Hindawi
International Transactions on Electrical Energy Systems
Volume 2023, Article ID 5320002, 15 pages
https://doi.org/10.1155/2023/5320002

Research Article

Resilient Operation of Electric Vehicles considering Grid Resiliency and Uncertainties

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Received 31 May 2023; Revised 22 October 2023; Accepted 26 October 2023; Published 11 November 2023

Academic Editor: Santoshkumar Hampannavar

This paper proposes a novel short-time optimization method based on a resiliency enhancement strategy for a smart distribution network during adverse weather conditions. The key idea is to integrate various electric vehicles (EVs) with different behaviour patterns and other distributed energy resources into emergency tools of distribution network operation such as topology reconfiguration and grid-supported services. In this regard, possible management programs for three types of EVs (with different levels of control potentials), energy resources, reconfiguration, and demand response programs impacts on boosting resiliency are investigated. The framework is organized on coordination and benefit sharing among distribution system operator (DSO), private sector, and EV owners to reduce possible side effects of failures that could be incepted by extreme weather conditions. A Monte Carlo-based stochastic simulation for modelling uncertainties such as EVs movement, state of change, arrival/departure time to charge stations, and weather-based failures is devised. In order to evaluate resiliency, metrics based on a multiphase method are analysed. The performance of the proposed method on extra benefit obtaining for DSO and private sector and also resiliency enhancement in disturbance progress, postdisturbance degraded, and restorative state are carried out on IEEE-33 bus test system, and obtained results are analysed in detail.

1. Introduction

1.1. Motivation. The emergence of electric vehicles (EVs) has opened up an interesting new research area in load and energy storages (ESs). However, the high presence of EVs and their potential for future cooperation with other grid resources present challenges for grid developers [1, 2]. In this regard, managing EVs with vehicle-to-grid (V2G) capability is a significant operational issue in distribution networks. Indeed, EVs housed in charge stations (CSs) can function as flexible demands and energy storages when not in use [3]. So, EVs can be modelled as mobile demands or possible ESs that could have power exchange with a network [4, 5].

Another recent topic is to optimal usage of the CSs with distributed energy resources (DER), and in this way, DERs can be operated to inject energy into the EVs and network. This interesting topic highlighted in the recent decade, so that DER-powered CSs have attention.

1.2. Literature Review. EVs are cooperated with DERs to exchange energy with the grid during various possible operational cases [6–10]. The charging/discharging strategies of EVs, and especially the adopted programs under which the EV is posed in charging/discharging conditions, are among the main challenges of operating the CS. Moreover, the integration of the DERs and CSs requires coordination of DERs generation and EVs charging/discharging behaviour. In other words, unsuitable management could lead to inappropriate operation such as extra losses or voltage sag due to feeder congestion [11]. Various researches have been conducted in response to such challenges, among which the following can be mentioned. In [12, 13], a stochastic method, using Monte Carlo (MC) simulation, to model the probabilistic nature of the EVs, such as daily travel distance and charging pattern, is presented.

Technical issues on scheduling, controlling, and operating EVs are reviewed in [14]. In [15], charging/discharging schedule of EVs is simply presented based on the market price; however, it does not consider the effect of the presented schedule on the load profile of the network. The authors of [16, 17] propose methods to coordinate DERs and EVs for the purpose of peak shaving and in sequence decrease in power losses and voltage sag. In [18, 19], with the purpose of resiliency improvement, the charging program of the EVs is modelled. Therefore, it can be concluded that the most optimal program is obtained when the benefits of the CS (or EV) owner and the distribution system operator (DSO) are considered simultaneously. This issue is discussed in the paper [20], and a method to share the benefits of the program implementation is proposed.

In all the above-mentioned papers, charging/discharging programs are mainly devised regardless of the resiliency of the grid during special time intervals such as storms, which is one of the drawbacks of the existing researches. In fact, such programs are only presented with the aim of flattening the demand profile, while in case of natural disasters, the charging/discharging behaviour of the CS must be changed to improve the resilience of the network. In recent studies, grid resiliency refers to the ability of the grid to prepare, survive, and rapidly recover itself during unexpected fault inception, like extreme weather conditions [21–23]. It should be noted that the development and implementation of the charging/discharging program with the aim of improving network resilience can reduce energy not supplied (ENS) to an acceptable level and thus reduce the cost of the DSO [24].

On the other hand, wind speed may affect the scheduling of the wind turbines. Thus, in addition to investigating the effect of extreme weather (like storms) on grid resilience, changes in wind turbine (WT) generation should also be considered. Comprehensive issues in DERs rescheduling weather impact on the failure rate of lines can be found in [25–27]. In the context of grid resilience improvement, various methods such as demand response programs (DRP), rescheduling of resources [28, 29], DER utilization, network reinforcement, and reconfiguration methods [30] have been proposed. However, in the matter of the CS, particularly integrated with DERs, developing an optimal and proportionate charging/discharging schedule can effectively improve network resilience. Risk-based operational planning for enhancing grid resiliency has been proposed in the paper [21]. Furthermore, in [21, 22], resilience improvement is obtained via infrastructure and minimization of outage duration.

1.3. Contribution of Paper. Based on the above discussion, in the existing research, EV management programs have been rarely devised in order to network resilience improvement. In view of such shortcomings, this paper presents an optimal charging/discharging program for EVs through its benefits of DSO and DER, and EV owners are optimally maximized. In the proposed methodology, as per the effective role of the EVs in improving grid resiliency, the idea of benefit sharing between DSO and EV owner is applied to encourage EV owners to cooperate with DSO and to enhance the resiliency level of the network against extreme weather conditions. In this regard, first, a stochastic framework, on the basis of MC simulation, is proposed to forecast changes in the line's failure rate to model random variables considering related uncertainties. In the next step, a formulation for optimal management of EVs is devised. In the proposed formulation, while optimizing power purchases from the utility, the benefits of all players and grid resilience in extreme weather conditions are also maximized. However, to encourage EV owners to optimal management and to participate in improving the plan of resiliency, the idea of benefit sharing on the basis of energy price modification is applied. Moreover, the coordination of DER, reconfiguration, and demand response program (DRP) is performed.

The resilience-oriented multiobjective optimization algorithm of this paper is solved using a modified genetic optimization algorithm (MGO), and Pareto front solutions are obtained. Applying hybrid sequential MC simulation and MGO algorithm improves the accuracy of obtaining optimal solutions set. Resiliency enhancement analysis is evaluated by$\Phi\Lambda E\Pi$metrics based on multiphase resilience trapezoid method, and all disturbance progress, post-disturbance degraded, and restorative states are assessed. In summary, the taxonomy of the most related research works is reported in Table 1.

2. Mathematical Formulation

In a practical situation, by employing telecommunication technologies and innovative methods like the Internet of Things, it becomes possible to formulate schedules for electric vehicles (EVs) using a combination of historical data predictions and analyzing user behaviours. During emergency situations, when the probability of failures and unforeseen trips in charging stations (CSs) is high, the distribution system operator (DSO) aims to assess probabilistic events and their potential consequences. This evaluation involves managing demands, resources, and EVs to improve the resilience and economic gains of all participants involved.

As shown in the schematic of Figure 1, at the start of the optimization process, we gather different factors such as demand, energy cost, state of charge (SOC) level, presence of electric vehicles (EVs), and branch failure rate. By incorporating the probabilistic nature of these parameters, we can achieve more realistic results. To account for the influence of these probabilistic factors in finding a solution, we utilize the Monte Carlo (MC) method. In the next phase, our proposed approach estimates the risk of power outages

Table 1: The taxonomy of the studied researches.

Contribution Ref	5	6	7	9	10	11–16	13	1–15	17–19	20	21-22	27	31-32	This paper
EVs probabilistic behaviours and movements	Yes	No	No	Yes	No	No	No	No	No	Yes	No	No	Yes	Yes
Integration of the DERs into CSs	No	Yes	No	Yes	No	No	Yes	No	No	No	No	No	Yes	Yes
Coordination of DERs and EVs for optimal operation of CS and grid	No	Yes	No	Yes	No	No	Yes	No	No	No	No	No	Yes	Yes
Management of CS for load profile flattering	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes
Optimal charging/ discharging schedule of the EVs	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes
Profit sharing between DSO and EVCS owner	No	No	No	No	Yes	No	Yes	Yes	Yes	Yes	No	No	No	Yes
Resilience improvement of the grid	No	No	No	No	No	No	No	No	No	No	Yes	No	No	Yes
Simultaneous investigation of the effect of EV management and storm on the grid resilience	No	No	No	No	No	No	No	No	No	No	Yes	No	No	Yes

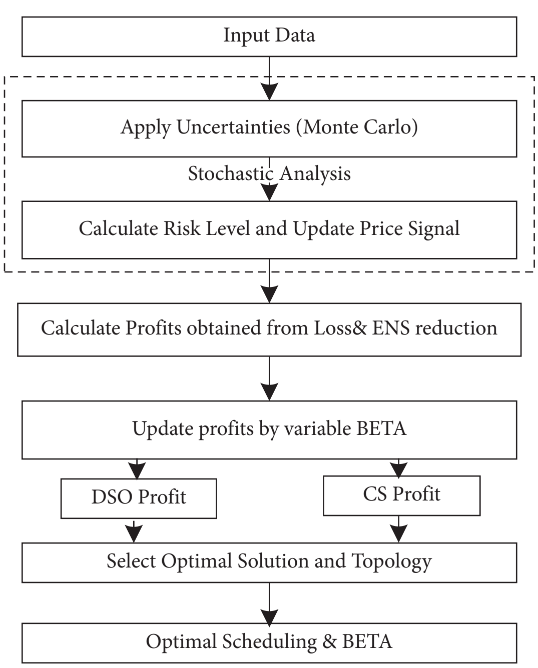

Figure 1: Schematic of proposed strategy.

caused by storms, enabling us to make adjustments to the operational planning. It is vital to note that the transition from economic operation to resilient operation is contingent upon the estimated risk value, which is quantified as the amount of ENS in this study. In simpler terms, as the risk increases, there is a corresponding increase in the adjustments made to the primary economic scheduling in order to minimize the anticipated ENS value. The rescheduling process relies on a modified signal price that is calculated by the distribution system operator (DSO). Through this mechanism, the DSO aims to reduce the penalty cost associated with ENS (in collaboration with the private sector) and facilitate the equitable sharing of benefits using the variable beta method for fair profit sharing. In order to problem formulation, a mathematical model for all influencing components is presented, and then, the proposed formulation for solving the problem is explained.

2.1. EV and CS Models. As explained earlier, EVs are parked within the CS in the charging/or discharging intervals. However, since the EV owners might not care about their effects on the grid operation, they do not specifically connect EVs to the grid. In this paper, a one-day period of EVs travel among several locations is considered. It is assumed that each EV daily traveling starts from a certain point at the beginning of the day and finishes in the same location at the end. Also, the aggregated storage of EV could be idle. Also, in order to have more realistic results, it is assumed that there are three different types of EVs with different behaviours as shown in Figure 2.

The first group (trivial) alternative is based on charge in local parking (home) and during the operational planning period that case is driven directly to the activity and is parked there during the activity without any power exchange. In this case, DRP could be applied during the charge period at home. The second group alternative is enroute charging as traditional vehicle behaviour in gas stations. In other words, vehicles stop enroute to the activity at a CS, wait for the charge process to be complete, and then continue to drive to the activity. In this case, during extreme conditions, the battery is only charged to 80% SOC. Normally, drivers use only fast charging stations for this purpose. The third group alternative is based on leaving EV in CS near the destination. This case is the best group for EV management, especially when the driver stays at the activity for several hours. For each group, the DSO has to consider which options are available during various operational conditions. Simply calculating the best management for EVs in different conditions could lead to changes in energy consumption, charging time, final cost, and resiliency of the grid. The alternative must also respect the energy constraints of the vehicle. In this paper, the third group of EVs is focused on and managed due to its behaviour. Hence, the operation time of the CS within the grid is uncertain unless an appropriate planning is made. Therefore, the uncertainties, like duration time for EVs, are connected, and energy consumption of EVs, price signals, and state of charge (SOC) value of EVs at the charging/discharging should be considered in the management of EVs [31]. In this respect, this paper employs the truncated normal distribution function for modelling independent random variables, including EVs battery capacity, the distance and duration time of EV movements, and the parking time of the EV within the CS.

One of the main limitations of the proposed method (and similar strategies) is its high dependability on predicting weather condition CSs allocation and behaviour of EV's owner. In other words, any changes in these parameters may change results. For more realistic results (with existing real data of drivers), the pattern recognition method could be used [32]. Pattern recognition is a data assessment technique that utilizes machine learning algorithms to automatically identify patterns and regularities in data. Pattern recognition systems can identify familiar patterns rapidly and precisely. They can also identify and categorize unfamiliar objects and recognize patterns and objects even if they are partially hidden [33].

Furthermore, the remaining dependent parameters such as arrival/departure patterns to/from CSs are calculated. The details of such stochastic modelling are given in [20]. Another parameter that affects the charging/discharging management during EV's presence at CS and is associated with uncertainty is the level of SOC of EVs. The modelling of

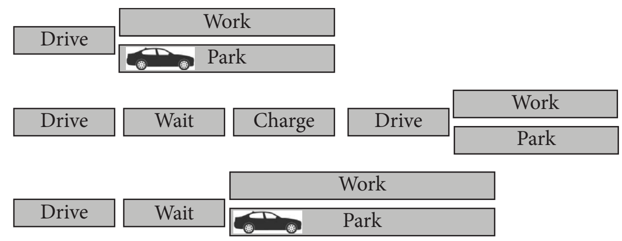

Figure 2: Various behaviours of EV owners.

power charging stations for input and output is influenced by various uncertain factors. These factors include the schedule for charging and discharging EVs, the type and capacity of the batteries in the EVs, the SOC for each individual EV, and the percentage of vehicles present at the CS. These parameters are not fixed and are subject to uncertainty. The access of EVs to the CS depends on the behaviour of the vehicle owners, and it can be described probabilistically. In this particular study, the time of arrival for EVs at the CSs is determined using Figure 3. This figure represents a normal probability density function (PDF) with a mean of 13.71 and a standard deviation of 4.52 [20]. Based on this, the percentage of EVs present at the CSs is determined to be between 10% and 90%.

The initial SOC of EV's batteries is influenced by uncertain factors such as the distance traveled and the type and efficiency of the batteries. Upon an EV's entry into the CSs, information regarding its initial SOC rate, desired final SOC, and exit time from the CS is collected. Based on this information, and considering the advantages of using EVs as ESs and the revenue generated from battery charging for driving purposes, an optimal charging/discharging plan is devised for the EV during its time at the CS. To accurately represent the presence of EVs and their initial SOC, the MC approach is employed to model the aforementioned uncertainties.

Both the presence of EVs and their initial SOC are assumed to follow a normal PDF with three states. The distribution curves for EVs and their initial SOC are depicted in Figure 4. The level of SOC and its changes are calculated according to the distance travelled (D_i) as follows:

$$
\begin{aligned}
\mathrm{SOC}_{\mathrm{int}}^{i} &= \left(1 - \frac{D_i}{D_{\mathrm{Total}}}\right) \times 100\%, \forall i \in N_{\mathrm{EVs}},\\
\mathrm{SOC}_{t}^{i} &= X_1\left(\mathrm{SOC}_{t-1}^{i} + \Delta t.\left(\mathrm{ch}_{\mathrm{rate}}\right)\right) \times 100\%, \forall i \in N_{\mathrm{EVs}}, \forall t \in \mathrm{T},\\
\mathrm{SOC}_{t}^{i} &= X_2\left(\mathrm{SOC}_{t-1}^{i} - \Delta t.\left(\mathrm{disch}_{\mathrm{rate}}\right)\right) \times 100\%, \forall i \in N_{EVs},
\end{aligned}
\tag{1}
$$

where $\mathrm{SOC}_{\mathrm{int}}^{i}$ presents the SOC value in arrival time of EV and charge/discharge rate of EV batteries in the time step of Δt is specified with $\mathrm{ch}_{\mathrm{rate}}/\mathrm{disch}_{\mathrm{rate}}$. Also, the simultaneous charging/discharging of the EVs is avoided by using binary variables X_1 and X_2.

As per the above *e* equations, the charging/discharging time of EVs and the total injected or stored energy in CS could be calculated as follows:

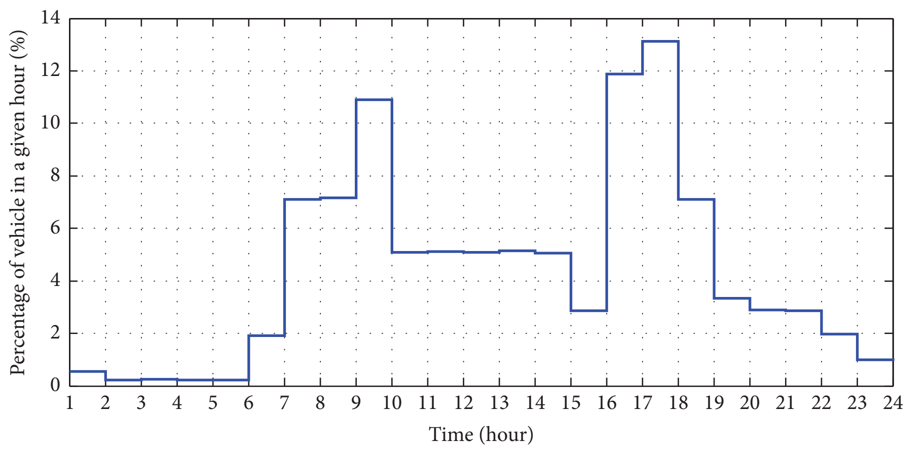

Figure 3: Hourly arrival of EVs at the CSs [20].

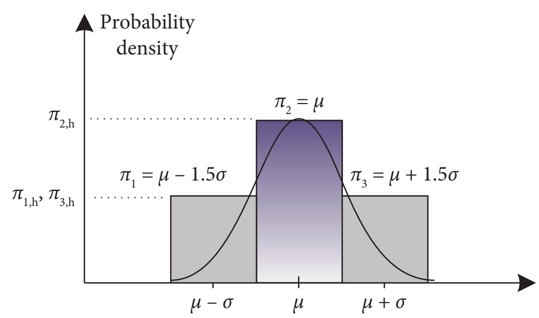

Figure 4: PDF for the arrival of EVs and their SOC.

$$
\begin{aligned}
t_{\text{charge}}(i) &= \frac{\left(\text{SOC}_{\max} - \text{SOC}_t^i\right) \times \text{ES}_i}{P_v},\\
t_{\text{discharge}}(i) &= \frac{\left(\text{SOC}_t^i - \text{SOC}_{\min}\right) \times \text{ES}_i}{P_v},\\
E_{\text{EVCS}}^{\text{discharge}} &= \sum_{i}^{N_{\text{EVs}}} \text{Pre}.T(i) \times C_i \times \left(\text{SOC}_{\text{int}}^i - \text{SOC}_{\min}\right) \forall \Delta t_{\text{discharge}},\\
E_{\text{EVCS}}^{\text{charge}} &= \sum_{i}^{N_{\text{Evs}}} \text{Pre}.T(i) \times C_i \times \left(\text{SOC}_{\max} - \text{SOC}_{\text{int}}^i\right) \forall \Delta t_{\text{charge}},
\end{aligned}
\tag{2}
$$

where $\text{Pre}.T(i)$ is the presence time of each EV at the CS and C is the battery capacity of EV number i.

In the field of modeling probabilistic parameters of EV/CS, in addition to the above equations, there are other stochastic variables, such as time of arrival/departure of EV, duration time of the EV's trip, and presence time of EVs inside the CS, that have been avoided to rewrite here due to the fact that they exist in the references like [13, 20]. However, the utilization of sequential MC simulation for the calculation of the final model of such parameters is required. Hence, after formulating the probabilistic model, MC simulation with repeated replications is utilized to obtain mean values during the simulation period. To this end, the stopping criterion is satisfaction of the coefficient of variation (CV) which is assumed to be less than 4%.

2.2. Load and Energy Price. As per the probabilistic behaviour of the demand, daily demand variation in each year of the planning period can be obtained by multiplying the base load ($P_{i,\text{base}}$ and $Q_{i,\text{base}}$) and demand level factor (DLF) [34]. In addition, by considering the rate of yearly load growth, the amount of active and reactive power is modelled as follows:

$$\begin{aligned}P^{e}_{i,t,h} &= P_{i,\text{base}} \times \text{DLF}^{e}_{i,t,h} \times (1+\alpha)^{t},\\ Q^{e}_{i,t,h} &= Q_{i,base} \times \text{DLF}^{e}_{i,t,h} \times (1+\alpha)^{t},\\ S^{D}_{i,h} &= P^{D}_{i,h,s} + jQ^{D}_{i,h},\end{aligned} \tag{3}$$

where DLF is obtained by the probability density function (PDF) as follows:

$$\text{DLF}^{e}_{i,t,h} = \mu^{D}_{i,t,h} + \lambda^{D,e}_{i,t,h} \times \sigma^{D}_{i,t,h}, \tag{4}$$

where λ is a random variable and is obtained by normal PDF with an average value of zero and a standard deviation of one for each demand level. $\mu^{D}_{i,t,h}$ is the predicted value for the load demand level with a standard deviation of $\sigma^{D}_{i,t,h}$, and α and t are the load growth rate and number of years, respectively.

The power price is cleared depending on the wholesale market price, and the demand level is obtained as follows [35, 36]:

$$\rho_h = \rho_{\text{base}} \times \text{PLF}_h, \tag{5}$$

where ρ_{base} is the basic electricity price and PLF_h stands for price level factor at time h_{th}.

Due to the importance of grid resilience, the actual price should be obtained according to energy purchasing cost and probable penalty costs could be caused by line failure, due to extreme weather conditions. In this paper, the actual price, which will be used as a signal price for DSO, is derived as follows:

$$\rho_h = \frac{\rho_{\text{base}}\text{PLF}_h + \rho_{\text{ENS}}\text{ENS}_h}{\text{PLF}_h}. \tag{6}$$

In this equation, the ENS cost is calculated as follows:

$$\text{ENSCost} = \sum_{i=1}^{N_L} \lambda_{\text{Line}} L_{\text{Line}} \rho_{\text{ENS}} \left(\sum_{i=1}^{N_{\text{bus}}} P_{\text{res}} \mu_{\text{Line}} \right) + \text{C}_{\text{repair}}, \tag{7}$$

where, ρ_{ENS} presents ENS cost and N_L stands for the number of lines with a length of L_{Line}. λ_{Line} and μ_{Line} are the failure and repair rate of the line. P_{res} states restored power once the line is repaired.

2.3. DRP Modelling. DRP is generally shifts load from peak hours to off-peak in order to reduce total operational costs and power loss [37]. In this study, it is assumed that ±15% of the load value can be shifted to other time intervals. Below is the relevant model for the applied DRP:

$$\begin{aligned}S^{\text{DR}}_{i,h} &= S^{D}_{i,h} + \Delta S_{\text{DRP}},\\ \Delta S_{\text{DRP}} &= \text{K}_{\text{DRP}} \times S^{D}_{i,h},\\ \sum_{h=1}^{24} \Delta S_{\text{DRP}} &= 0,\\ \text{K}^{\min}_{\text{DRP}} < K_{\text{DRP}} &< K^{\max}_{\text{DRP}},\end{aligned} \tag{8}$$

where $S^{\text{DR}}_{i,h}$ is the apparent value of power after implementation of DRP, ΔS_{DRP} is the values of apparent power transferred by DRP, and K_{DRP} presents the participation level of DRP.

2.4. Model of Wind Turbine (WT) Output. The output of a WT is not controllable, and it mainly depends on various parameters such as wind speed which is not generally specific and should be considered randomly. In this paper, the Rayleigh probability function is applied for modelling random behaviour of wind speed and WT output.

$$f_{\text{wg}}(v) = \left(\frac{2v}{c^2}\right) \exp\left(-\left(\frac{v}{c}\right)^2\right), \tag{9}$$

where v and c parameters present the average speed of wind speed and scale index in equation (9), respectively. With knowing the average of wind velocity, the scale index is calculated as follows:

$$\begin{aligned}v_m &= \int_0^{\infty} v f_{\text{wg}}(v) d_v = \int_0^{\infty} \left(\frac{2v^2}{c^2}\right) \exp\left[-\left(\frac{v}{c}\right)^2\right] \text{d}_v = \frac{\sqrt{\pi}}{2} c,\\ c &\cong 1.128 v_m.\end{aligned} \tag{10}$$

Based on the above equations and considered PDF, the power output of WT is obtained as follows:

$$P^{\text{WT}}_{i,t,h} = \begin{cases} 0, & \text{if} \quad v^{\text{cut}}_{\text{in}} \text{ or } v \geq v^{\text{cut}}_{\text{out}},\\ P^{\text{WT}}_{i,r} \dfrac{v - v^{\text{cut}}_{\text{in}}}{v_{\text{rated}} - v^{\text{cut}}_{\text{in}}}, & \text{if} \quad v^{\text{cut}}_{\text{in}} \leq v \leq v_{\text{rated}},\\ P^{\text{WT}}_{i,r}, & \text{else},\end{cases} \tag{11}$$

where $P^{\text{WT}}_{i,r}$ is the permitted capacity for power generation. $v^{\text{cut}}_{\text{in}}$, $v^{\text{cut}}_{\text{out}}$, and v_{rated} are cut-in, cut-out, and rated speed in WT, respectively. As per the above equations, wind speed changes the performance of WT, particularly, in extreme weather conditions where the WT may stop working. On the other hand, high-speed winds (storms) increase the probability of fault inception in lines and decrease the resiliency level and economic profit for the grid.

2.5. Resilience-Oriented Operation of the Network. It is proved that extreme weather conditions (storms) are the most common reason (about 65%) for the inception of various failures [23]. In such cases, line outage may occur, and therefore, network resiliency with increasing ENS is greatly reduced. As a side note, the main differences between reliability and resiliency depend upon the types of events, its impact timing, and the method of assessment. The main difference between reliability and resiliency usually is focusing on probabilities of impact of events. In this paper, probabilistic events could be caused by weather condition (storm) is studied [22, 29]. Furthermore, reliability studies are commonly conducted by considering all possible events and providing a better solution in larger time intervals with uniform failure rates.

In this respect, side effects of weather conditions (storms) on increment of failure rates are considered in this paper. In paper [26], the correlation between the number of events (N_{wind} and $N_{\text{lightning}}$) and wind speed (W)/numbers of thunder (L) is formulated for short-time intervals.

$$\begin{aligned} N_{\text{wind}} &= 0.0012 {W_{\text{speed}}}^2 - 0.0131 W_{\text{speed}}, \\ N_{\text{lightning}} &= 0.0001 L + 0.7014. \end{aligned} \tag{12}$$

It is obvious that storms could be forecasted with acceptable accuracy in wind speed prediction. In this regard, the changes in failure rates could be updated and the new status of the outages rate will be used in grid management during extreme weather conditions.

In this respect, the resiliency index is calculated; however, for evaluation of the effectiveness of the proposed strategy on resiliency, the evaluation metrics should be also introduced. In this paper, ΦΛΕΠ metrics proposed in the paper [27] are used, based on which a multiphase resilience trapezoid associated with the extreme weather is considered. Three phases can be clearly seen in the resilience trapezoid of Figure 5 as disturbance progress (Φ and Λ-metrics), post-disturbance degraded (E-metric), and restorative state (Π-metric). ΦΛΕΠ metrics would be defined to the operational and infrastructure resilience. Mathematical expression and measuring units for ΦΛΕΠ metrics are shown in Table 2.

2.6. Proposed Methodology for Resilience-Oriented Operation of Grid. During natural disasters, resiliency improvements of the network, i.e., its ability to predict, self-healing, and fast restoration, are vital actions. As explained earlier, one of the influencing approaches for resiliency improvement is the management of various groups of EVs (with different behaviours and management levels) by considering forecasted conditions, energy resource rescheduling, and DRP implementation. On the other hand, based on the uncertainty of weather conditions and in sequence updating the probability of failure ratios, EVs movement pattern, and uncertainty of SOC level for EVs, energy resources, demand response program, and reconfiguration will be rescheduled by considering high-risk time intervals condition. As a result, the application of these solutions, given their impact on the operation of the CS, must also be economically justified for the CS owner. In other words, an optimal trade-off between economic benefits and resilient operation should be made.

As a side note, the adopted schedule for EVs is generally based on tariff offered by the grid operator, so that the EV is charged during time intervals with lower energy prices. On the contrary, the discharging of excess energy in EV batteries is done during peak intervals when the energy price is higher. Accordingly, it can be concluded that if the DSO locally increases the reference for signal price in some intervals in order to improve the resilience, the CS owner will be encouraged to change the charging/discharging schedule and gain more profits. Based on this fact, in the proposed strategy of the paper, the actual operation cost is calculated by uncertainties.

In this regard, this paper proposes a novel resilience-oriented strategy, which with optimal interaction between rescheduling of DERs energy and EV's charging/discharging management, increases resiliency, and reduces total ENS during normal operation and extreme weather conditions. Also, profits of DSO and EV owners are calculated in detailed objective functions in order to maximize. To do so, the failure rate of branches, power generation of WT, EVs movement pattern, arrival/departure times, and SOC levels depend on weather conditions. In the following, a proposed formulation related to both DSO and CS owners is presented.

2.6.1. DSO Benefit Formulation. DSO, in supplying the network demand, must pay some costs, like the cost of purchasing energy from the upstream or utility (S_h^{Utility}) or the cost of purchasing energy from the wind turbine and CS in the discharging intervals. It also earns revenue from the sale of energy to the customers or to the CS in the charging intervals. As a result, the DSO benefits, which should be maximized during the next 24 hours in the proposed algorithm, are obtained by subtracting cost (C_{DSO}) and revenue (R_{DSO}).

$$R_{\text{DSO}} = \sum_{i=1}^{N_{\text{load}}} \rho_{\text{sell}}^{P} \cdot P_{i,t,h}^{e} + \frac{1}{T(i)} \sum_{i=1}^{N_k} \rho_{\text{sell}}^{P} \cdot E_{\text{EVCS}}^{\text{charge}}, \tag{13}$$

$$C_{\text{DSO}} = \lambda_h \cdot S_h^{\text{Utility}} + \text{ENSCost}_h + \rho_{\text{sell}}^{\text{WT}} \cdot P_{i,t,h}^{\text{WT}} + \frac{1}{T(i)} \sum_{i=1}^{N_k} \rho^{P} \cdot E_{\text{EVCS}}^{\text{discharge}}, \tag{14}$$

$$\text{OF}_{\text{DSO}} = R_{\text{DSO}} - C_{\text{DSO}}. \tag{15}$$

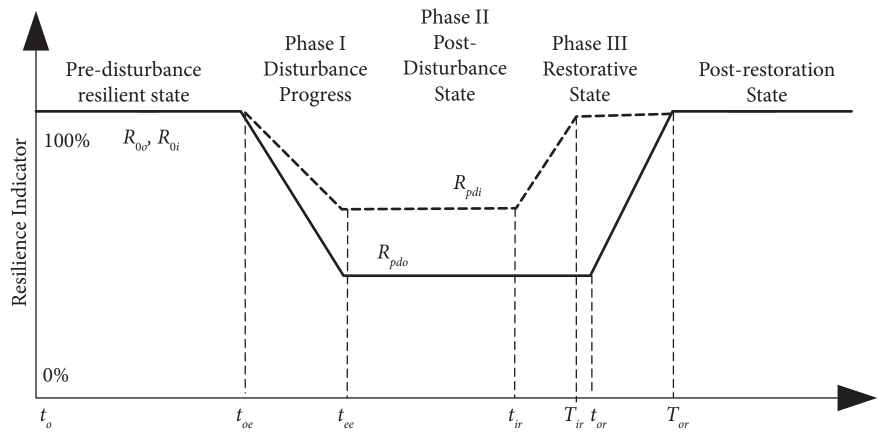

Figure 5: Resilience indicator and the multiphase resilience trapezoid [23].

Table 2: The mathematical relations and explains for ΦΛΕΠ metrics.

Metric	Mathematical expression		Measuring unit	
	Operational	Infrastructure	Operational	Infrastructure
Φ	$(R_{\mathrm{pdo}} - R_{0o})/(t_{\mathrm{ee}} - t_{\mathrm{oe}})$	$(R_{\mathrm{pdi}} - R_{0i})/(t_{\mathrm{ee}} - t_{\mathrm{oe}})$	MW (hour)	Number of lines tripped (hours)
Λ	$R_{0o} - R_{\mathrm{pdo}}$	$R_{0i} - R_{\mathrm{pdi}}$	MW	Number of lines tripped
E	$t_{\mathrm{or}} - t_{\mathrm{ee}}$	$t_{\mathrm{ir}} - t_{\mathrm{ee}}$	Hours	Hours
Π	$(R_{0o} - R_{\mathrm{pdo}})/(T_{\mathrm{or}} - t_{\mathrm{or}})$	$(R_{0i} - R_{\mathrm{pdi}})/(T_{\mathrm{ir}} - t_{\mathrm{ir}})$	MW (hour)	Number of lines restored (hours)
Φ	$(R_{\mathrm{pdo}} - R_{0o})/(t_{\mathrm{ee}} - t_{\mathrm{oe}})$	$(R_{\mathrm{pdi}} - R_{0i})/(t_{\mathrm{ee}} - t_{\mathrm{oe}})$	MW (hour)	Number of lines tripped (hours)

In the above equations, ρ_{sell}^{P}, λ_h, and $\rho_{\mathrm{sell}}^{\mathrm{WT}}$ are the sold energy cost for users, purchasing energy cost from utility energy purchasing fee from WT. It should be noted that the amount of purchased power from the utility or CS depends on the market electricity price. The purchased active/reactive power can be easily obtained from S_h^{Utility}.

Note that DSO is allowed to sell power to the market when S_h^{Utility} become negative. In equation (14), the ENS cost due to line outage is also modelled. In addition, the power exchanged with the CS depends on the charge/discharge schedule, which is presented in the next section as a method for its optimal programming.

2.6.2. CS Benefit Formulation. Usually, the EV owner's benefit is in increasing the presence of EVs and purchasing energy from the DSO at the lowest price. In other words, for the CS, the DSO profit (due to load characteristic correction and resilience improvement) is not important, unless it receives a profit from participating in these programs. Furthermore, charge/discharge rates ($\mathrm{ch}_{\mathrm{rate}}/\mathrm{disch}_{\mathrm{rate}}$) and charging/discharging time are effective in modifying the load characteristic. Therefore, the following objective is suggested to optimize charging/discharging values and timing. In fact, in this paper, first, the EV's charging/discharging planning is optimally calculated. In this way, the optimal charging and discharging times, in which attractive price signals are given, are calculated.

$$\begin{aligned}
\mathrm{OF}_1 &= a \times \sum_{t=1}^{T}\left(\frac{P_{L-\mathrm{Peak}}}{P_{L-\mathrm{peak}}^{\mathrm{Corrected}}} - 1\right)\Delta t_{\mathrm{discharge}} + b \times \sum_{t=1}^{T}\left(\frac{P_{L-\mathrm{Min}}^{\mathrm{Corrected}}}{P_{L-\mathrm{Min}}} - 1\right)\Delta t_{\mathrm{charge}} + (c \times \mathrm{MSE}),\\
\mathrm{MSE} &= \sum_{t=1}^{24}\left(P^{\mathrm{Load}}(t) - \sum_{i=1}^{N_{\mathrm{EVs}}} P^{\mathrm{EVCS}}(i) - P_{\mathrm{ref}}\right).
\end{aligned} \tag{16}$$

A weighted sum model is used for the objective function. In this function, a, b, and c are applied for normalizing different terms of the OF and converting them to [0-1] range. Forecasted demand profile and modified demand profile are calculated by mean square error (MSE). In other words, the charge/discharge schedule is achieved in such a way that effective peak shaving and load profile flattering are achieved by tracking P_{ref} minimizing MSE. $\Delta t_{\mathrm{charge}}$ and

$\Delta t_{\text{discharge}}$ are the total time when the battery of vehicles is charged or discharged, respectively.

Although the implementation of the above optimal schedule will make both DSO and the CS owner profitable, as mentioned, if network resilience in bad weather conditions is considered, the charging/discharging program will change. In other words, the CS owner's profit function needs to be formulated again. In this respect, the cost and revenue function of the CS have been modelled as follows. Moreover, the CS benefit, which should be maximized during the next 24 hours in the proposed algorithm, is obtained by subtracting cost and revenue.

$$\begin{aligned}
R_{\text{EVCS}} &= \rho_{\text{sell}}^{\text{WT}} \,.\, P_{i,t,h}^{\text{WT}} + \frac{1}{T(i)} \sum_{i=1}^{N_k} \rho^{P} \,.\, E_{\text{EVCS}}^{\text{discharge}},\\
C_{\text{EVCS}} &= \frac{1}{T(i)} \sum_{i=1}^{N_k} \lambda_h \,.\, E_{\text{EVCS}}^{\text{charge}} + C_k^{\text{deg}} \left(\sum_{k=1}^{N_k} \frac{E_{\text{EV}}^{\text{discharge}}}{\eta_k^{\text{discharge}}} + \eta_k^{\text{charge}} \,.\, E_{\text{EV}}^{\text{charge}} \right),\\
OF_{\text{EVCS}} &= R_{\text{EVCS}} - C_{\text{EVCS}}.
\end{aligned} \tag{17}$$

The CS's revenue includes the sale of wind energy and the energy of EV batteries during the discharge period, while charging EVs are costly for the owner. In this regard, C_k^{deg} and $\eta_k^{\text{charge}}/\eta_k^{\text{discharge}}$ are depreciation coefficient and efficiency of charging/discharging pattern of EV's battery, respectively.

2.7. Related Constraints. In the proposed formulation, constraints should also be considered, the most important of which is the power balance in the network. This issue, as per the implementation of DRP and also the charging/discharging schedule, can be formulated as follows. In addition, the bus voltage must be kept within its permissible ranges.

$$\begin{aligned}
P_h^{\text{Utility}} - \left((1 - \mathrm{K}_{\text{DRP}}) \times P_{i,h}^{D} + \Delta P_{\text{DRP}} \right) + \frac{1}{T(i)} \sum_{k=1}^{N_k} \left(E_{\text{EVCS}}^{\text{discharge}} - E_{\text{EVCS}}^{\text{charge}} \right) &= V_{i,h} \sum_j V_{j,h} \left(G_{\text{ij}} \cos \delta_{i,h} + B_{ij} \sin \delta_{j,h} \right),\\
Q_h^{\text{Utility}} - \left((1 - \mathrm{K}_{\text{DRP}}) \times Q_{i,h}^{D} + \Delta \mathrm{Q}_{\text{DRP}} \right) &= V_{i,h} \sum_j V_{j,h} \left(G_{\text{ij}} \cos \delta_{i,h} - B_{ij} \sin \delta_{j,h} \right),\\
\Delta S_{\text{DRP}} &= \Delta P_{\text{DRP}} + j \Delta \mathrm{Q}_{\text{DRP}},\\
V_i^{\min} \le V_{i,h,s} &\le V_i^{\max},\\
0 \le S_{\text{ij},h,s} &\le S_{\text{ij}}^{\max}.
\end{aligned} \tag{18}$$

2.8. Approach Overview. Management and control of charging/discharging of EVs with the aim of profitability for the distribution system operator (DSO) and the private sector are some of the challenges of operating CS. This paper proposes a novel methodology for optimal planning of charging/discharging of the hybrid wind-CS which, on the one hand, leads to correction of the load curve and, on the other hand, improves the grid resilience in extreme weather conditions.

In this paper, first, the probabilistic model of influencing components, including EVs (all groups), CS, load, energy price, DRP, and WT generation, is formulated, and then, final models using MC simulation are extracted. Furthermore, to have a proper analysis to evaluate the resiliency of the test case, failure rates, and ENS values are updated based on predicted weather conditions. In the next step, a methodology for the resilience-oriented operation of the grid is presented, in which the benefit formulation of both DSO and CS owner is calculated. In this respect, the benefit formulation of the CS is associated with the optimal scheduling of the EVs. Finally, the presented multiobjective optimization algorithm of the paper is solved using MGO, and the optimal solution is found.

3. Simulation and Numerical Results

In order to evaluate the effects of the resiliency-oriented operation of EVs and rescheduling of resources, simulations are implemented on an IEEE 33 bus test system with five switches [33] as shown in Figure 6. As a side note, the proposed methodology is devised in such a way that it can be implemented on any grid; however, its efficiency could be

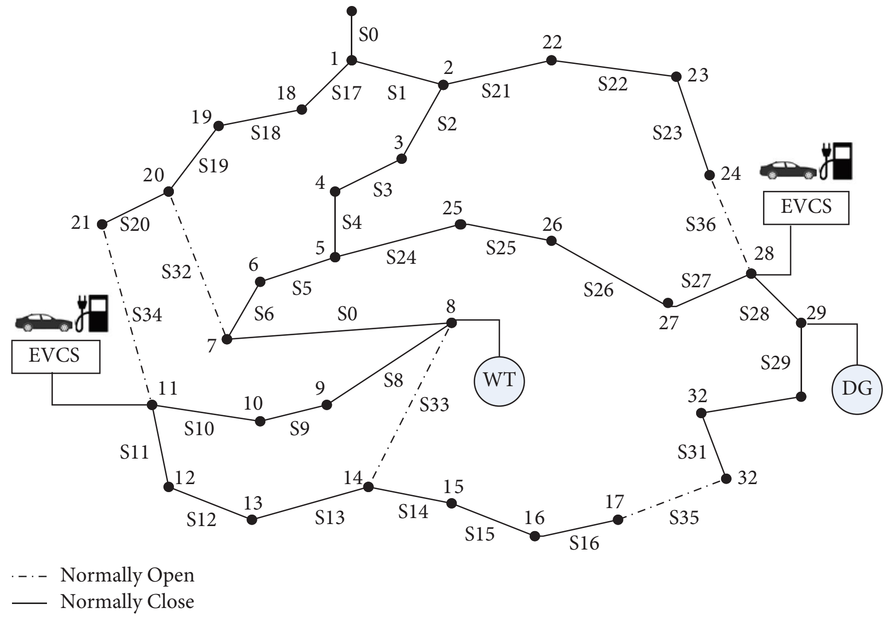

Figure 6: Test system of the paper.

different for each network. The data and information used in simulations are reported in Table 3.

To assess the efficiency, validation of optimality, and limitations of the method, a similar approach from reference [38] is utilized. By comparing the results of the proposed method with existing EV management methods, using similar test systems, distributed energy resources (DERs), and control strategies, we introduce certain adjustments to evaluate the unique benefits of the proposed method.

First, modelling of the demand is done based on the load pattern (daily, weekly, and annual) given in the standard reliability test system [25]. However, it should be noted in this study that the load of a working day is considered to reduce the required time for the execution of MC. Then, the energy price model is also done according mentioned before.

As explained, the placement of the CS is not the concern of this study, but due to the fact that their allocation affects the implementation of the proposed methodology, two CSs (normal CS for type 3 EVs and fast charge CS for type 2 EVs) with the capacity of 250 EVs are optimally allocated, based on the presented method of reference [34], in buses 11 and 28. Here, it is assumed that all EV drivers have almost the same pattern in driving, so that they park EV in a parking lot and come back to the initial point after work and park. As a side note, the proposed methodology is devised in such a way that it can be implemented on any grid; however, its efficiency could be different for each network. As explained, demand and price are considered as 24-hour patterns. A DG and WT, both with 1000 kW capacity, are located in 8 and 29 buses. A schematic of different EV types is shown in Figure 7. These two CSs are called administrative CS (fast charge and normal) and residential CS, respectively. Moreover, the capacity of the EV's battery is assumed to be 15 kWh, and the rated power of the batteries assumed is equal to 5 kW. Also, the depreciation rate is calculated based on approximately 10 years of lifetime for batteries. On the other hand, the behaviour of EVs (in fact EV driver) is probabilistic and uncertain. Therefore, by using the sequential MC method for each group, which is on the basis of repeated replications of the study, the final model of the stochastic parameter is calculated based on the mean value during the simulation period. The movement of EVs in the grid is also modelled as floating demand between some buses. Detailed patterns of movements are available in [36].

In the present study, a storm happens for a 4-hour interval. Also, it is assumed that failure numbers and repair time are similar for different simulation cases. In this respect, the MC simulation approach is rerun to study the probability of line failure which is subject to the extreme weather conditions. By obtaining the stochastic models, the proposed multistep optimization strategy, for jointly optimization of EVs schedule and DSO/CS profits, is solved. Since the studied problem is complex and vast, the particles may trap in the local optimum as they move towards a false Pareto front. To deal with this issue, an MGO algorithm is used here to find the Pareto solution of the problem. In the MGO algorithm, the exploration and exploitation of the algorithm and its convergence capability have been improved. In the utilized MGO of this paper, the pertinent parameters are set based on values obtained in [39].

In order to demonstrate the impact of the proposed methodology on the optimal schedule of the CS, two scenarios are defined as follows:

Table 3: Data and information table.

Value	Units	Comment
$0.02 \times \mu^{D}_{i,t,h}$		Standard deviation used for load
$0.1 \times \mu^{\rho}_{t,h}$		Standard deviation used for price
0.9/1.1	Pu	Min/max magnitude of voltage
0.046	f/km	Fault rate
10	kW	Charging/discharging power rate
0.90		Efficiency of V2G equipment
	Market price	
85	\$/MWh	Retail selling base price
75	\$/MWh	Wholesale purchasing base price
70	\$/MWh	Purchasing price from EVs
Other costs		
0.001	\$/kWh	Degradation cost
210	\$/MWh	Base price of energy not supplied
0/0075, 45, 25	—	Cost coefficients of DG

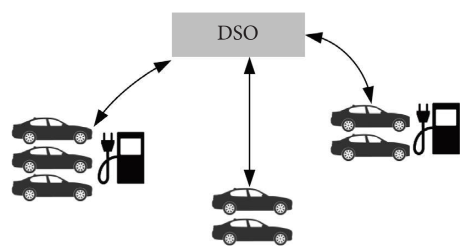

Figure 7: Schematic of EV drivers' behaviour type.

Scenario 1: Optimal schedule without considering grid resilience

Scenario 2: Resiliency-oriented operation

The optimal results for the above-mentioned scenarios are reported in Table 4. Note that in both scenarios, the DR program is applied. However, for type 2 EVs (using fast charging CS or residential charger), the charge/discharge levels are different in scenarios as mentioned. It is obvious that the charged energy value is more than the discharged energy value due to EV movement. In fact, the program has been designed so that the discharge of EV batteries does not interfere with the daily travel of EVs.

It is noticeable that the energy consumption of EVs and the V2G values are higher in the normal CS than in others. The reason is that when parked EVs in a normal CS, charge the EV storage at high rates before/after high risk time interval and discharge amount is higher during storm. In addition, when the EVs are in the CSs, the load characteristic sometimes encounters peak demand, so the high discharge rate and low charge are more attractive to the aggregator. However, maximum charge levels of EVs are limited during extreme weather conditions due to resiliency improvement.

On the other hand, in the second scenario where resilience improvement is considered, the discharge rate is reduced. Moreover, the peak-time hours are changed. In fact, in times of extreme weather conditions, the normal CS in the discharge cycle helps to supply network power and reduces ENS accordingly. On the other side, fast charger CS and residential chargers reduce the power charge rate to EVs during extreme weather conditions. In this study, the ENS is calculated as a resiliency index.

The changes in demands in both scenarios are shown in Figure 8. As seen in this figure, controllable load consumption changed by considering high-risk intervals (expensive energy prices obtained by equation (6)).

The obtained results for both scenarios are presented in Table 4. It is noticeable that DRP are considered in the results. As shown in Table 4, without benefit sharing ($\beta = 0$), there is no any interest for private sector to cooperate with DSO. In this scenario, the best Pareto solution for DSO is equal to 3.81. In scenario number 2, for ($\beta = 0.2$), the best Pareto solution is obtained and best solutions for DSO and CS are equal to 3.94 and 0.52, respectively.

So, it is clear that benefits sharing not only gives interest to the private sector but also increases benefits for DSO. It is essential to mention that the best solutions depend on forecasted weather conditions and other uncertain parameters. In this paper, the min-max method using the fuzzy decision-making method is used. In this way, per-unit values that normalized benefits for functions are calculated. Then, the maximum value of minimum values for objective functions among the Pareto set is selected as the best possible solution.

In Table 5, obtained results for EVs management and changes in power exchange are presented. The total power consumption of EVs in fast-charging CS and ENS value are reduced due to limitation in maximum SOC level. The charge/discharge level of EVs in the home is not changed. However, the charging time is changed by using DRP. It is

Table 4: Objective functions for Pareto solutions.

Solution number		Best for CS	Optimal	Best for DSO
Scenario 1	OF_{DSO}	3.031	—	3.813
	OF_{EVCS}	0	—	0
Scenario 2	OF_{DSO}	0.212	**3.942**	4.310
	OF_{EVCS}	0.794	**0.521**	2.234

These numbers are the optimal values among many solutions could be considered. Also, there are not any optimal solution in other scenario. They shows the output for best solution.

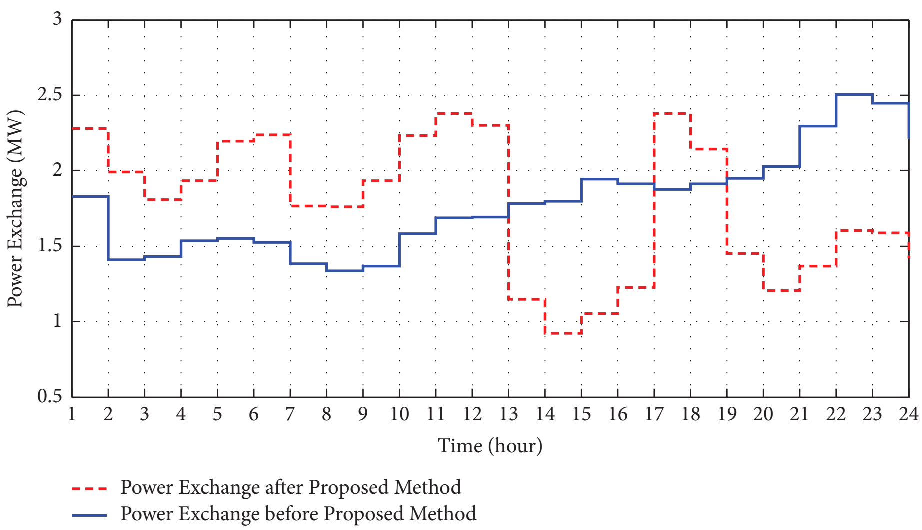

Figure 8: Power exchange in scenario 1 and scenario 2.

Table 5: Results for different EV group management.

Scenarios	Fast charge CS (administrative)		Normal CS (administrative)		CS (residential)	
	ch_{rate}	dis_{rate}	ch_{rate}	dis_{rate}	ch_{rate}	dis_{rate}
Scenario 1	14.22	0	16.73	8.32	10.91	0
Scenario 2	13.73	0	17.52	9.11	10.91	0

obvious that the charged energy value for EVs parked in CS is more than discharged energy due to EV movement supply needs. In fact, the program has been designed so that the discharge of EV batteries does not interfere with the daily travel of EVs. It is noticeable that the energy consumption of EVs and the V2G values is higher in the normal CS than others. The reason is that when parked EVs in a normal CS charge the EV storage at high rates before/after high-risk time intervals, the discharge amount is higher during storms. In addition, when the EVs are in the CSs, the load characteristic sometimes encounters peak demand, so the high discharge rate and low charge are more attractive to the aggregator. However, maximum charge levels of EVs are limited during extreme weather conditions due to resiliency improvement. Also, the charging/discharging pattern is changed. During extreme weather conditions, EVs in CS helped DSO to reduce ENS by discharging and providing extra energy inside the grid. In a similar way, EVS in fast charger CS and homes reduced power consumption during high-risk situations. So, by the reduction in demand during high-risk period, the amount of ENS reduced and, in sequence, resiliency and related benefits increased.

As mentioned before, controllable energy resources output increased by considering high-risk intervals (higher energy prices obtained by equation (6)). The modified energy price proposed by DSO is always higher than the primary energy price due to the positive value of ENS. So, DER could help power need from the upstream grid during high-risk time intervals.

Table 6 reports details of profit values for both DSO and CS in the best Pareto solution. In this table, the total benefits for DSO and CS in scenario number two are more than scenario number 1 and proposed method in [38]. It is noticeable that in order to evaluate the uncertainty of EV penetration and behaviour patterns, the sensitivity of the proposed method to variations in EV penetration is analysed. It is necessary to mention that the proposed method is sensitive to high-risk time intervals and the location/capacity of CSs, so results could depend on forecasted weather conditions. As can be seen, resilient-oriented operation

Table 6: The results of objective functions for scenario 1 and scenario 2, ref. [38], and double penetration.

Scenario	1	2	Ref. [38]	Double penetration
Profits of peak load reduction ($)	2.78×10^6	2.11×10^6	2.42×10^6	2.35×10^6
Profits of resiliency enhancement ($)	4.45×10^6	6.18×10^6	5.31×10^6	6.41×10^6
Profits of providing demand ($)	3.94×10^7	4.01×10^7	3.98×10^7	4.02×10^7
Profits of power loss reduction ($)	5.53×10^5	4.06×10^5	4.83×10^5	4.16×10^5
Total profit of DSO ($)	4.72×10^7	4.88×10^7	4.62×10^7	5.01×10^7
Profit of CS service ($)	0.58×10^6	0.69×10^6	0.65×10^6	0.74×10^6

Table 7: The ΦΛΕΠ metrics for different scenarios.

Metrics	Scenario 1		Scenario 2	
	Operational	Infrastructure	Operational	Infrastructure
Φ	−1	−1	−0.72	−0.78
Λ	1	1	1.34	1.25
E	1	1	0.39	0.39
Π	1.23	1	3.42	3.20

improved profits of resiliency enhancement; however, due to changes in demand level, peak shaving is less than normal economic operation. So, profits of peak load reduction and power loss reduction are reduced. On the other side, less power sold in fast-charging CS reduced total profits of providing demand. It means that operational logic estimates that ENS penalty cost risk is greater than the benefits that could be obtained by power sold to consumers during extreme weather conditions.

Upon comparing the results obtained from the proposed method and the method described in [38], it is evident that the proposed approach offers greater gains for both parties. This can be attributed to its improved enhancements in resiliency and equitable profit distribution. Furthermore, the management of fast CS and residential chargers exhibits similar characteristics in this scenario. Results show that the proposed method increased the benefits of DSO and CS and resiliency improvement by 5.6%, 6.2%, and 16.4%, respectively, during a certain operational planning period. Also, in case that EVs penetration is increased up to 200% (for normal CS), profits of DSO, CS, and resiliency index are enhanced 6.4%, 27.6%, and 44.0%, respectively. The results indicate that the proposed method has significantly increased the benefits for the DSO and CS, while also achieving a substantial improvement in resiliency during a specific operational planning period. Additionally, the findings demonstrate that a higher adoption rate of controllable EVs (group 3) enhances management capabilities. When comparing the outcomes of the suggested approach in scenarios where the penetration of controllable EVs (group 3) is doubled, it is evident that the economic benefits derived from improvements in resiliency increase by 38.4% and 67.1%.

In order to quantify the resilience enhancement, ΦΛΕΠ metrics are calculated for both scenarios. Four values of key metrics present effects of proposed resilient operation in resilience trapezoid are calculated. Also, improvements in mentioned indicates are per-unit based on existing condition in scenario number 1. Obtained results show that resilient operation Φ (how much side effect) and Λ (how low resiliency drops) in phase I (preparedness before event) improved 28% and 34%, respectively. E and Π are similar for both scenarios due to their similar potential in fault isolation and repair time in phase II (postdisturbance degraded state) and phase III (restorative state). In different circumstances, the effectiveness of the proposed methodology in grid resilience improvement is also evaluated through ΦΛΕΠ metrics and the pertinent results are calculated. In other words, to quantify the resilience improvement of applying the proposed strategy, ΦΛΕΠ metrics for both operational and infrastructure are calculated and tabulated in Table 7.

The output of Table 7, which corresponds to Figure 5 and Table 4, presents the value of the key metrics for the characterization of the resilience trapezoid to evaluate how fast (Φ) and how low (Λ) resilience drops in phase I, how extensive (E) is the postevent degraded state (phase II), and how promptly (Π) the network recovers to its preevent resilient state (phase III), considering both operational and infrastructure resilience in each phase.

As per the obtained results, the slope of the resilience degradation during the extreme weather is −1 for the first case, while, in the second scenario, the corrective actions are taken, the slope is decreased to −0.72. It should be noted that the grid reconfiguration through isolating the switch changes the topology of the network. Also, in the second scenario, the value of Λ is obtained equal to 1.34, which proves that the resilience value in this scenario has dropped less compared to the first scenario. In accordance with Λ merit, the duration of the postdisturbance is also degraded.

4. Conclusions

EVs are flexible demands with potential of vehicle to grid power injection. So, it is possible to improve grid resilience by rescheduling of EVs during extreme weather condition. In this paper, a novel two-stage stochastic optimization method for the optimal charging/discharging schedule of the CS is proposed. The obtained results indicate that the suggested approach brings about a 5% and 24.1% improvement in benefits for DSO and CS owners, respectively. Moreover, the implementation of this strategy leads to a significant reduction of 37.4% in ENS penalty costs. To elaborate further, the initial cluster of EV owners (specifically those with residential chargers) adjusted their electricity consumption based on signals provided by the DSO. As for the second group of EV owners (using fast charging stations), they decreased their charging activities during high-risk periods by approximately 3.9%. The final category of EVs (utilizing regular charging stations) adjusted their charging schedule by shifting their demand to periods with lower risk prices. Additionally, they increased the amount of energy charged by 5.2% (attributable to heightened interest) to be discharged during high-risk price intervals. Consequently, the discharged energy from this group saw a 9.5% increase. Interestingly, regardless of the proposed method, there was no change in the disparity between the amount of energy charged and the amount of energy injected. The outcomes have demonstrated that the suggested approach enhances the collaboration between the private sector and EVs with the DSO, driven by economic incentives. Additionally, the rescheduling of resources and effective management of EVs have contributed to an increase in resiliency. This highlights the positive impact of the proposed method, both in terms of fostering cooperation and improving overall system robustness. Finally, the proposed methodology is evaluated using ΦΛΕΠ metrics. The obtained results demonstrate that the utilization of the proposed reconfiguration method led to notable improvements in various metrics, specifically by 28%, 34%, 61%, and 25%. Looking ahead, future research could explore the potential of hub energy systems as test systems to further enhance cooperation between diverse energy resources. This avenue holds promising opportunities for advancing the integration and optimization of different energy sources. In future works, more detailed models for the behaviour of EVs using pattern recognition and considering related uncertainties will be studied.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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