Multi-Objective Optimization of DG and EV Integration in IEEE Bus Systems Using PSO and GWO

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Abstract: The move from standard automobiles to electric vehicles relies heavily on limited fossil fuel availability and fears on rising greenhouse gas emissions .More research on As a result, there's been a surge in research interest in determining the optimal placement of electric vehicle charging stations (EVCSs) to support the growing demand for EVs and to facilitate the electrification of transportation systems. Researchers have adopted various approaches, objective functions, and constraints in formulating problems related to EVCS optimization. Some common approaches include mathematical modeling, optimization algorithms, and simulation-based studies. Objective functions may prioritize factors such as infrastructure cost, user convenience, energy efficiency, or environmental impact, depending on the goals of the study. Constraints may include technical limitations, regulatory requirements, spatial constraints, and operational considerations.

The surge in demand for electric vehicles (EVs) over the past decade is primarily driven by their potential to reduce CO2 emissions and lower operational costs compared to internal combustion engine vehicles. Projections suggest that widespread adoption of EVs could significantly contribute to reducing CO2 emissions by 2030. However, transitioning to EVs presents challenges, including high upfront costs and limited charging infrastructure availability. The global EV market is expected to experience robust growth, with forecasts indicating a substantial increase in value by 2027. Despite this growth, challenges such as insufficient charging infrastructure persist, particularly as the number of EVs on the roads continues to rise. Integrating EVs into the distribution network introduces various issues, including increased power demand, voltage instability, power loss, and harmonic distortion.

Addressing these challenges will require investment in charging infrastructure expansion and upgrades to the distribution network to accommodate the growing number of EVs. Additionally, advanced technologies and smart grid solutions may be necessary to manage EV charging demand effectively and maintain grid stability. Collaboration between industry stakeholders and government entities will be crucial to overcoming these obstacles and facilitating the widespread adoption of EVs.

Keywords: PVD, PSO, EV, GWO.

1. Introduction:

With the sustainable development of the energy industry, the excessive exploitation of traditional fossil energy has brought increasingly severe environmental pollution problems such as energy resource shortage and climate change, making it extremely urgent to utilize renewable energy as an alternative for fossil fuels [1]. In recent years, the large-scale penetration of renewable resources and new energy equipment alleviates the energy crisis, while also bringing rigorous challenges to the power system optimizing configuration and secondary energy rational utilization. For example, the randomness and intermittency of power generated from wind turbines (WTs) or photovoltaic cells (PVs) and the time-space dimensional decentralization of electric vehicle (EV) charging, induce more uncertainty for present distribution network (DN) operations than ever before, as well as problems involving harmonic pollution, three-phase voltage imbalance [5], and transformers aging [3]. Particularly, the enlarged peak-to valley difference (PVD) of the load curve puts forward higher requirements for the power system. The safety and economy, expressed as node voltage excursion and active power loss respectively, are commonly regarded as crucial indices reflecting the operation state of the DN [9].

The serious peak load arisen from the aggregated charging behaviors of EV owners probably causes low-voltage even blackout, concurrently increasing system loss. Hence, guiding measures for coordinated regulation should be taken to minimize the negative influences of integrated renewable energy and EVs while satisfying the power and travel demands of customers. Recently, the integrated energy system (IES) has been greatly supported by the Chinese government and turned into a research hotspot, since it benefits the integration of renewable energy and the coordinated development of the multi-energy system. Under the background of the IES, the management idea for the DN has changed from supply-oriented to demand-oriented, which integrates the functions of distributed generation control, real-time monitoring, information sharing, and market transactions. This makes for better accommodation and scheduling abilities to diversify distributed energy equipment.

To stabilize the output fluctuation of renewable power generation, the battery energy storage system (BESS) has become a key supporting unit to improve the compatibility level for the WT and PV of the DN. By power transferring through electrochemical charging/discharging, the BESS not only enhances the utilization of clean energies, bringing higher economic benefits to the regional grid but further improves the reliability of the power supply. A hierarchical coordinated control strategy with the fast-response BESS to suppress high fluctuations associated with DGs outputs has been developed based on the MPC framework [6]. Moreover, as part of a vehicle-to-grid (V2G) system, EV can also be regarded as a controllable power resource, to realize the bidirectional power flow between the building cluster and DN.

2. Related Work:

based optimization (SFL-TLBO) to tackle the optimization problem concerning optimal parking lot locations. This method combines the advantages of shuffled frog leap and teaching learning-based optimization techniques, aiming to provide an effective and efficient solution for determining optimal locations for parking lots.

On the other hand, [11] utilized an upgraded shark smell optimization method to determine the optimal location and dimensions of electrical energy storage systems in microgrids. Their study considered various factors such as EV volume on roads, energy costs, and weather patterns to optimize the placement and sizing of energy storage systems, which is crucial for enhancing the resilience and efficiency of microgrids in the context of increasing EV adoption and renewable energy integration.

[12] utilized the genetic algorithm (GA) technique to address the proposed model for optimal EVCS placement. Their model included objective functions related to the construction cost of EVCS and the cost of charging station access. Additionally, the authors suggested multi-objective functions for optimization problems concerning sustainable cities, highlighting the importance of considering various factors to promote sustainable urban development.

Similarly, [13] proposed multi-objective functions for optimizing EVCS placement in sustainable cities. They emphasized factors such as yearly time opportunity cost, travel expenses, building costs, and running costs, aiming to find optimal solutions that support the sustainability goals of urban areas.

[14] suggested economic factors for economic modeling related to EVCS placement, including power loss, travel expenses, substation operating costs, and EVCS investment costs. They utilized GA to resolve the economic model for charging station placement, aiming to minimize power loss while addressing demand response at the load side.

3. Methodology:

Particle Swarm Optimization: Particle Swarm Optimization (PSO) is a computational optimization technique that draws inspiration from the social dynamics of natural systems, such as fish schools and bird flocks. It was developed as an optimization technique to find the optimal response within a search space.

Here's a brief rundown of how PSO functions:

Initialization: To begin, the algorithm generates a population of particles, or possible solutions. Any particle in the search space represents a possible solution.

Objective Function: A function that must be minimized or maximized defines the optimization challenge.

Movement and Update: Based on its own experience (personal best) and the collective experience of the swarm (global best), each particle moves through the search space by modifying its position. Particles travel in an iterative manner, guided by velocity vectors that change their positions.

Evaluation: Using the objective function as a basis, each particle's fitness is assessed.

Update Personal and Global Bests: A particle updates its personal best if it finds a solution that is better than its previous best. In the same way, if the worldwide best solution

Termination: Until a termination condition is satisfied, such as reaching a maximum number of iterations or arriving at a workable solution, the algorithm iterates through these phases.

PSO is renowned for its ease of use and potency in effectively searching and utilizing the search field. It has been used in a variety of optimization scenarios, such as neural network training, engineering design, and other fields where identifying the best solution is essential.

Figure1: Particle Swarm Optimization

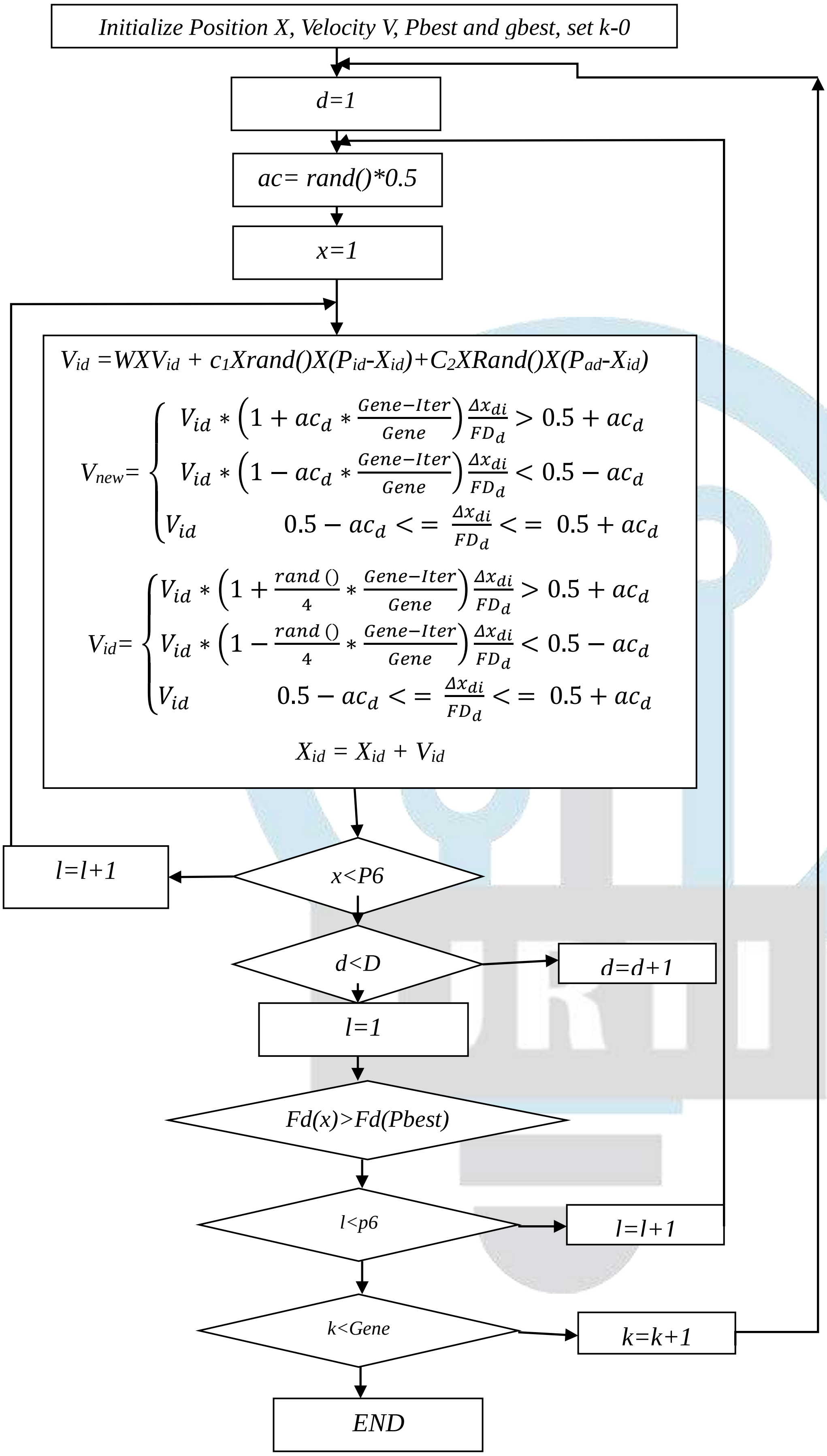

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Figure 2 Flowchart of PSO

Grey Wolf Optimization Algorithm

Metaheuristic optimization algorithms are getting familiar in applications based on engineering due to easy concepts, simple implements that do not require large amount of system information. The modern optimization schemes are capable to bypass local optima and commonly used in a wide range under different disciplines. Many algorithms are present that are based on multiple combinatorial optimization problems. Grey Wolf optimization is new approach [31] introduced in 2016. It is inspired by the grey wolves social behavior that working in leadership hierarchy for strategy to perform in hunting. Grey wolves are the top-level predators; living in group of 5 to 15 wolves. The strategy of hunting classified into four groups α, β, Δ, and Ω. α-wolves taken as leader of the group that has authority of making decision for hunting place, sleeping place and so on. α-wolves are dominant and instruct others to follow them. They perform a major role to produce new solutions. β-wolves comes to next level they assistant α-wolves in decision-making. They take decision when alpha wolves are passed away. They listen to the α-wolves decision and provide response to the α-wolves. The Δ-wolves are called subordinate wolves. They belong to elders, hunters, sentinels, caretakers and scouts. Δ-wolves follow alphas and betas and manage Ω-wolves. Ω-wolves are in lowest rank and play the role of scapegoat. They follow all other dominant wolves. They are not important help others from facing internal problems.

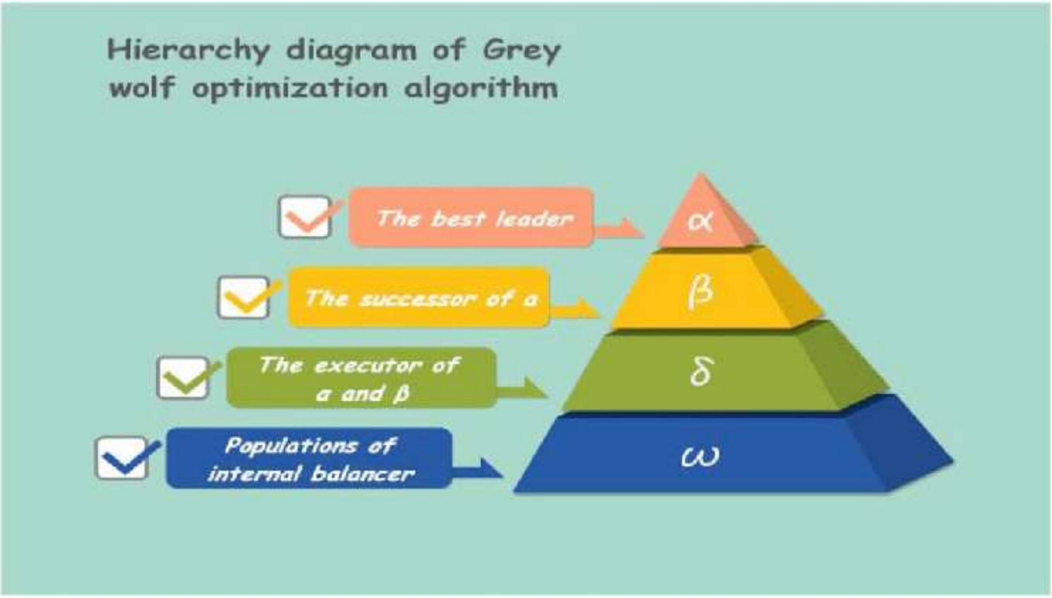


Fig3:**Hierarchy diagram of Grey wolf optimization algorithm**

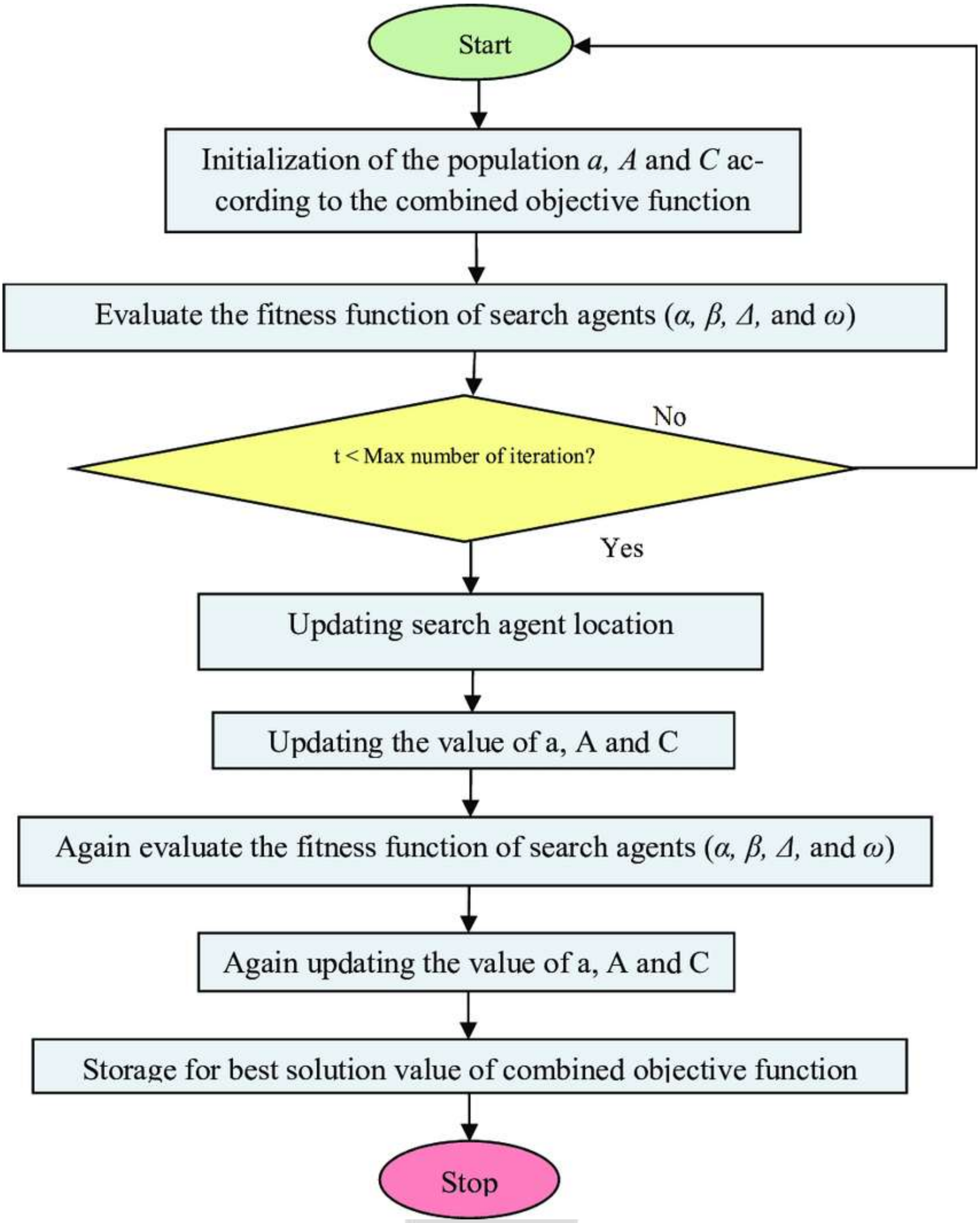


Figure4:Flow Chart of Grey Wolf Optimization

Modeling of EVCS

The charging current for the EV battery is supplied by EVCS. The capacity of an EV battery is specified in kWh and Ah. The modeling of EVCS is based on the assumption that it supplies only required real current [35] to EV battery and hence, when EVCS is connected to any bus corresponding real power is increased. Therefore, it is important to locate the EVCS at suitable locations where the branch currents are minimum. Figure 4 illustrates a portion of the RDS in which EVCS is placed optimally at bus d and draws a real power in addition to the power drawn by an existing load.

The main objective of this paper is to optimize the losses of the system after the placement of EVCS. The real power losses are calculated using load flow analysis by including EVCS at optimal locations. The location of EVCS can be optimized by using PSO. The algorithm for the proposed method is detailed in the succeeding section and the flowchart is shown in Figure 5[37].

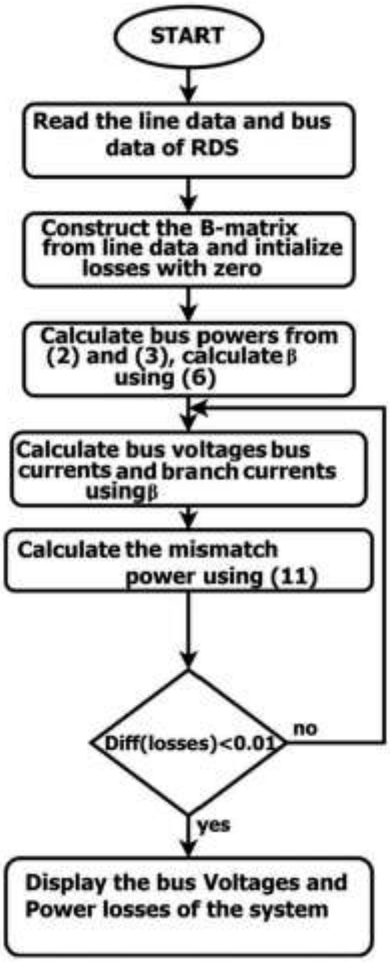


Figure 5. Flowchart of branch incidence matrix-based load flow.

4. Result and Discussion:

PSO Results 33 bus

Table 1:Allocation of EVCS locations without DG using PSO 33 bus

EVCS (Bus)	20,3,6,7,13	2,4,6,7,13	20,3,27,7,14	2,4,6,7,13
Minimum Voltage (pu)	0.86531	0.86531	0.8622	0.86531
VD (%)	25.401	25.417	26.065	25.417
Power-Loss (kW):	407.0787	408.4649	416.0212	408.4649
Power-Loss (kVAr):	273.8875	275.1488	281.4946	275.1488

Table 2:Allocation of EVCS locations with DG using PSO 33 bus

Minimum Voltage (pu)	0.94239	0.94239
VD (%)	5.9994	4.9877
Power-Loss (kW):	127.574	108.0222
Power-Loss (kVAr):	87.9325	77.1713
P Loss Reduction (kW)	280.87	300.42
P Loss Reduction (%)	68.766	73.552
DG Location	5,32,16	20,30,17
DG size	398,1125,620	398,1125,620
VD Reduction (%)	19.461	20.472
VD Improvement (%)	76.436	80.41

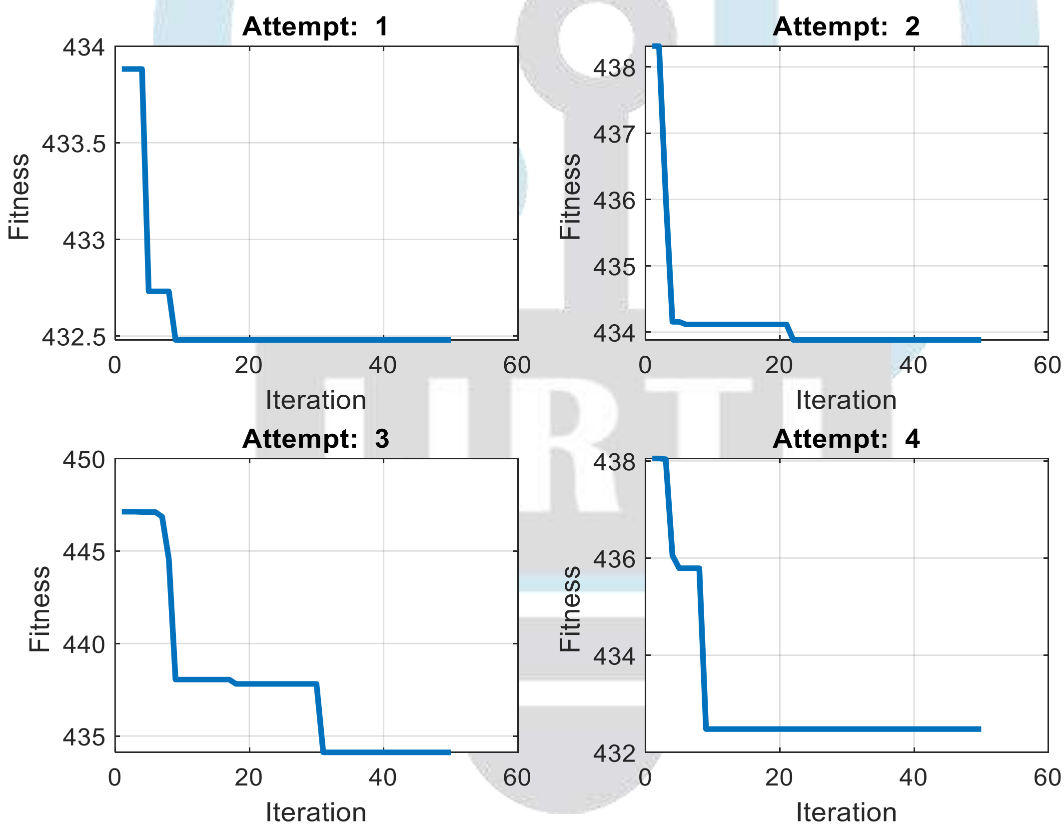
GWO Results 33 bus

Table 3:Allocation of EVCS locations without DG using GWO 33 bus

EVCS (Bus)	20,3,6,7,13	2,3,6,7,13	21,3,6,7,13	21,3,6,7,13
Minimum Voltage (pu)	0.86531	0.86531	0.86531	0.86531
VD (%)	25.417	25.401	25.42	25.401
Power-Loss (kW):	408.4649	407.0787	408.6962	407.0787
Power-Loss (kVAr):	275.1488	273.8875	275.4164	273.8875

Table 4: Allocation of EVCS locations with DG using GWO 33 bus

EVCS (Bus)	2,3,6,7,13	10,8,6,5,2
Minimum Voltage (pu)	0.93894	0.93894
VD (%)	67.952	3.474
Power-Loss (kW):	130.4359	96.2466
Power-Loss (kVAr):	85.8373	63.7174
P Loss Reduction (kW)	276.56	310.75
P Loss Reduction (%)	67.952	76.352
DG Location	6,13,7	6,13,7
DG size	401,1019,708	401,1019,708
VD Reduction (%)	18.658	21.926
VD Improvement (%)	73.456	86.323



Power Analysis and Voltage Profile of IEEE 14 system

Table 5: Test Allocation of EVCS locations without DG GWO 14 bus

	2,4,6,10,13	2,4,3,10,12	2,3,8,10,12	9,3,2,10,13
Minimum Voltage (pu)	0.99892	0.99894	0.99889	0.99873
VD (%)	0.00055401	0.00055409	0.00055402	0.00055312
Power-Loss (kW):	0.0080052	0.0080043	0.0080031	0.0080031
Power-Loss (kVAr):	0.74674	0.74635	0.0080031	0.74652

Table 6: Placing 3 DGs using GWO 14 bus

Minimum Voltage (pu)	1	0.99943
VD (%)	0.00014277	0.00027375
Power-Loss (kW):	0.2085	0.10626
Power-Loss (kVAr):	0.66755	0. 34539
P Loss Reduction (kW)	401.89	406.89
P Loss Reduction (%)	98.132	99.974
DG Location	3,13,7	3,13,7
DG size	487,430,343	487,430,343
VD Reduction (%)	25.4	25.4
VD Improvement (%)	99.999	99.999

Table 7: Allocation of EVCS locations without DG using PSO 14 bus

EVCs (BUS)	2,4,3,10,1	2,4,6,10,12	2,3,13,10,11	2,4,13,10,12
Minimum Voltage (pu)	0.99894	0.99894	0.99894	0.99982
VD (%)	0.0005540	0.00055409	0.00055409	0.00055523
Power-Loss (kW)	0.0080043	0.0080063	0.00800254	0.0080143
Power-Loss (kVAr)	0.74635	0.74692	0.74851	0.74671

Table 8: Allocation of EVCS locations with DG using PSO 14 bus

Minimum Voltage (pu)	0.99994	0.99953
VD (%)	$1.4136\text{x}10^{-05}$	0.00011956
Power-Loss (kW)	0.0042828	0.0044663
Power-Loss (kVAr):	0.76107	0.33254
P Loss Reduction (kW)	408.44	408.44
P Loss Reduction (%)	97.99	97.99
DG Location	2,8,9	4,6,13
DG size	438,1123,430	438,1123,430
VD Reduction (%)	25.46	25.46
VD Improvement (%)	96%	94%

5. Conclusion:

In summary, the work mentioned here appears to provide a comprehensive overview of the various aspects involved in optimizing charging station locations, including problem formulation, solution techniques, and considerations such as EV load modeling, uncertainty handling, renewable energy integration, and V2G strategies. Metaheuristic algorithms are highlighted as effective tools for achieving better optimization results in this context. In summary, the work mentioned here appears to provide a comprehensive overview of the various aspects involved in optimizing charging station locations, including problem formulation, solution techniques, and considerations such as EV load modeling, uncertainty handling, renewable energy integration, and V2G strategies. Metaheuristic algorithms are highlighted as effective tools for achieving better optimization results in this context.

Understanding the preferences and behaviors of EV users is crucial for effective planning and deployment of charging infrastructure as a future scope. By considering factors such as travel patterns, charging habits, and user preferences, planners can optimize the placement of charging stations to better meet the needs of EV users while minimizing the impact on the distribution network. This holistic approach will be essential for ensuring the successful integration of EVs into the transportation system while maintaining grid stability and reliability.

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