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Optimal use of vehicle-to-grid technology to modify the load profile of the distribution system

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ABSTRACT

Managing the use of electric vehicles (EVs) and power injections from their batteries pose the issue of controlling the charge and discharge of EVs as an attractive research field. Charging a large number of EVs' batteries will, if not controlled, hurt the power distribution system. By adopting optimal planning for the use of EVs, their parking stations can role as either load or energy source. In this paper, the effect of charging and discharging scheduling of EVs on load characteristic enhancement is investigated. On the other hand, the behavior of EVs' owners is probabilistic. Therefore, in the first step, the probabilistic model using Monte Carlo is developed for estimation of uncertain variables including: EVs arrival and departure time, the duration of the EVs' presence in parking lots, the battery capacity of each EV. Afterward, the scheduling of EVs' charging and discharging is determined by JAYA algorithm so that the daily load variance is reduced and the network load characteristic becomes smooth. The performance of proposed approach is investigated on the IEEE-69-bus system and simulation results show the advantages of the suggested approach.

1. Introduction

The popularity of electric vehicles (EVs) are growing more and more due to the environmental-friendly energy sources and reducing dependence on fossil fuels. However, the charging demand due to the high penetration of EVs causes considerable impact on the power distribution grid. Although EVs' batteries charging increases the power distribution grid load profile, it is possible to benefit from the battery's discharging capability, in the context of smart grids, such that the EVs' batteries charging/ discharging challenge turns into opportunities including load shaving [1–3]. Vehicle-to-grid (V2G) technology as a new concept in EVs has brought advantages to both grid and EVs' owners. The energy stored in EVs' batteries can be delivered to the electric grid and EVs owners can also benefit from the reduction of the fuel cost along with selling energy to the grid. Moreover, the power grid benefits from the stored energy to smooth fluctuation in distribution grid and to respond to unexpected outages. In comparison to the conventional power plants, V2G has far quicker response times. V2G with these mentioned characteristics can play an effective role in the regulation of the voltage and frequency [4,5]. More importantly, it can also enhance the technical performance of the grid in areas such as stability, reliability, efficiency, and generation dispatch [6].

On the other hand, the EV charging/ discharging modeling is dependent to the owners' behavior, which is however overlooked. There has been some possible factors such as social environment, urban planning and economic foundations, [7,8] distance, driving time and lifestyle [9,10] affecting the EVs' daily travel behavior. Stochastic simulation methods depend upon transportation data in order to capture the uncertainty of the main variables describing the behavior of EVs. These variables include EVs arrival and departure time, the duration of the EVs' presence in parking lots, the battery capacity of each EV.

The impact of V2G technology and EV charging coordination to minimize the system operation cost is investigated in [11]. The proposed approach was evaluated on a modified 33-bus distribution system with ten EVs connected to each bus and in order to consider the impact of uncertainties, the EV availability is selected randomly by the proposed algorithm, however, this algorithm cannot model EVs' daily travel behavior. An analysis of a 100% EV scenario on the energy

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system of the island of Bornholm in Denmark is proposed in [12]. In order to model EVs' daily travel behavior, real data from 10,000 users of EVs is grouped in eleven representative user profiles with similar driving patterns. The authors showed that due to a potential need for battery replacement the V2G strategy requires a more challenging operation, which reduces the lifetime of the battery and increases the total EV cost. However, by applying an optimal EVs' charging/ discharging scheduling the reduction in the annual charging cost can compensate the increase in the EV cost. In [13], V2G scheduling based on double layer multi-objective optimization algorithm is proposed, which minimize the grid load variance in the first layer while the grid voltage is regulated in the second layer. However, EVs' daily travel behavior is not studied in this paper. The impact of EVs and photovoltaic generation in radial distribution systems is assessed in [14], in which the typical parameters including the charging start time, the initial state-of-charge (SOC) of the battery and parking duration, are taken into account for the EV charging load modeling at home/parking lots.

Kavousi-Fard et al. investigated the optimal distribution feeder reconfiguration (DFR) strategy in the smart grids incorporating V2G along with the correlated wind turbines (WTs). The simulation findings demonstrated that the idea of V2G for the PEVs can reduce the cost of the system by storing energy in a bus and transferring it to the other buses [15]. In [16], scheduling of huge number of charging of EVs by a centralized EV charging-control model is investigated. Authors recommended that EVs with flexibility in their charging loads scheduled provides reducing charging costs, negative effects on the distribution system and sensitivity analyses as well as unserved EV-charging demand in comparison to simpler heuristics. A group of researchers has conducted the effect of plug-in EV (smart and direct) charging on energy costs and power systems scheduling, assuming an EV aggregators that shared the market on the side of the EV owners by optimally self-scheduling under the price-taking method [17]. Another study proposed a risk-aware day-ahead scheduling algorithm which minimizes the EV charging cost and the risk of the load mismatch between the forecast and actual EV loads, because of the random driving activities of EVs [18]. A new model of demand response management was introduced for the future smart grid integrating renewable distributed generators and plug-in EVs. It showed that demand curve is smoothed and cost paid by the utility company is reduced. In a paper [19], the contribution of the EV to the vehicle to home, V2G type of connections is able to reduce the household electricity payments with their bilateral energy transactions. In [20], the impacts of several demand response programs on operational behavior of a PEV parking lot were studied by a stochastic programing approach. In [21], the behavior of market participants and EV owners is investigated in both short- and long-term horizons. In [22] the plug-in EVs charging coordination problem is evaluated for multiple parking decks in multifamily dwellings in which the total utility of the charging service provider is maximized. Authors in [23] proposed plug-in hybrid EVs model to carry out the V2G technology in a residential distribution grid developed. Ref [24] proposed self-scheduling approach for a PEV aggregator buying energy in the day-ahead market and offering balancing services for a wind power producer. In this research, uncertainty in the driving patterns of PEVs and probabilistic battery model were considered. In [25] the realistic vehicular mobility pattern focusing on individual parking lots as well as centralized EVs recharge scheduling system for parking lots was investigated. In [26], a novel online coordination method was designed to for the charging of maximize the PEV owners' satisfaction and to minimize system operating costs without violating. In [27], the main aim is to develop a novel systematic method to coordinate the charging strategies of large-scale PEVs in a distributed way along with the consideration of the battery degradation cost. In [28] EVs scheduling in parking lots in distribution systems is investigated in order to minimize system costs such as network reliability, power loss and voltage deviation. Sadati et al. introduced a novel model combined with PL owner and smart distribution company (SDISCO) to develop operational scheduling of SDISCO [29]. Gampa et al. combined the grasshopper optimization algorithm (GOA) with fuzzy multi-objective model in order to solve the optimum sizing and placement of distributed generations (DGs), EV charging stations and shunt capacitors for distribution systems [30]. The authors of [31] used an analytical technique to estimate the fulfillment of voltage limits in the distribution grid with this combined interaction. In [32], EVs charging/ discharging scheduling is presented to maximize EVs aggregator profit. The EVs' uncertainties are modeled by information gap decision theory (IGDT) approach, however the considered EV's driving patterns is not realistic. In [33], V2G capability is used for delivering primary frequency control (PFC). The objective of EVs charging/ discharging scheduling is to minimize the operation cost from EVs aggregator point of view. The probability of EV owner's behavior is not modeled and it is assumed that the uncertain variables are known in advance. In [34], EVs battery charging/discharging management is developed to minimize cost of both power supply utility grid and customer. It is assumed that EVs owners driving pattern is known and the uncertainties are not considered. In [35], block chain based scheduling is proposed to optimize the charging/ discharging time period of EVs, however the charging/ discharging power is not considered as decision variable. The Monte Carlo is used for the EVs owners' behavior modeling and the proposed problem is solved by an improved krill herd (KH) algorithm. In [36], plug-in electric vehicles (PEVs) management in parking lot from the utility investor point of view is proposed. The Monte-Carlo simulation (MCS) method is used to generate 20 scenarios with equal probability of occurrence in order for the EVs owners' behavior modeling. In [37], the EVs charging/discharging effect on distribution network reconfiguration is studied. The travel behavior of EVs in transportation network is modeled by logistic regression to multiclass problems. In [38] the V2G effect on distribution network expansion planning is investigated, however the probability of EV owner's behavior is not considered in EVs charging/ discharging scheduling. In [39], EVs charging/ discharging effect on an industrial micro grid day-ahead scheduling is analyzed. The EVs are clustered based on arrival and departure time, therefore the generality of the proposed approach is restricted. In [40], a mathematical model for the optimal planning of EV charging/discharging process was developed. A number of distributed charging/discharging stations was considered. To achieve the optimal and efficient planning processes of EVs plug-in, a new smart grid architecture and optimizing the energy consumption were proposed. In [41], fair pricing strategy was proposed by considering the price of both discharging power service to the main grid as well as the price of the market load regulated separately. Several important features of distributed EV charging schemes were reviewed in [42].

The aim of this paper is to minimize the variance of the load curve of the studied distribution network, using optimal scheduling of EVs charge planning and discharge. Different methods have been proposed for solving optimization problems; classical methods of solving optimization problems apply limitations on objective functions, constraints, and dimensions of the problem. Also, these methods usually start from an initial point, and the optimal solution found by them is strongly dependent on the initial point. As a result, in recent years, another category of optimization methods, called meta-heuristic methods, has been popular among researchers. In the meta-heuristic algorithms, the process of finding the optimal solution begins with a primitive population, and during the repeated solutions, the population is updated randomly but purposefully. This trend continues until the benchmark is stopped. Unlike classical methods, these methods do not depend on initial conditions and also do not apply any restrictions on the objective functions and the constraints of the problem. There is no need for the objective function to be continuous and also no need to derivatives. Hence these are benefits of meta-heuristic algorithms. These algorithms find the optimal solution by the local and global searching [43–46]. JAYA algorithm is one of a variety of meta-heuristic ones that have been considered in recent years [47,48].

To solve EVs' batteries charging and discharging scheduling problem, JAYA algorithm will be used. Since the definite optimization methods for solving the problem depend on the accuracy of the input variables, the error in predicting the random input variables results in unreliable solutions. Therefore, the validity of commonly used optimization methods should be reviewed in the new conditions and methods should be provided for use in the presence of uncertainty to minimize the risks associated with design and operation. Hence, in this paper, the Monte-Carlo simulation is used to consider the uncertainties. The Monte Carlo simulation is commonly used to simulate physical, mathematical, and economical systems. The Monte Carlo simulation is a numerical algorithm and solves problems based on iteration. For this reason, as well as the use of random numbers, the computational time in this method is high. The Monte Carlo simulation is useful when variables are with associated degrees of freedom and when there is a lot of uncertainty in inputs. In this paper, the uncertainty regarding drivers' behavior and the status of charging and discharging EVs, the capacity of the battery, the distance traveled before arriving at the parking lot, the time of arrival in the parking lot, and the presence duration in the parking lot are considered. In the first step, a complete and probabilistic model of the EV assembly as a load, storage, and energy generator will be presented. The model has been extracted based on the smart charging and discharging operation strategy. To simulate and model the performance of EVs, the Monte Carlo simulation has been used. In addition, the implementation of smart charging and discharging strategies is carried out by a new hybrid method, including the JAYA algorithm and the Monte Carlo simulation. Eventually, using the proposed models, the effect of the EV utilization strategy on the characteristics of the distribution network load is evaluated. The main contribution of this paper are:

- Examining the impact of uncertainties of EVs, including: time of EVs arrival and departure, time of presence in parking, the energy status of the battery when arriving, and battery capacity of each EV.
- Integration of JAYA meta-heuristic algorithm with Monte Carlo simulation for solving the probabilistic scheduling of charging and discharging of EVs.

2. Problem formulation

2.1. Planning the charge and discharge of EVs

A large number of EV batteries being charged, if not controlled, will be a big challenge in the distribution system. If the control process of EVs' charging and discharging is focused on a specific parking lots, it can provide better coordination opportunities rather than single charging and discharging in homes. In this section, the probabilistic model of the behavior of the EV owners and the probabilistic characteristics of EVs (time of arrival and departure to any type of parking lot, parking time and capacity of the battery) is extracted by using Monte Carlo simulation. This suggests owners' inquiries for the EVs, the way they charge and discharge to meet their needs and flattening the network load profile (reducing the daily load variance). The issue output determines the amount of capacity or the amount of production and consumption of each type of EV parking lot.

2.2. Modification of distribution load characteristic

The modification of the load characteristics of the distribution network by using charge and discharge ability of the battery of EVs requires accurate and optimal programming. In addition, the random nature state of charge (SOC) of the EV battery and the driving pattern of its owners cause uncertainty and complexity in their programming. Therefore, to plan the charge and discharge of EVs, an optimization algorithm should be used to recognize the probabilistic properties of the problem. Therefore, in this paper, a hybrid method, including JAYA algorithm and Monte Carlo simulation have been used to optimize battery charging and discharge parameters daylong. After determining the optimal charging and discharging parameters, the load model and the production of a set of EVs are extracted. Thus, the probabilistic planning and modeling of EVs are designed to modify the load characteristic.

2.3. Probabilistic variables

EVs are usually used to travel in the city round. Therefore, it is assumed that the subscribers of the distribution network use EVs to commute work and home. The EVs charging and discharging scheduling will be based on travel time between residential and administrative parking lots, however, probabilistic variables related to the simulation of EVs behavior include EVs batteries capacity, EVs arrival and departure time to/from residential and administrative parking lots, distance traveled by EV, and the time interval the EV is in the parking lot. Random variables follow the truncated normal distribution function to restrain the production of random variables in the arbitrary interval.

The duration of the connection of ith EV to the network in residential (AVT^{i}_{hmp}) and administrative (AVT^{i}_{ofp}) parking lots is as follows (1) and (2) [49]:

$$AVT^{i}_{hmp} = \{1{:}\ T^{i}_{exh} \cup T^{i}_{exh} + T^{i}_{f\,tp} + T^{i}_{ofp} + T^{i}_{rtp}{:}\ 24\} \tag{1}$$

$$AVT^{i}_{ofp} = \{T^{i}_{exh} + T^{i}_{f\,tp}{:}\ T^{i}_{exh} + T^{i}_{ftp} + T^{i}_{ofp}\} \tag{2}$$

T^{i}_{exh} is the time of departure of the ith EV from the residential parking lot, $T^{i}_{f\,tp}$ the travel time of the ith EV to the workplace, T^{i}_{ofp} is the duration of the stay of ith EV in the administrative parking lot and T^{i}_{rtp} is the time it takes to return the ith EV to the residential parking.

By retrieving the distance traveled by each EV between residential and administrative parking, the lost charge and the charge status of each EV are obtained according to the following.

$$SOC^{i}_{t} = SOC^{i}_{t-1} - \frac{D^{i}}{D_{max}} \tag{3}$$

where D^{i} is the distance traveled by the ith EV and D_{max} is the maximum distance the EV can travel. The SOC of the ith EV's battery after charging and discharging is as follows (5):

$$SOC^{i}_{t} = (SOC^{i}_{t-1}\ \Delta t.\ (Ch_{rate}\ or\ Dch_{rate}))100\% \tag{4}$$

where Δt is the time step, Ch_{rate} and Dch_{rate} are the EV battery charge and discharge rate, respectively. The energy produced or consumed by the ith EV is as follows:

$$E^{i}_{agg} = \sum_{i=1}^{t} K^{i}\psi^{i}_{t} SOC^{i}_{t} \tag{5}$$

where K^{i} is the battery capacity of the ith EV and ψ^{i}_{t} is the condition of connecting or not connecting the ith EV to the network. A ψ^{i}_{t} being 1 means the connection to the network and being zero, means no connection to the network. The unknown parameters of the problem of charging and discharging the battery of EVs depend on the desired utilization strategy. In the optimal strategy, the times allowed for scheduling the charge and discharge of EVs are determined. Meanwhile, the SOC requirements of each EV are satisfied for its daily travel. In addition, charge and discharge rates of EVs affect the system's load characteristics. In this paper, the daily load curve variance is used as objective function to peak shaving, valley filling and flatten the load characteristic, which is defined as:

$$Min\ J = Var\ (Loads) = \sum_{t=1}^{T} \frac{1}{T}\ (Loads\ (t) - Mean\ (Loads))^{2} \tag{6}$$

The optimization constraints include the EVs' battery SOC level, charge and discharge rates defined as follows:

$$SOC_{min} \le SOC^{i} \le 1 \tag{7}$$

$$Ch_{rate}^{min} \leq Ch_{rate} \leq Ch_{rate}^{max} \tag{8}$$

$$Dch_{rate}^{min} \leq Dch_{rate} \leq Dch_{rate}^{max} \tag{9}$$

The SOC_{min} for administrative parking lot is large enough that the EV can travel back home. This parameter for residential parking lot is limited by the depth of battery discharge before midnight, and then after that to the extent to which the daily EV journey is guaranteed. Also, Ch_{rate}^{min} and Dch_{rate}^{min} are the minimum charging and discharging rates; Ch_{rate}^{max} and Dch_{rate}^{max} are the maximum charge and discharge rates, respectively.

3. JAYA algorithm

Assuming *f(x)* to be the objective function to be minimized, in each iteration *i*, it is assumed that m is the number of design variables (i.e. $j = 1, 2, \ldots, m$), *n* the number of solution solutions (that is, the size of the population is $k = 1, 2,\ldots, n$). The best solution has the best value (lowest value) of *f(x)* (that is, *f(x)* best) across solution queues and the worst solution has the worst (maximum) value of *f(x)* (i.e. *f(x)* worst across the solution's paths. If $X_{j,k,i}$ is the value of the *j*th variable for the *k*th solution in the *i*th iteration, this value is improved according to the following equation [48].

$$X'_{j,k,i} = X_{j,k,i} + r_{1\,j,i}\,(X_{j,best,i} - X_{j,k,i}) - r_{2\,j,i}\,(X_{j,worst,i} - X_{j,k,i}) \tag{10}$$

Where $X_{j,best,i}$, is the value of *j*th variable in the best solution in the *i*th iteration and $X_{j,worst,i}$ is the value of *j*th variable in the worst solution in the *i*th iteration. $X'_{j,k,i}$ is modified of $X_{j,k,i}$; and $r_{1\,j,i}$ and $r_{2\,j,i}$ are two random numbers for the *j*th variable in the *i*th iteration in range [0,1] . The expression $r_{1\,j,i}\,(X_{j,best,i} - X_{j,k,i})$ denotes the tendency of the solution ($X_{j,k,i}$) to approach to the best solution ($X_{j,best,i}$), while the expression $-\ r_{2\,j,i}\,(X_{j,worst,i} - X_{j,k,i})$ indicates the desire of the solution to get far from the worst solution ($X_{j,worst,i}$). If $X'_{j,k,i}$ leads to a better (lower) objective function than that of $X_{j,k,i}$, it is acceptable. All valid values of the function are preserved at the end of each iteration, and these values are considered as the population for the next iteration. The following steps are carried out to implement JAYA algorithm:

Step 1. Specifying an objective function such as *f(x)* to be minimized. Determining ordinary parameters that include: population size, number of design variables, upper and lower limits of design variables, and the number of iterations as terminating conditions.
Step 2. Creating a random population according to population size and number of design variables, the population size indicates the number of candidate solutions.
Step 3. Finding the best and worst solutions. Since the objective function is a minimizing function, the solution with the minimum *f (x)* is considered to be the best and with the maximum as the worst.
Step 4. Assuming random values (*r1* and *r2*) in the range [0 1], the solutions are modified based on (10).
Step 5. After obtaining new values for design variables in each modified solution, the value of the corresponding objective function is computed and compared with the previous values. After the comparison, the lowest one of each is considered in candidate solutions.
Step 6. The best and worst solutions are selected in the modified candidate solutions for the next iteration.
Step 7. Steps 4, 5 and 6 are repeated until the termination conditions are met.

This algorithm is named "JAYA" since it always tries to approach success (best solution) and avoid failure (moves away from the worst solution) [48].

In order to evaluate the performance of the JAYA algorithm, the results obtained from this algorithm were compared with the Particle Swarm Optimization (PSO) algorithm for the standard criterion function in Table 1, and the best, worst, mean and standard deviation values are presented in Table 2.

Table 1
Objective functions in order to evaluate the performance of JAYA optimization algorithm.

	Function	Objective Function	Number of variables	Equation
1	f_1	Sphere	10, 20, 30	$f(x) = \sum_{i=1}^{n} x^2$
2	f_2	Sum of Different Power	10, 20, 30	$f(x) = \sum_{i=1}^{n} \lvert x\rvert^{i+1}$
3	f_3	Step	10, 20, 30	$f(x) = \sum_{i=1}^{n} x_i + 0.5^2$

4. Application of the proposed method

In the first step, the probabilistic model using Monte Carlo simulation is developed for estimation of uncertain variables including: time of EVs arrival and departure, time of presence in parking lots, the initial energy status of the EVs' batteries, and battery capacity of each EV. Then the scheduling of EVs charging and discharging is determined by JAYA algorithm so that the daily load variance is reduced and the network load characteristic becomes smooth. In fact, Monte Carlo simulation determines the values of variables with uncertainty and transforms the problem from stochastic to deterministic. Once the uncertain variables are identified and the input parameters of the problem are known, the problem of charging and discharging EVs scheduling is solved as an optimization problem using JAYA algorithm to minimizing load variance. The EVs' Charging and discharging time and rate as decision variables, the SOC-related constraints and the maximum charge and discharge rate of batteries, play an essential role in solving the scheduling of charging and discharging problem using the JAYA algorithm. Fig. 1 shows the flowchart of the proposed approach.

The following procedure is carried out in order to solve the EVs charging and discharging scheduling problem:

Step1: Set the iteration of Monte Carlo simulation, $Iter_{MC} = 1$.

Step2: Generate the values of uncertain variables (time of electric vehicles arrival and departure, time of presence in parking lots, the initial energy status of the EVs' batteries, and the battery capacity of each EV) based on truncated normal distribution function (11). The values are provided in Tables 3 and 4.

$$f(x, \mu, \sigma, a, b) = \frac{\frac{1}{\sigma}\varphi\left(\frac{x-\mu}{\sigma}\right)}{\varphi\left(\frac{b-\mu}{\sigma}\right) - \varphi\left(\frac{a-\mu}{\sigma}\right)} \tag{11}$$

In (11) a and b are the upper and lower bounds for each random variable. φ is normal distribution function and μ and σ are mean and standard deviation of the random variables, respectively.

Step3: Set the iteration of JAYA algorithm, $Iter_{JAYA} = 1$

Step4: Initialize JAYA algorithm parameters, the number of design variables ($NEV{*}T = 110 \times 24 = 2640$), determine the population size ($NJAYA = 5{*}\ NEV{*}T = 5 \times 2640 = 13{,}200$) and the termination conditions (specify the maximum number of iterations $Max\_Iter_{JAYA} = 500$).

Step 5: Generate initial solutions based on (12)

$$X = X_{min} + R \times (X_{max} - X_{min}). \tag{12}$$

where X is the charge and discharge rate of each EV, X_{min} is the minimum charging and discharging rate, X_{max} is the maximum charging and discharging rate, and R is a random number in range [0,1].

Step 6: Calculate the objective function (load variance) for each solution.

Step 7: Identify the best and the worst solution in the current population based on load variance value corresponding to each solution.

Step 8: Improve each member of current population based on the

Table 2
Comparison of the performance of JAYA and PSO algorithms.

Objective function	Number of variable	JAYA Algorithm				PSO Algorithm			
		The best	The worst	Average	Standard deviation	The best	The worst	Average	Standard deviation
*f*1	10	3.70e-01	2.03e-00	7.90e-01	3.49e-01	5.24e-07	5.34e-05	4.79e-06	1.06e-05
	20	1.04e+0	3.20e+01	1.76e+01	4.67e-00	3.35e-02	1.48e-01	7.16e-02	2.82e-02
	30	2.23e+0	5.34e+01	3.92e+01	7.70e-00	7.80e-01	2.13e-00	1.32e-00	3.15e-01
*f*2	10	1.92e-04	1.46e-02	2.72e-03	2.66e-03	6.18e-07	2.12e-05	3.33e-06	5.42e-06
	20	2.66e-04	9.74e-03	2.74e-03	2.11e-03	8.42e-05	4.85e-03	3.84e-04	1.06e-03
	30	1.96e-04	1.83e-02	7.89e-03	4.61e-03	5.20e-04	3.61e-02	6.48e-03	7.33e-03
*f*3	10	1.78e+02	2.71e+03	1.08e+03	7.92e+02	0	1.00e-00	0	3.05e-01
	20	3.56e+03	9.57e+03	6.66e+03	1.37e+03	0	5.00e-00	1.00e-00	1.58e-00
	30	8.59e+03	2.62e+04	1.37e+04	3.89e+03	4	1.56e+02	1.40e+01	2.74e+01

best and the worst solutions according to (10).

Step 9: Calculate the load variance for improved solution.

Step 10: If load variance for improved solution is better (lower) than the load variance correspond to the current solution, the current solution is replaced by the improved solution.

Step 11: Control the termination criterion ($\text{iter}_{\text{JAYA}} = \text{Max\_Iter}_{\text{JAYA}}$), if it is satisfied, terminate the JAYA algorithm, otherwise, set $\text{iter}_{\text{JAYA}} = \text{iter}_{\text{JAYA}} + 1$ and go to Step 7.

Step 12: The average output value is calculated according to the following equation.

$$Y = \frac{1}{iter_{MC}} \left(\sum_{i=1}^{iter_{MC}} X_i \right). \tag{13}$$

Step 13: If the Monte Carlo simulation is converged ($\text{iter}_{\text{MC}} = \text{Max\_Iter}_{\text{MC}}$), the average value and the standard deviation of the calculated response (electric vehicles charging and discharging and load variance) are printed as outputs, otherwise, set $\text{iter}_{\text{MC}} = \text{iter}_{\text{MC}} + 1$ and go to Step 2.

5. Simulation results

In this paper, the optimization of charging and discharging of EVs to reduce the load variance was carried out. Accordingly, the demand is shifted from the peak to the load valley. The uncertain variables are determined using the Monte Carlo simulation. EVs' batteries charge and discharge time and rate as decision variables are determined using JAYA algorithm. The results are compared with those of PSO in order to evaluate the performance of JAYA algorithm. All simulations are performed in MATLAB software environment. MATLAB codes related to the results presented in this article are available at the following URL. https://github.com/ahmadi26/Electrical-Vehicle-to-grid-technology-V2G

The strategy of optimal charging and discharging of EVs for two residential parking lots with capacities of 40 and 70 EVs and an administrative parking lot with a capacity of 110 EVs has been investigated in the 69-bus IEEE radial test system (Fig. 2). It is assumed that these 110 EVs are present within the range of the distribution network studied. The locations of residential parking lots in bus 46 and 35 and administrative parking lot in bus 61 have been randomly selected. Owners of these EVs leave the residential parking lots in the morning at a certain time, each independently, then park the EVs in the administrative parking lot; then after finishing the office work, they return home and park the EVs in the residential parking lots. The range, mean and variance of random variables related to EVs are presented in Tables 3 and 4 for estimating the probabilistic behavior of each EVs and the capacity of EVs' batteries [50]. It is assumed that all random variables follow the normal distribution function.

In Fig. 3, the convergence diagram obtained from the two meta-heuristic algorithms of JAYA and PSO are shown by solving the problem of optimizing charge and discharge rates to minimize the load variance. As shown in Fig. 3, the results of JAYA algorithm are better (less) than those of PSO algorithm.

Fig. 4 shows the load profile of the system before and after determining the optimal state of charging and discharging of EVs using JAYA and PSO algorithms. As shown in Fig. 5, with the optimal scheduling of the EVs' batteries charging and discharging, the load curve is flattened, and the load variance decreases. Therefore, adopting a smart strategy for the use of EVs' charging and discharging not only eliminated the challenge of EVs' demand, but also by transferring a significant part of the peak energy to the valley, it improved the system load characteristic.

The SOC of the EVs' batteries, after determining the optimal charge and discharge level using the JAYA meta-heuristic algorithm and optimizing the particle swarm intelligence are shown in the Figs. 5 and 6. It is observed that, while the EVs are in the parking lot, the SOC of EVs' batteries are maintained in sufficient level such that EVs be able to travel to another parking lot. After determining the optimal scheduling of the charge and discharge of EVs, profile of consumption and delivered power of each type of parking lots can be achieved. Fig. 7 shows the load and the expected delivered power of residential and administrative parking lots for the optimal scheduling of EVs' batteries using JAYA and PSO algorithms. As shown in Fig. 7, the V2G capability is used in order to discharge EVs' batteries with an optimal rate when the system's load is high and during low load, the batteries of EVs connected to the network start charging at optimal rates. Also according to the results, the optimal utilization of EVs is so that EVs' batteries are charged in residential parking lots, and discharged in administrative parking lots, because when the EVs are in residential parking lots, the system's load is low, while it is high when the EVs are in the administrative parking lot. According to the results, the load variance has been decreased despite the addition of EVs as a new load in the power distribution system, which is achieved through optimal scheduling of EVs' batteries charging and discharging.

6. Conclusion

Optimal management of EVs charging and discharging can reduce the adverse effects on increasing demand in peak hours, and will result in a uniform load profile. The functional mode of the V2G in parking lots makes EVs flexible to be used as scattered energy sources. In this paper, a new hybrid method based on the JAYA meta-heuristic algorithm and Monte Carlo simulation for optimal charging and discharging of EVs is presented. In this regard, first, using the Monte Carlo simulation, the values of uncertains variables, including the EV battery capacity, the time of departure from the parking lot, the distance traveled between residential and administrative parking, the time of arrival in the parking lot, time spent in the parking lot, the time of departure from the parking lot and the time to return to the parking lot are determined. The probabilistic problem is accordingly changed into a deterministic problem. By defining the problem of determining the status and optimal amount of charge and discharge of EVs as an optimization problem with

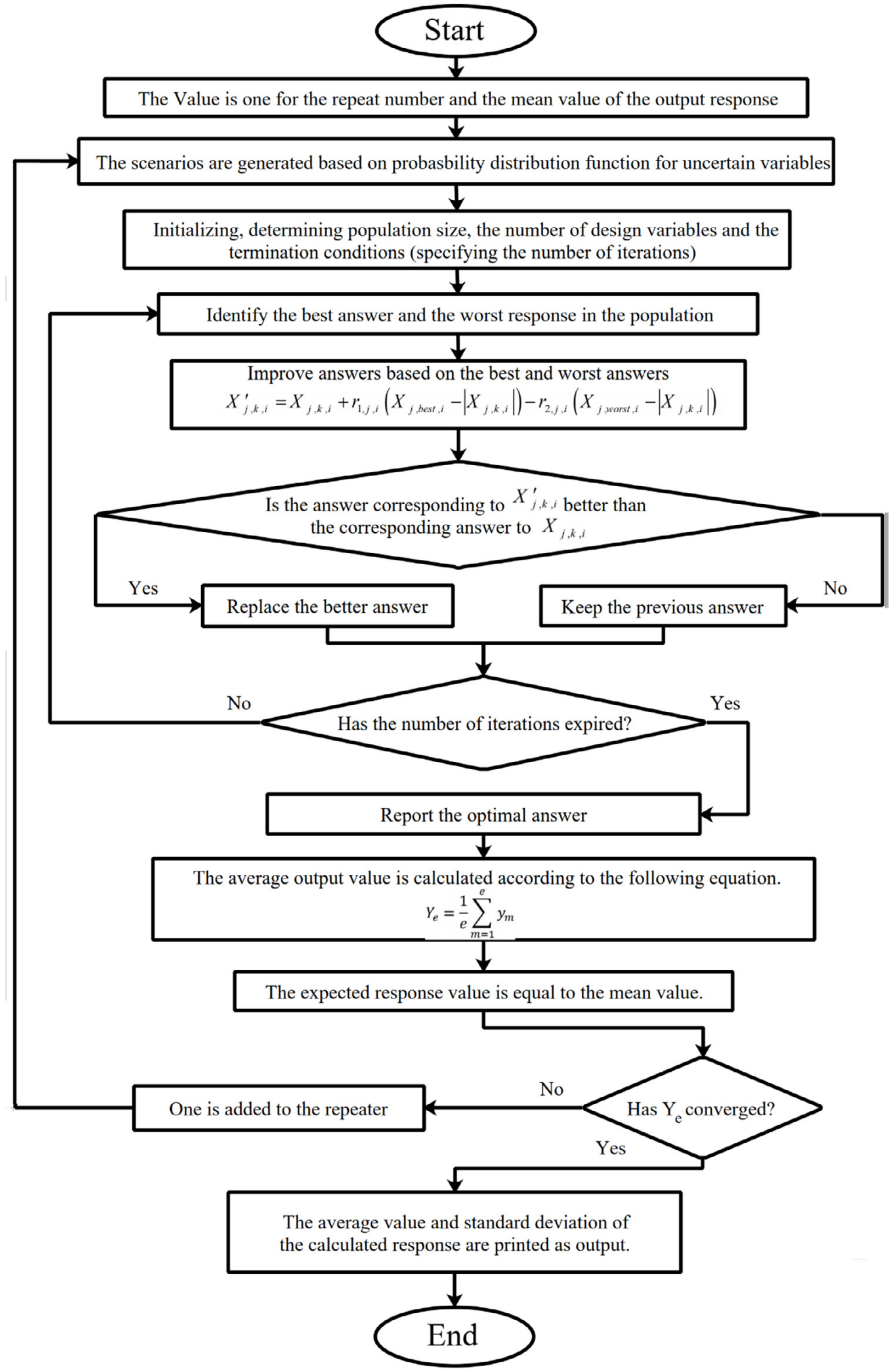

Fig. 1. Flowchart of the combined Monte Carlo simulation and JAYA algorithm for solving the EVs charging and discharging scheduling problem.

Table 3
Lower and upper bound of EVs' random variables.

Random variables	Lower bound	Upper bound
Texh, Tftp, Trtp, Tofp	0 h	24 h
D	0 Km	128 Km
K	5 KWh	30 KWh

Table 4
Mean and variance of EVs' random variables.

Random variable	Mean (μ)	Variance (σ^2)
Texh	7:15 AM	30 Min
Tofp	9 h and 20 Min	50 Min
Tftp, Trtp	30 Min	15 Min
D	25 Km	15 Km
K	25 KWh	5KWh

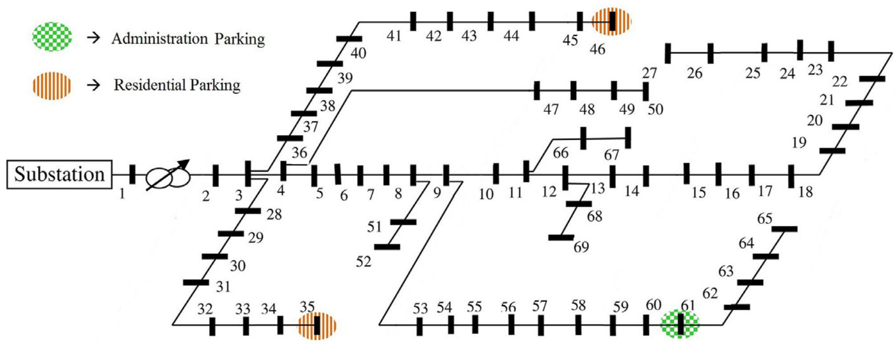

Fig. 2. The IEEE 69-bus test distribution network.

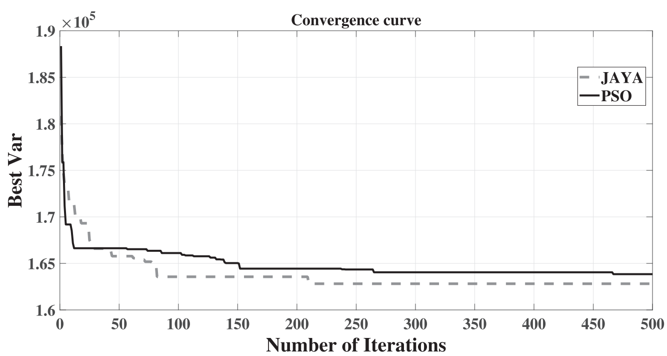

Fig. 3. The convergence diagram obtained from solving the problem of optimizing the charge and discharge of EVs' batteries in order to minimize load variance using the JAYA and the PSO Algorithms.

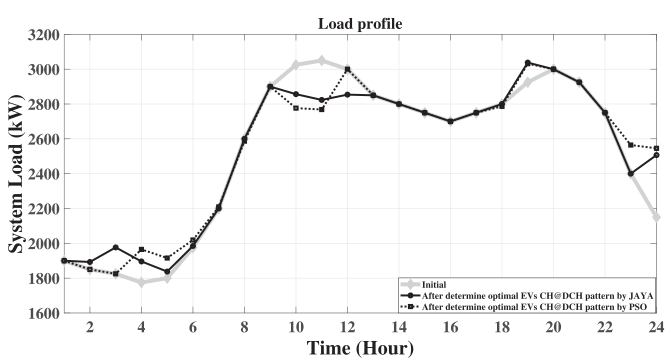

Fig. 4. Load profile before and after determining the optimal scheduling of EVs charging and discharging using JAYA and PSO algorithms.

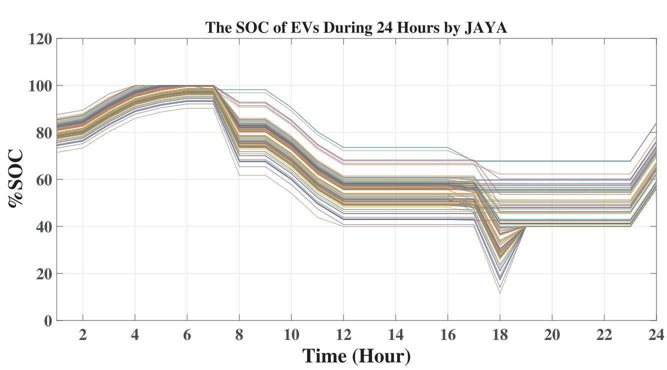

Fig. 5. % SOC profile of EV batteries after determining the optimal charge and discharge rate using JAYA algorithm.

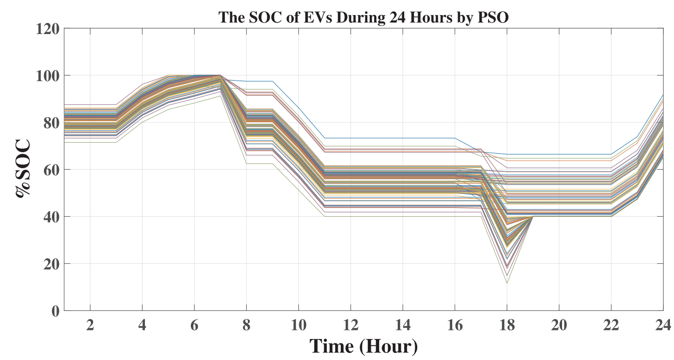

Fig. 6. % SOC profile of EV batteries after determining the optimal charge and discharge rate using PSO algorithm.

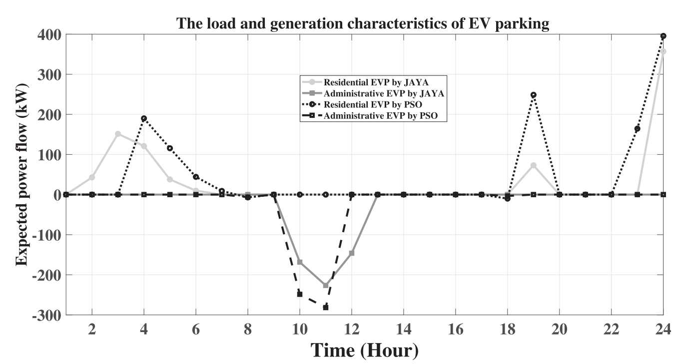

Fig. 7. Profile of consumption and delivered power of each type of parking lots after determining the optimal pattern of EVs' charging and discharging using the JAYA and PSO algorithms.

the objective function of decreasing the daily load variance of the system, the amount of optimal production and consumption of each type of parking of EVs is specified. This makes it possible to modify the characteristic of the distribution system load based on the model of consumption and production of each of the residential and administrative parking lots. The combined method of daily EV travel guarantees the most benefits to the distribution system. Accordingly, the challenge posed by the energy demand of EVs becomes an opportunity. By adopting an optimal utilization strategy of electric EVs, the demanded energy is transferred from peak hours to load valleys and the energy stored in EV batteries is delivered to the network at peak hours, which results in a peak clipping and dampening in the system's load characteristics and decreases the load variance. According to the results obtained in this study, it was observed that if the exploitation of EVs in a power distribution network is under a suitable strategy for determining the state and timing of charging and discharging in a smart grid, not only can it reduce the adverse effects of increasing the presence of EVs in the electric system, but by adopting a proper management approach it can be best-made use of the presence of these types of EVs, and can modify daily load curve as well.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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