Journal of Operation and Automation in Power Engineering
Vol. 11, No. 4, Dec. 2023, Pags: 277-284
http://joape.uma.ac.ir

Probabilistic Optimal Allocation of Electric Vehicle Charging Stations Considering the Uncertain Loads by Using the Monte Carlo Simulation Method

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Abstract- *Nowadays, the use of electric vehicles (EVs), in the form of distributed generation, as an appropriate solution is considered to replace combustion vehicles by reducing fuel consumption and supplying needed power. In this regard, the incorporation of EVs charging stations (EVCSs) in the power network can affect the distribution networks in different ways. On the other hand, the location of EVCS in distribution networks changes operational parameters includes electrical losses, and voltage deviations. Also, the probabilistic and uncertain behaviour of the loads and their daily changes can play a significant role on power distribution networks. To this end, in this paper, first, the modelling of the EVCSs affected by the behaviour of the EVs' owner in a power distribution network is discussed. Then, the optimal location and size of EVCSs to reduce their negative effects on the network, including network losses (active and reactive) and voltage deviations are addressed in the presence of uncertain loads. The probabilistic model is investigated based on using the Monte Carlo simulation (MCS) method. The simulation results in MATLAB software environment show a 10% increase in active and reactive power losses in most hours of the day, due to increased power flow, when EVCSs are located in the optimal placement. The power losses at 24:00-7:00. when the EVs load is very low, are reduced due to decreased power flow across the lines. The results also show that if the EVCSs are not optimally located, the voltage deviation will increase by an average of 30% over a day, while by optimal placement of EVCSs, the voltage deviation increases to a maximum of 8% of the nominal value.*

Keyword: Charging station, Electric vehicle, Load uncertainty, Optimal placement.

1. INTRODUCTION

The use of electric vehicles and their charging stations in distribution networks can have significant systemic effects, including increasing electrical losses, changing the voltage profiles, and cause the lines to be congested In this regard, modelling the EVCSs and considering different governing constraints has been addressed based on some technical and economic optimization methods, such as economic load dispatch, demand-side management, energy management, reactive power planning, and power system stability studies [1]. Adverse system effects of electric vehicles in the network are mainly due to their probable presence in charging stations. These effects are mainly to changing behaviour of stations in the distribution network and, for example, can increase the peak hours of the day.

Received: 26 Feb. 22
Revised: 13 Mar. 22
Accepted: 06 June 22
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DOI: 10.22098/joape.2023.10427.1738
Research Paper

Electrical losses increasing and reductions in voltage magnitude in some parts of the network impose some challenges to the system operation. These challenges include: increased peak load, increase of power losses, negative impact on voltage profile, reducing power quality, and possible overloading of distribution transformers, distribution lines, and cables. In particular, EV penetration has significant adverse impacts on voltage profiles and distribution network losses [2]. Therefore, analysing the use of appropriate strategies, techniques, and tools to control and operate the EVCSs are needed. These solutions are including storage devices, load sharing, voltage controllers, and network reconfiguration. Therefore, many studies and research have been done, with the aim of optimal location and reduction of negative effects. In Ref. [3], a new time management strategy for coordinating multiple EVCSs to reduce power losses and improve voltage profile is suggested. The RT-SLM (real-time intelligent load management) algorithm makes it possible to charge PEVs as soon as possible based on real-time (for example, every 5 minutes). In Ref. [4], a multi-objective method for planning EVCSs is presented, which improves the reduction of losses and voltage deviations.

In Ref. [5], the use of EVs has shown to be more profitable for their owners in frequency control programs than peak reduction programs by considering the battery life reduction parameter as a determining factor. In Ref. [6], EVs have been addressed to change the daily energy demand, and their economic benefits on the power system have been discussed. In Ref. [7], the initial challenges of EVs have been investigated. Also, in Ref. [8] an unconstrained traffic assignment model (UTAM), utilizing the Nesterov & de Palma (NdP) model, is suggested based the relaxation of road capacity constraints. Also, an EVCS location model (ECSLM) considering the EV driving range and traffic flow equilibrium is proposed, based on a mixed-integer linear programming (MILP) model. A multi-objective optimization problem framework for optimal allocation and sizing of EVCSs and renewable energy sources (RES) and managing vehicle charging process is suggested in Ref. [9], to reduce voltage fluctuations, power losses, demand and charging supplying costs, and EV battery cost. The Genetic Algorithm-Particle Swarm Optimization (GA-PSO) hybrid improved optimization algorithm is proposed to solve the problem in different scenarios of the IEEE 33-bus system. Awasthi et al. [10], have proposed the optimal planning of charging stations, including siting and sizing in the city of Allahabad, India, by applying a combination of genetic algorithm and improved particle swarm optimization. Also, the multi-criteria decision-making (MCDM) method is applied to EVCS problem in Ref. [11], by using the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to decide on environmental, economic and social criteria associated with a total of 11 sub-criteria. Also, in Ref. [12], an artificial neural network (ANN) technique is suggested to estimate the capacity fade in lithium-ion (Li-ion) batteries for EVs, to improve the state-of-charge (SOC) estimation accuracy over the life-time of the battery, and accurate prediction of the battery remaining service time.

In Ref. [1], the stochastic unit commitment problem is investigated in a 10-unit case study system integrated with an EVCS, a solar farm and a wind farm over a 24-h time horizon, based on using scenario generation with Monte Carlo simulation technique. Also, reducing consumers cost and fossil fuel consumption in a smart grid equipped with hybrid EVs, is addressed in Ref. [2], by using the game theory and non-cooperative game. In [13] a novel decision-making framework, based on two-stage programming, in a bilateral-pool market for an electricity retailer to procure the electric demand considering the charging and discharging of EVs is suggested. The authors applied a bi-level programming to maximize the retailer profit in upper sub-problem, and to minimize the aggregated EVs charging and discharging costs in the lower sub-problem, by using Monte Carlo Simulation (MCS). A two-stage scenario-based model to obtain optimal decision making of an EV aggregator has been proposed in Ref. [14]. They used the conditional value at risk (CVaR) method to handle different uncertainties. The energy management in the presence of electric vehicles for production and storage resources is addressed in Ref. [15]. Also, some uncertainties in market price of energy, and the prices quoted by distributed generation sources, are mentioned integrated with responsive loads. The load response programs used include the time of use and direct load control. The proposed linear mixed-integer planning was simulated in the GAMS software. In Ref. [16] a multi-objective optimization formwork is proposed for optimal placement of EVCSs by minimizing electrical grid loss, and EVs' power loss during travel towards CS. A probabilistic load modelling (PLM) approach is used to model the uncertain demand and EV behavior. Also, a two stages model for optimal allocation of PEVCSs is suggested in Ref. [17] considering Trip Success Ratio (TSR) to enhance CS accessibility for PEV drivers. Different driving habits, diversity of usage, and different trip types include In-city, and highway are modelled. A bi-level programming model for the coordinated DG and EVCSs planning problem, by maximizing the annual overall profit and applying the improved harmonic particle swarm optimization algorithm has been presented in Ref. [18]. Ref. [19] addressed a stochastic framework based on the Queuing Theory (QT) to the optimal allocation and sizing of the fast-charging stations by considering the traffic flow of EVs using the User Equilibrium-based Traffic Assignment Model (UETAM). Minimizing the annual investment cost, and the energy losses are considered as the objective functions. The authors applied the Gram-Charlier expansion and point estimation method to model the problem. Optimal siting and sizing of plug-in hybrid electric vehicles charging stations (CSs) based on a mathematical method has been presented in [20]. The rate of customers’ participation in demand response programs (DRPs) and uncertainties associated with the load values and electricity market price are considered. The GA with embedded MCS is used to solve the optimization problem in 9-bus and 33-bus networks.

In this paper, at first, modelling the EVCSs affected by the behaviour of EV owners in terms of load uncertainty using the MCS technique, which has been neglected in previous studies, is presented. Then, the optimal location and capacity of EVCSs in the 33-bus distribution network to reduce the negative effects on the network performance, including increasing network losses (active and reactive) and voltage deviation in different buses using gravitational search algorithm (GSA) is examined.

The most important contributions of this paper are as:

1. Considering an appropriate traffic model for EVCSs. A traffic model requires input data such as consumption rate, charge capacity, location and time, and types of charges with variable penetration coefficients for passenger cars.
2. Because in traffic analysis, a variety of random parameters are responsible, the answers are uncertain and some of them are more likely than others. Therefore, the answers are processed by MCS method and finally a probabilistic load model will be introduced in a 24-hour period.
3. Introducing the random load flow analysis in the presence of EVCSs and some methods of calculating the average power losses and voltage deviations using Expected value methods and alpha cutting.
4. Simulation case study on a standard 33-bus network for optimal placement of EVCSs and investigating power losses and voltage deviations in a 24-hour period.

The reminder of this paper is organized as follows. Section 2 presents modelling the charging mode of EVCSs. In section 3, objective function formulation detailed. Simulation results are addressed in section 4, and in the final section of the paper conclusions are drawn.

2. MODELLING THE CHARGING MODE OF ELECTRIC VEHICLE CHARGHING STATION

As mentioned earlier, EVCSs are suitable places to integrate EVs into the distribution network and act as one-time supply and receive electrical energy from the network. Therefore, the charging status of these vehicles plays an important role in the indicators and parameters of a distribution network. Also, in this section, a suitable model is introduced for planning and placement analysis to determine the charging status of these vehicles. In the proposed method, each EV is modelled as a voltage source converter (VSC) during charging process according to Figs. 1 and 2. Therefore, the power received by the EV from the network in the charging mode is obtained from Eq. (1) [21]:

$$P_{EV}^{charge}(t) = P_{EV_{max}}\left(1 - e^{-\alpha t/t_{max}}\right) + P_{EV0} \quad (1)$$

Which, P_{EV0} introduces the initial charging power of EVs, α is the EV battery charging time constant, t_{max} presents the total time required to charge EV battery from zero charge to maximum charge, and $P_{EV_{max}}$ describes the maximum EV charging capacity.

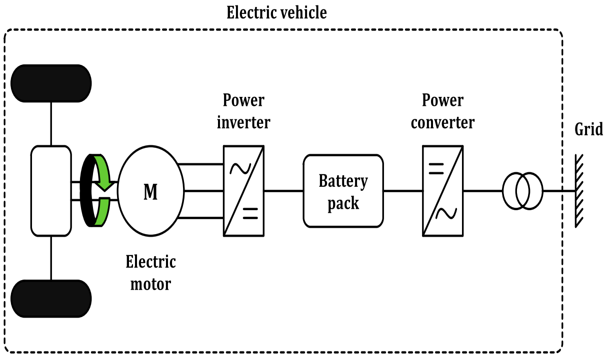

Fig. 1. Schematic of an EV connected to the network

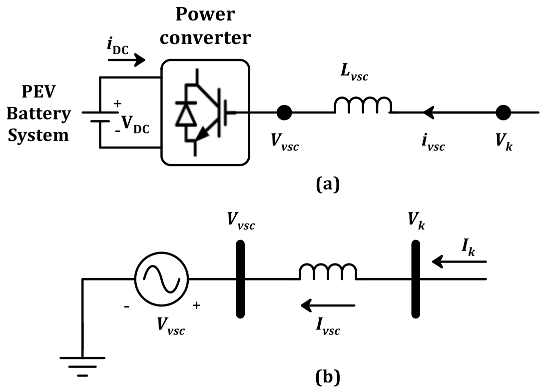

Fig. 2. Equivalent circuit of an EV connected to power grid

2.1. Probabilistic modelling of EV charging mode

As shown in Fig. 3, EVs are electrically connected to the network in series and parallel while charging. Therefore, the total power consumption of EVCSs is calculated by Eq. (2) [21]:

$$P_{EV}^{total} = \sum_{i=1}^{n}\sum_{j=1}^{m} P_{EV,ij} \quad (2)$$

The presence of EVs in charging stations is a function of the behaviour of EV owners, also the time required to charge EVs. Therefore, the active power received from the network by charging stations has a random and probabilistic nature that needs to be considered in modelling of Eq. (2). As mentioned earlier, charging stations are divided into three groupings slow, medium (battery switch), and fast stations based on the charging time. In this paper, the fast-charging method is used to model the charging behaviour of charging stations with the Markov probabilistic model. The diagram of the Markov probabilistic model for a rapid EVCS is shown in Fig. 4 [21]:

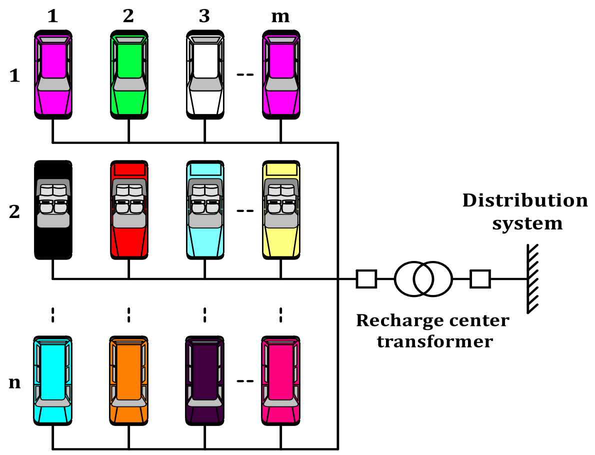

Fig. 3. How to connect electric vehicles to a charging station

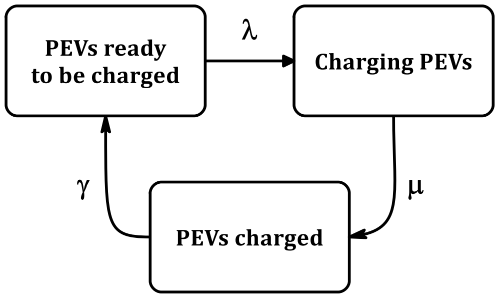

Fig. 4. Markov probabilistic model diagram for a fast EVCS

In Fig. 4, λ is the success rate of a vehicle to access the charge transfer converter, μ is also the success rate of a vehicle to complete the charging of its battery and finally, γ is the completion rate of charging the battery of an EV and going to the preparing stage for charging. Therefore, according to Fig. 4, the probable coefficient of power consumption in an electric vehicle charging station is obtained from Eqns. (3) and (4) as [22]:

$$p_N = \frac{\frac{(c\rho)^N}{(N)!}}{\sum_{i=0}^{c}\frac{1}{i!}\left(\frac{\lambda}{\mu}\right)^i+\sum_{j=c+1}^{N}\frac{1}{c^{j-c}}\times\frac{1}{c!}\times\left(\frac{\lambda}{\mu}\right)^j} : N < c \quad (3)$$

$$p_N = \frac{\frac{(c\rho)^c}{(c)!}(N-c)}{\sum_{i=0}^{c}\frac{1}{i!}\left(\frac{\lambda}{\mu}\right)^i+\sum_{j=c+1}^{N}\frac{1}{c^{j-c}}\times\frac{1}{c!}\times\left(\frac{\lambda}{\mu}\right)^j} : N < c \quad (4)$$

Which, p_N presents the possible coefficient of power consumption in an electric vehicle charging station, c is the number of charging devices to charge electric vehicles, and $\rho = \frac{\lambda}{c\mu}$ is the traffic intensity rate.

Therefore, using Eqns. (2-4), the potential power consumption of charging station is rewritten as Eq. (5).

$$P_{EV,N}^{total} = P_{EV}^{total} \times P_N \quad (5)$$

3. OBJECTIVE FUNCTION FORMULATION

3.1. Loss function modelling

One of the significant parameters in a system is power loss, which determines the degree of optimization, efficiency, and long-term costs of operating the system, so reducing it as much as possible is always one of the main goals of distribution network operators. In this paper, the total network losses are obtained by applying backward-forward load flow method and are used as one of the objective functions, which are obtained by using Eqns. (6-7), respectively, for active and reactive power losses:

$$P_{Loss}^{active} = \sum_{i=1}^{nl} Re(I_i)^2 \times R_i \quad (6)$$

$$P_{Loss}^{reactive} = \sum_{i=1}^{nl} Im(I_i)^2 \times X_i \quad (7)$$

3.2. Modelling the voltage deviation function

One of the overriding indicators and parameters of power quality analysis is the voltage deviation index. This index indicates the voltage profile smoothness. It is defined as one of the most important objectives of this research in locating and determining the optimal capacity of EVCSs, as:

$$F = \sum_{i=1}^{n}(1 - V_i)^2 \quad (8)$$

It should be noted that the lower the voltage deviation in a network, the more uniform and smooth the voltage profile of that network.

3.3. Voltage stability index

Voltage stability in a distribution network is the maximum electrical loading that can be applied to a network as long as the voltage across the bus is within the allowable range and does not suddenly become zero. Therefore, the voltage stability index in a distribution network whose lines and electrical loading are modelled according to Fig. 5 is obtained using Eq. (9).

$$VSI = V_s^4 - 4V_s^2(RP_L + XQ_L) - 4(RP_L + RQ_L)^2 \quad (9)$$

In the above relation, if the VSI value is closer to zero, the voltage stability margin decreases, and also the system enters the instability, and if this index becomes larger, the system is more stable.

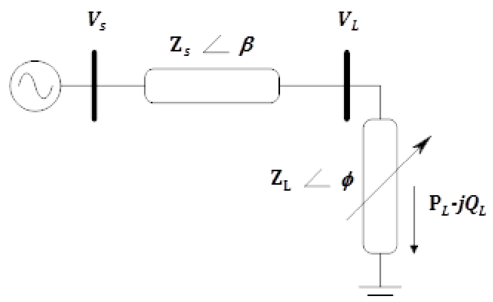

Fig. 5. Equivalent circuit of the distribution system to analyse voltage stability index

Table 1. Coded mode for gravity algorithm

	Location (bus number)	Nominal values (pu)
EVCS no. 1	2	0.25
EVCS no. 2	33	0.36

Table 2. Specifications of the EVs used in this study

EV Type	Usable battery capacity (kWh)	Weight (Kg)	Distance declared by EPA institute	Mileage per kW (Km)	Battery Type
Nissan Leaf	21.3	1493	95	4.46	Li-Ion
Chevrolet Volt	17	1721	60	3.53	Li-Ion
Toyota Perius	4.4	1420	20	4.54	Li-Ion

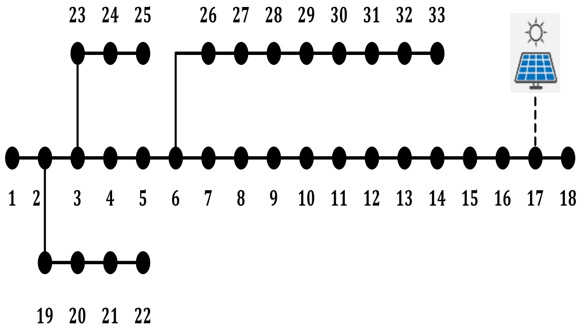

Fig. 6. IEEE Standard 33-bus standard network schematic

3.4. Problem constraints

To solve the problem, it is necessary to consider needed constraints, which are introduced below. By changing the manoeuvre points in the distribution network, a new configuration is created. However, it cannot be said that every new configuration obtained is necessarily acceptable. a feasible configuration must observe the following limitations:

$$V_{min} \leq V_i \leq V_{max} \quad (10)$$

$$I_{min} \leq I_i \leq I_{max} \quad (11)$$

Eq. (10) indicates the allowable voltage range of the bus bars, and Eq. (11) shows the acceptable flowing current across the lines. But the network should remain radial after reconfiguration. The radius of the network is such that, firstly, are created no loops in the network and secondly, no bus in the network is without electricity. For this purpose, two simple calculations (necessary and sufficient conditions) have used to satisfy these conditions. The first constraint (required condition) is that the number of lines in the network circuit must be one number less than the number of buses. The second calculation (sufficient condition) performed using the determinants of the branch and node matrix to prevent buses isolation after evaluating the first calculation, which shown in Eq. (12).

$$\det(A) = 1 \; or - 1 \quad (12)$$

$$\det(A) = 0 \quad (13)$$

Since electrical lines have limited heat capacity, their temperature increases with increasing power flow through transmission lines. Therefore, one of the constraints that should be considered in problem-solving is the power flow constraint through the transmission lines, which is defined as:

$$P_{T,j}^{min} \leq P_{T,j} \leq P_{T,j}^{max} \quad (14)$$

3.5. Objective function of the problem

In this section, to achieve the predefined objectives, the objective function of the problem is introduced for reducing losses, and voltage deviation. Hence, the appropriate function is first defined as the cost function, which contains all these constraints. This function is then optimized using the gravitational search algorithm (GSA), and the optimal parking location of the EV is determined. Therefore, according to objective functions total system cost function is defined as Eq. (15):

$$F_{system} = \frac{P_{Loss}^{Sc}}{P_{Loss}^{Normal}} + \frac{F_V^{Sc}}{F_V^{Normal}} + \frac{VSI^{Normal}}{VSI^{Sc}} \quad (15)$$

3.6. Gravitational search algorithm

First, to perform the calculations by the GSA, it is necessary to encode the parameters of the desired equation. In this research, four parameters of installation location, and capacity of two EVCSs are encrypted, and each is placed in one dimension by numbers (mass). The first number indicates the location of the charging station element, and the second number indicates the force applied to each object, which is determined according to Eq. (11). Table 1. shows an example of a coded mass.

4. SIMULATION RESULTS

This section tests and validates the proposed method for locating the EVCS in the IEEE 33-bus standard network to improve the voltage and loss profiles. The schematic of this network is shown in Fig. 6. As can be seen in Fig. 6, in this case, studies were used to consider the presence of DG in the network from a distributed generation source with a nominal capacity of 250 kW at bus number 17 with variable output power over 24 hours.

4.1. Case study data

4.1.1. Test network data

The standard 33-bus IEEE network is selected for simulation case studies, in which, bus 1 with *V*=1.06<0 *pu* is selected as the input substation.

4.1.2. Electric vehicles data

To take into account different types of EVs, different three EVs including of Nissan Leaf, Chevrolet Volt, and Toyota Perius as the long-, medium- and short-ranges vehicles are mentioned in this study. Table 2 shows the specifications of each vehicle.

4.1.3. Photovoltaic system specifications

As mentioned in this case, to consider the presence of DGs, a photovoltaic system with a nominal capacity of 250 kW has been used in bus number 17. The output power of photovoltaic arrays depends on the cell temperature and the intensity of solar radiation at the maximum power point, which is determined as:

$$P_{PV}(t) = \left[P_{PV,STC} \times G_T(t)/1000 \times \left[1-\gamma\left(T_i-25\right)\right]\right] \times N_{PVs} \times N_{PVp} \qquad (16)$$

$$T_j = T_{amp} + G_T / G_{T,STC} \times (NOCT-20) \qquad (17)$$

The temperature and solar radiation changes during 24 hours are shown in Figs. 7 and 8, respectively.

4.1.4 Load change coefficient during 24 hours a day

The normalized values for electrical demand are shown in Fig. 9. As can be seen, during the day, the demand for electric charge fluctuates by up to 65%. In this case, the peak demand for electricity is 3200 kW.

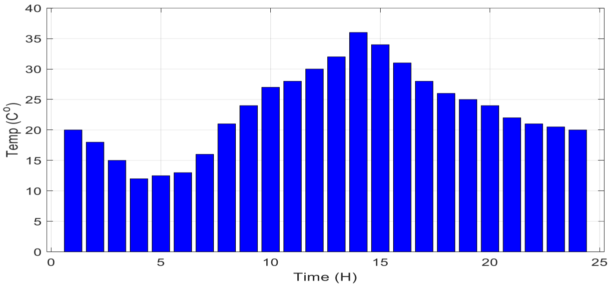

Fig. 7. Ambient temperature during day and night hours

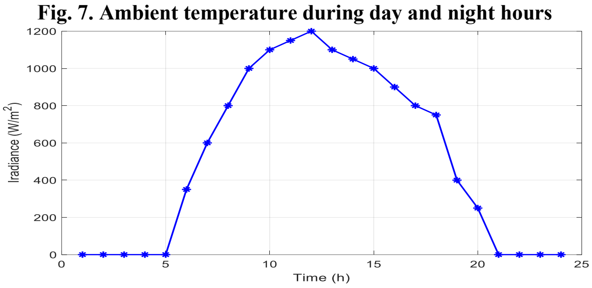

Fig. 8. Solar radiation during day and night hours

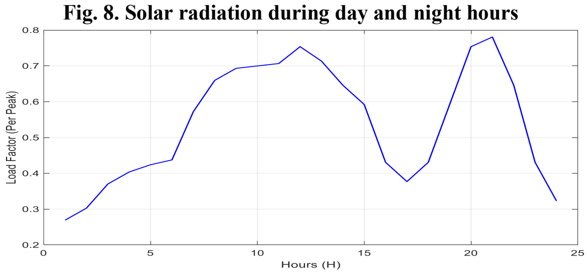

Fig. 9. The normalized electrical load

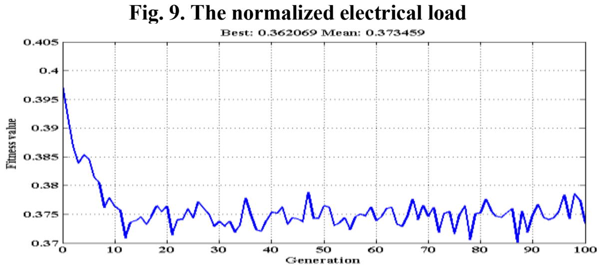

Fig. 10. Optimizing process of the objective function using GSA

4.2. Modelling results

The MCS method is used to model the load uncertainty over a 24-hours period. In this way, for probabilistic load flow analysis, the load in each bus, at any time, is described as an PDF based on the exact amounts of load. Therefore, solving the probabilistic load flow leads to some PDFs of outputs, include voltage, current, and losses. In this section, the results obtained from the placement simulation are examined of the EVCS. Fig. 10 shows the optimizing process of the objective function during different iterations Figs. 11 and 12 also show the probability density functions (PDFs) of the location and optimal capacity of the EVCSs.

Table 3 shows the optimal location and capacity of the most likely EVCSs in the network. Therefore, by placing the EVCSs in the mentioned buses, the losses, and voltage profiles are investigated. Figs. 13-15, show the diagrams of active, reactive losses and voltage deviations for the installation of EVCSs in the proposed buses, respectively. These figures show the status of the network parameters for the state before the presence of the EVCSs (red diagram) and after their presence (bus diagram) in 24 hours.

As can be seen in Figs. 13 and 14, the active and reactive losses of the lines in most hours of the presence EVCSs have always increased due to the increase of the current flowing through the lines. Meanwhile, the losses have decreased between24 and 7 in the morning, when the amount of EV load is very small, due to the power dispatch and power flow changes through the lines. On the other hand, according to Fig. 15, the voltage deviation from the value of one pu in all hours of the presence of the EVCSs is greater than the absence. This is also due to the increase in current flowing through the lines during the hour of increasing demand and causing more voltage drop on the lines.

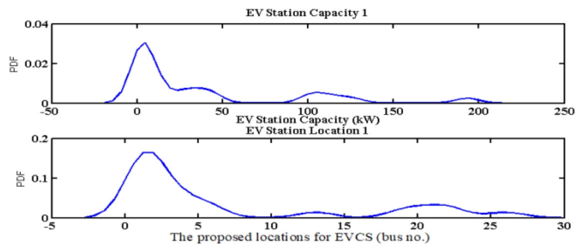

Fig. 11. Optimal location and capacity of EVCS for first station

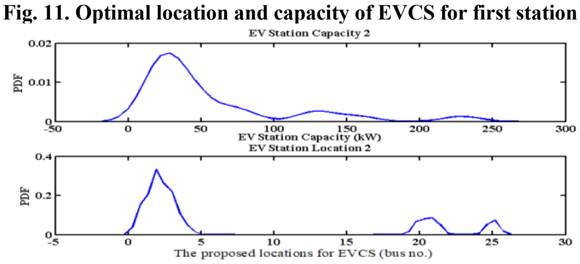

Fig. 12. Optimal location and capacity of EVCS for second station

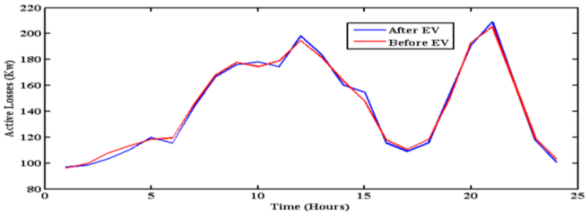

Fig. 13. Active losses in 24 hours of day and night, with and without the EVCSs

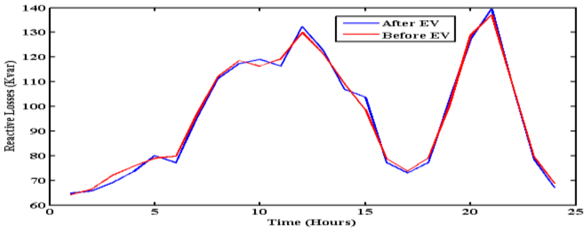

Fig. 14. Reactive losses in a 24-hour period of day and night, with and without the EVCSs

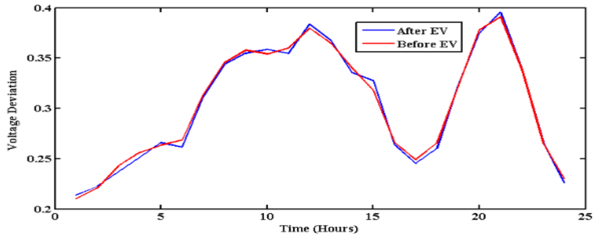

Fig. 15. Voltage deviation in a 24-hour period of day and night, with and without the EVCSs

Table 3. Optimal location and capacity of EVCSs

	Number of suggested bus	Proposed optimal capacity (kW)
Station no. 1	3	10
		28
	22	38
Station no. 2	2	40
		70
	21	100

Table 4. Comparative results

Applied Method	Proposed locations for EVCSs (bus no.)	Proposed capacity for EVCSs (kW)	Electrical losses (Average percentage)	Voltage deviations (Average percentage)
This work	3	10	+10	+12
	21	71		
GA Neglecting uncertainties	8	42	+15	+13
	19	120		
PSO Neglecting uncertainties	6	55	+12	+14

Table 4 shows a compression between the obtained results by the proposed method applying the GSA (considering the uncertainties), with other well-known algorithms such as GA, and PSO, neglecting the uncertainties.

5. CONCLUSION

In this paper, the proposed method for EVCSs placement on the power grid was simulated and validated, and the role of charging stations in different network locations on different parameters of electrical losses and voltage deviations was studied in 24 hours. As seen in the simulation results, depending on where the EVCSs are located in the network, the losses and voltage deviations is always different according to the power dispatch and power passing through the lines in the network. The simulation results in the IEEE 33 standard bus network show that even by determining the optimal location and capacity of the EVCSs in the network, the losses increase in most hours. Also, the bus voltage deviation from one puin all buses and at all hours, the presence of the EVCSs is more than the absence. Also, the results confirm that the power losses at 24:00-7:00., are reduced due to decreased power flow across the lines, as the EVs load is very low in this duration. The voltage deviation will increase by an average of 30% over a day, if the EVCSs are not optimally located. This item will limit to a maximum of 8% when EVCSs are sited appropriately. Analyzing the impacts of correlation between different sources of uncertainties, and the possibility of sudden overloading of the system, can be considered as some interesting subjects for future research.

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