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Optimal Siting and Sizing of Electric Vehicle Charging Stations and Distributed Generators in Distribution Systems by Meta Heuristic Techniques

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Abstract: The augmented interest towards sustainable transportation initiatives has led to a substantial expansion of the transportation sector's adaptation to electric vehicles (EVs). As the EV load cause an additional burden to the existing distribution system, may lead to the increase in actual power losses, a reduced voltage profile, and declined margins for voltage stability. In order to mitigate the impact of EV load on the Radial Distribution System (RDS), it becomes mandatory to strategically deploy Electric Vehicle Charging Stations (EVCSs) and Distributed Generators (DGs) at best locations within the system. The present study proposes an optimization technique with the simultaneous placement and sizing of EVCS and DG in the distribution systems. The problem at hand is framed with the objective of minimizing the real power losses and enhance the Voltage Stability Index (VSI) of the electrical distribution system using Grasshopper Optimization Algorithm. Simulation studies were conducted on the widely recognized IEEE 69-bus test systems in order to investigate and analyze the performance of the system.

Keywords: *Distribution System, Voltage Stability Index, Grasshopper optimization, Power Loss, Voltage profile*

1. Introduction

The rise in the penetration of EVs in the distribution system might place an additional burden during charging [1]. Over the past decade, this technology has experienced significant growth with impressive statistics reflecting the increasing adoption of EVs worldwide, by 2023's close, the global tally of sold electric vehicles is predicted to reach 14.5 million [2]. Hence, the charging infrastructure has expanded considerably to meet the rising demand. However, as electric vehicles become more prevalent, new challenges have emerged, especially concerning the power burdens they place on the electrical grid during the charging process. The increasing number of EVs being charged simultaneously can strain the power distribution network, leading to potential issues such as [3- 6].

a) Overloaded Transformers: High concentrations of EV charging in specific areas can overload local transformers, causing voltage fluctuations and potential equipment failures.

b) Peak Demand: During peak hours, when many EVs are charging at once, the sudden surge in electricity demand can put a strain on the power system, leading to increased operational costs and potential power outages.

c) Grid Congestion: In areas with inadequate charging infrastructure or limited grid capacity, the increased demand for electricity from EV charging can lead to grid congestion and reduced power quality.

d) Balancing Supply and Demand: The process of incorporating a significant number of EVs into the electricity grid requires effective load management to balance supply and demand and avoid grid instability. Author [4], discussed load impact on feeders.

e) Infrastructure Upgrades: The electrical system may need to be upgraded in order to accommodate the growing number of EVs with corresponding increase in the increased load, which can be costly and time-consuming.

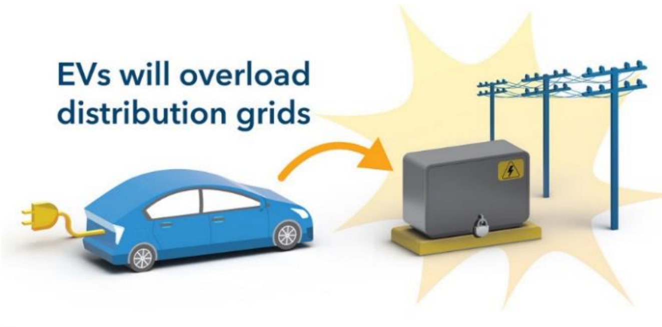

Fig. 1. Illustration of Overloading distribution network during charging [4]

To address these challenges, utilities, governments, and other stakeholders are actively working on implementing different smart solutions, in that one solution is decentralized renewable energy sources, i.e optimum allocation of EV charging station and DG's can help mitigate the power burdens on the grid caused by electric vehicles. The organizing of the paper with the Literature review in section 2, followed by problem formulation and methodology in section 3 and 4, with the results and discussion in section 5 and finally concluded in section 6.

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2. Literature Survey

The location of EVCSs, DGs, and DSTATCOMs which is most effective, determined by Arvind Pratap et al., using the African Vultures Optimization Algorithm (AVOA) [7]. The goal is to improve voltage stability while lowering actual power loss and voltage deviation indices. Additionally, by comparing the AVOA findings with those of the grey wolf optimizer (GWO) method, the AVOA results are verified. On 33 buses, 69 bus, and 136 bus systems, the proposed methodology is tested.

The best way to organize and size a garage for electric vehicle parking is discussed. by Faddel et al., in this research using a bilayer Pareto formulation of the multi objective optimization problem. The goal of the optimization formulation is to minimize distribution system operator losses and voltage fluctuations. while also maximizing revenues for the person who invested in the electric vehicle parking garage [8]. The ideal location and dimensions of the parking garage were chosen using a statistical metric as a deciding factor. The choice of the ideal size and location was also subjected to sensitivity analysis to demonstrate the impact of the various goals.

In order to monitor the voltage profile on a regular basis using the discharging way of operation, Amudha et al., suggests an optimization strategy to control the optimal location for an EV parking lot (EVPL) in the distribution system [9]. The suggested hybrid approach, also known as the BCMPO technique, combines the balancing composite motion optimization (BCMO) with the political optimizer (PO). By placing the EVPL in the best location possible, the suggested method is employed for a reduction in voltage swings, power loss, and active power consumption.

Through a multi-objective approach, Bitencourt et al., suggests a technique for locating optimal areas for semi-fast electric vehicle chargers (CS) at a community level. To design CS service zones that account for technological and mobility constraints, it employs a hierarchical clustering technique. Additionally, depending on the user's charging habits, it takes into account uncertainties connected to the capacity of the CS determined by the EV load profile [10]. The Pareto Frontier approach is used to assist in choosing the best site for the CS while taking utility and EV user preferences into account.

The placement of an EVCS and a DG unit in a distribution system is proposed by Chowdhury et al., as a straightforward apparent power loss-driven approach, taking into consideration time-dependent load models. While considering factors like traffic, weather, the electric vehicle's proportional distance driven, and the lack of an EVCS, the original State of the PEV is reconstructed by Dynamic Fault Tree Analysis and Bayesian optimization techniques. [11]. The best possible arrangement will take into consideration several sets of PEV with proportional distance coverage.

This study proposes a long-term method for scheduling and allocating public fast-charging stations (PFCSs), solar distributed generation (SDG) systems, and battery energy storage (BES) systems. Battery deterioration is taken into account, and a solution is found by reducing the energy loss, the voltage deviation index, the initial investment, and the ongoing operating and maintenance expenses of the PFCS, SDG, and BES [12]. This is solved using a two-stage optimization procedure. A radial distribution system with 33 nodes and its related traffic network is selected as a test case. Harris Hawks Optimization (HHO) and GWO are used to resolve the allocation issue.

A balanced radial distribution system's ideal DG unit size has been investigated in this study by Palanisamy et al., using an updated optimization approach known as the Ant Lion Optimizer (ALO). To determine the best bus locations for the installation of numerous DG units, an integrated technique combining both the voltage sensitivity factor and the loss sensitivity factor are used in this process [13]. Through the mitigation of the distribution network's overall real power loss, the ALO algorithm determines the suitable sizing of DG units for the respective identified bus location.

In order to maximize the effectiveness of the deployment of EVCSs inside the distribution network while simultaneously accommodating a significant number of PV systems located on randomly dispersed rooftops, Tounsi Fokui et al., proposes a hybrid bacterial foraging optimization algorithm and particle swarm optimization (BFOA-PSO) approach [14]. In order to reduce the real and reactive power losses, increase voltage stability index, and reduce average voltage deviation index, the formulation of the optimization problem is as a multi-objective optimization problem. Case networks are based on the IEEE 69 node distribution system.

To achieve the concurrent allocation and dimensioning of fast charging stations (FCSs) and DGs, Battapothula et al., outlined an optimization problem with several objectives is addressed in the proposed system, with constraints including the possible EVs in all zones and the maximum count of FCSs allowed by the road and electrical infrastructure [15]. To reduce the number of EV users that leave the system, the amount of power lost in the network, the money spent on developing the FCS, and the voltage drop across the grid, the challenge is posed as a mixed integer non-linear optimization problem (MINLP). The Non-Dominated Sorting Genetic Algorithm II (NSGA II) is used to solve the MINLP.

A DC microgrid in the work proposed by Krishnamurthy et al., comprises of fuel cells, solar photovoltaic systems, and wind power systems as sources associated with the public utility grid. In order to minimize the detrimental effects of their installation on distribution network operating parameters, EVCS sizing, and RES siting are all evaluated simultaneously. The location of the charging station is a problem that must take into account many objectives, with the power loss (VRP) index, reliability, cost, and voltage stability in terms of their objective functions [16]. The location and capacity of RES and EVCS are selected as the key variables. Analyses of performance are conducted using modified IEEE 33-bus and 123-bus radial distribution systems. The modified teaching-learning-based optimization (TLBO) approach is used to optimize the placement and size of an EVCS and RESs.

The existing literature provides the best placement and dimensions of DGs alone in the distribution system, placement of EVCS and load constraints with static and dynamic cases with constraints of a change in the voltage profile or the power loss in the distribution system. Only few of the researchers have gone through with simultaneous placement of EVCS and DGs with the constraints of Voltage drop and power loss in the grid with various optimization algorithms.

3. Problem Formulation

The main objective of this research is to minimize the PLoss of the Distribution System and the total voltage variation that had been identified across all buses. This will be achieved through the optimal integration of DGs and EVCS.

$$\sum_{k=1}^{24} P^{Loss}\ (k) \text{ ---------------------------(1)}$$

Where

P^{Loss} is the power loss at node k

$$P^{Loss}(k) = \sum_{k=1}^{24} I^2 . R_k \text{ ----------------------(2)}$$

I is the current, R_k is the Resistance

Constraints on the power balance

$$\sum_{k=1}^{24} P_G\ (k) + \sum_{k=1}^{24} P_{DG}\ (k) = \sum_{k=1}^{24} P_D\ (k) + P^{Loss}(k) + P_{EV}(k) \text{ ----------(3)}$$

Where

$P_G(k)$ is the Supply Power from distribution system

$P_{DG}(k)$ is the Power generated by DG

$P_D(k)$ is the Power demand

$P^{Loss}(k)$ is the Power Loss

$P_{EV}(k)$ is the EV load

Voltage Constraints

$$V_{k,min} \le |V_k| \le V_{k,max} \text{ -----------------------------------(4)}$$

DG size constraints

$$P_{k,min}^{DG} \le P_k^{DG} \le P_{k,max}^{DG} \text{-------------------------------------(5)}$$

The EV power charging bound within the equation limits

$$P_{ch,k} \le P_{ch,k}^{max} \text{ ---(6)}$$

4. Methodology

The proposed study makes the following contributions:

1. The utilization of VSI approach is employed in order to choose the best location of DGs at nodes with weaker voltage levels and EVCS at nodes with stronger voltage levels within the distribution system.
2. The present study employs a GOA to ascertain the optimal sizes of DGs for assigned load levels.
3. The true power loss and voltage profile is analyzed by integrating EVCSs and DGs into the distribution network simultaneously.
4. The efficacy of the suggested GOA is evaluated in comparison to the current optimization techniques.

4.1 Voltage Stability Index

By measuring the network stability in radial configurations with the use of this voltage stability index, there is possibility to take necessary action if the index shows a low degree of stability. The proper placement of DGs and EVCS may be determined using VSI on each bus. With this strategy, the optimal location is determined by taking into consideration the entire system load requirement for each hour. In order to locate the appropriate locations, this study utilizes VSI. Equation (7) may be used to determine a thorough examination of VSI. The computed value of VSI serves as the basis for rating and evaluating all buses. Based on the VSI the values which are near to 1 are selected as the strong bus for the placement of EVCS and the values that are close to 0 are reported to be the weak buses for locating the DGs. This technique is utilized for positioning of the EVCS at the strong bus and DGs in the weak bus.

$$VSI = 2V_s^2 V_r^2 - V_r^4 - 2V_r^2(PR + QX) - (P^2 + Q^2)|Z|^2 \text{ ---- (7)}$$

Vs & Vr are the sending and receiving voltages across the nodes

P&Q are the active and reactive powers

R, X&Z are the Resistance, Reactance and Impedance.

4.2 Grasshopper Optimization Algorithm

The Grasshopper optimization algorithm (GOA) is a computational method with Grasshoppers' foraging habits served as inspiration. This evolutionary technique aims to solve optimization problems by simulating the collective intelligence observed in swarms of grasshoppers during their search for food [17]. The GOA serves as a valuable tool in the field of optimization, specifically the best metrics for sizing and allocation of DG units to achieve desired objectives. The mathematical equations employed in the study of GOA are derived by leveraging the inherent food source seeking behaviors exhibited by swarms of grasshoppers. The grasshopper swarming behavior is known to be influenced by various factors, including social interaction among individuals, the force of gravity, and the movement of air currents [18].

The following equation provides a mathematical expression of the grasshopper's location inside the search area.

$$X_i = S_i + G_i + A_i \text{ ------------------------(8)}$$

where X_i is the grasshopper's current location, S_i is the social interaction, G_i is the gravitational force acting on the grasshopper on i, and A_i is the advection of the wind. The use of a parameter r between [0, 1] further provides unpredictability in Xi.

The mathematical equation used to solve the optimization issue is provided by

$$X_i^d = c\left(\sum_{j=1\ j\neq i}^{N} c\ \frac{ub_d - lb_d}{2} s\left(\left|x_j^d - x_i^d\right|\right) \frac{x_j - x_i}{d_{ij}}\right) + \hat{T}_d \text{ --- (9)}$$

where, X_i is the ith grasshopper, ub and lb are the boundaries in the dth dimension.

With regards to the iteration count, the coefficient c decreases the comfort zone as follows:

$$c = c_{mxa} - l\frac{c_{max} - c_{min}}{L} \text{ ---------------(10)}$$

where L is the most iterations that can be made and l is the current iteration.

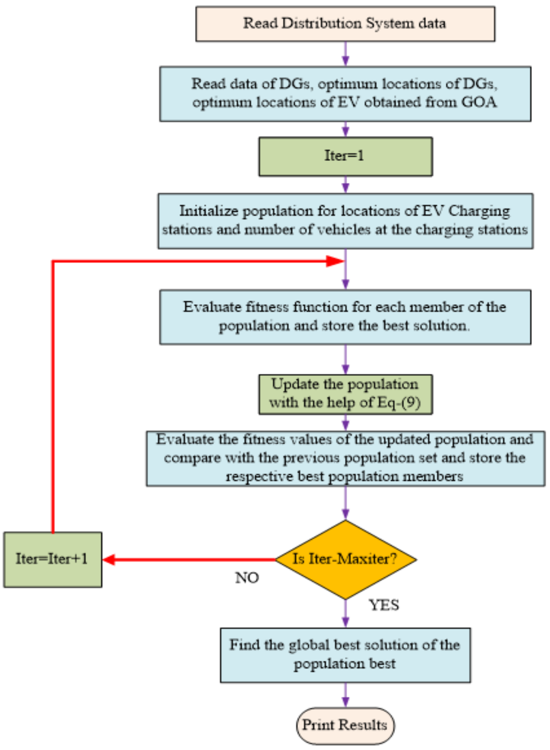

Fig. 2. Optimal sizing of EVCS and DG using GOA

5. Results and Discussion

In the proposed article, an IEEE69-bus test systems have been used to assess the efficacy of the suggested algorithm for the positioning and size of the DG and EVCS simultaneously. The real and reactive load powers of the 69-bus system are 3.8 MW and 2.69 MVAr respectively [19].

The optimal location of EVCS 3,6,10 buses are identified as the buses which are strong for the placement of EVCS and the DGs are located at weak buses 11 ,17 and 61 are determined using VSI method.

After the optimal location of EVCS and DGs, the sizing is obtained using the GOA. The simulated results have been considered for particular hour in day using different cases by GOA.

Case 1: The power loss in the base case of IEEE 69 test system are 225.0014 kW, voltage profile 0.9678 p.u and voltage stability index is 0.8773 p.u.

Case 2: With only one DGs integrated, the losses were decreased in the system to 63% using GOA method.

Case 3: With only two DGs integrated, the losses were decreased in the system to 67.3% using GOA method.

Case 4: With the three DGs integrated, the losses were decreased in the system to 69.58% using GOA method.

The results are shown in Table 1. for all the different cases.

Table 1. Using GOA simulated results with different cases (Static)

Different cases	Location of Bus No.	Sizing of DG in kW	P_{loss} in kW	% Dec P_{loss}	V_{min} in p.u.	VSI $_{min}$ In p.u.
Base Case	NA	NA	225.0014	NA	0.9678	0.8773
With 1 DG	61	1872.706	83.2231	63	0.9796	0.9209
With 2 DGs	11 61	915.6762 1718.971	73.6101	67.3	0.9899	0.9601
With 3 DGs	11 17 61	526.9108 380.4599 1718.921	68.4272	69.58	0.9916	0.9666

The evaluation of proposed method's efficiency of GOA performance is compared with other existing methods and the same represented in Table 2. Compared to all other optimization methods using 3 DGs reduced the power loss and enhance the voltage profile and stability the same presented in Figures 3, 4 and 5.

Table 2. GOA comparison with other existing algorithms

Optimization Method	SFSA [20]	QOSIMBO [21]	TLBO [22]	Proposed GOA
Size and area of DGs in kW	527.3 (11) 380.5 (18) 1719.82 (61)	618.9 (09) 529.7 (17) 1500 61)	591.9 (15) 818.8 (61) 900.3 (63)	526.9108 (11) 380.4599 (17) 1718.921 (61)
3 DGs Power Loss in kW	69.428	71.3	72.406	68.4272
% of reduced Power loss	69.14	68.31	67.82	69.58

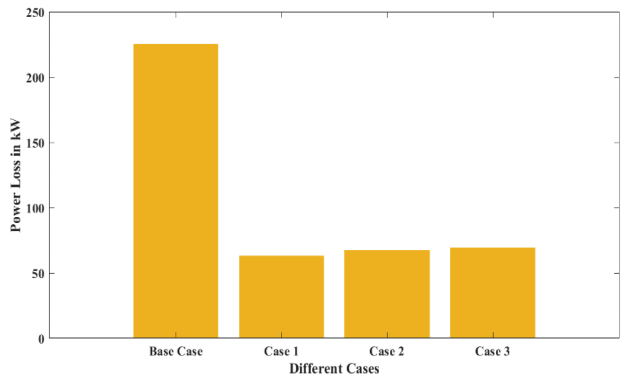

Fig. 3. Power loss comparison for different cases

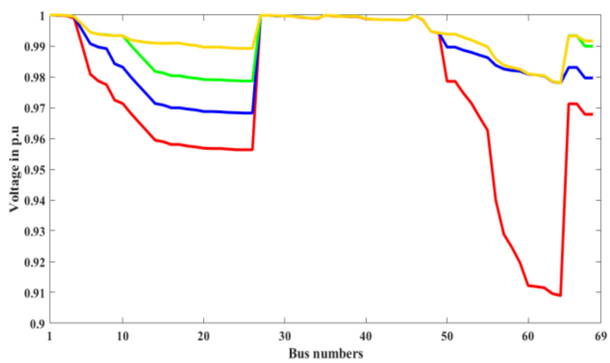

Fig. 4. Voltage profile for 69 bus

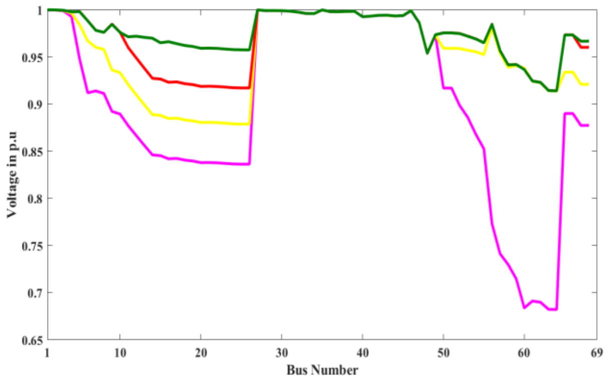

Fig. 5. VSI for 69 bus

5.1. Simultaneous installation of EVCS and DGs with Dynamic Analysis

In this section, based on power demand curve, the results are simulated on IEEE 69 test system using GOA method for different cases. Figure 6 represents power demand curve for 24hrs.

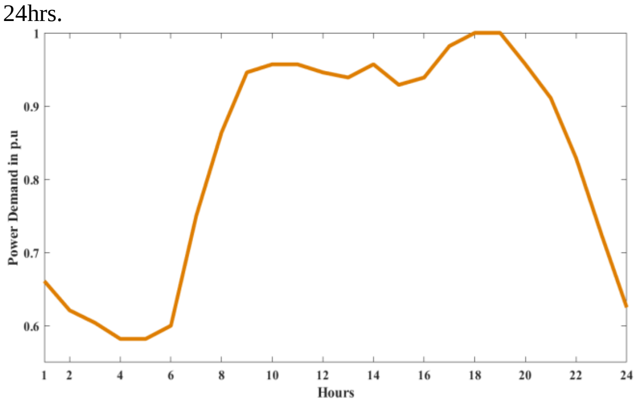

Fig. 6. Power demand for 24 hrs

The base case of 24 hrs power loss for IEEE 69 test system is 3746.383 kW. After integration of 3 DGs to the distribution system the power loss is reduced to 1176.149kW which is 68.6% of loss reduction. The same are represented in Table 3.

Table 3. Power loss using GOA for 24 hrs (Dynamic)

S.No	Base Case Power Loss	3 DGs Power Loss
1	92.6006	29.98607
2	81.18967	26.41547
3	76.58996	24.99391
4	70.85562	23.18992
5	70.85562	23.18667
6	75.52911	24.67434
7	121.0302	38.71991
8	163.856	51.58508
9	199.362	62.07688
10	204.4367	63.50671
11	203.0453	63.1055
12	199.362	62.0374
13	196.1716	61.09731
14	204.4367	63.51251
15	191.6663	59.7867
16	196.1716	61.10952
17	216.2509	66.96093
18	225.0014	68.4272
19	225.0014	68.4272
20	204.4367	63.50471
21	183.7105	57.44989
22	149.9173	47.43131
23	112.6126	36.14486
24	82.29349	26.76464

Table 4. Scheduling of the 3 DGs

S. No	DG1	DG2	DG3
1	329.05	248.068	1119.35
2	352.975	209.28	1060.72
3	319.713	231.228	1013.61
4	287.813	223.127	1003.74
5	359.779	180.575	990.114
6	392.262	184.443	1012.31
7	409.572	266.362	1297.84
8	473.558	298.378	1487.55
9	605.856	302.789	1612.8
10	541.157	329.251	1631.23
11	504.848	336.177	1646.8
12	531.42	330.739	1640.64
13	538.549	318.647	1612.44
14	533.436	322.792	1630.85
15	495.611	321.098	1604.55
16	537.72	331.029	1624.39
17	594.432	346.085	1692.56
18	571.834	352.573	1722.75
19	591.427	335.818	1712.41
20	539.416	323.566	1639.78
21	488.452	320.476	1563.66
22	465.087	284.789	1427.94
23	393.662	239.298	1243.2
24	328.377	209.384	1069.73

Table 5. Vmin, VSI min comparison with base case

Vmin in p.u		VSI min in p.u	
Base Case	3 DGs	Base	3 DGs
0.941822	0.98944	0.786447	0.95801
0.945546	0.98315	0.798984	0.93389
0.94712	0.97785	0.804327	0.91394
0.949148	0.98777	0.811256	0.95162
0.949148	0.98657	0.811256	0.94699
0.947489	0.98865	0.805586	0.95501
0.93343	0.98668	0.758733	0.94732
0.922454	0.97709	0.723597	0.91094
0.914392	0.97887	0.698577	0.91753
0.9133	0.98047	0.695236	0.92356
0.913598	0.97897	0.696147	0.91791
0.914392	0.98036	0.698577	0.92314
0.915086	0.97637	0.700704	0.90822
0.9133	0.98528	0.695236	0.94183
0.916076	0.97772	0.703746	0.91324
0.915086	0.97958	0.700704	0.92021
0.910806	0.97976	0.687659	0.92088
0.909003	0.97851	0.682216	0.91617
0.909003	0.97609	0.682216	0.90714
0.9133	0.96952	0.695236	0.88297
0.917851	0.98015	0.70923	0.9224

0.925852	0.982	0.73434	0.92941
0.935803	0.98244	0.766492	0.93115
0.945175	0.98746	0.797728	0.9504

Figure 7 gives the power loss comparison for 24hrs with reduction of losses compared to base case. The Table 4 provides the scheduling of the three DGs for 24hrs. Table 5 represents voltage profile and voltage stability index of 3 DGs compared with base case. The figures 8 and 9 clearly shows the comparison of base case, three DGs with increase in the voltage profile and voltage stability index.

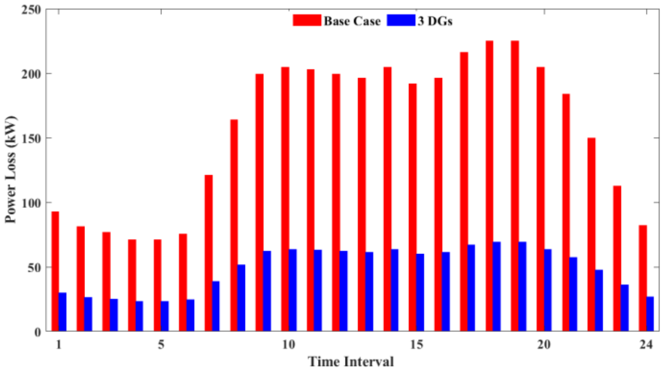

Fig. 7. Dynamic power loss comparison

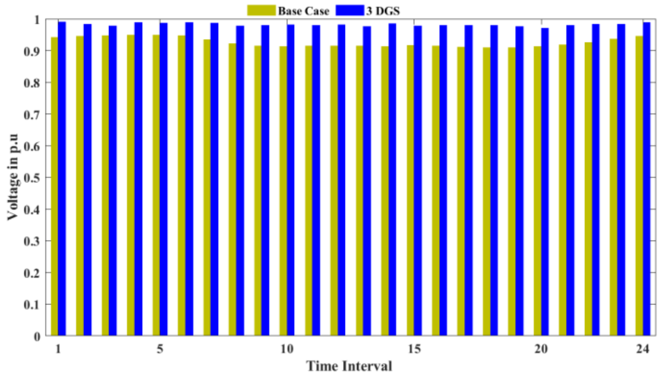

Fig. 8. Voltage profile comparison for 24 hrs

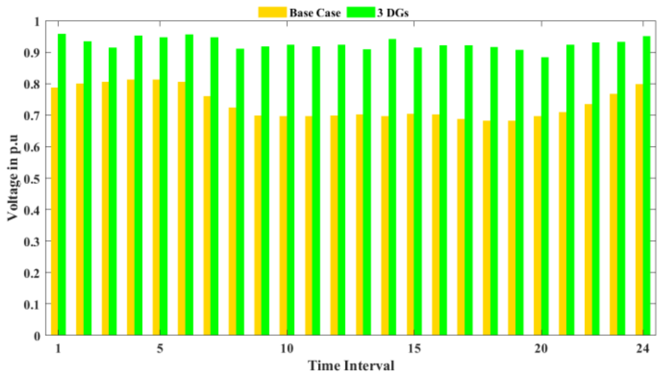

Fig. 9. VSI Comparison for 24hrs

5.2. Comparison of EV charging methods

EV specifications are taken from [23]. In this section different EV charging patterns considered to reduce power loss. 1. Dumb charging method. 2. Smart charging method

5.2.1. Dumb charging method

The end user of EV charge his vehicle without considering the load demand, known as dumb charging. The EVCS are placed on the strong bus, as per VSI method 3, 6 and 10 are the strong buses. First, estimated the 24hrs the power loss in the base case of IEEE 69 bus. When only EVCS are integrated into the system, at 18th, 19th and 20th hrs on each hour 20 EVs are injected to the system with the power losses hiked compared to the base case.
Compared to the only EVs, combination of DGs and EVs decrease 68.6% of power loss.

Table 6. EV Specifications and Ratings [23]

Specifications	**Ratings**
Battery or EV Capacity	16 kWh
The total number of EVs	60
SoC_{min}	0.2
SoC_{max}	0.9
Average electricity use per km	0.175 kWh/km
Average distance each EV travelled	30km

Table 7. Power loss comparison using Dumb Charging Method

S.No	**Base Case P_{Loss} in kW**	**With only EVCS P_{Loss} in kW**	**With both EVCS and DGs P_{Loss} in kW**
1	92.6006	92.6006	29.9776
2	81.1897	81.1897	26.4843
3	76.59	76.59	24.9803
4	70.8556	70.8556	23.1683
5	70.8556	70.8556	23.1683
6	75.5291	75.5291	24.6816
7	121.0302	121.0302	38.7272
8	163.856	163.856	51.5891
9	199.362	199.362	62.0798
10	204.4367	204.4367	63.5303
11	203.0453	203.0453	63.2017
12	199.362	199.362	62.0798
13	196.1716	196.1716	61.1195
14	204.4367	204.4367	63.5303
15	191.6663	191.6663	59.793
16	196.1716	196.1716	61.1195
17	216.2509	216.2509	66.9654
18	**225.0014**	**233.1983**	**68.4572**
19	**225.0014**	**233.1983**	**68.4572**
20	**204.4367**	**210.3191**	**63.71**
21	183.7105	183.7105	57.6225
22	149.9173	149.9173	47.4464
23	112.6126	112.6126	36.1427
24	82.2935	82.2935	26.7852

5.2.2. Smart Charging method

The end user of EV charge his vehicle by considering the load demand, known as smart charging. From the VSI method 3, 6 and 10 buses chosen as the best locations for the positioning of EVCS. In smart charging method 4th, 5th, and 6th hrs on each hour 20 EVs are injected to the system. Compared to the base case, instead of going for dumb charging method by using smart charging method [24], it has been noticed that there is a decrease in power loss.

Table 8. Power loss comparison using Smart Charging Method

S. No	Base Case P_{Loss} in kW	With only EVCS P_{Loss} in kW	With both EVCS and DGs P_{Loss} in kW
1	92.6006	92.6006	29.9776
2	81.1897	81.1897	26.4843
3	76.59	76.59	24.9803
4	**70.8556**	**75.11**	**23.17**
5	**70.8556**	**75.11**	**23.17**
6	**75.5291**	**78.87**	**24.76**
7	121.0302	121.0302	38.7272
8	163.856	163.856	51.5891
9	199.362	199.362	62.0798
10	204.4367	204.4367	63.5303
11	203.0453	203.0453	63.2017
12	199.362	199.362	62.0798
13	196.1716	196.1716	61.1195
14	204.4367	204.4367	63.5303
15	191.6663	191.6663	59.793
16	196.1716	196.1716	61.1195
17	216.2509	216.2509	66.9654
18	225.0014	225.0014	68.4272
19	225.0014	225.0014	68.4272
20	204.4367	204.4367	63.5303
21	183.7105	183.7105	57.6225
22	149.9173	149.9173	47.4464
23	112.6126	112.6126	36.1427
24	82.2935	82.2935	26.7852

6. Conclusion

In this article, the appropriate positioning and size of DGs and EVCS in the DS are concurrently solved using an efficient approach that is provided in this research. The IEEE 69 bus test systems with varying loads, the suggested method's efficacy is evaluated. At all load levels, the results produced by the suggested technique minimize the power losses, enhance the voltage profile and VSI. In comparison to base instances, simultaneous allocation of DGs and EVCSs on IEEE 69 bus test system reduces power loss from 225.0014kW to 68.4272 kW respectively. The improvement in the VSI performance is observed to be significant across all load levels when compared to the base case. A comprehensive analysis was conducted to compare different metrics using SFSA, KHA and TLBO techniques. The findings indicate that the GOA method demonstrates superior efficacy in managing constraints and resulting in improved outcomes. The future scope of the work can be extended with the specific Renewable DGs of solar, wind constraints and also by considering the Vehicle to Grid (V2G) along with G2V integrated to distribution system.

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