

OPTIMAL PLACEMENT OF SOLAR PHOTOVOLTAIC SYSTEMS AND ELECTRIC VEHICLE CHARGE STATIONS IN DISTRIBUTION POWER GRIDS, CONSIDERING THE CONSTRAINTS OF AREAS AND LOCATIONS

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Abstract. The increasing integration of photovoltaic (PV) generation and electric vehicle charging stations (EVCSs) into distribution power networks can significantly affect power losses and voltage performance, depending on their location and operating conditions. This study investigates the impacts of optimally installed PV units and EVCS location on the performance of a distribution power network. The Equilibrium Optimizer (EO) is employed to determine the optimal locations and rated powers of three PV units in the IEEE 33-node distribution network. The optimal PV units are located at Nodes 16, 25, and 31, resulting in a reduction in total active power loss from 0.211 MW in the base network to 0.090 MW, corresponding to a 57.3% reduction. Subsequently, an EVCS with a rated power of 1.080 MW is installed at three locations in turn: the end node (Node 33), the middle network (Node 6), and near the substation (Node 2). With the generation of PV units, the total active power losses are 0.175, 0.128, and 0.081 MW, respectively. In contrast, in the network without the generation of PV units, the losses increase to 0.425, 0.312, and 0.211 MW, respectively. The results demonstrate that EVCS location has a substantial influ-

ence on distribution network losses, with charging stations located farther from the substation producing greater impacts. Moreover, the generation of PV units effectively mitigates the adverse effects of EV charging by supplying power locally and improving voltage performance.

Keywords: Optimal placement, solar photovoltaic systems, electric vehicle charge stations, distribution power grids, area constraint, location constraints.

1. Introduction

The rapidly increasing installation of electric vehicle charge stations (EVCSs) is a hot topic in modern power distribution networks. As governments adopt EVCSs in power systems, the concurrent integration of EVCSs' charging infrastructure and renewable power sources (RES), especially solar photovoltaic units, into distribution grids has emerged as a core study field [1]. Distribution power systems must simultaneously satisfy the general power demand of previously available loads, the demand of EVCSs and power

losses on all distribution lines, challenging the demand coordinated planning and advanced optimization methodologies [2].

From a generation side, optimally renewable energy dispatch across power systems is very necessary for maintaining cost efficiency and grid stability. Multi-objective optimization issue dispatch strategies for vehicle-to-grid (V2G) enabled EVCSs fleets in microgrids with renewable power sources have proved to improve load profiles and reduce operation and maintenance costs [3]. At the transmission level, the target of minimizing the total electricity production costs for large-scale power systems with solar, wind and thermal units has been addressed using the Elk Herd Optimizer, offering a benchmark for operating performance [4]. The selection of an appropriate applied algorithm was useful to find both continuous and discrete decision variables for the optimization problems, such as the Starfish Optimization, Sand Cat Swarm Optimization, Weighted Average, and Mirage Search Optimization algorithms [5]. More complicated issues were considered, such as photovoltaic inverters to counter cyberattacks [6]. Battery energy storage systems (BESS) played a dual role in (high voltage direct current) HVDC grids by absorbing surplus renewable variability [7] and serving the power demand of EVCSs [8]. More complicated constraints, such as transmission line power flow limits and reliable grid operation [9]. Data-driven cooperative dispatch frameworks for power source-power grid-load demand-energy storage systems under the stable and effective operation of renewable and storage integration were proposed to improve operational robustness under measurement uncertainty [10].

Optimal siting and penetration level of EVCSs installation is a complex spatial decision problem in distribution power systems. The dynamic determination of optimal EVCS locations, BESS sizing and location was investigated to ensure that it supports all load demand in peak hours without overloading the feeder status [11]. Energy efficiency analysis of EVCS demonstrated that the structure and operation of stations (including power electronics topology) significantly affect the power quality of power grids [12]. The impacts on the power grid's power quality were reduced by installing more solar photovoltaic

units [13]. Constraints of nodes for placing EVCS were considered in distribution networks integrated with distributed generation (DG), applying heuristic approaches and reaching near-optimal global solutions [14]. The EVCSs installation in an urban distribution system, namely the Shanghai case study, showed the importance of determined location and capacity planning [15]. The optimal penetration level of photovoltaic units in distribution networks has been determined using the Pied Kingfisher Optimizer, balancing engineering and economic objectives across multiple feeder configurations [16]. The optimal integration of DG into distribution networks using a serial hybridization approach has achieved highly technical performance, economic viability, and environmental objectives [17], and demand response markets [18]. Capacitor placement was also a promising solution to reduce losses, improve voltage profiles, and defer network upgrades [19] and yielded great benefits [20].

The integration of EVCS into power systems with wind turbines, solar photovoltaic arrays, and thermal storage was studied to optimize charging convenience, renewable self-consumption, and grid curtailment [21], while maintaining acceptable user waiting times [22]. Unbalanced radial systems have been proposed to solve for benefit and technical objectives [23]. The long-term operational costs and network reliability were considered to be the most important [24]. Simultaneous optimization of station locations, sizes, and charging schedules was suggested in the study [25]. The BESS and solar photovoltaic array integration demonstrated that metaheuristic algorithms could reliably identify multi-objective problems with EVCSs for multiple performance criteria [26]. The economic factor was proposed to be considered in the grid with EVCSs [27, 28]. The Aquila Optimization Algorithm was used to place EVCSs, reaching competitive performance against conventional gradient-based methods and earlier swarm algorithms [29]. In addition, high-variability environments [30], power distribution grid congestion [31] and benefit maximization [32] were also considered for the system with EVCS placement. In general, the studied ob-

jectives were reached as expected for the grids with renewable power sources.

The Equilibrium Optimizer (EO) is a metaheuristic algorithm that is very potential and more effective than about ten other popular metaheuristic algorithms and high-performance optimizers [33]. Furthermore, recent studies have demonstrated the effectiveness and continuing development of EO for solving complex optimization problems. An adaptive EO with information enhancement was proposed for global optimization in [34], while an EO-based hybrid harmony search algorithm was developed for real-world optimization problems in [35]. EO and its hybrid variants have also been successfully applied to renewable-energy and power-system problems. A hybrid Grey Wolf-EO method was experimentally validated for maximum power point tracking in photovoltaic systems in [36], while EO was employed to solve a multi-objective economic-emission dispatch problem in a microgrid with high renewable-energy penetration in [37]. EO has also been applied to other complex optimization problems, including vehicle detection and classification [38]. In addition, a recent review summarized the development of EO variants and their applications in various engineering and optimization problems [39]. In this study, EO is used specifically to obtain an optimized PV configuration. Then, one EVCS is installed at the end node, middle network and near the substation in the IEEE 33 nodes to reduce the total branch losses. Therefore, the purpose of adopting EO is to provide an effective optimization mechanism for PV placement and sizing, rather than to demonstrate its superiority over other metaheuristic algorithms. The novelties are summarized as follows:

- Consider the EVCS location effects on distribution network losses and voltage profiles at different feeder positions.
- Coordinated consideration of the generation of PV units and EVCS integration under different EVCS placement scenarios with and without PV unit generation.

- EO is applied to find the optimal placement of three PV units to mitigate the adverse impacts of EVCS installations.
- Try different locations for EVCS installation and survey the loss and voltage for the cases.

The remainder of this paper is organized as follows. Section 2 formulates the general problem of installing PV units and EVCSs. Section 3 describes the applied optimization method. Section 4 presents simulation results on standard distribution test system. Section 5 concludes the obtained results and indicates contributions.

2. Problem Formulation

The problem of optimally placing PV units and EVCSs in distribution power grids is formulated in this section. The objective is to minimize the total distribution line power loss and enhance the voltage quality of the network while satisfying all system operating constraints, such as active and reactive power balance, generation limits and thermal limits of lines. The integration of renewable energy resources and EVCSs significantly affects the power flow characteristics, voltage stability, and network reliability. The objective and constraints are expressed as follows:

2.1. Objective Function

In this study, the total active power loss is minimized as shown in the following model:

$$P_{Loss} = \sum_{li=1}^{N_{Brs}} I_{li}^2 \times R_{li} \quad (1)$$

where, P_{Loss} is the total active power losses (kW); I_{li} (in Ampere) is the operating current of the li th distribution branch ($li = 1, 2, \dots, N_{Brs}$); N_{Brs} is the number of distribution branches in the network; and R_{li} is the self resistance of the branch li .

2.2. Constraints

1) Active Power Balance Constraint

The total generated active power must satisfy the active load demand and system losses:

$$P_{\text{Grid}} + \sum_{p=1}^{NSPVs} P_{\text{SPV},p} = \sum_{m=1}^{NB} P_{D,m} + \sum_{e=1}^{NEVCSs} P_{\text{EVCS},e} + P_{\text{Loss}} \quad (2)$$

where:

- P_{Grid} is the active power supplied from the utility grid,
- $NSPVs$ is the number of solar PV systems,
- $P_{\text{SPV},p}$ is the active power generated by solar PV unit p ,
- $P_{D,m}$ is the active load demand at bus m ,
- NB is the number of nodes in the network,
- $NEVCSs$ is the number of EVCSs,
- $P_{\text{EVCS},e}$ is the active charging demand of EVCS e .

2) Reactive Power Balance Constraint

The reactive power equilibrium of the system is expressed as follows:

$$Q_{\text{Grid}} + \sum_{p=1}^{NSPVs} Q_{\text{SPV},p} = \sum_{m=1}^{NB} Q_{D,m} + \sum_{e=1}^{NEVCSs} Q_{\text{EVCS},e} + Q_{\text{Loss}} \quad (3)$$

where:

- Q_{Grid} is the reactive power supplied from the utility grid,
- $Q_{\text{SPV},p}$ is the reactive power generated by PV unit p ,

- $Q_{D,m}$ is the reactive load demand at bus m ,
- $Q_{\text{EVCS},e}$ is the reactive power consumption of EVCS e ,
- Q_{Loss} is the reactive power loss of the network.

3) PV Generation Limits

The operating power of each PV unit must remain within its allowable limits:

$$P_{\text{SPV},p}^{LB} \leq P_{\text{SPV},p} \leq P_{\text{SPV},p}^{UB}, \quad p = 1, 2, \dots, NSPVs \quad (4)$$

where:

- $P_{\text{SPV},p}$ is the active power generated by the p^{th} solar PV unit,
- $P_{\text{SPV},p}^{LB}$ is the lower bound operating limit of the p^{th} solar PV unit,
- $P_{\text{SPV},p}^{UB}$ is the upper bound operating limit of the p^{th} solar PV unit.

4) EV Charging Station Limits

The charging power of each EVCS is constrained as follows:

$$P_{\text{EVCS},e}^{LB} \leq P_{\text{EVCS},e} \leq P_{\text{EVCS},e}^{UB}, \quad e = 1, 2, \dots, NEVCSs \quad (5)$$

where:

- $P_{\text{EVCS},e}$ is the charging power demand of the e^{th} EVCS,
- $P_{\text{EVCS},e}^{LB}$ is the minimum allowable charging power of the e^{th} EVCS,
- $P_{\text{EVCS},e}^{UB}$ is the maximum allowable charging power of the e^{th} EVCS.

5) Utility Grid Power Limits

The imported power from the utility grid must satisfy:

$$P_{\text{Grid}}^{LB} \leq P_{\text{Grid}} \leq P_{\text{Grid}}^{UB} \quad (6)$$

where:

- P_{Grid} is the active power imported from the utility grid,
- P_{Grid}^{LB} is the minimum allowable imported power from the utility grid,
- P_{Grid}^{UB} is the maximum allowable imported power from the utility grid.

6) Voltage Constraints

The voltage magnitude at each bus must remain within the permissible operating range as shown in the following model:

$$Vol_m^{LB} \leq Vol_m \leq Vol_m^{UB}, \quad m = 1, 2, \dots, NB \quad (7)$$

where:

- Vol_m is the voltage magnitude at bus m (p.u.),
- Vol_m^{LB} is the minimum allowable voltage magnitude at bus m ,
- Vol_m^{UB} is the maximum allowable voltage magnitude at bus m .

7) The location constraint of PV units and EVCSs in the grid

The installed PV units and EVCSs have the locations within all the nodes in distribution networks. So, the location must follow the constraints below:

$$2 \leq L_{\text{SPV},p} \leq NB \quad (8)$$

$$2 \leq L_{\text{EVCS},e} \leq NB \quad (9)$$

where, $L_{\text{SPV},p}$ and $L_{\text{EVCS},e}$ are the location of the p th PV unit and the e th EVCS.

8) The constraint of operating current

The current when the distribution line is working must not be higher than the maximum allowable current of the conductor. So, the constraint below is requested.

$$0 \leq I_{li} \leq I_{li}^{max} \quad (10)$$

where, I_{li} and I_{li}^{max} are the operating value and the maximum allowable value of the current on the li th distribution branch.

3. Applied Equilibrium optimizer

Each search particle is initialized based on the population size and problem dimensionality through uniform random sampling within the feasible bounds, as expressed below [33]:

$$SP^{Init} = SP^{lb} + rf_1 \times (SP^{ub} - SP^{lb}) \quad (11)$$

where:

- SP^{ub} , SP^{lb} : The upper and lower bounds of optimized control variables,
- SP^{Init} : The initial randomly produced solution set,
- rf_1 : Random factor between 0 and 1.

The most optimal solution set OSP^{Set} , which is selected from the whole population, is expressed as follows:

$$OSP^{Set} = [SP_{(1)}; SP_{(2)}; SP_{(3)}; SP_{(4)}; SP_{(Avg)}] \quad (12)$$

where:

- $SP_{(1)}, SP_{(2)}, SP_{(3)}, SP_{(4)}$: the four most effective solutions, including the most, second-most, third-most, and fourth-most effective solutions,
- $SP_{(Avg)}$: the average solution of the four most effective solutions.

EO uses one old particle SP_i^{cur} from the existing population and one randomly drawn particle from the candidate set SP_k^{Set} to produce an updated particle SP_i^{upd} :

$$SP_i^{upd} = SP_k^{Set} + (SP_i^{cur} - SP_k^{Set}) \times Cb + \frac{G}{ld \times V_e} \times (1 - Cb) \quad (13)$$

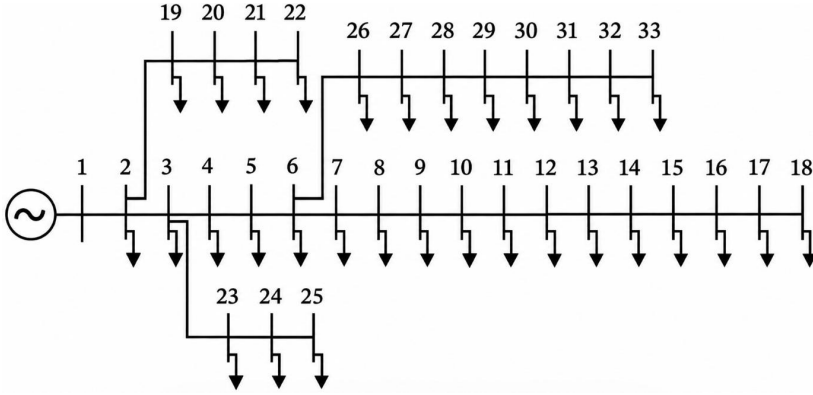


Figure 1: The single line illustration of the IEEE 33-node DPN.

In the above equations, V_e is set equal to 1, and other parameters are calculated as follows:

$$Cb = c1 \times \text{sign}(\text{rand} - 0.5) \times (e^{-ld \times \tau} - 1) \quad (14)$$

$$G = Cb \times [PCT \times (SP_k^{\text{Set}} - ld \times SP_i^{\text{cur}})] \quad (15)$$

$$PCT = \begin{cases} 0.5 \times \text{rand}, & \text{rand} \geq 0.5 \\ 0, & \text{else} \end{cases} \quad (16)$$

$$\tau = \left(1 - \frac{T_{\text{cur}}}{T_{\text{max}}}\right)^{\left(c2 \times \frac{T_{\text{cur}}}{T_{\text{max}}}\right)} \quad (17)$$

where, T_{cur} , T_{max} are the current computation iteration and maximum computation iteration; rand and ld are random numbers generated between 0 and 1; $c1$ and $c2$ are set to 2 and 1, respectively.

4. Results and Discussions

To evaluate the impact of EVCSs and solar photovoltaic systems on the distribution grid, EO is employed and coded in MATLAB 2018a programming language. The program codes and MATLAB are run on a personal computer with an Intel(R) Core(TM) i7-14700 processor (2.3 GHz) and 8 GB of RAM. An IEEE 33-node DPN is considered for installing EVCSs and Solar PV units. The grid has the load demand with the active power of 3715 kW and the reactive power of 2300 kVar. The lines' data and loads' data that are employed are taken from [40]. The single-line network is shown in Figure 1.

After building the network in PowerWorld, the results of power flows and losses are reported in Figure 2. The total system load is 3.715 MW and 2.300 MVar, with total active and reactive power losses of 0.211 MW and 0.144 MVar, respectively. The rated voltage of the grid is 12.660 kV.

4.1. Optmizing the location and rated power of three PV units

In this section, we apply EO to find the best power and location of the three PV units. The population size and iteration number are set to 20 and 200 for each run, and twenty runs are executed to find the best solution. The average time of one run is 2.4 seconds. As a result, the three optimal locations are nodes 16, 25 and 31, with the rated power of 0.466 MW, 0.6599 MW, and 0.6785 MW. The simulation model in Powerworld is shown in Figure 3. The total power loss is 0.09 MW and 0.061 Mvar.

Figure 4 presents the comparison of the branch loss of the base grid and the grid with three optimally installed PV units. The total active power loss decreases from 0.211 MW to 0.090 MW, a reduction of 0.121 MW, or 57.3% of the base grid's total loss. Approximately all branches of the modified grid have smaller losses than the others of the base grid. The largest individual branch loss, occurring in Branch 2 at the feeder head, is reduced from 51 kW to 21 kW,

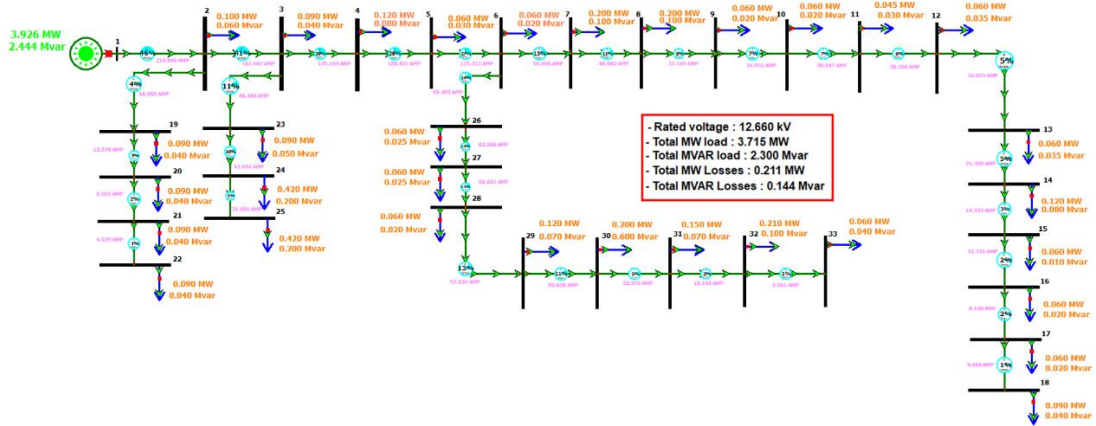


Figure 2: Power flows and loss information of the base grid.

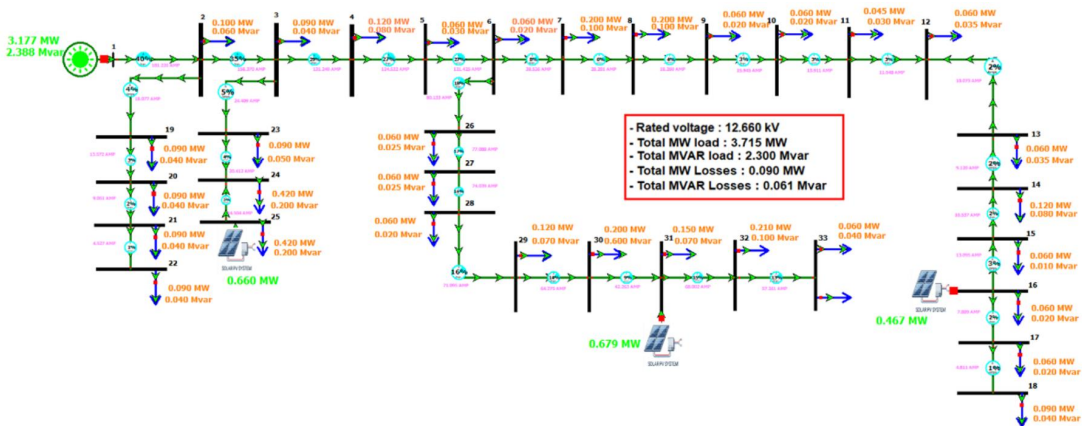


Figure 3: Power flows and loss information after installing three PV units.

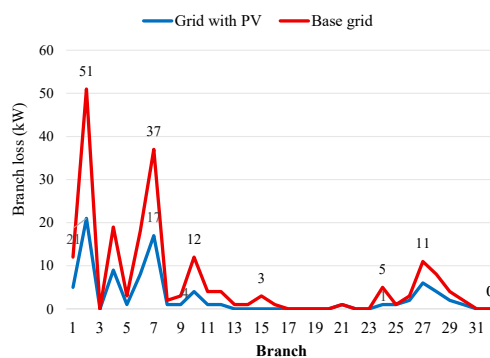


Figure 4: Comparison of branch loss for base grid and the grid with PV units.

from the three PV units installed at Nodes 16, 25, and 31.

4.2. Installation of EV charge stations

In this section, EVCS with the rated power of about 25% of the total load is respectively installed at the end node, middle node and the near substation node.

1) Case 1: EVCS is installed at Node 33

corresponding to a reduction of 58.8%. This reduction is mainly the contribution of 1.804 MW

Figure 5 illustrates the results of power flows and losses for the IEEE 33-node network with

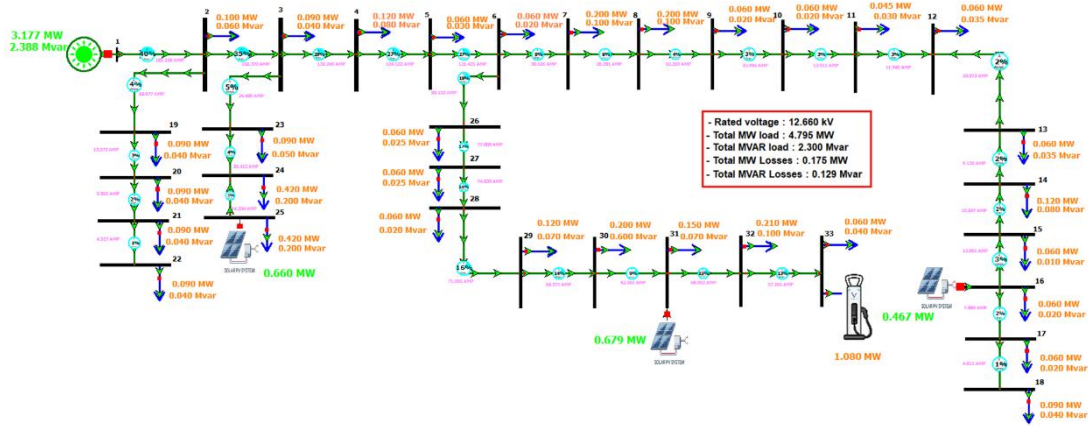


Figure 5: The IEEE 33-node network with three PV units and one EVCS at node 33.

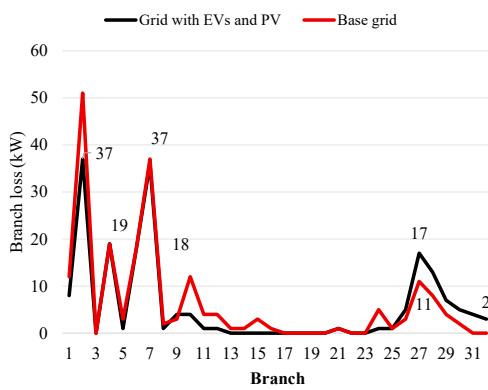


Figure 6: Comparison of branch loss for base grid and the grid with PV units and EVs at node 33.

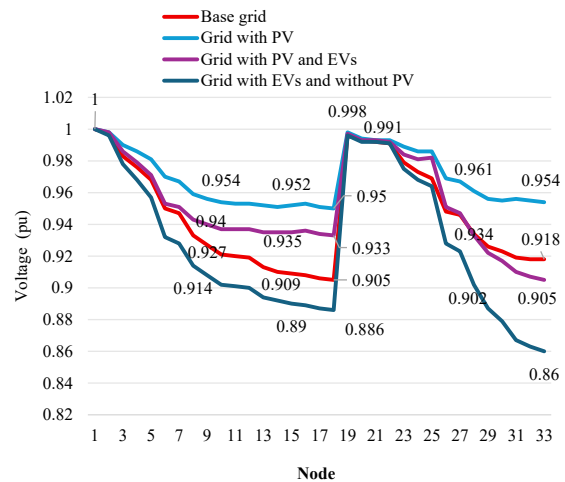


Figure 8: Comparison of voltage profile for the case of installing EVs at node 33.

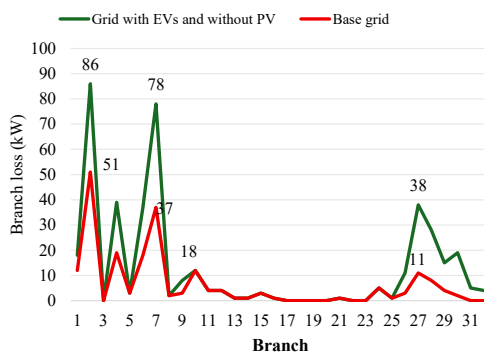


Figure 7: Comparison of branch loss for base grid and the grid without PV units and EVs at node 33.

three PV units and one EVCS. The total load increases 4.795 MW; meanwhile, the active and

reactive power losses change to 0.175 MW and 0.129 Mvar. Clearly, the sum of the branch losses decreases from 0.211 MW to 0.175 MW, corresponding to a modest reduction of 17%. The main reason is the power of 1.080 MW from the EV charging station and the power of 1.8 MW from three PV units.

Figure 6 compares the branch losses of the base grid with those of the grid with three PV units and EVs at Node 33. Almost all branches in the base grid have higher loss values than in the grid with EVs and PV units, except for branches 26–32.

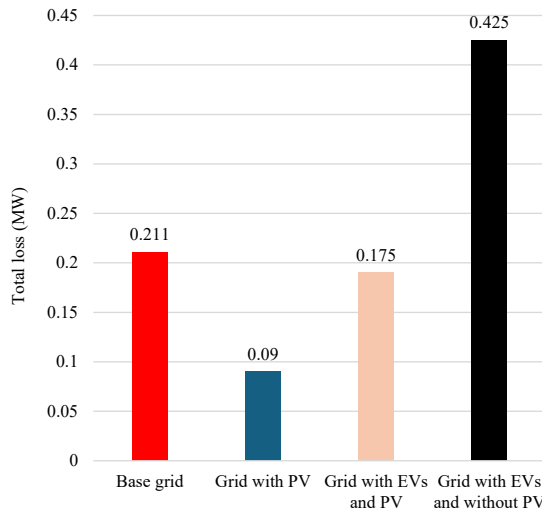


Figure 9: Comparison of power loss for the case of installing EVs at node 33.

When PV units cannot supply power to the grid, the loss on branches increases, as shown in Figure 7. In this case, the maximum branch loss, occurring in Branch 2, increases from 51 kW to 86 kW, corresponding to a 68.6% increase. In addition, a new local peak of approximately 38 kW appears in Branch 27. This increase in branch losses is directly associated with the 1.080 MW EV charging load at Node 33, which must be supplied from the substation, thereby causing substantial additional current to flow through the upstream branches, particularly Branches 27–32.

The corresponding voltage profiles of the grid with different installations of electric components are shown in Figure 8. The grid with the three PV units has the best profile since its highest voltage is 0.952 pu. The grid with EVs but without PV units has the worst profile, with many values under 0.9 pu. The base grid has the third-best voltage profile, and the grid with PV units and EVs has the second-best voltage profile. Clearly, the contribution of PV units is significant in the case of producing power for the grid.

Figure 9 summarizes the total active power losses under the four operating scenarios. The total loss decreases from 0.211 MW in the base case to 0.090 MW with the three PV units only, corresponding to a 57.3% reduction. When the

EVs with 1.080 MW are added at Node 33, the total loss increases to 0.175 MW, about a 10.0% reduction relative to the base case but an increase of 111.1% compared with the PV units only case. Without PV unit installation, the total loss further increases to 0.425 MW, corresponding to increases of 101.4% relative to the base case and 372.2% relative to the PV-only case. Overall, the increase in loss demonstrates that the EVs at the end node of the feeder substantially erode the loss-reduction benefits provided by the generation of the PV units: the total loss increases from 0.090 MW to 0.175 MW, effectively eliminating approximately 91% of the loss reduction achieved by the PV generation alone. When PV generation is completely removed, the total losses more than double relative to the base grid, highlighting the important role of local PV generation in mitigating the adverse impacts of the EVCSs on the distribution grid.

2) Case 2: EVCS is installed at Node 6

Figure 10 illustrates the results of power flows and losses for the IEEE 33-node network. Figure 11 summarizes the total active power losses under the four operating scenarios when the EV charging station is located at Node 6. The total loss decreases from 0.211 MW in the base case to 0.090 MW with the generation of PV units. When the EVs are installed at Node 6, the total loss increases to 0.128 MW, about 32.7% of the base case, but a 57.8% increase compared with the case with three PV units. In the case without the PV generation, the total loss further increases to 0.312 MW, representing an increase of 47.9% relative to the base case and 246.7% relative to the case with the three PV units.

The corresponding voltage profiles are presented in Figure 12. The smallest voltage is 0.889, 0.905, 0.935 and 0.95 pu for the grid with EVs and without PV units, the base grid, the grid with PV units and EVs, and the grid with PV units only. The results indicate that the load is very important in keeping the voltage within an allowable value range. The grid with EVs but without PV units cannot operate stably because the voltage at many nodes is about 0.889 pu.

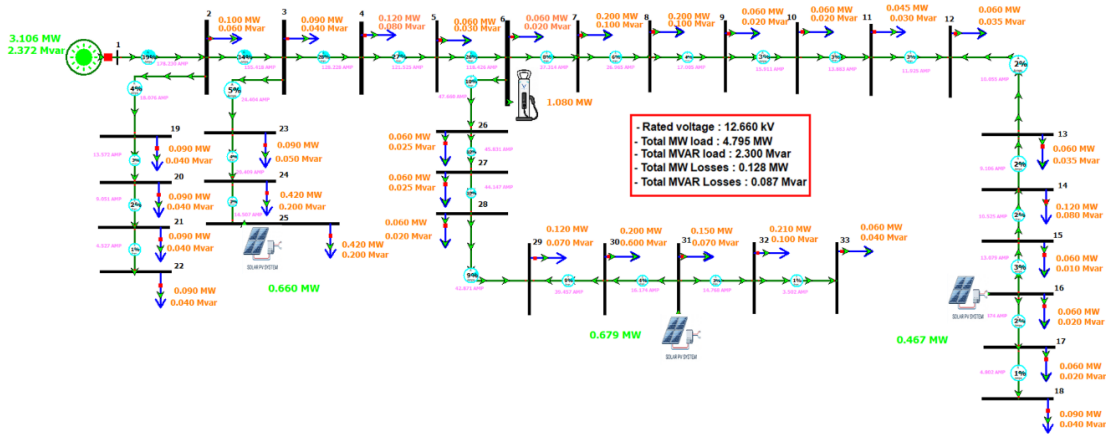


Figure 10: Power flows and loss information after installing three PV units and EVs at node 6.

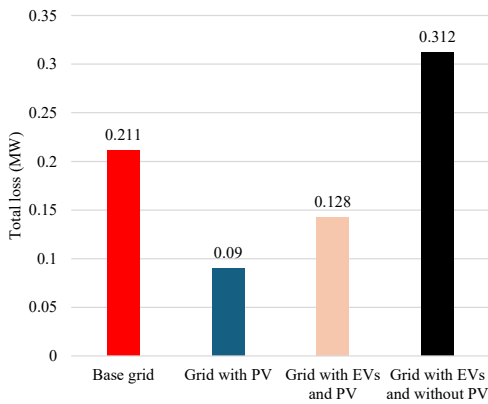


Figure 11: Comparison of power loss for the case of installing EVs at node 6.

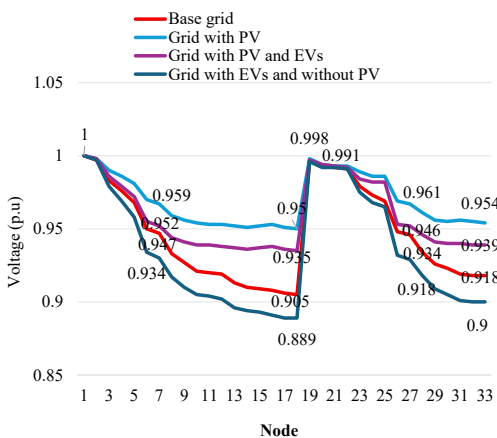


Figure 12: Comparison of voltage profile for the case of installing EVs at node 6.

3) Case 3: EVCS is installed at Node 2 (Near the main substation)

Figure 13 illustrates the results of power flows and losses in the IEEE 33-node network for the case of installing the EVCS at node 2. Figure 14 presents the voltage profiles when the charging station for EVs is located at Node 2. With both PV units and the EVs, the minimum bus voltage is 0.950 pu at Node 14. This value is identical to the minimum voltage obtained in the case with PV units only, indicating that the station of EVs at Node 2 has no measurable impact on the worst voltage of the distribution grid. Without the generation of PV units, the minimum voltage decreases to 0.905 pu at Node 18. Therefore, at this location, the EVs do not have a negative impact on the grid.

Figure 15 summarizes the total active power losses for the different operating scenarios with the EV charging station at Node 2. The total loss is equal for the base grid and the grid with EVs and without PV units. This indicates that the installation of more loads at a location near the substation does not have a high impact on the grid loss.

4.3. Summary of the Effect of EVCS Location

Figure 16 compares the total active power losses for EV charging stations located at Nodes

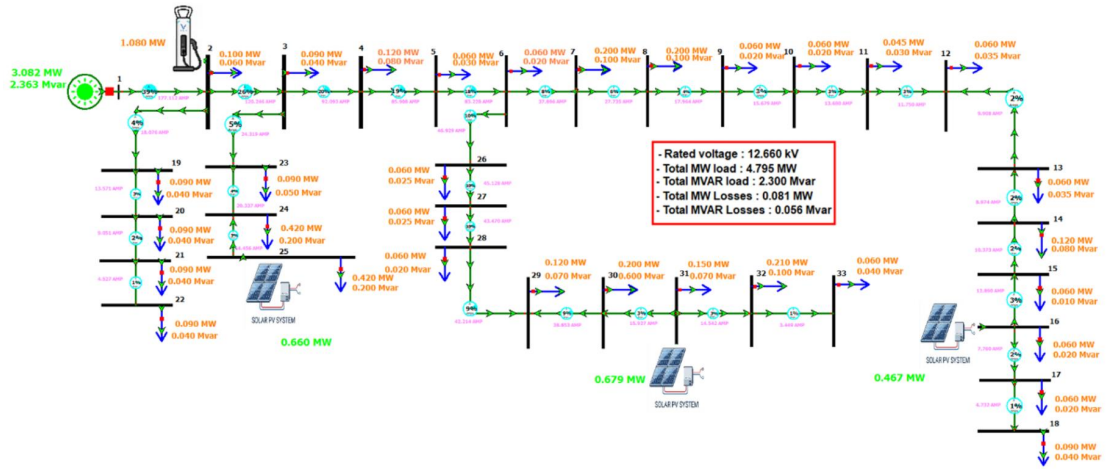


Figure 13: Power flows and loss information after installing three PV units and EVCS at node 2.

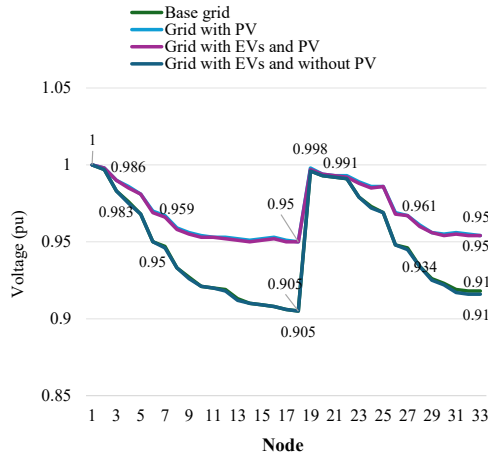


Figure 14: Comparison of voltage profile for the case of installing EVs at node 2.

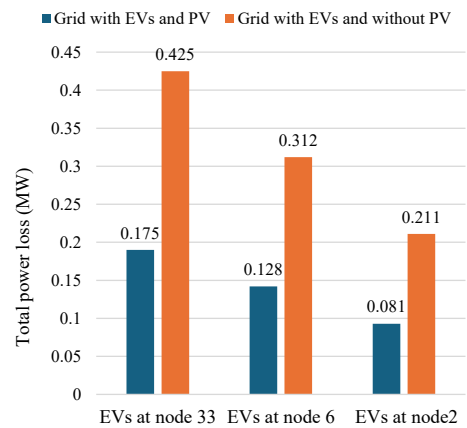


Figure 16: Comparison of total power loss for different locations of EVs.

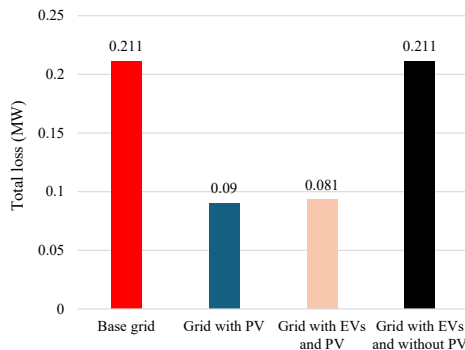


Figure 15: Comparison of power loss for the case of installing EVs at node 2.

33, 6, and 2, with and without PV support. With the generation of PV units, the losses are 0.175, 0.128, and 0.081 MW at Nodes 33, 6, and 2, respectively, which correspond to 10.0%, 32.7%, and 55.9% of the base grid. Without the generation of the PV units, the losses increase to 0.425, 0.312, and 0.211 MW, respectively. These values correspond to increases of 101.4%, 47.9%, and 0.0% relative to the base case. At each location, removing the PV units can increase the total loss by approximately 2.2 times. The value demonstrates that the generation of PV units halves the network losses regardless of the location of the EVs.

5. Conclusions

This study investigated the impacts of the generation of the installed PV units and EVCS location on the power loss and voltage performance of an IEEE 33-node distribution power network. The Equilibrium Optimizer (EO) was employed to determine the optimal locations and rated powers of three PV units in the IEEE 33-node distribution power network. Then, PowerWorld was run to calculate power flows, node voltage and losses on all branches for different cases of installing EVCS on nodes in the grid. The main contributions and findings of this study can be summarized as follows:

- EO found the optimal PV unit locations at Nodes 16, 25, and 31, with a total installed capacity of approximately 1.804 MW. The total active power loss was reduced from 0.211 MW to 0.090 MW, corresponding to a 57.3% reduction.
- The impact of EVCS location on distribution network performance was systematically investigated by installing a 1.080 MW EVCS at three representative locations: Node 33 at the end of the feeder, Node 6 in the middle of the network, and Node 2 near the substation.
- With PV generation, the total active power losses were 0.175, 0.128, and 0.081 MW for EVCSs located at Nodes 33, 6, and 2, respectively. Compared with the PV-only case, the EVCS increased the total active power loss by 111.1% at Node 33, 57.8% at Node 6, and only 3.3% at Node 2.
- Without PV generation, the total active power losses increased to 0.425, 0.312, and 0.211 MW for EVCSs located at Nodes 33, 6, and 2, respectively. The minimum voltage decreased to approximately 0.89 pu when the EVCS was installed at Node 33, whereas it remained at 0.950 pu when the EVCS was installed at Node 2.
- The results demonstrate that EVCS location has a significant impact on distribution network performance, with EVCSs located farther from the substation causing greater

power losses and voltage degradation. PV generation can effectively mitigate these adverse effects by supplying power locally and improving the voltage profile.

Overall, the results indicate that the placement of PV units and EVCS locations should be carefully considered. The generation of PV units can compensate for the additional power demand from EVCSs, while locating high-power EVCSs closer to the substation can further limit network losses and voltage degradation. These findings provide useful guidance for coordinated planning of installed PV units and EV charging infrastructure in distribution networks as electrification increases.

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