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Optimal Allocation of Electric Vehicle Charging Stations With Adopted Smart Charging/Discharging Schedule

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ABSTRACT Modeling and allocation of the Electric vehicles Charging Stations (EVCS) within the distribution network, as per the growing use of Electric vehicles (EVs) is a challenging task. In this paper, to manage the EVCS, first, with the aim of peak shaving, valley filling, and flattening the load curve of the network, the optimal planning of EV's charging/discharging is devised. In this regard, after modeling involving random variables, a novel hybrid method, based on the Multi Objective Particle Swarm Optimization (MOPSO) optimization algorithm and sequential Monte Carlo simulation is presented. The purpose of the presented optimal charge/discharge schedule is to control the rate and time of charging/discharging of EVs. In the proposed model, various battery operation strategies, including Uncontrolled Charging Mode (UCM), Controlled Charging Mode (CCM), and Smart Charge/Discharge Mode (SCDM) are also considered. In the next step, in order to implement the charge/discharge schedule of the EVCS profitably, a new formulation is presented for the allocation of two EVCSs (administrative and residential EVCS). In the proposed formulation, various objective functions such as power loss reduction, reducing power purchases from the upstream network, reducing voltage deviation in buses, improving reliability is addressed. Moreover, to incentivize the owner to construct the EVCS with adopted charging/discharging schedule, the optimal profits sharing between Distribution System Operator (DSO) and EVCS owner is also performed. The proposed formulation is applied to a standard network (IEEE 69 buses) and encouraging results are achieved.

INDEX TERMS Charging station, electric vehicle, optimal allocation, smart charging/discharging schedule.

I. INTRODUCTION

Nowadays, the use of electric vehicles (EVs) has expanded due to various environmental and economic benefits. However, given that EVs are considered as loads that are not fixed in one place and can be connected to different parts of the power system at different times, challenges are undeniable [1]. In fact, contrary to the benefits such as reduced fuel costs and reduced pollution of EVs compared to conventional vehicles, the presence of EVs, particularly the accidental and their unplanned connection to a distribution network, can have adverse effects on the system, and be an issue for the power system operators.

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On the other hand, the EV's batteries are by far the most cost-efficient form of energy storage, which can enable the stored energy to be pushed back to the grid and balance variations in energy production and consumption. Thus, thanks to bi-directional charging capability, the EVs can bring special benefits to the network, like active power regulation, peak shaving, and valley filling in the load curve.

In summary, from the point of view of the power system, EVs for Distribution System Operator (DSO) fall into the following categories [2], [3]:

- A simple load that consumes a constant power from the network while charging.
- A complex load whose charging period can be adjusted or be delayed.
- More importantly, an energy storage device, which can be charged and discharged according to network

conditions. In other words, it would store the energy produced while demand is lower, and feeding it back into the grid when demand is higher. This concept is known as Vehicle To Grid (V2G) and it's easy to imagine the advantages of this technology as EVs become more widespread [4], [5].

The V2G concept, as well as paying attention to the behavior of EVs owners to park their vehicles most of the time, has raised the idea of constructing and planning EV Charging Stations (EVCS). Considering the EVCS for parking and connecting EVs to the power grid, it is possible to provide some of the power required by the network during peak hours, by discharging the EVs battery and injecting power from the EV to the network [6], [7]. In [8] based on the injecting power capability of EVs, a demand response program to reduce the peak load of the system is presented. Also, during the off-peak hours, the EV battery could be charged for personal use by the owner. Nevertheless, ignoring effective planning and management of EVCS can cause some unexpected problems such as feeder congestion, aggravated power loss, voltage deviation, and unwanted outages [7], [9]–[11]. In [12] a multi-level game approach for energy management of EVCSs is devised based on which the profit of all EVs, EVCSs and DSO is maximized. However, the issues of charging/discharging strategy and placement of EVCS within the network are not addressed.

In this regard, accurate and suitable placement and allocation of the EVCS are crucial. This is a nonlinear and complex problem due to its dimensions and many parameters involved, are generally addressed in terms of two main aspects: The first one is modelling of the EVCS with considering influencing factors such as probability aspect of EVs owners' behavior and their presence in the EVCS, uncertainties of State Of Charge (SOC), appropriate charging/discharging schedule [10], [13], load profile of the system, and demand response programs [14], [15]. In [16], with considering EV battery capacity, state of charge (SOC) of battery, the trip type and driving habits of EV's owner, a probabilistic model to determine an EV charging pattern is devised.

Moreover, the formation of the allocation problem requires careful modeling of its dimensions, mainly including load model, energy or market price model [17], [18], driver behavior and EV model, and SOC, some of which have uncertain characteristic. Therefore, probabilistic and forecasting trend methodology should also be used.

The charging/discharging behavior of EVs has been analyzed in [19] to provide a probabilistic method for characterizing the stochastic nature of EVs. Moreover, the daily travel distance of EVs considering related uncertainties are modeled using Monte Carlo simulation.

The second aspect deals primarily with solving methods of the allocation problem. In this regard, adopting heuristic methods to find the optimal solutions regarding various objective functions is quite effective. It is also necessary to use stochastic algorithms, which accounts for uncertainties, in order to enhance the accuracy of modeling and achieve optimal solutions. In [20], [21] a multiobjective optimization problem is solved with the aim of minimizing power loss, voltage deviation, and cost to optimally allocate the EVCS in candidate buses. In [22] bi-level optimal allocation model is presented for allocating an EVCS with the aim of maximizing the coordinated benefits of the EVCS investor and EV owners, but the benefits of DSO is not considered. In [23] a multi-objective program is proposed, based on hybrid chicken swarm and teaching-learning-based optimization algorithm, to obtain the best EVCS placement. Although the obtained Pareto solution improves the voltage stability, reliability, and power loss of the grid, the EV/ EVCS owner's profit is not considered. In [24] to improve the profitability of the EVCS owner, it is suggested to incorporate renewable resources. However, the investment costs of constructing these resources and the intermittent behavior of such resources are serious challenges that have not been addressed.

Importantly, the adopted program for charging/ discharging of EV's battery is one of the main components of EVCS allocation, which is not considered in some papers such as [20], [22], [23], [25]–[27]. On the other hand, this program has a significant impact on distribution network performance and operation. A comprehensive review on scheduling, strategies for connecting and controlling EVs is presented in [28]. In [29] a charging and discharging strategy based on the market price is presented, however, in this paper effect of charging/discharging program on load profile and EV behavior is not considered in the proposed strategy. In [30], [31] EV charging load model is obtained system with the aim of improving the reliability of the system, but the generation model of EVs in the discharge mode has not been studied.

Although the methods presented in the above papers take a comprehensive look at the issue of EVCS modelling and placement, it should be noted that considering electrical factors, such as reducing losses or peak shaving during peak hours, which leads to higher operating profit of DSO, does not necessarily encourage investors to construct EVCS. In this paper, in order to address this issue, a methodology based on sharing the total profit obtained from the EVSCs placement between the DSO and the owner is suggested. Also, since the EVs charging/discharging program has a major impact on the profitability of the DSO, a new method is also proposed for smart and optimal charging/discharging schedule of EVs. The smart schedule enables the aggregator to control the charging/ discharging rate and time of EVs according to load profile of the network. For this purpose, first, a complete and probabilistic model of the presence of EVs has been introduced in two different residential and administrative parking lots (or EVCS). In this context, by modeling the charge/ discharge of EV's batteries, the load and generation model of each EVCS are also obtained. Then, due to the probability of the EV's model and in order to optimally present these vehicles in the power system, the rate and time of charging/ discharging of battery of EVs has been optimized using a new combined method including PSO algorithm and Monte Carlo simulation. By calculating the optimal charge/ discharge schedule, the final models of load/generation of EVCSs are obtained in such a way that it can modify the system load characteristic according to the charge and discharge time.

In addition, if the EVCS is located properly, its performance according to the obtained load/generation model can improve the operating conditions of the network, in terms of reducing losses and improving the voltage profile. Therefore, in the next step of the paper, using the extracted models as well as probabilistic models of network load, and based on the proposed objective function of profit sharing, EVCS has been optimally allocated. Finally, the proposed methodology will be applied to a case study, on the basis of the standard IEEE 69-Buses network, and efficiency of method is evaluated comprehensively.

II. MATHEMATICAL MODELLING AND PROBLEM FORMULATION

In this section, first, the model is presented for all components of the allocation problem, and then the proposed formulation is described.

A. EV AND EVCS MODELS

EVs are good for storage because they have batteries, but the storage capacity of an EV is limited compared to the power system scale, and therefore its output power does not considerably affect the power system. In order for EVs to be effective when connected to the grid, they must be used as an aggregate charging demand in a parking lot or EVCS [32]. On the other hand, EVs are not always connected to the network, as the owners might not care about the effect on the power system. Therefore, the EVCSs are not operating constantly, and their planning will be uncertain. In summary, uncertainties in the modeling of EVs and EVCS include the following [5], [9], [33]:

- The length of time each EV is connected to the network
- Distance traveled by each EV
- The SOC level of each EV at any given time

As a result, to study the effect of EVs on the grid, it is necessary to model the above uncertainties and consider the appropriate assumptions. The fundamental assumptions in this paper are as follows:

- Battery storage capacity does not change during the study period
- All EV owners have the same behavior and driving pattern on a working day, so that they go to work in the morning and park their EV in a parking lot, which is hereinafter referred to as "Administrative EVCS (Adm-EVCS)" in this paper. The owners also return home after work and park their car in another parking i.e., "Residential Parking (Res-EVCS)". Therefore, another assumption is that EVs are connected to the grid during parking.

It should be noted that in order to simulate the real model of EVCS with related uncertainties, it is necessary to use a logical and reasonable model, along with probabilities. Here, the probabilities considered include the battery capacity of EVs, the distance traveled by the EVs, the duration of the trip, the duration of parking the EV in the Adm-EVCSý, and the time of leaving the Res-EVCS. In this regard, if the number of EVs is $N_{EVs} = \{i : i = 1, 2, \ldots, N_{EV}\}$ and the study time is considered $T = \{t : t = 1, 2, \ldots, T\}$, the time to start the EV trip to go to the Adm-EVCS, the time of the EV to travel from the Adm-EVCS to the Res-EVCS and vice versa, the parking time of the EV in the parking lots, EV battery capacity (C_i) and distance traveled by EV (D_i) are independent random variables.

In this paper, to limit the production of these random variables (x) in the desired range, i.e. [a, b], Truncated Normal Distribution function is employed, where Φ is the normal distribution function in which μ and σ are the mean and standard deviation of the function [34].

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

By obtaining independent random variables, other dependent random variables such as the time of arrival of the EV to the Adm-EVCS, the time of departure from the Adm-EVCS, the time of return of the EV to the Res-EVCS can be calculated as follows.

$$T^i_{en.Adm} = T^i_{ex.\mathrm{Res}} + T^i_{Adm.trip}, \quad \forall i \in N_{EVs} \tag{2}$$

$$T^i_{ex.Adm} = T^i_{en.Adm} + T^i_{park}, \quad \forall i \in N_{EVs} \tag{3}$$

$$T^i_{en.\mathrm{Res}} = T^i_{ex.Adm} + T^i_{\mathrm{Res}.trip}, \quad \forall i \in N_{EVs} \tag{4}$$

$$\Pr e.T^i_{\mathrm{Res}} = \Big\{1 : T^i_{ex.\mathrm{Res}} \cup T^i_{ex.\mathrm{Res}} + T^i_{Adm.trip} + T^i_{park} + T^i_{\mathrm{Res}.trip} : 24\Big\} \tag{5}$$

$$\Pr e.T^i_{Adm} = \Big\{T^i_{ex.\mathrm{Res}} + T^i_{\mathrm{Res}.trip} : T^i_{ex.\mathrm{Res}} + T^i_{Adm.trip} + T^i_{park}\Big\} \tag{6}$$

where $T^i_{en.Adm}(T^i_{ex.Adm})$ and $T^i_{en.\mathrm{Res}}(T^i_{ex.\mathrm{Res}})$ stand for entrance (exit) times to the Adm-EVCS and Res-EVCS. $T^i_{Adm.trip}$ and $T^i_{\mathrm{Res}.trip}$ are the duration time of the EV's trip. T^i_{park} indicates how long the EVs is parked in the parking lot. and $\Pr e.T^i_{\mathrm{Res}}$ and $\Pr e.T^i_{Adm}$ are time of EVs presence in the parking lot.

The values considered for EVs and EVCSs modeling (according to the formulation expressed in 1 to 6) are reported in Table 1, where have been extracted based on the information given in [35] in such a way that it can model the comprehensive and dominant behavior of drivers as much as possible. In addition, for deeper understanding and as an example, the probability distribution function obtained for the entrance duration of EV ($T^i_{en.Adm}$) is shown in Figure 1. Importantly, the probability distribution function assumed for $T^i_{en.Adm}$ is similar to Figure 1 and only the plug-in times change from 13 to 22 P.M.

Another parameter associated with uncertainty in modeling EVs and EVCSs is the SOC level of EVs when connected to the grid. This parameter can also be calculated by obtaining

TABLE 1. Range, mean, and standard deviation of random variables used in the modeling.

x	a	b	μ	σ
$T^i_{ex.\mathrm{Res}}$	0	24 hr	7:15 A.M	50 min
$T^i_{Adm.trip}$, $T^i_{\mathrm{Res}.trip}$	0	24 hr	30 min	15 min
T^i_{park}	0	24 hr	560 min	50 min
D_i	0	128 km	25 km	15 km
C_i	5	30 kWh	25 kWh	5 kWh

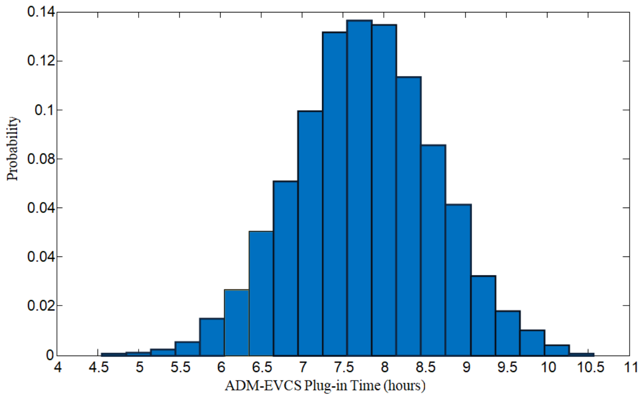

FIGURE 1. The probability distribution function obtained for the entrance time of EVs to Adm-EVCS.

the distance traveled (D_i) as follows [10], [16]:

$$SOC^i_{\mathrm{int}} = \left(1 - \frac{D_i}{D_{\max}}\right) \times 100\%, \quad \forall i \in N_{EVs} \tag{7}$$

$$SOC^i_t = X_1 \left(SOC^i_{t-1} + \Delta t.(ch_{rate})\right) \times 100\%, \quad \forall i \in N_{EVs}, \quad \forall t \in T \tag{8}$$

$$SOC^i_t = X_2 \left(SOC^i_{t-1} - \Delta t.(disch_{rate})\right) \times 100\%, \quad \forall i \in N_{EVs}, \quad \forall t \in T \tag{9}$$

where SOC^i_{int} is the initial SOC of EV, and Δt is the time step. Equations 8 and 9 represent the SOC level of EVs while charging and discharging. In these equations, ch_{rate} and $disch_{rate}$ are the charge and discharge rate of EV batteries. Further, in these equations two binary variables X_1 and X_2 (for charging and discharging states, respectively) are applied to avoid the simultaneous charging and discharging of the EVs.

At last, the injected/absorbed energy of the EVCS can be modeled as follows:

$$E_{EVCS} = \begin{cases} E^{disch\arg e}_{EVCS} = \sum_i^{N_{EVs}} \Pr e.T(i) \times C_i \times (SOC^i_{\mathrm{int}} - SOC_{\min}) \quad \forall \Delta t_{disch\arg e} \\ E^{ch\arg e}_{EVCS} = \sum_i^{N_{Evs}} \Pr e.T(i) \times C_i \times (SOC_{\max} - SOC^i_{\mathrm{int}}) \quad \forall \Delta t_{ch\arg e} \end{cases} \tag{10}$$

where $\Pr e.T(i)$ is the percentage times of EVs at the EVCS (as per equations 5 and 6). Furthermore, based on 10, the injected/absorbed power of EVCSs during charging/discharging time ($\Delta t_{ch\arg e}/\Delta t_{disch\arg e}$) can be calculated.

In this paper, by introducing the model of EVs and its relations, and also considering the probability of the model, sequential Monte Carlo simulation has been utilized. In this method, which is done by repeated replications of the simulation, the output model of the desired parameter is actually its mean value during the simulation period. The simulation stop criterion is also taken into account to satisfy the Coefficient of Variation (CV) of the studied parameter (here less than 4%). Implementation of this program will lead to the extraction of load and generation models of EVCSs.

III. PROPOSED METHODOLOGY FOR SMART EVs CHARGING/DISCHARGING SCHEDULE

With the advent of smart grids and the possibility of online communication, the two-way power exchange capability of EVs can be used to charge and discharge vehicles at the appropriate time [4], [36]. In this way, the parking lots of EV (here EVCS) could be used as a new example of distributed energy resources, which will be able to correct and improve the load characteristic of the network with a smart and optimal planning. This is one of the most important features of adopting a proper strategy for charging and discharging EVs batteries, through which the inclusion of EVCSs is regarded as an opportunity in the competitive and smart electricity market [37]. For this purpose, the presence of EVs is optimized from two perspectives. The first one deals with the optimization of charge/discharge schedule of EVs with different strategies inside the EVCS. In the second prospective, two EVCSs, which are operated based on the adopted charge/discharge schedule, are optimally allocated within the distribution network, which is described in Section IV.

In the first issue, a novel methodology is presented which is a combination of an evolutionary algorithm to calculate the optimal charging and discharging parameters of EVs batteries during the day and night, as well as using a sequential Monte Carlo simulation to investigate the probabilistic properties of the problem.

In this paper, in order to improve the performance of the EVCS and its positive impact on the operation of the network, EV's charging/discharging planning has been discussed from the perspectives of the DSO and the EV's owners [38]. From the DSO's point of view, peak shaving, valley filling and flattening the load curve [38]–[40] are the main goals according to which the following objective function is introduced:

$$OF_1 = a \times \sum_{t=1}^{T} \left(\frac{P_{L-Peak}}{P^{Corrected}_{L-peak}} - 1\right) \Delta t_{disch\arg e} + b \times \sum_{t=1}^{T} \left(\frac{P^{Corrected}_{L-Min}}{P_{L-Min}} - 1\right) \Delta t_{ch\arg e} + (c \times MSE) \tag{11}$$

$$MSE = \sum_{t=1}^{24} (P^{Load}(t) - \sum_{i=1}^{N_{EVs}} P^{EVCS}(i) - P_{ref}) \tag{12}$$

It should be noted that the above objective function is modeled based on the weighted sum model in which Parameters a, b and c, as adjustment coefficients, are used to normalize the different terms and convert them to intervals [0-1]. $P_{Load}(t)$ is the load at time t (predicted by the load curve), and the MSE is the mean square error between the modified load profile and the reference line. In fact, by minimizing the MSE, the load profile closely tracks P_{ref} and achieves an effective peak shaving. $\Delta t_{disch\arg e}$ is the sum of minutes when the load exceeds the Peak Shaving Percentage (XPSP) and $\Delta t_{ch\arg e}$ is the sum of minutes when the load is lower than Valley Filling Percentage (XVFP).

As mentioned, factors such as charge and discharge rate (ch_{rate} and $disch_{rate}$) and charging/discharging hours play a major role in correcting the load characteristic of the grid. Therefore, in the above formulation, the objective is to optimize the above parameters.

It is necessary to explain that by implementing intelligent planning, the EV owners also benefit because they consume energy during the hours that have the lowest price. Another point to note is that the optimal parameters in the EV battery charging/discharging schedule depend on the operating strategy desired by the EV owner. In view of this issue, in this paper, the implementation of the optimal charging/discharging has been scheduled according to the following three operating modes [10], [41].

Uncontrolled Charging Mode (UCM) in which there is no control over the charging of electric batteries and the EV is charged as soon as it is connected to the EVCS.

Controlled Charging Mode (CCM) where the time and rate of charge of the EV's battery can be controlled via aggregator. In other words, the EVs are charged at specific charge rates during off-peak times so as not to adversely affect the peak load. In addition, this strategy fills the valley in the load curve.

Smart Charge/Discharge Mode (SCDM) according to which besides charging time and rate, the aggregator also controls discharge time and rate. Based on the SCDM strategy, the battery is discharged to the extent that it does not interfere with EV travel. This strategy causes peak shaving and valley filling of the grid load profile.

IV. EVCS ALLOCATION

As explained earlier, with the rapid emergence of EVs in the near future, and due to the fact that these vehicles are parked most of the time, location of the parking lots (or EVCSs) has a great impact on the operation of the distribution network. In other words, improper allocation of the EVCSs may have adverse effects on network losses and voltage profile. This challenge can be avoided by optimizing the placement of the EVCSs. However, with the construction of the EVCS, both the network party and the owner seek to maximize their profits. For example, the network seeks to reduce power losses or control voltage, and on the other hand, the EVCS owner aims to earn higher revenue regardless of the amount of its impact on the network. In this regard, several objective functions have been proposed in the references to establish a compromise between the benefits of both parties and to obtain the most optimal solution [7], [20], [21], [25], [42]. In the optimal EVCSs allocation problem of this paper, the following main functions have been defined as the objective function:

$$B_{DSO} = B_{total}^{load} + B_{total}^{loss} + B_{total}^{ENS} \tag{13}$$

$$B_{EVCS} = B_{total}^{disch\arg e} + B_{total}^{ch\arg e} - C_{total}^{inv} \tag{14}$$

B_{DSO} and B_{EVCS} are the benefits functions of the DSO and the EVCS owner, respectively. In the following, the formulation of the components of these functions is presented:

A. DSO BENEFIT FORMULATION

B. BENEFIT OF REDUCING POWER PURCHASE FROM THE UPSTREAM NETWORK

By installing EVCSs within the distribution network, the amount of power purchased from the upstream network is reduced, which is profitable for the DSO according to the following relationships:

$$B_{Total}^{load} = R_{Total}^{load} - C_{Total}^{load} \tag{15}$$

$$R_{total}^{load} = \sum_{t=1}^{T} \sum_{h=1}^{N_h} (P_{t,h}^{Load} \times \rho_{t,h} \times \tau_{t,h}) \times (\frac{1+InfR}{1+IntR})^t \tag{16}$$

$$C_{total}^{load} = \sum_{t=1}^{T} \sum_{h=1}^{N_h} (P_{t,h}^{grid} \times \rho_{t,h}^{grid} \times \tau_{t,h}) \times (\frac{1+InfR}{1+IntR})^t \tag{17}$$

$$P_{t,h}^{grid} = \begin{cases} P_{t,h}^{Load} + P_{t,h}^{loss} - \sum_{i=1}^{N_{EVs}} P_{i,t,h}^{EVCS} & \text{for peak-shaving times} \\ P_{t,h}^{Load} + P_{t,h}^{loss} + \sum_{i=1}^{N_{EVs}} P_{i,t,h}^{EVCS} & \text{for valley-filling times} \\ P_{t,h}^{Load} + P_{t,h}^{loss} \end{cases} \tag{18}$$

where B_{Total}^{load} models the benefit function of reducing power purchase from the upstream network.

C_{total}^{load}, R_{total}^{load} are total cost paid for purchasing energy with price $\rho_{t,h}^{grid}$ and revenue earned from selling energy with price $\rho_{t,h}$, respectively. $P_{t,h}^{grid}$, $P_{t,h}^{Load}$, $P_{t,h}^{loss}$ and $P_{t,h}^{EVCS}$ are power injected from upstream network, power sold to consumers, power loss and power injected from EVCS. In these equations, h denotes load level and is commensurate with the optimal charging/discharging schedule, expressed in equations 11-12. $InfR$ and $IntR$ are inflation and interest rates, respectively. Finally, for implementing Monte Carlo simulation, each year of the planning period is divided into N_h levels (24 hour) of load and the duration of each load level is τ_h.

C. BENEFIT OF REDUCING ACTIVE POWER LOSSES

Power injection by the EVCSs, especially during peak hours, can reduce losses, thereby bringing the following benefits to the DSO.

$$B_{Total}^{loss} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}[(Ploss_{t,h}^{withEVCS} - Ploss_{t,h}^{withoutEVCS}) \times \rho_{t,h} \times \tau_{t,h}] \times (\frac{1+InfR}{1+IntR})^t \quad (19)$$

B_{Total}^{loss} models the total benefits of reducing active power losses after allocation of the EVCS.

D. BENEFITS OF IMPROVING RELIABILITY

Distribution networks are always prone to power outage that degrade the level of reliability by reducing energy not supplied (ENS-according to 13). Nevertheless, if the EVCSs are installed, these stations can be used as an alternative source in such cases and improve reliability.

$$C_{ENS} = [\sum_{l=1}^{N_l} C_{\text{int}} \times \lambda_l \times L_l \times (\sum_{res=1}^{N_{res}} P_{res}t_{res} + \sum_{rep=1}^{N_{rep}} P_{rep}t_{rep})] + C_{equip} \quad (20)$$

$$B_{Total}^{ENS} = \sum_{t=1}^{T}(C_{ENS}^{WithEVCS} - C_{ENS}^{WithoutCS}) \times (\frac{1+InfR}{1+IntR})^t \quad (21)$$

where N_l is number of lines, λ_l is line outage rate, L_l is line length, N_{res} and N_{rep} are the number of disconnected buses and repaired buses, P_{res} and P_{rep} are disconnected loads and restored loads and t_{res} and t_{rep} are fault clearance time and repair time.

Also, $C_{ENS}^{withEVCS}$ and $C_{ENS}^{withoutEVCS}$ are the ENS penalty cost function for the cases of with/without EVCS where the total benefits of improving reliability B_{Total}^{ENS} is obtained by subtracting between them.

E. EVCS OWNER BENEFIT FORMULATION

As stated in relations 11-12, the owner of the EVCS earns income in both charging and discharging times of the EVs in accordance with the adopted smart charging/discharging program, the profit of which can be calculated after deducting the relevant costs. These benefits are expressed under the headings of charge benefits ($B_{Total}^{ch\arg e}$) and discharge benefits ($B_{Total}^{disch\arg e}$) according to the following relations.

$$B_{Total}^{ch\arg e} = R_{Total}^{ch\arg e} - C_{Total}^{ch\arg e} \quad (22)$$

$$R_{Total}^{ch\arg e} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{EVs}} \rho_{t,h} \times P_{i,t,h}^{EVCS} \times \tau_{t,h} \times (\frac{1+InfR}{1+IntR})^t \quad (23)$$

$$C_{Total}^{ch\arg e} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{EVs}} (\frac{\rho_{t,h,pur}^{grid}}{\mu_{conv}} + c_d) \times P_{i,t,h}^{EVCS} \times \tau_{t,h} \times (\frac{1+InfR}{1+IntR})^t \quad (24)$$

$$B_{Total}^{disch\arg e} = R_{Total}^{disch\arg e} - C_{Total}^{disch\arg e} \quad (25)$$

$$R_{Total}^{disch\arg e} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{EVs}} \rho_{t,h} \times P_{i,t,h}^{EVCS} \times \tau_{t,h} \times (\frac{1+InfR}{1+IntR})^t \quad (26)$$

$$C_{Total}^{disch\arg e} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{EVs}} (\frac{\rho_{t,h,pur}^{EV}}{\mu_{conv}} + c_d) \times P_{i,t,h}^{EVCS} \times \tau_{t,h} \times (\frac{1+InfR}{1+IntR})^t \quad (27)$$

where C_d is the cost of equipment depreciation during the operation time, and μ_{conv} is the efficiency of the EVCS convertors. Finally, the EVCS owner incurs a station construction cost at the beginning of the project, which is modeled with the following relationship.

$$C_{Total}^{inv} = \sum_{i=1}^{N_{EVs}} (C_i^{equ} + C_i^{cons}) \times CP_i = \sum_{i}^{N_{EVs}} C_{ac} \times CP_i \quad (28)$$

C_{Total}^{inv}, C_i^{equ}, C_i^{cons} and CP are investment cost, equipment cost, construction cost and capacity of EVCS, respectively.

Note that in solving EVCS allocation problem, as in all optimization problems, there are different constraints that must be met. The main constraints studied in this paper are the load flow, bus voltage, thermal limits of lines and bus bars, and those pertinent to the operation of EVCS, the mathematical model of which is given in [7], [42].

V. DETAILS OF THE PROPOSED EVCS ALLOCATION STRATEGY

Although the problem formulation described above locates optimal solutions for allocating the EVCSs, forcing the owner to build a station at a specific point is associated with several problems, because the investor in the construction of the EVCS does not generally consider the profit of the DSO and it only considers the profitability of the project.

On the other hand, incentive regulatory mechanism should be taken into account to incentivize the owner to implement the charging/discharging programs obtained in section III. In order to address this issue and according to the profit that is obtained through the optimal allocation of the EVCSs for the DSO, in this paper, the idea of profit sharing between DSO and EVCS owner is proposed.

The implementation of this contribution is based on the introduction of a new objective function (as below), according to which, while obtaining the most optimum answer in the objective functions of both parties (equation 31 and 32), the optimal profits sharing is also performed. In fact, after implementing the proposed algorithm, a set of optimal solution (Pareto set) is obtained, each of which can be used as the optimal EVCS allocation within the network.

$$OF^{DSO} = B_{DSO,withEVCS} - \lambda \times (B_{DSO,withEVCS} - B_{DSO,withoutEVCS}) \quad (29)$$

$$OF^{EVCS} = B_{EVCS} + \lambda \times (B_{DSO,withEVCS} - B_{DSO,withoutEVCS}) \quad (30)$$

The OF^{DSO} function is for the DSO and the OF^{EVCS} function is for the EVCS owner. λ is sharing coefficient and is measured at 100% and determines the level of participation of both the DSO and owner. The objective function is defined in

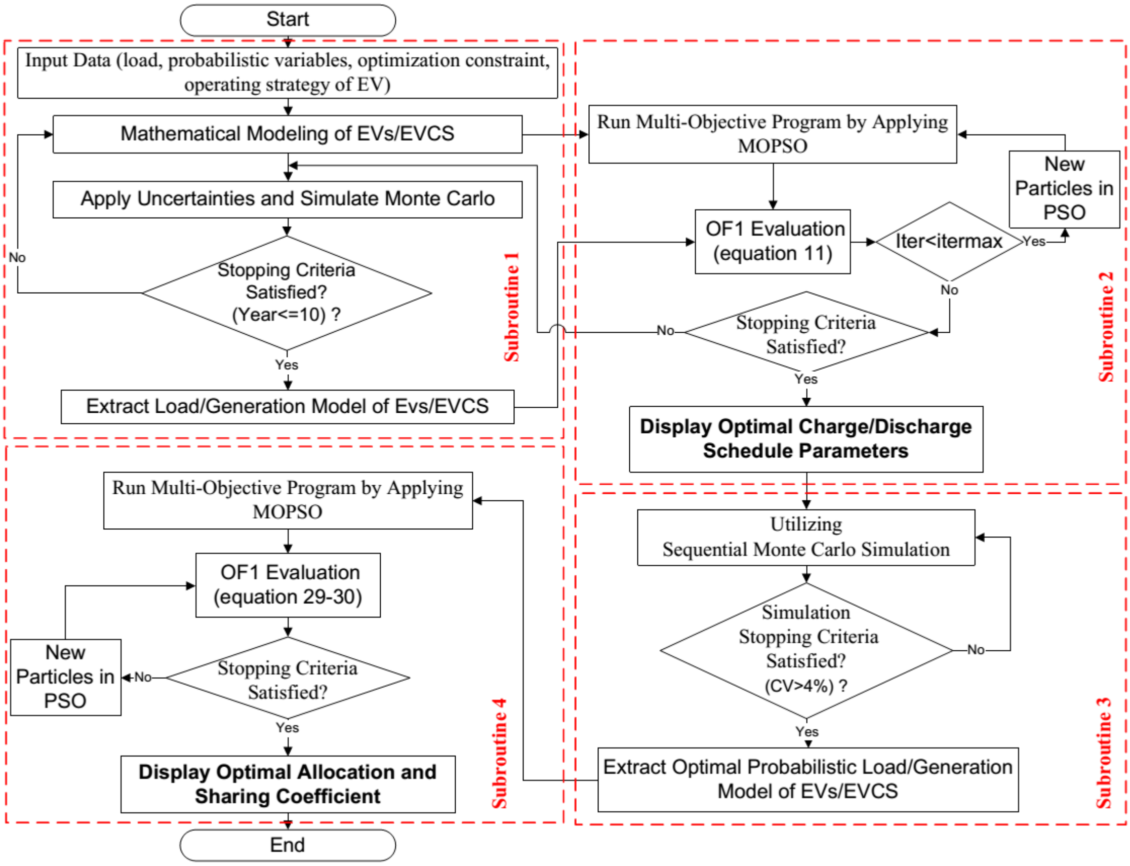

FIGURE 2. Flowchart of the proposed methodology.

such a way that after solving the problem, an optimal amount of profit obtained for the DSO after the installation of the EVCS (profit difference in the two cases of presence and absence of EVCS) is allocated to the owner. In solving the presented allocation problem, as in the charging/discharging schedule problem, a combination of the sequential Monte Carlo and optimization methods has been used. The Monte Carlo method is adopted to obtain the load model, electricity price model and ENS index because these components have an uncertain nature [43].

The flowchart of the proposed methodology is depicted in Figure 2. In this flowchart, four main parts of the methodology are specified and explained as follows:

Subroutine 1: Extract load/generation model of EVCS using Monte Carlo simulation (with limited replication). The condition for the convergence of the Monte Carlo algorithm is the end of the simulation iteration, which is considered 10 years (or 3650 days).

Subroutine 2: Solve the optimization problem to modify the load characteristic by the MOPSO algorithm (combined with Monte Carlo method of Subroutine 1) and calculate the optimal charge/discharge schedule

Subroutine 3: Then, with the optimal parameters, the final model of load/generation of the EVCS to correct the load characteristic of the network is again obtained by applying Monte Carlo simulation with many replications. At this subroutine, the condition for convergence to the final model is to satisfy the Coefficient of Variation (CV) of the studied parameter.

Subroutine 3: In this subroutine, by applying the MOPSO algorithm and solving the objective functions expressed in Equations 29-30, the optimal placement of the EVCS is calculated.

VI. TEST SYSTEM AND SIMULATION RESULTS

The proposed methodology of the paper is implemented on a 50-buses test case, which is part of the 69-bus IEEE radial test system [44] and is derived from removal of one of the long and light loaded lateral feeders (see Figure 3). The reason for applying this modification is to ensure the most optimal solution for allocating two EVCSs within the network. It should be noted that the methodology of the paper could be applied to any type of network, however, by selecting such network, which is one of the wide and large test systems, the ability to implement the proposed methodology on large systems is also examined. The first step is modeling the system load, which in this paper is done based on the load model presented in the standard Reliability Test System (RTS) [45] is utilized. This load pattern determines the load information on a daily, weekly and annual basis for different seasons as well as

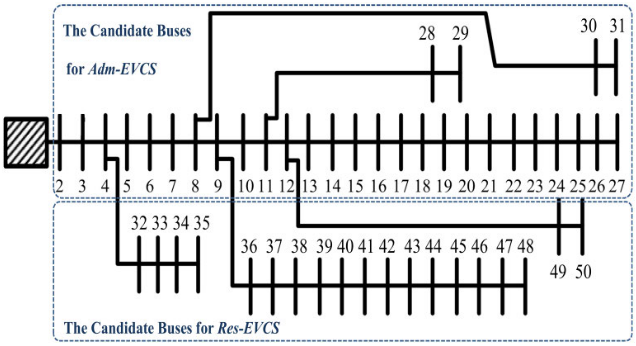

FIGURE 3. The test system.

different days of the week. Checking the annual load in the process of EVCS allocating and executing the Monte Carlo simulation requires 8760 load flows in each iteration, which will be extremely time consuming. Therefore, due to the difference in driving pattern on weekdays and weekends, one working day (Wkdy) and one weekend day (Wknd) of each season have been selected as the representative load of that season. Based on the proposed methodology, the load profile has been modified for these days. The load level of a weekend day is assumed 75 percent of a working day.

On the other hand, according to the load pattern given in the RTS, the load profile is almost the same in spring and fall, so a total of six days are considered as the representative of the days of the year (As per table 2). Representative days have the highest peak load on weekdays and weekends of that season.

In the next step, the electricity price should be modeled which depends upon demand level and its changes can be modeled by multiplying two parameters, the basic electricity price (ρ) and the price level factor [29], [46].

$$\rho_{t,h} = \rho \times PLF^{e}_{t,h} \tag{31}$$

$PLF_{t,h}$ denotes price level factor at year number t and h time interval and is calculated using the probability density function:

$$PLF^{e}_{t,h} = \mu^{\rho}_{t,h} + \lambda^{\rho,e}_{t,h} \times \sigma^{\rho}_{t,h} \tag{32}$$

$$\sigma^{\rho}_{t,h} = 0.1 \times \mu^{\rho}_{t,h} \tag{33}$$

where $\lambda^{\rho,e}_{t,h}$ is a random variable, and $\mu^{\rho}_{t,h}$ and $\sigma^{\rho}_{t,h}$ are the price predicted values and its standard deviation, respectively. The maximum value of standard deviation for price is set at 10 percent of a forecasted price for each time interval.

The two EVCSs in this paper, as described earlier, are allocated for two parking lots, Adm-EVCS and Res-EVCS, each with a capacity of 125 EVs. Moreover, the intended capacity for an EV's battery is assumed 25 kWh. The batteries are charged and discharged in 5 hours. As a result, their rated power is 5kW on average. Battery life is also estimated to be approximately 10 years.

The candidate busses for the construction of these EVCSs have been specified in Figure 3. It should be noted that in such a problem, that has a vast search space, and each node along the feeder could be a candidate, the initial population might locate far away from the real global optimal solution. In such a situation, the exploration capability of the PSO degrades, and so the particles quickly move towards a false Pareto front, which could be a local optimum, and lead to premature convergence. In this paper, to deal with this issue, a modified multiobjective PSO algorithm [27] is utilized in which the exploration and exploitation of searchability and convergence capability of the algorithm have been improved.

TABLE 2. The representative load information.

Study Day	Abbreviation	Peak/Total Peak
Wkdy-Spring,Fall	SF_Wkdy	0.8
Wkdy-Summer	S_Wkdy	0.9
Wkdy-Winter	W_Wkdy	1
Wknd-Spring,Fall	SF_Wknd	0.8*0.75
Wknd-Summer	S_Wknd	0.9*0.75
Wknd-Winter	W_ Wknd	1*0.75

The results of the proposed methodology on the test case of this paper are presented here with focusing on two parts, namely optimal charging/discharging schedule and optimal allocation of EVCSs.

A. PART 1: EFFICIENCY OF THE PROPOSED METHODOLOGY IN OPTIMAL CHARGING/DISCHARGING SCHEDULE AND ITS EFFECT ON NETWORK LOAD CHARACTERISTIC CORRECTION

It is assumed that for a working day, EV owners move from the Res-EVCS to the workplace and park within the Adm-EVCS in the morning. After finishing work, the EVs owners return home and the EVs are parked at the Res-EVCS. For the weekend, it is also assumed that there are no EVs in the Adm-EVCS, and the EVs are either parked in the Res-EVCS or leave town for Recreation. It should be also added that the probabilistic behavior of the EVs are modeled based on relations 1-6.

Note that EVs are charged/ discharged in the context of smart grids under the supervision of an aggregator in the station. Optimization of charging /discharging schedule of EVs batteries has been ensured with the aim of load shifting. As there is no control strategy in UCM, the optimization is done for CCM and SCDM for representative working and weekend's days, as stated in Table 2.

Using the proposed combined methodology presented in the flowchart of Figure 2, the optimized parameters of the charging/discharging schedule of EVs that have a SCDM and CCM operation strategy are calculated. These parameters, which are optimized to modify the load characteristic of the distribution network, are reported in the Table 3. It should be noted that the proposed methodology is not applied for EVs with UCM operating strategy, as no control over the rate and time of charging/discharging of the battery is given.

Table 3 shows that SOCmin has never fallen below 20% to avoid reducing EVs battery life, and so, there is always 20% energy in the EV batteries. Over the weekend, due to

TABLE 3. The optimal results of implementing charging/discharging schedule.

Study Day	Operating mode	% XPSP	% XVFP	% SOC_{min}	Res-EVCS		Adm-EVCS		Charge Hour	Discharge Hour
					ch_{rate}	$disch_{rate}$	ch_{rate}	$disch_{rate}$		
SF_Wkdy	CCM	100	65	*	20	*	11	*	1-7	8-15 17-22
	SCDM	91.82	65	46	20	8.3	11	12.5		
S_Wkdy	CCM	100	65	*	16.7	*	14.2	*	1-8	9-19
	SCDM	94.9	65	45	16.7	4.2	14.2	16.7		
W_Wkdy	CCM	100	65	*	16.7	*	7.7	*	23-24 1-7	2-8
	SCDM	94.74	65	47.3	16.7	5.9	7.7	14.2		
SF_Wknd	CCM	100	65	*	20	*	20	*	2-8	19-23
	SCDM	93.27	65	40	20	4.2	20	20		
S_Wknd	CCM	100	65	*	16.7	*	11	*	2-9	17-22
	SCDM	93.03	65	51.35	16.7	20	11	14.2		
W_Wknd	CCM	100	65	*	11	*	11	*	2-8	17-21
	SCDM	95	65	40.20	11	4.2	11	20		

the constant presence of some EVs in the parking lot, their batteries have been allowed to be further discharged. This is due to the sufficient time to charge and discharge the batteries of EVs. At the same time, due to the reduction of the number of EVs connected to the network and the lack of use of Adm-EVCS on weekends, the peak shaving is performed in a higher percentage, or in other words, the peak-shaving rate is reduced. In this table, the optimal period of time for charging and discharging of the EVs are determined.

It is also observed that the discharge rate in all seasons is less than the charge rate. This is to ensure the travel of EVs so as not to disrupt their daily travel due to the full discharge of their batteries. Another noteworthy point is that the charge rate is higher in the Res-EVCS than in the Adm-EVCS; and the discharge rate in the Adm-EVCS is higher than the Res-EVCS. This is because in the times EVs are parked in the Res-EVCS, the network is at off-peak hours, so charging the battery at a high rate and discharging it at a low rate is more profitable for the aggregator.

With reference to the results of Table 3, in the CCM strategy, because EVs are not discharged, peak shaving is not realized and only valley filling in the load curve has been done. Optimum times for charging/ discharging of EVs are obtained using XPSP% and XVFP%. These times for SCDM have been shown in the last column of the table 3.

It can be concluded that the obtained results verify the efficiency of implementing optimal charge/discharge schedule is correction of the network load characteristic. In fact, after obtaining the network load characteristic and the load / generation characteristic of the EVCSs by the Monte Carlo algorithm and combining them, the load characteristic is modified by applying peak-shaving and valley filling.

B. PART 2: OPTIMAL EVCS ALLOCATION

Although the optimal charge/discharge scheduling algorithm, as reported in the previous section, is efficient, it can only have the highest impact on the power system and modify the network load characteristic when the EVCSs are located optimally. In other words, while considering the network demand curve modification objective function, loss reduction and voltage improvement goals should also be accounted for to obtain the most optimal placement for the EVCSs. In this regard, by obtaining the load/generation of EVCSs, the proposed methodology of the paper for locating EVCSs within the test case - considering two cases based on profit sharing - is employed.

1) CASE I: NO PROFIT SHARING

In this case, traditional placement is implemented, i.e., in the optimization program, maximizing the benefit of the DSO and EVCS is done independently and separately ($\lambda = 0$). In other words, the EVCSs do not receive any share of the DSO's benefit, which is obtained through the construction of the EVCS. The best solutions obtained (Pareto set) for simulating this case are given in Table 4.

2) CASE II: PROFIT SHARING BETWEEN DSO AND EVCS OWNER

From the results of Table 4, it can be concluded that the installation and operation of the EVCS, according to the optimal charge/discharge planning, which is actually run with the aim of improving the network load characteristic, does not bring significant benefits to the EVCS owner; even in some cases, its related costs are more than income. In order to solve this problem and encourage investors to construct EVCS along the distribution network, the proposed formulation in equations 33-34, which is on the basis of profit sharing, is implemented in this case. Accordingly, a new Pareto-optimal set or a set of optimal solutions are obtained which identify the optimized location of the EVCSs and the optimal value of λ.

As can be seen in Table 4, the ten best solutions of the program are reported. The difference in profits of DSO and EVCS owner in solutions is due to the difference in sharing of profits between DSO and the EVCS owners, affecting their enthusiasm for running the joint program. However, the optimal solution among the Pareto set can be defined by expert analysis and trade-off. In addition, in order to better

TABLE 4. The objective functions of DSO and EVCS in two study cases.

Solution No.	Case I		Case II		
	OF^{EVCS}	OF^{DSO}	OF^{EVCS}	OF^{DSO}	λ
1	-0.013	1.175	1.6407	2.7403	0.5648
2	-0.017	2.276	0.8598	3.5426	0.3013
3	-0.034	3.453	1.4269	2.9594	0.4925
4	-0.026	3.060	2.058	2.447	0.8734
5	-0.009	-0.232	1.808	2.595	0.6501
6	-0.044	3.814	1.178	3.278	0.4450
7	-0.027	2.294	1.2285	3.0453	0.6096
8	**-0.031**	**3.335**	**0.4278**	**3.9058**	**0.2716**
9	-0.0435	2.2406	1.7932	2.7285	0.7124
10	-0.0761	5.0638	1.6320	3.2942	0.6164
	All calculated values are multiplied by 10^7				

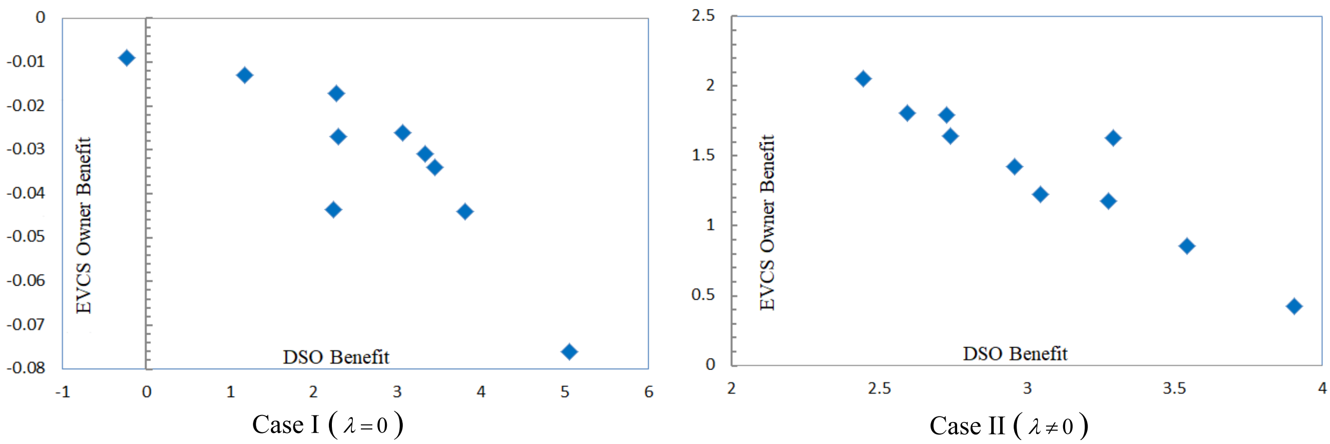

FIGURE 4. Pareto solutions for Case I and Case II.

TABLE 5. The optimal values of objective functions for different strategies.

Operating Strategy		UCM	CCM	SCDM
[Bus Number, Optimum No. of EVs]	**Adm-EVCS**	[7,103]	[16,115]	[20,123]
	Res-EVCS	[32,117]	[37,120]	[39,125]
Benefits of load profile correction ($)		0	1.414×10^6	2.153×10^6
Benefit of reducing power purchase ($)		3.923×10^7	4.048×10^7	4.239×10^7
Benefits of power loss reduction ($)		4.587×10^5	5.034×10^5	5.145×10^5
Benefits of improving reliability ($)		7.320×10^5	7.683×10^5	8.232×10^5
Total Benefits of DSO ($)		4.042×10^7	4.176×10^7	4.373×10^7

show the efficiency of the profit-sharing idea, the reported Pareto front solution are shown in Figure 4.

Based on solution No. 8 (see Table 4), the optimal results of EVCSs allocation, i.e., optimal location of EVCS and optimal number of EVs in each EVCS) are reported in Table 5. As it is known, the results have been presented for three different strategies of EV operation (i.e., UCM, CCM, SCDM) in order to determine their impact on the EVCSs allocation and also on the profit of the DSO resulting from the construction of the EVCS. In solving the allocation problem, as shown in Figure 3, all buses along the specified feeders could be a candidate.

According to the results of table 5, if the EV operating strategy is UCM, the EVCS will be located closer to the upstream network to reduce the resulting power losses. However, even with these conditions, the benefits of power loss reduction in the UCM strategy is less than the value obtained for the CCM and SCDM strategies. Also, regarding the results of this table, the total benefit of the DSO is 4.042×10^7 when the UCM strategy is adopted, which is less than the profit obtained in the SCDM mode (4.373×10^7). The main reason for this is the lack of participation of the EVCSs (in the mode of UCM) in power generation and supply of part of the network load.

VII. CONCLUSION

In this paper, modeling EVs and related charging stations (EVCS) has been studied in order to present a smart and optimal charging/discharging schedule. The purpose of the proposed schedule is to control the rate and time of charging/discharging of EV's battery to correct the load characteristic of the network. For this purpose, first, using Monte Carlo algorithm, a probabilistic model for load and generation of the EVCS is extracted, in which the existing uncertainties such as battery capacity of EVs and state of its charge, the distance traveled by the EVs, the duration of the trip, the duration of parking the EV in the EVCS, the time of leaving the EVCS, and the time of arrival of the EV to the EVCS are precisely modeled. The proposed model also studies various battery operation strategies, including Uncontrolled Charging Mode (UCM), Controlled Charging Mode (CCM), and Smart Charge/Discharge Mode (SCDM). Finally, the optimal rate and time of charging/discharging of EVs is calculated using PSO algorithm.

However, charging/discharging schedules in an EVCS lead to a correction of the network load characteristic and profitability for the DSO if the EVCS have a suitable location and capacity. Therefore, in the next step, a new formulation is presented for the allocation of two EVCSs (Administrative and residential EVCS). In the proposed formulation, while considering the various objective functions such as power loss reduction, reducing power purchases from the upstream network, reducing voltage deviation in buses, improving reliability, the idea of profit sharing between the DSO and EVCS owner is also presented. The aim of this contribution is to incentivize the owner to implement the proposed charging/discharging schedule. The proposed formulation is applied to a standard network (IEEE 69 buses) using a hybrid methodology, including modified multi-objective PSO algorithm and Monte Carlo simulation, to calculate the optimal capacity and location of the EVCSs within the network. The obtained optimal results clearly show the efficiency of the proposed method.

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