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Voltage and energy control in distribution systems in the presence of flexible loads considering coordinated charging of electric vehicles

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A B S T R A C T

Maintaining a desirable energy and voltage profile in large-scale power distribution systems has been remained a challenging concern particularly due to the rushing arrival of uncertainties and high proliferation of intermittent renewables. This challenge has been exacerbated by an increased interest in the adoption of highly-uncertain electric vehicle (EV) loads as distributed energy storage (DES) devices since the owners' attitudes and EV's charging and discharging patterns are radically random. In this paper, in addition to the stochastic modeling of the random behavior of EV's charging patterns, EVs' charging statuses are optimally coordinated to support the control of voltage and energy in the system with the adaptive deployment of controllable loads. Moreover, fast and normal charging modes of EVs and the corresponding charging and discharging challenges to the grid are investigated. Distinct scenarios of EVs-only and EV-controllable loads are proposed and investigated through solving an optimization problem. In doing so, improved mixed real and binary vector-based swarm optimization algorithm is used to optimize the distribution system's operation while addressing the impacts of EVs' coordination on energy and voltage control (EVC). The efficiency and applicability of the proposed algorithm are tested and verified on the IEEE 69-bus and 119-bus test systems.

1. Introduction

1.1. Motivations and problem statement

Electric power transmission and distribution systems are becoming drastically inductive due to the augmented presence of small, medium and large scale inductive loads such as electronic devices, controllable loads, household appliances, etc. This calls for advanced mechanisms to be deployed in order to maintain and increase the effective utilization of reactive power resources in the evolving power grids. The necessity of such mechanisms becomes more serious in the case of augmented penetration of renewable sources as they affect power quality parameters [1,2]. Series and shunt capacitors are the main passive elements supporting the reactive power requirements in electricity grids. Series capacitors typically support the line reactance while the shunts locally compensate the system reactive power loss by changing the load phase angle which, in turn, results in improvements in power factor, voltage profiles, and network loadability. Since many loads in power grids are attributed with a leading power factor, the shunt capacitors are widely employed to compensate the out-of-phase current factor needed for inductive loads [3].

Deployment and integration of Electric vehicles (EVs) for urban transportation has seen a widespread rise in the past decade, with potentials to keep growing drastically. EVs may be interpreted as an energy storage resource that can be connected to the electric network and provide the desired electrical energy to the power grid and/or customers. Moreover, two third of the oil consumptions is currently used in transportation systems in which 97% of the energy belongs to the fossil fuels. While EVs facilitate an electrified mobility in modern power grids offering lots of flexibility and supportive benefits locally and grid-scale, there are few challenges

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Nomenclature

E_{Cost}	cost of consumed energy
VD_{Cost}	cost of voltage deviation
SC_{Cost}	cost of shunt capacitor switching
TC_{Cost}	cost of transformer tap changing
E^p	(E^q) total daily active (reactive) energy consumption
λ^p	(λ^q) cost of active (reactive) power per kWh (kVAr)
$v_{i,h}$	voltage at bus i at the hth hour
$P^D_{i,h}$	active power consumed at bus i at the hth hour
C_V	penalty applied constantly or linearly in case the voltage value exceeds $V_{\min}$ or $V_{\max}$
$V^T_{\max}(V^T_{\min})$	thresholds for the maximum (minimum) voltage magnitudes
$P_N(t)(Q_N(t))$	active (reactive) powers injected from the upstream network to the distribution grid at time t
$P^b_{loss}(t)(Q^b_{loss}(t))$	active and reactive power losses of branches
$P^i_L(t)(Q^i_L(t))$	active and reactive loads at bus i
$P^j_{EV}(t)$	active power consumed by or injected from the jth EV in the sth parking lot
D^j_{EV}	charging/discharging status of the jth EV
$N_{bus}(N_{br})$	number of buses (branches) in the system
N_{CS}	number of parking lots
$N_{EV,S}$	number of EVs in the sth parking lot at time t
$U^i_L(t)$	amount of power supplied by the controllable load at bus i
η	EV's battery efficiency
MPB^i	maximum power of the battery of the ith EV delivered to the grid, which
$N^C_{EV,S}$	($N^D_{EV,S}$) number of EVs that are being charged (discharged) in the sth parking lot at time t
$N^s_D(t)(N^s_C(t))$	number of EVs in the discharging (charging) modes at time t
$N^s_{EV}(t)$	total number of EVs at time t at the sth parking lot
$N^s_{NC}(t)$	number of EVs that are in the normal mode at time t at the sth parking lot
$N^s_{FC}(t)$	number of EVs that are in the fast charging mode at time t at the sth parking lot
$S^s_{\max}$	thermal limit of the line connecting the sth parking lot to the grid
$S^s_L(t)$	apparent power provided by the sth parking lot
$Q^s_L(t)$	line reactive power flowing through the line connecting the sth parking lot to the grid
CS_i	status of ith capacitor
Tap_{Status}	number of transformer tap
U_L	amount of controllable load

concerning the widespread deployment of EVs, among which are the significant randomness in driving patterns and the re-charging capacities. EVs are targeted as the emerging large loads in power grids; different from the conventional loads, EVs are able to function as both energy storage resource and a distributed energy unit that, at times and if necessary, can support the power distribution grid stability, reliability, and resilience [4].

1.2. Literature review

Voltage and active/reactive power control strategies can be generally categorized into centralized and decentralized clusters. In the first category, widespread data communications across the network to a central station is needed for controlling voltage and active/reactive power in the system. Examples of significant studies in the related literature are as follows. To address the influence of high penetration of renewable energy sources integrated into active distribution networks, a distributionally robust chance constraint model considering discrete reactive power compensators is proposed in [5]. A classification of DERs into four reactive power categories: Type P-RQ, Type P-IQ, Type P-CQ and Type P–V-Q, based on their reactive power characteristics is proposed in [6]. A centralized nonintrusive voltage and reactive power control strategy for distribution systems is developed in [7], where the photovoltaic inverter control with the reactive power fed by PVs were employed to cooperate with a nine-zone diagram control. A multi-control vehicle-to-grid charger is proposed in [8] that can perform vehicle battery charging and discharging operations, as well as reactive power compensation, power factor correction, and grid voltage regulation. On the other hand, in the second category the decentralized algorithms are placed which are centered on the local data acquisition and are characterized with a faster response. For example, a decentralized short-term control strategy for active power control in distribution systems is proposed in [9]. A decentralized coordinated voltage control scheme for VSC HVDC-connected wind farms is suggested in [10] where a model predictive control (MPC)-based voltage control optimization is first formulated for wind farms and then solved in a decentralized manner using the alternating direction method of multipliers. Authors in [11] proposed a novel decentralized coordinated voltage control scheme for a distribution system consisting of DC microgrid, doubly fed induction generator based wind system, on-load tap changer and DSTATCOM.

According to the Energy Information Administration (EIA) report on November 2017, the number of EVs in 2015 is estimated as 1.2 million which is accounted for 1% of the total automotive vehicles [12]. Therefore, it is essential to investigate and analyze the requirements and impacts of EVs on different aspects of electrical grids. As an example, in [13] authors have studied the operation economy and power quality of distribution systems subject to the fluctuating and stochastic power outputs of distributed generation (DG) units and electric vehicles using a multi objective optimization model for network reconfiguration. In another work presented in [14] authors intended to establish an effective coordination between high penetration of plug in electric vehicles (PEVs) and optimal operation management of distribution network. To do that, they proposed an effective fuzzy logic controller, which focuses on coordinated smart charge/discharge control of high penetration of PEVs with optimal operation management in an iterative optimization process. A methodology for assisting electricity distribution companies in identifying candidate connection points for fast charging stations to reduce new installations and network reinforcement investments are other issues investigated in [15]. The routing of an EV with maximum efficiency relative to the terrain has been investigated in [16]. Authors in [17] studied the demand response programs and smart charging/discharging of plug-in electric vehicles for improving the reliability of radial distribution systems adopting particle swarm optimization algorithm. The challenge of the large-scale construction of fast charging stations for EVs in order to determine the optimal planning, especially the siting and sizing of these stations in the electrical distribution system is studied in [18]. Authors in [19] proposed an optimization model to jointly deploy electric vehicle charging stations and distributed generation resources, during which the vehicle-to-grid function of electric vehicles is comprehensively considered. A coordinated charging scheduling method for EVs in microgrid to shift load demand from peak period to valley period is defined in [20]. The purpose of [21] is to evaluate a hybrid DC fast charging station with the aim of reducing peak demand during charging periods. A smart charging management system considering the elastic response of electric vehicle users to electricity charging price is proposed in [22]. A novel location planning method of fast charging stations, in order to achieve the overall optimization of operators, drivers, vehicles, traffic condition, and power grid is considered in [23].

1.3. Contribution

With the increasing growth in the deployment and integration of EVs and controllable loads into the grid, the created challenges and their unique characteristics need to be further researched. In this context, one of the main challenges is the energy and Voltage Control (EVC). A survey on the related literature shows that there are few studies in this field demonstrating the broad impact of EVs on voltage control and energy consumption in power distribution grids [14]. Therefore, in this paper, the impact of presence of EVs and their coordinated charging on voltage control of distribution system as an important issue will be examined. In doing so, we have addressed, analyzed, and compared the impact of EVs and controllable loads on the EVC practices in power distribution systems through multiple scenarios. The solution of our analyses are obtained through applying an improved mixed real and binary vector-based swarm optimization (IMVBSO) algorithm to an optimization problem defined in this paper. This optimization problem is defined so that, by optimal adjusting of transformers and capacitors, the low-cost daily operation of distribution grid from a technical point of view is assured. Briefly speaking, the main contributions of the paper are highlighted as follows:

- The paper proposes a solution to evaluate the impact of EVs and controllable loads on the EVC performance in power distribution systems.
- Different from the past literature, both regular and fast charging scenarios, as well as thermal limitation impacts on the EVC performance are addressed and investigated in the proposed methodology in order to accommodate the obtained solution to the reality of distribution systems as much as practical.
- The optimization model is designed such that the statues of capacitor switches and transformer taps can be optimally selected taking into account the minimization of the operation cost. The operation cost contains costs related to the energy consumption, voltage deviation, capacitor switches and transformer tap changing actions.

1.4. Paper organization

The rest of the paper is organized as follows. A background on the challenges around the EV penetration into modern active power distribution grids and the concept of controllable loads are introduced and discussed in Section 2. The suggested model for energy and voltage control in distribution systems, the proposed optimization formulation as well as the coordinated charging procedure of EVs are introduced in Section 3. Section 4 introduces IMVBSO algorithm as the solver of the proposed optimization problem. Simulations and numerical analysis are elaborated in Section 5, and finally come the conclusions in Section 6.

2. Background on EVs and controllable loads

2.1. Electric vehicle proliferation and challenging concerns

With the rushing arrival of EVs into the electric vehicle charging discharging stations, the electric industry has realized the need for advanced mechanisms to address the impact of variable EV loads in the power grid operation—including the impacts on EVC—and electricity markets. The random EV charging and discharging patterns are primarily originated from the stochasticity in the frequency of EVs visiting the parking lots and in the EV's level of charges. A simple 7-bus distribution system is illustrated in Fig. 1 to realize the impact of EVs on energy and voltage control. Assuming an EV is charged at bus 5, the active and reactive power consumption increase and the bus voltage decreases. Thus, the transformer tap as well as the number of capacitor switching will increase in order to improve the voltage profile and decrease the reactive power consumption. The conditions are reversely observed in situations where the EVs discharge. It is noteworthy that if EVs in the charging mode request power from the grid that is beyond the thermal threshold of the connected line, the network cannot supply this power request. In such circumstances, EVs in fast-charging modes should first change the mode to the normal-charging until the thermal threshold of the connected line gets within its normal limit. If all the EVs in fast-charging mode are changed to normal charging modes and the challenge still remains, the solution would be to reduce the maximum SOC of the EVs. This usually takes place within the fast-charging mode of EVs which takes more power off the grid in a short time interval. If the EVs are in discharging mode and the line connected to the lot is not capable of transmitting the injected power from EVs to the grid, the grid then faces EV Power Spillage (EVPS) issue. To overcome this, some EVs need to be placed in queue to transfer their power in the next few hours until the congestion is cleared.

2.2. Controllable loads in power grids

Controllable loads are categorized into two groups [24]:

Controllable Loads-Type I: Represent the loads that are considered passive and not able to inject power to the grid. Some residential and industrial loads are placed in this category. They are, at times, managed so as to eliminate them from the electric grid or time-shifted. Such controllable loads are extensively studied in this paper where the contributions to EVC is investigated. Controllable loads-Type I are commonly referred to as “controllable loads” in this paper.

Controllable Loads-Type II: Such controllable loads can be charged (consuming the electric power from the grid) or discharged (injecting electric power to the grid). Among such loads are batteries, EVs, as well as the combined heat and power systems. These controllable loads are attributed a high level of flexibility to support the loads and are introduced as the “*active controllable loads*” in the power grid. However, in this paper, EVs and their impacts have been considered separately from controllable loads.

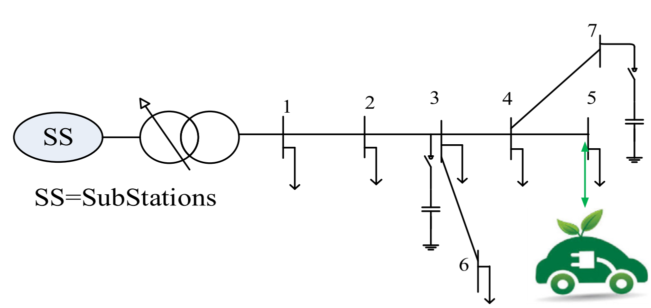

Fig. 1. A 7-bus distribution system integrated with EVs.

3. Proposed optimization problem for EVC

The increase in demanding for more reliable electricity in modern distribution systems with heterogeneous smart devices engenders an escalated reactive power loss which in turn rises the voltage drops on the demand side. Strategies based on the optimal capacitor bank (CB) switching together with transformer load tap changing (LTC) are among the effective practices in electric industry to minimize the costs associated with energy consumption and voltage deviation at buses. However, due to the time-varying nature of loads, the CB switching and LTC implementations should closely follow the load variability and stochasticity to ensure an optimal and low-cost solution. To achieve this goal, this paper proposes an optimization formulation for the centralized EVC with massive penetration of EVs in active distribution systems.

3.1. Load level modeling

A typical daily load level in a distribution grid with a time step of 1 h is presented in Fig. 2. To achieve this 24-h load profile, the 12-month load profile is borrowed from [25] in which the monthly data encapsulates the daily average load profile during a given month. In this paper, the average load data is extracted and taken as the daily load profile.

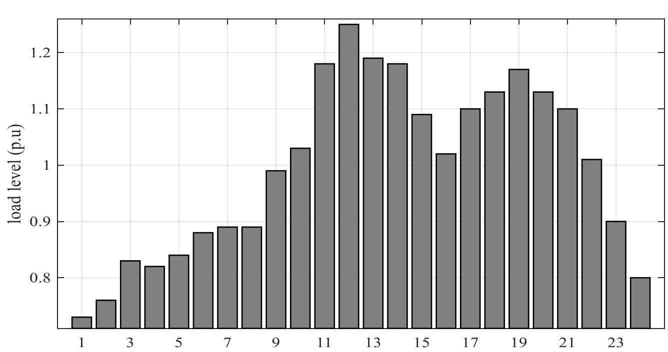

Fig. 2. The daily time-varying load profile.

3.2. Problem formulation

A multi-objective optimization problem with four objective functions is proposed to simultaneously minimize the operation cost as follows.

$$OF = E_{Cost} + TC_{Cost} + SC_{Cost} + VD_{Cost} \tag{1}$$

where E_{Cost} is the cost of consumed energy; VD_{Cost} is the cost of voltage deviations; SC_{Cost} is the cost of shunt capacitor switching; and TC_{Cost} is the cost of transformer tap changing. The cost for regulating the transformer tap is found by using the total cost including the capital cost and the maintenance cost over the maximum allowed regulation times over the lifetime. In the optimization framework, it will be converted to the cost peroff-nominal ratio. The cost of switching a shunt capacitor is found similar to the transformer tap cost, which is finally converted to the monetary per MVar [26], while the cost of energy consumption is calculated as follows.

$$E_{Cost} = \lambda^p E^p + \lambda^q E^q \tag{2}$$

where, E^p (E^q) denotes the total daily active (reactive) energy consumption, and λ^p (λ^q) is the cost of active (reactive) power per kWh (kVAr) [26]. Finally, to calculate the cost raised due to voltage deviation at buses, (3) will be used [27].

$$VD_{Cost} = \sum_{h\in H}\sum_{i\in N} P^D_{i,h} UC^{VD}_{i,h} \tag{3}$$

where

$$UC^{VD}_{i,h} = \begin{cases} 0 & \text{if } V_{\min} < v_{i,h} < V_{\max} \\ \dfrac{C_V}{V^{LL}_{\max} - V_{\max}}(v_{i,h} - V_{\max}) & \text{if } V_{\max} < v_{i,h} < V^{LL}_{\max} \\ \dfrac{C_V}{V_{\min} - V^{LL}_{\min}}(V_{\min} - v_{i,h}) & \text{if } V^{LL}_{\min} < v_{i,h} < V_{\min} \\ C_V & \text{otherwise} \end{cases} \tag{4}$$

In (3) and (4), $v_{i,h}$ and $P^D_{i,h}$ are the voltage and the active power consumed at bus i both at the hth hour, while C_V is a penalty applied constantly or linearly in case the voltage value exceeds $V_{\min}$ or $V_{\max}$. As it can be seen from (4), when the magnitude of voltage is between 0.95 pu ($V_{\min}$) and 1.05 pu ($V_{\max}$), no cost will exist. $V^T_{\min}$ and $V^T_{\max}$ are the thresholds for the maximum and minimum voltage magnitudes, respectively.

One main constraint in distribution systems relates to the active and reactive power flow through the system. In other words, as defined in (5), active and reactive power supply in the whole system must be assured:

$$P_N(t) = \sum_{i=1}^{N_{bus}} U^i_L(t) P^i_L(t) + \sum_{s=1}^{N_{CS}} \sum_{j=1}^{N_{EV,S}} D^j_{EV}(t) P^j_{EV}(t) + \sum_{b=1}^{N_{br}} P^b_{loss}(t) \tag{5.a}$$

$$Q_N(t) = \sum_{i=1}^{N_{bus}} U^i_L(t) Q^i_L(t) + \sum_{b=1}^{N_{br}} Q^b_{loss}(t) \tag{5.b}$$

where, $P_N(t)$ and $Q_N(t)$ are the active and reactive powers injected from the upstream network to the distribution grid at time t, which are always injected through bus 1. Moreover, $P^b_{loss}(t)$ and $Q^b_{loss}(t)$ are the active and reactive power losses of branches, $P^i_L(t)$ and $Q^i_L(t)$ are the active and reactive loads at bus i, and $P^j_{EV}(t)$ is the active power consumed by or injected from the jth EV in the sth parking lot. D^j_{EV} defines the charging/discharging status of the jth EV. When the EV is in its charging and discharging mode, D^j_{EV} is equal to 1 and -1, respectively. In addition, N_{bus} is the number of buses in the system, N_{br} is the number of branches, N_{CS} is the number of parking lots, and $N_{EV,S}$ is the number of EVs in the sth parking lot at time t.

$U^i_L(t)$ determines the amount of power supplied by the controllable load at bus i, and takes a value as follows.

$$U^{\min}_L \le U^i_L(t) \le U^{\max}_L \tag{6}$$

Since the maximum controllable load at each bus is assumed here to be 20%, we will have: $U^{\min}_L = 0.8$; $U^{\max}_L = 1$.

3.3. Coordinating EVs charging in parking lots

In a modern public parking lot, a part of parking area is equipped with chargers to be used by EVs during their parking period (see Fig. 3). During the day and night, both EVs and fuel cars enter and leave the parking lot. As it can be seen from Fig. 3, fuel cars as well

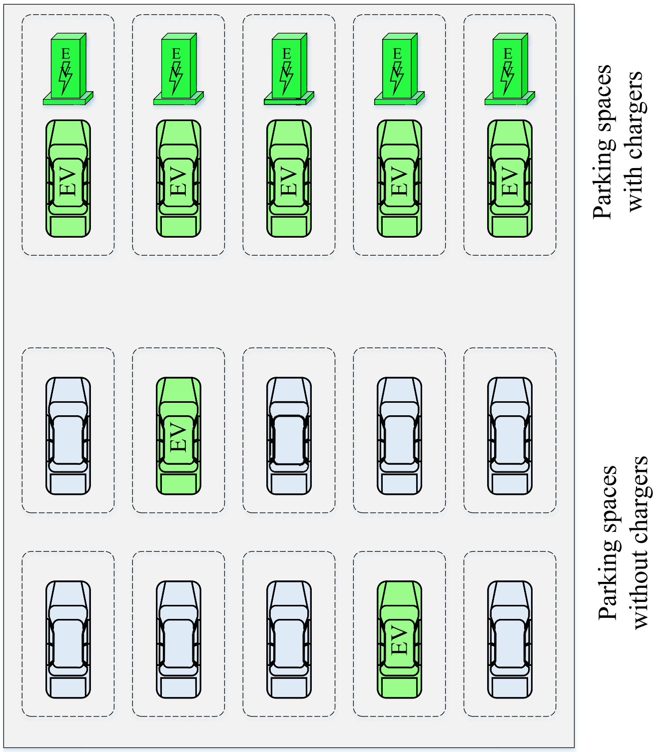

Fig. 3. Schematic of a parking lot with EV chargers.

as EVs which does not wish to be charged are parked in parking spaces without chargers. In working hours of the day, many people use their EVs to go to work, and they need to park their cars near to their work places. In this regard, if the power in batteries of their cars are low, car owners prefer their cars to be charged during the parking time period. Accordingly, the EV entering a parking lot for charging/discharging is characterized with three characteristics as follows:

- Its tendency for discharging or charging (fast or normal).
- Its desirable time to stay in the parking lot.
- Its level of charge at the time of arrival.

The above characteristics must be considered in the optimization problem in order to achieve a more practical solution regarding the real electrical behavior of parking lots.

Technically speaking, each EV will receive some active power from the grid when in the charging mode, while it delivers active power to the grid when in the discharging state, as follows.

$$P_{EV}^{i}=\begin{cases}\dfrac{D_{EV}^{i}*MPB^{i}}{\eta^{i}} & \text{if EV is in the charging mode}\\ D_{EV}^{i}*MPB^{i}*\eta^{i} & \text{if EV is in the discharging mode}\end{cases} \tag{7}$$

where η denotes the EV's battery efficiency; MPB^i reflects the maximum power of the battery for the ith EV delivered to the grid, which also indicates the nominal EV capacity. Equation (7) indicates that considering the battery efficiency, more power should be supplied by grid during the charging mode to have the battery charged. Accordingly, during the discharging mode, the EV injects less power to the grid [28]. A parking lot is assumed to have N_S charging stations. In order to simplify the analysis and without loss of generality, it is assumed that the EVs located in the parking lots can operate in two different states: (i) the EV is fully charged and can transfer power to the electric grid, (ii) the EV is depleted and needs to be re-charged. Usually, two EV charging modes (normal or fast) are considered. It is also assumed that if all the stations in the lot are occupied by EVs that are in normal charging mode, the limitation of the line connecting the lot to the grid is not exceeded. However, in case some of EVs are in fast charging mode, this limitation would be exceeded. To mitigate this cases, it would be necessary to determine the number of EVs that are allowed to be in fast charging mode according to the charging and discharging statuses of other EVs in the lot.

It is assumed that the EV arrives at the station at T_{ai} and departs at T_{di}. This duration is called "parking time duration (PTD)" which is assessed as $PTD = T_{di} - T_{ai}$. Although PTD can follow a stochastic distribution pattern, in order to simplify the analysis, it is assumed in this paper that PTD for EVs that want to use the fast charging mode is 2 h while EV owners who intend to charge their car in the normal charging mode will stay in the lot for 8 h. During this time, EVs can be charged or discharged with a constant power rate. According to the literature, a full discharging will takes about 4 h for typical batteries, while an EV needs 20 min or 4 h to be charged in the fast or normal charging modes, respectively [29]. Note that PTD is a parameter dependent to the tendency of the EV owner and not to the EV's battery type or the initial charge level. Therefore, since the thermal and other limitations of the parking lot may not allow the EVs to enter the charging stations right after entering the lot and therefore EVs may be put in the queue, considering a parking time hour of 2 h for EVS with fast charging tendency and 8 h for EVS with normal charge tendency is necessary to let them become fully charged.

In this paper, it is assumed that an EV can be charged in the fast charging mode up to 10 times faster than its normal charging rate, reflecting the fact that more power should be transferred to the EV in a shorter time interval. This feature can be reflected using the index. In so doing, the time duration that an EV remains in charge is multiplied by TS_{PEV}^{i} which is defined in (8).

$$TS_{PEV}^{i}=\begin{cases}1 & \text{if charging status is normal}\\ 0.1 & \text{if charging status is fast}\end{cases} \tag{8}$$

According to (8), if the EV is in the fast-charging mode, the charging time would be 90% less and the receiving rate of power is 10 times higher. In general, the active power demanded by an EV when charging at time t, i.e. $P_{EV}^{j}(t)$, which is in kW, will be determined as follows:

$$P_{EV}^{j}(t)=\begin{cases}P_{EV,\min}^{j} & \text{if charging status is normal}\\ P_{EV,\max}^{j} & \text{if charging status is fast}\end{cases} \tag{9}$$

where $\frac{P_{EV,\max}^{j}}{P_{EV,\min}^{j}}=10$. Therefore, for the sth parking lot where a part of cars are being charged and some are being discharged at time t, the total power (at time t) which is delivered to or demanded from the grid by the charging lot is determined as follows.

$$P_{L}^{s}(t)=\sum_{j=1}^{N_{EV,S}} D_{EV}^{j}(t)P_{EV}^{j}(t)=\sum_{j=1}^{N_{EV,S}^{C}} P_{EV}^{j}(t)\ -\sum_{j=1}^{N_{EV,S}^{D}} P_{EV}^{j}(t) \tag{10}$$

where, $N_{EV,S}^{C}$ ($N_{EV,S}^{D}$) is the number of EVs that are being charged (discharged) in the sth parking lot at time t. If $P_{L}^{s}>0$, it shows that the power flow is from the grid to the lot, whereas $P_{L}^{s}<0$ indicates the power is injected to the grid. Considering the thermal limitation of the line connecting the parking lot to the grid, this constraint needs to be addressed to examine the grid ability for transferring power to EVs. This limitation most likely to appear in the EV fast-charging mode where EVs take more power at time t from the grid. The thermal constraint is formulated in 11(a)-(d) as follows:

$$S_L^s(t) \le S_{\max}^s \ \ \forall t \in \{1, 2, 3, ..., T\} \tag{11.a}$$

$$S_L^s(t) = \sqrt{\left(\sum_{i=1}^{N_{FC}^s(t)} r_i^{\max} + \sum_{i=1}^{N_{NC}^s(t)} r_i^{\min} - \sum_{i=1}^{N_D^s(t)} r_i^{\min}\right)^2 + \left(Q_L^s(t)\right)^2} \tag{11.b}$$

$$N_{FC}^s(t) + N_{NC}^s(t) = N_C^s(t) \tag{11.c}$$

$$N_C^s(t) + N_D^s(t) = N_{EV}^s(t) \tag{11.d}$$

where, $N_D^s(t)$ and $N_C^s(t)$ are the number of EVs in the charging and discharging modes at time t, respectively, $N_{EV}^s(t)$, $N_{NC}^s(t)$ and $N_{FC}^s(t)$ are the total number of EVs, the number of EVs that are in the normal mode, and the number of EVs that are in the fast charging mode, respectively, all at time t at the sth parking lot. $S_{\max}^s$ denotes the thermal limit of the line connecting the sth parking lot to the grid. $S_L^s(t)$ represents the apparent power provided by the sth parking lot. $Q_L^s(t)$ indicates the line reactive power flowing through the line connecting the sth parking lot to the grid.

In this study, EVs arrive at the parking lot and will wait in a queue. Therefore, the priority list of cars is obtained according the time of arrival of each EV at the lot. It is assumed that the number of cars that arrive at the lot as well as their tendency to be charged (fast or normal) or discharged follow random distributions. According to the above charging preferences and charging priorities, a charging coordinating scheme can be established in a parking lot as follows.

- Every 20 min, the parking lot is checked for unoccupied charging stations. If there is any, the car in the first place in the priority list will go to the charging station if it is intended to be discharged.
- In case the car wants to be charged fast, it must be checked whether the thermal limit of the line connecting the lot to the grid allows for fast charging. If the answer is yes, the car can go to the charging station for charging, otherwise it should wait for another 20 min and then the next car in the priority list with a normal charging preference will be summoned.

4. Using IMVBSO to solve the problem

Fig. 4 illustrates the flowchart for the proposed optimization problem. According to Fig. 4, the number of EVs in each parking lot is determined at first using a normal probability distribution function. The number of vehicles with the charging or discharging status will be evaluated. Then, the normal and fast charging statuses of EVs will be determined. The thermal limitation and EVPS conditions will be then checked. If the distribution line is not capable of power delivery, the number of charging and discharging EVs must be amended. In case of having thermal limitation violations, it is necessary to limit the number of fast charging EVs so that the EVs that desire to be normally charged get priority.

In order to solve the proposed optimization problem, the IMVBSO is utilized in this paper due to its capability to solve an optimization problem with objective function as those defined in

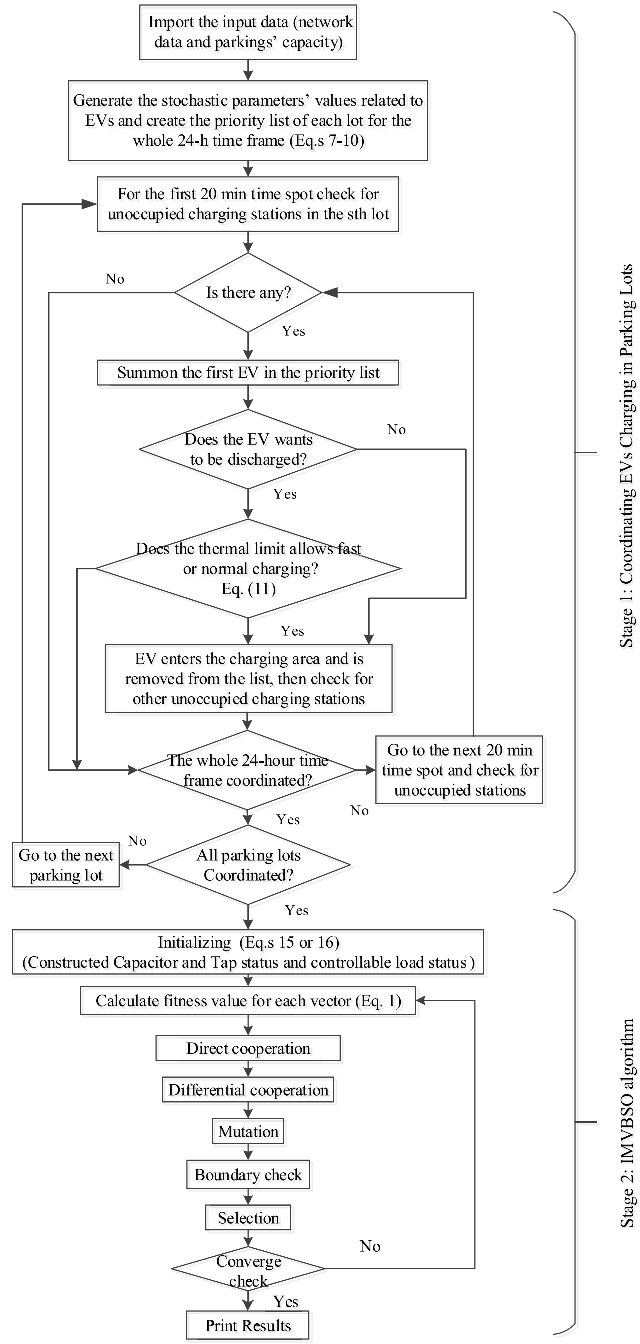

Fig. 4. Flowchart of the proposed optimization algorithm.

(3) which is a cost function of four objectives.

The IMVBSO is the evolved version of the Particle Swarm Optimization (PSO) and the Differential Evolutionary (DE) algorithms where the population explorer is characterized in the form of a vector. In this paper, an IMVBSO algorithm is utilized to maintain the EVC in active distribution systems with massive penetration of EVs. The steps of this algorithm are explained in [26]. However, a summery these steps is given below:

Step 1: formation of the initial population. The initial population vector are similar to the final solution defined in (12)-(14) with the objective function (OF) excluded.

Step 2: merit functions in vector optimization. In this step, the fitness of each vector is evaluated based on the objectivefunction introduced in (1).

Step 3: population updating based on merit functions. Using the IMVBSO algorithm, the new vectors are calculatedthrough the following four stages: reproduction, mutation, boundary check, and selection. Reproduction combines several vectors to determine the best information and can be categorized into a direct cooperation vector and differential cooperation vector to control the exploration and searches.

Step 4: termination condition. With a precision of 0.01, the solutions of the objective function in two consecutive iterations are the same. If the termination condition is not satisfied, this process will be iterated from *Step 2*.

In the proposed IMVBSO algorithm, the format of the solution in scenarios 2 and 3 is a matrix containing the values of decision variables together with the value of the objective function for a 24-h time frame as follows.

$$SM = [\, sm_1 \quad sm_2 \quad \ldots \quad sm_{24} \,]^T \tag{12}$$

where

$$sm = [\, \mathrm{CS}_1 \quad \ldots \quad \mathrm{CS_n} \quad \mathrm{Tap_{Status}} \quad \mathrm{OF} \,] \tag{13}$$

In (13), CS_i is the status of ith capacitor which is a binary value (zero for a disconnected capacitor and unity value for a connected capacitor), Tap_{Status} is defined as the number of transformer tap, and OF is the objective function. The objective functions is the operation cost, which is explained in (1). Note that in the fourth scenario $CL = 1 - U_L$ in which U_L is defined as the amount of controllable load will be added to sm as follows.

$$sm = [\, \mathrm{CS}_1 \quad \ldots \quad \mathrm{CS_n} \quad \mathrm{Tap_{Status}} \quad \mathrm{CL} \quad \mathrm{OF} \,] \tag{14}$$

It is worthy to note that in each iteration the population is generated representing the settings of the *CB Switching State* and the *Transformer Tap State*. This population structure offers an inherent flexibility such that all CBs can be either connected to or disconnected from the network, which, as stated, is enforced by a binary variable that can take either 0 or 1 (0: disconnection; 1: connection).

5. Case studies and numerical results

5.1. Model assumptions and test cases description

In this paper, the proposed approach is tested on the IEEE 69-bus test system with 7 laterals (see Fig. 5 for the one-line diagram) and the IEEE 119-bus test system. The total active (reactive) power in these systems are 3801.5 kW (2694.6 kVAr) and 22709.7 kW (17041.1 kVAr), respectively. In the former case, we assume that 10 three-phase shunt capacitors of 300 kVAr are located at nodes 9, 19, 31, 37, 40, 47, 52, 55, 57, and 65 which can be connected to and disconnected from the network [30]. In the latter case study, 10 three-phase shunt capacitors of 1000 kVAr are located at nodes 8, 12, 33, 36, 40, 36, 75, 79, 99 and 118 which can be connected to and disconnected from the network [31]. A transformer with three tap ratio of ±0.02 p.u. is located in the upper node to maintain the node voltage level within the desirable interval of [0.94, 1.06] p. u. in both networks [31]. The transformer tap is assumed to be 0.02 with at most three tap changes corresponding to the ±3 level of voltage drop or rise of 0.94 p. u. and 1.06 p. u, respectively.

In calculating the cost function in (1) it is assumed in this paper that, SC_{Cost} and TC_{Cost} are 0.133 $/MVar and 1.33 $/tap respectively, whereas $V^{LL}_{\min}$, $V^{LL}_{\max}$ and C_V are assumed to be 0.8 pu, 1.2 pu and 3.4 $/kWh, respectively [27]. Moreover, according to [26], the values of λ^p and λ^q are set on 0.06 $/kWh and 0.02 $/kVArh, respectively.

Four scenarios have been applied to analyze the EVC in the grid: (a) *Scenario 1*: base-case condition; (b) *Scenario 2*: operation cost assessment considering the daily load profile in the absence of EVs; (c) *Scenario 3*: operation cost assessment taking into account both daily load profile and EVs charging behavior; (d) *Scenario 4*: operation cost assessment in the presence of controllable loads and EVs.

In the first scenario, the proposed optimization algorithm is not applied, so its results will be compared with other scenarios to make it possible to prove the effectiveness of proposed algorithm applied in the rest of scenarios. The second scenario is designed to evaluate the effects of the 24 h planning of transformer tap changing and capacitors switching on the operation cost. The aim in the third scenario is to evaluate the presence of EVs with their stochastic natures on the objectives of the optimization problem considering the 24 h planning of transformer tap changing and capacitors switching. In the fourth scenario, controllable loads are entered into the optimization problem to show how they can effectively play a positive role in minimizing transformer tap changing actions and the number of capacitors switching.

It is worthy to note that, as explained in Section 4, in scenarios 2 and 3, the format of the solution in the *IMVBSO* matrix is a matrix containing the values of decision variables together with the value of the objective function. Therefore, as 10 capacitors are assumed to exist in both 69 and 119-bus systems, there would be 10 decision variables in sm associated with the capacitors along with one variable associated with the tap of the transformer and another element in the vector associated to the value of the objective function (see Eq. (15)).

$$sm = [\, \mathrm{CS}_1 \quad \ldots \quad \mathrm{CS}_{10} \quad \mathrm{Tap_{Status}} \quad \mathrm{OF} \,] \tag{15}$$

Also the format of sm in the fourth scenario will be as in (16).

$$sm = [\, \mathrm{CS}_1 \quad \ldots \quad \mathrm{CS}_{10} \quad \mathrm{Tap_{Status}} \quad \mathrm{CL} \quad \mathrm{OF} \,] \tag{16}$$

5.2. Case study 1: IEEE 69-bus system

Scenario 1: Base-Case Condition.

The voltage profiles for various light, nominal and heavy load levels shown in Fig. 2 are illustrated in Fig. 6. Note that, in all simulations provided in this paper the daily load profile in Fig. 2 has been used. According to Fig. 2, light and heavy load levels pertain to the first and 12th hour of the time frame and are with values 0.73 and 1.25 of the nominal load, respectively. One can see from Fig. 6 that the load increment results in a higher voltage drop across the system. Table 1 presents the active and reactive power losses, and the cost value defined in (1) taking for the above load levels. Moreover, the total cost for the whole 24-h time frame is obtained as 42143.1 $. Note that in this scenario, SC_{Cost} and TC_{Cost} would be zero.

Scenario 2: Voltage Control and Reactive Power Assessment Considering the Daily Load Profile.

Implementing the proposed optimization problem discussed in Section 3, the capacitors statuses and transformer tap states are determined. To analyze the efficiency of the proposed algorithm, the results in Scenario 1 and Scenario 2 under different loading levels (light, nominal, and heavy) are compared as tabulated in Table 2, where the consumed active and reactive powers are in terms of kW and kVAr, respectively. Moreover, in order to better validate the results and the efficiency of the proposed algorithm, the problem defined in this scenario is solved using PSO as well. It was found that the optimal solution obtained from PSO is similar to

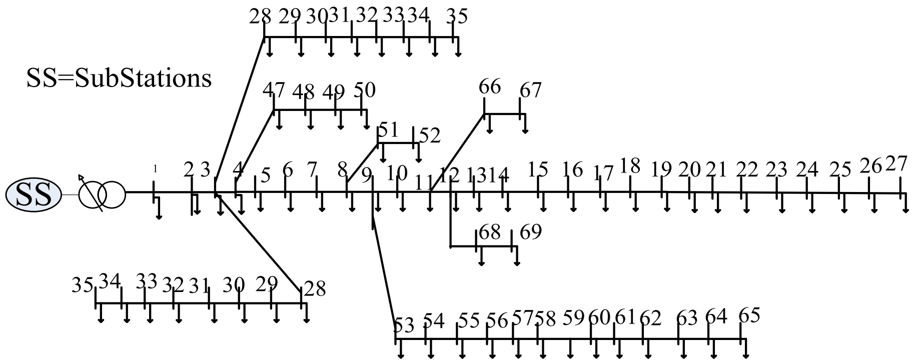

Fig. 5. The one-line diagram of the IEEE 69-bus test system.

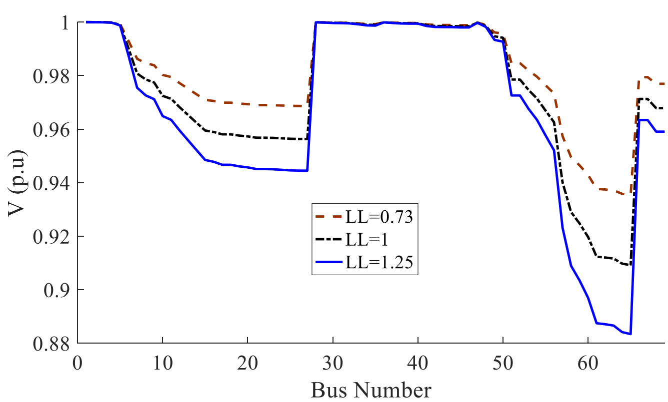

Fig. 6. The network voltage profile in the IEEE 69-bus test system: Scenario 1.

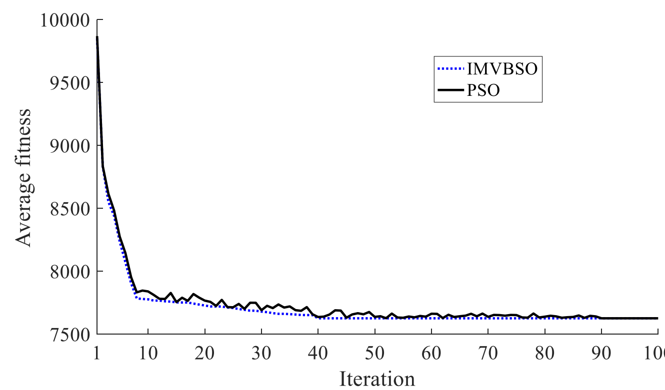

Fig. 7. Convergence characteristics of proposed IMVBSO and PSO algorithms (scenario 2).

Table 1
Base results obtained for the IEEE 69-bus system (scenario 1).

Loading State	P_{loss} (kW)	Q_{loss} (kVar)	Cost ($)
Light	11.43	5.20	532.72
Nominal	20.89	10.22	1681.3
Heavy	36.91	16.71	3305.2

the one obtained from IMVBSO. However, IMVBSO has better performance in this example in terms of convergence speed. According to Fig. 7, the convergence speed of the proposed IMVBSO algorithm is faster than the PSO algorithm (IMVBSO converges in the fifty iteration while PSO converges in the ninety iteration).

Note that in the fifth column of Table 2 *Cost_E* is used which represents the value of cost function defined in (1) excluding the cost of voltage deviations. According to Table 2, it can be seen that in the first scenario a significant part of the operation cost pertains to the cost of voltage deviations, which has been mitigated in the second scenario due to the improvement in the voltage profile.

Scenario 3: Voltage Control and Reactive Power Assessment Considering both Daily Load Profiles and EVs.

In this scenario, the EVC in the presence of EVs is investigated. It is assumed that there are a total of five parking lots with details presented in Table 3 [28]. The last column in Table 3 represents the thermal limitation of the line connecting each parking lot to the grid. As one can realize, the parking lots 1, 2 and 4 have lower thermal limitations and might impose a higher risks of charging operation. Thus, the last column of this Table is somewhat a reflection of the maximum number of EVs allowed to be charged in the fast-charging mode.

The electric capacity of each EV is assumed to be 10 kW. Moreover, the connection of EVs to the grid and their charging and discharging statuses are randomly assigned and evaluated using normal probability distributions. Fig. 8 illustrates the spatio-temporal details of the EVs analyzed in this scenario. According to the proposed approach, the number of EVs allowed for fast charging is limited so that the thermal limit will not exceeded. Another stochastic parameter is the level of EVs charge at the time

Table 2
EVC results obtained for the IEEE 69-bus system (scenarios 1 and 2).

Scenario	Loading State	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost_E ($)	Cost_V ($)	Cost_T ($)
S1	Light	2787.0	1972.3	206.7	326.1	532.7
	Nominal	3824.6	2704.8	283.6	1397.8	1681.3
	Heavy	4789.5	3385	355.1	2950.1	3305.2
S2	Light	2784.8	1471.3	196.5	0	196.5
	Nominal	3821.0	2103.2	334.5	167.3	271.3
	Heavy	4781.3	2381.2	271.3	0	334.5

Table 3
Details of parking lots in IEEE 69-bus test system.

Parking Lot #	Bus #	Capacity (charging stations)	Thermal limit (kVA)
1	30	60	1455
2	32	100	5823
3	45	60	1455
4	48	60	1455
5	63	100	5823

of arrival which is randomly selected among four values, i.e. 10 %, 20%, 30% and 40%.

Having obtained the information on the EVs at each parking lot as illustrated in Table 3, the proposed IMVBSO optimization algorithm is applied and the operation cost in the presence of EV loads is analyzed. Table 4 displays the results observed in Scenario 3 under different loading conditions (light, nominal, and heavy).

While the results in Scenario 2 and Scenario 3 are found almost similar in terms of the total cost, the number of switched shunt capacitors and transformer tap changes are different. This observation is primarily supported by the dynamic nature of the EV's charging and discharging actions, resulting in different capacitor and transformer tap changing strategies. The proposed optimization algorithm was proven to be able to reduce the randomness of EVs by an additional number of transformer tap changing as well as the flexibility in harnessing the capacitor banks.

Scenario 4: Voltage Control and Reactive Power Assessment Considering Controllable and EV Loads.

In this scenario, the voltage control and reactive power analysis in the presence of both EVs and controllable loads are investigated. In this scenario, the load on bus 61 has been selected as the controllable load. Thus, the control action is applied on this bus where the active and reactive loads are 1244 kW and 888 kVar, respectively. Note that the active and reactive load at bus 61 is one third of the total load in the 69-bus test system meaning that the control action in this bus is critical and has considerable impacts on the loads and reactive power profile across the grid.

The parking lot dataset used in this scenario is the dataset detailed in Table 3 and Fig. 8. Similar analytics, as presented in Scenarios 1 to 3, are implemented in this scenario and the corresponding results in different loading conditions are tabulated in Table 5. Effective utilization of controllable loads together with EVs would also result in a significant reduction in transformer tap switching actions. During the studied 24-h time interval, the transformer tap state would be set continuously constant in the first positive tap state, which will increase the transformer life time and reduce the maintenance and repair costs in a long run (see Table 6).

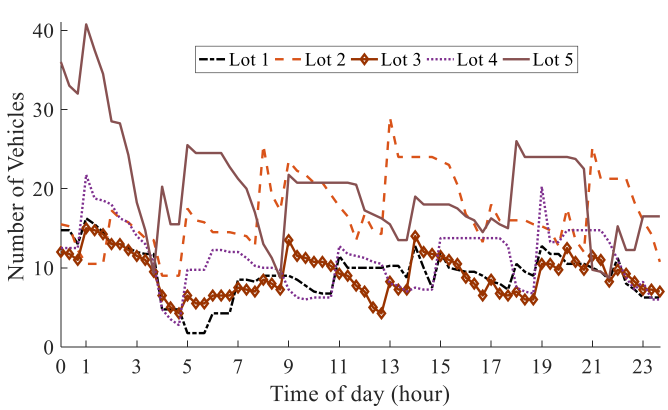

Fig. 8. Number of EVs in each parking lot during the 24-h time frame (IEEE 69-bus system).

Table 4
EVC results obtained for the IEEE 69-bus system (scenario 3).

Loading State	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost ($)	CB#	Tap #
Light	3045.2	970.1	202.1	8	+2
Nominal	3838.1	1705.3	264.4	10	+3
Heavy	4376.3	2381.5	310.2	9	+3

One main observation in Scenario 4 is that the capacitor switching actions are reduced to 2, which happened at hour 1 and hour 22. Such advantages highlight the fact that utilizing the controllable loads could reduce the operation cost. Comparing the simulation results in Tables 4 and 5, one can realize that in all loading conditions except one, the active/reactive power consumption and the voltage deviation are improved. The reason lies in the fact that the random behavior and stochasticity in EVs (unknown charging and discharging status) are effectively compensated in the grid by managing the controllable loads.

5.3. Case study 2: IEEE 119-bus distribution system

Scenario 1: Base-Case Condition.

Fig. 9 illustrates the voltage profile and Table VI summarizes the power flow results under different loading levels for the 119-bus system in the absence of capacitor banks and EVs.

Scenario 2: Voltage Control and Reactive Power Assessment Considering the Daily Load Profile.

The results of this scenario is detailed in Table 7. It can be seen that using IMVBSO for solving the proposed optimization problem has resulted in reducing the total cost along with improving the voltage profile. Particularly, the improvement in the voltage profile has a significant impact on the total cost reduction. Compared to the first scenario, the total cost has been reduced by 64.4%, 79.8% and 75.3% for the light, normal and heavy loading conditions, respectively.

One can clearly observe that the calculated consumed reactive power varies from 10.74% to 13.94% by the proposed method as a function of the problem in the network. In this scenario, the transformer tap as well as the number of capacitor switching increased as the load level rises (to maintain the voltage profile and active and reactive power consumption within the limits). The transformer tap increases from +1 position to +3 position and accordingly, the number of CB switching actions increases from five to six.

Scenario 3: Voltage Control and Reactive Power Assessment Considering both EVs and Daily Load Profile.

In this scenario, it is assumed that there exists a total of 9 parking lots with details presented in Table 8. The electric capacity of each EV and assumptions are the same as those explained earlier for previous case study. Fig. 10 illustrates the spatio-temporal details of the EVs analyzed in this scenario. Table 9 reflects the objective function and consumed active and reactive power in this scenario when the IMVBSO optimization algorithm is applied. The result advocates that as more EV power is discharged, the number of transformer tap changing actions and switched shunt capacitors

Table 5
EVC results obtained for the IEEE 69-bus system (scenario 4).

Loading State	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost ($)	CB#	Tap #
Light	2918.1	979.7	194.7	7	+1
Nominal	3592.4	1831.1	252.2	7	+2
Heavy	4075.6	2268.6	289.9	9	+2

Table 6
Base results obtained for the IEEE 119-bus system (scenario 1).

Loading State	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost ($)
Light	17228.6	12931.7	3547.3
Nominal	23992.2	18007.4	9809.4
Heavy	30496.4	22885.3	19344.9

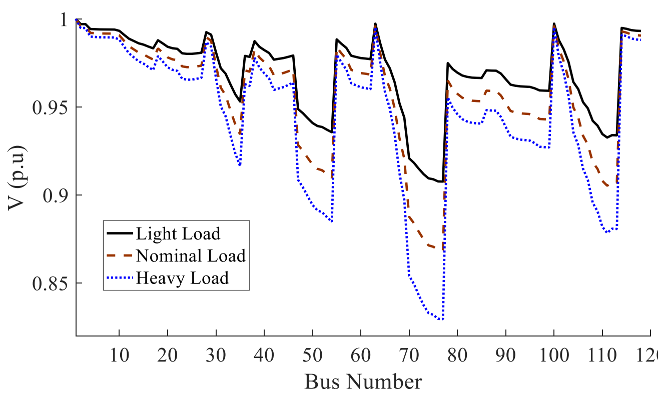

Fig. 9. The network voltage profile of the IEEE 119-bus test system (Scenario 1).

decrease compared to Scenario 2. Comparing the result in Scenario 2 and Scenario 3, it is observed that the dynamic behavior of the EV's charging and discharging could positively impact the 119-bus distribution system contrary to the IEEE 69-bus distribution system studied earlier.

Scenario 4: Voltage Control and Reactive Power Assessment Considering EVs and Controllable Loads.

With the parking lot database remaining the same as in Scenario 3, Table 10 demonstrates the results in Scenario 4. In this scenario, it is assumed that the active and reactive power of the controllable loads at bus 50 are 918.37 kW and 1205.1 kVar, respectively. This load accounts for 4% and 7% of the total active and reactive power in the grid. Again, from the results obtained in this scenario one can clearly observe how the flexibility in controllable loads is harnessed to compensate the stochasticity in the EVs (unknown charging and discharging statuses).

6. Discussion

In order to demonstrate the effectiveness of the proposed optimization problem, the results of four scenarios in the 24-h time frame for the IEEE 69-bus and 119-bus systems have been provided in Tables 11 and 12, respectively. Note that the calculation time in the last column of these tables is obtained through carrying out the simulations on a PC with 3.4 GHz Core i7 CPU and 16 GB of DDR4 RAM. In the fourth column of these tables, *Cost_E* represents the sum of energy consumption, transformer tap changing and capacitor switching costs. As it can be realized from Table 11, the optimization algorithm has an effective impact on reducing the costs in scenarios 2, 3 and 4. Moreover, by comparing the results of the third and fourth scenarios, it can be concluded that utilizing the controllable load in scenario 4 has resulted in a significant reduction (about 75%) in the voltage deviation cost making the total cost to be reduced by 12% compared to the third scenario.

Similar remarks can be seen in Table 12 as well. It can be seen from this table that the proposed optimization algorithm has worked well in controlling voltage and energy in scenarios 2, 3 and 4. Moreover, the results of the fourth scenario show that utilizing the controllable load can mitigate the effect of EVs on controlling voltage and energy in the system and as a result causes a reduction in the total operation cost.

Another issue which may arise when dealing with stochastic parameters in optimization problems is the dependency of the

Table 8
Details of parking lots in IEEE 119-bus test system.

Parking Lot #	Bus #	Capacity (charging stations)	Thermal limit (kVA)
1	9	60	1455
2	16	100	5823
3	27	60	1455
4	34	60	1455
5	45	100	5823
6	61	100	5823
7	76	60	1455
8	99	60	1455
9	118	100	5823

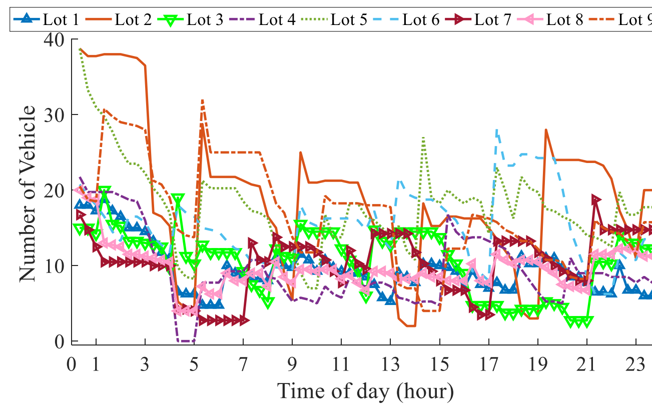

Fig. 10. Number of EVs in each parking lot during the 24-h time frame (IEEE 119-bus system).

Table 9
EVC results obtained for the IEEE 119-bus system (scenario 3).

Loading State	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost ($)	CB#	Tap #
Light	15658.2	10835.8	1156.2	7	+2
Nominal	23716.8	14852.9	2292.7	10	+3
Heavy	30019.2	21352.1	6088.7	8	+3

Table 7
EVC results obtained for the IEEE 119-bus system (scenarios 1 and 2).

Scenario	Loading State	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost ($)	Improvement (%)
S1	Light	17228.6	12931.7	3547.3	–
	Nominal	23992.2	18007.4	9809.4	–
	Heavy	30496.4	22885.3	19344.9	–
S2	Light	17159.2	11542.4	1260.4	64.4
	Nominal	23754.2	15497.3	1976.0	79.8
	Heavy	30131.7	19933.4	4768.4	75.3

Table 10
EVC results obtained for the IEEE 119-bus system (scenario 4).

Loading State	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost ($)	CB #	Tap #	CL%
Light	15482.1	10,293	1134.8	7	+2	11.9
Nominal	23501.8	14579.2	2280.9	8	+3	20
Heavy	29675.6	19274.2	5894.4	9	+3	20

Table 11
Cost and power consumption values obtained in different scenarios (IEEE 69-bus system).

Scenario	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost_E ($)	Cost_V ($)	Cost_T ($)	Calculation Time (sec)
S1	91423.2	64651.9	6778.4	35364.7	42143.1	37
S2	91323.4	51407.1	6507.5	1119.6	7627.1	121
S3	94375.2	41710.8	6496.7	652.3	7149.0	190
S4	88675.6	40172.3	6124.0	165.2	6289.2	235

Table 12
Cost and power consumption values obtained in different scenarios (IEEE 119-bus system).

Scenario	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost_E ($)	Cost_V ($)	Cost_T ($)	Calculation Time (sec)
S1	545,916	409655.6	40948.1	205222.9	246,171	54
S2	466346.8	308282.9	34147.4	13009.5	47155.9	180
S3	568098.4	385780.6	41801.5	19390.5	61,192	258
S4	562385.8	351297.8	40769.1	17,293	58062.1	361

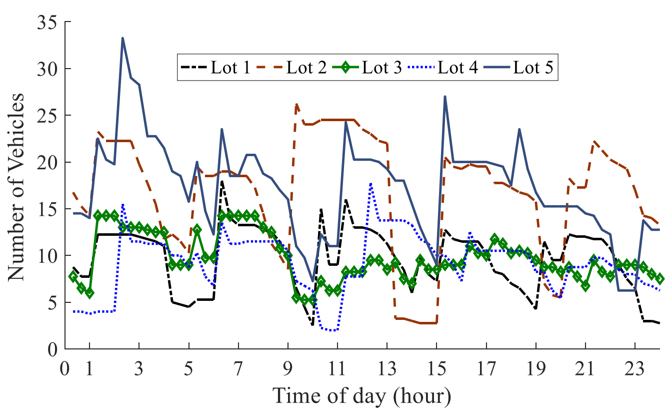

Fig. 11. Number of EVs in each parking lot during the 24-h time frame (IEEE 69-bus system).

optimal solution to the values of such parameters. In the proposed optimization approach utilized in this paper, the number of EVs arriving at the parking lots and their characteristics are considered as stochastic parameters. Therefore, it is necessary to show that how the final solution obtained by the proposed optimization problem changes as the values of these parameters change. To do that, another simulation with new randomly selected values of the stochastic parameters has been performed for the IEEE 69-bus system. Fig. 11 shows the new random patterns of the number of EVs in the parking lots used in the second simulation. The results of applying IMVBSO to this case along with the results of the third and fourth scenarios obtained in Section 5.2 are tabulated in Table 13. It can be seen from this table that the change in the stochastic inputs of the problem has changed the optimal solutions in scenarios 3 and 4 slightly. However, considering the results of scenarios 1 and 2 in Section 5.2, these comparisons demonstrate that although a slight change can be seen in the final solutions obtained in two cases (shown in Table 13), the overall impact of the proposed optimization problem in reducing the operation cost would be unchanged.

7. Conclusions

This paper studied the minimization of the operation cost in distribution systems in the presence of massive penetration of EVs. The control strategies are proposed through shunt capacitor switching and transformer tap changing actions. The allocation of EVs in the parking lots and the corresponding charging/discharging stochasticity are randomly distributed and an improved mixed real and binary vector-based swarm optimization algorithm is proposed as the solution technique to solve the multi-objective optimization formulation. Several scenarios are extensively analyzed and compared to demonstrate the impact of controllable loads on the operation cost. Our findings revealed that the active/reactive power control and voltage regulations are directly driven by the dynamic and unpredictable nature of EVs in the system. Considering the number of EVs located in the parking lots at each hour, and the corresponding coordinated charging and discharging states, the numerical results demonstrated how the proposed algorithm can effectively control the network voltage and active/reactive power by optimally adjusting the tap changer and shunt capacitors.

Table 13
Comparison of two simulations with different stochastic input values (IEEE 69-Bus Test System).

Scenario	First simulation			Second simulation		
	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost_T ($)	$P_{consumed}$ (kW)	$Q_{consumed}$ (kVAr)	Cost_T ($)
S3	94375.2	41710.8	7149.0	98141.7	42288.9	7357.8
S4	88675.6	40172.3	6289.2	92471.9	40769.7	6366.6

Simulation results in two case studies verified the efficiency of the proposed strategy: the impact of EV randomness was compensated by controllable loads and, hence, the number of transformer tap changing and shunts switching actions was significantly reduced.

Credit author statement

Mohammad Hasan Hemmatpour: Conceptualization, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing, Visualization, Project administration, Validation, Mohammad Hossein Rezaeian Koochi: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization, Validation, Pooria Dehghanian: Review & editing, Visualization. Payman Dehghanian: Review & editing, Validation, Visualization.

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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