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Electric Vehicle Co-ordination Strategies for Enhancing System Resilience in Multi-Energy Microgrids

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ABSTRACT

Electric Vehicle (EV) penetration is rapidly increasing across the world and utilization of these in vehicle-to-grid (V2G) services can provide benefits to not just operation costs, but also resilience. To optimize the operation of EVs, as well as other local generation, demand and storage, the concept of microgrids has widely been used in the literature for smart control of local resources. During disruptive events such as microgrid islanding, EVs can act similarly to battery storage to minimize loss of critical loads. In this paper, day-ahead schedules are generated for EV operation in an urban multi-energy microgrid (MEMG) every 15 minutes for a 24-hour period. At each 15-minute timestep, individual EVs are updated based on a rolling EV dispatch strategy and real time data is fed back into the day-ahead schedule. After a predetermined time, an outage causes the microgrid to enter islanded mode. The combined and individual benefits of preventive and corrective control of EVs in increasing resilience is assessed, in addition to a comparison of the value of two novel rolling EV dispatch strategies. Results show that both control strategy and EV dispatch strategy can have a considerable effect on resilience enhancement provided by EVs.

Keywords: Electric Vehicles, V2G, Resilience, Microgrid, Multi-Energy, Day-Ahead Scheduling

1. INTRODUCTION

Traditionally, reliability metrics were used to ensure uninterrupted and high-quality supply of power, but increasing frequency of natural disasters, weather-related and other high-impact, low-probability events has been leading to the emergence of resilience as an important metric [1]. The shift from large and flexible generators to smaller, more distributed, and usually renewable generation has made microgrids an attractive option to utilize this changing landscape. Microgrids can take advantage of distributed energy resources (DERs) as well as other local generation, storage and demand side response (DSR) during outages [2].

During normal operation, the objective of the microgrid's energy management system (EMS) is to utilize its resources to reduce total operation cost. During an outage, the reduction of load shedding, particularly essential loads becomes a priority. Consideration of multiple energy vectors can provide flexibility for reducing essential, as well as non-essential and heat load shedding. In a multi-energy microgrid (MEMG), the electric power system (EPS) can provide flexibility to heat loads through electric heat pumps (EHP), gas can provide flexibility to both heat and the EPS through Combined Heat and Power (CHP) generators and boilers, while heat can provide flexibility to the EPS by adjusting its EHP demand. Demand side response, such as smart appliances (SA) shift electrical demand. Battery energy storage (BESS) can shift supply from low to high price periods or from high to low supply in the case of an outage. Thermal energy storage (TES) is typically represented as demand side response — buildings can be pre-heated/cooled to shift heat/cooling demand. However, TES can also provide supply flexibility by storing energy in heat pipe networks. Similarly, electric vehicles (EVs) can both provide demand flexibility by changing charging hours and provide supply flexibility through vehicle-to-grid (V2G) services by discharging to reduce operation cost during high price periods or to reduce essential load shed during outages [3].

Only limited research has been focused on modelling resilience provided by EVs in microgrids [4-9]. Gouveia [4] et al. coordinated frequency and demand response to improve resilience, while Amirioun [5] et al. proposed a

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framework to quantify resilience for EPS-based microgrids immediately following islanding. However, neither considered preventive or corrective measures. Duo Shang [6] also focused solely on an EPS-based microgrid, but from an economic perspective to determine effective market pricing strategies. Hussain [7] et al. used robust optimization to guarantee feasible islanding against sudden power disruptions. Increase in operation cost was negligible compared to the significant increase in resilience in their case studies, however, this approach to always be on alert may not be economically feasible for many microgrids. Gholami [8] et al. used stochastic optimization to provide resilience against upcoming disruptions, based on the most likely scenarios which were generated from probability distribution functions. Balasubramaniam [9] et al. used corrective control of resources to reduce essential load shed considering 95% confidence intervals for demand and renewable generation. Two strategies were used — one where scheduling was determined at the start of the outage, and a second where scheduling was updated at each 5-minute dispatch. However, the approaches used in [8] and [9] lack high confidence in protecting against disruptions compared to more robust methods.

None of the above works focus on the benefits of MEMG or compare the benefits of different EV operation strategies. In this paper we propose a robust day-ahead MEMG optimization model, that periodically updates using real-time data to mitigate microgrid uncertainties. Comparisons between resilience provided by preventive, corrective and combined corrective & preventive control will be presented, in addition to differences between two novel real-time dispatch strategies.

The rest of the paper is organized as follows. Section II presents the model outline; section III presents case studies and results, while section IV concludes the work.

2. MODEL OUTLINE

2.1 Model Overview

A linearized DC microgrid model is developed in this work based on the linear matrix model described by Wang [10] et al. The model is expanded to include typical MEMG functionalities such as PVs, multiple loads, the ability to sell back to the grid, demand side response and V2G capable EVs.

The day-ahead schedule of the microgrid is optimized over 96 15-minute timesteps, with schedule recalculation performed at each timestep using real-time data. Disconnection from the utility grid at the point of common coupling (PCC) occurs from timesteps 21 to 96 (from 5am–0am). The MEMG is shown in fig. 1.

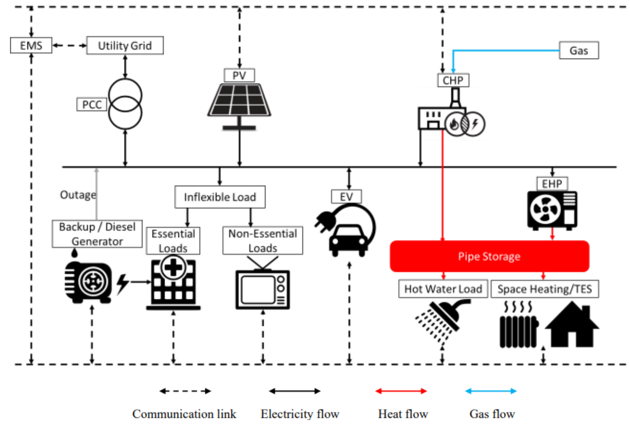


Fig. 1. Diagram of the multi-energy microgrid in this work.

2.2 Individual EV Modelling

The feasible operating region of a single EV is represented in Fig. 2. t_s represents plug-in time, t_e represents leaving time, SOC_{min} and SOC_{max} are set at 20% at 100%. Mean SOC_{ini} for EVs at t=1 is 50%, EVs joining have a mean initial SOC of 30%. SOC_{exp} is the SOC expected by the EV owners at t_e.

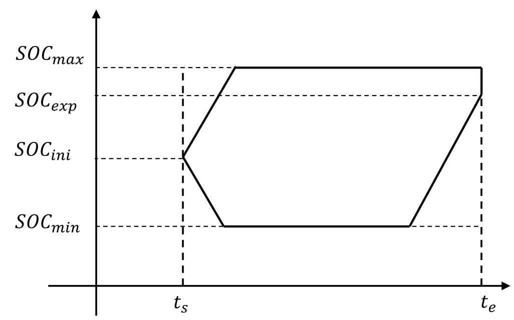


Fig. 2. SOC limits for a single EV.

2.3 EV Aggregation

To represent EV operation in the microgrid, individual EV SOCs are aggregated to provide total energy, as well as charging and discharging limits. In the day-ahead optimization, aggregated EVs are represented as a large battery that has energy losses (EVs unplugging) and energy gains (EVs plugging-in) at each timestep.

To predict the charging and discharging limits, the model checks the SOC of EVs plugged in at each timestep and checks whether a charging/discharging action would cause an EV to exceed the boundaries shown in Fig. 2 and possible actions are aggregated for all EVs.

2.4 Microgrid Day-Ahead Optimization

The day-ahead optimization schedules resources to meet the following objectives in a descending order of priority, by applying descending penalties:

1. **Minimizing essential load curtailment.**
2. **Minimizing EV load curtailment.**
3. **Minimizing non-essential load curtailment.**
4. **Minimizing heating demand curtailment.**
5. **Minimizing electricity, gas and diesel cost.**

When preventive control is used, the microgrid prepares resources to maximize resilience. When corrective control is used, resources are scheduled to maximize resilience over the scheduling horizon, as opposed to prioritizing the current timestep.

2.5 Rolling EV Dispatch

After obtaining aggregate EV power from the optimization for the next timestep, the real-time V2G service is determined based on dispatch strategy.

2.5.1 Normal EV Dispatch

Individual EV charging/discharging at each timestep, t, is determined by the response margin ratio (RMR):

$$SOC\ margin = 1 - SOC(t) \tag{1}$$

$$Time\ response\ margin = t_e - t \tag{2}$$

$$RMR = \frac{\text{SOC margin}}{\text{Time response margin}} \tag{3}$$

EVs with higher RMR are prioritised for charging, while EVs with lower RMR are prioritised for discharging.

2.5.2 Emergency EV Dispatch

The suggested EV curtailment from the day-ahead optimisation is compared with the predicted EV curtailment, by summing $\left(1 - SOC_t^j\right) \cdot EV_j^{capacity}$ for all leaving EVs at each timestep. If predicted curtailed EV is higher/lower than suggested, EVs can be charged/ discharged respectively. EVs departing soon and low/high SOCs are prioritised for charging/discharging respectively. If charging/discharging is still required after checking EV curtailments, lowest RMR will be prioritized for discharging, and lowest response buffer ratios (RBR) will be prioritized for charging:

$$SOC\ buffer = SOC(t) - SOC_{min} \tag{4}$$

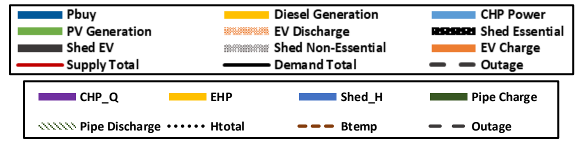
$$RBR = \frac{\text{SOC buffer}}{\text{Time response margin}} \tag{5}$$

This curtails EVs when necessary to reduce essential load shed, but also maximises SOC as a secondary objective.

3. RESULTS AND DISCUSSION

3.1 Number of EVs Sensitivity

In Fig. 3 we see that EVs are charged in the early hours of the morning when price signals are lowest. When there are 0 EVs there is considerable essential load shed during the morning and evening peaks compared to both the 1000 and 2000 EVs cases.



Legends for Figs. 3-6 power (top) and heat (bottom).

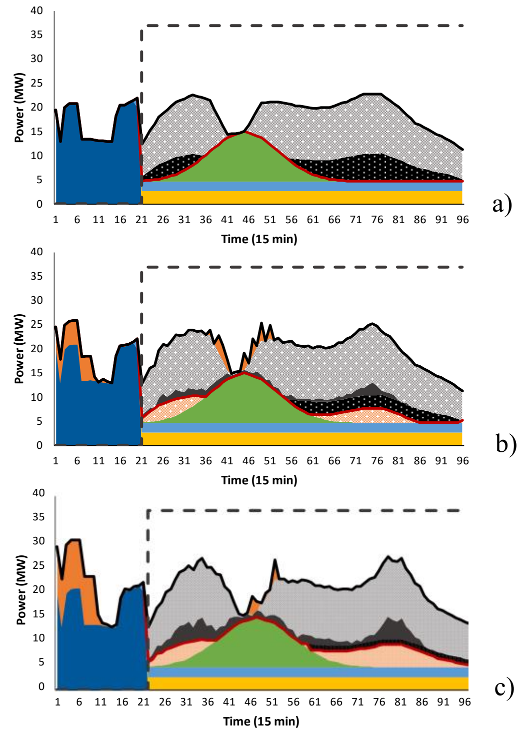


Fig. 3. Preventive and Corrective: 0, 1000 and 2000 EVs.

In the 0 EVs case the load shed is zero at noon, however, non-essential load is curtailed in the 1000 and 2000 EV cases to charge EVs and later supply essential load. In the 2000 EV case less charging is required to recharge the EVs to full, as EVs that were leaving soon were used to supply the morning peak. Total EV discharged in the evening in the 2000 EV case is twice that of the 1000 EV case, despite the overall curtailment of essential load being less than double in the 2000 EV case, due to both scenarios fully supplying essential load in the morning. The 2000 EV scenario resulted in more total curtailed EV.

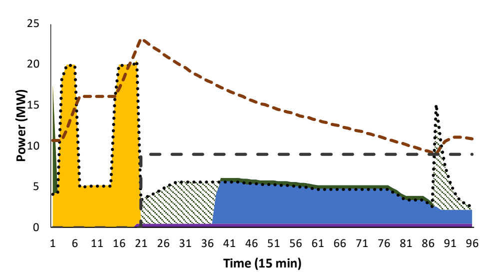


Fig. 4. Heat schedule.

In all scenarios, electricity bought from the grid pre-outage is inflated by EHP pre-heating houses and storing energy in pipes to reduce heat demand, as seen in Fig. 4.

3.2 Comparison of Control Methods

Compared to baseline — Fig. 3b, Fig. 5a shows that with only corrective control, essential load at the start of the outage suffers due to discharging beforehand, but PVs allow the EVs to fully charge around noon and provide an identical evening response. Fig. 5b shows that with only preventive control, the total load curtailment at the start of the outage is more than in Fig 3b. The result is depleted EVs unable to reduce load shed in the evening.

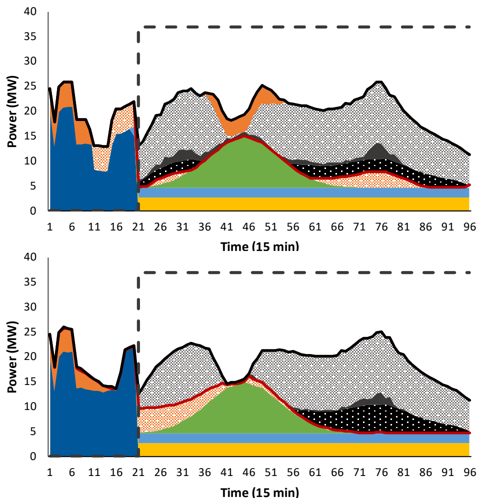


Fig. 5. Only corrective (top) vs. only preventive (bottom).

3.3 Comparison of Rolling Optimization Strategies

In the normal dispatch strategy shown in Fig. 6, EVs are charged if they are leaving soon and EVs that are staying longest are discharged. Conversely, the emergency dispatch strategy shown in the baseline case — Fig. 3b, discharges EVs that are leaving soon and charges the EVs staying the longest if their curtailment is suggested by the day-ahead optimization. The result is EVs that are present during load shed are depleted/charged in the normal/emergency strategies respectively, while charged/depleted EVs have already left in the normal/emergency strategies respectively.

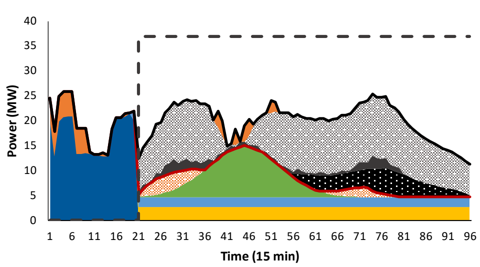


Fig. 6. Normal EV Dispatch.

4. CONCLUSIONS

In this paper, sensitivity of resilience to number of EVs in a microgrid was studied. Preventive and corrective control were shown to be critical for reducing essential load shed. Comparisons between two novel EV dispatch strategies also showed a significant improvement in essential load shed for the emergency strategy.

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