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Optimal Placement of Type-1DGs in EV Incorporated Radial Distribution Systems

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Abstract: Minimizing power losses in distribution systems is crucial for ensuring energy efficiency and reliable operation. Among the various strategies available, the integration of Distributed Generation (DG) is one of the most effective approaches to achieve this objective. With the increasing deployment of Electric Vehicle Charging Stations (EVCSs) to support the growing adoption of Electric Vehicles (EVs), optimal planning of these stations has emerged as a critical challenge for distribution system operators. The rising penetration of EV loads introduces significant issues such as generation-demand imbalances, elevated power losses, voltage drops, and reduced voltage stability margins. To mitigate these adverse impacts on Radial Distribution Systems (RDS), the strategic placement of EVCSs is essential. EVs, through their charging and discharging operations, interact dynamically with the grid, playing a role in energy management. However, improper planning of EVCS locations can lead to voltage deviations and increased system losses.

To address these challenges, the integration of DG units with EVCSs is proposed. DGs help maintain acceptable voltage profiles, reduce power flows and losses, and enhance overall power quality and system reliability. Nevertheless, improper placement or sizing of DGs can introduce issues such as protection malfunctions, voltage rise, and reverse power flows. Therefore, it is vital to optimally allocate and size DGs in conjunction with EVCSs. This paper presents a methodology for minimizing power losses through the optimal placement and sizing of multiple DG units in EV-integrated RDS. The proposed approach includes the coordination of various types of renewable DGs alongside EVCSs. Implementation is carried out using the Particle Swarm Optimization (PSO) technique, applied to IEEE 33-bus, 69-bus, and 119-bus test systems in MATLAB. The performance of the PSO algorithm for optimal placement of EVCS along with DG in reconfigured RDS is compared against other well-known techniques, namely the Plant Growth Simulation Algorithm (PGSA) and the Harmony Search Algorithm (HSA) to validate the effectiveness of the proposed approach. The outcome of this research is an optimal planning model that integrates EV charging stations with DG systems. The MATLAB simulation results demonstrate that the proposed method significantly reduces power losses and enhances voltage profiles, leading to improved efficiency and performance of the distribution system through optimal planning and operation of both DGs and EV infrastructure.

Index Terms: Distributed Generation, Particle Swarm Optimization (PSO), EV Charging Station, Radail distribution system

1. Introduction

The rapid advancements in battery technology, coupled with growing concerns over environmental pollution and rising energy consumption, have ushered in a new era of electrification in the transportation sector. Electric Vehicles (EVs) are increasingly being recognized as a viable and sustainable alternative for road transport. Their widespread adoption helps reduce dependence on fossil fuels while significantly lowering greenhouse gas emissions and air pollutants, both of which contribute to global warming. According to Business Intelligence and Strategy (BIS) Research, the EV market is projected to grow at a Compound Annual Growth Rate (CAGR) of 43.13% between 2019 and 2030 [1]. While this expansion presents substantial opportunities, it also poses significant challenges for power system operators due to the escalating demand for EV charging. Effective planning and operation are therefore essential to minimize operational risks and ensure the existing distribution networks can accommodate the large-scale

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deployment of EVs. Beyond environmental benefits, researchers are also exploring the potential of EVs to support the power grid.

Traditionally, EVs were connected solely for battery charging; however, with the evolution of Smart Grids (SGs), the role of EVs has expanded. Smart Grids facilitate the seamless integration of renewable and sustainable energy sources and enable bi-directional power flow. In this context, EVs can act as loads when ample active power is available and serve as power suppliers during shortages, helping suppress voltage fluctuations and maintain system reliability. However, the proliferation of Electric Vehicle Charging Stations (EVCSs) places additional stress on power networks, particularly when fast-charging infrastructure is involved. These high-power charging requirements can degrade the operational performance of the distribution system. Large-scale EV integration may lead to increased power losses, infrastructure aging, voltage deviations, and harmonic distortions. To mitigate these adverse effects, the strategic siting of EVCSs is crucial. Distribution System Operators (DSOs) must carefully plan EVCS deployment to prevent network overloading and to enhance operational flexibility. To further reduce the impact of EVCS integration and improve grid performance, Distributed Generation (DG) units are increasingly being co-located with EVCSs. DG plays a vital role in meeting growing energy demand by alleviating stress on distribution networks. These modular, small-scale power generators have seen significant technological advancement over the past 10–15 years. For optimal effectiveness, it is essential to determine the appropriate capacity and location of DG units within the network.

Integrating DG with EVCS not only offsets the charging burden imposed by EVs but also helps reduce power losses, improve voltage profiles, and avoid issues such as voltage rise, reverse power flow, and protection failures. Optimal placement and sizing of both DGs and EVCSs are therefore critical to maximizing system efficiency and operational reliability. Looking ahead, harnessing the full potential of EVs—particularly their ability to support grid operations and promote renewable energy adoption—represents a promising pathway toward a more sustainable and resilient energy ecosystem.

The primary objective of this study is to determine the optimal placement and sizing of both renewable and non-renewable Distributed Generation (DG) units alongside Electric Vehicle Charging Stations (EVCS), using an optimization strategy that minimizes total power losses while maintaining system reliability and voltage stability. The key contributions of this research are outlined as follows:

- **Optimal Siting of EVCS:** Identifying the most suitable locations for EVCS within the distribution system, with the primary objective of minimizing power losses and improving voltage profiles.
- **Coordinated Placement of DGs and EVCS (EVCS as Load):** Simultaneously determining the optimal locations and sizes of DG units and EVCS, where EVCS are considered as loads. This is achieved while adhering to system operational constraints to effectively reduce losses.
- **Simultaneous Siting and Sizing of DGs and EVCS:** Extending the coordinated planning by jointly optimizing the placement and sizing of DGs and EVCS, further minimizing system losses under defined constraints, and enhancing overall system performance.

2. Relevant Background

Numerous studies have focused on the optimal placement and sizing of Electric Vehicle Charging Stations (EVCS) to enhance the performance of power distribution networks. Md. Mainul Islam et al. [5] provided a comprehensive review of various methodologies for improving EVCS siting and sizing. Mondeep Mazumder and Sanjoy Debbarma [6] evaluated the integration of EVs into existing distribution systems, considering both slow and fast charging, and compared G2V (Grid-to-Vehicle) and V2G (Vehicle-to-Grid) technologies. Sanchari Deb et al. [7] investigated the impact of EVCS loads on voltage stability, power losses, reliability, and economic performance. Yuttana Kongjeen and Krischonme Bhumkittipich [8] introduced a voltage-dependent control strategy to assess the static voltage stability of EV-integrated systems using a novel load flow approach. Galiveeti Hemakumar Reddy et al. [9] analyzed EV integration from a reliability perspective, proposing an energy not charged (EENC) index to determine optimal EVCS locations under system failure conditions.

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Kang Miao Tan et al. [10] reviewed the framework, benefits, and challenges of V2G systems and outlined major optimization methods involving multiple constraints. Mingsheng Zhang [11] developed a model aimed at minimizing investment and charging costs for optimal EVCS placement. Priyanka Shinde and K. Shanti Swarup [12] proposed optimization of EV reactive power to enhance voltage profiles. M. Bagheri Tookanlou et al. [13] formulated a scheduling strategy aligning incentives for both V2G and G2V stakeholders. Xiangwu Yan et al. [14] presented a multi-objective model using a hierarchical genetic algorithm to optimize both system losses and investment costs. Heuristic optimization techniques have gained popularity for addressing the combined placement of EVCS and DGs. Hassan Fathabadi [15] analyzed the combined effects of EVs, PHEVs with V2G functionality, and renewable DGs on distribution systems. Leila Bagherzadeh [16] addressed a multi-objective smart grid scheduling problem involving EVs and DGs, incorporating uncertainty through Beta and Weibull distributions and solving it using the Cuckoo Search Optimization Algorithm.

Mahnaz Moradijoz [17] conducted simultaneous placement of DGs and EV parking lots, demonstrating a significant reduction in losses. The study also showed that variations in EV numbers and charging rates influence optimal siting outcomes. Zhipeng Liu [18] developed a mathematical model for optimal EVCS sizing aimed at minimizing total planning costs. Building upon these contributions, the present study proposes an efficient method for minimizing power losses through optimal siting and sizing of multiple types of DGs, along with the strategic placement of EVCSs. The optimization is carried out using the Particle Swarm Optimization (PSO) technique. In this framework, EVs are modeled as static loads, with charging behavior over time not considered, and analysis is performed under balanced load conditions. By fixing the DG size and optimizing the EVCS locations, the proposed method demonstrates significant benefits in reducing power losses and improving system performance. The effectiveness of the approach is validated on IEEE 33-bus, 69-bus, and 119-bus radial distribution systems.

3. Methodology

This paper presents a Particle Swarm Optimization (PSO)-based methodology for the optimal placement and sizing of Distributed Generators (DGs) and Electric Vehicle Charging Stations (EVCS) in radial distribution systems. The study evaluates system performance with and without DG integration to assess the impact of EVCS deployment on power losses and voltage profiles. Relevant operational constraints for both DGs and EVs, including their maximum allowable capacities, are incorporated into the optimization framework. Type-1 DGs are considered for this analysis, and the proposed method is implemented across multiple standard IEEE bus systems. The coordinated placement of EVCS and type-1 DGs demonstrates a substantial reduction in power losses. Furthermore, the influence of EVCS on real power loss, reactive power loss, and voltage magnitude is comprehensively analyzed, highlighting the effectiveness of the proposed approach in enhancing the efficiency and reliability of the distribution network.

4. Modeling of EVCS

An EV load model is expressed as:

$$EV_{Power} = S_0 \times k_p \times \left(\frac{V_i}{V_{i0}}\right)^{n_{pi}}$$

In this study, EV load is modeled as a static load with real power injection. The apparent power demand S_0 corresponds to the load at the nominal voltage V_{i0}, n_{pi} . The exponential index for EV load is taken as n_{pi}=2.59, while the load power factor k_p is assumed to be 0.995 lagging based on the specifications of commercially available EV chargers. The integration of EVs results in an increase in the total system load. Specifically, the real power demand increases from baseline values of 1226.4 kW, 3715 kW, 3802.2 kW, and 2569.3 kW to 1544.09 kW, 3926.41 kW, 4093.04 kW, and 2880.92 kW for the IEEE 33-bus, 69-bus, and 119-bus systems, respectively, when load flow analysis is performed. These results highlight that the inclusion of EVs significantly raises the overall load on the distribution system. Therefore, their integration must be carefully planned to maximize both technical and economic benefits and to support broader adoption of EV technologies in a sustainable manner.

The amount of power needed to charge an EV with the efficiency of the charger is as follows:

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$$P_{Chrgng} = \eta_{Charging/Injected} \times P^{rate} \tag{2}$$

EVs with Li-ion batteries are considered for modeling the EVCS and assumed that it delivers only required real powerto batteries of EV. In this paper, charging level of type 3 fast charging EVCS is considered which has the charging power of 50 kW for each EV and rated voltage/current of 480V/167A.

5. Modeling Equations for Renewable Distributed Generators (DG)

Modeling Equations for Photovoltaic (PV) Systems

PV Cell Output Current (Single-Diode Model)

$$I = I_{ph} - I_0 \left(e^{\frac{q(V+IR_s)}{nKT}} - 1 \right) - \frac{V + IR_s}{R_{sh}}$$

Where:

I_{ph}: Photocurrent (dependent on irradiance and temperature)
I_0: Diode saturation current
R_s, R_{sh}: Series and shunt resistances
q: Electron charge
V: Terminal voltage
T: Temperature
n: Ideality factor
K: Boltzmann's constant

Modeling Equations for Wind Turbine Generators (WTGs)

Power Extracted from Wind

$$P = \frac{1}{2}\rho A C_p(\lambda, \beta) v^3 \tag{3}$$

Where

ρ: Air density
A: Rotor swept area
Cp: Power coefficient (depends on tip speed ratio λ and blade pitch β)
v: Wind speed

Tip Speed Ratio

$$\lambda = \frac{R\omega}{v} \tag{4}$$

Where:

R: Rotor radius
ω: Rotor angular speed

Power Flow and Grid Connection Models

PQ Model (for inverter-based DG)

$$S = P + jQ \tag{5}$$

Where:

- P: Real power injected
- Q: Reactive power injected or absorbed

Dynamic Models:

Inverter controls include: droop control, PLL, current control loops
d-q axis transformations for synchronous reference frame.

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6. Objective Function

The line losses are estimated as:

$$P_{LOSS}=\sum_{i=1}^{nb} I2\, R \tag{6}$$

Hence, growing demand for load of a single bus would lead to net growth in the distribution network's total power losses. Minimization of the total power losses including both active and reactive power losses and enhanced voltage profile with EVs inclusion are the main objectives of this paper:

$$\text{Minimization}\{P_{Loss}\} \tag{7}$$

7. DG and EV Constraints

Current limit

$$|I_{ij}| \leq I_{maximum} \tag{8}$$

Where I_{ij} is the capacity of line current flow between I and j, I_{max} is the maximum current carrying capacity of the powerline.

Voltage limit

$$V_{Bus\_min} \leq V_{Bus} \leq V_{Bus\_max} \tag{9}$$

$$0.95 \text{ pu} \leq V_{Bus} \leq 1.05 \text{ p} \tag{10}$$

where V_{Bus} is the bus voltage, V_{Bus_min} is the minimum allowable bus voltage, and V_{Bus_max} is the maximum allowablebus voltage.

EV battery SOC limit

EV battery SOC (State of Charge) should be kept within the specified range to reduce battery degradation. In addition, the EV battery cannot completely be discharged because those energy quantities are allocated for use with the EV drive.

$$EV_{SOC\_min} \leq EV_{SOC} \leq EV_{SOC\_max} \tag{11}$$

where EV_{SOC} is the state of charge for EV, EV_{SOC_min} is the minimum acceptable EV SOC and EV_{SOC_max} is themaximum acceptable EV SOC.

Power distribution limit

The electric energy supplied form the grid and DGs including the EVs connected to the grid should meet thedemand for load and system losses with EVCS.

$$P_{Grid} + \sum^{N} P_{DGi} = \sum^{N} (P_{iLoad} + P_{iEVCS}) + P_{Losses} \tag{12}$$

Where P_{Grid} is the power generated from grid generator, P_{EVCS} is the power related to EVCS and P_{iLoad} is the loaddemand.

DG sizing limit

$$50 \leq DG_{Sizing} \leq 3500 \tag{13}$$

8. Particle Swarm Optimization (PSO) Methodology

The Particle Swarm Optimization (PSO) technique was first introduced by Kennedy and Eberhart as a stochastic optimization method inspired by the social behavior of swarms. It is particularly effective for solving complex, constrained nonlinear optimization problems involving numerical maximization or minimization. In this study, PSO is adopted due to several advantages it holds over other heuristic optimization algorithms. Its adaptability to the nature of the objective function, coupled with low memory requirements and reduced computational time, makes it a highly efficient approach. Furthermore, PSO

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exhibits reduced dependency on initial conditions, which enhances its robustness and flexibility in achieving global convergence.

In PSO, particles traverse a multi-dimensional search space with a specific velocity. Each particle represents a potential solution and is capable of interacting with other particles in the swarm. This interaction allows particles to adjust their velocities based on both their individual experiences and the successes of their neighbors. Such dynamic behavior helps avoid premature convergence to local minima and encourages exploration of the search space. During the optimization process, each particle evaluates its position based on the objective function. If the current position yields a better result than any previously visited position, it is recorded as the personal best position, denoted as $P_{best.}$ The best position found among all particles in the swarm is stored as the global best $G_{best.}$

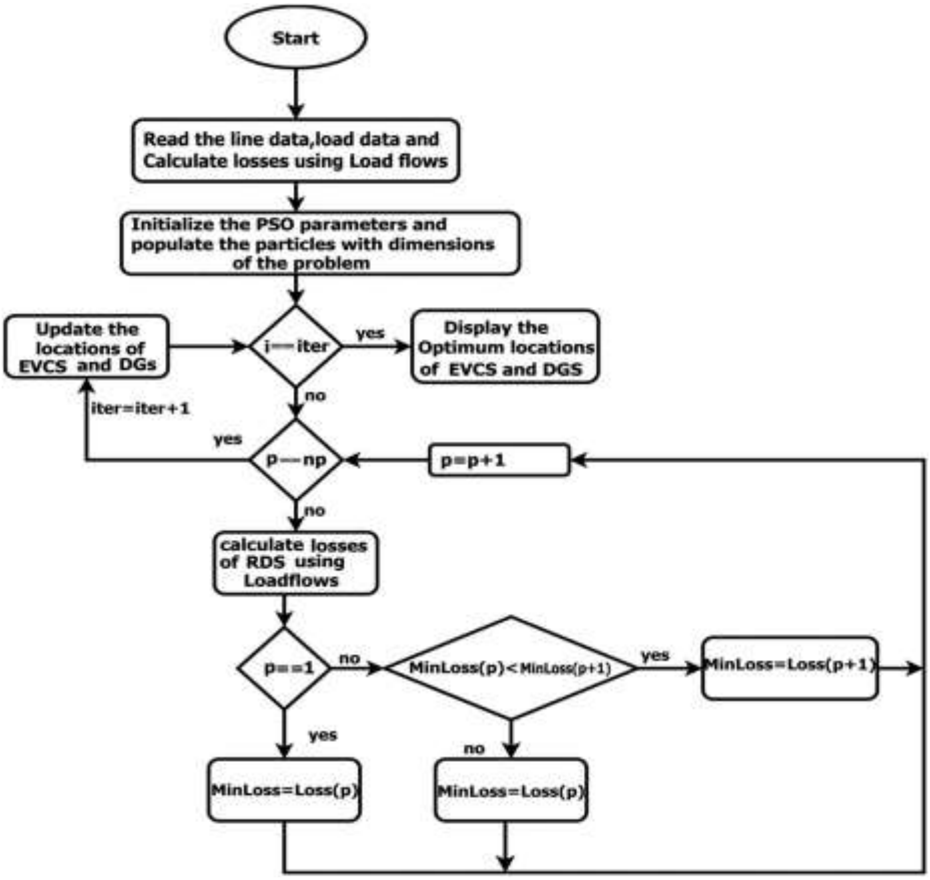

Fig.1. Flowchart for optimal placement of DG and EVCS using PSO methodology

Once the Particle Swarm Optimization (PSO) parameters are initialized, as listed in Table 1, each particle in the swarm is assigned a set of branch numbers obtained from the Loop Matrix (LM). These branches represent potential tie-lines that can be opened to achieve reconfiguration. The particle matrix is then constructed, with dimensions determined by:

- The number of particles (n_p), representing the candidate solutions, and
- The number of decision variables (n_{tie}), i.e., the number of switches (branches) to be opened for reconfiguration.

Each particle in the matrix encodes a possible switch combination, which is evaluated against the objective function to determine its effectiveness. Through iterative updates, the PSO algorithm converges toward the configuration that yields the minimum system losses.

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Table 1: Parameters of PSO considered for this study

S.No	Parameter	Value
1	Number of particles (N)	50
2	Maximum number of iterations	100
3	Maximum Inertia (w_{max})	0.9
	Minimum Inertia (w_{min})	0.2
4	Initial Velocity (v_1)	2
5	Final Velocity (v_2)	2

The overall framework for solving the optimal placement of multiple Distributed Generators (DGs) and Electric Vehicle Charging Stations (EVCS), along with the sizing of four different types of DGs operating at various power factors using the Particle Swarm Optimization (PSO) technique, is illustrated in Fig. 1**.**

The step-by-step procedure for applying the PSO algorithm to address the optimal allocation of EVCS and DGs is outlined as follows:

Step 1: Initialize the bus data, number of DGs and EVCSs subjected to equality and inequality constraints
Step 2: Initialize the parameters corresponding to upper and lower limits of DG sizes in kW, EVCSs, PSOparameters and maximum number of iterations
Step 3: Initialize population of particles having positions X
and velocities VStep 4: Set iteration =1
Step 5: Using forward-backward load flow, evaluate the initial population and objective function values (3) andfind the index of the best particle
Step 6: Select P_{best} and G_{best}
Step 7: Update positions and velocities of particles using (12) and (13)
Step 8: Evaluate fitness and find the index of the best particle for both
DGs and EVCSStep 9: Update P_{best} and G_{best} of total population and
calculate error
Step 10: If iteration is equal to maximum iterations, then increment iteration by 1 and go to step 6 instead go tostep 11
Step 11: Print G_{best} as the optimal solution and stop.

9. Results and Discussions

Case-1: IEEE 33 bus system

In this case EVCS with 1.715 MW, 2 MW and DG's with the size of 737.24 kW and 368 kW are considered in IEEE 33 radial bus system. The results after implementing PSO algorithm for optimal placement and sizing of EVCS and renewable based DG [32] on IEEE 33 bus system [49] are shown in table 2 and the results obtained are compared with the results of PGSA and HSA implemented for the same proposed system.

Voltage profile of IEEE 33 bus system for optimal placement and sizing of EVCS and renewable based DG using HSA algorithm is shown in Figure 2.

Fig 2: Voltage profile comparison in IEEE

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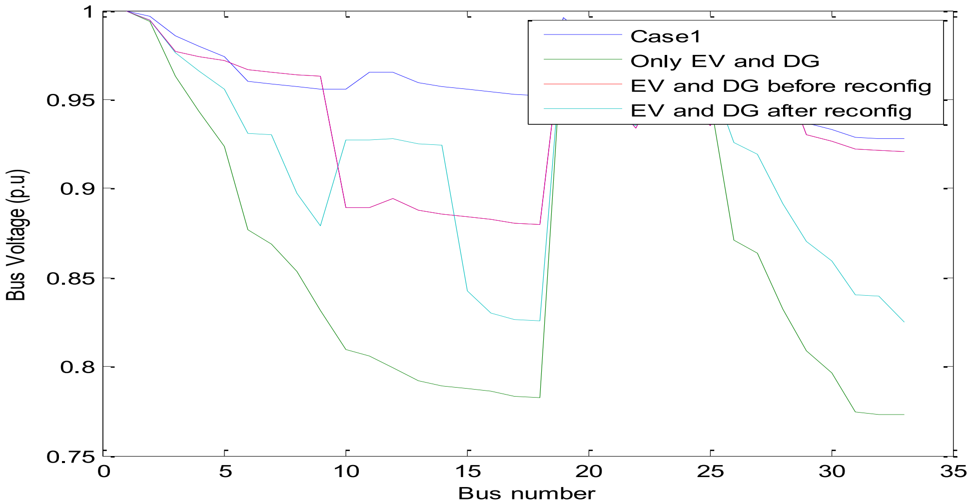

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bus system with EVCS and DG along with reconfiguration using PSO

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Table 2 Comparison of PSO, PGSA and HSA algorithm results after placement of EVCS and DG on IEEE 33 bus system

Algorithm	Losses without reconfiguration (kW) (Scenario-1)	Opened Switches	Losses with reconfiguration (kW) (Scenario-2)	Reconfiguration switches	EVCS Location	EVCS Size (MW)	Losses with Reconfiguration and EVCS (Simultaneous approach) (Scenario-3)	DG Location	DG Size (kW)	Losses with Reconfiguration, EV and DG (Scenario-4)
PSO	202.76	33 34 35 36 37	139.5	7 14 9 32 37	2,19	1.715,2	189.17	11,23	1.134, 0.378	135.2
PGSA	202.76	33 34 35 36 37	146.5	9 33 34 28 36	2,[7]	1.715,2	401.23	16,31	1.134, 0.378	140.85
HAS	202.76	33 34 35 36 37	155.75	10 33 36 34 37	2,27	1.715,2	346.12	12,31	1.134, 0.378	152.24

From the above comparison table, results shows that in all four scenarios the losses are less with the implementation of PSO algorithm for optimal placement and sizing of EVCS and DG in reconfigured IEEE 33 bus radial distribution system. The results of PSO algorithm in all four scenarios are compared with the results of PGSA and HSA algorithms implemented for the IEEE 33 bus radial distribution system. The proposed PSO algorithm has less losses and better voltage profile when compared to the PGSA and HSA algorithms.

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Case-2: IEEE 69 bus system

For IEEE 69 radial bus system the EVCS with 1.5 MW, 3 MW and DG's with the size of 737.24 kW and 368 kW are considered. The results after implementing PSO algorithm for optimal placement and sizing of EVCS and renewable based DG on IEEE 69 bus system are shown in table 3

Voltage profile of IEEE 69 bus system for optimal placement and sizing of EVCS and renewable based DG using HSA algorithm is shown in Figure 3.

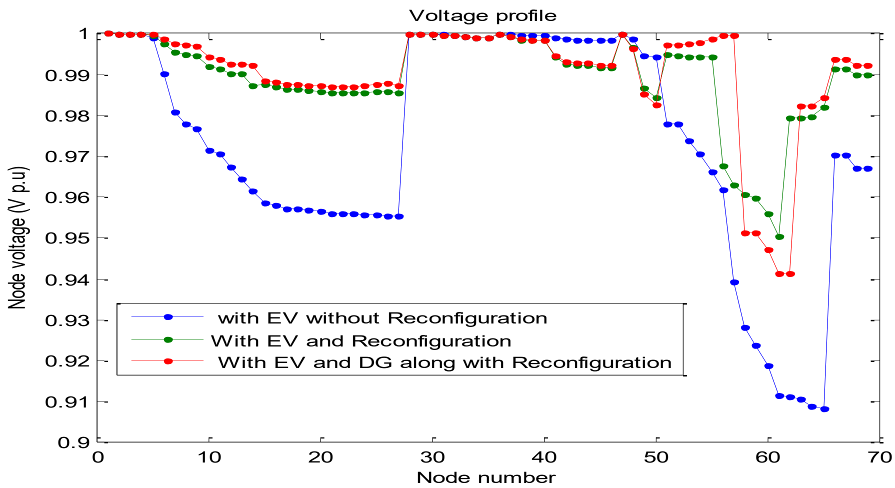

Fig 3: Voltage profile comparison in IEEE 69 bus system with EVCS and DG along with reconfiguration using PSO

Case-3: IEEE 119 bus system

For IEEE 119 radial bus systems EVCS with 4.4 MW, 4.4 MW and DG's (type-1) with the size of 737.24 kW and 368 kW are considered. The results after implementing PSO algorithm for optimal placement and sizing of EVCS and renewable based DG on IEEE 119 bus system are shown in table 4 and the results obtained are compared with the results of PGSA and HSA [4] algorithms implemented for the same proposed system.

Voltage profile of IEEE 119 bus system for optimal placement and sizing of EVCS and renewable based DG using PSO, PGSA and HSA algorithms is shown in Figure 4.

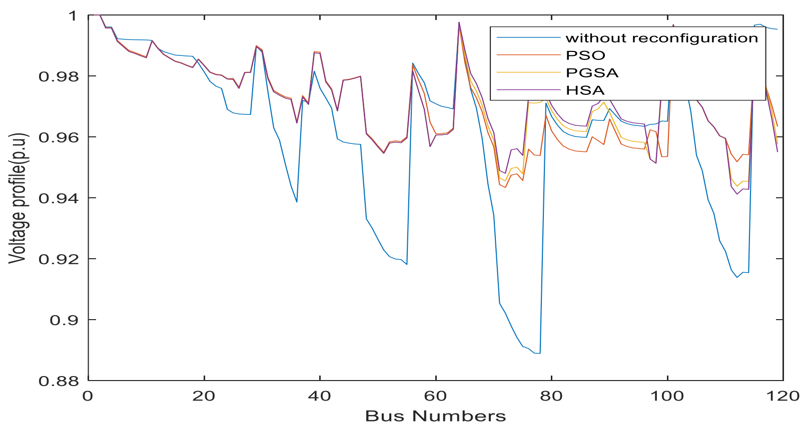

Fig 4: Voltage profile comparison in IEEE 119 bus system with EV and DG along with

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reconfiguration using PSO, PGSA and HSA algorithms

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Table 3 Comparison of PSO, PGSA and HSA algorithm results after placement of EVCS and DG on IEEE 69 bus system

Algorithm	Losses without reconfiguration (kW) (Scenario-1)	Opened Switches	Losses with reconfiguration (kW) (Scenario-2)	Reconfiguration switches	EV Location	EV Size (MW)	Losses with Reconfiguration and EV (Simultaneous approach) (Scenario-3)	DG Location	DG Size (kW)	Losses with Reconfiguration, EV and DG (Scenario-4)
PSO	2[7].43	69 70 71 72 73	108	14 58 61 69 70	2,28	3,1.5	120.24	26,56	737.24, 368	106.24
PGSA	2[7].43	69 70 71 72 73	144.6	18 58 62 69 70	2,36	3,1.5	157.24	2,24	737.24, 368	108.24
HSA	2[7].43	69 70 71 72 73	166.24	19 57 61 69 72	2,47	3,1.5	185.84	2,24	737.24, 368	112.6

From the above comparison table, results shows that in all four scenarios the losses are less with the implementation of PSO algorithm for optimal placement and sizing of EVCS and DG in reconfigured IEEE 69 bus radial distribution system. The results of PSO algorithm in all four scenarios are compared with the results of PGSA and HSA algorithms implemented for the IEEE 69 bus radial distribution system. The proposed PSO algorithm has less losses and better voltage profile when compared to the PGSA and HSA algorithms.

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Table 4 Comparison of PSO, PGSA and HSAalgorithm results after placement of EVCS and DG on IEEE 119 bus system

Algorithm	Losses without reconfiguration (kW) (Scenario-1)	Opened Switches	Losses with reconfiguration (kW) (Scenario-2)	Reconfiguration switches	EVCS Location	EVCS Size (MW)	Losses with Reconfiguration and EV CS(Simultaneous approach) (Scenario-3)	DG Location	DG Size (kW)	Losses with Reconfiguration, EV and DG (Scenario-4)
PSO	1065.2	119120 1211221231241[7]126 127128129130131	726.4	42 [7] 23 121 50 58 39 95 71 74 97 129 130 109 34	2,64	4.4,4.4	735.6	113,48	737, 368	602.4
PGSA	1065.2	119120 1211221231241[7]126 127128129130131	740.3	24 27 35 40 43 52 59 72 75 96 98 110 123 130 131	2,101	4.4,4.4	875.8	113,94	737, 368	706.3
HAS	1065.2	119120 1211221231241[7]126 127128129130131	780.4	24 26 35 40 43 51 59 72 75 96 98 110 122 130 131	2,29	4.4,4.4	1040.6	113,33	737, 368	812.5

From the above comparison table, results shows that in all four scenarios the losses are less with the implementation of PSO algorithm for optimal placement and sizing of EVCS and DG in reconfigured IEEE 119 bus radial distribution system. The results of PSO algorithm in all four scenarios are compared with the results of PGSA and HSA algorithms implemented for the IEEE 119 bus radial distribution system. The proposed PSO algorithm has less losses and better voltage profile when compared to the PGSA and HSA algorithms.

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The effectiveness of the proposed PSO algorithm is tested on IEEE 33, IEEE 69 and IEEE 119 bus radial distribution systems. The real power losses displayed are less in scenario-4 (Placement of EVCS and DG (type-1) along with reconfiguration for an existing radial distribution system using PSO when compared to all other scenarios. The proposed PSO algorithm as displayed better results when compared to other algorithms PGSA and HSA.

10. Conclusions and Future Scope

Conclusions

The primary focus of this research is the optimal placement of electric vehicle charging station (EVCS) within radial distribution systems (RDS). Three scenarios are considered for analysis (i) optimal placement of EVCS before reconfiguration of the RDS, (ii) optimal placement of EVCS on a reconfigured RDS and (iii) Simultaneous optimization of EVCS placement along with network reconfiguration. The methodology is implemented on standard IEEE test systems including the IEEE 33-bus, IEEE 69-bus, and IEEE 119-bus RDS using the Particle Swarm Optimization (PSO) algorithm. The results demonstrate that the PSO algorithm efficiently determines the optimal placement and sizing of EVCS and also among the studied scenarios, the optimal placement of EVCS on a reconfigured RDS yields the most favorable outcomes in terms of reduced power losses and improved system reliability. The performance of the PSO algorithm is compared against other well-known techniques, namely the Plant Growth Simulation Algorithm (PGSA) and the Harmony Search Algorithm (HSA).

Further this research proposes a comprehensive optimization framework that simultaneously determines the optimal placement of EVCS along with DG in reconfigured RDS. To uphold the principles of sustainable energy this study proposes the use of distributed generation (DG) units based on renewable sources such as solar and wind energy. In this research, Type-1 DG units which supplies only real power are considered. The proposed methodology is implemented on standard IEEE test systems, including the IEEE 33-bus, IEEE 69-bus, and IEEE 119-bus RDS, using the Particle Swarm Optimization (PSO) algorithm. The results demonstrate that the PSO algorithm efficiently determines the optimal number and placement of DG units in systems integrated with EVCS. The performance of the PSO algorithm is compared against other well-known techniques, namely the Plant Growth Simulation Algorithm (PGSA) and the Harmony Search Algorithm (HSA)

This research concludes that the optimized placement for EVCS along with DG in reconfigured RDS using PSO algorithm is achieved with minimum losses and improved voltage profile and system reliability. The performance of the PSO algorithm is compared against other techniques namely the Plant Growth Simulation Algorithm (PGSA) and the Harmony Search Algorithm (HSA) where PSO algorithm outperforming the other compared algorithms in terms of loss minimization and system efficiency.

Future Scope:

The proposed work can be further extended by incorporating the reconfiguration of unbalanced distribution systems in conjunction with the integration of EVCS and DG. Additionally, the scope of the study can be broadened to include demand-side management (DSM) strategies, such as valley filling and peak clipping, which can be implemented through effective coordination of EVCS operations to help flatten the system load curve. Furthermore, the application of advanced optimization techniques may be explored to achieve improved objectives particularly in minimizing power losses and enhancing the voltage profile of the distribution system.

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