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Modified Artificial Hummingbird Algorithm for Determining Optimal Location of EVCS in Power Grid

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Abstract

The rapid increase in the adoption of electric vehicles (EVs) in recent years is leading to a significant impact on the electric grid. To ensure sufficient power to these EVs, multiple electric vehicle charging stations (EVCSs) need to be deployed strategically in the electrical power network. Randomly adding these EVCSs can cause potential power quality problems and necessitate additional infrastructure like new distribution/transmission lines, transformers and sub-stations. This can be overcome by optimal deployment of EVCSs. Many existing optimization techniques suffer from premature convergence, sensitivity to initial parameters, the curse of dimensionality and not performing well on non-linear problems. This leads to suboptimal results. To address these drawbacks, a novel method, based on the Artificial Hummingbird Algorithm (AHA), has been developed to identify the optimal location of EVCSs. The novel method, the Modified Artificial Hummingbird Algorithm (MAHA), has been applied to the standard power network–IEEE-57 bus system to find the optimal placement of EVCSs. When compared to existing methods of AHA, Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO), the results show that MAHA is more effective in determining the optimal placement of EVCSs.

Keywords: artificial hummingbird algorithm; electric vehicles; electric vehicle charging stations; modified artificial hummingbird algorithm; power quality

1. Introduction

The rise in gasoline prices and pollution is driving the shift from internal combustion engine (ICE) vehicles to electric vehicles (EVs). The increasing number of EVs on the road will burden the electric grid and further deteriorate its performance. In order to keep up with the increasing demand for EVs, it is inevitable that a greater number of charging stations will be installed in the electric distribution network. The random placement of electric vehicle charging stations (EVCSs) in the electric distribution network may lead to increased losses in the system, the erection of new power lines, and the installation of additional transformers and other electrical equipment. For the EV transition to be hassle-free and to reduce economic burden, strategic placement of EVCSs is necessary.

From a real-world deployment perspective, EVCS planning is constrained not only by user accessibility and land availability but also by grid-side practical limits such as the hosting capacity of the local network, transformer and line thermal loading, voltage magnitude/regulation limits, and the operational impacts of large power-electronic converters (e.g., reactive power demand and potential power quality concerns). In addition, charging demand is highly time-varying and uncertain, driven by traffic patterns, charging behavior,

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and coincident peaks, which makes it necessary for planners to evaluate multiple scenarios rather than a single deterministic snapshot. Utility interconnection processes and economic considerations (upgrade deferral, equipment reinforcement, and operational costs) further motivate grid-aware siting methods that can identify locations with lower incremental losses and reduced stress on network operating constraints.

In the literature, several works have been reported; overall, the existing studies have clear strengths and limitations when applied to grid-based EVCS planning. Sensitivity-based and heuristic screening techniques (e.g., index-based algorithms), which are computationally lightweight and interpretable, become less effective when the problem is extremely non-linear or when more than one operational limit is applied. Although metaheuristic optimizers such as PSO, GWO, GOA, BAT, AHA, and others that promise adaptability between goals (like loss, voltage deviation, and cost) are flexible, their performance can be affected by parameter settings, constraint-handling design and the discrete encoding of candidate locations, resulting in premature convergence or variable solutions across different scenarios. Mathematical programming approaches (e.g., MILP) can yield globally optimal computations based on specified assumptions but often come with the need for linearization and may not scale well as network size or scenario count increase. These findings drive an optimizer that is simple to combine with standard AC power flow analysis while increasing the robustness of the exploration–exploitation tradeoff for discrete EVCS siting. Overall, the current studies present strong evidence but present significant limitations when used for grid-aware EVCS planning. Sensitivity-based and heuristic screening approaches (e.g., LSF- or index-based algorithms) are computationally light and interpretable and less applicable to very non-linear problems or problems in which multiple operational limits are entangled. Metaheuristic optimizers, e.g., PSO, GWO, GOA, BAT and AHA, have been proven to produce robust search performance and to be able to flexibly approach objectives (loss, voltage deviation or cost), but their performance may depend on parameter settings, the design of constraint-handling mechanisms, and the encoding of candidate locations and might converge too early or yield unequal performance across scenarios. On the contrary, strict mathematical programming methods such as MILP are capable and able to lead to globally optimal solutions in modeling; they can produce only a few effective solutions, which usually result in the need to linearize and perform careful Big-M formulation and hence require higher computation as the network increases in scale and number of scenarios. These findings suggest the need for an optimization method that is easy to integrate with common AC power flow analysis and that can make the exploration–exploitation balance more robust to discrete EVCS siting problems. In [1], application of the Artificial Hummingbird Algorithm (AHA) to EV route optimization proves to be successful, highlighting its capability in improving energy efficiency and cutting down on travel time. Moreover, the researchers in [2] expanded the use of AHA by creating a multi-objective optimization model to reduce active power loss, reactive power loss, and voltage deviation in radial distribution networks. AHA surpasses Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) in effectiveness and efficiency for optimal placement and sizing of DGs. In [3], the superior performance of AHA is shown in the case of Renewable Distributed Generators (RDGs) for IEEE 33 and 69 bus systems, even when accounting for uncertainties in renewable sources. AHA outperformed both improved Harris Hawks and Particle Swarm Optimization algorithm (HHO-PSO) and Phasor Particle Swarm and Gravitational Search Algorithm (PPSOGSA) algorithms in the benchmarking tests. The authors of [4] investigated the use of AHA in long-term generation expansion planning (GEP) for a 14-year period. This research focused on minimizing costs while considering projected peak demand, renewable energy sources, and measures of reliability, demonstrating AHA's viability in long-term energy strategy.

AHA's ability to adapt is also shown in reconfiguring distribution systems to reduce losses. In [5], AHA was utilized by the authors to optimize the IEEE 69 bus system, and its performance was evaluated against six other optimization methods, with AHA demonstrating superiority once more. Advancements in the AHA group consist of the chaotic AHA (CAHA), which was presented in [6] for locating faults in transmission lines, surpassing the Genetic Algorithm (GA), Harmony Search (HS), and Teaching Learning-Based Optimization (TLBO) in terms of accuracy. AHA was used in renewable energy to optimize solar panel parameters in [7], and the outcomes were compared with four different optimization algorithms. The results demonstrated that AHA's precision closely aligned with actual hardware configurations, solidifying its dependability. AHA's usefulness also applies to unmanned aerial vehicles (UAVs), as shown in [8], where AHA was used for path planning. It surpassed the Firefly Algorithm in both experimental and simulation outcomes. Furthermore, a binary AHA (BAHA) was developed for discrete optimization problems, as referenced in [9], with BAHA showing superior performance to AHA in benchmark experiments. The authors of [10] utilized AHA in antenna design optimization to enhance wireless power transfer efficiency, leading to improvements in input impedance, gain, and efficiency, demonstrating AHA's effectiveness in optimizing communication systems. In addition to traditional plug-in chargers, wireless electric vehicle charging (WEVC) is emerging as a feasible solution to enhance user access and provide hands-free charging experiences. Recent work introduced wireless chargers in EVs integrated in a non-intrusive manner with the onboard charger interface, achieved 95.60% dc–dc efficiency at an LD-to-CL ratio of 0.51 in an on-vehicle demo [11]. For the charging station at the grid level, an equivalent fixed power injection/withdrawal at the candidate bus is modeled in this study, and hence the proposed siting method remains applicable to either wired or wireless charging infrastructures, with wireless conversion losses represented through an efficiency factor in the net grid demand.

The work in [12] introduced AHA, inspired by hummingbird foraging strategies, which was tested on ten engineering design case studies, demonstrating better results than traditional algorithms. Different combinations of algorithms have been investigated in the field of EVCS. An example is [13] which analyzed the best way to design EVCSs with combined photovoltaic (PV) and battery energy storage systems (BESSs). In this study, PSO, the Sparrow Search Algorithm (SSA), and the Arithmetic Optimization Algorithm (AOA) were compared, with PSO being identified as the top performer. Similarly, the authors of [14] examined the placement of EVCS by combining MATPOWER and extended ant colony optimization, achieving optimal outcomes in the IEEE 30 bus system through a reduction in grid power imports. In [15], the comparison of Loss Sensitivity Factor (LSF) with PSO and HHO in optimizing the placement of EVCSs is also addressed. In [16] the Allahabad region of India, a revised Balanced Mayfly Algorithm (BMA) was implemented for EVCS and DG placement in the IEEE 30 bus system. By improving precision using chaotic elements, BMA surpassed the standard Mayfly and GA-PSO techniques. Studies are described in [17,18] that utilize PSO for placing EVCSs and DGs simultaneously. In [19], a combination of the Grasshopper Optimization Algorithm (GOA) and PSO was utilized to optimize placement in IEEE 33 and 69 bus systems in Bangalore, India, resulting in notable reductions in system losses. Similarly, the authors of [20] used BAT optimization for positioning EVCSs and DGs, achieving positive outcomes in the IEEE 33 and 69 bus networks, demonstrating once again the effectiveness of metaheuristic algorithms such as AHA for power system optimization.

The authors of [21] examine all of the commonly utilized optimization algorithms for the ideal positioning of EVCSs. The study demonstrates potential factors to consider when creating optimization problems such as problem definition, goal functions, limitations, and strategies. The authors of [22] showcase the optimal positioning of EVCSs through

the utilization of the Symbiotic Organisms Search (SOS) algorithm. The algorithm was implemented on the IEEE 33 bus system in two scenarios: one aimed at decreasing transmission losses and the other focused on minimizing network loss cost. Another important research study [23] examines the optimization of battery swapping and charging station locations in Pune, India, with the goal of lowering charging and investment expenses. The authors evaluate nature-inspired algorithms like the Genetic Algorithm (GA), PSO, Teaching-Learning-Based Optimization (TLBO), Artificial Bee Colony (ABC), and Cuckoo Search Optimization (CSO) in a critical review [24]. They highlight the increasing possibilities of hybrid algorithms, which merge the advantages of these methods, providing better performance in the optimal positioning of EVCSs. Social Network Optimization (SNO), a novel algorithm explored in [25], focuses on residential density and quality of service (QoS) for optimal placement of EVCSs, proving efficient for EV service provision.

In [26], a method for optimal planning of road infrastructure and power network expansion is suggested using mixed-integer linear programming (MILP) with improved Big-M strategies to minimize both operational and investment expenses. Furthermore, the study conducted in [27] utilized PSO to find the optimal locations for EVCSs, resulting in the identification of 58 out of 320 potential sites in Jakarta. This led to decreased operational expenses and improved accessibility for EV users. In [28], a method combining PSO with a reconfiguration step for EVCS placement was introduced, investigating four distinct scenarios. The research found that combining the two-step approach is more efficient in minimizing power losses than relying solely on PSO. Similarly, the authors of [29] suggested a method based on a greedy strategy for optimal positioning of battery swapping stations, aiming to reduce operational expenses. This method shows the possibility of deploying EVCS in a cost-effective manner as the adoption of EVs grows. Research examining a variety of optimization algorithms, including PSO, GA, CSO, GWO, TLBO, and ABC, shows that hybrid algorithms are typically more effective than individual methods. This is further corroborated in [30,31], which offers a thorough examination of the different factors impacting ideal EVCS placement, such as defining the optimization issue, managing uncertainty, incorporating renewable energy sources, and Vehicle-to-Grid (V2G) tactics.

Based on the above literature review, it appears that existing optimization algorithms are often tailored to address specific objectives and constraints, which can limit their broader applicability. There is a notable gap in the literature regarding the optimal placement of EVCSs with specific capacity considerations. To address these gaps, this paper introduces a novel Modified Artificial Hummingbird Algorithm (MAHA), specifically designed to tackle the above-mentioned challenges. It is to note here that the proposed MAHA is an enhanced version of AHA that draws inspiration from the foraging strategies and flying capabilities of hummingbirds. AHA reaches a balance in exploration versus exploitation of the search space, which is critical in solving complicated optimization problems. However, many optimization techniques including AHA have a specific scope within which the effectiveness of that technique has a lot of limitations. Moreover, one of the major modifications made was the implementation of an exponential exploration rate and improved foraging strategies in MAHA. This greatly reduces the memory and storage requirements, hence improving convergence time—particularly within power system optimization. While AHA represents a powerful technique in general optimization, the modifications accorded by MAHA make the algorithm more adaptive and accurate, therefore pointing out the evolving demands of problems being solved.

To emphasize the novelty of MAHA, it is important to distinguish it from other recent AHA-related developments such as binary/discrete AHA variants and chaotic/multi-strategy enhancements that primarily target general-purpose benchmark optimization. In the EVCS siting problem studied here, the decision variable is inherently discrete (candidate bus index), and each candidate must be evaluated through an AC power flow solution.

MAHA introduces (i) an exponentially decaying exploration rate to transition systematically from wide exploration to refined search, and (ii) a periodic global-reset mechanism to mitigate premature convergence when the population collapses around suboptimal buses. These modifications are designed specifically to improve robustness and convergence behavior for discrete EVCS placement under AC power flow evaluation.

This paper focuses on optimal placement of EVCSs in the active power network by reducing transmission losses, maintaining system levels (voltage, active and reactive power generation) within the specified limits and balancing currents. This way, the electric grid does not require immediate upgrades and installation of new infrastructure, which in one way reduces the extra capital investment and in turn benefits the environment by efficiently utilizing the electricity produced by the generating station. In this work, all of the simulations were performed in MATLAB version 24.1, using parallel computing and MATPOWER toolboxes on an Intel i7, 32 GB RAM, 8 GB RTX4060 graphics card-equipped system.

In summary, the novelty and major contributions of this work stand on the following facts.

(i) This paper proposes MAHA, a novel approach in optimizing EVCS placement within a power network. It offers superior convergence in time and better memory efficiency compared to traditional AHA, PSO and GWO algorithms and reduces transmission losses. It uniquely applies fixed load—5 MW for the IEEE 57 bus system, representing real-world fast-charging stations—something which is largely overlooked in prior research that tends to be focused on variable or theoretical loads. By considering this realistic load condition, the present work has demonstrated the scalability and adaptiveness of MAHA in a medium-sized electrical power network.
(ii) To the best of our knowledge, this is the first effort to take a 5 MW fixed EVCS load for the IEEE 57 bus system in single-objective optimization, thus providing a practical, implementable solution for the optimization of EVCS placement in modern power systems.
(iii) MAHA is used to tackle this optimization problem of a single objective function to minimize transmission losses in an active power system.
(iv) The performance of the proposed MAHA optimization algorithm has been compared with that of AHA, PSO and GWO in optimizing EVCS placement.

The remainder of the paper is structured as follows. Section 2 presents the problem statement. Section 3 formulates the methodology and implementation of the optimization study. Section 4 presents the results and analysis of the IEEE 57 bus benchmark system and four various algorithms. Finally, Section 5 concludes the paper and suggests future directions for this study.

2. Problem Statement

The increasing demand for EVs enforces the requirement for perfect placement of charging stations to avoid integration with existing power systems. Improper placement of EVCSs can lead to many problems such as increased power losses, voltage instability, and increased infrastructure cost especially for large and complex power networks. Also, improper placement of EVCSs may lead to underutilizing the EVCSs, which further affects the cost of charging; strategic placement of EVCSs will improve user accessibility which in turn encourages users to adopt broader adaptation of EVs. Aligning EVCS placement with traffic flow ensures the efficient use of EVCSs, thereby increasing reliability. Proper placement of EVCSs also indirectly reduces emissions by promoting greener transportation.

Existing optimization techniques like PSO, GWO, GA and CSO often struggle to handle the non-linear and high-dimensional nature of this problem quickly and robustly, resulting in suboptimal solutions. Many algorithms rely on simplistic assumptions which

may not reflect real-world scenarios. Some of them also struggle to perform efficiently when applied to large systems, demonstrating potential scalability issues. On the other hand, advanced algorithms have increased computational demands, making them the worst performers for real-world scenarios. Many existing algorithms may not adapt well to the dynamic nature of EV charging demand, which is inherently dependent on factors like weather, traffic pattern and user behavior. To address these limitations, this study explores a new optimization algorithm aiming to improve the solution accuracy and computational efficiency for optimal placement of EVCSs. This fact motivates the proposed research.

This work involves grid-side siting for equivalent EVCS load (single-station case); corridor coverage (multiple stations between distant nodes with spacing/range constraints) requires a coupled transportation–power planning formulation that will be left for future work.

3. Proposed Methodology and Implementation

The main objective of this study is to optimally place EVCSs in a power network such that the transmission losses in the system are minimized. The single objective function is formulated as:

$$\text{Min } f(x) = \sum_{k=1}^{N_b} P_{loss}(x_k) \tag{1}$$

$$P_{loss} = 1/2 \sum_{i=1}^{N_b} \sum_{j=1}^{N_b} G_{ij} \left(V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij} \right) \tag{2}$$

where N_b is the number of buses, x_k is the bus number indicating the presence of an EVCS at bus k and $P_{loss}(x_k)$ represents the total power loss when an EVCS is placed at bus k, G_{ij} is the conductance between buses i and j, V_i and V_j are the voltage magnitudes at buses i and j, respectively, and θ_{ij} is the phase angle difference between buses i and j. The constraints were to set the generation of active and reactive powers within the specified limits to make sure that the voltage per unit (pu) is between 0.97 and 1.03 pu, the current flows in the system are balanced, and the AC power flow equations are satisfied at each bus i. In this study, the decision variable x_k indicates the selected candidate bus index for 5 MW EVCS placement.

It should be noted here that this study adopts a single-objective formulation (loss minimization) to isolate and quantify the grid-side impact of EVCS placement under a fixed charging demand scenario and to enable a clear benchmarking of MAHA against other optimizers. We acknowledge that practical EVCS planning is inherently multi-objective, typically involving additional criteria such as capital and reinforcement cost, charging demand distribution, service accessibility/coverage, and stakeholder constraints (land availability, permitting, and interconnection requirements). These objectives can be incorporated in future work through (i) weighted-sum or goal-programming formulations or (ii) Pareto-based multi-objective MAHA to generate trade-off fronts between grid performance and service/economic metrics.

Active power generation constraint:

$$P_{gen}^{min} \leq P_{gen} \leq P_{gen}^{max} \tag{3}$$

Reactive power generation constraint:

$$Q_{gen}^{min} \leq Q_{gen} \leq Q_{gen}^{max} \tag{4}$$

Voltage constraint:

$$0.97 \text{ pu} \leq V_i \leq 1.03 \text{ pu} \tag{5}$$

Current constraint:

$$I_{i \text{ entering}} = I_{i \text{ leaving}} \tag{6}$$

AC power flow equations:

$$P_i = V_i \sum_{j=1}^{N_b} V_j \left(G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}\right) \quad (7)$$

$$Q_i = V_i \sum_{j=1}^{N_b} V_j \left(G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}\right) \quad (8)$$

where are the active and reactive power injections at bus *i*, are the voltage magnitudes at bus *i* and *j*, are the conductance and susceptance of the line between buses *i* and *j*, and is the voltage angle difference between buses *i* and *j*. The power flow is computed using the MATPOWER toolbox and Newton–Raphson method. In the loss and power flow expressions, the indices i and j represent separate buses connected by a branch (i.e., the summations are over network connections and the i = j case is excluded). The AC power flow is solved using MATPOWER (version [v8.1]) via the Newton–Raphson method (runpf). A 5 MW EVCS load is modeled for the candidate buses by updating the corresponding bus real-power demand in the case data, and a new power flow is executed from the same base-case initialization.

The voltage band is chosen as a conservative planning target (±3% around nominal) to preserve a margin of typical service-voltage tolerance guidance (e.g., ANSI C84.1 Range A is around ±5% around nominal), particularly at high EV penetration and demand uncertainty.

MAHA is derived from a metaheuristic-based AHA-inspired optimization algorithm that uses the amazing foraging behavior of hummingbirds to solve complex optimization problems. The key features of AHA include foraging strategies, randomness, balanced exploration and exploitation and good recap memory of food sources. MAHA is modified such that guided and territorial foraging strategies are adapted to improve exploration and exploitation, respectively, and the migration foraging strategy is modified such that the algorithm will reset the positions of birds every n iterations based on problem complexity.

In this study, the reset mechanism triggers if the global fitness value remains unchanged even after 5 consecutive iterations. At that point, the current best solution is retained and all of the remaining hummingbirds are reinitialized uniformly within a feasible bus-index set.

The detailed steps of MAHA are given below, and Algorithm 1 shows a brief overview of the developed MAHA.

Algorithm 1. Modified AHA.

1. Initialize Parameters
   - Set the number of hummingbirds
   - Maximum iterations
2. Identify Valid Solution Placement
3. Randomly Initialize Hummingbird Positions
4. Evaluating Initial Fitness
5. Update Global Best
6. Foraging Strategies
   - Exploration:
     if rand < exploration rate
   - Exploitation:
     else follow global best bird
   - For every n iteration:
     follow global best
7. Terminate Algorithm
8. Display Results

Step 1: Initialization: The population of hummingbirds is assigned at different potential solutions randomly within the entire search space.

$$x_i^0 = \text{rand}(L_o, H_o) \forall i \in [1, N] \tag{9}$$

where x_i^0 is the initial position of the i^{th} hummingbird, L_o and H_o are the lower and upper bounds of the bus indices and N is the number of hummingbirds.

Step 2: Fitness evaluation: Each hummingbird's fitness is evaluated by calculating the system losses for a given EVCS placement, based on the provided objective function and constraints.

Step 3: Position update mechanism: After the fitness evaluation at one bus, hummingbirds try to explore the different search spaces around their current position for the calculation of a new fitness solution in this phase. In this step, hummingbirds will restrict themselves around their current position only to maximize the exploration of search space.

$$x_i^{t+1} = \begin{cases} x_i^t + \alpha \ (2 \ \text{rand}(r) - 1) \text{ if } r > \in \\ x^t_{\text{global}_{\text{best}}} \qquad \text{otherwise} \end{cases} \tag{10}$$

$$\in (t) = 0.8 * e^{-0.1 * t} \tag{11}$$

where x_i^{t+1} is the position of the i^{th} hummingbird at iteration t + 1, r is a random number uniformly distributed between 0 and 1, $\in$ is the exploration rate and $x_{\text{global_best}}$ is the position of the global best hummingbird.

Step 4: Global reset: When the current iteration is equal to the given number according to the problem complexity and number of total iterations, this step triggers. This aids in exploitation and encourages hummingbirds to move far away from their current positions.

$$P_i^{new} = \begin{cases} \arg\max \text{distance}(P_i^{old}, \ v); \\ \qquad = 0, \ v \in V_i \\ x^t_{\text{global}_{\text{best}}} \qquad \text{otherwise} \end{cases} \tag{12}$$

where P_i^{old} is the current position of the hummingbird, P_i^{new} is the new position of the hummingbird after reinitialization, V_i is the valid set of positions or nodes available for the hummingbird, and distance (a, b) is a function that measures the distance between a and b.

The global reset is triggered when the best fitness does not improve for 5 (in this particular case) consecutive iterations (stagnation window). When triggered, all of the hummingbirds are reinitialized uniformly over the feasible bus set while retaining the current global best. This increases population diversity and helps to escape local minima, being observed as reduced plateaus in the convergence curves.

Step 5: Termination: The algorithm will stop once the number of iterations reaches the specified max iterations or the convergence for loss is achieved.

One of the key differences between MAHA and AHA is the exploration rate. MAHA's exploration rate is dynamic and adaptable as shown in Equation (11), while AHA has a fixed exploration rate throughout the search. The key differences are shown in Table 1 below.

Table 1. COMPARISON BETWEEN AHA AND MAHA.

Aspect	AHA	MAHA
Exploration–Exploitation	Fixed	Exponential decay: $\in(t) = 0.8 \times e\hat{}(-0.1 \times t)$
Movement Strategy	Mostly random	Random and towards global best solution
Fitness Evaluation	Static	Dynamic improvement based on global best
Search Adaptation	Constant exploration	Adaptive exploration–exploitation balance

Table 1. *Cont.*

Aspect	AHA	MAHA
Convergence Speed	Slower	Faster due to focus on global best
Algorithm Complexity	Simple	More complex, adaptive strategies
Suitability for Complex Problems	Higher risk	Lower risk due to dynamic focus

Note: In Equation (12), the exploration rate is defined using a single equality (i.e., (t) = 0.8e^(−0.1t)), and the duplicated = symbol in the earlier version was a typographical error.

For the MAHA algorithm, considering the IEEE 57 benchmark system, sensitivity analysis was performed and parameters like the number of birds, number of iterations and exploration rate were decided, and the number of birds and number of iteration values were kept the same for AHA, PSO and GWO to ensure fairness in the comparison. All three of these algorithms well-known for their optimization capabilities were used to compare with MAHA.

Transmission losses in the system are the sum of active power losses in all branches of the network and, similarly, reactive power losses are the sum of reactive power losses in all branches of the network. Though generation, voltage levels and current balance constraints were considered, they were measured at the end to ensure they were within acceptable limits.

In this study, the three optimization techniques AHA, PSO, and GWO were also implemented to compare the performance of MAHA in optimizing EVCSs.

3.1. Existing AHA Method

AHA is inspired by the food searching behavior of hummingbirds. In this algorithm, hummingbirds have 3 foraging strategies to search for food sources, guided, territorial and migration, as shown in Algorithm 2. Based on the best global solution, all of the remaining birds will choose to either follow the best bird or search for further solutions near their current position and/or far away from their current position. If the number of iterations reaches the multiple value of the birds, then the positions of all the birds will be reset in the search space. The tradeoff between exploration and exploitation is balanced by the initialized exploration rate. As all the visits of birds are logged in a visit table, the algorithm has more memory consumption but in contrast it is simpler to implement and scalable. This algorithm will be one of the benchmark systems to compare the performance of the developed MAHA.

Algorithm 2. Artificial Hummingbird Algorithm.

1. Initialize Parameters
    - Set the no. of hummingbirds
    - Exploration rate
    - Maximum iterations
2. Identify Valid Solutions
3. Randomly Initialize Hummingbird Positions
4. Evaluating Initial Fitness
5. Update Global Best
6. Foraging Strategies
    - Guided foraging, territorial foraging
    - Migration strategy
7. Track Visits
8. Terminate Algorithm
9. Display Results

Differences between AHA and MAHA: (i) Specification that MAHA takes an exponentially decaying rate for exploration (Equation (11)) instead of a fixed rate; (ii) Step 4 global reset differs from AHA migration; (iii) continuous bird positions are mapped to discrete bus indices (round/clamp into valid buses) before running MATPOWER. MAHA changes the search dynamics in comparison to AHA in two different manners: First, the exploration rate is made iteration-dependent using an exponential decay (Equation (11)) that changes search from exploration to exploitation; second, a periodic global-reset operator reinitializes a small fraction of agents to restore diversity once no search runs. Because EVCS siting is a discrete bus-index problem, we map each updated position to a valid integer bus index (by rounding and clamping to the feasible bus set) before determining the candidate using AC power flow (MATPOWER).

Every candidate EVCS placement requires solving the AC power flow; thus, with N agents and T iterations, an O(N·T·CPF) scaling of the computational cost happens, where CPF is the cost of one Newton–Raphson power flow solution for the considered system. The additional MAHA operations (exploration scaling, stagnation test, and occasional reset) only introduce O(N) overhead per iteration and are negligible in the context of repeated power flow evaluations.

3.2. Existing PSO Method

PSO is a population-based optimization algorithm inspired by the social behaviors of birds flocking and fish schooling. In PSO, particles are a group of candidate solutions that move within the problem space by position updating, with the reference of their own previous best positions and the entire swarm's best position. The algorithm of PSO is shown in Algorithm 3. The main parameters in PSO are the inertia weight, cognitive weight, and social component that influence the movement of particles. In fact, it is widely used for optimization problems because of its simplicity, ease of implementation, and ability to search in a large space. In this study, PSO serves as a benchmark technique against the proposed MAHA.

Algorithm 3. Particle Swarm Optimization.

1. Initialization:
    a. No. of particles, positions and velocities
    b. No. of iterations, inertia weight
    c. Personal/global best weights.
2. Fitness Evaluation:
3. Update Global Best:
4. Store Results:
5. Update Velocities:
    a. $V_i(t) = w * \ V_i(t-1) + c_1 * r_1 * (p_best_i - x_i) + \ + c_2 * r_2 * (g_best_i - x_i)$
6. Update Positions:
    a. $x_i(t) = x_i(t-1) + v_i(t)$
7. Repeat for All Iterations:
8. Display Result:

3.3. Existing GWO Method

GWO is inspired by nature and is considered as one of the metaheuristic algorithms. The hunting behavior of grey wolves is based on social hierarchy. The algorithm develops a leadership and hunting strategy. To consider a scenario: The wolf family consists of four

types of wolves based on leadership and decision-making policies—alpha, beta, delta, and omega wolves. Grey wolves change their positions according to the position of alpha, beta, and delta in the process of optimization, as shown in Algorithm 4, while hunting their prey. Since GWO has a simple structure with good exploration and exploitation capabilities, it has been applied to many different optimization problems. GWO is also used in this work as another comparative technique in assessing the performance of MAHA.

Algorithm 4. Grey Wolf Optimization.

1. Initialization:
    - No. of wolves, initial positions
    - No. of iterations
    - Exploration parameter 'a'
2. Fitness Evaluation:
3. Update Alpha, Beta, and Delta Wolves:
    - Identify the three best wolves:
    - $\propto$ (1st best solution)
    - β (2nd best solution)
    - δ (3rd best solution)
4. Store Results:
    - Track the best solution at each iteration
5. Update Positions:
    - $X_i(t) = \frac{X_\propto(t)+X_\beta(t)+X_\delta(t)}{3} - A.D$
6. Display Results

Algorithm parameters were chosen based on the recommended ranges found in the original references. A modest sensitivity estimate was carried out by varying population size, iteration budget, and exploration coefficients and selecting stable solutions for the base case without overfitting to a single random seed. All compared algorithms use the same population size and maximum iterations for fairness.

4. Results and Analysis

In this work, simulations have been performed to evaluate the performance of the MAHA for the optimal placement of EVCSs. One of the widely used power system models, i.e., the IEEE 57 bus system [32], has been considered to test the effectiveness and scalability of the proposed approach. The IEEE 57 bus system is one of the standard benchmark systems used for power flow analysis in mid-sized power grids [33]. It has 57 buses, 7 generators, 80 transmission lines, and 15 transformers and load buses, as shown in Figure 1.

Although IEEE 57 is a widely used benchmark, validation on additional IEEE test systems (e.g., 14-, 30-, 118-bus) and/or distribution feeders will be considered in future work to further assess generality.

The results obtained from these simulations were compared against three of the most popular optimization techniques, AHA, PSO and GWO. It is evident that MAHA provided superior performance among three techniques in terms of efficiency, convergence speed, and memory consumption.

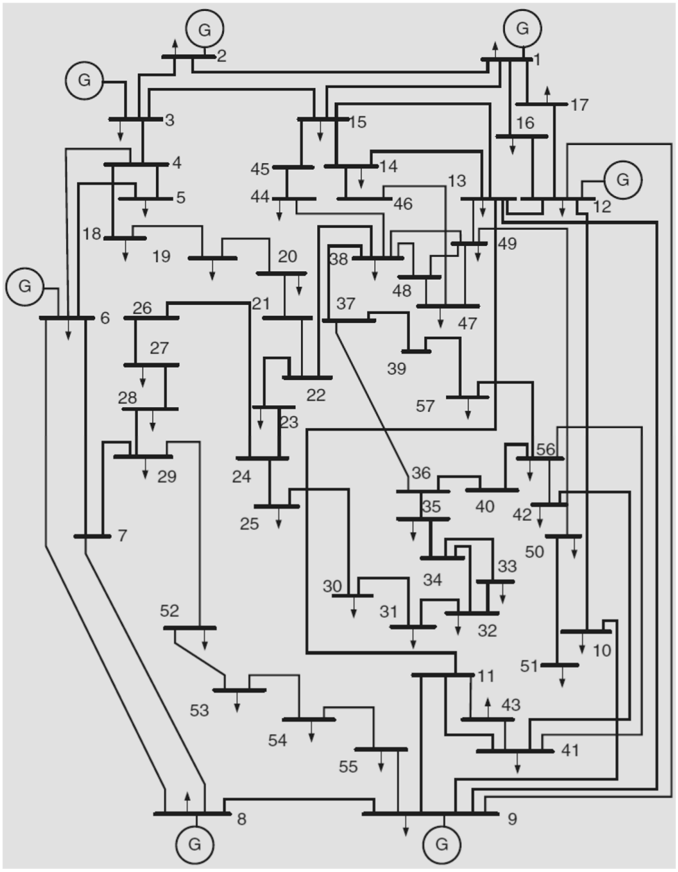


Figure 1. IEEE 57 bus system [32].

4.1. Results Obtained for IEEE 57 Bus System

4.1.1. MAHA

Figure 2 represents the transmission losses incurred in an IEEE 57 bus system, when 5 MW EVCS load is placed at various buses using MAHA and the optimal bus is found to be bus 1 with the least losses of 25.2 MW among all the buses.

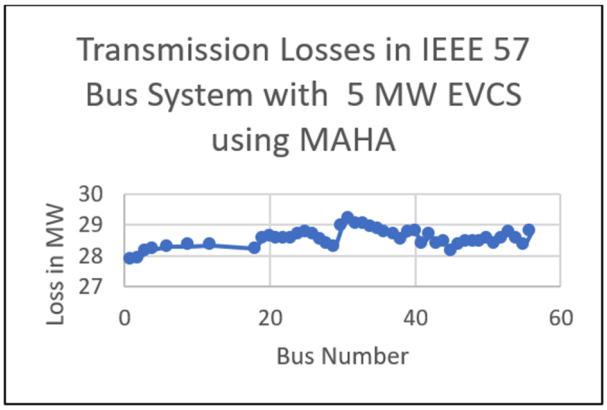


Figure 2. Transmission losses in IEEE 57 bus system with 5 MW EVCS using MAHA.

4.1.2. AHA

Figure 3 represents the transmission losses incurred in an IEEE 57 bus system, when 5 MW EVCS load is placed at various buses using AHA. The optimal bus is found to be bus 1 with the least losses of 27.8 MW among all the buses.

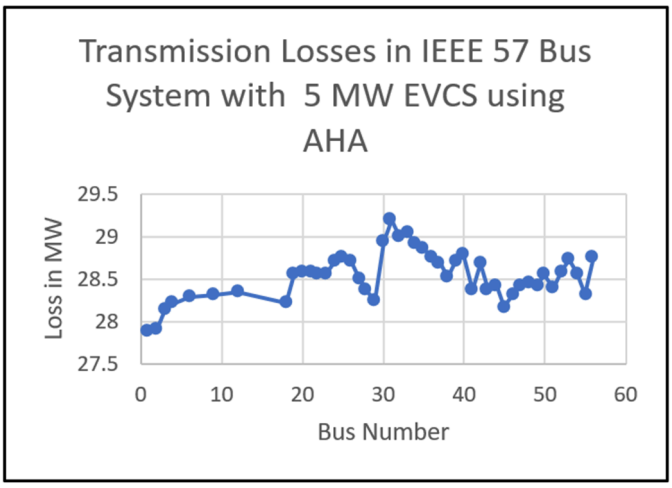


Figure 3. Transmission losses in IEEE 57 bus system with 5 MW EVCS using AHA.

4.1.3. PSO

Figure 4 shows the graph between transmission losses in MW versus bus number for an IEEE 57 bus system when PSO is used to optimize the location of 5 MW EVCS. The least losses are found to be zero entries at buses 30, 38, 40, 42, 44, 50, and 51. These zero loss entries cannot be interpreted as feasible physical losses but rather indicate non-convergence. This indicates that PSO did not converge at the optimal spot.

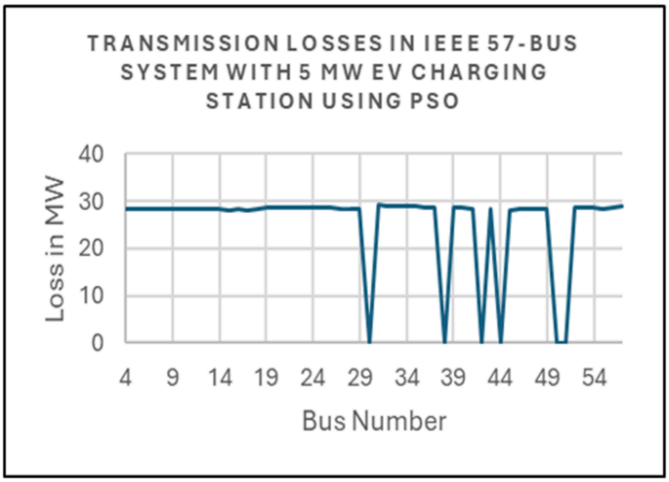


Figure 4. Transmission losses in IEEE 57 bus system with 5 MW EVCS using PSO.

4.1.4. GWO

Figure 5 illustrates the variation in transmission losses in the IEEE 57 bus system with a 5 MW EVCS load using GWO. The optimal location from the graph is found to be bus 45 with the least losses of 28.596 MW.

PSO and GWO are selected as representative baseline metaheuristics widely used in power-system optimization; extending the benchmark suite to additional recent optimizers under the same discrete-encoding and constraint-handling framework is left to future work. Table 2 illustrates the comparison of MAHA, AHA, PSO, and GWO optimization methods, focusing on four key parameters: convergence time, memory consumed, number of iterations and number of agents. Firstly, in terms of efficiency, MAHA demonstrates the least convergence time at 7.4 s, making it the faster method. Secondly, regarding memory usage MAHA and PSO show a lower memory consumption of 25.37 KB and 25.94 KB, respectively, whereas GWO uses 26.9 KB. Thus, MAHA and PSO are more memory efficient

than GWO. Lastly, it should be observed that all of the methods are performed under the same conditions, using 30 iterations and 20 agents each to ensure a fair comparison. Overall, PSO and GWO failed to converge at a bus and resulted in many zero loss buses, showing their inefficiency compared to MAHA in optimizing EVCS location. It can be concluded that MAHA is the most efficient method for optimizing EVCS location in the IEEE 57 bus system.

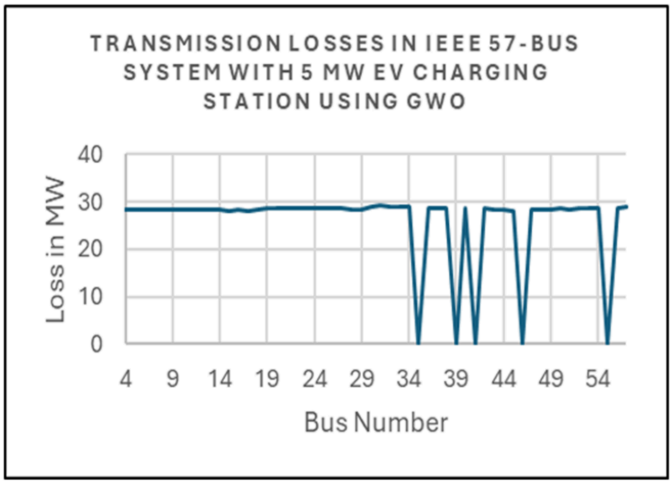


Figure 5. Transmission losses in IEEE 57 bus system with 5 MW EVCS using GWO.

Table 2. COMPARISON OF OPTIMAL PLACEMENT METHODS FOR EVCS IN IEEE 57 BUS SYSTEM.

Parameter	MAHA	AHA	PSO	GWO
Convergence time (sec)	7.4	8.6	15.8	17.9
Memory consumed (KB)	25.37	54.8	25.94	26.9
No. of iterations	30	30	30	30
No. of agents	20	20	20	20

This is to note that the reported convergence time (in seconds) is provided only as an indicator of computational efficiency under identical hardware and solver settings. Since EVCS placement represents a strategic planning problem, the decision to invest in the solution is based on the quality and feasibility of the solution (loss reduction and satisfaction of network constraints) rather than the variations of a few seconds in runtime involved in the solution. Even so, better computational efficiency is still of use in a practical sense, since it allows the evaluation of more planning scenarios (various EVCS capacities, multiple-station cases, and loading levels) under a single planning cycle.

All timing and memory figures were obtained on the same workstation (Intel i7, 32 GB RAM) by measuring MATLAB wall-clock runtime for a full optimization run and recording MATLAB process memory usage under identical iteration/agent settings.

4.2. Sensitivity Analysis

The hyperparameters in each algorithm are selected based on the trial-and-error method and are also verified with the parameter variation tests conducted in MATLAB Simulink to see the effect on the results due to changes in the parameters. The effect of parameter variation assesses the effect of changes in input factors on the output of the model [34]. Evaluating the robustness and reliability of an algorithm is important in both

optimization and machine learning. The systematic alteration of a wide array of prominent parameters (for example the number of particles, iterations, exploration rate, etc.) in the implementation of sensitivity analysis allows us to determine which parameter most extensively contributes to performance metrics, including losses and optimal solutions. It further refines parameter selection for computational models to make them more efficient and accurate. The IEEE57 bus system is chosen here to compare the sensitivity analysis of the algorithms.

The MAHA algorithm sensitivity analysis illustrates its high efficiency in load placement improvement by analyzing the effect of important parameters. The number of particles influences system losses, which are very small; this is shown in Figure 6, where increasing from 3 to 5 particles reduces the losses from 26 MW to 25.3 MW while subsequent changes stabilize, showing that MAHA operates optimally with a small number of particles. Likewise, Figure 7 shows that loss succession remains at about 25.5 MW, thereby demonstrating MAHA's excellent rapid convergence rate, eliminating the need for plentiful iterations as it varies from 3 to 15. This robustness is reinforced in Figure 8, where losses are presented and stable regardless of the exploration rate (0.1–0.4), demonstrating MAHA's independence of exploration when maintaining performance without manual fine-tuning.

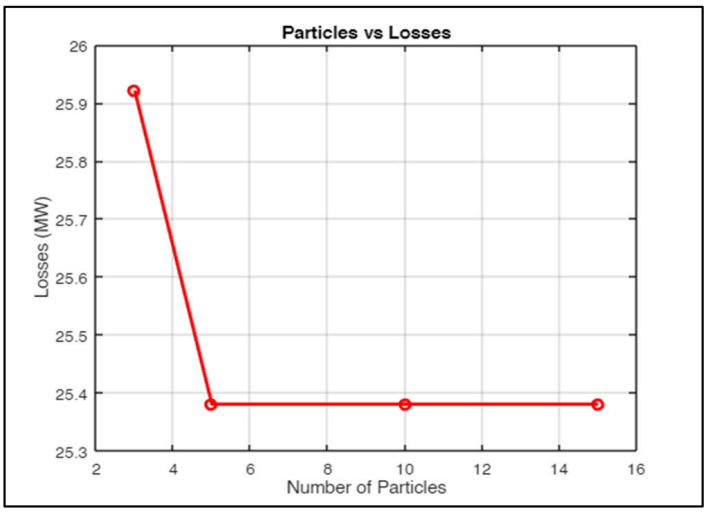


Figure 6. MAHA sensitivity to loss for different numbers of birds.

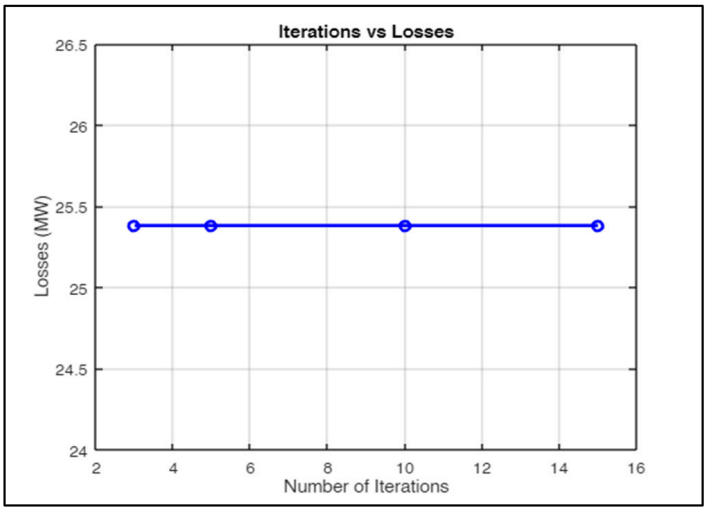


Figure 7. MAHA sensitivity to loss for different numbers of iterations.

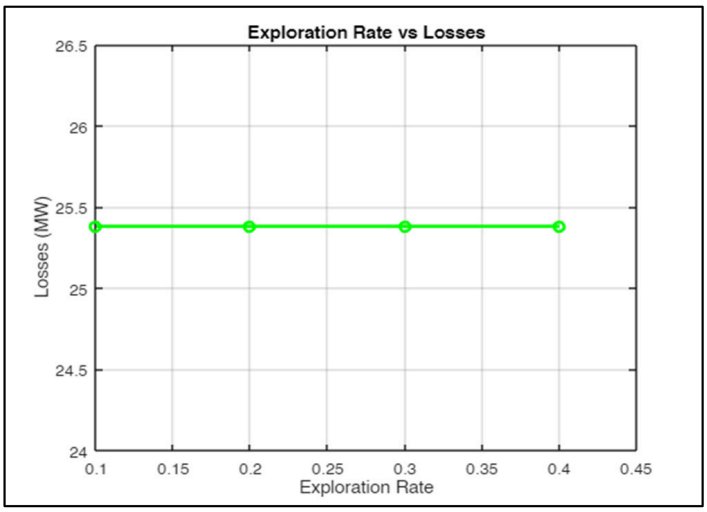


Figure 8. MAHA sensitivity to loss for different exploration rates.

The balance between exploration and exploitation also becomes evident in the analysis, as the current best bus is significantly reinforced after 3 or 5 particles (although improving more dramatically between 3 and 5 particles as shown in Figure 9), indicating that the algorithm converges quickly. Finally, Figure 10 shows that the number of iterations has no significant impact on the best bus selection, so MAHA picks the best bus without any redundant calculations. Finally, as we vary the exploration rate in Figure 11, the best bus selection remains the same, which shows both the robustness and stability of MAHA across different optimization scenarios. These results highlight not only that MAHA is more able to achieve efficient load placement than traditional algorithms, but it does so with significantly less runtime, meaning it is a more scalable and powerful optimization methodology.

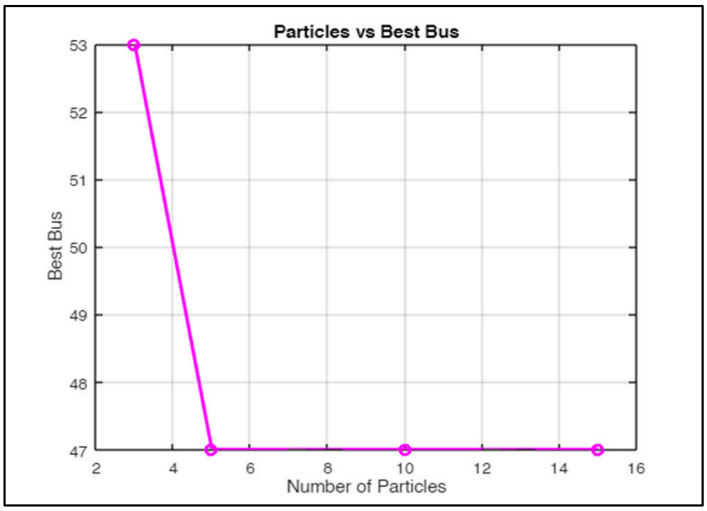


Figure 9. MAHA sensitivity to best bus for different numbers of birds.

The results of sensitivity analysis confirm that MAHA is more stable and efficient in the load placement optimization process. However, MAHA is least sensitive to parameter tuning and has significantly better loss minimization and the best bus selection compared to both algorithms. As a result, MAHA proves to be the most efficient optimization among the three while being robust.

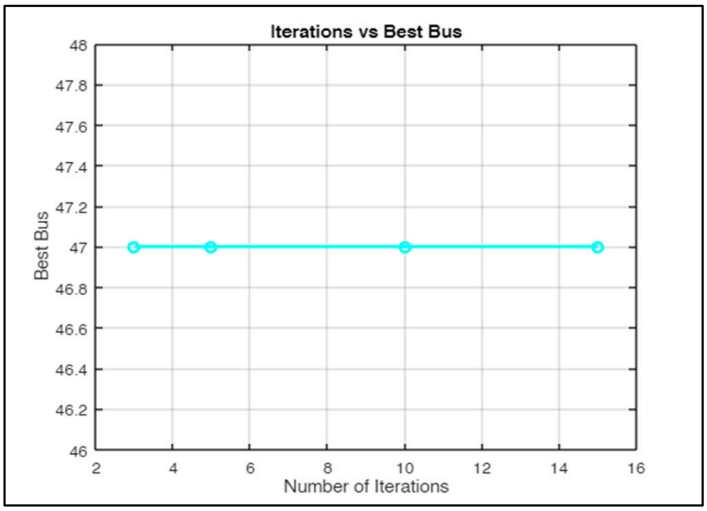


Figure 10. MAHA sensitivity to best bus for different numbers of iterations.

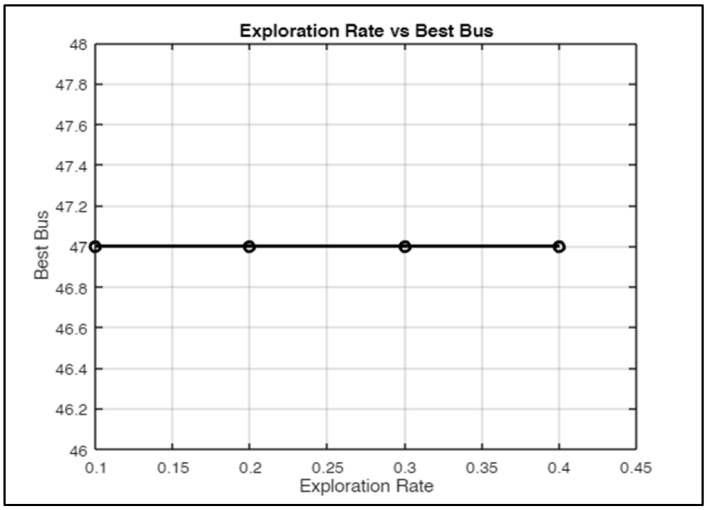


Figure 11. MAHA sensitivity to best bus for different exploration rates.

5. Conclusions

In this work, a novel method based on the Artificial Hummingbird Algorithm has been developed to identify the optimal location of EVCSs. The research on the placement of EVCSs upon the application of the MAHA for the IEEE 57 bus system has proved quite promising in terms of improvement in energy efficiency by means of a reduction in transmission losses in active distribution networks. The performance of the proposed MAHA method has been compared with that of other optimization techniques, like AHA, PSO, and GWO.

For the IEEE 57 case with 5 MW EVCS addition, MAHA identified bus 1 as the best location and achieved the lowest loss found by the tested methods at the same iteration/agent budget (MAHA best loss 25.2 MW vs. AHA best loss 27.8 MW).

Based on the obtained results, the following conclusions can be made.

(i) **Improved convergence speed:** The convergence speed of MAHA is higher compared to AHA, PSO and GWO. Though PSO converged comparably fast in the IEEE 57 bus system, both ended up giving a suboptimal solution. Thus, MAHA is more effective in solving large-scale optimization problems in EVCS placement.

(ii) **MAHA outperforms AHA, PSO and GWO:** MAHA gives better results than AHA, PSO and GWO in the optimal placement of EVCSs, which provides fewer power losses and improved system voltage stability.
(iii) **Cost-effectiveness**: The MAHA method turns out to be a more effective and robust technique in placing charging stations; thus, the overall infrastructural and investment cost can be reduced.
(iv) **Scalability across test systems:** MAHA showed its effectiveness in the IEEE 57 bus system. Thus, it can also be scalable for different-sized network configurations like IEEE 14, 30 and 118 bus systems.
(v) **Improved system stability:** The solution obtained from MAHA leads to a more balanced load distribution and better voltage regulation in the network without any zero loss solutions, improving the overall stability of the power system.
(vi) **Multi-objective strategies** for minimizing the losses/voltage deviation jointly take into account installation and reinforcement costs.
(vii) **Multiple-station siting** includes discrete set-encoding, uniqueness constraints, and service coverage requirements.
(viii) **Time-dependent charging** profiles and uncertainty-aware scenario analyses, alongside coordinated planning with distributed renewables and storage (EVCS + PV/BESS) including explicit branch thermal limits (or AC-OPF based evaluation), allow increased penetration.

In terms of future work, it opens up a whole new perspective wherein the integration of renewable energies, such as solar and wind, can potentially further enhance the sustainability of the entire system. Management of the variability in these renewable inputs by using appropriate optimization algorithms, linked with real-time data from smart grids, shall facilitate arriving at more reliable EVCS gridding flexibility. In addition, with the incorporation of machine learning models for demand pattern prediction and multi-objective optimization techniques studying economic cost, environmental impact, and user convenience, EVCS placement will become more holistic in the days to come.

Although the presented sensitivity analysis is performed on the effect of population size, number of iterations and exploration rate, future work will focus on the dedicated sensitivity parameter for the MAHA reset mechanism, which may include stagnation-window length and reset frequency as these parameters can influence convergence speed and diversity recovery.

Future works will include the benchmark set to include variants like binary AHA, chaotic AHA and other recent AHA methods under the same EVCS siting formulation.

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