Real-World Application of Sustainable Mobility in Urban Microgrids

Mariem Khemir ⓘ, Mauricio Rojas, Raisa Popova, Tiba Feizi ⓘ, Jan F. Heinekamp ⓘ,
and Kai Strunz ⓘ, *Senior Member, IEEE*

Abstract—**The impact of microgrid applications expands with the increasing share of renewable energy resources in the energy supply and the progressing electrification of the transport sector. The additional energy demand of electric vehicles (EVs) may cause increased peak loads, leading to growing burdens on the power system. In this regard, microgrids allow to cover the energy demand of EVs utilizing local renewable energy resources and a battery storage system, thereby lowering the utilization of the power system. This article discusses a self-consumption operational strategy for a real-world microgrid at the EUREF-Campus in Berlin, Germany. A rule-based control algorithm for the sustainable energy supply of EV charging stations is implemented and validated. Measurements are recorded with high resolution over three years from 2017 to 2019. The performance of the microgrid operation is assessed with regards to three distinct key indicators: Self-consumption, autarky, and emission rate. The influence of selected operating parameters under real-world and ideal operating conditions are investigated. The results indicate that self-consumption and autarky rates are sensitive to the rated power capacity of a battery storage system rather than to its rated energy capacity. Moreover, the reduction of emissions through battery deployment for EV charging amounts up to 37 % under ideal operating conditions. This underlines the potential of the microgrid concept for the sustainable application of EVs in urban areas.**

Index Terms—**Electric vehicles, microgrid, real-world application, renewable energy, self-consumption.**

I. INTRODUCTION

IN THE last decade, taking action against climate change and environmental pollution has turned into one of the major

Raisa Popova and Tiba Feizi are with the DB Energie GmbH at DB Energie GmbH, 10557 Berlin, Germany (e-mail: raisa.popova@deutschebahn.com; tiba.feizi@rwth-aachen.de).

Mariem Khemir and Mauricio Rojas are with this paper as independent researchers, (e-mail: khemir.ma@gmail.com; cmrojas@yahoo.com).

Jan F. Heinekamp and Kai Strunz are with the Chair of Sustainable Electric Networks and Sources of Energy, School of Electrical Engineering and Computer Science, Technische Universität Berlin, 10623 Berlin, Germany (e-mail: j.heinekamp@tu-berlin.de; kai.strunz@tu-berlin.de).

challenges for the sustainable development of industries. As a consequence, the efficient use of decentralized and renewable energy resources (DERs) and low-carbon transportation became a prevalent research topic. Besides utility scale integration, DERs can be established in industrial and urban areas to form a local microgrid. This rises the potential for increasing the power quality and decreasing the costs of grid expansion [2]. Especially energy storage technologies can provide additional technical and economic benefits to microgrid and system operators. For instance, battery storage systems (BSSs) are utilized as a buffer for photovoltaic power plants (PVs), compensating the fluctuating energy generation and making renewable energy available on demand [3].

When integrating electric vehicles (EVs) in microgrids as a sustainable mobility option, suitable operational strategies and control algorithms are necessary to match the volatile generation of renewable energy resources with the additional and user-dependent energy demand [4].

In literature, various approaches for EV integration in microgrid operations are presented, of which examples are given in [5]–[8]. However, most approaches are investigated in simulative studies, while real-world applications in microgrids are rarely discussed. In that regard, the authors in [9] analyze proactive and reactive operational strategies for microgrids based on a real-world implementation in California, USA. The microgrid incorporates PVs, BSSs, and local loads, whereby the evaluations are based on weekly measurements. The operation of microgrids requires a sophisticated interaction of the involved actors. Such are represented by the microgrid operator, the system operator, and consumers among others. Each actor holds their own interests and responsibilities. Hence, in [10] a comprehensive analysis on microgrid operation with regards to this interaction is carried out. Distinct use cases are modeled based on real-world datasets of a smart grid with various DERs including EVs in Vaasa, Finland. Moreover, the authors in [11] evaluate the performance of a real-world microgrid in Agra, India, with regards to self-consumption incorporating a PV, BSS, and a building load over one year.

It appears that within the discussed literature the microgrid operation is mainly evaluated regarding to economic efficiency or stability of operation. This further applies to the impact of appropriate microgrid setup. Several studies exist on optimal sizing of microgrid assets, especially of BSSes, for instance in [12]–[14]. Thereby, the study in [14] stands out by analyzing pareto fronts regarding energy autonomy, power autonomy,

capital cost, and payback period over sizing parameters of PV and BSS. However, little attention is given to the real-world operating conditions that contribute to a sustainable operation.

The microgrid investigated within this work is located at the EUREF-Campus[1] in Berlin, Germany. The microgrid consists of PVs and a combined heat and power plant (CHP) for local energy generation, a lithium-ion BSS, and private-public EV charging stations as loads. In previous work, a day-ahead optimization demand side management algorithm for EV charging was developed and analyzed in numerical simulations [15]. The results are validated with real-world datasets of the microgrid and yield an optimized load curve, increasing the local self-consumption. Economic evaluations of charging infrastructure operation and expansion in microgrids are carried out in [16] and [17], respectively.

This article is a revised and extended version of the conference publication in [1]. Compared to the previous work and the existing research, both papers focus on assessing the operating performance of an urban microgrid with integrated PVs, BSSs, and EVs. A control algorithm is implemented within a local framework that follows a self-consumption operational strategy. Measurements from over three years are evaluated with regards to distinct key performance indicators (KPIs), namely, self-consumption and autarky rate, outlining the main influences on microgrid operation and possible challenges occurring in real-world applications. In extension to the previous conference version, the literature review is thoroughly updated. The mathematical formulation and implementation scheme of the proposed control algorithm are presented explicitly. The elaborations on the operational framework setup are extended in terms of the communication architecture. Further, the occupancy of charging stations within the microgrid, representing the user-dependent charging behavior, is depicted in detail. The performance of microgrid operation is evaluated considering an additional KPI, the savings of CO_2 emissions, thereby assessing sustainable mobility in urban microgrids. The gained insights are of great importance for increasing the efficiency of microgrid operation as well as for the composition and sizing of integrated assets. The main contributions of this article are threefold as follows.

1) Real-world implementation and validation of a control algorithm following a self-consumption operational strategy.
2) Analyzing long-term operational data and operating conditions of a real-world microgrid with EV charging stations over three years.
3) Assessing the impact of rated power and energy capacities of BSSs on sustainable energy supply of EVs.

The article is structured as follows. The fundamental notions on operational strategies for microgrids considering the current legal conditions in Germany are outlined in Section II. The KPI for evaluating the performance of microgrid operation are defined and the mathematical model of the control algorithm is formulated. In Section III, the operational framework including the communication architecture for the real-world implementation of the control algorithm is described. The performance assessment under real-world and ideal operating conditions is presented in Section IV with regards to the defined KPIs. Finally, the key findings on real-world application of microgrids are summarized in Section V.

II. OPERATIONAL STRATEGIES FOR MICROGRIDS

This section provides information on the regulatory framework in Germany and defines the KPIs for assessing the performance of microgrid operation. Furthermore, the mathematical model of the control algorithm is formulated.

A. Legal Conditions and Regulatory Framework

Considering the current legal conditions in Germany [18], [19], two operational strategies can be realized profitably for microgrids: Load management and self-consumption. These operational strategies provide direct financial benefits to the microgrid operator without the necessity of extended organizational measures, e.g., renouncing the remuneration for renewable energy generation or gaining permission for the application of nonstandardized measurement concepts. Load management operational strategies include load leveling for grid relief, counteracting the necessity of grid expansions. Self-consumption indicates a smart charging and scheduling strategy for BSSs and EVs, deployed to increase autarky or self-consumption rates, thereby able to reduce energy costs by larger independence from the upstream grid [20]. The cost advantage of local generation is given as several levies, taxes, and grid fees are either reduced or not raised. In Germany, these charges make up to approximately 77 % of the total electricity price, while the electricity procurement amounts to the remaining 23 %. These numbers are based on the continuously updated analysis of electricity prices from the German Association of Energy and Water Industries.[2] However, due to the volatility of renewable energy generation, a connection of the microgrid to the upstream grid is required to ensure the local energy supply at any time. When drawing power from the upstream grid, the levies and taxes are raised proportionally to the annual energy demand. The grid fees f^{grid}, as defined in (1), can be reduced in a targeted manner by applying a distinct operational strategy

$$f^{\text{grid}} = E_{\text{d,a}}^{\text{grid}} \cdot f_{\text{E}}^{\text{grid}} + P_{\max}^{\text{PCC}} \cdot f_{\text{P}}^{\text{grid}}. \qquad (1)$$

This fee is calculated based on the annual energy demand $E_{\text{d,a}}^{\text{grid}}$ at the point of common coupling (PCC) times the grid energy fee $f_{\text{E}}^{\text{grid}}$, as well as the recorded maximum power demand $P_{\max}^{\text{PCC}}$ times the grid power fee $f_{\text{P}}^{\text{grid}}$. Load management operational strategies aim at the reduction of $P_{\max}^{\text{PCC}}$ to meet power capacity requirements or, in the phase of grid planning, to reduce investment costs related to peak power. Self-consumption operational strategies aim at maximizing the utilization of locally generated energy, and thus, reducing the energy export to the upstream grid. This yields a simultaneous reduction of $E_{\text{d,a}}^{\text{grid}}$ and corresponding levies and taxes. Within the investigated microgrid the accruing load refers to the user-dependent energy demand of EVs. The microgrid operator is unable to control the
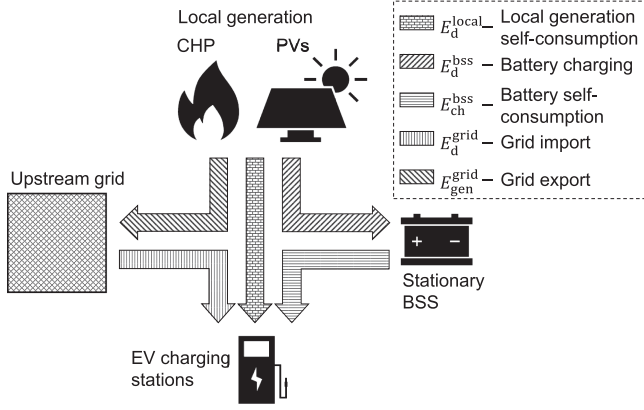
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[1][Online]. Available:https://euref.de/en/welcome/.

[2][Online]. Available:https://www.bdew.de/

Fig. 1.   Energy flows between microgrid assets and the upstream grid.

TABLE I
FLEXIBILITIES AND RESTRICTIONS OF MICROGRID ASSETS

asset	flexibility	technical restrictions
CHP	power increase and decrease	operating region, thermal energy demand
PV	power decrease	volatile generation
BSS	power increase and decrease	state of charge, rated capacity
EV	power increase and decrease	state of charge, duration of parking, mobility requirements, rated capacity

energy demand and corresponding load as the user's mobility requirements are prioritized. As a result, this work focuses on the implementation and performance assessment of a self-consumption operational strategy in a real-world application.

B. Definition of Key Performance Indicators

The self-consumption rate s and the autarky rate a are used as KPIs to measure the performance of self-consumption operational strategies [21]. In the following elaborations, the superscript of a distinct amount of energy E indicates its source. The subscript indicates its use, whereas d stands for covering the local energy demand and subscript gen for energy export to the grid. The self-consumption rate is calculated by (2). The energy demand covered by local energy generation $E_{\mathrm{d}}^{\mathrm{local}}$ and energy discharged from the battery $E_{\mathrm{d}}^{\mathrm{bss}}$ is divided by the total local generation E^{local}. As illustrated in Fig. 1, the local generation incorporates energy from PVs $E_{\mathrm{d}}^{\mathrm{pv}}$ and the CHP $E_{\mathrm{d}}^{\mathrm{chp}}$. The autarky rate a describes the independence from the upstream grid. It is defined by (3) as the ratio of $E_{\mathrm{d}}^{\mathrm{local}}$ plus $E_{\mathrm{d}}^{\mathrm{bss}}$ and total energy demand E_{d}.

$$s = \frac{E_{\mathrm{d}}^{\mathrm{local}} + E_{\mathrm{d}}^{\mathrm{bss}}}{E^{\mathrm{local}}} = \frac{E_{\mathrm{d}}^{\mathrm{chp}} + E_{\mathrm{d}}^{\mathrm{pv}} + E_{\mathrm{d}}^{\mathrm{bss}}}{E^{\mathrm{local}}} \tag{2}$$

$$a = \frac{E_{\mathrm{d}}^{\mathrm{local}} + E_{\mathrm{d}}^{\mathrm{bss}}}{E_{\mathrm{d}}} = \frac{E_{\mathrm{d}}^{\mathrm{chp}} + E_{\mathrm{d}}^{\mathrm{pv}} + E_{\mathrm{d}}^{\mathrm{bss}}}{E_{\mathrm{d}}} \tag{3}$$

In order to evaluate the performance of the self-consumption operational strategy with regards to sustainability, and as an extension to the previous conference version in [1], the emission rate e as defined in (4) is introduced.

$$e = \frac{E_{\mathrm{d}}^{\mathrm{chp}} \cdot C^{\mathrm{chp}} + E_{\mathrm{d}}^{\mathrm{pv}} \cdot C^{\mathrm{pv}} + E_{\mathrm{d}}^{\mathrm{bss}} \cdot C^{\mathrm{bss}} + E_{\mathrm{d}}^{\mathrm{grid}} \cdot C^{\mathrm{grid}}}{E_{\mathrm{d}} \cdot C^{\mathrm{grid}}} \tag{4}$$

The emission rate results from the total CO_2 emissions associated with the utilized energy covering the local energy demand, divided by the total CO_2 emissions when the local energy demand is exclusively covered using the energy mix from the upstream grid. The total CO_2 emissions are calculated as the sum of self-consumed energy from a distinct asset of the microgrid, i.e., $E_{\mathrm{d}}^{\mathrm{chp}}$, $E_{\mathrm{d}}^{\mathrm{pv}}$, and $E_{\mathrm{d}}^{\mathrm{bss}}$, times the respective

specific emission values C^{chp}, C^{pv}, and C^{bss}. Moreover, the energy imported from the upstream grid $E_{\mathrm{d}}^{\mathrm{grid}}$ multiplied with the specific CO_2 emissions from the energy mix C^{grid} is added. The latter can be calculated by assigning specific CO_2 emissions to each type of energy source that is contributing to the energy supply from the upstream grid.

C. Mathematical Formulation of the Control Algorithm

Algorithms for controlling microgrid assets can be either formulated as an optimization model or in a rule-based manner. Miscellaneous approaches for optimization-based algorithms regarding microgrid operation are presented in literature, e.g., [15], [22], [23]. Optimization-based approaches require generation and consumption forecasts [24], while rule-based algorithms are able to operate in real time without consideration of uncertainty [25]. Moreover, as no energy market participation is intended within the operational strategy, predictive scheduling in day-ahead or intraday operation is not necessary. In addition to that, the authors in [26] show that a rule-based algorithm in energy management applications can provide a similar performance in less processing time. Therefore, the control algorithm is formulated in a rule-based manner in terms of sequential calculations based on the active power measurements of the microgrid assets.

For the mathematical formulation of the control algorithm, the microgrid assets are examined with regards to the level of flexibility as listed in Table I.

The CHP offers generation flexibility in terms of power increase and reduction within a specified operating region. However, the energy generation is bound to the thermal energy demand. Thus, the CHP's electric energy generation is approximately proportional to its thermal energy generation and cannot be controlled in this case. PV only offers flexibility in terms of power reduction. Due to the prioritization of feed-in from renewable energy resources, specified in the German Renewable Energy Sources Act, PVs are assumed to be uncontrolled. BSSs are technically constrained by the installed energy and power capacities. Regulations regarding the remuneration of energy feed-in from renewable energy resources only allow the battery to discharge if the local demand exceeds the local generation. Thus, a direct energy export from the battery to the upstream grid is prevented. EVs can offer consumption flexibility in terms of charging power increase or reduction. Here, the main restriction is given by the mobility requirements, i.e., arrival and departure times of the EVs as well as required energy demand. Further

restrictions exist regarding the rated capacity of the charging stations. However, in real-world applications, due to the absence of real-time data on the mobility requirements, the charging power is assumed to be uncontrolled. As a result, the main goal of the control algorithm following the self-consumption operation strategy is to cover the energy demand of the EVs with the local generation of the CHP and PVs. Thereby, energy from the upstream grid is only drawn in case of insufficient local generation. The BSS is utilized as a fully flexible asset, taking into account the technical and regulatory restrictions.

The mathematical formulation of the self-consumption control algorithm differs depending on the prioritized rate. Considering the mutual influence of s and a as discussed in [1], within the real-world application presented in this work, the self-consumption rate is selected. As the BSS appears to be the only asset actively contributing to the self-consumption operational strategy, the control algorithm aims for determining a set point for the charging or discharging power P_t^{bss}. The respective mathematical formulation is derived in (5). The set point is determined for every discrete time step t based on the real-time measurements of CHP generation P_t^{chp}, PV generation P_t^{pv}, and EV demand P_t^{ev}. Note that the mathematical formulation follows the passive sign convention, i.e., negative power values refer to generation or battery discharging and positive power values vice versa. In case the set point violates the technical restrictions of the BSS, i.e., state of charge or rated capacity, the nearest value of charging or discharging power that complies with the constraints is applied

$$P_t^{\mathrm{bss}} = -(P_t^{\mathrm{ev}} + P_t^{\mathrm{chp}} + P_t^{\mathrm{pv}}). \tag{5}$$

The mathematical formulation uses the restricted flexibilities of the microgrid assets to its advantage by condensing the decision-making to a single equation. This favors the computational efficiency in terms of real-time operation and suitability for real-world implementation.

III. REAL-WORLD IMPLEMENTATION

This section describes the operational framework in terms of the deployed software and communication architecture of the microgrid that are required for the real-world implementation of the proposed control algorithm.

A. Operational Framework

The foundation for operating the real-world microgrid lies in the exchange of information between the microgrid assets and a supervisory control and data acquisition (SCADA) system with an integrated energy management system (EMS). The SCADA system enables the functionality of collecting, storing, and visualizing data as well as the creation of virtual environments, by creating subsets of the microgrid without changing hardware connections. Fig. 2 displays an overview of the communication architecture within the real-world microgrid.

Each microgrid asset is connected to a central aggregation node, which acts as a data hub from which the SCADA collects measurements and sends commands including power set points for the BSS. The protocols used for this are MODBUS and
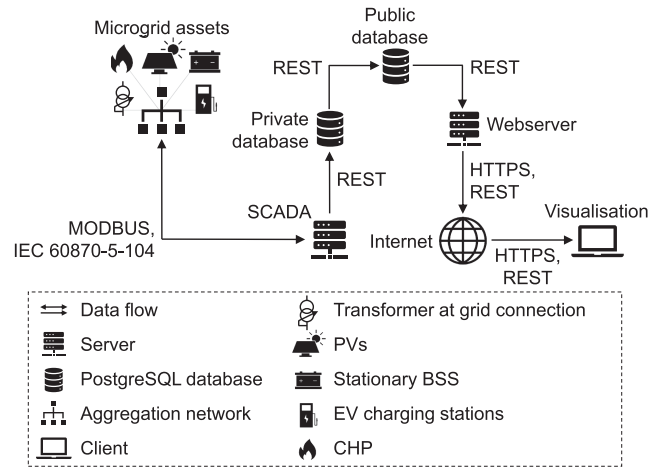

Fig. 2. Network diagram of the real-world microgrid communication architecture.

IEC 60870-5-104 due to their reliability in real-time operation. The control algorithm itself is implemented within the EMS of the SCADA, running on the SCADA server. Further details are given in Section III-B. As the data storage capabilities of the SCADA server are limited, a synchronized private database stores the acquired data in the long term. This data base represents the main data source for the investigations carried out in Section IV. For the mitigation of cyberattacks, there is no direct connection to the Internet. In order to grant access, e.g., for external partners interested in data visualization, the private database is partially mirrored into a public database. A web server is deployed with implemented REST-API that allows access only with authorization. With the exception of the web server no device is able to react to an external requests. As a result, data access and visualization may be performed safely, while the microgrid's integrity is preserved.

B. Implementation of the Control Algorithm

The control algorithm of the self-consumption operational strategy is implemented within the EMS, using programmable logic controller design. Based on the mathematical formulation described in Secion II-C, the determination of the charging or discharging power of the BSS P_t^{bss} follows a sequence of calculations taking into account the real-time measurements of the microgrid assets in each time step t. Fig. 3 displays the function block diagram of the rule-based algorithm. Note that the PVs and EV charging stations are subdivided into separate plants or charging points, respectively. This is indicated by the consecutive numbers in the superscript and based on the real-world installation of the respective assets. The AND- and NEGATE SIGN-blocks are used to process the measured power values. The function blocks are performing addition and algebraic sign negation, respectively. The CHECK CONSTRAINTS-block (CONST.) contains a series of conditionals to verify or adjust the set point value in accordance with the technical and regulatory restrictions.
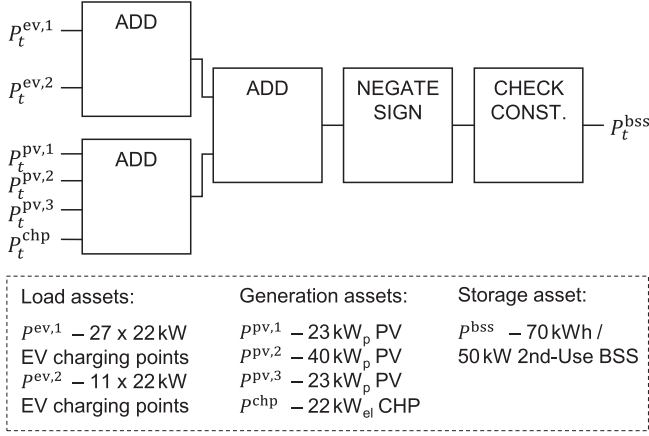
Fig. 3. Function block diagram of the control algorithm following the self-consumption operational strategy.

Fig. 4. Number of charging sessions at the charging stations integrated within the microgrid at the EUREF-Campus.

IV. REAL-WORLD APPLICATION AND EVALUATION

The control algorithm of the self-consumption operational strategy was implemented within the framework of the microgrid during the years 2017 to 2019. Within this section, the operational performance of the microgrid is assessed with regards to energy generation and demand characteristics, self-consumption and autarky rates, as well as the sustainability potential in terms of reducing the total CO_2 emissions. The evaluations are performed with 5-min average values, providing a deeper insight in real-world operations than the time increment of 15 min commonly used for electricity metering.

A. Energy Generation and Demand Characteristics

Within the analyzed microgrid, the local energy generated is mainly based on a CHP and three rooftop PVs. In total, the load of the system comprises 38 EV charging points, each with a rated capacity of 22 kW, that are supplied under application of the self-consumption operational strategy. A BSS with a rated energy capacity of 78 kWh, maximum charging power of 45 kW, and maximum discharging power of 60 kW was integrated as a buffer for charging power peaks or solar power surplus. Due to unreliable operation beginning in October 2017, and the rising importance of 2nd-use batteries, the BSS was replaced by batteries from dismantled EVs in 2019, featuring a total rated energy capacity of 70 kWh and total rated power of 50 kW for charging and discharging.

The microgrid offers three supply concepts for the EV users: "Park & Charge" for occasional users, monthly parking space related contracts for external fleet operators, and monthly parking space related contracts for local companies. The total number of charging sessions for each month from 2017 to 2019 is shown in Fig. 4. Occasional users are mostly represented by external visitors to the EUREF-Campus or corporate customers during working hours. It can be seen that during the summer vacation months July and August, the number of charging sessions decrease. The number of charging sessions peaked at the beginning of 2017 thanks to a contract with a fleet operator of a ride sharing
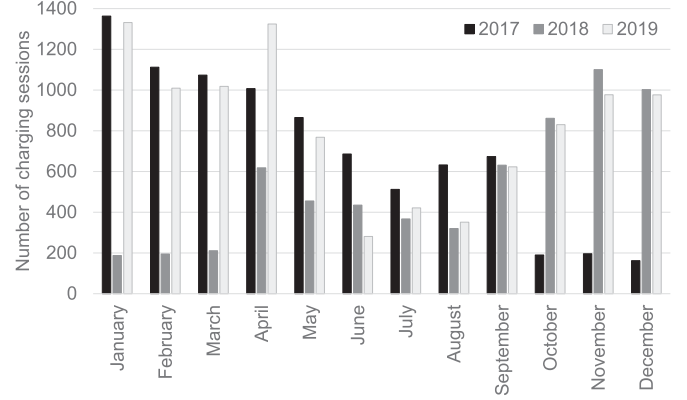
company. The usage of the charging stations with regards to fleet operators is depending on the respective business hours, which were mostly night hours for this specific case. The drop in the number of charging sessions in October 2017 is due to the closure of the fleet operator's contract. In April 2018, several EVs, as company vehicles, were acquired, leading to an increase in the number of charging sessions. It is expected that the number of charging sessions directly influences the energy demand characteristics during microgrid operation.

The monthly energy generation and demand as well as the exchange with the grid of the included assets from 2017 to 2019 are illustrated in Fig. 5. The challenges associated with increasing self-consumption become clear by the comparison of the local PV generation with the respective electrical demand. Despite the fact that the demand exceeds the generation in 2017, energy is still imported from and exported to the grid, indicating a mismatch of coincidences between generation and demand. The energy demand of the EVs follows the trend of the total number of charging sessions. The BSS is utilized as a buffer for PV generation as indicated by the peak of charged and discharged energy during the summer months. In 2018, the generated energy exceeds the demand, accompanied by an increased grid export. Taking into consideration that the CHP was put into operation in 2019, a greater energy generation surplus is observed. However, to ensure comparability between the years, the CHP is not included in further analysis.

In order to assess the performance of microgrid operation applying the self-consumption operational strategy, three scenarios were analyzed with regards to the defined KPIs. These investigated scenarios are specified as follows.

- *Scenario 1*: Minimal self-consumption (real-world data analysis without BSS).
- *Scenario 2*: Achieved self-consumption (real-world data analysis with BSS under real-world operating conditions).
- *Scenario 3*: Maximal self-consumption (real-world data analysis with simulated BSS under ideal operating conditions).

The minimal (min) scenario does not consider the battery storage, thus, only the coincidences of generation and demand
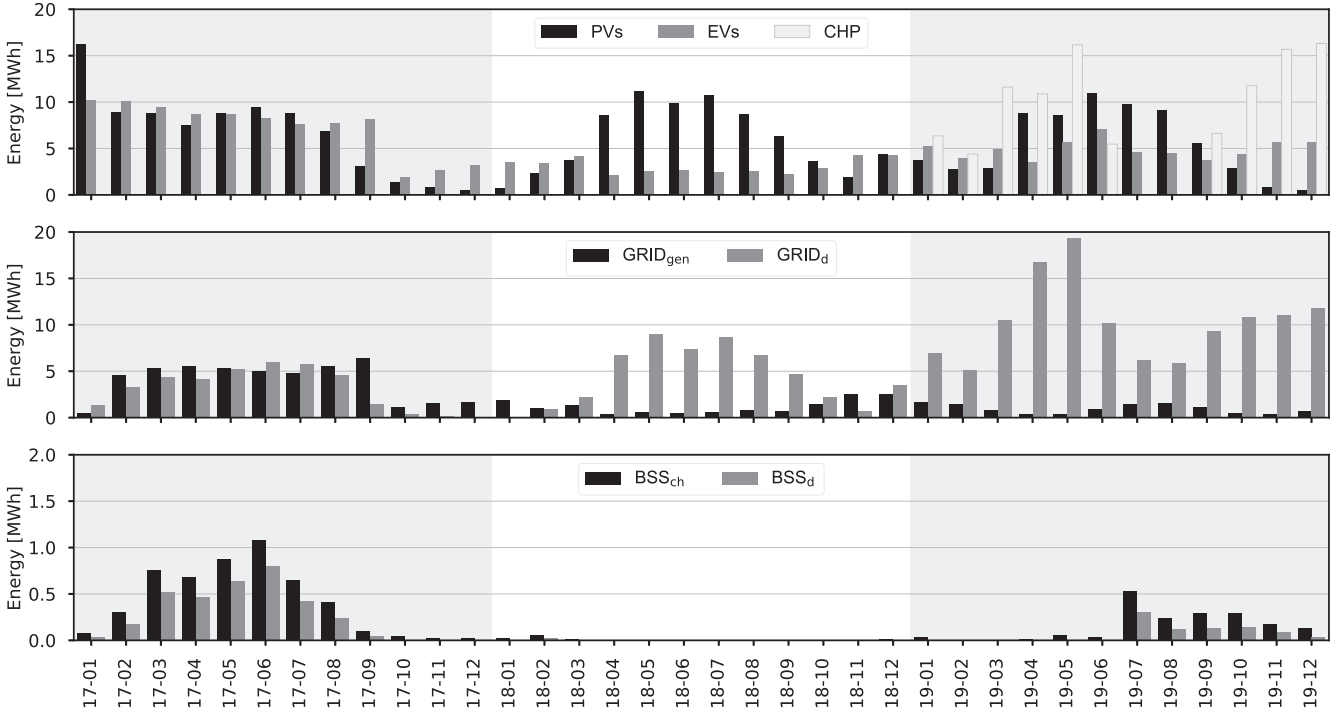
Fig. 5. Total energy generation and demand of the microgrid assets at EUREF-Campus from 2017 to 2019.

TABLE II
AVERAGE VALUES OF AUTARKY AND SELF-CONSUMPTION RATES
FROM 2017 TO 2019

year	a_{min}	a_{ach}	a_{max}	s_{min}	s_{ach}	s_{max}
			(%)			
2017	40.93	47.88	60.93	31.90	38.51	57.48
2018	37.41	41.48	67.80	19.72	19.92	50.99
2019	35.59	37.76	66.36	26.30	27.96	61.25

are investigated. The achieved (ach) scenario displays the real energy flows in the microgrid. As the battery system was partially out of service, the maximal (max) scenario is set up to show the theoretical potential of the self-consumption operational strategy by adding an ideal BSS to the microgrid.

B. Analysis of Autarky and Self-Consumption Rates

The average autarky and self-consumption rates for the three scenarios are listed in Table II. For scenarios 1 and 2, the autarky rate decreases from 2017 to 2019. Thereby, the decrease from 2017 to 2018 is caused by missing buffer functionalities of the BSS, while the decrease from 2018 to 2019 is mainly impacted by the additional EVs charging regularly at the microgrid charging stations. This indicates the importance of the battery system as a buffer among the microgrid assets. In comparison to the autarky rate, the self-consumption rate decreases for all three scenarios from 2017 to 2018 as the PV generation surplus, and, thus, the grid export increases. However, due to the additional EV charging in 2019 the self-consumption rate increases compared to 2018, as more local energy is utilized. In addition, when comparing the trend of the autarky rate to the self-consumption

rate [1], the autarky rate underlies seasonal fluctuations and shows higher rates during the summer than the winter months. This is caused by the increasing PV generation, which leads to an increase of the autarky rate that is derived from (3). The self-consumption rate, in accordance to (2), slightly decreases during the summer months as excess energy is exported to the upstream grid.

The deviations of total energy generation and demand reveal influences of external conditions related to seasons or the number of EV charging sessions. Further, short-term fluctuations of PV generation can significantly affect the balance between supply and demand. For instance, the total EV energy consumption E_d^{ev} in 2017 is around 85 MWh, of which 94 % could have been supplied by the total PV generation of around 80 MWh. However, due to the time differences between generation and demand, neither a self-consumption rate of $s = 1$ nor an autarky rate of $a = 1$ are achieved.

Based on the previous findings about the positive impact of BSS deployment, it is investigated which parameters, i.e., installed energy capacity or rated power, are influencing the operation of the BSS with ideal operating conditions. Compared to [14], in addition to the impact of the rated energy capacity, the rated power is taken into account. Further, within the real-world microgrid of this work, the main purpose is the energy supply of EVs that shows a different load pattern than residential load profiles. The resulting average autarky and self-consumption rates with varying installed capacity and rated power are presented in Figs. 6 and 7.

The results reveal that the rated energy capacity has little influence on the average autarky and self-consumption rates. Both a and s do not appear to scale or to increase proportionally
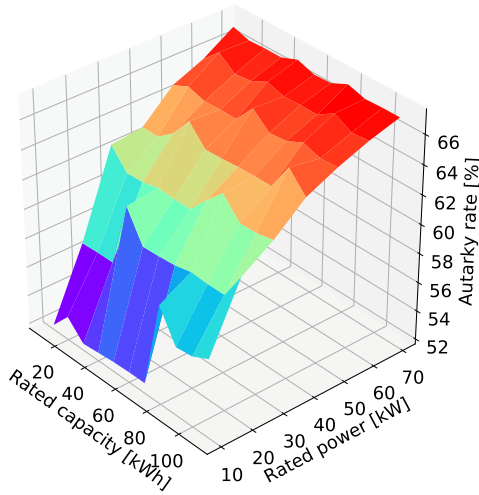
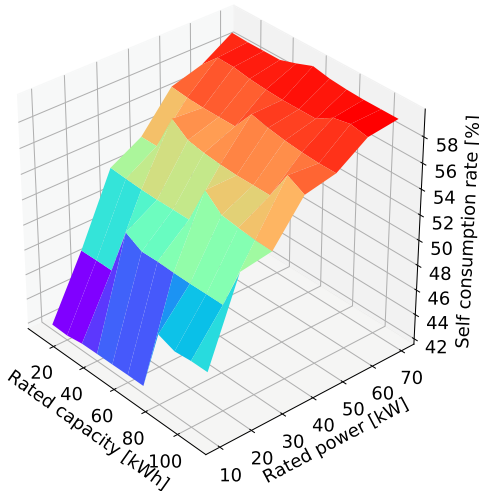Fig. 6. Simulated average autarky rate depending on rated energy capacity and rated power.

Fig. 7. Simulated average self-consumption rate depending on rated energy capacity and rated power.

with the rated energy capacity. However, the system is more sensitive to the rated power. This is due to the short-term fluctuations of PV generation, caused by changing meteorological conditions. Thereby, the BSS is able to buffer the surplus energy for self-consumption with EVs.

C. Sustainability Assessment

As one of the main motivations for establishing microgrid structures and as an extension to the previous conference version in [1], the sustainability performance is assessed with regards to the total CO_2 emissions and emission rate e for the three defined scenarios.

Detailed hourly information on the share of each energy type contributing to the energy mix is provided by the German Federal Network Agency[3] for the 50Hertz control area in which

[3][Online]. Available:https://www.smard.de/

the EUREF-Campus is located. The specific CO_2 emissions, including the CO_2 equivalent (CO_2e) of other pertinent greenhouse gases, are taken from [27] and [28] and listed as follows:

- biomass: $230 \frac{gCO_2e}{kWh}$
- hydro: $24 \frac{gCO_2e}{kWh}$
- wind offshore: $12 \frac{gCO_2e}{kWh}$
- wind onshore: $11 \frac{gCO_2e}{kWh}$
- photovoltaic: $48 \frac{gCO_2e}{kWh}$
- geothermal: $38 \frac{gCO_2e}{kWh}$
- lignite: $1137 \frac{gCO_2e}{kWh}$
- coal: $835 \frac{gCO_2e}{kWh}$
- natural gas: $399 \frac{gCO_2e}{kWh}$
- other: $819 \frac{gCO_2e}{kWh}$

Local emissions are considered in terms of the energy generated from PVs, the CHP, and BSS. The specific CO_2 emissions for PV refer to the listed value. In this regard, the CHP is referred to as biomass. No specific CO_2 emissions are defined for the BSS, as the value changes with every charging process. The specific CO_2 emission value is continuously updated by accounting for the total emissions generated during charging, divided by the total amount of energy stored in the battery. Internal losses are assumed to be constant and modeled in a linear manner. Note that the life cycle emissions are not included in these calculations as the BSS is composed of 2nd-life EV batteries.

The total CO_2 emissions for each month are shown in Fig. 8. With the aim of having a common reference point, the base emissions are calculated assuming the grid being the only energy source, i.e., no local generation and no battery are deployed for charging the EVs. The base emissions follow the trend of the number of charging sessions, as discussed in Section IV-A. When adding PVs to cover part of the energy demand with local generation, a significant drop of the CO_2 emissions for scenario 1 is observed. This is especially notable in 2017, in which the fleet operator was charging the EVs during the day due to operating hours at night. Thus, a significant share of the locally generated energy by the PVs is utilized for charging sessions. Further improvements can be seen in scenarios 2 and 3, in which the BSS is deployed with realistic and ideal operating conditions, respectively. Consequently, this results in a reduction of the total CO_2 emissions. The values range from 1.7 tCO_2e to 7 tCO_2e during winter and from 3.8 tCO_2e to 5.8 tCO_2e during summer. During winter, this increase is mainly attributed to the increased energy import from the upstream grid. Vice versa, the decrease of CO_2 emissions is assigned to the increase of power generation from local PVs during summer.

For the purpose of examining the influence of self-consumption and autarky rates on the emission rate, Fig. 9 shows the three defined KPIs for each year from 2017 to 2019. In addition, the energy import from the upstream grid is depicted as a ratio of the total energy demand of the EVs. This ratio represents the influence of CO_2 emissions derived from the energy mix of the upstream grid.

Compared to scenario 1, the achieved self-consumption and autarky rates in scenarios 2 improve only in the year 2017, as this is the only year with full availability of the BSS. As a result, the energy import from the upstream grid and the total CO_2 emissions are slightly reduced. Considering ideal operating conditions, the self-consumption and autarky rates increase
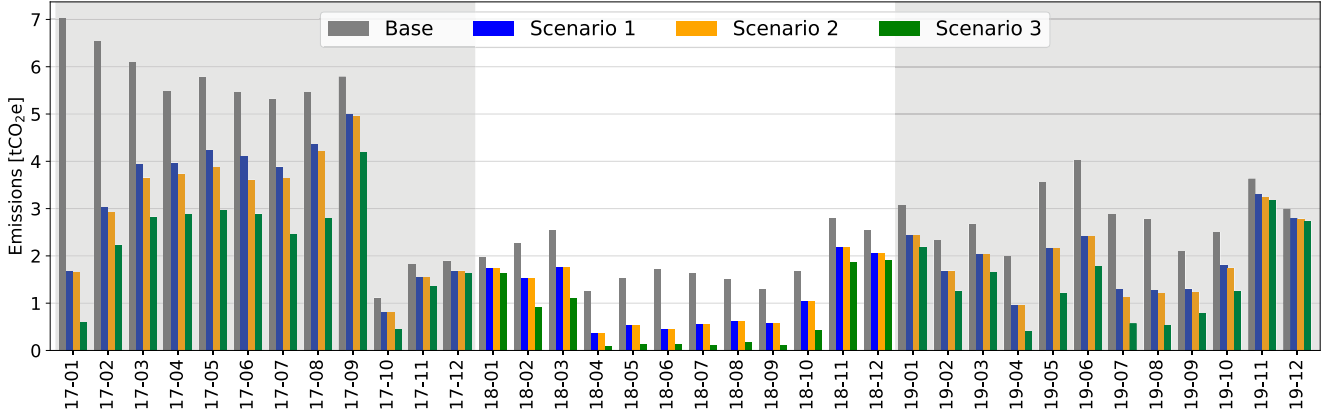
Fig. 8. Comparison of total CO_2 emissions for the three evaluated scenarios from 2017 to 2019.
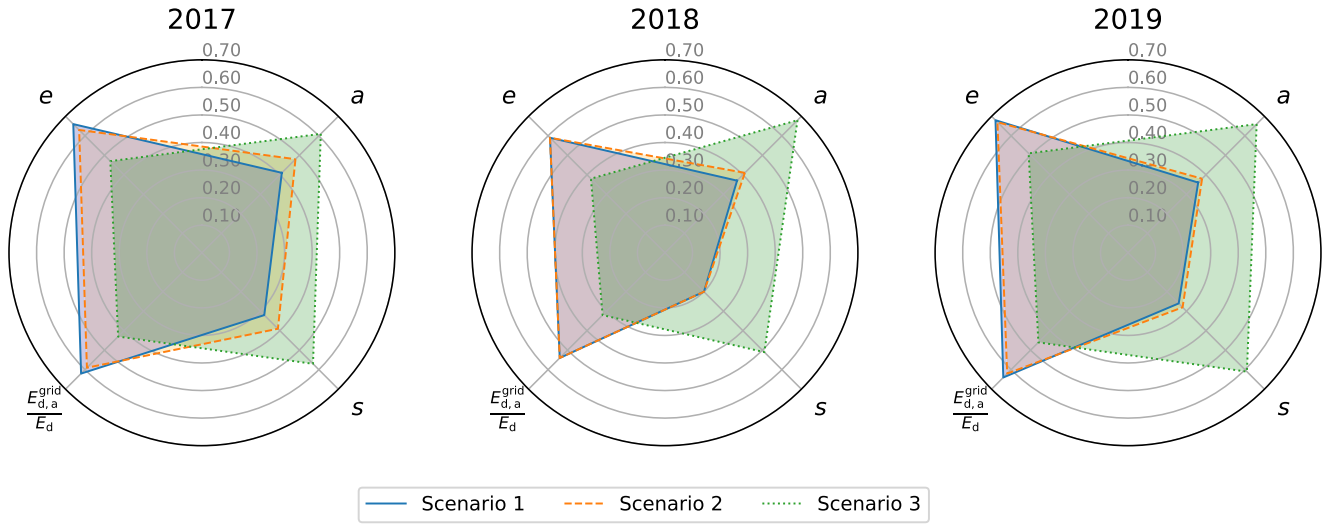

Fig. 9. Comparison of the defined KPIs over the years 2017–2019.

as discussed in Section IV-A. With regard to scenario 2, the emission rate in scenario 3 decreases by additional 26%, 37%, and 26% for the years 2017 to 2019, respectively. The particular reductions in terms of energy import from the upstream grid are 27%, 41%, and 27%. It becomes clear that a reduction of the energy import from the upstream grid leads to a decrease of CO_2 emissions as local renewable energy resources can be utilized. Overall, the total CO_2 emissions can be significantly reduced when utilizing BSSes within the operation of the microgrid, contributing to the sustainable application of electric mobility in urban micro smart grids.

V. Conclusion

In this article, a real-world operational framework for the implementation of a control algorithm, applying self-consumption operational strategy, is presented. A comprehensive study assessing the performance of microgrid operation over three years is carried out for three different scenarios, i.e., without

deployment of a BSS, real-world operation, and under ideal operating conditions. Seasonal influences, operational characteristics of included assets, and the impact of battery deployment on self-consumption and autarky rates are discussed. It appears that the sensitivity of autarky and self-consumption rates depends on the rated power rather than on the rated energy capacity of BSSs. As an extension to the previous conference version, the emission rate is considered as an additional KPI within the performance assessment. With the deployment of a BSS, the total CO_2 emissions can be reduced by up to 37% under ideal operating conditions for the investigated microgrid. The results indicate great sustainability potential of the microgrid concept for the energy supply of electric mobility in urban areas. Future investigations on the influence of battery capacity and rated power in microgrid operation on smaller time scales must be conducted. In that regard, a comparison to other storage technologies can be taken into account which may include the utilization of EVs as mobile storage systems. Under the assumption that real-time data on mobility requirements is accessible to

the microgrid operator, this would further allow an investigation of operational strategies other than self-consumption.

ACKNOWLEDGMENT

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Mariem Khemir received the M.Sc. degree in electrical engineering and information technology from the TU Munich, Munich, Germany, in 2018.

As a Research Associate, she contributed to the project Research Campus Mobility2Grid by ensuring the operation of the Micro Smart Grid on the EUREF campus, Berlin, Germany, as well as setting viable market-based organizational models from the research results.

Mauricio Rojas received the M.Sc. degree in renewable energy (PPRE) from Oldenburg University, Oldenburg, Germany, in 2007.

He is one of the technical team members in charge of the deployment, test, operation, and maintenance of the EUREF-Campus Micro Smart Grid, Berlin, Germany, since 2014. His reseach interests includes the integration of systems and in the development and implementation of control strategies for microgrids.

Raisa Popova received the M.Sc. degree in electrical engineering from the Technische Universität Berlin, Berlin, Germany, in 2018.

Since 2019, she has been coordinating the activities of the research area Smart Grid Infrastructures as part of the Research Campus Mobility2Grid. She works with DB Energie, Berlin, Germany, as a Project Manager and Technical Consultant in the field of innovation, renewable energy and electric mobility. Her research interests include microgrid operational strategies, voltage control, control strategies, economic deployment, and business models for microgrids.

Tiba Feizi received the M.Sc. degree in electrical engineering from RWTH Aachen University, Aachen, Germany, in 2015.

Since 2016, she has been working as a Technical Consultant and a Project Manager with DB Energie, Berling, Germany. As part of her work, she participated in the project "Research Campus Mobility2Grid". Her research interests include optimization modeling of operational strategies such as demand side management, virtual power plants economics, and data analytics in smart grids.

Jan F. Heinekamp received the M.Sc. degree in 2019, from the Technische Universität, Berlin, Germany, where he is currently working toward the Ph.D. degree with the Chair of Sustainable Electric Networks and Sources of Energy (SENSE).

As a Research Associate, he contributes to the research project Research Campus Mobility2Grid in smart grid infrastructures. His research inerests include modeling of virtual power plants and mathematical optimization of multienergy-systems in smart grid environments.

Kai Strunz (Senior Member, IEEE) received the Dipl.-Ing. and Dr.-Ing. (*summa cum laude*) degrees from Saarland University, Saarbrücken, Germany, in 1996 and 2001, respectively.

From 1995 to 1997, he pursued research with Brunel University, London, U.K. From 1997 to 2002, he worked with the Division Recherche et Développement of Electricité de France, Paris, France. From 2002 to 2007, he was an Assistant Professor of electrical engineering with the University of Washington, Seattle, WA, USA. Since September 2007, he has been the Chair Professor of Sustainable Electric Networks and Sources of Energy, Technische Universität, Berlin, Germany.