

Optimal Charging/Discharging Control of Electric Vehicle Charging Station Considering Grid Resiliency

Emad Hadian¹, Hamidreza Akbari^{2†}, Mehdi Farzinfar³, and Seyed Amin Saeed⁴

^{1,2,4} Department of Electrical Engineering, Yazd Branch, Islamic Azad University, Yazd, Iran

³ School of Engineering, Damghan University, Damghan, Iran

A Management and control of charging/discharging of Electric vehicles (EVs) with the aim of profitability for the
B Distribution System Operator (DSO) and the private sector is one of the challenges in operating Electric vehicles Charging
S Stations (EVCS). This paper proposes a novel methodology for optimal planning of charging/discharging of the hybrid
T wind- EVCS which on the one hand, lead to correction of the load curve and on the other hand, improves the grid
R resilience in extreme weather conditions. In the proposed methodology, since the weather based outages lead to consumer
A interruptions, the idea of profit sharing between DSO and EVCS owner is proposed to incentivize the owner to implement
C the obtained charging/discharging schedule. To this end, firstly, a Monte-Carlo based stochastic framework for forecasting
T probability of weather based line outages and also modelling uncertainties is devised. Then, a resilience-oriented
 multi-objective optimization algorithm is presented that, while coordinating operation of the wind turbine, EV management
 and Demand Response Programs (DRP), the profits of both EVCS and DSO are maximized during daily operation
 planning. The resiliency improvement of the proposed method is evaluated by using $\Phi\Delta E\Pi$ metrics. The obtained optimal
 results prove effectiveness of the proposed method in increasing resiliency and benefits for all players.

Article Info

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Control of Charging/Discharging, Electric Vehicle, Extreme Weather Condition, Multi-Objective Optimization, Resilience

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I. INTRODUCTION

The growing use of Electric Vehicles (EVs) within the grid is one of the interesting topics in the concept of smart grid, particularly, as EVs can be integrated in as mobile demand or Energy Storage (ES). However, the accidental and unplanned connection of EVs to the distribution network is a challenge for operation of the power system [1, 2]. In this regard, the idea of constructing and planning EV Charging Stations (EVCS), as per the V2G capability of EVs, has been implemented. In fact, EVs are parked within the EVCSs when not in use [3]. In this way, EVs can be modeled as a load that consumes a power from the network while charging,

and as an energy storage device, which is discharged to feed the stored energy back into the grid [4, 5].

Another recent topic is to equip the EVCSs with Distributed Energy Resources (DER), and in this way, DERs can be operated to inject energy into the EVCS and network. This interesting topic has attracted attentions in the recent years, so that, solar, wind, and hybrid wind-solar powered charging stations have been studied and realized. In the most cases, the EVCS is linked to the distribution network and can supply its energy from both grid and renewable resources (DERs) [6-10]. In this regard, charging/discharging strategies of the EVs, and especially the adopted programs under which the EV is posed in charging/discharging conditions, are among main challenges of operating the EVCS. Moreover, integration of the DERs and EVCSs requires coordination of DERs generation and EVs charging/discharging behavior. In other words, lack of suitable methods for EVs management

[†] Corresponding Authors; h.akbari@iauyazd.ac.ir
 Department of Electrical Engineering, Yazd Branch, Islamic Azad University, Tel: +98-3531872742, Fax: +98-3538215034

may lead to unexpected events such as feeder congestion, increasing active power losses, voltage drop, decreasing economic profits and reliability [11]. Various researches have been conducted in response to such challenges, among which the following can be mentioned. In [12, 13] a stochastic method, based on Monte Carlo simulation, for modelling the probabilistic nature of the EVs, like daily travel distance, charging pattern is presented.

Technical issues on scheduling, controlling and operating of 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 presented schedule on load profile of the network. In [16, 17], considering all available opportunities, optimal coordination of DERs and EVs for the purpose of load shaving during peak load hours, reducing active power losses and voltage drop is done. In [18, 19], with the purpose of reliability improvement the charging program of the EVs is modeled. However, the discharging schedule of EVs is not studied. Therefore, it can be concluded that the most optimal program is obtained when the benefits of the EVCS (or EV) owner and the Distribution System Operator (DSO), are considered simultaneously. This issue is discussed in paper [20] and a method to share the benefits of the program implementation is proposed.

In all above mentioned papers, charging/discharging programs are mainly devised regardless of resiliency of the grid, which is one of the drawbacks of the existing researches. In fact, such programs are only presented with the aim of flattening load curve of the network, while in case of natural disasters; charging/discharging behavior of the EVCS must be changed to improve resiliency of the network. In the power systems, the grid resiliency is defined as ability of the network to prepare, survive, and rapidly recover itself in face of unforeseen events, like extreme weather conditions, as it has effects on outage rate of lines [21-23]. It should be noted that 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 cost of the DSO [24].

On the other hand, wind speed may affect scheduling of the wind turbines. Thus, in addition to investigating effect of extreme weather (like thunder) on the grid resilience, changes in wind turbine generation should also be considered. Comprehensive challenges in DERs scheduling and forecasting wind effects on outage rates can be found in [25-27].

In the context of the grid resilience improvement, various methods such as Demand Response Programs (DRP) [28, 29], DER utilization, network reconfiguration methods [30] have been proposed. However, in the matter of the EVCS, particularly integrated with DERs, developing an optimal and proportionate charging/discharging schedule can effectively improve network resilience. A risk-based operational planning for enhancing grid resiliency has been proposed in paper [21]. Further, in [21, 22] resilience improvement is obtained via infrastructure and minimization of outages duration.

Based on the above discussion, in the existing researches, charging/discharging programs of EVs has been rarely devised with the aim of network resilience improvement. In the view of such shortcoming, this paper proposes a novel methodology for optimal charging/discharging program of the EVCS which through it benefits of both DSO and EVCS owner are optimally maximized. In the proposed methodology, as per effective role of the EVCS in improving grid resiliency, the idea of profit sharing between DSO and EVCS owner is applied to incentivize the EVCS owner to implement the devised charging/discharging schedule; and to increase the resiliency of the network against extreme weather conditions. In this regards, firstly, a stochastic framework, on the basis of Monte Carlo simulation, is proposed to forecast probability of weather based line outages and also to model random variables considering related uncertainties. In the next step, a formulation for optimal charging/discharging schedule of the EVCS is devised. In the proposed formulation, while optimizing power purchases from the utility, bus voltage deviation, power loss, grid resilience in the extreme weather condition is also maximized. However, to incentivize the EVCS owner to implement the optimal charging/discharging schedule and to participate in improving plan of resiliency, the idea of benefit sharing on the basis of energy price modification is applied. Moreover, the coordination of wind turbine, EV management and Demand Response Programs (DRP) is performed.

The resilience oriented multi-objective optimization algorithm of this paper is solved using a Modified Particle Swarm Optimization algorithm (MMPSO) and Pareto front solutions are obtained. Applying hybrid sequential Monte Carlo simulation and MMPSO algorithm increases the accuracy of achieving optimal solutions set. Finally, the proposed methodology is evaluated using Φ AEIT metrics which through a multi-phase resilience trapezoid method all disturbance progress, post-disturbance degraded and restorative state are assessed. In summary, taxonomy of the most related research works is reported in Table I.

TABLE I
TAXONOMY OF THE LITERATURE REVIEW

Contribution	Ref	5	6	7	9	10	11-16 -18	13	1-15	17-19 -8	20	21-22- 24	27	31 32	This paper
optimal EVCS allocation		yes	no	no	yes	no	no	no	no	no	yes	no	no	yes	no
integration of the DERs into EVCSs		no	yes	no	yes	no	no	yes	no	no	no	no	no	yes	yes
coordination of DERs and EVs for optimal operation of EVCS and grid		no	yes	no	yes	no	no	yes	no	no	no	no	no	yes	yes
management of EVCS for load profile flattening		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 effect of charging/discharging schedule and extreme weather on the grid resilience		no	no	no	no	no	no	no	no	no	no	yes	no	no	yes

II. MATHEMATICAL MODELLING AND FORMULATION OF THE PROBLEM

In this section, first, the mathematical model for all influencing components is presented, and then the proposed formulation for solving the problem is described.

A. EV and EVCS Models

As explained earlier, EVs are parked within the EVCS 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. Hence, the operation time of the EVCS within the grid is uncertain unless an appropriate planning is made. Therefore, the uncertainties, like duration time each EV is connected, distance traveled by each EV, the State of Charge (SOC) level of each EV at the charging/discharging time should be considered in the modeling of EVs and EVCS [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 the trip, the parking time of the EV within the EVCS. Further, remaining dependent variables such as time of arrival/ departure of the EV to/from the EVCS is calculated. The details of such stochastic modeling are given in the [20].

Another parameter which affects the charging/discharging plan for the EV during the EV's presence at the EVCS, and is associated with uncertainty is the SOC level of EVs when connected to the grid. The SOC level of EVs while charging and discharging can be calculated according to the distance traveled (D_i) as follows [20]:

$$SOC_{int}^i = \left(1 - \frac{D_i}{D_{Total}}\right) \times 100\% \quad , \forall i \in N_{EVs} \quad (1)$$

$$SOC_t^i = X_1 \left(SOC_{t-1}^i + \Delta t \cdot (ch_{rate}) \right) \times 100\% \quad , \forall i \in N_{EVs}, \forall t \in T \quad (2)$$

$$SOC_t^i = X_2 \left(SOC_{t-1}^i - \Delta t \cdot (disch_{rate}) \right) \times 100\% \quad , \forall i \in N_{EVs}, \forall t \in T \quad (3)$$

Where SOC_{int}^i is the initial SOC of EV, the charge/discharge rate of EV batteries in the time step of Δt are specified with $ch_{rate}/disch_{rate}$. Also, the simultaneous charging/discharging of the EVs is avoided by using binary variables X_1 and X_2 .

As per above equations, charging/discharging time of EVs, and the total injected or absorbed energy of the EVCS can be modeled as follows:

$$t_{charge}(i) = \frac{(SOC_{max} - SOC_t^i) \times ES_i}{P_v} \quad (4)$$

$$t_{discharge}(i) = \frac{(SOC_t^i - SOC_{min}) \times ES_i}{P_v} \quad (5)$$

$$E_{EVCS}^{discharge} = \sum_i^{N_{EVs}} PreT(i) \times C_i \times (SOC_{int}^i - SOC_{min}) \quad \forall \Delta t_{discharge} \quad (6)$$

$$E_{EVCS}^{charge} = \sum_i^{N_{EVs}} PreT(i) \times C_i \times (SOC_{max} - SOC_{int}^i) \quad \forall \Delta t_{charge} \quad (7)$$

Where $PreT(i)$ is the presence time of each EV at the EVCS, C_i is battery capacity of EV number i .

In the field of modeling probabilistic parameters of EV/EVCS, in addition to the above equations, there are other stochastic variables, like time of arrival/departure of EV, duration time of the EV's trip, presence time of EVs inside the EVCS, that have been avoided to rewrite here due to the fact that they exist in the references like [13, 20]. However, utilization of the sequential Monte Carlo simulation for calculation of final model of such parameter is required. Hence, after formulating the probabilistic model, the Monte Carlo simulation with repeated replications is utilized to obtain the 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%.

B. Load and energy Price

As per probabilistic behavior of the demand, daily demand variation in each year of the planning period can be obtained by multiplying base load ($P_{i,base}$ and $Q_{i,base}$) and Demand Level Factor (DLF) [8, 32]. In addition, by considering the rate of yearly load growth, the amount of active and reactive power, is modeled as follows:

$$P_{i,t,h}^e = P_{i,base} \times DLF_{i,t,h}^e \times (1+\alpha)^t \quad (8)$$

$$Q_{i,t,h}^e = Q_{i,base} \times DLF_{i,t,h}^e \times (1+\alpha)^t \quad (9)$$

$$S_{i,h}^D = P_{i,h}^D + jQ_{i,h}^D \quad (10)$$

Where DLF is obtained by using the Probability Density Function (PDF) as:

$$DLF_{i,t,h}^e = \mu_{i,t,h}^D + \lambda_{i,t,h}^{D,e} \times \sigma_{i,t,h}^D \quad (11)$$

Where λ is a random variable and is generated using the normal PDF with an average value of zero and standard deviation of one for each demand level. $\mu_{i,t,h}^D$ is the predicted values for the load demand level with standard deviation of $\sigma_{i,t,h}^D$, and α and t are the load growth rate and number of year, respectively.

The power price is cleared depending on the wholesale market price and demand level, and is obtained as follows [33, 34]:

$$\rho_h = \rho_{base} \times PLF_h \quad (12)$$

where ρ_{base} is the basic electricity price and PLF_h stands for price level factor at demand level h .

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

$$\rho_h = \frac{\rho_{base} PLF_h + \rho_{ENS} ENS_h}{PLF_h} \quad (13)$$

In this equation, ENS cost is formulated as follows:

$$ENS \text{ Cost} = \sum_{i=1}^{N_L} \lambda_{Line} L_{Line} \rho_{ENS} \left(\sum_{i=1}^{N_{bus}} P_{res} \mu_{Line} \right) + C_{repair} \quad (14)$$

Where, ρ_{ENS} presents ENS penalty cost for each load level, N_L stands for numbers of lines with length of L_{Line} .

λ_{Line} and μ_{Line} are the failure and repair rate of the line. P_{res} states restored power once line is repaired.

C. Demand Response Program (DRP) Modeling

DRP is generally used to transfer demand from peak hours to off-peak, and on this way, the operational costs of

DSO are reduced [35]. In this study, it is assumed that only $\pm 15\%$ of demand could be transferred. Below is the relevant model for the applied DRP:

$$S_{i,h}^{DR} = S_{i,h}^D + \Delta S_{DRP} \quad (15)$$

$$\Delta S_{DRP} = K_{DRP} \times S_{i,h}^D \quad (16)$$

$$\sum_{h=1}^{24} \Delta S_{DRP} = 0 \quad (17)$$

$$K_{DRP}^{\min} < K_{DRP} < K_{DRP}^{\max} \quad (18)$$

$S_{i,h}^{DR}$ is apparent power after applying DRP at demand

level number h . ΔS_{DRP} is the values of apparent power transferred by DRP. K_{DRP} is amount of participation in the load response plan.

D. Model of Wind Turbine Output

With utilization of hybrid EVs and DERs, like wind turbine, inside the EVCS, determining coordinated stochastic models becomes important. Power output of a wind turbine mainly depends on the wind speed parameter which is not generally specific and should be considered randomly. In this paper, the Rayleigh probability density function, which is a special case of the Weibull distribution, is applied for modeling random behavior of the wind speed (see Fig. 1) [24, 36].

$$f_{wg}(v) = \left(\frac{2v}{c^2}\right) \exp\left(-\left(\frac{v}{c}\right)^2\right) \quad (20)$$

Where v and c are the wind speed and scale index in the Weibull distribution, respectively. With knowing the average value of the wind velocity for the study site, the scale index is calculated as follows:

$$v_m = \int_0^{\infty} v f_{wg}(v) dv = \int_0^{\infty} \left(\frac{2v^2}{c^2}\right) \exp\left[-\left(\frac{v}{c}\right)^2\right] dv = \frac{\sqrt{\pi}}{2} c \quad (21)$$

$$c \cong 1.128 v_m \quad (22)$$

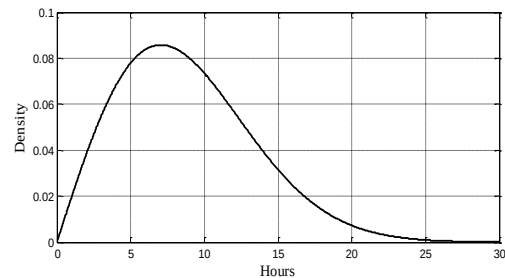


Fig. 1. Probability density function considered for modelling wind speed during 24 hours

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

$$P_{i,t,h}^{WT} = \begin{cases} 0 & \text{if } v \leq v_{in}^{cut} \text{ or } v \geq v_{out}^{cut} \\ P_{i,r}^{WT} \frac{v - v_{in}^{cut}}{v_{rated} - v_{in}^{cut}} & \text{if } v_{in}^{cut} \leq v \leq v_{rated} \\ P_{i,r}^{WT} & \text{else} \end{cases} \quad (23)$$

Where $P_{i,r}^{WT}$ is the permitted capacity for power generation.

v_{in}^{cut} , v_{out}^{cut} , and v_{rated} are cut-in, cut-out and rated speed in the wind turbine, respectively.

As per the above equations, wind speed affects performance of the wind turbines, particularly, in the extreme weather conditions that the wind turbines may stop working. On the other hand, this issue, by increasing the outage rate of lines, affects the resiliency of the network and, consequently, the operation of the EVCS.

E. Resilience- oriented operation of the network

It is proved that extreme weather conditions (such as high speed wind and lightning) are the main reason (about 65%) for inception of various faults [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 types of event, its impact timing and the method of assessment. Reliability usually focuses on high probability events that have little impact on the network operation, but resiliency focuses on high-impact and rare events, like line outages due to extreme weather conditions [22, 29]. Further, reliability studies are commonly conducted by considering all possible events and providing a long-term solution to minimize the amount of energy not supplied (ENS) is the first goal. On the contrary, resiliency focuses on a specific incident category and can provide short-term to long-term solutions to reduce ENS.

In this respect and in order to have a proper analysis to evaluate weather condition effect on outage rate, weather-caused (wind or lightning) faults are considered in this paper. In paper [24] correlation between number of events (N_{wind} and $N_{lightning}$) and wind speed (W)/numbers of thunder (L) are formulated for short-time intervals.

$$N_{wind} = 0.0012W_{speed}^2 - 0.013W_{speed} \quad (24)$$

$$N_{lightning} = 0.0001L + 0.7014 \quad (25)$$

In this paper, it is assumed that average wind speed and lighting probability could be predicted in one hour time intervals, and for each time interval the medium quantity of wind speed and the number of thunders are used. Then, by considering the forecasted wind speed, probability of outages is modeled.

In this respect, the resiliency index (based on ENS) is calculated; however, for evaluation the effectiveness of the proposed strategy on resiliency, the evaluation metrics should be also introduced. In this paper, $\Phi\Lambda E\Pi$ metrics proposed in paper [23] are used, based on which a multi-phase

resilience trapezoid associated to the extreme weather is considered (see Fig. 2). Three phases can be clearly seen in the resilience trapezoid of Fig. 2 as: disturbance progress (Φ and Λ -metrics), post-disturbance degraded (E -metric) and restorative state (Π -metric). $\Phi\Lambda E\Pi$ metrics would be defined to the operational and infrastructure resilience. Mathematical expression and measuring units for $\Phi\Lambda E\Pi$ metrics are shown in Table II.

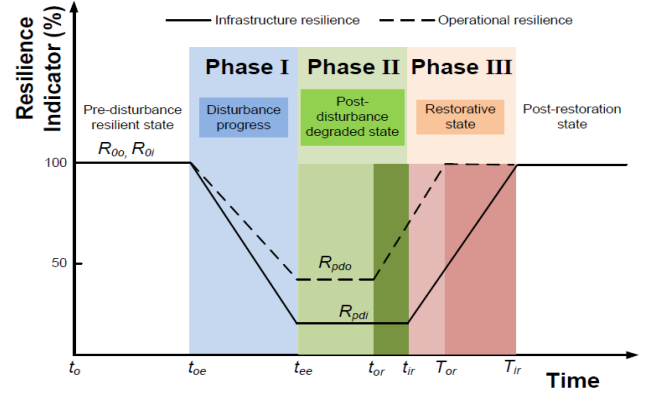


Fig. 2. Resilience indicator and the multi-phase resilience trapezoid [23]

TABLE II
MATHEMATICAL OPERATIONAL AND
INFRASTRUCTURE FORMULATION OF RESILIENCE
METRICS

Metric	Mathematical Expression		Measuring Unit	
	Operational	Infrastructure	Operational	Infrastructure
Φ	$\frac{R_{pdo} - R_{0o}}{t_{ee} - t_{oe}}$	$\frac{R_{pdi} - R_{0i}}{t_{ee} - t_{oe}}$	MW/hour	number of lines tripped/hours
Λ	$R_{0o} - R_{pdo}$	$R_{0i} - R_{pdi}$	MW	number of lines tripped
E	$t_{or} - t_{ee}$	$t_{ir} - t_{ee}$	hours	hours
Π	$\frac{R_{0o} - R_{pdo}}{T_{or} - t_{or}}$	$\frac{R_{0i} - R_{pdi}}{T_{ir} - t_{ir}}$	MW/hour	number of lines restored/hours
Φ	$\frac{R_{pdo} - R_{0o}}{t_{ee} - t_{oe}}$	$\frac{R_{pdi} - R_{0i}}{t_{ee} - t_{oe}}$	MW/hour	number of lines tripped/hours

F. Proposed methodology for Resilience- oriented operation of the grid

In the face of natural disasters, resiliency improvement of the network, i.e., its ability to prepare, survive, and rapidly recover, is a vital action. As explained earlier, one of the influencing solutions for resiliency enhancement is rescheduling of DERs, DRP implementation, appropriate management of EV's charging/discharging schedule. On the other hand, the uncertainty of weather based outages, available EVs in stations and their SOC level affect DER scheduling and DRP program. As a result, the application of these solutions, given their impact on the operation of the EVCS, must also be economically justified for the EVCS owner. In other words, an optimal balance between economic profits and resiliency should be made.

As a side note, the adopted charging/ discharging schedule for EVs are generally based on price signals offered by market, so that, the EV is charged during off-peak intervals. On the contrary, discharging of extra power in the EV's battery is done during peak intervals when the energy price is higher. Accordingly, it can be concluded that if the DSO locally increase reference for signal price in some intervals in order to improve the resilience, the EVCS 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 real operation cost for each time interval is calculated by considering weather condition and uncertainty of outages.

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, increase resiliency of the grid and decreases total ENS during normal operation and extreme weather conditions. In the proposed optimization method, profits of both EVCS and DSO are modeled as objective functions which must be maximized during daily operation planning. To do so, the outage rate of lines, power generation of wind turbine, movement of EVs and their available energy depend on weather conditions. In the following proposed formulation related to both DSO and EVCS owner are presented.

1) DSO Benefit Formulation

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

$$R_{DSO} = \sum_{i=1}^{N_{load}} \rho_{sell}^P \cdot P_{i,t,h}^e + \frac{1}{T} \sum_{i=1}^{N_k} \rho_{sell}^P \cdot E_{EVCS}^{charge} \quad (26)$$

$$C_{DSO} = \lambda_h S_h^{Utility} + ENS \text{ Cost}_h + \rho_{sell}^{WT} \cdot P_{i,t,h}^{WT} \quad (27)$$

$$+ \frac{1}{T} \sum_{i=1}^{N_k} \rho_{sell}^P \cdot E_{EVCS}^{discharge} \quad (28)$$

$$OF_{DSO} = R_{DSO} - C_{DSO}$$

In the above equations, ρ_{sell}^P , λ_h , and ρ_{sell}^{WT} are the price of sold energy to consumers, the price of purchasing energy from utility and the price of energy purchasing from wind units. It should be noted that the amount of purchased power from utility or from EVCS depends on the market electricity price. The purchased active and reactive power can be easily obtained from $S_h^{Utility}$.

Note that DSO has the ability to sell energy to market

when $S_h^{Utility}$ become negative. In equation (27) the ENS cost due to line outage is also modelled. In addition, the power exchanged with the EVCS depends on the charge/discharge schedule, which is presented in the next section as a method for its optimal programming.

2) EVCS Benefit Formulation

Usually, the EVCS owner's profit is in increasing the presence of EVs and purchasing energy from the DSO at the lowest price. In other words, for the EVCS, the DSO profit (due to load characteristic correction and resilience improvement) is not important, unless it receives a profit from participating in these programs. Further, as mentioned, factors such as charge/discharge rate (ch_{rate} and $disch_{rate}$) and charging/discharging time are effective in modifying the load characteristic. Therefore, the following objective is suggested to optimize the above parameters. In fact, in this paper, first, the EV's charging/discharging planning is optimally calculated. In this respect, the following formulation with the purpose of peak shaving, valley filling and flattening the load curve is used. In this way, the optimal charging and discharging times, in which attractive price signals are given, are calculated.

$$OF_1 = a \times \sum_{t=1}^T \left(\frac{P_{L-Peak}}{P_{L-Peak}^{Corrected}} - 1 \right) \Delta t_{discharge} + \quad (29)$$

$$b \times \sum_{t=1}^T \left(\frac{P_{L-Min}^{Corrected}}{P_{L-Min}} - 1 \right) \Delta t_{charge} + (c \times MSE)$$

$$MSE = \sum_{t=1}^{24} (P^{Load}(t) - \sum_{i=1}^{N_{EVCS}} P^{EVCS}(i) - P_{ref})$$

The above objective function is modeled based on the weighted sum model. In this function, a , b and c are applied for normalizing different terms of the OF and converting them to intervals [0-1]. The load power, predicted by the load curve, is stated by $P_{Load}(t)$, based on which and modified load profile the mean square error (MSE) is calculated. In other words, charge/discharge schedule is achieved in such a way that effective peak shaving and load profile flattening are achieved by tracking P_{ref} minimizing MSE. Δt_{charge} and $\Delta t_{discharge}$ are the total time when the EVs are charged and discharged, respectively.

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

$$R_{EVCS} = \rho_{sell}^{WT} \cdot P_{i,h}^{WT} + \frac{1}{T} \sum_{i=1}^{N_k} \rho^p \cdot E_{EVCS}^{discharge} \quad (30)$$

$$C_{EVCS} = \frac{1}{T} \sum_{i=1}^{N_k} \lambda_h \cdot E_{EVCS}^{charge} + C_k^{deg} \left(\sum_{k=1}^{N_k} \frac{E_{EV}^{discharge}}{\eta_k^{discharge}} + \eta_k^{charge} \cdot E_{EV}^{charge} \right) \quad (31)$$

$$OF_{EVCS} = R_{EVCS} - C_{EVCS} \quad (32)$$

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

Related Constraints

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

$$P_h^{Utility} - \left((1 - K_{DRP}) \times P_{i,h}^D + \Delta P_{DRP} \right) + \frac{1}{T} \sum_{k=1}^{N_k} (E_{EVCS}^{discharge} - E_{EVCS}^{charge}) = V_{i,h} \sum_j V_{j,h} (G_{ij} \cos \delta_{i,h} + B_{ij} \sin \delta_{j,h}) \quad (33)$$

$$Q_h^{Utility} - \left((1 - K_{DRP}) \times Q_{i,h}^D + \Delta Q_{DRP} \right) = V_{i,h} \sum_j V_{j,h} (G_{ij} \sin \delta_{i,h} - B_{ij} \cos \delta_{j,h}) \quad (34)$$

$$\Delta S_{DRP} = \Delta P_{DRP} + j \Delta Q_{DRP} \quad (35)$$

$$V_i^{\min} \leq V_{i,h,s} \leq V_i^{\max} \quad (36)$$

$$0 \leq S_{ij,h,s} \leq S_{ij}^{\max} \quad (37)$$

G. Approach overview

Management and control of charging/discharging of Electric vehicles (EVs) with the aim of profitability for the Distribution System Operator (DSO) and the private sector is one of the challenges of operating Electric vehicles Charging Stations (EVCS). This paper proposes a novel methodology for optimal planning of charging/discharging of the hybrid wind- EVCS which on the one hand, lead 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 EV, EVCS, load, energy price, DRP, wind turbine generation, is formulated and then final models using Monte Carlo simulation is extracted. Further, to have a proper analysis to evaluate resiliency of the test case, by considering the forecasted wind speed, probability of outages is modeled and the resiliency index (based on ENS) is calculated accordingly. In the next step, a methodology for resilience-oriented operation of the grid is presented, in which

benefit formulation of both DSO and EVCS owner is calculated. In this respect, the benefit formulation of the EVCS is associated with optimal charging/discharging schedule of the EVs. Finally, the presented multi-objective optimization algorithm of the paper is solved using a Modified Particle Swarm Optimization algorithm (MPPSO) and the optimal solution is found.

III. TEST SYSTEM AND SIMULATION RESULTS

The proposed methodology of the paper for resiliency-oriented operation of grid is implemented on a 50-buses test case, which is part of the 69-bus IEEE radial test system [37] (see Fig.3). As a side note, the proposed methodology is devised in such a way that it can be implemented on any network; however, by selecting such network, which is one of the wide and large test systems, its efficiency is examined in large networks.

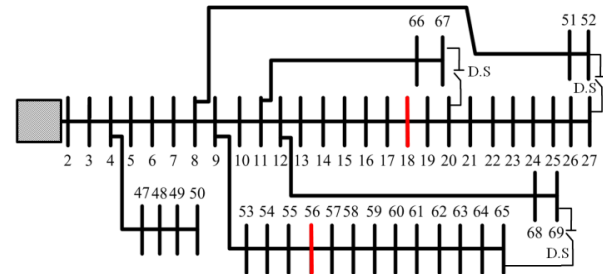


Fig. 3. Test system of the paper

First, modelling of the demand is done based on the load pattern (daily, weekly and annual) given in the standard Reliability Test System (RTS) [37]. However, it should be noted, in this study the load of a working day is considered to reduce the required time for execution of Monte Carlo. Then, the energy price model is also done according to section B.

As explained, the placement of the EVCS is not concern of this study, but due to the fact that their allocation affects the implementation of the proposed methodology, two EVCS with the capacity of 125 EVs are optimally allocated, based on the presented method of reference [20], in buses 18 and 56. 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 return home after work and park their car in another parking. These two EVCSs are called Administrative EVCS and Residential EVCS, respectively. Moreover, capacity of the EV's battery is assumed to be 25 kWh, and they are charged/discharged in 5 hours. As a result, rated power of the batteries is 5kW on average. Battery life is also estimated to be approximately 10 years. On the other hand, the behavior of EVs (in fact EV driver) is probabilistic and uncertain. Therefore, by using sequential Monte Carlo method, which is on the basis of repeated replications of the simulation, the final model of stochastic parameter is calculated based on the mean value during the simulation period.

In the present study, a storm happens for a 4-hours interval (here 14 -18 p.m. of the studied day). In addition, it is assumed that weather condition, outage number and the repair time are similar. In this respect, the Monte-Carlo simulation approach is rerun to study probability of line outage (failure) which is subject to the extreme weather. By obtaining the stochastic models, the proposed multi-step optimization strategy, for jointly optimization of EVs charging/discharging schedule and DSO/EVCS 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, a Modified Multiobjective PSO (MMPSO) algorithm [38, 39] is used here for finding Pareto solution of the problem. In the MMPSO algorithm the exploration and exploitation of the algorithm and its convergence capability have been improved. In the utilized MMPSO of this paper, the pertinent parameters are set based on the values obtained in the [40].

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

Scenario 1: Optimal charging/discharging schedule without considering grid resilience

Scenario 2: Optimal charging/discharging schedule with considering grid resilience

The optimal results for the above mentioned scenarios are reported in the Table III. Note that in both scenarios DR program are applied.

TABLE III
THE OPTIMAL RESULTS OF IMPLEMENTING
CHARGING/DISCHARGING SCHEDULE FOR SCENARIOS
1 AND 2

Scenarios	EVCS (Administrative)		EVCS (Residential)		Charge/discharge intervals	
	ch _{rate}	disch _{rate}	ch _{rate}	disch _{rate}	Charge Hour	Discharge Hour
scenario 1	14.2	16.7	16.7	14.2	1-7 12-17	8-12 19-24
scenario 2	16.7	14.2	20	11.2	1-7	8-12 12-18 19-24

It is observed that the discharge rate is always less than the charge rate. This is to ensure the travel of EVs. In fact, the program has been designed so that the discharge of EVs batteries does not interfere with the daily travel of EVs.

Another noteworthy point is that the charge rate is higher in the residential EVCS than in the Administrative and the discharge rate is higher in the Administrative EVCS than in the residential parking lot. This is because when EVs are parked in a residential EVCS, the load characteristic is often low (at midnight) and it is more attractive for the aggregator (EVCS owner) to charge the EV battery at a high rate and discharge it at a low rate. In addition, when the EVs are in the Administrative EVCS, the load characteristic sometimes encounters peak demand, so the high discharge rate and low

charge are more attractive to the aggregator.

On the other hand, in the second scenario where resilience improvement is considered, the discharge rate is reduced. Moreover, the charging/discharging hours are changed. In fact, in times of extreme weather conditions, the EVCS in the discharge cycle helps to supply network power and reduces ENS accordingly. In this study, the ENS is calculated as the resiliency index and also the penalty cost.

In the next step, by solving the proposed formulation related to benefit of DSO an EVCS owner, the optimal results are calculated. As already mentioned, contrary to the single-objective optimization scenario, there is an optimal set of solutions or alternatives, called Pareto optimal set, where each solution can be selected as final one. Table IV reports the five Pareto optimal solutions for each scenario. Further, every Pareto solution in repository is depicted in the Fig. 4.

In this paper, to find the best solution, the min-max method, on the basis of fuzzy satisfaction method, is employed. In this method, the minimum values for per-unit and normalized profits of both objective functions (OF_{DSO} and OF_{EVCS}) are obtained. Afterwards, the maximum value of min (OF_{DSO} and OF_{EVCS}) among Pareto set is calculated to select the best solution. In this way, solutions number 2 and 5 are selected for scenarios 1 and 2, respectively (as can be seen in the results of Table IV).

Table V reports the optimal benefits of DSO and EVCS related to the best non-dominated solutions, which through it the effectiveness of the proposed strategy can be evaluated. In this table, total benefits of DSO and EVCS owner, including benefits due to load profile correction, benefits of improving resiliency, and benefit of reducing power purchase from utility, benefits of power loss reduction in line with proposed strategy are separately given.

Table V reports the optimal benefits of DSO and EVCS related to the best non-dominated solutions, which through it the effectiveness of the proposed strategy can be evaluated. In this table, total benefits of DSO and EVCS owner, including benefits due to load profile correction, benefits of improving resiliency, and benefit of reducing power purchase from utility, benefits of power loss reduction in line with proposed strategy are separately given.

As can be seen in Table V, in the second scenario, the profit due to the resilience improvement is increased due to the participation of the EVCS in supplying the load (during discharge interval). In this way, the total benefit of the DSO will increase (4.821×10^7). It is worth saying that the cost of ENS in all-weather condition is a positive quantity; hence, the EVCS owner gains more benefits from price modification and is more interested in cooperation with DSO. In other words, this matter is also profitable for the EVCS due to the increase in energy prices in the time of extreme weather condition, so that the EVCS owner's profit has increased from

2.08×10^5 to 2.92×10^5 . According to this table, the cost of purchasing energy from the upstream network has also

decreased, which in turn leads to the profit of the DSO.

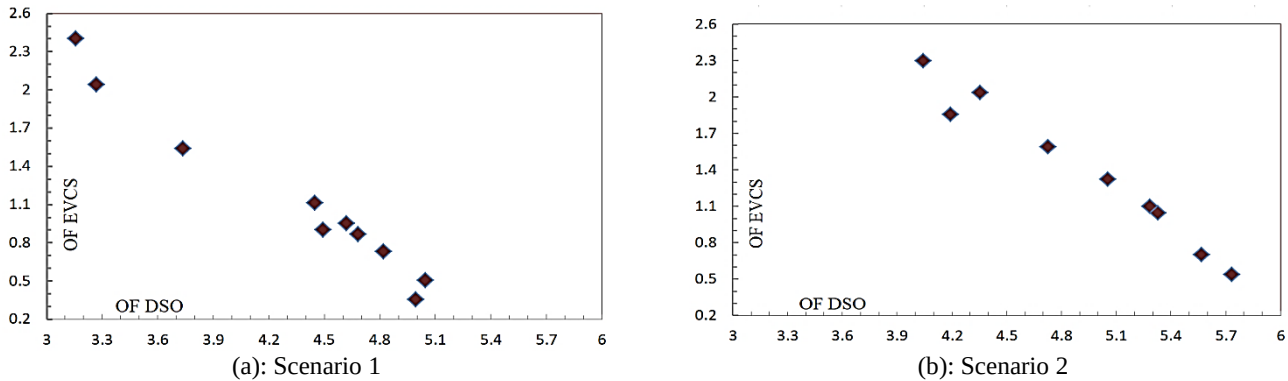


Fig. 4. Pareto front solutions for (a) scenarios 1 and (b) scenario 2

TABLE IV
OBJECTIVE FUNCTIONS FOR PARETO SOLUTIONS

Solution number		1	2	3	4	5
scenario 1	OF _{DSO}	3.158	4.820	4.620	4.449	4.682
	OF _{EVCS}	2.402	0.732	0.953	1.112	0.868
scenario 2	OF _{DSO}	4.356	5.283	3.495	5.054	5.329
	OF _{EVCS}	2.034	1.098	2.877	1.320	1.046

TABLE V
THE OPTIMAL VALUES OF OBJECTIVE FUNCTIONS FOR TWO SCENARIOS

Scenario	1	2
benefits of load profile correction (\$)	2.153×10^6	1.830×10^6
benefits of improving resiliency (\$)	8.232×10^5	9.729×10^5
benefit of reducing power purchase (\$)	4.239×10^7	4.725×10^7
benefits of power loss reduction (\$)	5.145×10^5	5.837×10^5
benefits of DSO (\$)	4.073×10^7	4.821×10^7
benefits of EVCS (\$)	2.08×10^5	2.92×10^5

In different circumstances, the effectiveness of the proposed methodology in grid resilience improvement is also evaluated through $\Phi\Lambda E\Pi$ metrics and the pertinent results are calculated. In other words, to quantify the resilience improvement of applying proposed strategy, $\Phi\Lambda E\Pi$ metrics in the operational and infrastructure are calculated and tabulated in Table VI.

The results of Table VI, that correspond to Fig. 2 and Table II, presents value of the key metrics for characterization the resilience trapezoid to evaluate how fast (Φ) and how low (Λ) resilience drops in Phase I, how extensive (E) is the post-event degraded state (Phase II) and how promptly (Π) the network recovers to its pre-event resilient state (Phase III), considering both operational and infrastructure resilience in

each phase.

TABLE VI
 $\Phi\Lambda E\Pi$ METRICS TO OPERATIONAL AND INFRASTRUCTURE RESILIENCE

Metric	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

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 that the corrective action are taken, the slope is decreased to -0.72. It should be noted that the grid reconfiguration, through isolating switch (shown with D.S in Fig. 3) change 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 post disturbance is also degraded.

IV. CONCLUSIONS

During extreme weather conditions with high probability of fault inception, energy resources, charging/discharging schedule of the Electric vehicles Charging Stations (EVCS), flexible loads are rescheduled to improve grid resilience. In this paper, a novel two-stage

stochastic optimization method for optimal charging/discharging schedule of the EVCS is proposed. In this regard, the probabilistic and uncertain behavior of line outages due to extreme weather conditions, demand variation, EV driver pattern and State of Charge (SOC) of EV batteries are modeled by applying sequential Monte-Carlo simulation algorithm. Then, a new resilience-oriented multi-objective optimization algorithm for maximizing benefits of both DSO and EVCS owner is implemented for two hybrid wind-EVCS. One of the salient features of the proposed methodology is profit sharing between DSO and EVCS which not only lead to resiliency improvement of the grid, but also optimize benefits of the EVCS. Finally, the proposed methodology is evaluated using ΦAEP metrics which through a multi-phase resilience trapezoid method all disturbance progress, post-disturbance degraded and restorative state are assessed.

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Emad Hadian received the B.Sc. and M.Sc. degree in electrical engineering from Birjand University, Birjand, Iran, in 2015, and is currently working toward the Ph.D. degree in electrical engineering at the Azad University, Yazd Branch, Iran. His research interests include Microgrid, Electrical Vehicles, and Optimization



Hamidreza Akbari was born in Yazd, Iran, in 1980. He received the B.Sc. and M.Sc. degrees in electrical engineering from Amirkabir University of Technology, Tehran, Iran in 2001 and 2004, respectively and the Ph.D. degree in electrical engineering from Islamic Azad University, Science and Research Branch, Tehran, Iran in 2011. He is currently working as an Assistant Professor of Electrical Engineering in Islamic Azad University, Yazd Branch. His main research interests include modeling, analysis and design of electrical machines, power electronics and renewable energies.



Mehdi Farzinfar received the B.Sc., in electrical engineering from Shahid Beheshti university, the Power and Water Institute of Technology Campus, Tehran, Iran, in 2008; and M.Sc., and Ph.D. degrees from Semnan University, Semnan, Iran, in 2010, and 2015 respectively. From 2013–2015 he was research assistant at the Power System Group

of the University of Auckland, Auckland, New Zealand, where he was engaged in the national project of Green Grid. He is currently an Assistant Professor with the School of Engineering, Damghan University, Damghan, Iran. His research interests include power system protection, Smart Grids, Microgrids, Electric vehicles.



Seyed Amin Saied received the M.Sc. and Ph.D. degrees in electrical engineering from the K. N. Toosi University of Technology, Tehran, Iran, in 2006 and 2012, respectively. He is currently with the Department of Electrical Engineering, Yazd Branch, Islamic Azad University, Yazd, Iran. His main research interests include the design and modeling of electrical machines, and electrical parameter estimation of electrical machines.