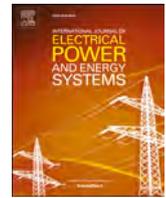


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Optimal capacity management applied to a low voltage distribution grid in a local peer-to-peer energy community[☆]

Bharath Varsh Rao^{a,*}, Mark Stefan^a, Thomas Brunnhofer^a, Roman Schwalbe^a, Roman Karl^a,
Friederich Kupzog^a, Gregor Taljan^b, Franz Zeilinger^c, Peter Stern^c, Martin Kozek^d

^a Austrian Institute of Technology, Giefinggasse 4, 1210 Vienna, Austria

^b Energienetze Steiermark GmbH, Leonhardgürtel 10, 8010 Graz, Austria

^c Siemens Aktiengesellschaft Oesterreich, Siemensstraße 90, 1210 Vienna, Austria

^d Institute of Mechanics and Mechatronics, Vienna University of Technology, Getreidemarkt 9, 1060 Vienna, Austria

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ABSTRACT

This paper presents a methodology to optimally share the available grid capacity among customer assets connected within a low voltage distribution grid. Distributed energy resources (DERs) and a new generation of loads such as heat pumps, thermal, hydrogen, electric storages, and vehicles are increasingly being connected to distribution grids. These DERs and loads are intermittent and it is essential to optimally control them for the safe operation of the grid. Additionally, there is increased interest in the local generation, production, trading, and consumption of energy. New regulations to establish local energy communities (LEC) have come to fruition among member nations across Europe. This is to provide a control, market, and legal framework for managing such distributed generators and flexibilities in low and medium-voltage distribution grids and conclusively empower end-users to democratize the energy system. Within a LEC, a local energy market (LEM) is to be implemented. A significant constraint of a LEM or energy accounting system is the grid settlement process. The grid should remain in a steady state when the bids in the market are executed. The methodology discussed in this paper will preemptively stabilize the grid and generate limiting profiles at various locations for individual flexibilities that are part of the local energy market. This is achieved by using an Optimal Capacity Management system which generates limiting profiles at the points of common couplings of various controllable devices in the grid. The controllable devices are required to maintain their active power injection and consumption within the generated limiting profiles to ensure optimum grid level. This will ensure that grid limits are maintained, which are simulated on a test feeder and also applied to a real network model from the Heimschuh pilot site in Styria, Austria.

1. Introduction

Clean energy for all Europeans, as part of the Clean Energy Package from the European Commission, for the first time, recognizes the formation of energy communities [1]. Energy communities can induce both challenges and opportunities in the energy ecosystem. They can encourage the community members to increase renewable energy production and provide flexibility services to the network operators. Load aggregation can lead to communities offering flexibility services such as grid congestion management, peak load shaving, and improve power quality. However, although energy management within the community

may decrease costs locally, overall system costs may increase due to individual loads and renewable energy generators' coordination.

Blockchain Grid project funded by the Austrian Research Promotion Agency [2], demonstrates a blockchain-based peer-to-peer local energy community (LEC). The project does not consider how to deal with excess renewable energy production but rather how to use remaining free grid resources (time-varying power and voltage bands) in the community's merit. Such a system is possible due to the utilization of a high level of trusted automation provided by Blockchain technology. The method is to implement a Blockchain-based application that allows prosumers to share free grid resources for their surplus generation and load. The

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* Corresponding author.

E-mail address: bharath-varsh.rao@ait.ac.at (B.V. Rao).

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distribution system operator (DSO) acts as a facilitator. Technical and organizational requirements are analyzed for a distributed solution in which grid customers can share excess grid capacities for their flexible loads. One of the focuses is on potential regulatory designs and the challenge to design equity among grid participants, given that users are physically different depending on their localization within the grid.

In Austria, LEC will facilitate the creation of a local energy market (LEM), located in a low or medium voltage distribution grid. Community members can trade the energy, locally. With the roll-out of a large number of smart meters and measurement devices, distribution grids are becoming more observable. Simultaneously, with a large number of smart devices connected with the distributed renewable energy sources and a new generation of loads like heat-pumps, thermal, electric, hydrogen storage, and vehicles, increasing the controllability. However, LEMs have a significant limitation. The bids in the market need to be managed and therefore, a settlement mechanism is needed to be implemented to ensure grid security, when the bids agreed in the market are executed. This is discussed further in Section 2.1.

In the literature, various methods related to capacity management are presented. Most of the methods are based on either numerical iteration or optimization. Optimal hosting capacity, grid capacity, and optimal placement problems are fundamental variations of optimal power flow (OPF) described in [3]. Hosting capacity is commonly used in the context of distributed renewable energy (DER) generators (photo-voltaic (PV), micro-wind, micro-hydro...) connected to distribution grids [4–6]. However, this term can be extended to loads such as heat pumps, thermal, hydrogen, electric storage, and electric vehicles (EV), or any other kind of controllable and uncontrollable loads. Nevertheless, the term grid capacity is used mostly for loads.

Authors in [7] have developed a methodology to provide power regulation services to the DSO using aggregated EV. This method can be used to calculate the regulation of power in the upward and downward direction of the EV fleet, providing voltage services to the grid. Furthermore, the research work does not present the impact on the grid when these services are active, and since they are aggregated, insufficient control is provided to a single customer or a charging station. Additionally, more intensive control mechanisms are required within a local energy market (LEM) for concluding settlement procedures. In [8], authors present a probabilistic hosting capacity method with the inclusion of uncertainties related to RES and loads. The method is mostly used for planning purposes and is bench-marked using a network model. However, the method cannot provide schedules or control set-points to individual generators or loads and cannot be included in a LEC without major modifications. In [9], a stochastic optimization method is presented. Similar to [8], it cannot be used for set-point generation meant for individual flexibility or RES units connected at a particular bus in the grid. A methodology to optimally control EVs within a region (region-based) is provided in [10]. This is used to generate an EV chargeable region and an EV charging upper limit for active power for each bus. This method can be compatible with the local peer-to-peer energy market but is limited only to electric vehicles and does not consider other types of loads or RES generation. In the research work presented in [11], an electric storage system is used to provide voltage regulation services to the grid and to increase PV hosting capacity. However, the method is designed for instantaneous control and does not focus on scheduling flexibilities. Authors in [12] postulate a deterministic and probabilistic control scheme for EV control to improve power quality in a distribution grid. This paper, similar to [8], does not focus on control of individual EVs. Authors in [13], have presented a scalable optimization problem to optimally configure the RES placement to maximize the hosting capacity. The optimization approach looks promising as it can deliver global optimum, the method is not suitable for real time operation but rather for planning purpose. Research work described in [14], presents a novel energy management system to manage inter-connected micro-grid. It involves the creation of a step-wise demand response strategy to manage various assets in the micro-grids with two

levels of control. A major limitation of this approach is the not being able to reach a global optimum due to multi-level control. Very detailed information about the assets are needed. In [15], a bi-level power and energy management system for a micro-grid is presented. It consists of an upper level which is responsible for power management and lower level for energy, using evolutionary algorithms. This approach has similar disadvantages as [14]. A global optimum is difficult to achieve. Moreover, the set-points are directly transmitted to the flexibilities, where as, in this paper, a band of limiting profiles are generated. Authors in [16] presented a stochastic energy management system to manage RES units like solar, wind and tidal sources in the presence of the demand response program and storage devices, in a micro-grid. It uses a linear multi-objective programming method. It does not however, include a method to segregate the load types and provide a method to include multiple variety of flexibilities without the need for comprehensive data. In [17], the authors describe an optimal control problem using two approaches, direct method and Bellman's Dynamic Programming Principle, respectively and the method looks promising. However, it does not include the power flow. This method cannot be extended to a low voltage distribution grid consisting of power lines, where power flows need to be taken into consideration. An energy management strategies is presented in [18], which uses deep reinforcement learning, within an energy internet. The approach is similar to OPF type C, as presented in [19], where a load flow solver is used in conjunction with an OPF solver for power flow related information and OCM is based on OPF Type C (see Section 2, for more information).

From the literature, it can be established that currently a methodology does not exist that can generate active power set-points (operation band or limits) by calculating the hosting or grid capacity at each node in the low voltage distribution grid, including multiple RES and load types. Additionally, methods cited above are not readily compatible with a LEM to provide settlement services for grid stability. A holistic methodology that can accommodate all flexibility types coupled with DERs is missing or needs improvement. Moreover, such a system should be able to run online with a short reaction or sampling time to counter stochastic RES and loads.

Therefore, this paper presents the following contributions which are beyond the state-of-the-art,

1. A holistic methodology, which includes multiple flexibilities and load types, entitled Optimal Capacity Management (OCM) control scheme to manage available grid capacity in low voltage distribution grid (see Section 2.2).
2. A real-time local peer-to-peer energy market settlement process alongside its relation to OCM (see Section 2.1).
3. OCM methodology which is based on holomorphic embedding load flow method (HELM) and genetic algorithm (GA) with various objectives and constraints for test and real grid scenarios (see Sections 2, 2.2.2 and 2.2.3) to generate the limiting profiles for market settlement process, in a peer-to-peer LEC.
4. Validation of the methodology using test (see Section 3) and a real feeder (see Section 4) located in Austria with real measurements.

This paper is structured as follows; the OCM methodology is presented in Section 2, the introduction to the relationship between OCM and a local peer-to-peer energy market is presented in Section 2.1. OCM formulation, objectives, inequality and HELM used as equality constraints are presented in Sections 2.2, 2.2.2 and 2.2.3, respectively. Results based on a test feeder and Heimschuh pilot site is presented in Sections 3 and 4, respectively. Finally, conclusions and outlooks are presented in Section 5. Table 1 is a list of abbreviations used in the paper.

2. Methodology

Local energy communities are generally located in a low or medium

Table 1

Abbreviations.

OCM	Optimal Capacity Management
DER	Distributed Energy Resources
DSO	Distribution System Operator
TSO	Transmission System Operator
RES	Renewable Energy Sources
OPF	Optimal Power Flow
LEC	Local Energy Community
LEM	Local Energy Market
EV	Electric Vehicles
PV	Photo Voltaic
HELM	Holomorphic Embedding Load flow Method
GA	Genetic Algorithm
CS	Charging Station
CB	Community Battery
UL	Uncontrollable Load

voltage distribution grid, as represented by a general schematic shown in Fig. 1, comprising a low voltage distribution feeder connected to a certain number of uncontrollable loads (UL01, UL02, ...) and flexibilities like a community battery (CB), connected at Bus05 and electric vehicle charging stations (CS01 and CS02) at Buses 07 and 09, respectively. Customers connected to the distribution grid have the opportunity to either opt-in (agree) or opt-out (decline) when participating as part of the LEC. Flexibilities either on the customer premises or at the grid level can be part of the community [20]. They can support the grid and the community, either directly or through a local ancillary services market. In the Heimschuh pilot site, a large community battery and two charging stations were provided as available flexibilities and are part of the community (see Section 4).

The DSO is required to maintain the grid security at the distribution level and this role is to be continued after the formulation of a LEC [20]. Since LEMs are located at the distribution grid level they should contain a settlement mechanism that ensures high power quality and supply continuity. This is to make sure that the bids agreed upon in the market, when executed, will not cause grid instability. OCM is presented in this paper to enable the DSOs to enforce power quality. OCM will be deployed at the DSO control center or the LEC authority premises. At the Heimschuh pilot site, the OCM is deployed at the location of the community battery.

OCM involves the generation of limiting active power profiles (P_t^{min} and P_t^{max}) at the buses where flexibilities are connected (see Fig. 2). This is pertaining to Fig. 1. Similar limits are generated at all the flexibilities in the grid. This is based on the method presented in [21], where limiting profiles are generated at the bus where controllable loads are located. However, in this paper, the limiting profiles are generated directly for the flexibility itself. This enables multiple flexibilities at the

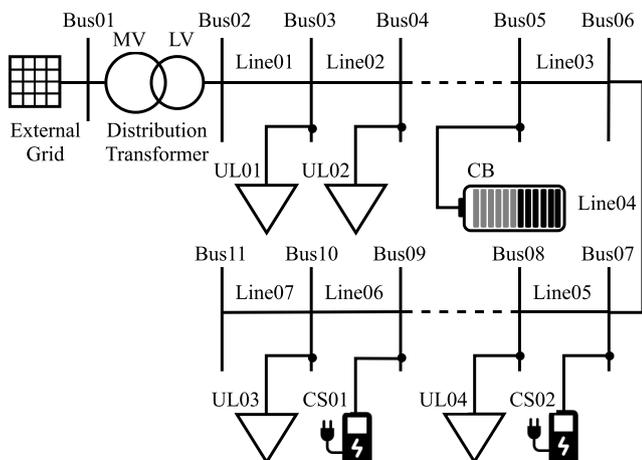


Fig. 1. General schematic of a LEC.

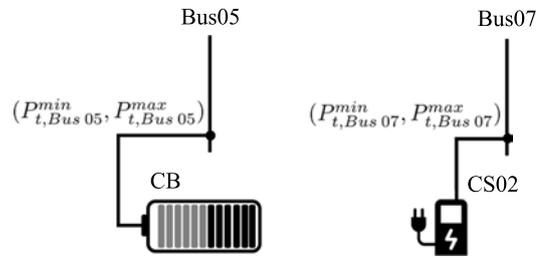


Fig. 2. Limiting active power profiles (P_t^{min} and P_t^{max}) generated at Buses 05 and 07, respectively, where the community battery and charging station are connected.

same bus to participate in the LEM. Additionally, in [21], poor reactive power control is observed due to the lack of reactive power controllable devices in the grid. Therefore, reactive power limits (Q_t^{min} and Q_t^{max}) are omitted. Moreover, reactive power is irrelevant in a LEM. Compared to [21], this paper presents additional explanation and validation of the OCM and relation to LEM, along with a detailed explanation based on two experimental setups.

Limiting profiles can be observed in Fig. 10 (adapted from the figure presented in [21]). Subsequently, this can also be observed in Fig. 3 which represents the P_t^{min} and P_t^{max} profiles for a particular flexibility. Such profiles are generated for all the flexibilities participating in the LEM. The active power consumed by the flexibility during market operation is required to be in-between the P_t^{min} and P_t^{max} limits to maintain the grid within its prescribed limits. The limiting profiles can take both positive (power consumption) and negative (power injection) values. This is applicable to the community battery, which can either charge and discharge. The load flow analysis of a power grid suggests that, for a particular grid loading condition, the grid capacity is constant i.e. the power that can be fed-into or consumed for a particular feeder is fixed. This is due to the non-causal nature of the load flow solution. This is also affected by the distance from the transformer and voltage drop along the lines. These specific limiting profiles are sharing the available grid capacity among the flexibilities depending on the objective function and constraints. This is observed in a simple example presented in Section 3 and Fig. 6.

The flexibilities are required to remain within the operation range provided by the OCM while participating in the LEM. Doing so will ensure that no limits are violated at any of the buses in the distribution grid.

2.1. Relevance to local peer-to-peer energy markets

Traditionally, in national or European level energy markets, the physical settlement process is done by the transmission system operator (TSO) who is responsible for maintaining transmission grid security. This is possible due to the fact that transmission grids are over observed and controllable. However, such a market structure, cannot be readily transposed to a distribution grid, which is neither controllable nor observable.

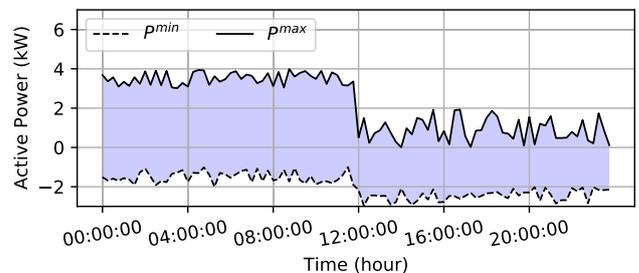


Fig. 3. Representation of limiting profiles of a flexibility in a LEC.

In recent years, distribution grids are moving towards increased controllability and observability, with the help of smart meters and a new generation of loads and distributed generators. Contrary to TSO, a DSO cannot be responsible for managing the settlement process due to the large number of distributed loads and generators. Therefore, a control mechanism is needed to preemptively controlled the flexibilities even before the market bidding begins. OCM generates the limiting profiles and if the flexibilities operate within the limits, the physical settlement has occurred. This will ensure that the bids in the LEM, when enacted, will not lead to grid violations or power quality issues. The Blockchain Grid project addresses this issue by coupling the LEM with the OCM system.

In this publication, the LEM structure is not presented, as it is out of the scope of this study. Rather, the linkage between the OCM and the market is provided. There are multiple blockchain based energy markets approached available in the literature [22–24]. The system architecture of the Blockchain Grid project is presented in Fig. 4. A permissioned public Blockchain, based on Parity Ethereum is used in the project. The consensus algorithm used is "proof of authority" procedure. Each authorized participants (so-called "sealers"), can generate blocks with transactions into the Blockchain. The platform can dynamically add or remove participants. This feature is essential as sealers in the "proof of authority" mechanism generate blocks in a well defined sequence and the block is only generated by the next sealer, if one sealer fails.

There are two smart contracts considered, the first focusing on enabling peer-to-peer trading in the energy market and, second, the managing of the grid capacities. Customers in the pilot can own a certain amount of battery capacity in the community battery and be part of the market. Additionally, charging stations are connected to the blockchain to provide flexibility services. Measurement devices in the field record the active and reactive powers, voltage and phase angle (P, Q, V, Θ) at all the customers in the low voltage grid. This data is directly written into the blockchain and is available at all other nodes in the system in the next sample. The sampling rate of the system is 1 min.

Active powers are used in the market smart contract for market action, which will lead the generation of battery power (P_{CB}) values (charging or discharging). This is dependent on the market mechanism.

OCM will receive the P, Q, V, Θ to generate p^{min} and p^{max} values and is acquired by the capacity smart-contract. Flexibilities are required to operate within the provided limits and community battery limits are considered in the market mechanism, which calculates the battery power.

2.2. Optimal capacity management

As discussed in Section 1, OCM is based on OPF. OPF problems are non-linear and non-convex in nature [3]. In [3], OPF methods are classified into two classes. Class A set of algorithms is based on an intermediate load flow solution. As the optimal solution is close to those generated by a complete load flow, it is assumed to be operable, and the optimum is determined iteratively using Jacobian and sensitivity relationships. Class B involves using the entire search space by using a solver that can handle non-linearity and non-convexity or by convex relaxation methods. In [19], authors present Class C type of algorithms which combines class A and B. OCM is based on the OPF Class C presented in [19]. However, in [19], the objective is to minimize the three phase voltage unbalance in contrast to OCM, which has the objective to generate limiting profiles and integrating it into a LEM. It uses a non-linear non-convex solver wrapped around a reliable load flow method like HELM to generate a global optimum.

OCM is defined as an optimization problem as,

$$\begin{aligned} &\text{minimize} && F(x, u) \\ &\text{subject to} && H(x, u) = 0, \\ &&& G(x, u) \leq 0 \end{aligned} \tag{1}$$

where, $F(x, u)$ is the objective function of OCM. $H(x, u)$ and $G(x, u)$ are the equality and inequality constraints respectively.

x, u are the state and input variables. For a low voltage distribution grid containing only load buses, in the context of load flow, input variables are active and reactive power injection or consumption at loads, while the state variables are voltages, phase angles and reactive powers at all the buses.

Active power limiting profiles are to be generated at all the controllable buses in grid, as discussed in Section 2.

2.2.1. Objective function

As presented in Figs. 2 and 3, limiting profiles are generated by defining the objective function as,

$$F(x, u) = \sum_t \sum_{c \in C} P_{c,t} \tag{2}$$

Limiting profiles (p_t^{min}, p_t^{max}) are generated as follows,

$$\begin{aligned} p_t^{min} &= \underset{u}{\text{minimize}} && F(x, u) \\ p_t^{max} &= -\underset{u}{\text{minimize}} && F(x, u) \end{aligned} \tag{3}$$

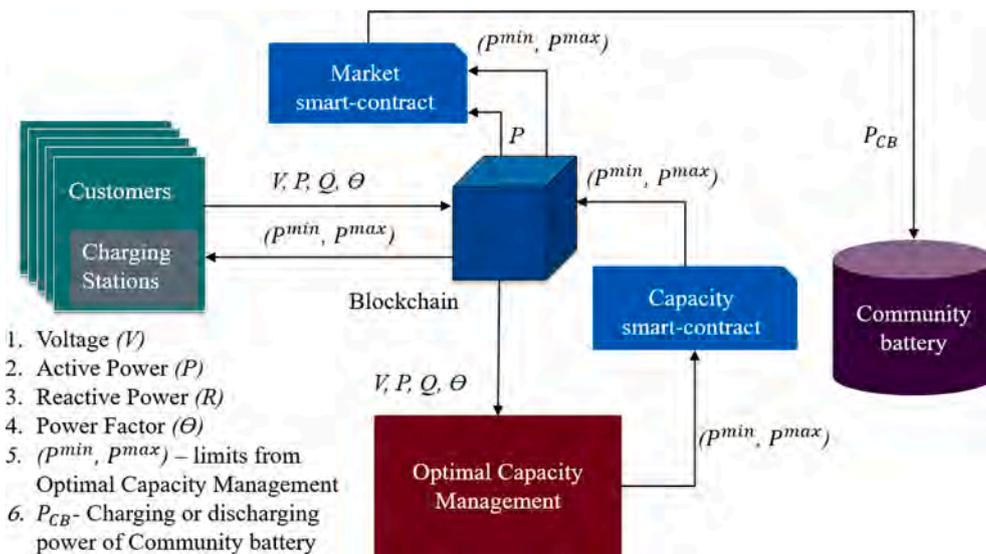


Fig. 4. System architecture of the Blockchain Grid project at the Heimschuh pilot site.

where $P_{c,t}$ are the active powers at the controllable devices and at the time step t . C , represents the set of controllable devices/flexibilities. T is the optimization time horizon. Eq. 2 is minimized and maximized (-minimized) to generate P^{min} and P^{max} values as represented in Eq. 3.

2.2.2. Inequality constraints

Set of inequality constraints $G(x, u)$ in Eq. 1, are described as follows,

Limits on active power of controllable devices, $c \in C$, set of controllable devices and $t \in T$, time horizon,

$$P_{c,t}^{low} \leq P_{c,t} \leq P_{c,t}^{high} \quad (4)$$

Limits on voltage, $\omega \in \Omega$ represents all the buses in the grid,

$$|V_{\omega,t}^{low}| \leq |V_{\omega,t}| \leq |V_{\omega,t}^{high}| \quad (5)$$

Phase shift angles limits,

$$\theta_{\omega}^{low} \leq \theta_{\omega} \leq \theta_{\omega}^{high} \quad (6)$$

Limits on shunt reactances or capacitances,

$$s_{\omega,t}^{low} \leq s_{\omega,t} \leq s_{\omega,t}^{high} \quad (7)$$

Upper limits on active power flow in distribution transformer or lines, between ω 'th and l 'th nodes,

$$P_{\omega,l,t} \leq P_{\omega,l,t}^{high} \quad (8)$$

Limits on voltage angles between ω 'th and l 'th nodes,

$$\Theta_{\omega,t}^{low} \leq \Theta_{\omega,t} - \Theta_{l,t} \leq \Theta_{\omega,t}^{high} \quad (9)$$

P, Q, V and θ are active power, reactive power, voltage and phase shift angle respectively. s is the shunt reactances or capacitances. Θ is the voltage phase angle. (See Fig. 5)

2.2.3. Equality constraints

Load flow results are used as equality constraints $H(x,u)$, as described in the type C class of OPF algorithms. Load flow methods based on numerical techniques are capable of solving a system of nonlinear equations [25]. Convergence of such methods cannot be ensured as the operable solution is directly dependent on the assumed initial seed (starting point or initial condition). If the system has multiple solutions, it becomes difficult to determine whether the converged solution is operable. Therefore, to overcome the limitations of iterative numerical solutions, HELM is used in this research work. The distribution grid is modeled based on the methodology developed in [26].

HELM, described in [25], involves a non-iterative load flow approach which guarantees an operable solution if it exists. Eq. 10 refers to the power balance in the load bus. Inherently, it is non-holomorphic (non-analytical) in nature. A function is said to be holomorphic if it satisfies the Cauchy-Riemann condition.

$$\sum_l Y_{\omega,l} V_l(\alpha) = \frac{\alpha S_{\omega}^*}{V_{\omega}(\alpha^*)} - \alpha Y_{\omega,shunt} V_{\omega}(\alpha), \quad \omega \in \Omega_{PQ} \quad (10)$$

where $Y_{\omega,l}$ is the ω 'th and l 'th element of the series bus admittance matrix. V_l is the voltage at bus ω . Similarly, $Y_{\omega,shunt}$ refers to the shunt admittance matrix. Ω_{PQ} is the set of PQ buses. S represents the apparent power.

By the process of embedding a complex variable α, V becomes a function of this new complex variable. This new function is holomorphic

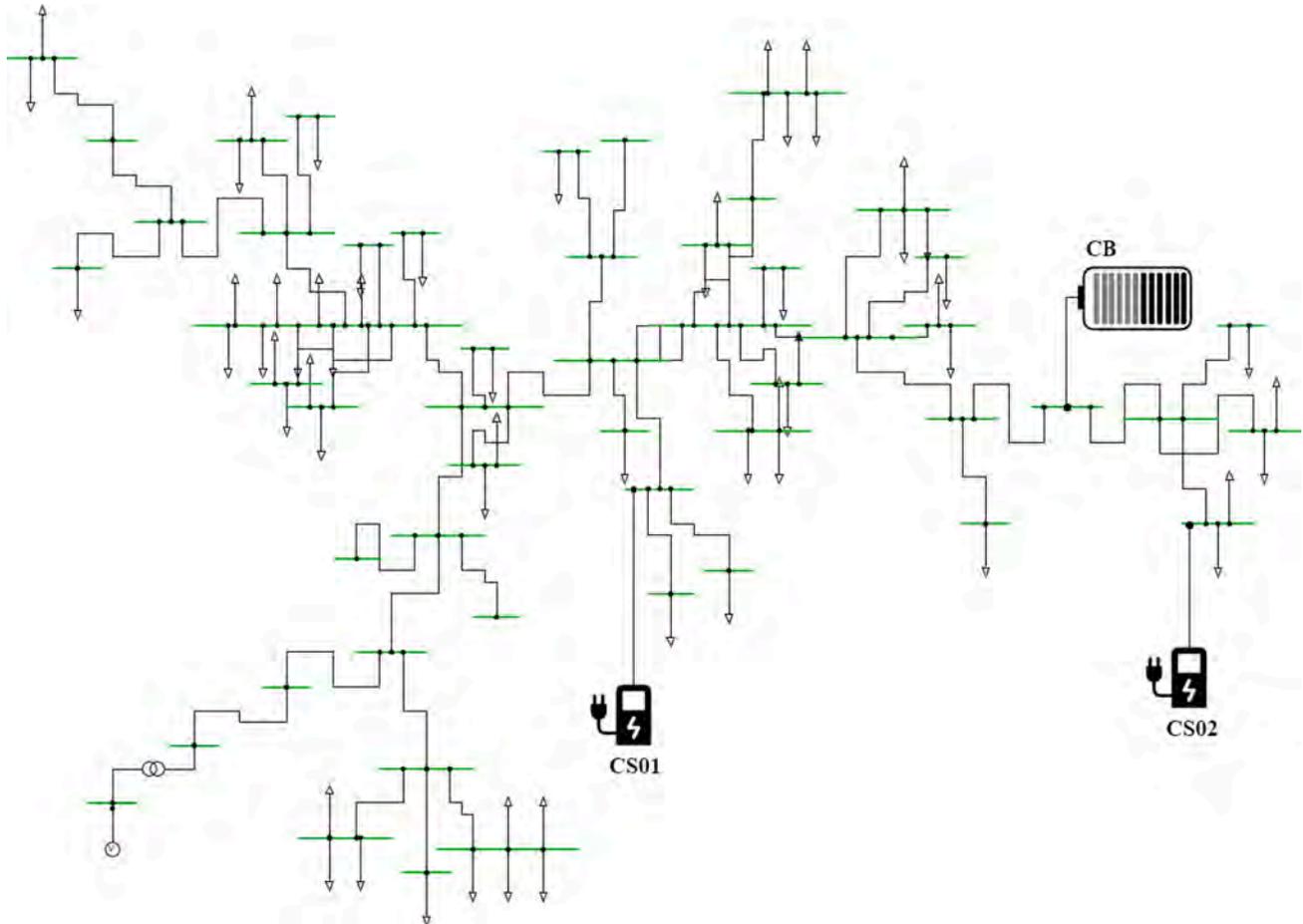


Fig. 5. Topology of the Heimschuh low voltage test feeder.

in nature. If $\alpha = 0$, there is an exact mathematical solution to the problem, but it is not the desired solution. $\alpha = 1$ provides the desired solution. It can be expressed as a power series, specifically as a Taylor or Maclaurin series represented in Eqs. 11 and 12 and which, in-turn, is a function of bus active and reactive power injections. By calculating the coefficients of series, bus voltages can be approximated. This eliminates the use of the computationally expensive Jacobian matrix. For $\alpha = 0$, $S = 0$, Eq. 10 becomes linear and the solution is mathematically exact. In order to use the linear solution, the admittance matrix is split into series and shunt elements.

The term αS is varied to determine the voltage function from $\alpha = 0$ to $\alpha = 1$ and thus, embedding is essential.

$$V_\omega(\alpha) = \sum_{n=0}^{\infty} V_\omega[n]\alpha^n, \quad \omega \in \Omega \quad (11)$$

$$V_\omega^*(\alpha) = \sum_{n=0}^{\infty} V_\omega^*[n]\alpha^n, \quad \omega \in \Omega \quad (12)$$

The coefficients of Maclaurin series are determined using Pade approximation. The Pade approximation gives the rational approximation of a function. It accelerates the convergence with more accurate results with less coefficients. The approximation is valid for over a small domain. In this case, the domain $\alpha = [0, 1]$.

$$H(x, u) = V_\omega = f_{HELM}(P_\omega), \quad \omega \in \Omega \quad (13)$$

Generalized equality constraint is presented in Eq. 13. P_ω is the active power injections at all the PQ (Load) buses.

3. Experimental setup I: Low voltage test feeder

OCM is applied to a low voltage test feeder to demonstrate its effectiveness. The test network consists of five buses. Two uncontrollable loads and two charging stations are connected to it. The topology of the test feeder is presented in Fig. 6. The test feeder consists of only one branch to produce logical and understandable results. Moreover, only loads are included in the feeder to eliminate multi-directional power flows, also leading to an understandable solution.

To validate the generated limiting profiles as described in Section 2.2, the results from the OCM are fed back into the load flow from Section 2.2.3 and Eq. 13, to get the voltage values along with other state and unknown variables. For the sake of simplicity and with a focus on voltage management, the right-hand side of the Eq. 14 (for a low voltage distribution grid with PQ buses) only contains bus voltage magnitudes while voltage angles are not considered.

$$V_\omega = f_{HELM}(P_{UL01}, P_{CS01}, P_{CS02}, P_{UL02}) \quad (14)$$

where $\omega \in \Omega$ represents all the buses in the grid.

Fig. 7.a. represents the limiting profiles ($P_{CS01}^{min}, P_{CS01}^{max}$) and ($P_{CS02}^{min}, P_{CS02}^{max}$), for the two charging stations, respectively. The limits on the two charging stations are, $0kW \leq P_{CS01} \leq 22kW$ and $0kW \leq P_{CS02} \leq 22kW$. It also

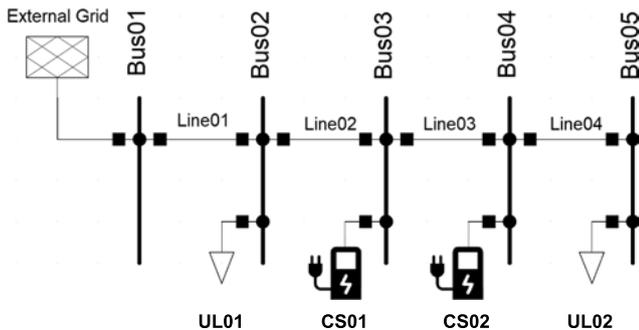


Fig. 6. Topology of the low voltage test feeder.

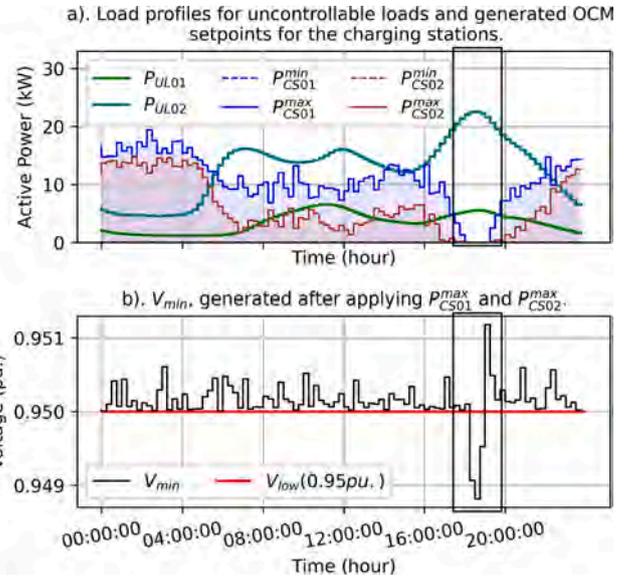


Fig. 7. Limiting profiles generated for the charging stations.

shows the active power profiles for the two uncontrollable loads (P_{UL01}, P_{UL02}). It can be observed that the total maximum available capacity is $P_{CS01}^{max} + P_{CS02}^{max}$ as the voltages are very close to 0.95 pu in Fig. 7.b. This shows that the OCM shares the available capacity between the two charging stations. Since CS01 is closer to the transformer, more capacity is assigned to it. It is also influenced by the two uncontrollable loads and voltage drops across the lines. The flexibility closest to the transformer is naturally able to accommodate more loads and generation and therefore leads to an unfair scenario for the flexibilities at the end of the feeder. The objective function can be modified to make the problem more fair. This is however not included in this paper as the authors are interested in presenting a pure power system solution, without the social factors.

Fig. 7.b is generated using Eq. 14, where $P_{CS01} = P_{CS01}^{max}$ and $P_{CS02} = P_{CS02}^{max}$, and V_{min} is obtained. This represents the worst case scenario with maximum loading. It can be observed that all the voltage values are above V_{low} (0.95pu), as described in Section 2.2.2.

However, in the highlighted region, V_{min} goes below V_{low} , indicating an under-voltage violation. Only V_{min} (under-voltage violation) is provided since there is no in-feed considered in this test scenario, which could lead to a over voltage violation.

This is caused due to high loading on P_{UL01} (an uncontrollable load). OCM reduces the P_{CS01}^{max} and P_{CS02}^{max} values to 0 to counter the increased loading. Since the charging station values cannot go below 0 (start injecting), voltage violations will sustain. This can be rectified with electric storage, which can take both positive and negative values.

Recalling from Section 2, as long as $P_{CS01}^{min} \leq P_{CS01} \leq P_{CS01}^{max}$ and $P_{CS02}^{min} \leq P_{CS02} \leq P_{CS02}^{max}$ holds, no voltage violations can occur.

In Fig. 8.d, V_ω values are obtained by considering random values for P_{CS01} (see Fig. 8.a) and P_{CS02} (see Fig. 8.b) while maintaining $P_{CS01}^{min} \leq P_{CS01} \leq P_{CS01}^{max}$ and $P_{CS02}^{min} \leq P_{CS02} \leq P_{CS02}^{max}$, respectively.

It can be observed that as long as the limiting profiles are considered by the flexibility, no voltage violations occur. Similarly, as previously explained, in the highlighted region, under-voltage violations are observed.

4. Experimental setup II: Heimschuh pilot site feeder

Heimschuh is a town in the federal state of Styria, Austria, with the largest concentration of PV installations (200 kWp installed generation capacity) in the grid owned by the Energienetze Steiermark GmbH, a DSO responsible for management of the Styrian distribution grid. The power generation is mostly concentrated on one low voltage feeder. The

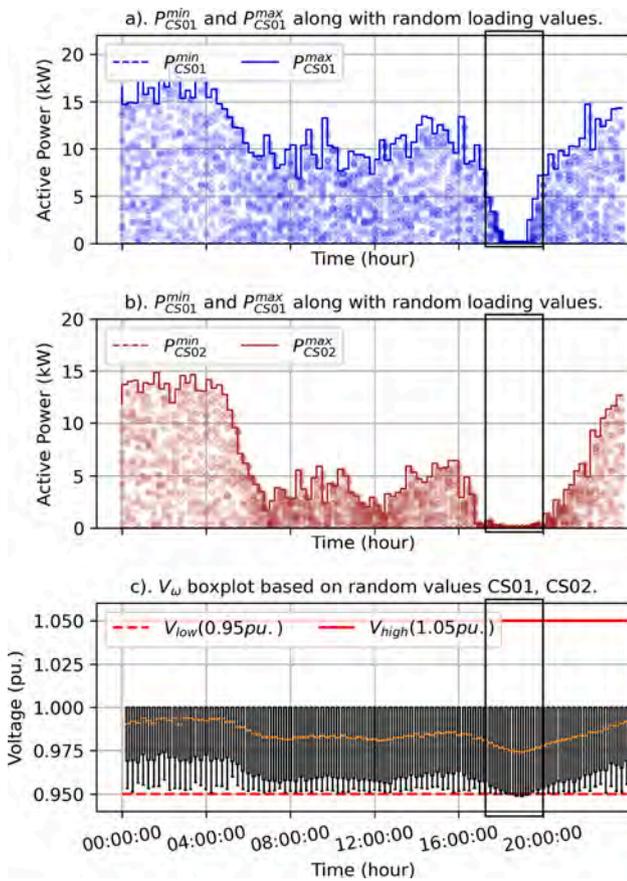


Fig. 8. Random values for P_{CS01} and P_{CS02} while observing the limiting profiles and the corresponding V_w boxplots for each time step based on Eq. 14.

generated PV power is straining the grid and it is at its capacity limit. Therefore, the additional 50 kWp of PV installations and a micro-CHP cannot be connected to the grid without grid reinforcement or a smart grid solution with active generation load management.

There is a large utility sized battery on site with 100 kWh of community electric storage (see Fig. 9). A number of buildings/households are involved in the project demonstration. Twenty-one single or multi-family home customers are participating, all of which are fitted with controllers and measurement devices. Other customers are involved passively with measurements collected from smart meters for modeling and validation. OCM algorithm is running on an industrial computer installed inside the container where community electric storage is located (see Fig. 9).

For the Heimschuh pilot site, the OCM objective presented in Section



Fig. 9. Community battery located at the Heimschuh pilot site in Styria, Austria.

2.2 is modified into a two step optimization problem. As the community battery is part of the LEC and community members own a share of the battery capacity as part of LEM, priority is first given to the community battery above any other flexibility participating in the community. OCM is connected to the blockchain network and receives measurements from customers who part of the pilot and transformer located at the secondary substation.

The modified two step OCM is presented in Eqs. 15 and 16.

$$F_{CB}(x, u) = \sum_{t \in T} (P_{CB,t}) \tag{15}$$

where $F_{CB}(x, u)$ is the community battery objective function. $P_{CB,t}$ is the active power of the community battery. $(P_{CB,t}^{min}, P_{CB,t}^{max})$ is generated using the Eq. 3.

$$F_{CS}(x, u) = \sum_{t \in T} \sum_{CS \in C} (P_{CS,t}) \tag{16}$$

where $F_{CS}(x, u)$ is the charging station objective function. CS_t is the active power of the two charging stations. $CS \in C$ represents the set of flexibilities (two charging stations). $(P_{CS,t}^{min}, P_{CS,t}^{max})$ is generated using the Eq. 3.

Similarly to the low voltage test feeder in Section 3, limiting profiles are generated for the three flexibilities in the pilot site for each sample time of 1 min. This can be observed in Fig. 11.a. and.b. V_{min} is generated when $P_{CS01} = P_{CS01}^{max}$ and $P_{CS02} = P_{CS02}^{max}$ and $P_{CB} = P_{CB}^{max}$ and can be observed in Fig. 11.d. As expected, V_{min} are located around V_{low} (0.95pu). V_{max} is generated when $P_{CS01} = P_{CS01}^{min}$ and $P_{CS02} = P_{CS02}^{min}$ and $P_{CB} = P_{CB}^{min}$. This is the least loading or power injection condition. It can be observed that there is capacity left over to accommodate more power

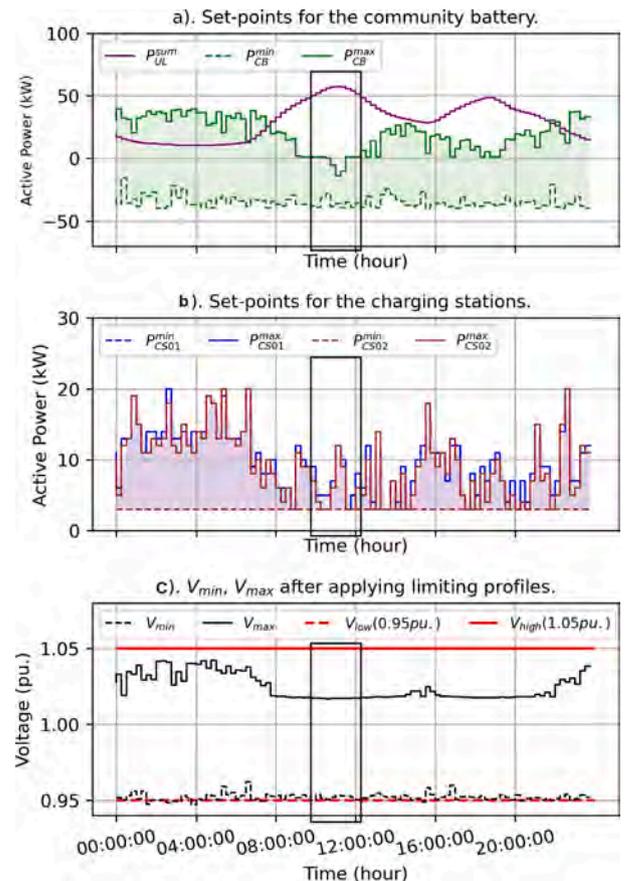


Fig. 10. Limiting profiles for the community battery and the two charging stations, similar to Fig. 7.

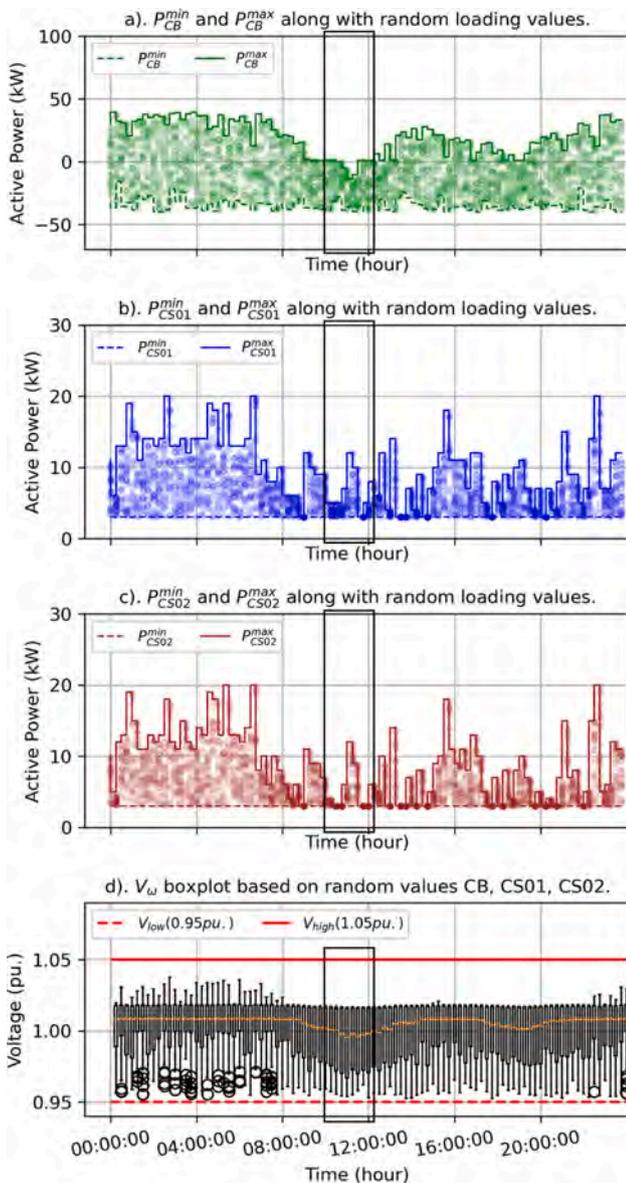


Fig. 11. Random values for P_{CB} , P_{CS01} and P_{CS02} while observing the limiting profiles and the corresponding V_{min} boxplots for each time step based on Eq. 14. Voltage reference at the transformer is at 1.01 pu.

injection into the grid. However, to accomplish this, in the highlighted region in Fig. 11.a, the community battery had to momentarily discharge. This is attributed to high loading conditions observed in the feeder P_{UL}^{sum} , which is the sum of all uncontrollable loads. With the necessary discharge, and having both P_{CS01} and P_{CS02} , close to zero kW, the voltages in Fig. 11.c are clustered around the 0.95 pu. limit. Therefore, by actively managing the low voltage distribution grid with a community battery, more PV or generators can be hosted.

Similar to Fig. 8, V_{ω} values are calculated by considering random values for P_{CB} (see Fig. 11.a), P_{CS01} (see Fig. 11.b) and P_{CS02} (see Fig. 11.c). V_{ω} values are in-between the prescribed limits as mentioned in Section 2.2.2. $V_{\omega} \leq 1pu$ because, there are no power injections in the feeder.

5. Conclusion

In order to facilitate the market settlement process, OCM was presented. OCM is used to generate limiting profiles (P_t^{min} and P_t^{max}) values at all the flexibilities in a LEC, participating in the LEM. The flexibilities are required to operate within these limits to avoid voltage violations.

By doing so, the bids in the market are preemptively grid secure and, when executed, will not lead to power quality issues. OCM and its relation to blockchain LEM was presented along with the system architecture. OCM is based on OPF type C using a non-linear non-convex solver, GA, wrapped around a reliable load flow, HELM. This method was tested using a low voltage test feeder, and a detailed explanation of the results was provided. It was proved in both experimental setups that when the limiting profiles are applied and the flexibilities are operated within its limits, voltages at all the buses will remain within the prescribed (+5, -5%) pu. voltage. This is observed in Figs. 8 and 11. However, if the flexibilities are not able to respect the limits, the voltage constraints cannot be fulfilled and is observed in Fig. 7. Based on the test feeder's learning, the method was applied to a real pilot feeder from Heimschuh, Austria. It was proven in Fig. 11, that no voltage violations will be observed as long as the limits were observed.

5.1. Future research

In this paper, only voltage violations are mitigated. In the future, the algorithm will be adapted to include line loading constraints. Since the OCM uses a non-linear, non-convex optimization solver, it is numerically expensive to calculate the global optimum. Therefore, for field deployment, machine learning models will be trained to behave like the OCM based on real and simulated data from the field and simulations, respectively. The machine learning model will be deployed in the field to cope with the low sampling time.

CRediT authorship contribution statement

Bharath Varsh Rao: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Mark Stefan:** Methodology, Validation, Formal analysis, Writing - original draft, Writing - review & editing, Project administration. **Thomas Brunnhofer:** Methodology, Software, Writing - review & editing. **Roman Schwalbe:** Methodology, Software, Writing - review & editing. **Roman Karl:** Methodology, Software, Writing - review & editing. **Friederich Kupzog:** Conceptualization, Validation, Investigation, Writing - review & editing. **Gregor Taljan:** Methodology, Validation, Data curation, Writing - review & editing, Project administration. **Franz Zeilinger:** Methodology, Validation, Writing - review & editing. **Peter Stern:** Methodology, Validation, Data curation, Writing - review & editing. **Martin Kozek:** Conceptualization, Validation, Investigation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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