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Penetration Levels of Electric Vehicle Charging Stations and Renewable Energy Sources in Distribution Power Systems for the Energy Loss Reduction and Voltage Improvement

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Abstract- The paper applies Equilibrium Optimizer (EO) and War strategy optimization algorithm (WSO) for optimizing the site of electric vehicle charging stations (EVCSs) and renewable energy systems (RESs) in the IEEE 69-node distribution network. The study implements two study cases: 1) Minimize the power loss without voltage constraint and without RESs; 2) Minimize the total added power of RESs, constraining the minimum voltage of 0.925 and 0.95 per unit (Pu). Three power demand levels from EVCSs are simulated by running EO and WSO, including 1,728.5, 3,011.5, and 4,740 kW. The increased power demand levels result in a high voltage drop and high power loss. So, the distribution network becomes worse regarding technical and economic factors. The voltage profile is improved by using the minimum generation from RESs, and the power loss is also decreased. The power loss is about 225 kW, and the minimum voltage is around 0.9 Pu for different power demand levels without RESs. However, the power loss is reduced significantly, under 120 kW, and minimum voltage increases to higher than 0.925 and 0.95 when using RESs. For the three power demand levels, the added power of RESs is under 350 kW for the minimum voltage of 0.925 Pu and 1,000 kW for the minimum voltage of 0.95 Pu. So, using RESs is very beneficial for building EVCSs in distribution networks (DNs), although the power demand for EVCSs is very high.

Keywords Electric vehicles, power loss, voltage drop, renewable energy systems, charging stations, equilibrium optimizer.

1. Introduction

Conventional power sources from burning fossil fuels release polluted emissions and cause unexpected greenhouse effects [1]. The Paris Agreement was one of the most suitable solutions to reduce the product of Carbon dioxide (CO2) and the earth's temperature [2]. Moreover, the importance of cutting CO2 volume was highly emphasized at the 28th UN Climate Change Conference (COP28) in Dubai (UAE) in 2023, while the world witnessed the warmest year record, which is 1.4 oC higher than the average temperature of the pre-industrial year period [3]. In addition, all the members have decided to open new funding for mitigating losses and damages caused by the increase of CO2 in the industry, especially from producing and consuming fossil fuels. The use of modern transportation technology, such as electric vehicles powered by batteries and hybrid electric and fuel vehicles, can reduce emissions, but it is still high, with about 25% of the old data [4]. In the study, the use of electric vehicles is considered, and the impacts of them are investigated, proposing solutions to unexpected results. In fact, it was indicated that the placement of (EVCSs) causes high power loss and voltage drop [5].

In the past decade, the placement of EVCSs in distribution networks (DNs) has attracted attention from people and operators of DNs [5] due to the proportion of electric cars rapidly increasing and becoming more competitive compared to petrol cars. Notably, a series of promotion activities to encourage the development of EVs have been employed, including consumer incentives, building charging infrastructure, planning, policies, and other promotion activities [6]. As a result, the sale of electric vehicles (EVs) in the US market in 2014 was triple compared to 2011 [7]. Besides, Japan also quickly became the second-largest market for consuming EVs and all kinds of batteries supplied for EV production [7]. Additionally, the governments of Japan, China, and many European nations have shown interest in investing, manufacturing, and selling all kinds of EVs [7]. The study [8] presented detailed discussions and analyses about the future of EVs in the worldwide market. Besides, the environmental problems and the impact on distribution networks related to the broad use of EVs are also assessed. The study [9] estimated Lithium-ion battery State-of-Charge by using a modified Coulomb-Counting method and uncertainty evaluation. In [10], the authors investigate different strategies for developing heavy-duty electric vehicles using particular data, results, patents, and critical technologies cited from previous studies. The study mainly focused on the research published from 2010 to 2019, including more than 25,000 references in many subjects such as EV operation, controlling, thermal management, battery modules, and the facilities involved in serving EV operation.

In addition, previous studies have proven the significant impact of EVCSs on the economic and technical factors of the networks. As the number of electric vehicles increased to 10%, the load increased to 18% [11]. Behind the increase of load, the current on conductors increases, leading to a high voltage drop and power loss [12]. Furthermore, the number of peak hours also increased, causing the overload operation of distribution lines and transformers. The solutions to the negative results had to be proposed [13-14]. The previous studies have concerned the same or different objectives. All electric components had to operate within their allowable ranges [15]. Both technical and economic factors were selected to be significant [16]. The study [17] proposed a model to forecast the charging behavior of EVs in the IEEE-33 node and then presented the evaluation of charging behavior to the grid regarding power losses, node voltage drop, and load condition transformation. A bi-objective function, including voltage deviation and active power loss minimization, was considered in [18], while two costs regarding charging and capital factors were minimized in [19]. The study [20] reduced the carbon dioxide emission produced by vehicles. The study [21] presented a detailed analysis of the importance of implementing EVSCs in practice, focusing on electromobility and customer acceptance.

The study [22] minimized the total environment and operation costs when placing EVSCs in distribution systems. The study [23] considered the costs applied in [22] and other costs regarding charging time and waiting time of vehicles when vehicles are in EVSCs. The investment cost of EVSCs was reduced under the consideration of voltage limits, and reactive power loss was considered in [24]. The study [25] minimized the total costs of construction, operation, and maintenance. The study [26] indicated and reduced the influences of EVSCs on voltage and overload status at peak load hours. The study [27] showed unexpected effects on the housing market in California, America, when expanding the locations and capacity of EVSCs. The study [28] optimized the operation of capacitors to improve the voltage profile, and results from the obtained solutions were employed to determine the energy loss reduction. The study [29] reduced the emission from transformers at slack nodes in distribution systems and conventional vehicles. The study [30] maximized the generation from solar photovoltaic systems when installing EVSCs and renewable energies-distributed generators in distribution systems. The study [31] critically analyzes solar-powered EVCSs, while vehicle-to-grid (V2G) deployment is broadly accepted. The study [32] considered optimal reconfiguration for distribution power systems with EVSCs, capacitor banks, and distributed generators for a multi-objective function, including power loss, penetration level, and voltage. The study [33] proposed a model that combines photovoltaic systems and EVCSs to effectively reduce emissions and retain the balance of grid operation while EVs increase load demand.

The authors in [34] have proposed a multivariate model for tuning the related parameters of the EVCSs, including the EV charging start time, the EV charging end time, and the EV daily distance traveled. Using the mentioned model, the authors have successfully simulated the practical implementation of EVCSs in practice while maintaining their operation's inherent variability and complex dependencies. The study [35] offered an extensive view of planning, operation, coding, and standards for implementing ECVSs. Besides, challenges and future works for the sustainable growth of ECVS are also issued. As seen from the previous studies, the integration of ECVSs into the distribution grid was implemented by several methods to mitigate the negative impact on the original grid and primarily renewable energy-based distributed generators (REDGs). The presence of such REDG reduces the burden of the grid due to the increase of load demand and reduces toxic emissions. This implementation was highly influential in crowded cities and towns where diesel generators will exacerbate environmental problems.

In general, the previous studies had significant contributions to technical, environmental, and economic issues. The contributions can be summarized as follows:

- Improve the voltage profile of distribution systems when installing EVSCs combined with capacitor banks, photovoltaic systems, or renewable-based distributed generators.

- Reducing the waste of time thanks to the improvement in charging time, accelerating the transportation of all goods and commodities on the market, and enhancing the economic benefit.

➢ Reduce costs regarding investment, operation, and maintenance.

➢ Reduce the impacts of fossil fuels on the environment and gas emissions from conventional vehicles.

However, these studies have not clarified the penetration levels of EVSCs in distribution power systems and their impacts on the distribution power systems. Behind this, solutions to avoid the adverse effects have yet to be presented clearly. So, the study simulates the penetration levels of EVSCs to show the negative impacts on distribution power systems. Then, the capacitor placement solutions for each penetration level are applied and optimized. Two robust algorithms, including Equilibrium Optimizer (EO) [36] and War strategy optimization algorithm (WSO) [37], are applied to the work. EO has successfully reached high performance for optimizing the placement of solar power systems in distribution power systems [38], optimizing the placement of distributed generators in distribution power systems considering harmonic flows from the added distributed generators [39], solving the Directional Overcurrent Relays' linear and non-linear coordination [40]. WSO has been applied for optimal solar photovoltaic system parameter estimation [41], generation improvement of solar photovoltaic systems [42], and Air Pollutants Classification [43]. The two algorithms are applied for an IEEE 69-node DN to optimize the placement of EVCSs. The novelty of the paper is as follows:

➢ Test different numbers of EVCSs in the IEEE 69-node DN. The test can survey the impacts of EVCSs on the technical and economic issues.

➢ Consider two single objectives, including power loss and generation of RESs for different power demand levels of EVCSs.

➢ Apply EO and WSO for the simulation. The two algorithms are first applied to the problem of placing EVCSs in the IEEE 69-node DN.

By running EO and WSO for the system with different objectives and scenarios, the contributions of the paper can be summarized as follows:

➢ Found feasible and effective solutions for placing EVCSs in the IEEE 69-node DN. The power loss in the system with EVCSs' different power demands can be equal to that in the base system. Meanwhile, the voltage profile of the two systems is approximately the same.

➢ The voltage profile of the system with EVCSs is improved much better than that in the base system when optimizing the placement of RESs.

➢ The power loss of the system with EVCSs and RESs is reduced significantly compared to the base system.

2. Problem Formulation

The study focuses on the power loss reduction and voltage improvement. To reach the targets, two objective functions are implemented, meanwhile the same conditions are constrained.

2.1. Objective Functions

The objective functions are minimization of power loss and minimization of generation produced by RESs. The two single objectives are respectively presented as follows [44]:

$$\text{Minimize } \Delta P = \sum_{i=1}^{N_I} (3.I_i^2.R_i) \text{ (kW)} \tag{1}$$

$$\text{Minimize } P_{tc} = \sum_{j=1}^{N_J} (P_{c,j}) \text{ (kW)} \tag{2}$$

where ΔP is the total distribution line power loss; N_I is the number of distribution lines; R_i and I_i are the *ith* distribution line's resistance and current; P_{tc} is the RESs' total generation; $P_{c,j}$ is the *jth* RES's generation; and N_J is the number of RESs installed in the system.

2.2. Constraints

Active and reactive power balance constraints

The system is composed on the balance between demand and supply. This is called active and reactive power balances, as expressed by:

$$P_s = \sum_{n=1}^{N_N} P_{l,n} + TP_{L\text{-}1} + TP_{L\text{-}2} + TP_{L\text{-}3} + \Delta P - P_{tc} \tag{3}$$

$$Q_s = \sum_{n=1}^{N_N} Q_{l,n} + \sum_{i=1}^{N_I} (3.I_i^2.X_i) \tag{4}$$

where P_s and Q_s are the active and reactive power supplied by the slack node; $P_{l,n}$ is the active power demand of the load at the *nth* node; and N_N is the load number; $Q_{l,n}$ is the reactive power demand of the load at the *nth* node; and X_i is the reactance of the *ith* distribution line.

In the study, we suppose to build three EVCS types, including Level-1, Level-2, and Level-3. The full charging power for each electric vehicle in Level-1, Level-2 and Level-3 EVCS are 1.9, 4.0 and 100 kW, respectively [12]. The full charging power and efficiency of the EVSCs are expressed by (P_{L-1}, P_{L-2} and P_{L-3}) and (η_{L-1}, η_{L-2} and η_{L-3}). So, TP_{L-1}, TP_{L-2} and TP_{L-3} in Eq. (3) are the total power demand of all Level-1, Level-2 and Level-3 EVCSs, respectively.

Current and voltage constraint

When placing EVSCs on distribution power systems, current on distribution lines increases and voltage at nodes decreases, although the EVSCs are not placed on the lines or at these nodes. So, the line current and node voltage must be kept within their range as follows [45]:

$$I_i \le I_i^{UB} \tag{5}$$

$$Vol^{LB} \leq Vol_n \leq Vol^{UB}; n = 1, \dots, N_N \tag{6}$$

where I_i^{UB} is the maximum current limit of the *ith* distribution line's conductor; Vol_n is the voltage of the *nth* node; and Vol^{LB} and Vol^{UB} are the minimum and maximum voltage limits.

EVCS location limits

Each EVSC can be placed from Node 2 to Node N_N in each distribution power system; however, the same node cannot allow to place more than one EVSC [44]:

$$2 \leq Lo_{L-1,t},\ Lo_{L-2,y},\ Lo_{L-3,u} \leq N_2 \tag{7}$$

$$Lo_{L-1,t} \neq Lo_{L-2,y} \neq Lo_{L-3,u} \tag{8}$$

where $Lo_{L-1,t}$, $Lo_{L-2,y}$ and $Lo_{L-3,u}$ are the *tth*, *ith* and *uth* Level-1, Level-2 and Level-3EVCS, with t=1, …, $N_{S\text{-}L1}$; y=1, …, $N_{S\text{-}L2}$; and u=1, …, $N_{S\text{-}L3}$; and $N_{S\text{-}L1}$, $N_{S\text{-}L2}$ and $N_{S\text{-}L3}$ are the Level-1, Level-2 and Level-3 EVCS numbers.

3. Equilibrium Optimizer

The section presents the application of EO for a general optimization problem. The EO structure comprises population initialization, population evaluation, new population update, and outstanding population selection. Among the steps, EO's new population update is different from that of others, and this step is clearly expressed in the study as follows:

$$S_x^{new} = S_{top} + (S_x - S_{top}).\partial + \frac{\emptyset}{\delta} \times (1 - \partial) \tag{9}$$

where S_x^{new} is the new *xth* solution; S_{top} is one out of the five promising solutions, including the four best solutions and the average point of the four best solutions. S_x is the *xth* solution in the current population, which needs to be updated. In addition, other parameters are obtained by:

$$\partial = 2 \times sign(R_{0-0.5}) \times [e^{-F_{Gn}} - 1] \tag{10}$$

$$F_{Gn} = \left(1 - \frac{Gn}{Gn_{Max}}\right)^{\frac{Gn}{Gn_{Max}}} \tag{11}$$

$$\emptyset = \partial.R_{0-0.5}(S_{top} - F_{Gn}.S_x) \tag{12}$$

where $R_{0-0.5}$ is a randomly produced value within 0 and 0.5; and Gn and Gn_{Max} are respectively the current and maximum iteration.

4. Numerical Results

In this section, EO and WSO are applied to optimize the site of EVCSs and capacitors' location and rated power in the standard IEEE 69-node DN, presented in Figure 1 [45]. The system's data, including load demand at nodes and resistance and reactance of lines, were taken from [44]. The total active power loss of the system is 225.01 kW [46]. As indicated in [12], each Level-1, Level-2, and Level-3 charger has rated power of 1.9, 4.0, and 100 kW. We suppose that the capacity of the Level-1, Level-2, and Level-3 EVCSs is, respectively, 1,000, 1,000 and 10 electric vehicles. The charge efficiency is selected to be 0.92. The electric power of each Level-1, Level-2, and Level-3 EVCS is 206.5, 435 kW, and 1087 kW. Three study cases corresponding to different EVCS numbers and the total active power of all added EVCSs are reported in Table 1.

Table 1. Three study cases' EVCS number and total power

Case	Number of Level-1 EVCSs	Number of Level-2 EVCSs	Number of Level-3 EVCSs	Total power of all EVCSs (kW)
1	1	1	1	1,728.5
2	3	3	1	3,011.5
3	4	4	2	4,740.0

For each study case above, four scenarios are implemented as follows:

- Scenario 1: No consideration of the optimal placement of RESs and voltage constraint.
- Scenario 2: Optimize the site and rated power of RESs with the voltage range of 0.925-1.0 Pu.
- Scenario 3: Optimize the site and rated power of RESs with the voltage range of 0.95-1.0 Pu.

For each scenario, the two algorithms are coded for fifty runs on Matlab program language on a personal computer with a 4.0-GB RAM and a 2.0-GHz processor. The population and iteration numbers are set to 50 and 1000 for the two algorithms. The selection can assure that the two algorithms have the same fitness evaluation number [47], which is a fair comparison criterion for meteheuristic algorithms [48].

Note that the type of EVCS used in the research is the AC charging station, characterized by Level 1, Level 2, and Level 3. The reasons for choosing this type of EVCS are as follows:

- AC charging stations provide alternating current to charge EVs, and those charging stations do not require the converter inside to convert AC to DC [49].
- They are commonly found in homes, workplaces, and public parking areas.
- They can provide different charging levels, currently offering more selection for the consumer based on the status of their vehicles. As stated in [12], Level 1, with a low voltage value, often around 120 V, is usually placed at home and provides a slow charging time. In contrast, Levels 2 and 3 are primarily seen in public parking areas or company headquarters. Those levels allow the customer to charge their vehicles with a more considerable voltage value of 240V or higher, and the charging time will be faster but come with a higher service fee.
- AC chargers use the vehicle's onboard charger to convert AC power to DC for the battery.

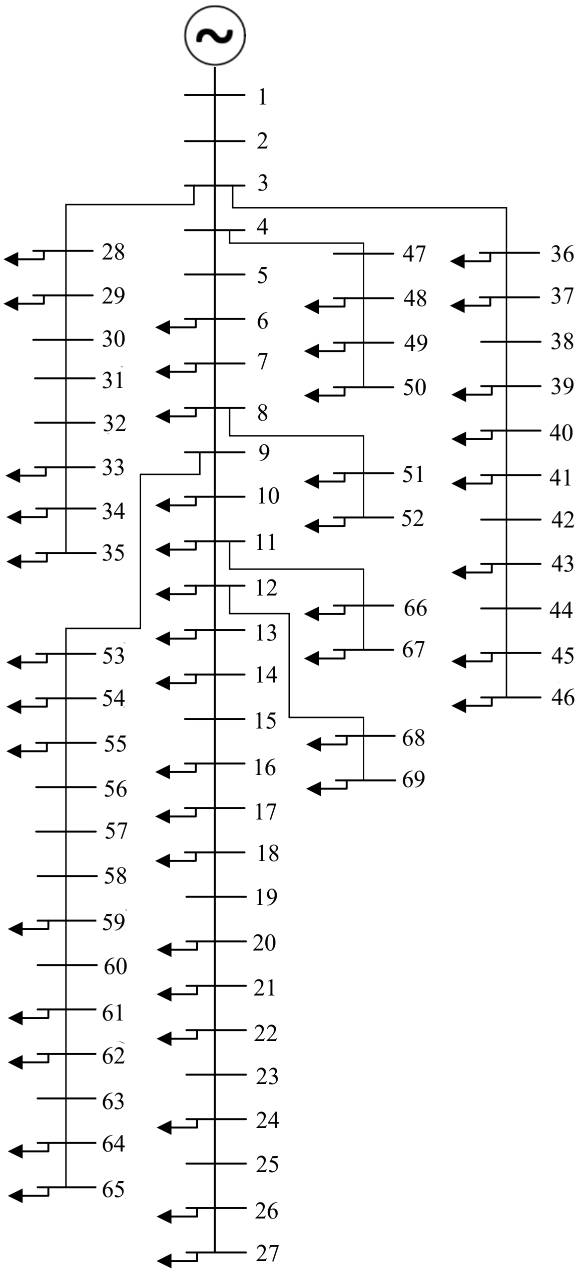

Fig. 1. The IEEE 69-node DN.

In practice, DC-EVCSs are less popular than AC-EVCSs due to their engineering characteristics, which require more complex engineering standards in operation and maintenance and higher initial capital costs. However, DC-EVCSs, or fast charging stations, are also seriously improved and developed for better usability, focusing on the following terms:

➢ Reduce the power loss in the charging process, as addressed in [50], while the authors compared the standard and fast charging stations.

➢ The integration of DC-EVCSs also requires accompanying solutions similar to AC-EVCSs to mitigate the adverse effects on the grid, especially in terms of active power loss and voltage drop in the grid, as concluded by authors in [51].

➢ Solving the problems regarding the pulse rectifier and DC/DC converter to enhance the system's efficiency, as conducted in [52]. Besides, the usability of DC-EVCSs can be improved more by developing a converter that provides the capability of transforming power in both directions at different levels and scales, as performed in [53].

4.1. Results for Power Loss Minimization Objective Function

This section presents the results obtained by EO and WSO for the power loss minimization shown in Eq. (1). From the fifty trial runs, the best power loss values in Scenario 1 are plotted in Figure 2. The summary of the fifty runs is reported in Table 2. Table 2 indicates that EO could find the same loss as WSO for Case 1 but a smaller power loss than WSO for Case 2 and Case 3. Figure 2 indicates that fifty optimal solutions of EO have higher quality than those of WSO once EO's loss is under WSO's at each run. So, EO is more suitable than WSO for Scenario 1 with three different cases.

Table 2. Summary of results obtained by EO and WSO for Scenario 1

Loss (kW)	Method	Case 1	Case 2	Case 3
The best	EO	225.056	225.281	226.167
	WSO	225.056	225.298	226.428
The worst	EO	225.061	225.477	227.121
	WSO	225.259	226.097	256.183
The mean	EO	225.057	225.350	226.407
	WSO	225.104	226.097	234.814

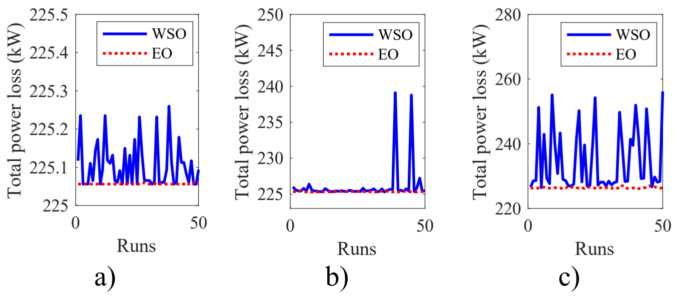

Fig. 2. Power loss of fifty trial runs obtained by EO and WSO for Case 1 (a), Case 2 (b) and Case 3 (c).

4.2. Results for Power Loss Minimization Objective Function

In this section, EO has been run to minimize the total generation of RESs shown in Eq. (2). The results are summarized in Table 3. We focus on columns 3 and 4 with the compensated power minimization objective. For Case 1 (i.e., installing one Level-1 EVCS, one Level-2 EVCS, and one Level-1 EVCS with a total demand of 1,728.5 kW), the distribution power grid needs 329.34 kW from added RESs for Scenario 2 (i.e., voltage of nodes is constrained in the range between 0.925 and 1.0 Pu), and 980.28 kW for Scenario 3 (i.e., Voltage of nodes is constrained in the range between

0.95 and 1.0 Pu). Similarly, for Case 2 and Case 3 (i.e., total demand of 3,011.5 and 4,740 kW for added EVCSs), the grid needs about 330 kW and 980 kW from added RESs. However, the power loss increases when the power demand of the added EVCSs increases. For Scenario 2, it is 176.87 kW for Case 1, 178.94 kW for Case 2, and 191.26 for Case 3. For Scenario 3, it is 116.22 kW for Case 1, 119.00 for Case 2, and 123.35 for Case 3. Clearly, Scenario 3 reached a smaller loss than Scenario 2 at the same case. It means that when voltage of nodes increases from 0.925 to 0.95 pu, the power loss is decreased.

In summary, the power grid needs higher compensated reactive power from RESs to improve the minimum voltage from 0.925 to 0.95 Pu. In addition, when the voltage profile is improved, the power loss also reduces as a result of reactive power compensation.

Table 3. Summary of results obtained by EO for Minimizing total compensated reactive power

Study case	Results	Scenario 2	Scenario 3
1	ΔP (kW)	176.87	116.22
	P_{tc} (kW)	329.34	980.28
2	ΔP (kW)	178.94	119.00
	P_{tc} (kW)	329.57	977.44
3	ΔP (kW)	*191.26*	123.35
	P_{tc} (kW)	329.86	980.90

4.3. The Voltage Profiles of the System with EVCSs and RESs

This section discusses the voltage profile of the IEEE 69-node DN for different simulations reported in the two sections above. Figure 3, Figure 4, and Figure 5 present voltage profiles of scenarios and objectives in Case 1, Case 2 and Case 3.

Figure 3 indicates that the Base system before installing EVSCs and the modified system with EVCSCs and Scenario 1 have approximately the same voltage profile. Note that the loss of the base system and the modified system with Case 1 and Scenario 1 is approximately equal, about 225 kW. By constraining the minimum voltage up to 0.925 and 0.95 pu, the profiles of active power compensation minimization are much better than the base case and loss minimization without voltage constraint. The red curve associated with the voltage constraint up to 0.925 Pu has nodes 57-65 under 0.95 Pu. Meanwhile, the blue curve associated with the voltage constraint up to 0.95 Pu has a higher voltage quality. Figure 4 and Figure 5 have the same shape as Figure 3. The voltage profile in Scenario 3 is the best, and that in Scenario 2 is the second best. The profile in the base system and Scenario 1 are approximately the same.

In summary, the voltage profile in the IEEE 69-node DN is approximately the same for the base case and other cases of Scenario-1 without voltage constraint. However, EO has been applied to reach the power loss minimization. As we know, the voltage of the node has impacts on the power loss via the equation below [54]:

$$\Delta P_{x-y} = \frac{P_{x-y}^2 + Q_{x-y}^2}{U_y^2} . R_{x-y} \quad (13)$$

In Eq. (13) $\Delta P_{x-y}$is the power loss on the distribution line between nodes x and y. $P_{x-y}$and $Q_{x-y}$are the active and reactive power flows through the distribution line between nodes x and y; $R_{x-y}$is the resistance of the distribution line between nodes x and y; and U_y is the voltage at node y, where node y is the end-terminal of the distribution line.

So, when the voltage increases, the power loss also decreases, and the use of EO has led to the voltage increase as a result.

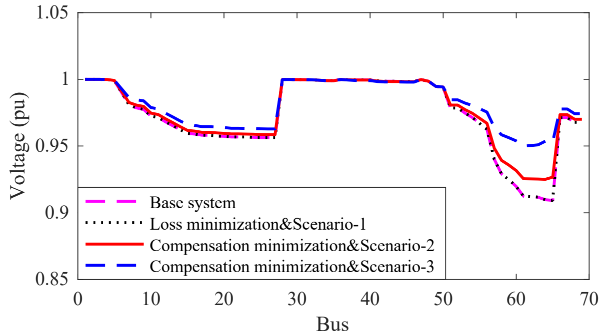

Fig. 3. Voltage profiles for scenarios and objectives in Case 1.

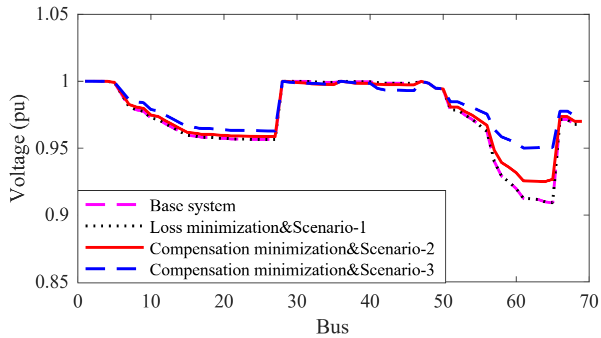

Fig. 4. Voltage profiles for scenarios and objectives in Case 2.

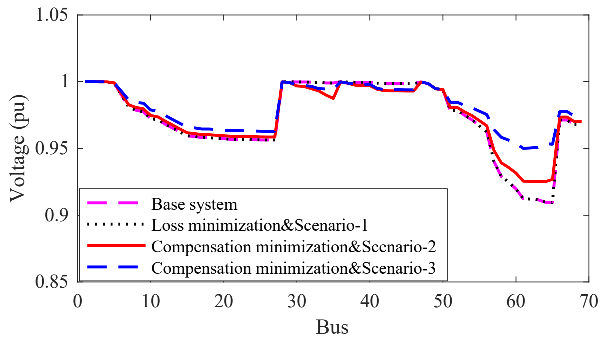

Fig. 5. Voltage profiles for scenarios and objectives in Case 3.

5. Conclusion

The paper has applied Equilibrium Optimizer (EO) and War strategy optimization algorithm (WSO) for optimally placing EVCSs in the IEEE 69-node DN. Two single objective functions, power loss minimization, and added active power compensation minimization, are implemented. For the first objective, the node voltage was not constrained because RESs were not used. For the second objective, the minimum node voltage was constrained, not smaller than 0.925 and 0.95 Pu. For every single objective, three power demand levels from EVCSs are simulated by running EO and WSO, including 1,728.5, 3,011.5, and 4,740 kW. The simulation results were summarized and concluded as follows:

- EO was more suitable than WSO. EO's power loss was smaller than WSO's for the three power demand levels. In addition, the fifty loss values of EO for each power demand level were approximately the same as the smallest loss, whereas those from WSO fluctuated significantly.
- The power loss was around 225 kW, and the minimum voltage was around 0.9 Pu when installing EVCSs with three power demand levels. The results indicated that applying metaheuristic algorithms could benefit the DN significantly even if the power demand of the EVCSs increased from 1,728.5 kW to 4,740 kW. So, DNs could be flexible for building EVCSs.
- By using RESs with a generation of under 1,000 kW, the power loss could be improved from 225 kW to about 123 kW, and voltage could be increased from 0.9 to 0.95 Pu even if the additional power demand was 4,740 kW.

In general, the study's contribution was very significant for distribution networks, which were expanded to install many EVCSs. The use of metaheuristic algorithms could bring advantages to economy and technique. However, the study also coped with shortcomings that should be improved in future work, such as the feasibility of locations for installing EVCSs in real regions or real cities, the consideration of renewable energies in DNs, and so on. In future work, these factors will be considered for simulation results and discussion.

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Author Contributions

Minh Quan Duong was responsible for the conceptualization, validation, resources, data curation, software development, and project administration. Chau Le Thi Minh and Trung Hieu Trinh jointly contributed to the methodology, formal analysis, investigation, original draft preparation, review and editing, visualization, supervision, and funding acquisition.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and publication of this article.

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