CI can be utilized for grid stress relief caused by RE generation, as well as the optimization of self-supply for EV charging [8]; smart microgrid operation algorithms aim at both optimization goals [9]. Another leverage to improve CI profitability is the optimization of the CI expansion [10]. In terms of CI planning, it is important to consider the user behavior [11], [12].

This work presents an approach to optimize the CI expansion in order to increase profitability. The approach is evaluated using real-world data. A linear optimization problem that considers CI planning is formulated. On this basis, different expansion scenarios are derived. In order to evaluate their profitability, the operation according to different business models within a microgrid is simulated by means of an optimization based algorithm. Concluding, economic performance indicators of the different business models and scenarios are calculated. In contrast to [10], the proposed CI optimization model focuses not only on the number of installed CPs but also their respective charging power. The proposed method is applied on data from a micro grid located at EUREF campus area in Berlin, Germany [13].

The paper is structured as follows. First, the three steps of the methodology is presented in Sec. II. Second, the case study characteristics and data set is examined in Sec. III. Third, in Sec. IV, the results are presented, step-by-step. Finally, the results are being discussed and an outlook is issued in Sec. V.

II. METHODOLOGY

A. Charging Infrastructure Planning

The aim of the optimization-based planning is to reduce the CI CAPEX. This is done by reducing the number of CSs as well as the power class of the individual CSs.

Assuming that all EVs shall be served, the minimum number of necessary CPs can be identified by simply determining the highest simultaneity occurring. In order to identify the

The term charging infrastructure describes an entity of several charging stations (CS); one CS again can comprise multiple charging points (CP) [2].

978-1-7281-4701-7/20/$31.00 ©2020 IEEE
minimum necessary power class of the charging stations, a mixed integer linear program is formulated. The data used in the optimization problem is provided by CS bookings $i$. These include start time stamps $t_{\text{start}},i$, end time stamps $t_{\text{end}},i$ as well energy demand $E_i$. The time difference between $t_{\text{start}},i$ and $t_{\text{end}},i$ results in the booking duration $\tau_i$.

The energy demand is served by the CPs $j$ with their maximum charging power $c_j$. If a booking $i$ is processed on CP $j$ at time point $t$ is indicated by the binary variables $x_{i,j,t}$. The allocation of bookings to CPs is represented by the integer variables $x_{i,j}$ and binary variables $k_{i,j}$. The variables $x_{i,j,t}$ and $c_j$ are decision variables in the optimization problem.

As part of the data preprocessing, the temporally resolved booking data is resampled in order to reduce the number of variables in the optimization. Therefore, time delta $\Delta t$ is defined and $t_{\text{start}},i$ and $t_{\text{end}},i$ are accordingly manipulated. The latter is done in a conservative manner, the duration of bookings is always equal or shorter than before resampling.

It is assumed that time interval of CP usage is equal to the time interval of the booking. That means that EVs will not change the parking place when fully charged and that EVs block a CP until the booking is over.

$$\min \sum_j c_j \quad \text{(1a)}$$

subject to:

$$\sum_t x_{i,j,t} \leq 1 \quad \forall \, j, t, \quad \text{(1b)}$$

$$x_{i,j,t} = 1 \quad \forall \, t \in T_i, \, i, \quad \text{(1c)}$$

$$\sum_t x_{i,j,t} = 0 \quad \forall \, t \not\in T_i, \, i, \quad \text{(1d)}$$

$$\sum_t k_{i,j} x_{i,j,t} = x_{i,j} \quad \forall \, j, i, \quad \text{(1e)}$$

$$\sum_j k_{i,j} = 1 \quad \forall \, i, \quad \text{(1f)}$$

$$c_j \geq \frac{E_i}{\tau_i} x_{i,j,t} \quad \forall \, t \in T_i, \, i, \, j \quad \text{(1g)}$$

In total, four constraints are formulated to describe the logical connections between the bookings and CPs over time. First, in every time step of the optimizations time horizon maximally one booking can be processed per CP, which is described by Eq. 1b. Second, every booking is processed by one CP during the time of the booking (Eq. 1c), during the rest of the time horizon the booking is not served by any CP (Eq. 1d). Third, the Eqs. 1e and 1f constitute a so called SOS1-constraint, which says that a CP is occupied during the whole time interval of a booking. Fourth, the maximum charging power of a CP must be greater or equal to the minimum charging power needed by every booking served by the specific CP. In order to minimize CAPEX and thereby the maximum charging power of the CPs, Eq. 1a serves as objective function.

As computing resources are limited and long time horizons cannot be solved in a reasonable time, the problem is decomposed temporally. Therefore, the program is solved for single weeks, incorporating bookings that take place in more than one week in all weeks concerned. Subsequently, the results are recomposed by sorting the resulting maximum charging powers of the CPs according to their magnitude, which is done for every week. Concluding, the maximum charging power of every CP is calculated by taking the temporal maximum per CP as the value for $c_j$. According to the optimization results, the maximum charging power of the allocated CP is registered for every booking which serves as an input for the optimization algorithm of the microgrid operation.


B. Microgrid Integration

When operated in microgrids with local generation, CI can be supplied by local energy sources. This strategy aims at a higher independence from the grid, which leads to a higher supply security, as well as a lower electricity price. Moreover, integration of batteries or other type of storage can increase the amount of energy used locally. In the case of an EV, the control of its charging times supports this economical focus of microgrid operation. EVs offer an economically beneficial flexibility when charging times are lower than parking times.

Here, a demand side management algorithm which is described in detail in [9] is applied to replicate an economical driven operation of microgrids with local generation, storage and CI. Its operating principle is outlined in Fig. 1. The algorithm objective function Eq. 2 minimizes the cost of energy supply consisting of average electricity price for grid supply $P_{\text{grid}}$, grid supply power $P_{\text{grid}}$, average PV feed-in revenue $e_{\text{pv}}$, grid feed-in power $P_{\text{grid}}$, power price per day for the annual maximum grid load $e_{\text{app}}$ and maximum grid supply power $P_{\text{grid}}$.

$$\min \sum_{k=1}^{n_k} \left( e_{\text{grid}} \cdot P_{\text{grid}} + P_{\text{gen}} + e_{\text{app}} \cdot P_{\text{max}} \right) \quad \text{(2)}$$

When no local generation is present the algorithms objective function is changed to grid peak supply minimization:

$$P_{\text{grid}} \geq P_{\text{grid}} \forall \, k \quad \text{(3)}$$

The corresponding constraints described in [9] consider the energy demand, parking time and CP maximum charging power. Therefore, this algorithm can be used to evaluate the results of the charging infrastructure planning algorithm from the energy supply perspective. In the following the algorithm will be applied for different numbers of CPs; see Sec. IV-B.

C. Microgrid Economics

The economics of CI can be divided in capital expenditure CAPEX [\( \text{\euro} \)] and in operational expenditure OPEX [\( \text{\euro}/\text{a} \)].

CAPEX are highly dependent on costs for underground work and the charging site’s grid connection, which is also
called pre-installation, and less dependent on the charging station itself.

OPEX are cost drivers for the charging point operator (CPO). Especially, variable usage-dependent operational costs \( OPEX_{\text{var}} \) are of significance, which strongly depend on consumed energy of the particular charging events. For a fixed period of one year, \( OPEX_{\text{var}} \) is given by Eq. 4 with the consumed charging energy \( E^\text{ch} \) [kWh/a] and maximum power price \( e_{\text{app}} \) [€/kWh]:

\[
OPEX_{\text{var}} = E^\text{ch} \cdot e_{\text{ave}} + P^\text{grid}_{\text{max}} \cdot e_{\text{app}}. 
\]

Parameter \( e_{\text{ave}} \) and \( P^\text{grid}_{\text{max}} \) can be reduced by application of intelligent charging strategies or by direct usage of local power generation. Hence, \( e_{\text{ave}} \) can be modified by Eq. 5 by increasing the ratio of locally generated energy consumption with lower \( LCOE \) price:

\[
e_{\text{ave}} = a \cdot LCOE + (1 - a) \cdot e, 
\]

where the local autarky rate \( a \) is defined by the ratio of charging supplied by the local PV panel \( \sum_k (E^\text{PV,ch}_k + E^\text{bat,ch}_k) \) to total consumption by charging of all EVs \( \sum_k \sum_{\text{EV}} E^\text{ch}_k \) in Eq. 6:

\[
a = \frac{\sum_k (E^\text{PV,ch}_k + E^\text{bat,ch}_k)}{\sum_k \sum_{\text{EV}} E^\text{ch}_k}. 
\]

For the CPO, the payback period \( t_{\text{pp}} \) is of economic interest as it characterizes the profitability of the CI investment. \( t_{\text{pp}} \) is specified by the ratio in Eq. 7:

\[
t_{\text{pp}} = \frac{CAPEX}{CF}, 
\]

where the annual net cash flow per year \( CF \) [€/a] is described by Eq. 8:

\[
CF = REV - OPEX - TAX, 
\]

the sum of the achieved revenue \( REV \) net of operational expenditure \( OPEX \) and taxes \( TAX \) including value added tax (VAT) as well as taxes on profits. \( REV \) is generated by the provision of electricity for charging of EVs by an electricity markup resulting in an user fee \( e_{\text{uf}} \) [€/kWh] and therefore is given by Eq. 9:

\[
REV = E^\text{ch} \cdot e_{\text{uf}}. 
\]

III. CASE STUDY MICRO SMART GRID OF EUREF CAMPUS

The analysis executed in this paper is performed on EV fleets and CI data from the microgrid of EUREF Campus. The EUREF campus is a city quarter on the area of about 5.5 ha within the district Schöneberg in Berlin. The area is home to companies in the fields mobility, energy, and sustainability, further its offices and function areas like auditoriums and showrooms. A microgrid is located within the area comprising PV generation, combined heat and power plant, battery storage, and CI as well as a supervisory control and data acquisition system (SCADA) [13]. On the area of EUREF campus, the CI is divided in the two charging sites zeeMobase and Messehalle. These are located at a distance of approximately 75 metres from each other. The fleets using the CI contain mostly company and car sharing vehicles. The CI consisting of 16 charging stations with each 2 x 22 kW CPs is installed on the charging sites. A scheme of the network structure investigated in this study including PV, stationary battery, and CI as consumers is depicted in Fig. 2. The business models (BMs) specified in Tab. 1 are considered in the operation evaluation section to display different microgrid configurations.

The PV generation profile \( p^{PV} \) is derived from real-world measurements in 15 minute resolution. Battery power \( p^{bat} \) and CI power \( p^{ch} \) is calculated by the operation algorithm, see Sec. II-B.

The dataset evaluated in this study consists of 2,993 bookings for the whole year of 2018. Every booking comprises the following quantities: booking ID, start of booking, end of
booking, energy charged, charging duration, charging station ID and charging socket ID.

In a first step, bookings were eliminated, where no charging has taken place, either when no energy was charged or the charging duration had the value zero. This filtering results in 2,162 valid bookings, which have a median booking duration of 7 hours 24 minutes, whilst the mean booking duration is 33 hours 36 minutes. The whole distribution is depicted in Fig. 3. It shows that approximately 13 % of the booking last less than one hour, one third of the booking less than 3 hours 22 minutes. Slightly more than 30 % of the booking last longer than 24 hours.

The time related capacity factor of the 16 CSs is about 26 %, while the energy related capacity factor is approximately 0.4 %.

IV. RESULTS CASE STUDY

A. Charging Infrastructure Planning

As stated in Sec. III, the current CI expansion state are 16 CSs with 2 CPs and 22 kW charging power each. The company fleets as well as the car sharing service on the campus are completely electrified and it is uncertain how the fleet sizes will develop. Therefore, it is assumed that the CI usage in the following years will remain consistent with the usage in 2018. The status quo of the CI is defined as reference scenario S1. In Fig. 4 the number of parallel booking is displayed. It shows that at no point in time more than 17 CPs are in operation. Consequently, under the premise that all EVs needs to be served, the minimum number of CPs is 17. As it is assumed that the same type of CSs with 2 CPs each are eligible to be installed at the site, the number of CSs in Scenario S2 is reduced to 9, which results in 18 CPs at 22 kW charging power. In order to further decrease CAPEX, the optimization algorithm from Sec. II-A is applied. The resulting CP power classes compose Scenario S3 and are listed in Tab. 2, alongside with Scenarios S1 and S2.

Tab. 2: Resulting CI Scenarios: Number of CPs

<table>
<thead>
<tr>
<th>CP Power</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.7 kW</td>
<td>32</td>
<td>18</td>
<td>18</td>
</tr>
<tr>
<td>7.4 kW</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>11 kW</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>22 kW</td>
<td>0</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Total</td>
<td>32</td>
<td>18</td>
<td>18</td>
</tr>
</tbody>
</table>

By optimizing the CI expansion, the capacity factors can be improved (cf. Tab. 3). A simple reduction of the number of CSs results in an increase of the time related utilized capacity by 78 % from 26 % (S1) to approximately 46 % (S2 and S3).
In terms of energy, the capacity factor increases from 0.4 % (S1) to 1.73 % (S3), which denotes an improvement by 333 %.

<table>
<thead>
<tr>
<th>Capacity factor</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time related</td>
<td>26 %</td>
<td>46.3 %</td>
<td>46.3 %</td>
</tr>
<tr>
<td>Energy related</td>
<td>0.4 %</td>
<td>0.7 %</td>
<td>1.73 %</td>
</tr>
</tbody>
</table>

B. Microgrid Operation

Results of the impact of CP expansion on microgrid operation are summarized in Tab. 4. In S1, BM2 and BM3 microgrid configurations lead to autarky rates of 72.9 % and 86.5 %, respectively. These high rates can be explained by the high PV generation. Approximately 73 % of the energy generated locally is supplied to the grid and not consumed locally. The flexibility added by PV generation and storage is impacting the maximum charging power $P_{\text{ch}}^{\text{max}}$. In BM1 case $P_{\text{ch}}^{\text{max}} = 55$ kW, in BM3 case $P_{\text{ch}}^{\text{max}}$ is higher and has a value of 81.9 kW. The value of grid supply maximum power $P_{\text{grid}}^{\text{max}}$ is decreasing by adding the flexibility of PV generation and battery. The results show, that a system with higher flexibility given by local generation and storage, such as in the case BM3, impact the operation KPI’s positively.

In S3, the load flexibility of the charging procedures was reduced by charging power limitation and the resulting longer charging times. The algorithm is using the flexibility of the optimization problem formulation, although the maximum grid supply values $P_{\text{grid}}^{\text{max}}$ are going up, also due to the lower load flexibility. At the same time, the energy related capacity factor is increased by the expansion optimization. However, the energy charged in different scenarios varies slightly (less than 0.4 %). On the one hand, the operation optimization algorithm works with a penalty that serves as an incentive to fully charge the EVs. One the other hand, the costs for maximum demand as part of the objective function are minimized. Therefore, the little differences in energy charged between the different scenarios effect an economy of high maximum demand costs.

C. Microgrid Economics

The results of the economic assessment are shown in Tab. 5. By optimizing the CI expansion, CAPEX is reduced by 10 % (S2) and 24 % (S3), respectively. CAPEX reduction is caused by lower costs for the CI itself. The construction work and pre-installation part of the CAPEX has similar costs despite the charging site expansion downsizing.

LCOE does not differ in the scenarios, but between the business models. The lowest LCOE is reached at €0.13/kWh in S2 where there is PV generation but no stationary battery storage. $e_{\text{ave}}$ varies only between the business models, but not between the scenarios. This is due to the fact that $e_{\text{ave}}$ depends only on electricity supply and not on the demand side. However, microgrid integration decreases $e_{\text{ave}}$ from €0.30/kWh to €0.16/kWh in case of BM2. By also integrating battery storage (S3), $e_{\text{ave}}$ can be reduced to at least €0.20/kWh. OPEX vary only very little between the scenarios. However, by installing PV generation and battery storage, OPEX can be reduced by 36 % (S2) and 20 % (S3), respectively.

Optimizing the CI expansion, $t_{\text{pp}}$ is shortened by up to 7 (BM1), 3.4 (BM2) 4.5 (BM3) years, respectively (S1 vs. S3). A user fee price of $e_{\text{uf}} = €0.45/kWh is applied. By reducing the number of CSs installed and their charging power (S3) and installing PV generation (BM2), $t_{\text{pp}}$ of less than 10 years can

<table>
<thead>
<tr>
<th>S1 and S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>BM1</td>
<td>BM2</td>
</tr>
<tr>
<td>BM1</td>
<td>BM2</td>
</tr>
<tr>
<td>BM1</td>
<td>BM2</td>
</tr>
<tr>
<td>BM1</td>
<td>BM2</td>
</tr>
</tbody>
</table>

Tab. 4: CI operation: resulting key performance indicators (S1 and S2 identical)
be realised (8 years and 10.5 months). All other combinations need longer than 10 years to reach the break-even point.

V. CONCLUSION

The investigation shows that in the case study of EUREF campus, the CI expansion can be considerably reduced. On the one hand, the number of CSs can be diminished by 44%. On the other hand, it is not necessary that all CPs are able to provide high charging powers.

Installing PV generation increases the autarky significantly (approximately 73%), the installation of battery storage even on slightly more than 86%. The current PV dimension also leads to a high amount of excess energy resulting in more annual PV generation than EV charging demand.

The economic assessment shows that the integration of CI in microgrids including PV generation lowers the payback period in all scenarios by more than 55%. Additionally, if battery storage is also part of the microgrid, the payback period can be decreased by at least approximately 40%.

Through the optimization of CI expansion, CI related CAPEX is economized. By simply reducing the number of CSs (S2) payback periods are shortened by approximately 11% over all business models. By also minimizing the CP charging powers, payback periods even decrease by 25 to 28%.

Concluding, CI expansion optimization is a key to make EV charging more profitable. At the same time, as CI installation and operation is only profitable on the long term, future developments need to be considered, i.e., charging behavior or even EV use behavior could change. This could for example lead to a higher of energy demand or shorter recharging times. Also, charging technologies could change. E.g. Vehicle2Grid (V2G) technologies could arise, so that flexibility on the demand side can be monetized. In that case, higher charging power of the CSs can be necessary to increase flexibility. Furthermore, the introduction of autonomous driving and automated charging enables new opportunities. The duration of the charging processes, and therefore the time a CS is blocked, will not anymore depend on the parking time, but on the EVs energy demand and the CSs power output. However, the mentioned developments are still uncertain. This study presents options and methods to increase microgrid and CI profitability under today’s circumstances. The presented methods serve as a data-driven decision support system for CPOs.

Acknowledgement

This work was supported in part by the Federal Ministry of Education and Research of the Federal Republic of Germany (BMBF) through Research Campus Mobility2Grid - Sustainable Development of Energy and Mobility by Coupling Intelligent Grids and Electromobility (MOBILITY2GRID) funding.

References


Tab. 5: Characteristic values economic evaluation

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BM1</td>
<td>BM2</td>
<td>BM3</td>
</tr>
<tr>
<td>CAPEX_C [€]</td>
<td>50000</td>
<td></td>
<td></td>
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<tr>
<td>LCOE [€/kWh]</td>
<td>0.30</td>
<td>0.13</td>
<td>0.20</td>
</tr>
<tr>
<td>ε_a [€/kWh]</td>
<td>0.30</td>
<td>0.16</td>
<td>0.21</td>
</tr>
<tr>
<td>OPEX_var [€/a]</td>
<td>6670.19</td>
<td>4259.82</td>
<td>5340.57</td>
</tr>
<tr>
<td>t_pp [a]</td>
<td>27.7</td>
<td>12.3</td>
<td>16.7</td>
</tr>
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</table>