Resilience Enhancement of Urban Energy Systems via Coordinated Vehicle-to-grid Control Strategies

Lascelle Mauricette, *Student Member*, *IEEE*, Zihang Dong, Linan Zhang, Xi Zhang, *Member*, *IEEE*, Ning Zhang, *Senior Member*, *IEEE*, and Goran Strbac, *Member*, *IEEE*, *Fellow*, *CSEE*

***Abstract*—Coordinated vehicle-to-grid (V2G) control strategies can sustain essential loads of an energy system during islanding, thereby increasing resilience. In this context, this paper investigates the resilience enhancement benefits of smart V2G control, the value of electric vehicle (EV) owner cooperation on system resilience, as well as the complementary effects of PV and EV interaction in an urban multi-energy microgrid (MEMG). By using a rolling horizon approach to optimize day-ahead operation of the MEMG and subsequently dispatching EVs, uncertainties in outage start time, EV arrival/departure times, and initial state of charge (SOC) are mitigated. Results show that smart V2G control can provide a substantial essential load curtailment reduction compared to a non-EV scenario, meanwhile, non-coordinated grid-to-vehicle (G2V) operation was shown to slightly burden the system with a slight increase in non-essential load curtailment. Investigations into the influence of EV cooperation on resilience showed that a high percentage of system-prioritized (SP) EVs could help greatly further reduce essential load curtailment compared to individual-prioritized (IP) EVs. Finally, the complementary benefits of smart V2G control and PV were demonstrated, showing a reduction in both PV and essential load curtailments with increasing numbers of EVs. Overall, the application of smart V2G control, especially with cooperation of EV owners, can drive significant resilience enhancement during islanding, while further benefits can be obtained through having a sufficient number of EVs to utilize high PV penetration.**

***Index Terms*—Multi-energy system, renewable energy sources, resilience, rolling horizon optimization, vehicle-to-grid.**

I. INTRODUCTION

CLIMATE change is leading to an increasing number of high-intensity low-probability (HILP) events which can cause disruptions to our energy systems. Meanwhile, to shift reliance from fossil fuels which drive anthropogenic climate change, electrification of our energy systems is necessary and alternative, often renewable, distributed energy resources (DERs) are required. However, the stochastic natures of DERs such as wind turbines and PVs are leading to growing pressure on the electric power system (EPS) to supply loads under uncertain conditions. Despite this challenge in utilizing DERs, following HILP events that result in islanding, local networks can be operated as microgrids to control local resources and supply local loads — providing a valuable resilience benefit over traditional long-distance transmission. In this context, as distributed and increasingly widespread local resources, electric vehicles (EVs) will play a crucial role in enhancing resilience during islanding through the provision of vehicle-to-grid (V2G) services [1], [2].

Manuscript received August 3, 2022; revised November 10, 2022; accepted November 21, 2022. Date of online publication December 9, 2022; date of current version January 10, 2023. This work was supported by the UK Engineering and Physical Sciences Research Council (EP/L015471/1; EP/R045518/1).

L. Mauricette, Z. H. Dong (corresponding author, email: zihang.dong14@imperial.ac.uk), L. N. Zhang, and G. Strbac are with the Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, United Kingdom.

X. Zhang is with the Department of Grid Digitalization Technology, State Grid Smart Grid Research Institute Co., Ltd, Beijing 102209, China.

N. Zhang is with the State Key Lab of Power Systems, Department of Electrical Engineering, Tsinghua University, Beijing 100084, China.

DOI: 10.17775/CSEEJPES.2022.05270

Approaches to quantify the resilience of a system vary across literature — references [3] and [4] discuss how resilience can be a combination of physical, price and geopolitical security and described in terms such as people served, economic activity, availability of critical infrastructure, and load served. Meanwhile, references [1] and [5] employ the concepts of resilience triangles and trapezoids which assess resilience across multiple stages of a disruption.

Only limited research has been focused on resilience enhancement provided by microgrids [6]–[11]. Amirioun *et al*. [6] proposed a framework to quantify resilience for electric-only microgrids immediately following islanding, while Gouveia *et al*. [7] coordinated frequency and demand response to improve resilience. Duo Shang [8] also focused solely on an electricity-based microgrid, but from an economic perspective to determine effective market pricing strategies. Hussain *et al*. [9] used robust optimization to guarantee feasible islanding against sudden power disruptions. Increase in operation cost was negligible compared to the significant increase in resilience obtained in their case studies, however, their approach to always be on alert may not be economically feasible for many microgrid configurations. Gholami *et al*. [10] increased resilience against anticipated upcoming disruptions, based on likely scenarios which were generated from stochastic probability distribution functions. However, this approach is limited to scenarios with access to highly accurate data.

Balasubramaniam *et al*. [11] used corrective control to scheduled resources to reduce essential load shed for scenarios up to the 95% confidence intervals for demand and renewable generation. Two strategies were used — one where scheduling was determined at the start of the disruption, and a second where scheduling was continually updated at each 5-minute dispatch. Counterintuitively, it was found the schedule

2096-0042 © 2022 CSEE

determined at the start outperformed the continuously updating schedule. This may highlight the importance of careful and effective rolling horizon control.

Each of the above references neglect to consider the value of EV dispatch strategies in improving microgrid resilience, while many diverse V2G dispatch strategies have been shown to facilitate operational benefits [12]–[17]. In [12] a decentralized approach was used to dispatch EVs, considering multiple optimization priorities such as cost, state of charge (SOC), power system contingency and load levelling. In [13] game theory was used to optimally control networked charging stations. In [14] deep reinforcement learning was used to optimally schedule decentralized EVs under uncertainty. Hussain & Kim [15] compared different multi-objective optimization techniques for energy allocation during disruptions and it was found that a genetic algorithm had the lowest performance while carrying a high computational complexity, highlighting the caution required when using machine learning techniques. Meanwhile, the lexicographic approach had the best performance when accurate information was available. Wang *et al*. [16] considered EV routing strategies to optimally distribute EVs in networked microgrids, while Zhou *et al*. [17] proved the feasibility of obtaining cooperation of owners and accurate EV information by developing a mobile app able to efficiently operate on a city scale.

Consideration of multiple energy vectors has been shown to enable economic and resilient operation [18]–[27]. In a multi-energy microgrid (MEMG), the EPS can convert electricity to heat and cooling, the heat network can shift consumption between electricity and gas, both heat and cooling loads can shift electricity consumption temporally, and the gas network can enable electricity and heat generation independent of the utility grid often through low emission biogas [18], and transport, through V2G services can supply electricity and shift demand [19]. The benefits of considering multiple energy vectors are quantified in [20] where it was found that a hybrid electricity-hydrogen approach could significantly reduce yearly costs in the order of billions per annum. References [21]–[23] also assessed the advantages of multi-energy systems and demonstrated reduced cost and increased resilience of supply, while references [24]–[27] focused on the optimal operation and design of multi-energy systems. However, to the best of our knowledge, none of the existing research has considered multi-energy integrated into a V2G-focused resilience framework.

Given that multiple energy vectors increase system flexibility and there are still gaps between existing works and the resilience benefits of V2G control, dispatch strategies and cooperation of EV owners, this paper extends the conference paper [28] and is dedicated to assessing these benefits through the lens of an urban multi-energy microgrid.

Compared to existing works, key contributions of the proposed work are summarized as follows:

1) It assesses the value of coordinated V2G services in enhancing resilience of urban energy systems. Specifically, the resilience-driven response capabilities of numerous EVs during disruptive events are aggregated and fit into a rolling horizon optimization framework. Additionally, a complementary EV dispatch strategy is proposed to realize resiliency-oriented operation based on the optimization results.

2) It uniquely considers the effect of EV owners' willingness to support system operation on resilience. Specifically, the impact of the ratio of system-prioritized (SP) EVs to individual-prioritized (IP) EVs on resilience, is assessed.

3) It investigates the complementary benefits of V2G services and PVs for increasing resilience and reducing PV curtailment. Specifically, the effect of the number of EVs in the microgrid on PV and essential load curtailment is evaluated.

The rest of the paper is organized as follows: Section II presents an overview of the MEMG operation, while also showcasing the methodology for modeling individual and aggregate EVs, Section III details the rolling day-ahead optimization of the MEMG, including rolling EV dispatch strategies and the classification of EV owners' cooperability status. Section IV presents and discusses case studies aimed at assessing the benefits of the three main contributions listed above and finally conclusions and future works are discussed in Section V.

II. Modeling and Formulation

A. Multi-Energy Microgrid System with V2G Services

Deep electrification of various urban energy loads establishes fundamental links between different energy carriers, bringing opportunities for flexibility sharing across multiple urban energy sectors. MEMGs, in this context, play an important role in facilitating the synergies of diversified local energy sources through appropriate smart control strategies, and thereby enhancing resilience of urban energy systems.

Figure 1 demonstrates the conceptual MEMG framework investigated in this work, where various distributed resources in multi-energy vectors, e.g., electricity, heat, gas, and transport, are considered. In normal operational conditions, the MEMG is connected with the utility grid through the point of common coupling (PCC) and interacts with the upstream electricity system by trading energy and providing system services, etc. If there is a contingency, the MEMG can operate in islanded mode to alleviate the operational strains of the utility grid while the energy management system (EMS) manages to autonomously maintain uninterrupted, or optimally deliver compromised, supply of local loads [29]. The predicted occurrence of the disruptive event resulting in the MEMG switching from normal mode to islanded mode is normally within a time interval, but this paper adopts the earliest possible contingency time for robustness purposes. Although this conservative prediction may increase economic cost, it can provide better supply to the local demand.

Due to backup of the utility grid, local generation resources are typically not able to fully cover local demand. Therefore, in islanded mode, it is necessary to differentiate the criticality of different loads so that adverse impacts of disruptive events can be mitigated by prioritizing the supply of essential loads with limited local resources. In this context, smart control, enabling preventive preparation prior to the occurrence of disruptive events to drive seamless islanding, and exploitation

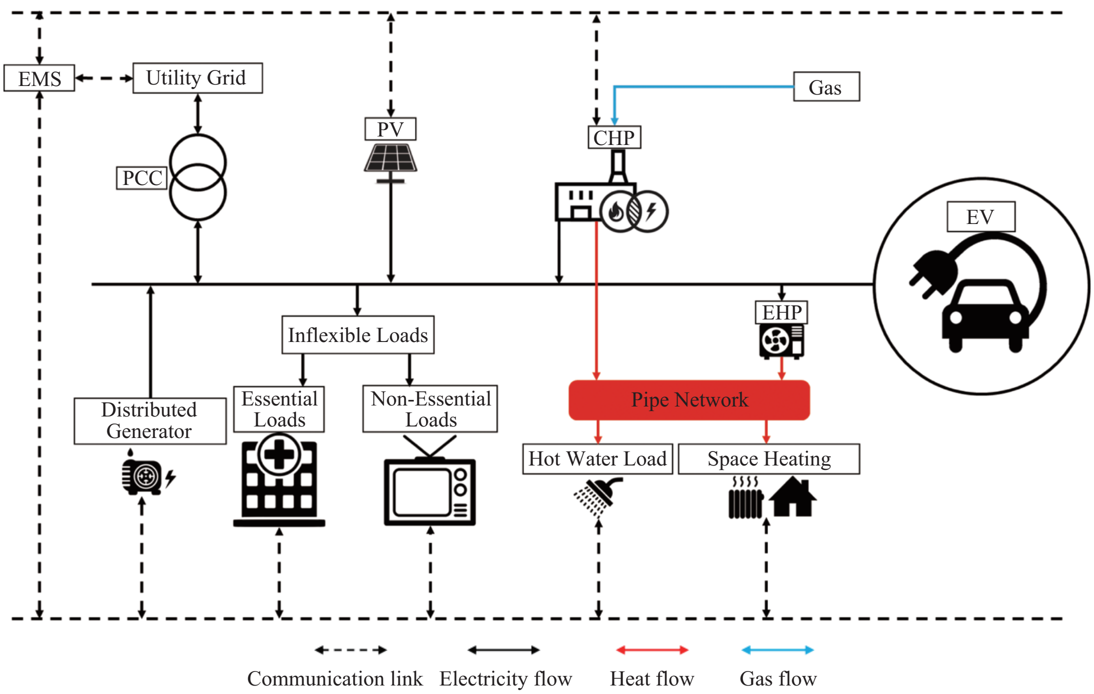


Fig. 1. Diagram of the fictional multi-energy microgrid, located in London, UK.

of flexibility of the MEMG to prioritize the supply of essential load is critical in optimizing the resiliency-oriented operation of MEMGs.

The availability of local energy sources e.g., PV, combined heat and power generation (CHP), and distributed generation, as well as local flexibility e.g., pipe storage that can temporally shift inflexible generation, fundamentally determines the resiliency level of a MEMG. As the focus of this work is the resilience enhancement value of V2G services, the pipe network and buildings are unable to store energy and smart loads are not considered. Since EVs carry considerable amounts of energy and can serve as storage through V2G services, they are characterized as both sources of energy and flexibility, qualifying them to be promising candidates for enhancing system resilience. Although their increasing penetration due to tighter emission regulations and decreasing costs makes the utilization of EVs a cost-effective option for supporting the resilient operation of urban energy systems [30], they present some challenges in their use. Design of an effective V2G coordination algorithm can alleviate problems such as increased loads, increased uncertainty, greater control computation burdens, a changing system dynamic to decentralized distribution, uncertainties in availabilities, diversified customer preferences, and necessity of aligning individual benefits and system interests. However, additional challenges associated with larger reliance on power electronics, increased communication resources, and increased contract costs to provision use of these EV services are problems beyond the scope of this paper and deserve study in their own right.

A general definition of resilience can be stated as "the ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such events" [30]. Load curtailment when analysed temporally and categorized into essential and non-essential is a suitable variable to quantify magnitude (amount and criticality) and duration under different operational measures which may impact the ability of the microgrid to anticipate, absorb, adapt to, and rapidly recover from an outage.

A comparative analysis of similar works verifies the suitability of approaches used in this paper. According to Silvente *et al.* [31], approaches to address uncertainty in scheduling problems can be classified as either proactive or reactive. The former usually consists of robust and stochastic methods, which may be overly conservative or incur significant computational costs, especially in the stochastic case. Reactive approaches focus on modifying a schedule, often in response to updated system information. By combining both approaches in the form of a robust rolling horizon approach, we retain the benefits of a robust approach, while ensuring we reduce conservatism as we gain updated information. Regarding EV aggregation, Gouveia *et al.* [7] aggregated EVs into a single homogenous battery. Though their approach was suitable in their work, using this approach to represent a large number of diverse EVs with different states of charge, preferences, and joining/departing times etc., introduces some accuracy problems. Conversely, [32] models each EV and its system interactions individually. However, this would become computationally infeasible with large numbers of EVs. Our approach, which combines the benefits of those aforementioned, converts the EVs to an aggregate battery to reduce complexity, while including aggregate constraints to limit the operation to that which is feasible. Additionally, real-time dispatch at each timestep ensures that EVs are updated on an individual level to preserve model accuracy.

B. Individual EV Modeling

1) Normal Operation Mode

The feasible operating region of a single EV providing V2G services is demonstrated in Fig. 2. Specifically, the operation of each EVi can be described by a series of parameters including plug-in time t_i^{in}, plug-out time t_i^{out}, initial state of charge SOC_i^{ini}, expected state of charge before leaving SOC_i^{exp}, and minimum/maximum state of charge $SOC_i^{\min}/SOC_i^{\max}$. The feasible SOC region is defined by these parameters as shown in Fig. 2. Three V2G-associated actions comprising charging, idling, and discharging are represented by upwards, rightwards, and downwards arrows. Considering the dynamics of EV battery operation, five scenarios are distinguished in Fig. 2. Red arrows represent actions that violate physical limits associated with battery capacity; blue arrows represent violations of customers' requirements; green arrows represent violation-free actions.

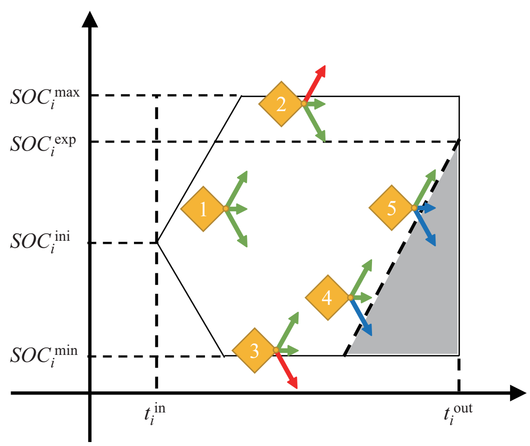


Fig. 2. Operational limits, scenarios (1-5), and actions (arrows) for an EV.

2) Islanded Operation Mode

In islanded operation mode, local generation sources may not be able to supply all local demand; in this case, EVs will be requested to compromise their own energy supplies to prioritize maintenance of essential load. During islanding, EVs must still operate within the physical limits ($SOC_i^{\min}$ and $SOC_i^{\max}$), but their willingness to compromise their energy supply should be categorised into two cases, which must be willingly contracted to protect EV owners' rights:

Individual-prioritized (IP) operation: In this case, individual customers are unwilling to share their energy for system benefits when their own preference of SOC is not satisfied as a result of idling or discharging actions. Reaching the preferred SOC is compromised if the SOC enters the shaded region (bounded by the dashed line with a slope equal to the charging rate), as shown in Fig. 2. Depending on how close the SOC is to entering the shaded region, we can define two scenarios, 4 and 5, to prevent entering this critical region. In scenario 4, discharging will cause the SOC to enter the shaded region in the next timestep and violates the customers' requirements but charging and idling are allowed. In scenario 5, the current SOC is closer to the shaded region, so both idling and discharging are prohibited actions that would cause the SOC to enter the shaded region and violate the customers' requirements.

System-prioritized (SP) operation: In this case, individual customers prioritize system benefits, e.g., reduce the curtailment of essential load, by sharing their energy, disregarding their own preferences. Unlike IP operation, where idling and discharging are constrained to avoid violating the customers' requirements, the actions of EVs in scenarios 4 and 5 are unconstrained and the EV is allowed to be operated within the shaded area, as shown in Fig. 2. Note to protect owners' rights, only limited EV information such as scenario number and a single dispatch metric, later described in Section III-B, will be required to be shared with the microgrid's central controller. In addition, rarity of these disruption events alleviates both privacy and battery health right concerns, which can pose a large problem during frequent use [33]. An appropriate market mechanism is essential to incentivize individual EVs to align their interests with the operator and perform SP operation and reduce their rights and priority during disruptions [34]. This will also increase complexity for the central controller, but the associated economic compensation is omitted as it is out of the scope of this paper.

Table I summarizes the relationships between EV types with SOC scenarios and actions.

TABLE I
EV SOC SCENARIOS AND THEIR FEASIBLE ACTIONS

Scenario	Individual-Prioritized			System-Prioritized		
	Charge	Idle	Discharge	Charge	Idle	Discharge
1	√	√	√	√	√	√
2	×	√	√	×	√	√
3	√	√	×	√	√	×
4	√	√	$\underline{\times}$	√	√	$\underline{\surd}$
5	√	$\underline{\times}$	$\underline{\times}$	√	$\underline{\surd}$	$\underline{\surd}$

Underscoring highlights the key differences between individual-prioritized and system-prioritized operation modes.

C. Aggregate Characteristics of Numerous EVs

1) Aggregate Response Capability

The aggregate response capability of EVs is defined as the ability of providing/absorbing extra power at a particular timestep in response to system requirements during contingencies. It is dependent on the real-time SOC of EVs, i.e., the five predefined scenarios. For an individual EV, if its current SOC allows it to charge/discharge, then the upper/lower bounds of its instantaneous response capability are P_i^c/P_i^d. Since numerous EVs can be integrated into a MEMG, it is essential to evaluate their collective response capability, i.e., the maximum combined charging/discharging power $\overline{P}_t/\underline{P}_t$ of all plugged-in EVs, when providing resilience-associated services during disruptive events.

Denote the set of individual-prioritized EVs by I_t^{IP} and the set of system prioritized EVs by I_t^{SP}. Accordingly, the set of all plugged-in EVs are $I_t = I_t^{\text{IP}} \cup I_t^{\text{SP}}$, where $\cup$ represents the union of the two sets. The SOC scenario is represented by the subscript of the EV sets, e.g., $I_{t,\text{k}}^{\text{IP}}$ is the set of individual-prioritized EVs in scenario $k \in \{1, 2, 3, 4, 5\}$. Then the upper bound of the response capability can be formulated in (3).

$$\overline{P}_t^{\mathrm{IP}} = \sum_{i \in I_t^{\mathrm{IP}} \setminus I_{t,2}^{\mathrm{IP}}} P_i^c \tag{1}$$

$$\overline{P}_t^{\mathrm{SP}} = \sum_{i \in I_t^{\mathrm{SP}} \setminus I_{t,2}^{\mathrm{SP}}} P_i^c \tag{2}$$

$$\overline{P}_t = \overline{P}_t^{\mathrm{IP}} + \overline{P}_t^{\mathrm{SP}} \tag{3}$$

where $\setminus$ denotes exclusion from a set, while the lower bound of the response capability is calculated in (6).

$$\underline{P}_t^{\mathrm{IP}} = \sum_{i \in I_{t,1}^{P} \cup I_{t,2}^{\mathrm{IP}}} -P_i^d + \sum_{i \in I_{t,5}^{\mathrm{IP}}} P_i^c \tag{4}$$

$$\underline{P}_t^{\mathrm{SP}} = \sum_{i \in I_{t,1}^{\mathrm{SP}} \cup I_{t,2}^{\mathrm{SP}} \cup I_{t,4}^{\mathrm{SP}} \cup I_{t,5}^{\mathrm{SP}}} -P_i^d \tag{5}$$

$$\underline{P}_t = \underline{P}_t^{\mathrm{IP}} + \underline{P}_t^{\mathrm{SP}} \tag{6}$$

Note the aggregate response capability of the next timestep is accurate since it is calculated based on current SOC. However, since a specific EV dispatch is carried out in real-time, calculation of the response capability in the future has to be revised considering information updates, therefore, rolling horizon optimization ideally suits the modeling requirements and is introduced in more detail later.

2) Aggregate EV Energy

Considering all plugged-in EVs, aggregate EV energy E_t^{EV} is expressed in (7), while the upper and lower limits for E_t^{EV} are formulated as (8) and (9) respectively:

$$E_t^{\mathrm{EV}} = \sum_{i \in I_t} SOC_{i,t} Cap_i, \ t \in \boldsymbol{T} \tag{7}$$

$$\underline{E}_t = \sum_{i \in I_t} SOC_i^{\min} Cap_i, \ t \in \boldsymbol{T} \tag{8}$$

$$\overline{E}_t = \sum_{i \in I_t} SOC_i^{\max} Cap_i, \ t \in \boldsymbol{T} \tag{9}$$

$$\underline{E}_t \le E_t^{\mathrm{EV}} \le \overline{E}_t \tag{10}$$

Since the number of plugged-in EVs is constantly changing due to the arrival of new EVs and departure of existing EVs, it is necessary to quantify the impacts of EVs joining/leaving on variations of aggregate EV energy.

For this purpose, we denote the set of plugging-in EVs at time t by I_t^{in} and the set of plugging-out EVs at time t by I_t^{out}. To this end, the variations of EV energy in the sets I_t^{in} and I_t^{out} are calculated as:

$$E_t^{\mathrm{in}} = \sum_{i \in I_t^{\mathrm{in}}} SOC_i^{\mathrm{ini}} Cap_i \tag{11}$$

$$E_t^{\mathrm{out}} = \sum_{i \in l_t^{\mathrm{out}}} SOC_{i,t} Cap_i \tag{12}$$

Additionally, to facilitate EV charging operation so as to meet customer requirements, EV energy curtailment $E_t^{\mathrm{ct,EV}}$ is defined as the aggregate energy shortage between expected and actual SOC at plugging-out time, viz.,

$$E_t^{\mathrm{ct,EV}} = E_t^{\mathrm{ct,EV_{IP}}} + E_t^{\mathrm{ct,EV_{SP}}} \tag{13}$$

where the energy curtailment of two types of EVs are expressed as:

$$E_t^{\mathrm{ct,EV_{IP}}} = \sum_{i \in I_t^{IP,\mathrm{out}}} \left(SOC_i^{\exp} - SOC_{i,t}\right) Cap_i$$

$$E_t^{\mathrm{ct,EV_{SP}}} = \sum_{i \in I_t^{\mathrm{SP,out}}} \left(SOC_i^{\exp} - SOC_{i,t}\right) Cap_i$$

with $I_t^{\mathrm{IP,out}}$ and $I_t^{\mathrm{SP,out}}$ representing the set of individual-prioritized and system-prioritized plugging-out EVs, respectively.

III. Rolling Day-Ahead Microgrid Scheduling

A. Day-Ahead Optimization

At subsequent discrete timesteps across the day, day-ahead optimal operation of the aggregated EVs and the rest of the microgrid is calculated using robust intervals for uncertain data, while the rolling horizon approach allows the current timestep to utilize near to real-time data, mitigating uncertainties and inherent conservativeness related to arrival and departure times, outage occurrence and PV generation. Following this calculation, actual real-time operation follows the first timestep of the day-ahead optimization which is performed using current information, while decisions for real-time dispatch of energy sources and updates of aggregated EV response capability are calculated based on aggregate EV discharge during this first timestep. The framework of the optimization is formulated as a mixed-integer linear programming (MILP) problem, with decision variables $\{P$, P^{EV_c}, P^{EV_d}, u, v, P^{EV}, E^{EV}, $E^{\mathrm{ct,EV}}$, $E^{\mathrm{ct,EV_{IP}}}$, $E^{\mathrm{ct,EV_{SP}}}$, $E^{\mathrm{ct,EL}}$, $E^{\mathrm{ct,NEL}}\}$ presented as follows.

1) Objective of the Day-Ahead Optimization Problem

The priority list in the framework of resilience enhancement is minimizing curtailment of essential loads (EL), EV loads, non-essential loads (NEL), and minimizing operational costs. Based on this list, the objective function is formulated as:

$$\text{Objective} = \sum_{t \in T} \Big[c^{\mathrm{EL}} E_t^{\mathrm{ct,EL}} + c^{\mathrm{NEL}} E_t^{\mathrm{ct,NEL}} + \rho P_t \Delta t + C_t^{\mathrm{ct,EV}} \Big] \tag{14}$$

where $E_t^{\mathrm{ct,EL}}$ and $E_t^{\mathrm{ct,NEL}}$ represent the curtailment of essential and non-essential loads, while $\mathrm{c^{EL}}$ and $\mathrm{c^{NEL}}$ are the associated weighting coefficients. ρ is energy price while $P_t \Delta t$ is energy consumption for timestep Δt and their product represents operation costs.

Particularly, the cost of EV load curtailment $C_t^{\mathrm{ct,EV}}$ is composed of two elements for IP and SP EVs, as given in (15).

$$C_t^{\mathrm{ct,EV}} = C_t^{\mathrm{ct,EV_{IP}}} + C_t^{\mathrm{ct,EV_{SP}}} \tag{15}$$

For the curtailment of IP EV load, the associated cost is formulated as (16):

$$C_t^{\mathrm{ct,EV_{IP}}} = c^{\mathrm{EV_{IP}}} E_t^{\mathrm{ct,EV_{IP}}} \tag{16}$$

The situation of the curtailment of SP EVs is more complicated.

From the system perspective, in order to retain more energy for local use, it is desired that departing EVs do not take any energy away. To achieve this goal, the system operator should fully exploit the energy in SP EVs to maximize their contributions for essential load maintenance. In this context, we define $I_t^{\mathrm{SP}_d}$ as the set of SP EVs that should discharge at the current timestep to minimize the energy removed from the system by departing EVs.

Specifically, $I_t^{\mathrm{SP}_d}$ is a subset of I_t^{SP} that includes SP EVs that would enter the shaded region in the next timestep by charging or idling and is determined based on the assumption that SP EVs try to drain their energy (reach $SOC_i^{\min}$) by discharging before t_i^{out}. This concept is shown in Fig. 3 and the black arrow represents the transition from I_t^{SP} to $I_t^{\mathrm{SP}_d}$ through either a charging or idling action, the green arrow represents an unconstrained action, and the orange arrows represent actions that make departing EVs take energy away thus potentially resulting in additional essential load curtailment.

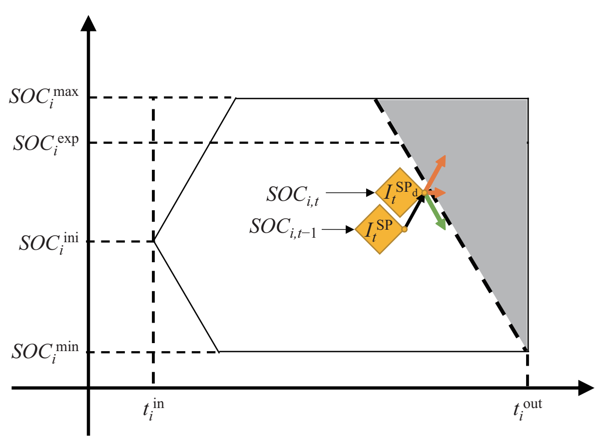


Fig. 3. Transition of a system-prioritized EV at $t-1$ (belonging to the set I_t^{SP}) to a subset of EVs $I_t^{\mathrm{SP_d}}$ that should consider discharging at t.

In this context, the associated cost for the curtailment of the SP EV load is formulated as (17):

$$c_t^{\mathrm{ct,EV_{SP}}} = c^{\mathrm{EV_{IP}}} E_t^{\mathrm{ct,EV_{SP}}} + c^{\mathrm{EV_{SP}}} \Delta t \max\left[P_t^{\mathrm{SP}} - P_t^{\mathrm{EV}}, 0\right] \tag{17}$$

where $P_t^{\mathrm{EV}_d}$ is actual net discharging power, and the cost coefficient $\mathrm{c}^{\mathrm{EV_{SP}}}$ is set far higher than $\mathrm{c}^{\mathrm{EV_{IP}}}$ to favor discharging of SP EVs for essential load supply, over reducing EV curtailment.

Particularly, $P_t^{\mathrm{SP}_d}$ is the required minimum aggregate discharging power of the EVs in the set $I_t^{\mathrm{SP}_d}$ to reduce essential load curtailment, considering the limits of available EV power in the set and remaining essential load not supplied by generation as given in (18).

$$P_t^{\mathrm{SP}} = \min\left(\sum_{i \in I_t^{\mathrm{SP}_d}} P_i^d, P_t^{\mathrm{EL}} - P_t^{\mathrm{gen}}\right) \tag{18}$$

where $\sum_{i \in I_t^{\mathrm{SP}_d}} P_i^d$ is the maximum discharge capability of the set $I_t^{\mathrm{SP}_d}$, and $P_t^{\mathrm{EL}} - P_t^{\mathrm{gen}}$ represents net essential load curtailment at any time step t.

If $\sum_{i \in I_t^{\mathrm{SP}_d}} \mathrm{P}_i^d$ is higher than the net curtailment of essential load, as shown on the left of Fig. 4, discharging power from SP EVs belonging to the set $I_t^{\mathrm{SP}_d}$ only needs to equal the net curtailment, since any extra discharging would not supply essential load and would just result in extra EV curtailment. If $\sum_{i \in I_t^{\mathrm{SP}_d}} \mathrm{P}_i^d$ is lower than net curtailment, as shown on the right of Fig. 4, then every SP EV belonging to the set $I_t^{\mathrm{SP}_d}$ should be discharged, since this extra EV curtailment will be used to supply higher priority essential loads.

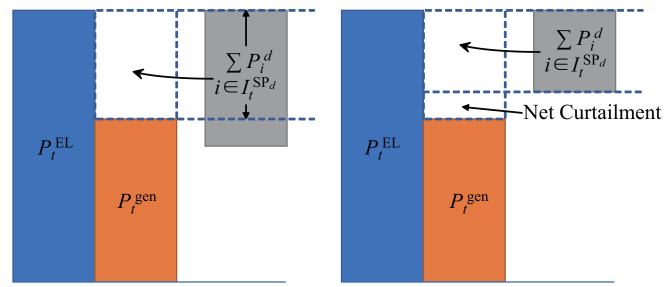


Fig. 4. Essential load, generation and maximum discharging power of system-prioritized EVs belonging to the set $I_t^{\mathrm{SP_d}}$, which are used to minimize essential load curtailment over the time horizon.

2) Constraints of the Day-Ahead Optimization Problem

All EVs connected to the grid are represented by an aggregator, and they are assumed to have homogenous power ratings and charging/discharging efficiencies. Embedding the aggregate EV energy and response calculations (1)–(13), the constraints regarding the operation of EVs are formulated as:

$$0 \le P_t^{\mathrm{EV_c}} \le \overline{P}_t,\ 0 \le P_t^{\mathrm{EV_d}} \le \underline{P}_t \tag{19}$$

$$\begin{aligned} P_t^{\mathrm{EV}} &= P_t^{\mathrm{EV_c}} u_t - P_t^{\mathrm{EV_d}} v_t \\ u_t + v_t &\le 1 \\ u_t, v_t &\in \{0,1\} \end{aligned} \tag{20}$$

$$\begin{aligned} E_{t+1}^{\mathrm{EV}} &= E_t^{\mathrm{EV}} + \Delta t P_t^{\mathrm{EV_c}} \eta^{\mathrm{c}} u_t + \Delta t \frac{P_t^{\mathrm{EV_d}}}{\eta^{\mathrm{d}}} v_t \\ &\quad + \left(E_t^{\mathrm{EV_{in}}} - \left(E_t^{\mathrm{EV_{out}}} - E_t^{\mathrm{ct,EV}}\right)\right) \end{aligned} \tag{21}$$

$$\underline{E}_t \le E_t^{\mathrm{EV}} \le \overline{E}_t \tag{22}$$

$$E_t^{\mathrm{ct,EV}} = E_t^{\mathrm{ct,EV_{IP}}} + E_t^{\mathrm{ct,EV_{SP}}} \tag{23}$$

where (19) and (20) constrains EV response to charging and discharging components, (21) represents updated EV energy after each timestep increment Δt, (22) represents EV energy limits, and (23) expresses total curtailment as the sum of individual- and system-prioritized curtailments.

Also considered in the modeling but not a focus of this work are generation unit constraints, power balance constraints and thermal energy storage constraints. However, examples of these can be found in [35], [36].

The summary of the modeling process is shown in Fig. 5. Following day-ahead scheduling at each timestep, the optimal aggregate EV response P_t^{EV} is used to inform the dispatch strategies, as discussed in Section III-B.

B. Real-Time Operation and EV Dispatch

After day-ahead optimization is performed at each timestep, the microgrid operates according to the first timestep of the

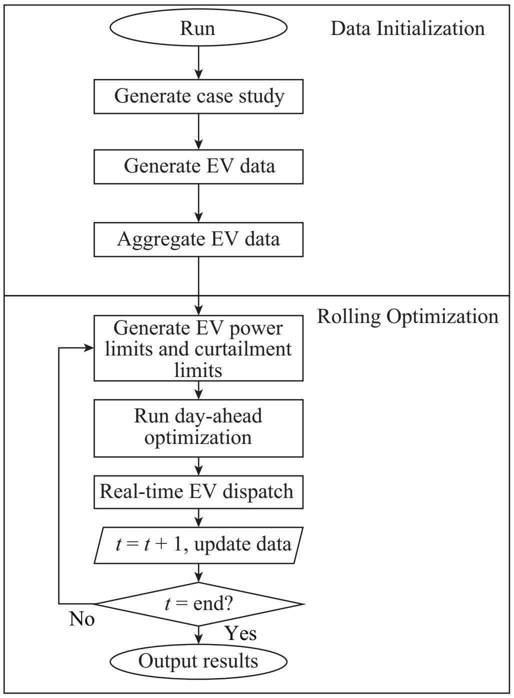


Fig. 5. Modeling algorithm using in this paper.

day-ahead operation, except for the EVs, which are dispatched in real-time at each timestep. Specifically, the optimal aggregate EV response P_t^{EV} is used to determine the total number of EVs dispatched, while the selection of these EVs is decided according to the relevant dispatch strategy, based on real-time data received from EVs. Particularly, two strategies have been considered, each designed for either IP or SP EVs. Since the MEMG includes both types of EVs, EV dispatch uses a combination of these two strategies.

If day-ahead optimization suggests net charging of EVs, IP EVs will be charged first, followed by SP EVs if necessary to reach the desired response. If day-ahead optimization suggests net discharging of EVs, SP EVs will first be discharged, followed by IP EVs if further discharging is still required. When the total response reaches P_t^{EV} the remaining EVs in set I are idled.

The available response of each EV is governed by its current scenario from 1–5 (see Fig. 2).

1) Dispatch Strategy for Individual-Prioritized EVs

This strategy respects the fact that IP EV owners are unwilling to discharge if it would compromise reaching $SOC_i^{\exp}$. This reflects a dispatch strategy that has to work within the constraints shown in Fig. 2. However, the system will still prioritize supplying essential loads over EVs and some EV curtailment may still occur. EVs in the set I_t^{IP} are dispatched according to the response margin ratio (RMR):

$$\gamma = SOC_i^{\exp} - SOC_{i,t} \tag{24}$$

$$\delta = t_i^{\mathrm{out}} - t \tag{25}$$

$$RMR = \frac{\gamma}{\delta} \tag{26}$$

EVs with higher RMRs are prioritized for charging, while EVs with lower RMRs are prioritized for discharging. The purposes of the strategy are to ensure the SOCs of individual EVs are as high as possible before departure.

2) Dispatch Strategy for System-Prioritized EVs

This strategy takes advantage of the fact that SP EV owners are willing to discharge for the benefit of the system, even if it would compromise reaching $SOC_i^{\exp}$. First, EVs in the set $I_t^{SP_d}$ are discharged according to $P_t^{SP_d}$, for the purposes of minimizing essential load curtailment. Second, remaining EVs in the set I_t^{SP} are dispatched using RMR in an identical manner to the IP dispatch strategy but without the idling or discharging restrictions of IP EVs. However, this strategy can be further differentiated by encouraging EVs to minimize the energy they take away from the system when departing, according to (17). The purpose of this strategy is to utilize the cooperation of SP EVs to minimize essential load shed.

IV. Case Studies

A. Assumptions and Parameters

In this section, the value of smart V2G services and the willingness of EV owners to support the system are assessed in the context of resilience, meanwhile the potential of coordinated operation between EVs and PVs to reduce both PV and essential load curtailment is investigated for the urban MEMG depicted in Fig. 1. Specifically, due to a powerful storm a wide-scale outage of the transmission network is predicted to occur between 5am and 6am, with a robust predicted occurrence time of 5am. As a result of the outage, the demand-supply balance of the system is broken and the microgrid disconnects at the PCC to ensure supply of local essential loads while reducing pressure on the recovery of the utility grid. It was assumed the SOCs of both initial EVs and EVs joining during the day follow Gaussian distributions with limits $SOC_i^{\min}$ and $SOC_i^{\max}$. It was also assumed that disruption and subsequent islanding was not known about until 0am and that most EVs were waiting for lower price signals to fully charge. Therefore, at 0am, EVs had a mean SOC of 60%, whereas joining EVs had a slightly lower mean SOC of 50%. Battery capacity was assumed to vary slightly due to different car models and degradation and followed a Gaussian distribution with lower and upper bounds and a mean of 60 kWh. The following values were assumed to be homogenous across all EVs: charging and discharging capacities P_i^c, P_i^d of 10 kW, which represent power transfer to and from the car from the grid perspective; charging and discharging efficiencies η^c, η^d of 92%, which adjust power transfer from the EV perspective; minimum and maximum states of charge $SOC_i^{\min}$, $SOC_i^{\max}$ which were 20% and 100%; and expected state of charge when plugging out $SOC_i^{\exp}$ which was 80%, unless the EV would not be plugged in long enough to reach this value, in which case $SOC_i^{\exp}$ would be the maximum SOC possible after continuous charging.

The number of EVs in the microgrid at any one time, as well as the load profiles used in this work, are shown in Fig. 6. It was assumed that numbers were lower during midday when EV owners were at work.

Using real-time data updates on a rolling-basis at each 15-minute timestep, the day-ahead schedule of the microgrid was optimized, followed by EV dispatch.

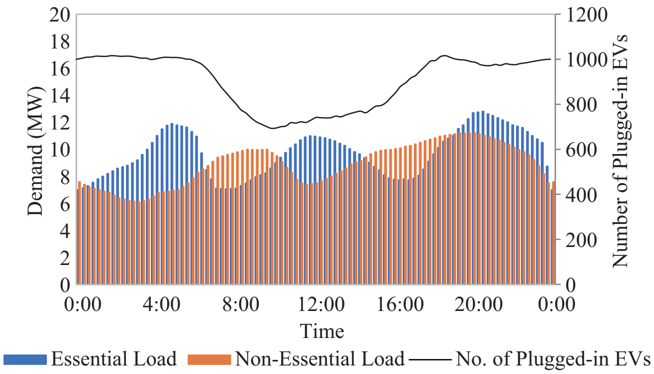


Fig. 6. Essential and non-essential load profiles and number of plugged in EVs vs time of day.

Throughout the case studies, three distinct cases were considered for EV operation.

Case 1: No EVs are considered in the MEMG. This is used as the benchmark.

Case 2: 2000 EVs are considered, but the coordinated control of these EVs is absent. Specifically, all EVs follow a fixed charging mode, e.g., continuous charging until the expected SOC is reached, regardless of the needs of the system during contingencies.

Case 3: 2000 EVs are considered while the coordinated control of these EVs is present. The resiliency-oriented EV dispatch strategies proposed in Section III-B are used, attempting to reduce curtailment of essential load during contingencies. Unless otherwise specified, only IP EVs are used in case studies.

As discussed in the introduction, the benefits of multi-energy vectors have been widely analysed, and so to focus on the benefits of V2G services, results are concerned only with the electrical aspect of the MEMG.

The proposed method was implemented in the YALMIP [37] optimization toolbox using MATLAB R2018a and solved by MOSEK 9.2.35. The numerical experiments were performed on a computer with an Intel Core CPU i5-7300HQ processor running at 2.50 GHz and 8 GB of RAM.

B. Benefits of Coordinated V2G Services

The benefits of coordinated control of EVs in enhancing system resilience are assessed through comparisons across Case 1 to Case 3.

In Fig. 7, the MEMG in all three cases is switched to islanding mode at 5am due to a contingency. Before the contingency, local loads are supplied by both imported power and local generators with the objective of minimizing operational costs.

From initiation of islanding at 5am, until 9am, local energy resources (thermal generators and PV) cannot fully supply essential loads. In Case 1 this results in significant curtailment of both essential and non-essential loads. This is similar in Case 2, but due to the lack of coordinated control, the charging demand of EVs squeezes the chance of other loads being supplied, which further burdens the local energy balance of the MEMG. In Case 3, due to the presence of coordinated

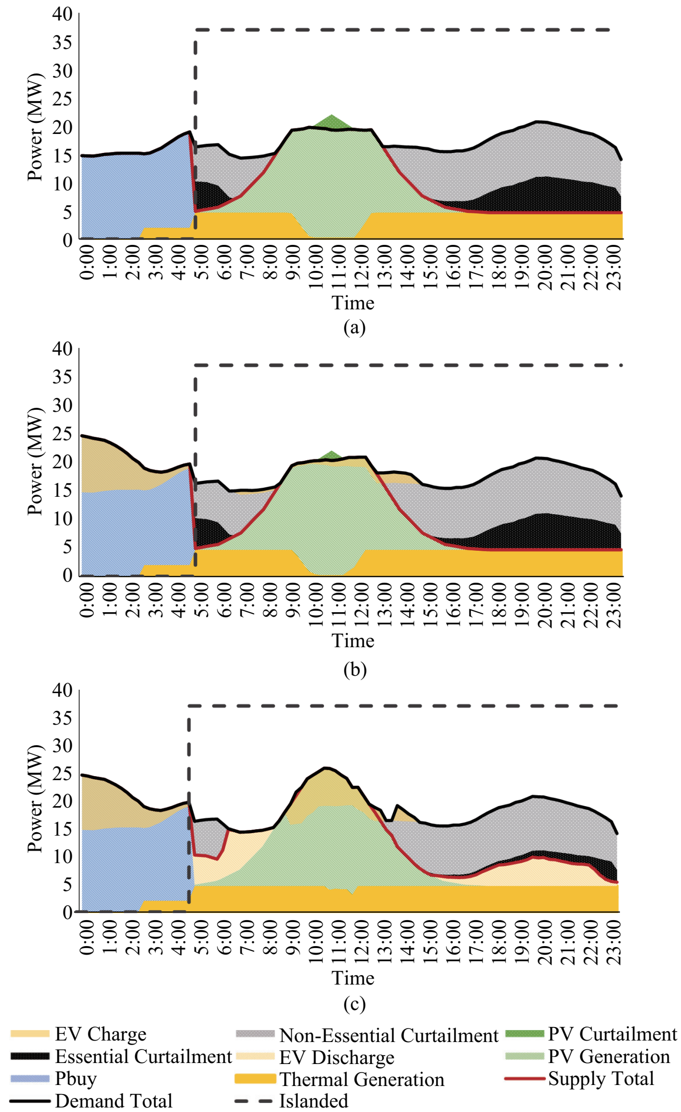


Fig. 7. Day ahead operation of the MEMG undergoing islanding (a) Case 1, (b) Case 2 and (c) Case 3.

control, EVs can charge and discharge in an organized way from the system perspective, consequently, essential load is fully supplied, meanwhile non-essential load curtailment is significantly reduced. It is noted that depleting EV batteries during this period is important for leaving more storage capacities to absorb excess PV generation during midday, which would otherwise be curtailed.

From 9am until 3pm, essential loads are fully supplied, however, due to high output of PV generation, its effective accommodation presents a big challenge. In Case 1, thermal generation output is reduced to prioritize accommodation of PV generation. In Case 2, EVs can barely absorb excess PV power, since they are already fully charged by 9am. In Case 3, since EVs are discharged prior to 9am, EVs can be used to mitigate PV curtailment and additional required energy is compensated by thermal generation output, thus reserving more energy for later use. This benefit is clearly observed after 3pm where essential load curtailment is significantly reduced in Case 3 compared to the other two cases.

Introduction of EVs improves local energy reserve due to continuous EV charging before islanding. However, without coordinated control, the EV-associated energy reserve does not participate in local energy balance since there is no central controller to guide individual EVs about when and how much to supply essential load. On the other hand, when coordinated control is available, all EVs follow dispatch signals based on an optimized requirement. Across the total duration of islanding, Case 2 slightly burdens the system with 3.84% more non-essential load curtailment compared to Case 1, while not alleviating any essential load. In Case 3, EVs provide a moderate 7.84% reduction in non-essential load curtailment and a significant 73.47% reduction in essential-load curtailment.

C. Benefits of EV Owners' Willingness to Support the System Operation

The willingness of EV owners to support operation of the microgrid during contingencies can be critical because this can provide more energy when there is a severe curtailment of essential load. This case study aims to quantify the benefits of SP EVs by comparing essential load curtailments for different percentages of SP EVs.

In Fig. 8 we see a downwards trend in essential load curtailment as we increase the percentage of SP EVs. SP EVs sacrifice their preferred states of charge to discharge more energy to the system, resulting in an essential load curtailment reduction of 39.75% with 100% SP EVs compared to a case with only IP EVs, and an 84.01% reduction compared to the Case 1 baseline. It is important to stress that an effective incentive mechanism aiming at encouraging customers to help the system withstand HILP events is the foundation to realize a high SP to IP ratio.

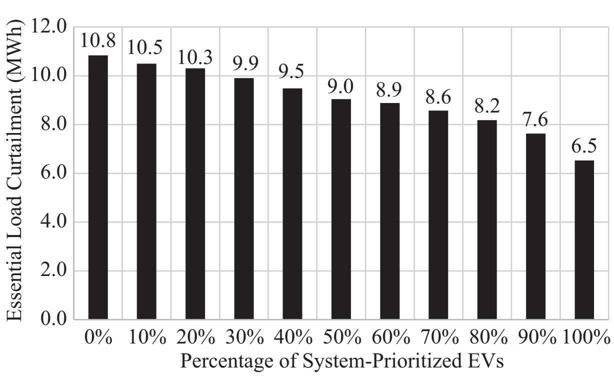


Fig. 8. Influence of the ratio of system-prioritized EVs on essential load curtailment for Case 3 EVs.

D. Complementary Effects of EV and PV

Coordination of PV and EV is crucial during contingencies because EVs can reduce PV curtailment through charging and can take advantage of high PV penetrations by temporally shifting generation in cases of severe essential load curtailment. This case study aims to assess the sensitivity of resilience to the number of EVs in a high PV penetration microgrid.

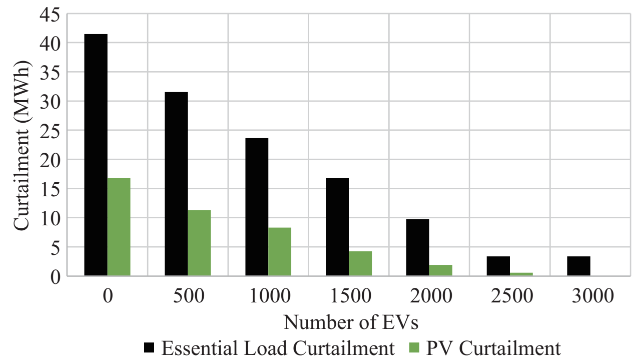


Fig. 9. The influence of number of EVs on essential load and PV curtailment.

Figure 9 shows the increase in EV number effectively drives reduction of both essential load curtailment and PV curtailment. However, essential load reduces at a faster rate. This is driven by two factors. First, additional EVs allow more PV energy to be shifted temporally to supply essential load. Second, EVs bring energy to the system when they arrive and are able to transfer this to essential loads. When EV number is above 2500, essential load curtailment plateaus due to limitations of IP dispatch, which ensures EVs leave the system with as much energy as possible, resulting in later negative effects which might be against the benefits of system, rather than ensuring sufficient EV response is available to eliminate essential load curtailment. Therefore, the benefit of an increased number of EVs is saturated.

V. CONCLUSION

Electric vehicles are promising resources for increasing the resilience of urban multi-energy microgrids. In this paper, the aggregation of EV response capacity is integrated into a rolling horizon control framework, which effectively guides coordinated operation of numerous EVs aimed at enhancing the resilience of the MEMG through V2G services. Simulation results demonstrate that EVs, as an important energy carrier in the MEMG, can facilitate up to a 73.47% essential load curtailment reduction compared to when EVs are not present by using the proposed dispatch strategy. Investigations showed the importance of the influence of EV owner cooperation on resilience and that a high percentage of system-prioritized EVs could provide up to a 39.75% further decrease in essential load curtailment compared to individual-prioritized EVs. Furthermore, the complementary benefits of PV and EV were displayed, showing that increasing numbers of EVs reduced both PV and essential load curtailment. Overall, smart control of V2G services can provide a substantial resilience enhancement during islanding, especially if EV owners are willing to cooperate for the benefits of the system, while further advantages can be gained through having an adequate number of EVs to absorb excess PV generation in a high PV system.

In our future work we aim to explore the benefits of EV rerouting services for resilience enhancement through congestion management and the potential for thermal energy storage to enhance resilience through dedicated thermal energy storage, building inherent storage and pipe network storage.

REFERENCES

[1] M. Panteli, P. Mancarella, D. N. Trakas, E. Kyriakides, and N. Hatziargyriou, "Metrics and quantification of operational and infrastructure resilience in power systems," *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4732–4742, Nov. 2017, doi: 10.1109/tpwrs.2017.2664141.

[2] Z. Y. Li, M. Shahidehpour, F. Aminifar, A. Alabdulwahab, and Y. Al-Turki, "Networked microgrids for enhancing the power system resilience," *Proceedings of the IEEE*, vol. 105, no. 7, pp. 1289–1310, Jul. 2017, doi: 10.1109/jproc.2017.2685558.

[3] UK Energy Research Centre. (2011). Building a resilient UK energy system. [Online]. Available: http://nora.nerc.ac.uk/id/eprint/16648/1/UKERC_energy_2050_resilience_Res_Report_2011.pdf.

[4] M. Ouyang, L. Dueñas-Osorio, and X. Min, "A three-stage resilience analysis framework for urban infrastructure systems," Structural Safety, vol. 36–37, pp. 23–31, May/Jul. 2012, doi: 10.1016/j.strusafe.2011.12.004.

[5] M. Panteli, D. N. Trakas, P. Mancarella, and N. D. Hatziargyriou, "Power systems resilience assessment: hardening and smart operational enhancement strategies," Proceedings of the IEEE, vol. 105, no. 7, pp. 1202–1213, Jul. 2017, doi: 10.1109/jproc.2017.2691357.

[6] M. H. Amirioun, F. Aminifar, H. Lesani, and M. Shahidehpour, "Metrics and quantitative framework for assessing microgrid resilience against windstorms," International Journal of Electrical Power & Energy Systems, vol. 104, pp. 716–723, Jan. 2019, doi: 10.1016/j.ijepes.2018.07.025.

[7] C. Gouveia, J. Moreira, C. L. Moreira, and J. A. P. Lopes, "Coordinating storage and demand response for microgrid emergency operation," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 1898–1908, Dec. 2013, doi: 10.1109/tsg.2013.2257895.

[8] D. Shang, "Pricing of emergency dynamic microgrid power service for distribution resilience enhancement," *Energy Policy*, vol. 111, pp. 321–335, Dec. 2017, doi: 10.1016/j.enpol.2017.09.043.

[9] A. Hussain, V. H. Bui, and H. M. Kim, "Resilience-oriented optimal operation of networked hybrid microgrids," *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 204–215, Jan. 2019, doi: 10.1109/tsg.2017.2737024.

[10] A. Gholami, T. Shekari, F. Aminifar, and M. Shahidehpour, "Microgrid scheduling with uncertainty: the quest for resilience," *IEEE Transactions on Smart Grid*, vol. 7, no. 6, pp. 2849–2858, Nov. 2016, doi: 10.1109/tsg.2016.2598802.

[11] K. Balasubramaniam, P. Saraf, R. Hadidi, and E. B. Makram, "Energy management system for enhanced resiliency of microgrids during islanded operation," *Electric Power Systems Research*, vol. 137, pp. 133–141, Aug. 2016, doi: 10.1016/j.epsr.2016.04.006.

[12] L. Wang, S. Sharkh, A. Chipperfield, and A. Cruden, "Dispatch of vehicle-to-grid battery storage using an analytic hierarchy process," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 4, pp. 2952–2965, Apr. 2017, doi: 10.1109/tvt.2016.2591559.

[13] J. Zhang, L. Che, X. Wan, and M. Shahidehpour, "Distributed hierarchical coordination of networked charging stations based on peer-to-peer trading and EV charging flexibility quantification," *IEEE Transactions on Power Systems*, vol. 37, no. 4, pp. 2961–2975, Jul. 2022, doi: 10.1109/tpwrs.2021.3123351.

[14] T. Qian, C. C. Shao, X. L. Li, X. L. Wang, Z. P. Chen, and M. Shahidehpour, "Multi-agent deep reinforcement learning method for EV charging station game," *IEEE Transactions on Power Systems*, vol. 37, no. 3, pp. 1682–1694, May 2022, doi: 10.1109/tpwrs.2021.3111014.

[15] A. Hussain and H. M. Kim, "Evaluation of multi-objective optimization techniques for resilience enhancement of electric vehicles," *Electronics*, vol. 10, no. 23, pp. 3030, 2021, doi: 10.3390/electronics10233030.

[16] Y. Wang, A. O. Rousis, and G. Strbac, "A resilience enhancement strategy for networked microgrids incorporating electricity and transport and utilizing a stochastic hierarchical control approach," *Sustainable Energy, Grids and Networks*, vol. 26, pp. 100464, Jun. 2021, doi: 10.1016/j.segan.2021.100464.

[17] B. W. Zhou, F. Yao, T. Littler, and H. G. Zhang, "An electric vehicle dispatch module for demand-side energy participation," *Applied Energy*, vol. 177, pp. 464–474, Sep. 2016, doi: 10.1016/j.apenergy.2016.05.120.

[18] P. Y. Wang, J. X. Wang, R. Y. Jin, G. Y. Li, M. Zhou, and Q. Xia, "Integrating biogas in regional energy systems to achieve near-zero carbon emissions," *Applied Energy*, vol. 322, pp. 119515, Sep. 2022, doi: 10.1016/j.apenergy.2022.119515.

[19] A. Hussain, A. O. Rousis, I. Konstantelos, G. Strbac, J. Jeon, and H. M. Kim, "Impact of uncertainties on resilient operation of microgrids: a data-driven approach," *IEEE Access*, vol. 7, pp. 14924–14937, Jan. 2019, doi: 10.1109/access.2019.2891786.

[20] Imperial College London. "Analysis of Alternative UK Heat Decarbonisation Pathways. Committee on Climate Change. [Online]. Available: https://www.theccc.org.uk/publication/analysis-of-alternative-uk-heat-decarbonisation-pathways/

[21] P. Mancarella, "MES (multi-energy systems): an overview of concepts and evaluation models," *Energy*, vol. 65, pp. 1–17, Feb. 2014, doi: 10.1016/j.energy.2013.10.041.

[22] P. Gabrielli, M. Gazzani, E. Martelli, and M. Mazzotti, "Optimal design of multi-energy systems with seasonal storage," *Applied Energy*, vol. 219, pp. 408–424, Jun. 2018, doi: 10.1016/j.apenergy.2017.07.142.

[23] X. Zhang, G. Strbac, N. Shah, F. Teng, and D. Pudjianto, "Whole-system assessment of the benefits of integrated electricity and heat system," *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 1132–1145, Jan. 2019, doi: 10.1109/tsg.2018.2871559.

[24] D. Xu, Q. W. Wu, B. Zhou, C. B. Li, L. Bai, and S. Huang, "Distributed multi-energy operation of coupled electricity, heating, and natural gas networks," *IEEE Transactions on Sustainable Energy*, vol. 11, no. 4, pp. 2457–2469, Oct. 2020, doi: 10.1109/tste.2019.2961432.

[25] Y. J. Ye, D. W. Qiu, X. D. Wu, G. Strbac, and J. Ward, "Model-free real-time autonomous control for a residential multi-energy system using deep reinforcement learning," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3068–3082, Jul. 2020, doi: 10.1109/tsg.2020.2976771.

[26] W. J. Huang, E. S. Du, T. Capuder, X. Zhang, N. Zhang, G. Strbac, and C. Q. Kang, "Reliability and vulnerability assessment of multi-energy systems: an energy hub based method," *IEEE Transactions on Power Systems*, vol. 36, no. 5, pp. 3948–3959, Sep. 2021, doi: 10.1109/tpwrs.2021.3057724.

[27] T. F. Ma, J. Y. Wu, L. L. Hao, W. J. Lee, H. G. Yan, and D. Z. Li, "The optimal structure planning and energy management strategies of smart multi energy systems," *Energy*, vol. 160, pp. 122–141, Oct. 2018, doi: 10.1016/j.energy.2018.06.198.

[28] L. Mauricette, Z. H. Dong, X. Zhang, and G. Strbac, "Electric vehicle co-ordination strategies for enhancing system resilience in multi-energy microgrids," in *Proceedings of the International Conference on Applied Energy*, 2021.

[29] L. Ahmethodžić, M. Musić and S. Huseinbegović, "Microgrid energy management: Classification, review and challenges," in *CSEE Journal of Power and Energy Systems*, doi: 10.17775/CSEEJPES.2021.09150.

[30] IEEE PES Industry Technical Support Task Force. 2018. The definition and quantification of resilience. [Online]. Available: https://grouper.ieee.org/groups/transformers/subcommittees/distr/C57.167/F18-Definition&QuantificationOfResilience.pdf.

[31] J. Silvente, G. M. Kopanos, E. N. Pistikopoulos, and A. Espuña, "A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids," *Applied Energy*, vol. 155, pp. 485–501, Oct. 2015, doi: 10.1016/j.apenergy.2015.05.090.

[32] D. W. Qiu, Y. Wang, T. Q. Zhang, M. Y. Sun, and G. Strbac, "Hybrid multiagent reinforcement learning for electric vehicle resilience control towards a low-carbon transition," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 11, pp. 8258–8269, Nov. 2022, doi: 10.1109/TII.2022.3166215.

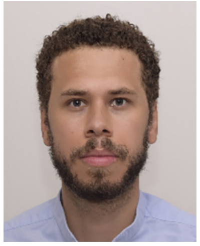
[33] C. Yin, J. X. Wang, W. Y. Tang, G. Y. Li, and M. Zhou, "Health-aware energy management strategy toward internet of storage," *IEEE Internet of Things Journal*, to be published, doi: 10.1109/jiot.2022.3173488.

[34] S. Lu, B. Han, F. Xue, L. Jiang and K. Qian, "Research on multi-objective optimization of EV charging and discharging for different stakeholders," in *CSEE Journal of Power and Energy Systems*, doi: 10.17775/CSEEJPES.2020.02300.

[35] H. S. Zhou, Z. G. Li, J. H. Zheng, Q. H. Wu, and H. B. Zhang, "Robust scheduling of integrated electricity and heating system hedging heating network uncertainties," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1543–1555, Mar. 2020, doi: 10.1109/tsg.2019.2940031.

[36] E. H. Mathews, P. G. Richards, and C. Lombard, "A first-order thermal model for building design," *Energy and Buildings*, vol. 21, no. 2, pp. 133–145, Dec. 1994, doi: 10.1016/0378-7788(94)90006-x.

[37] J. Lofberg, "YALMIP: a toolbox for modeling and optimization in MATLAB," in *Proceedings of 2004 IEEE International Conference on Robotics and Automation*, 2004, pp. 284–289, doi: 10.1109/CACSD.2004.1393890.



Lascelle Mauricette received B.Eng. and M.Sc. degrees in Mechanical Engineering and Structural Integrity from Brunel University, London, United Kingdom, in 2014 and 2015, respectively. Currently he is pursuing his Ph.D. at the Department of Electrical and Electronic Engineering, Imperial College London, United Kingdom. His main research interests include resilience in multi-energy systems.

Zihang Dong received a Ph.D. degree in Control Theory from Imperial College London, UK, in 2019. He is currently a research associate at the Department of Electrical and Electronic Engineering of Imperial College London. His research interests include robust economic model predictive control, flexible demand response and the design of control strategies for the smart grids.

Linan Zhang received bachelor's and master's degrees in Electrical Engineering from North China Electric Power University, Beijing, China, in 2016 and 2019, respectively. She is currently pursuing a Ph.D. degree with Imperial College London, London, U.K. Her research interests include resilience, multi-energy system modeling, planning and operation.

Xi Zhang received B.Sc. and M.Sc. degrees in Electrical Engineering from Tsinghua University, Beijing, China, in 2012 and 2014, respectively and received a Ph.D. from Imperial College London in 2019. He is currently a researcher at State Grid Smart Grid Research Institute Co., Ltd., China. His research is focused on whole-energy system planning, and multi-vector energy system modeling.

Ning Zhang received both B.S. and Ph.D. degrees from the Electrical Engineering Department of Tsinghua University in China in 2007 and 2012, respectively. He is now an Associate Professor at the same university. His research interests include multiple energy systems integration, renewable energy, and power system planning and operation.

Goran Strbac is a Professor of Electrical Energy Systems at Imperial College, London, U.K. His current research interests include electricity generation, transmission and distribution operation, planning and pricing, and integration of renewable and distributed generation in electricity systems.