Adaptive Operation Strategies for Electric Vehicle Charging Stations

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***Abstract*—Several electric vehicle (EV) charging algorithms have been recently suggested to meet different optimization objectives in power grids. In this paper, a holistic mechanism is proposed to manage the operation of EV charging stations (EVCSs). The proposed framework offers adaptive operation strategies for the EVCS operators to effectively manage the EVCS under different penetration levels of EVs, considering both normal operating conditions and restoration processes during interruptions and emergencies. The performance of the proposed approach is tested with real data and numerically analyzed on the system operational costs under different EV and PV penetration scenarios. We also demonstrate that the proposed adaptive operation mechanism could bring significant advantages to the operation and control of power grids when facing different operating conditions.**

***Index Terms*—Electric vehicle (EV); charging strategy; EV charging station (EVCS); PV system; power system planning.**

NOMENCLATURE

A. Indices

k	Index for time-steps (1,...,K).

B. Parameters

α_c, α_d	Charge/discharge efficiency of the battery.
β	Percentage of Total Energy.
γ	Penalty factor.
λ	Locational marginal price of the electricity ($/MWh).
Λ_R	Total power output of renewables (MW).
c_d	Battery degradation cost ($/MWh).
E_C	Forecasted energy consumption of PEVs in the next 24 hours.
L_O	Load of original customer demand.
V_C	Value of renewable curtailment.

C. Variables

L_C	Load of PEV.
P_C	Curtailed power of renewables.
P_E	Active power from the external grid.
P_R	Effective active power of renewables integrated into the grid.
u_c	Converted power to stored energy.
u_d	Converted power from EVCS to electricity.

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I. INTRODUCTION

THE research and development on power grid flexibility and resilience have been intensified over the past decade facilitated by the advent of emerging technologies in realizing a smarter electricity grid. Such technologies include battery energy storage systems (BESSs), distributed generators (DGs) and electric vehicle charging station (EVCSs) with smart charging algorithms and smart mechanisms for communication with the electric vehicles (EVs), to name a few. The BESS has been deployed to reduce the system operational costs and provide ancillary services to the grid—e.g., frequency regulation [1] in normal operating conditions as well as grid support services during emergencies [2]. However, BESSs are attributed a high capital cost at the moment and the frequent charge and discharge actions will expedite their degradation over time. Hence, the deployment scale of the BESS is currently limited and the investment on the BESS technologies is restricted by the economic constraints in practice [3]. The DGs using diesel generators and natural gas will enhance the reliability performance of the distribution system and reduce the network losses. The conventional DGs are typically employed to supply the critical loads in normal and emergency operating conditions. However, with the intensified environmental concerns and the target for a sustainable grid of the future, the intermittent renewable energies, such as photovoltaic (PV) solar and wind power, are widely being deployed in the distribution systems as distributed energy resources (DERs) [4]. EVs are also considered one critical asset that can help reduce the carbon emissions in the transportation sector [5]. With the smart charging mechanisms managed by the EVCS operators, EVs can be utilized as an energy storage unit to respond to the intermittent renewable energies [6] and for an enhanced feeder resilience during emergencies. Different from the BESSs, the enhanced grid flexibility provided by the EVs does not impose additional capital costs as the EVs are owned by the customers. EVs can also be charged through the power delivered by the intermittent DERs and the battery degradation cost is paid by customers. The increasing penetration of EVs and the expansion of EVCSs will bring about potentials for huge flexibility provision in the power grids of the future.

There are several challenging concerns when planning to incorporate EVs and EVCSs to the power grid. The uncoordinated charging of plug-in electric vehicles (PEVs), which assumes EVs to charge upon arrival at a particular location, will significantly increase the peak demand and may require gradual or immediate upgrade of electricity delivery infrastructure in power distribution systems [7]. The operation strategies of EVCS becomes further important when facing an increasing trend in deploying EVs in the grid. Peak-shaving algorithms have been proposed to improve the performance of combined EV and PV systems during normal operating conditions [6]. The use of EVs to improve the grid reliability has been studied in [8]. Several countries are promoting projects to incentivize higher EV penetrations, aiming to replace the combustion cars by EVs up to 100 percent [9]. Solutions and strategies facilitating the adaptive operation of EVCSs to meet the grid performance requirements under different operating conditions and different EV penetration levels are needed to address this emerging grid transformation.

The paper's main contributions are summarized as follows:

1) An adaptive operation framework including four strategies is proposed for EVCSs to handle various operating conditions and EV penetration levels.
2) We numerically demonstrate the economic benefits of the proposed adaptive operation framework for the EV-PV integrated systems.

The rest of the paper is organized as follows. Section II presents the charging strategies of EVCSs under normal operating conditions. Section III introduces the different restoration processes for EVCSs considering various interruptions. Section IV presents the numerical case studies and simulation results, followed by the conclusions in Section V.

II. Economic Dispatch Methods for EVCSs under Normal Operating Conditions

The impacts of EVs and renewables on the grid performance requirements vary depending on the penetration levels, spatio-temporal characteristics, and the imposed stochasticity. Very low penetration of EVs and renewables in a feeder will not significantly impact the grid and, hence, uncoordinated EV charging algorithms can be employed in such circumstances where there will be no renewable curtailments. The increasing penetration of EVs and renewables in the feeder will have a significant impact on the load curves and economic operation of the feeder. Smart charging algorithms should be developed and employed that can account for the renewable curtailments and are compatible with the communication networks with smart meters.

A. Price-based Optimization of EVCSs under Low Penetration of Utility-Scale EVs

The price-based economic dispatch is suitable for operating microgrids with DERs such as EVCSs and PVs, when the utility-scale DER penetration is low. The pricing signals, i.e., the locational marginal prices (LMPs), are generated by the transmission level economic dispatch. The penetration level of DERs in the microgrid can be high in such cases, as long as the percentage of controllable loads and power generation remains relatively low in the utility with little impacts on the LMPs. In other words, the ratio of the dispatchable DERs to the total load in the utility should remain small so that the DERs' operation strategies do not significantly affect the transmission-level economic dispatch results. EV charging can be scheduled during the lower price time intervals, and the EVs' flexibility can be used to avoid the renewable curtailments.

The joint optimization problem to dispatch both EVCS and PV systems is formulated in equation (1) – (12). The objective function of the price-based economic dispatch is to minimize the operational costs of the combined EVCS and PV systems based on the acquired pricing signals.

$$\min \quad \sum_{k=1}^{K}(\lambda(k)u_c(k)+(2c_d-\lambda(k))u_d(k)+V_C P_C(k)) + OF_{EV}+OF_{PV} \tag{1}$$

s.t.

$$L_C(k+1)=L_C(k)+\alpha_c u_c(k)-(\alpha_d)^{-1}u_d(k) \qquad \forall k \tag{2}$$

$$\sum_{k_1}^{k_2}\alpha_c u_c(k)-(\alpha_d)^{-1}u_d(k)\geq \beta E_C \tag{3}$$

$$0 \;\leq\; u_c(k) \;\leq u_c^{max} \qquad \forall k \tag{4}$$

$$0 \;\leq\; u_d(k) \;\leq u_d^{max} \qquad \forall k \tag{5}$$

$$P_C(k)+P_R(k)=\Lambda_R(k) \qquad \forall k \tag{6}$$

$$0 \;\leq\; P_R(k) \;\leq \Lambda_R(k) \qquad \forall k \tag{7}$$

$$P_R(k)+P_E(k)-u_c(k)+u_d(k)=L_O(k) \qquad \forall k \tag{8}$$

$$P_E^{min} \;\leq\; P_E(k) \;\leq P_E^{max} \qquad \forall k \tag{9}$$

$$\begin{aligned}-P_L \leq &P_R(k+1)-u_c(k+1)+u_d(k+1)-(P_R(k)\\ &-u_c(k)+u_d(k))\leq P_L \qquad \forall k\in[1,K-1]\end{aligned} \tag{10}$$

$$OF_{EV}=\gamma(L_C(K+1)-E_C)^2 \tag{11}$$

$$OF_{PV}=-\sum_{k=1}^{K}\lambda(k)P_C(k) \tag{12}$$

The objective function (1) consists of (i) the cost for charging EVs, (ii) the revenue for discharging EVs—the degradation cost of EVs are considered when the vehicle to grid (V2G) operating mode results in extra battery cycles to EV customers, (iii) the curtailment cost of PV power, (iv) the penalty cost for deviations from daily energy consumption of the PEVs reflected in (11), and (v) the revenue for PV systems to follow the dispatch signals presented in (12). Constraint (2) represents the state equation describing dynamics of the EV batteries, where self-discharge is ignored. Constraint (3) describes the required charging demand of the EVCS during a certain time interval. Multiple levels of charging demand during different time intervals can be described in (3) with different selections of k_1, k_2 and β, the values of which can be obtained though historical datasets. Constraints (4) and (5) enforce the EVCS power to the charge and discharge capacity limits. Constraints (6) and (7) represent the effective PV power output and curtailment, limited above by the total power output of the PV system. Constraint (8) enforces the power balance requirements. Constraint (9) specifies the exchange power limits of the feeder. In (10), the DER power variation in two consecutive time-steps is restricted to a pre-specified value. We define the joint dispatch of EVCSs and PV system through the proposed optimization problem (1)–(12) as the *EVCS Operation Strategy 1*.

B. Cost-based Economic Dispatch of EVCSs under Massive Penetration of Utility-Scale EVs

The price-based economic dispatch optimization is useful when the utility-scale EV penetration level is low. Under medium or high utility-scale penetration of EVs and renewables in the grid, the prices will be impacted significantly by the dispatch of DERs. Hence, the EVs and renewables should be accurately modeled and wisely dispatched at the transmission level, with the exception of the small-scale EVCSs with high uncertainty of EV customer behaviors or a few EVCSs participating in the transactive markets. Cost-based economic dispatch that minimizes the total system cost can be employed to optimize the dispatch and EV charging schedules, where the dispatch problem at the transmission level should not violate the distribution system constraints.

As the optimization problem with thousands and millions of EVs is very large and hard to solve, there exist two approaches to deal with this computationally-intensive challenge: (i) in the current regulated electricity markets with independent system operators (ISO), multi-agents system can be employed to manage the EV charging locally and communicate with the ISO. In such scenarios, only the aggregated EV information is considered by a central station and the optimization problem becomes a moderate-size problem to solve. (ii) in the deregulated electricity markets, the optimization problem can be distributed to all nodes. Each station or node solves its own optimization problem, considering coupling information from the neighboring nodes or the globally coupled information. We here define the cost-based transmission-level economic dispatch of EVs as the *EVCS Operation Strategy 2*. Further research is needed to address the scalability of the optimization problem and efficient algorithms accordingly.

III. Restoration Strategies for EVCSs under Interruptions and Emergency Operations

We utilize the EVs' flexibility to reduce the system operational costs during normal operating conditions, while mitigating the impacts of the *feeder-level* interruptions during emergencies. If there is an outage in the feeder, the unused EVs can serve as a grid-support resource: EVs can discharge some energy to support the interrupted load during interruptions, and EVs can charge or swap the batteries in other feeders during the recovery process or during their travels. This potential for EVs and PVs can be further highlighted for feeder resilience support when considering the rapid deployment of such technologies in modern power distribution systems; furthermore, as more charging facilities are available in other feeders, EVs can be regarded as mobile energy batteries to support the loads in the feeder when necessary.

The system-level blackouts or other high-impact low-probability (HILP) events driven by extreme weather conditions may result in the majority of the feeders in the system being interrupted [10]. We regard the conventional restoration mechanisms with load pick-up and crew dispatch [11] as the primary restoration strategy. We here define and investigate a restoration approach focusing on the EVs and distributed generators as the *ancillary restoration* process. The proposed framework for ancillary restoration can be seen in Fig. 1. It is a complementary restoration approach that facilitates the primary restoration process, and it can be used under both low and high penetration levels of DERs. The restoration steps are described as follows:

1) The EVCSs will charge the EV batteries to high SOCs during the normal operating conditions several hours ahead of the HILP events with available or projected weather forecasts.
2) During the interruption, the EV and PV systems can form a microgrid to supply the feeder or the home depending on the scale of the DERs.
3) During the Recovery Action stage
    a) The communication between the EVCS and the utility should be connected first so that the EV load can be estimated and scheduled along with the primary restoration actions. The EV load scheduling and EV load recovery methods under low EV and high EV penetration levels are different.
    b) With low EV penetration in the utility, the EVCS can maximize the power recovery of connected EVs within the feeder constraints. Other survived or recovered feeders with battery swapping stations can help swap the batteries for the EVs that could not be charged to the desired SOC for the trip.
    c) The utility needs to seek a trade-off between the amount of recovery power and increased EV load demand under high EV penetrations. This is because the EV load demand is high at the beginning of the recovery stage due to the EV battery energy supply during the disruption. Only the critical EV loads should be charged once the feeder is energized, and EV load curtailment should be considered when necessary. The EV load should be restored gradually to meet the EV customer trip demand after the inelastic load in the system is restored. The average SOC of EVs in the utility can be increased using cost-based economics dispatch after the majority of the generators and the system original loads are recovered.

The above Steps 1, 2, 3.a and 3.b can be employed as the operation strategy for EVCSs during restoration processes under low utility-scale penetration of EVs and we here define it as the *EVCS Operation Strategy 3*. If k_3 is the start time during normal operating conditions to increase the EV load, and k_4 is the start time of the disruption, the optimization problem to schedule the EV charging during the time period starting from k_3 to k_4 can be represented by (1) – (11) and (13). Equation (13) is a soft constraint enforcing the EVCS to

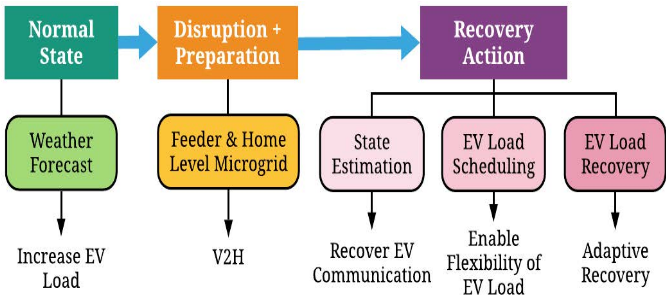

Fig. 1. The ancillary restoration process by flexible loads such as EVs.

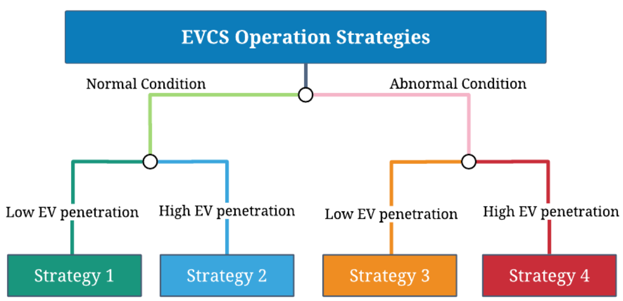

Fig. 2. The holistic framework of adaptive operation of EVCSs.

charge the EVs with maximum power capacity.

$$OF_{EV} = \gamma(L_C(k_4) - u_c^{max}(k_4 - k_3))^2 \tag{13}$$

The Steps 1, 2, 3.a and 3.c is employed as the operation strategy of EVCSs during restoration process under high utility-scale penetration of EVs and we here define it as the *EVCS Operation Strategy 4*.

IV. The Proposed Framework for Adaptive Operation of EVCSs

The EVCSs needs to adjust the charging algorithms with different EV penetration levels under normal operating conditions. They also have to consider the EV charging algorithm and restoration processes when interruptions occur. Hence, the EVCS operator should consider all the conditions and employ a suite of adaptive operation strategies to manage the EVs as different scenarios unfold. The overall architecture of a holistic solution proposed for EVCS adaptive operation is demonstrated in Fig. 2. It requires the communication system to be built, the EVs to be connected with smart meters, and the interaction between the utility and the EVCSs to be enabled. According to Fig. 2, only the operation strategies need to be adjusted as different conditions unfold in the grid once the communication system is established. This is achieved at minimum effort for the EVCS operators to take in order to meet the system requirements when transitioning through different operating states over time.

V. Numerical Case Studies

Real-life data is imported to simulate and evaluate the effectiveness of the proposed algorithms under low utility-scale penetration of EVs. The historical load profile of a feeder in year 2015 is utilized. The feeder supplies 549 customers in the US District of Columbia (DC), with the average feeder load of 1.52 MW and yearly peak load of 3.28 MW. It is corresponding to an overhead line feeder supplying majorly the residential customers and a few commercial customers. The modified IEEE 13-node test feeder is employed as the typology for the test system, the one-line diagram of which is illustrated in Fig. 3. We here assume the all loads are balanced three-phase loads. The total load of the feeder is proportionally distributed to the nodes. We also assume that the transformer connected to the feeder is of 5 MVA capacity, and reverse power flow is not allowed. The minimum net-load of the feeder is 0.3 MW. The integrated EVCS and PV system is located at node 635 (see Fig. 3), and connected to the grid through a transformer. The weather data is taken from the National Solar Radiation Database around Washington DC area [12]. The global horizontal irradiance data in year 2015 is used and the overall PV system efficiency is assumed to be 20%. V_C is set to 25 \$/MWh. A PV system with a total capacity of 9 MW can generate the equivalent electricity satisfying yearly energy demand in the feeder. The penetration level of PV in the feeder is defined as the percentage of PV capacity to 9 MW PV system. The hourly LMPs in year 2015 from the PJM market are used as the pricing signals [13]. The uncoordinated PEV load is acquired from [14] to assess the daily EV demand and make a comparison with the coordinated EV charging strategies. The scale factor for the EV load is 7. We assume there are 2400 vehicles in the feeder based on the daily EV demand. The EVCS in the feeder is assumed to charge at least 10% of the EV daily energy demand during the time period of 9 a.m. to 9 p.m., and charge at least 30% during other time intervals of the day. Then $\beta_1 = 0.1$ and $\beta_2 = 0.3$. The charge/discharge rate of the EVCS is 6 MW with the efficiency of 95%. c_d is set to 20 \$/MWh.

A. Uncoordinated vs. Smart Charging Strategies

We assume a 2.7 MW PV system and 1440 EVs in the feeder. Hence, the PV and EV penetration levels are 30% and 60%, respectively. The PV output and the feeder load profile of a typical winter day in year 2015 is illustrated in Fig. 4. Compared with the uncoordinated charging strategies in Fig. 5, the smart charging could follow the LMP and charge during low-price time periods.

In a summer day when the PV power is nearly its output capacity (see Fig. 6), the PV output is higher than the original load demand. The uncoordinated charging of EVs will cause a significant curtailment of PV generation during the day. However, the proposed joint optimization mechanism will schedule the EV loads by taking into account the LMP and to decline the PV curtailment by following the PV output power. The V2G is also used to minimize the cost of the integrated EV-PV system without violating the grid constraints. The results are illustrated in Fig. 7. The net-load is the aggregated

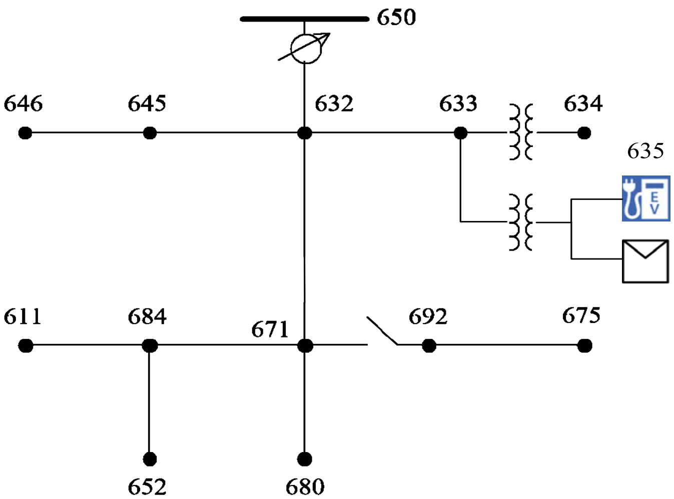

Fig. 3. The modified IEEE 13-node test feeder with EVCS and PV system located at node 635.

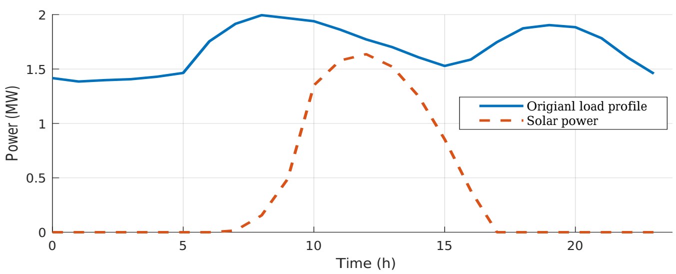

Fig. 4. The feeder load profile and solar power output during a winter day.

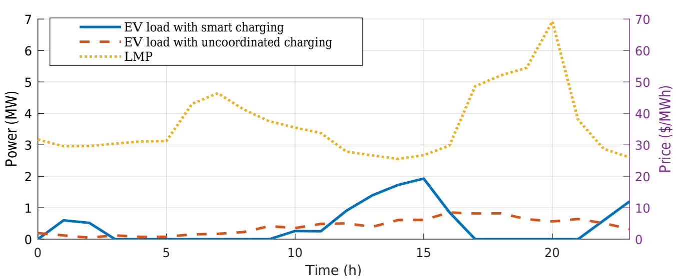

Fig. 5. Different EV load profiles under different charging algorithms in the feeder, and the LMP profile of the feeder. The y axis corresponding to EV load is on the left, and that of the LMP is on the right.

load of the feeder, and is equal to the total load including the original load and the EV loads minus the PV actual output.

Considering the transformer upper constraint, the maximum EV penetration in the case of an uncoordinated charging is 87.5% if one assumes no PV system in the feeder. With smart charging mechanisms, the maximum EV penetration can be 100% and the EVs will be charging during low LMP time intervals to meet the customer trip demand.

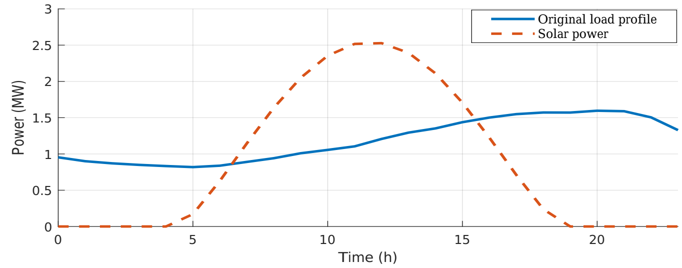

Fig. 6. The feeder load profile and solar power output during a summer day.

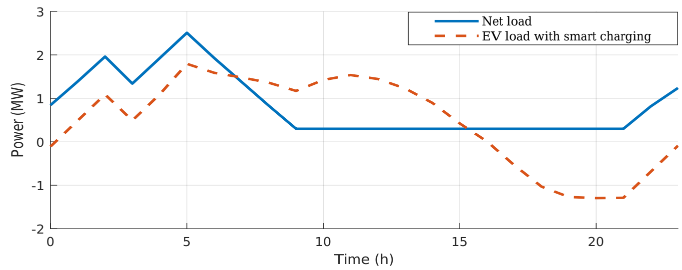

Fig. 7. The net load profile and the EV load profile of the feeder.

B. PV Curtailment under Different Levels of EV Penetration in the Feeder

Without EVs, a 8.6% PV penetration level in the system results in the minimum load of 0.3 MW in the feeder without curtailment. The PV penetration level can increase to 16.6% when there is 100% EV penetration with uncoordinated charging, if a 2-hour slightly overload of the transformer is allowed. A small percentage of PV curtailment should be allowed and smart charging algorithms should be employed by the EVCS operators to increase the PV system integration capacity.

EVCSs with smart charging mechanisms can improve the PV penetration significantly. The PV power curtailment and the operation cost of the integrated EV-PV system in the feeder are demonstrated in Fig. 8 and Fig. 9. The PV power curtailment under different EV and PV penetration levels is illustrated in Fig. 8. The intersection points between 2% PV curtailment (dashed curve) and PV power curtailment curves under different EV penetration levels indicate the marginal conditions—the percentage of PV penetration level—to economically invest on PV systems. The operational cost of the combined system decreases almost linearly until more than 2% of PV curtailment happens in Fig. 9. Hence, the PV penetration level with 2% PV curtailment in Fig. 8 can be regarded as the upper bound when seeking an economic investment under a certain level of EV penetration.

C. Restoration Strategy of EVCSs under Low Utility-Scale Penetration of EVs

With the same penetration level of PV and EVs as in Section V-A, we apply the Strategy 3 to manage the operation of the EVCSs under interruptions and in emergency operating conditions. The PV output and load profile of a typical spring

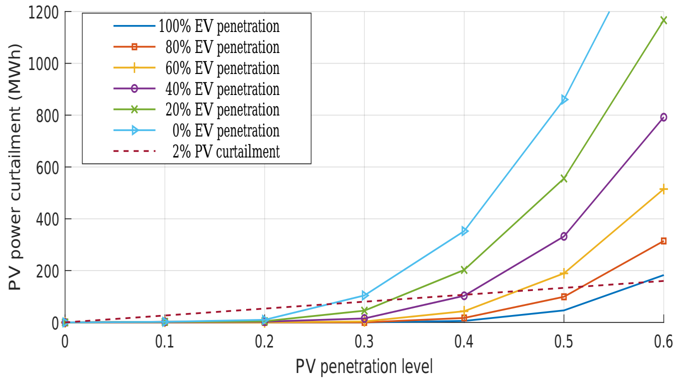

Fig. 8. PV energy curtailment against the penetration level of PV systems. Each line represents the EV penetration level.

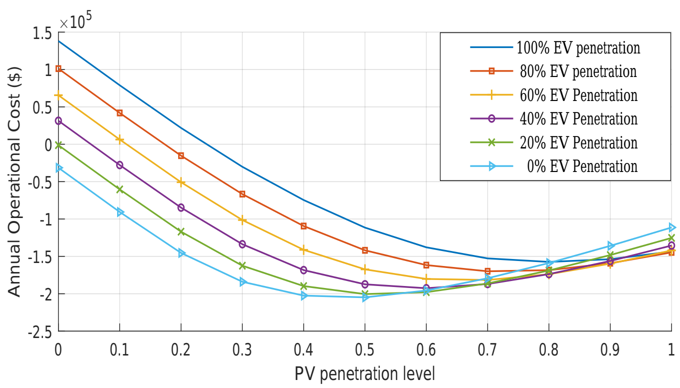

Fig. 9. The operational cost of the integrated EV-PV system in the feeder during 2015 vs. the penetration level of PV systems. Each line represents the EV penetration level.

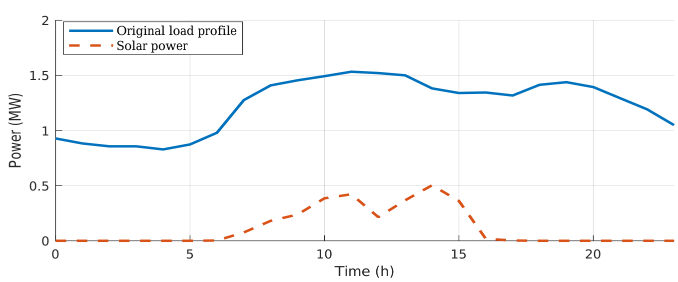

Fig. 10. Feeder load profile and solar power output during a fall season day.

or fall day in year 2015 is illustrated in Fig. 10. We assume that the EVs have the battery capacities of 70 kWh. At 12 a.m., all the EVs are assumed to be in the EVCSs and the EVCSs have 40% aggregated SOC. At 1:00 a.m. the EVCS receives the weather information reflecting a HILP storm that is approaching the system during the day with a strong wind profile, and the overhead distribution line connected to the feeder is vulnerable to be broken. We assume that the main grid fails to supply the feeder from 6:00 a.m. to 3:00 p.m. during the day due to the inclement weather.

Table I presents the implementation results when Strategy 3 is applied during each stage of restoration. The EVCS wish to charge as much energy to the EVs in Strategy 3 before the interruption occurs so as to avoid the penalty of energy interruption (during outages) in the feeder. The actual energy charged to the EVs in the EVCSs, 20.25 MWh, is observed less than the expected value due to the grid constraints. As the repair time of the outage elements, i.e., the interruption duration, depends on many factors, the actual energy supplied by the EVCS may be more or less than the energy stored in the EVs during the first stage. The EVCS needs to acquire the SOC of EVs and reschedule the EV charging during the Recovery Action stage. Following the interruption, there is a 13.15 MWh energy that remains unused, which is higher than the EVCS daily demand of 9.85 MWh. Hence, no EV demand should be scheduled at the immediate hour following the restoration process is accomplished.

TABLE I
ENERGY CONSUMPTION AND SUPPLY OF THE EVCS DURING EACH STAGE OF THE RESTORATION PROCESS

Stage	schedule (MWh)	actual (MWh)
Normal State	30	20.25
Disruption & Preparation	-20.15	-10.16
Recovery Action	6	0

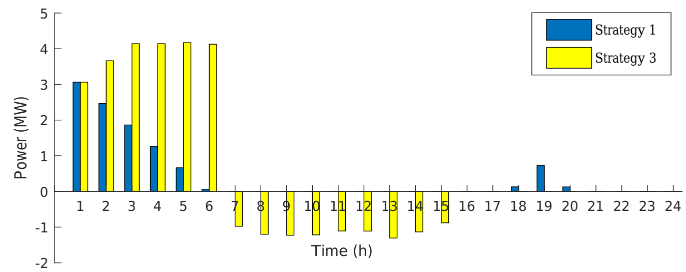

Fig. 11. Different EV charging strategies during the ancillary restoration process in the feeder. Positive values are the EV loads, and negative values are the energy supplied by the EVCS to the load.

The EV charging curve with and without Strategy 3 applied is shown in Fig. 11. The operation strategy without considering the interruptions will only follow the electricity pricing signals before the interruption occurs, and then charge the other part of EV demand following the interruption. The charging Strategy 3, however, will charge more energy to the battery before the interruption occurs, and supply the feeder during the interruption.

VI. Conclusion

The increasing penetration of EVs will bring about potentials to improve the maximum capacity of intermittent renewable energies that the feeders can accommodate cost-effectively. With the increasing penetration of EVs, the adaptive EVCS operation strategies enable the EVCSs to safely operate in the modern distribution systems. The proposed ancillary restoration framework utilizes the EVs as the grid support resources to harnesses the EVs' flexibility in providing additional energy before the interruptions, provide energy to customers during interruptions, and facilitate recovery of EV loads following the interruptions. The proposed framework requires smart communication platforms that can help the EVCS operator make effective decisions as different grid operating conditions unfold over time.

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