Distribution System Optimal Operation of Smart Homes with Battery and Equivalent HVAC Energy Storage for Virtual Power Plant Controls

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***Abstract*—Battery energy storage systems (BESS) that can be utilized for demand response (DR) and load shifting are limited in adoption by high capital cost. Large residential loads such as electric water heaters (EWH) and heating, ventilation and air-conditioning (HVAC) may be controlled using distributed energy resource management systems (DERMS) to perform functions like batteries, such as reducing cost and decreasing energy storage capacity requirements when implemented at the aggregate level. Increasing levels of renewable generation further incentivizes shifting loads in time through controls and energy storage to reduce curtailment and carbon footprint. This paper proposes techniques for the optimization and control of distributed energy resources (DER) using DERMS. The CTA-2045 standard, an industry communications protocol, is used for generalized energy storage (GES) controls and operations. A case study is conducted to compare discharging of residential BESS with HVAC equivalent energy storage controls and electric vehicles (EV) on a distribution feeder with over 350 houses, realistic load profiles, and home characteristics. It is shown that HVAC setpoint controls for pre-cooling through "load-up" and "shed" commands may successfully reduce evening peak load.**

***Index Terms*—Distributed energy resources (DER), Generalized energy storage (GES), CTA-2045, Battery energy storage systems (BESS), Renewable energy, Electric vehicles (EV), OpenDSS**

I. Introduction

With increasing population and energy consumption, there is growing demand for sustainable energy production, such as wind and solar PV [1]. Due to the stochastic nature of wind and solar, increasing levels of renewable generation further incentivizes shifting loads in time through controls and energy storage to reduce grid power fluctuation and curtailment [2]. Distributed energy resources (DER), such as battery energy storage systems (BESS), distributed solar PV, and local loads, may reduce peak demand and energy cost with large-scale implementation. Control of DER can be applied using DER management systems (DERMS), model predictive control (MPC), and forecasting to minimize energy costs, reduce battery cycling, and shift loads to times of high PV generation.

An effective method for load shifting is to store energy in BESS during off-peak hours or times of high PV generation, then discharge during peak hours. Results from an energy storage analysis in [3] suggested that 12-hour storage with 5.5 TWh capacity can meet more than 80% electricity demand in the US with mixtures of wind and solar generation. Additionally, distributed solar PV paired with residential BESS can decrease power exchange between the customer and utility, which in turn reduces grid power losses [4].

The main disadvantage of BESS is high capital cost, and large residential loads such as electric water heaters (EWH), heating, ventilation, and air-conditioning (HVAC), may be controlled to perform the grid support functions like a battery. Through the use of DERMS, residential BESS, EWH, HVAC, and EV batteries may be coordinated and controlled at the aggregate level to decrease peak demand and shift loads, while also operating within human comfort constraints and offering customer incentive with time-of-use (TOU) pricing [5].

With the rise of electric vehicles (EVs), utilities must reduce peak demand to support charging load. Intensive charging during peak hours may cause overloading and reduce voltage quality [6]. Many studies have proposed control of DERs as a solution to reduce "shark curve" and voltage sag caused by EV charging during peak hours. The authors of [7] propose utilities control a permitted percentage (PP) of BESS on the distribution system to mitigate EV grid impact. A study in [8] developed a generative model to disaggregate EV load from smart meter data. This would allow utilities to obtain non-intrusive and accurate estimations of EV charging load, which could be used for forecasting and scheduling [9].

Smart charge management (SCM) strategies may be another way to mitigate EV grid impact. A case study in [10] simulated five SCM strategies on a distribution feeder with 200 EVs. It was found that the TOU-immediate strategy caused a second demand peak and even more voltage sag than the uncontrolled case, due to the majority of customers charging at the start of the TOU window. The SCM strategies with the best results for voltage and power control were centralized aggregator and random-start. Vehicle-to-grid (V2G) is another approach in which EV batteries supply power to the grid when connected. Studies by our group in [11], [12] have simulated V2G operation on distribution systems to provide virtual power plant (VPP) support, while also ensuring a minimum 50% SOC in EV batteries remain after DR.

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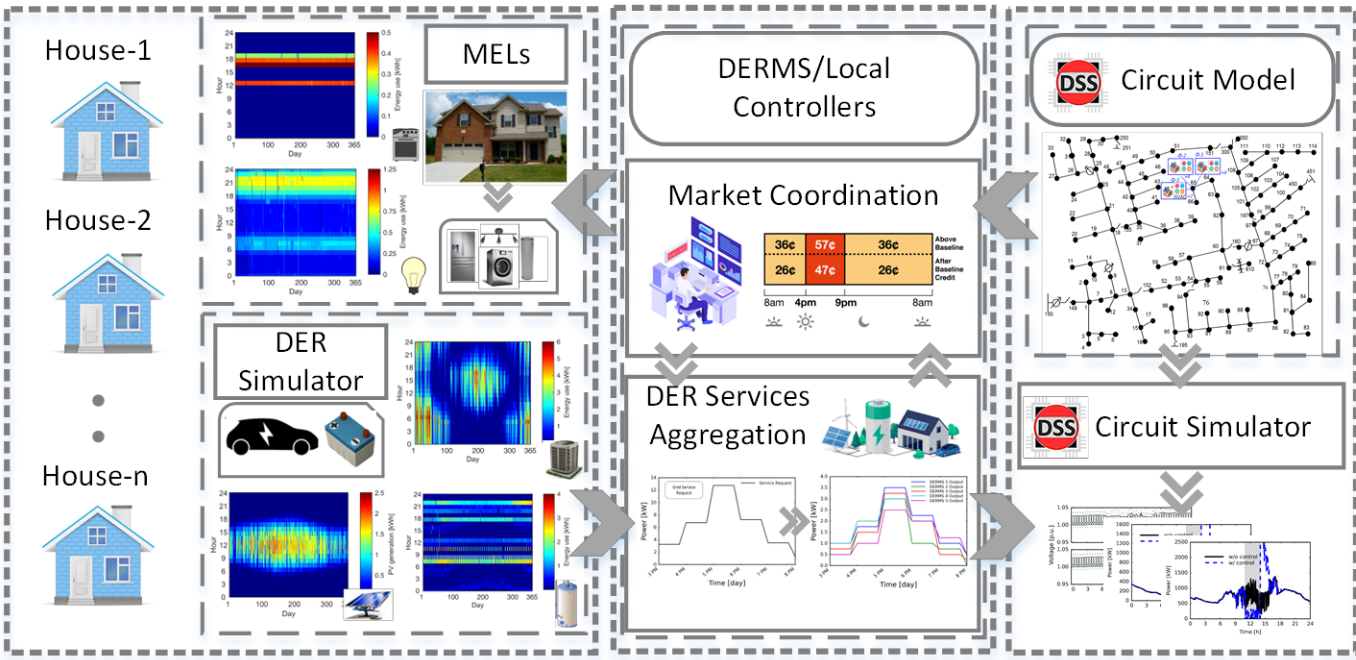

Fig. 1. Proposed co-simulation framework for DERMS to implement DR events and load shifting based on optimization of HVAC setpoints. At the aggregate level, multiple DERMS can coordinate with one another to fulfill service requests from the grid. The framework is demonstrated in this paper through a benchmark study employing realistic synthetic data for the smart home modules.

This paper follows up on a previous conference publication by the same research group, which introduced a novel co-simulation framework that acts as a testbed for control strategies, which may employ various GES systems, particularly HVAC systems, and DERs based on the Consumer Technology Association (CTA) 2045 standard [13], [14]. The evaluation of control cases at both the power system and individual building levels is enabled by the framework, which is facilitated by a physics-informed machine learning modeling procedure that is much faster than conventional white-box implementations.

This continued work includes considerably improved control methodologies based on those described in [15], which further incorporate HVAC system phasing, more gradual changes in setpoint temperatures, and inherent consideration of occupant thermal comfort. Also, the proposal of a multi-objective control optimization concept with solution selection based on objective priority is provided with objectives to maximize local PV utilization, minimize power peaks, minimize thermal comfort violations, and minimize electricity costs. The full details of the optimization procedure and methods are provided in

II. Applications of DER Management Systems and Generalized Energy Storage

Large-scale implementation of DERMS can greatly optimize the use of DER by reducing battery cycling and shifting loads to times of high PV generation. Multiple DERMS in a community could coordinate to supply grid service requests for demand response (DR) events. Using model predictive control (MPC), DERMS coordinate controllable loads, battery charging/discharging, and distributed PV generation to optimize energy usage [16]. The MPC controller optimizes DER behavior for the next 24 hours to minimize cost while also considering comfort and objective constraints, then issues commands to execute the first optimized 15-minute interval. The MPC then loads the latest datasets and repeats the optimization process for the next 24 hours, starting at the previously second time step of 15-minutes.

A DERMS in [17] predicted solar generation at multiple time intervals for the next 24 hours, then used software algorithms to predict movement of clouds based on imagery from satellites. This approach allows each local controller to plan availability of PV generation more accurately than algorithms based only on historical data or full-day weather forecasts. Another model in [18] used a demand size management (DSM) scheme to optimize use of BESS and distributed solar PV generation.

The proposed DERMS configuration, shown in Fig. 1, features multiple DERMS in a community, which can coordinate with one another to supply service requests from the grid. The controllers will include market coordination by considering TOU pricing to optimize energy cost. To implement this technology, signals must be sent back and forth from DERMS to the grid. For optimal control of DER such as BESS, solar PV, and large residential loads, the DERMS must fulfill grid service requests within an acceptable tolerance. As illustrated in Fig. 2, the output may have slight variation due to noise. The DERMS must operate within the specified range for optimal

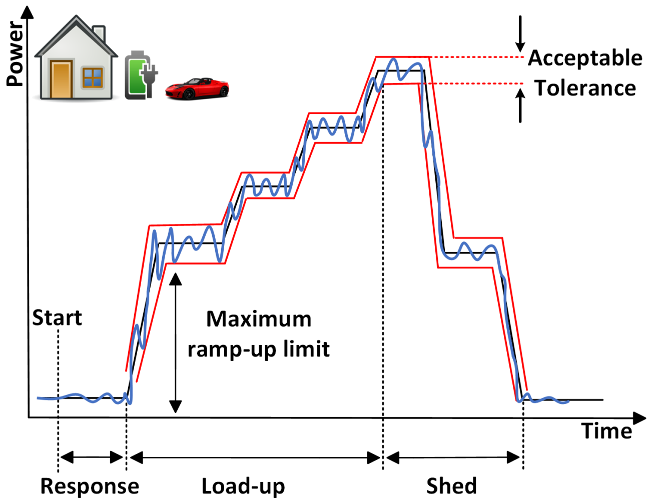

Fig. 2. Output signal for DERMS during an extended multi-step DR event. While the output is not a perfect "staircase" due to noise and delay between event start time and DER response time, the output must remain within an established tolerance for optimal control.

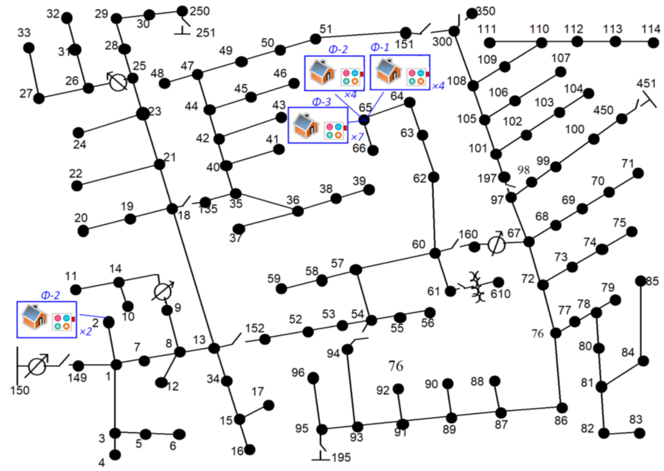

Fig. 3. The IEEE 123 node test feeder modified with home loads and employed for the study described in the paper. The home loads are synthetically generated and considered representative of a large residential subdivision.

control of the system. There is also an expected delay between start time of the event and response time of DERs, after which the "load-up" and "shed" events can be implemented. Additionally, the output is not an ideal/perfect "staircase" as it takes a small amount of time to ramp-up when output is increased.

One of the largest barriers for large-scale implementation of BESS is represented by high capital cost. Controlling large residential loads like EWH and HVAC may perform some functions of a battery to reduce energy storage capacity requirements. Algorithms are developed to control these appliances for optimized energy and cost, shifting energy usage of controllable loads to have a significant combined effect on the distribution system. This effect could greatly reduce energy usage and peak demand for utilities. Results from a previous study in [19] concluded that controllable loads like EWH that respond to a DR signal by postponing the heating process may be used to shift in time power at the aggregate level, while also conforming to human comfort constraints.

The study in [13] simulated aggregated use of HVAC energy storage on the IEEE 123 node test feeder (Fig. 3) using machine learning (ML) to train and develop EnergyPlus models that capture thermal energy use of HVAC, indoor temperature, and external weather effects. For this simulation, software was developed to generate many unique building models with different HVAC and building characteristics. The results from this study found that the aggregated use of HVAC energy storage significantly reduced evening peak of the system while conforming to human comfort restraints and without any voltage violations. The baseline and HVAC controlled demand are used for a case study in Section III, where the use of equivalent HVAC energy storage will be compared to distributed BESS for their applications to DR and load shifting.

III. Case Study: HVAC Energy Storage, V2G, and BESS Comparison

As an expansion of the study conducted by our research group in [13], the IEEE 123 Bus node system with realistic home loads, HVAC, and PV was used for CTA-2045 DR. When a CTA-2045 command such as "load-up" or "shed" is issued, individual indoor temperature setpoints are adjusted based upon their estimated equivalent energy capacities. During a shed event, operation is avoided to allow stored energy to decrease. While in load-up, the appliance will operate and store more energy, if capacity and comfort allow. In this simulation, load-up was during hours 7-15, while a shed event took place from hours 15-22. The data from this study was converted into 15-minute time steps by taking the average over each 15-minute period, corresponding to typical smart meter time resolution.

The use of HVAC energy storage was then compared to discharge of a typical residential battery for DR and load-shifting to coordinate with distributed solar generation. For this study, residential BESS in the simulation was assumed to be charged at full capacity early in the day during off-peak hours, then discharged during peak hours, reserving a minimum of 50% SOC in order to ensure available supply for the next day.

To compare demand reduction effectiveness between BESS and HVAC, percentage power reduction during DR window was calculated for each. As stated in [20], the percentage power reduction is calculated as:

$$R_i = \frac{\sum_{u=1}^{n} P_u - \sum_{c=1}^{n} P_c}{\sum_{u=1}^{n} P_u}, \qquad (1)$$

where P_u and P_c are the one-minute uncontrolled and controlled average powers [kW], respectively, and n is the total number of timesteps. For the simulated DR event from hours 15-22, HVAC and residential BESS percentage peak reductions were 3.9% and 22.9% respectively. The simulated V2G control on the same system resulted in 90.9% peak reduction. This very large reduction was possible due to the much higher capacity of EV batteries in comparison to residential BESS.

The controlled demand using HVAC energy storage is compared with discharge of BESS on the same system. Illustrated in Fig. 4 is the BESS discharge for DR event. At the beginning and end of DR hours, the residential BESS service was gradually increased/decreased to reduce ramping. As visualized in Fig. 5, while generally having a much smaller capacity, controlling HVAC to behave as energy storage can implement a DR event similarly to BESS. While not as much storage can be used from the HVAC as BESS, the demand can still be decreased by a substantial amount when implemented for multiple houses in a community. These results indicate that controlling large appliances to behave as energy storage can significantly reduce capital cost by decreasing the amount of BESS required for load shifting and peak load reduction. The HVAC controlled case is implemented without any voltage violations, as shown in Fig. 6.

In Fig. 7, discharge of residential BESS is compared to V2G service for the same community. Due to the much higher capacity in EV batteries, V2G service can decrease the peak demand significantly more in comparison to residential BESS. This method takes advantage of the fact that most EV owners complete their daily commute using only a fraction of their EV battery capacity.

The discharge of individual residential BESS and EV batteries during DR hours is shown in Fig. 8 and Fig. 9 respectively. In both simulations, a minimum of 50% SOC was reserved in each battery to ensure available capacity for the next day. The residential BESS simulation was a maximum use case of aggregate battery control, as the minimum target SOC was reached across the community. In the V2G simulation, approximately one-third of EV batteries are discharged, which suggests that V2G services may have a strong impact even in communities with less than 50% EV penetration.

IV. Discussion

The simulation results indicate that residential BESS can provide significantly more peak reduction in comparison to HVAC control. Still, HVAC control did decrease the peak load during the DR period, and successfully shifted load from evening to midday, when solar PV generation is higher. While not as effective, HVAC is still a viable option to decrease energy storage capacity requirements and capital cost. The rise of EV penetration is another reason this practice should be used. It is highly desirable to have a method for reducing evening peak to avoid the “shark curve” due to many EV owners charging their vehicles at the same time after work or before a forecasted natural disaster or storm.

Utilities may offer TOU pricing to provide incentives for customers to use less energy during peak hours. Typically the highest TOU rates are from hours 16-21, which does not align with solar generation. This could motivate customers with rooftop PV to buy/utilize residential BESS or HVAC energy storage to utilize generation from solar PV during high TOU hours.

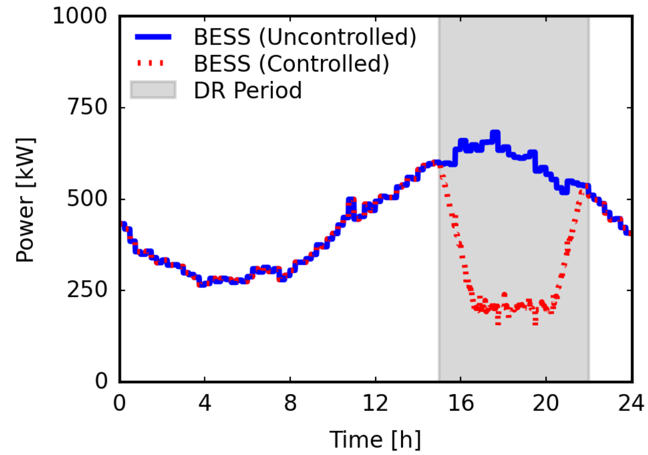

Fig. 4. Discharge of residential battery for DR event from hours 15-22, with gradual increase/decrease at the beginning/end of DR window to decrease ramping. The percentage power reduction for the DR event shown is 22.9%.

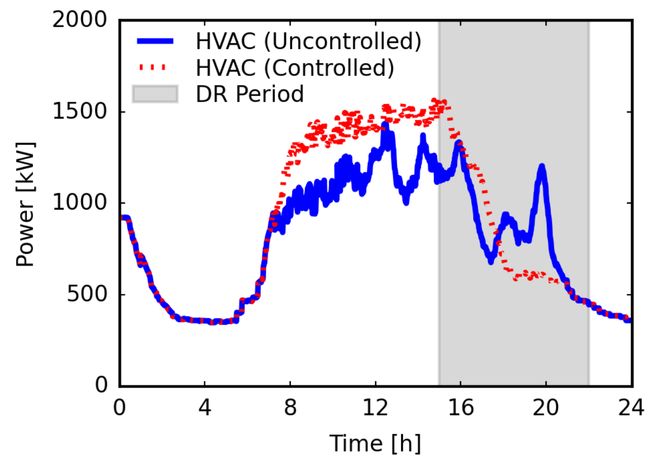

Fig. 5. Energy storage control for HVAC based on the study in [13]. The DR event was during hours 15-22, and reduced the peak load by 3.9% during this time. In this case, evening demand was reduced by loading-up HVAC earlier in the day, which may be beneficial to communities with distributed solar PV.

V. Conclusion

The new research reported in the paper includes considerably improved control methodologies, which incorporate HVAC system phasing, more gradual changes in setpoint temperatures, and inherent consideration of occupant thermal comfort. The proposal of a multi-objective control optimization concept with solution selection based on priorities is provided with objectives to maximize local PV utilization, minimize power peaks, minimize thermal comfort violations, and minimize electricity costs. A benchmark study was completed on a modified IEEE test feeder with over 350 houses to reduce peak demand.

To summarize, BESS may be used for DR and load shifting, though they have high capital cost. Large residential loads

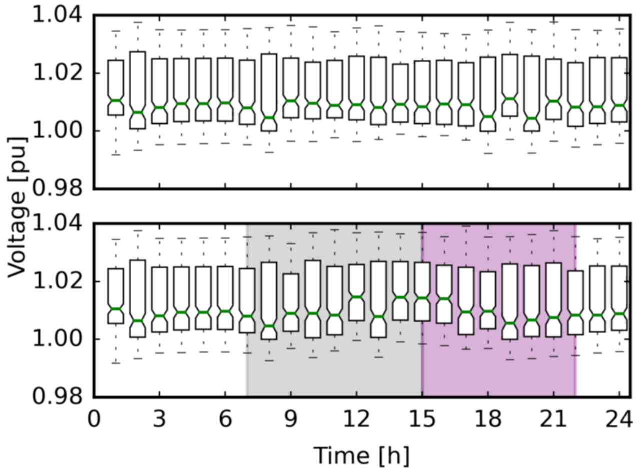

Fig. 6. Voltage across the system with HVAC DR controls remained within the acceptable margin. Load-up and shed periods for the controlled case are shaded in grey and purple respectively. The HVAC control did not cause any voltage violations during the day.

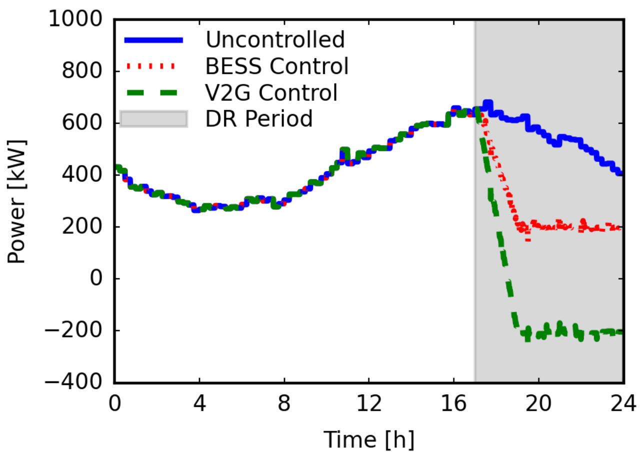

Fig. 7. Comparison of residential BESS and EV battery for a DR event on the IEEE 123 node modified circuit with discharge hours 17-24. The V2G control decreased peak load by 90.0%, while residential BESS decreased peak by 28.4% during DR hours. Due to the much higher capacity of EV batteries, V2G reduced demand much more than residential BESS, even supplying power to the grid for some time.

such as EWH and HVAC may be controlled to perform these same functions, which may decrease battery capacity requirements. Through the use of DERMS at the aggregate level, these resources may shift loads to times of high PV generation, decrease peak demand, and implement DR events while also conforming to human comfort restraints. With increasing popularity of EV ownership and field deployment of V2G services, this practice is also important to avoid the ”shark curve” due to large EV charging load around 5 PM and before natural disasters.

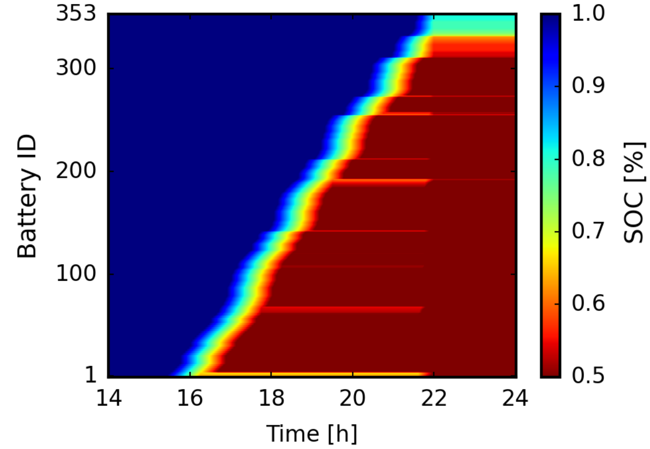

Fig. 8. Discharge of residential BESS on the distribution feeder during DR hours. The simulation was a max use case for aggregate battery control, as the target SOC of 50% was reached across the community..

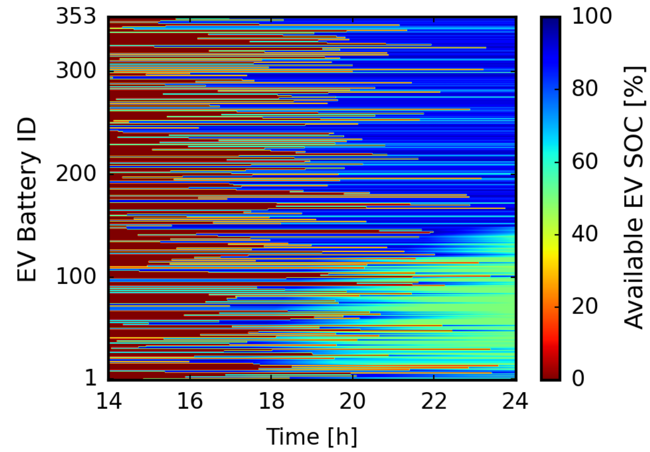

Fig. 9. Discharge of EV battery on the distribution feeder during DR hours. Available SOC is shown as 0% during times when EVs have not returned from their daily commute. Approximately one-third of EV batteries are discharged during the DR period, which suggests that V2G services may have a strong impact even in communities with less than 50% EV penetration..

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