Multi-Objective Optimization of RES and EV Charging Station Placement for Loss Minimization and Voltage Profile Enhancement in Distribution Systems

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Abstract

This paper addresses the challenges posed by the unpredictable nature of renewable energy sources (RES) and electric vehicle (EV) loads, which can impact power system reliability through issues like power quality degradation, increased losses, and voltage instability. To mitigate these effects, it proposes an innovative method for the combined optimal placement and sizing of RES and EV charging stations, along with a coordinated charging management strategy. The approach uses a multi-objective optimization framework aimed at minimizing power losses, voltage fluctuations, costs related to charging and energy supply, as well as EV battery expenses. The model incorporates factors such as wind speed, solar radiation, and hourly peak demand, to encourage EV charging during off-peak periods, thereby improving system efficiency and stability. The paper proposes a hybrid metaheuristic algorithm called Harris Hawk Optimization–Sine Cosine Algorithm (HHO-SCA) for optimizing renewable energy sources (RES) and electric vehicle (EV) charging systems. By integrating features of the Sine Cosine Algorithm (SCA) into Harris Hawk Optimization (HHO), the hybrid algorithm enhances both exploration and exploitation capabilities, leading to improved global search efficiency and optimized energy use. The HHO-SCA's performance was validated using benchmark functions and then applied to solve the proposed optimization problem under five different scenarios. Its effectiveness for the simultaneous optimal siting and sizing of RES and EV charging stations was demonstrated on the IEEE 33-bus system. Results show that HHO-SCA outperforms other methods by effectively avoiding local optima and achieving superior convergence behavior.

Keywords: Cost minimization, Electric Vehicle, Renewable Energy, Distribution Network, Optimization.

1. Introduction

The global dependence on fossil fuels, especially in transportation and electricity generation, is rising rapidly. This trend leads to higher energy costs and substantially contributes to greenhouse gas emissions and environmental harm. The *International Energy Outlook* (2011) forecasts a 54% increase in energy consumption in the transportation sector by 2035, which will likely intensify both costs and air pollution. In response, countries worldwide are seeking alternatives to traditional combustion-engine vehicles, with increasing focus on environmentally sustainable transportation solutions. Electric vehicles (EVs) offer a greener and more cost-effective alternative to gasoline-powered cars. Equipped with advanced batteries and power electronics, EVs can serve as flexible, grid-integrated energy storage units. The vehicle-to-grid (V2G) technology, which allows EVs to interact dynamically with the power grid, has gained substantial practical interest due to incentives related to ancillary services and grid regulation. In general, most of the EVs are stalled in the mode of parking for almost 85% of the day. This idle time presents an opportunity to support grid services such as frequency and voltage regulation using V2G technology [4]. This approach motivated the vehicles owners to earn additional income by engaging in V2G programs. Furthermore, utilizing the potential of the (EVs) and plug-in hybrid electric vehicle (PHEV) charging infrastructure can help to mitigate various power grid issues. In recent years, renewable energy sources (RES) have gained significant attention as viable alternatives to conventional fossil-fuel-based power generation [5]. Due to their proximity to load centres, RES can help reduce power losses, mitigate voltage fluctuations, and lower infrastructure investment costs [6]. However, their widespread integration into the grid introduces challenges due to the inherently variable and unpredictable nature of their output. To address this issue, large capacity Energy Storage Systems (ESS) are necessary to maintain grid stability [7]. Within this framework, Electric Vehicle (EV) charging stations can function as decentralized ESS through Vehicle-to-Grid (V2G) technology. These stations are capable of storing excess electricity generated by RES and supplying it back to the grid during peak demand periods, effectively decentralizing energy resources and alleviating stress on the distribution site [8]. The effective coordination of Plug-in Hybrid EV (PHEV) charging stations and RES not only reduces emissions but also provides a practical solution to various technical and economic challenges [9]. In this research, the Harris Hawk Optimization and Sine Cosine Algorithm have been considered for the optimal operation of the power distribution network with Res and EVs. HHO [10-12] and SCA [13-15] have contributed appreciable output in their respective fields of power system application. But it has been observed that HHO can get trapped in the local optima region due to initial parameter settings and system constraints. To address the limitations of Harris Hawk Optimization (HHO), particularly its inefficiency in long-distance exploration and extended convergence time, it is integrated with the Sine Cosine Algorithm (SCA), which possesses strong exploration capabilities. This hybridization is designed to improve both the convergence behavior and the exploratory efficiency of the overall optimization framework. Incorporating the characteristics of SCA into the exploitation phases enhances the accuracy of prey position tracking, reduces the spatial gap between the hawks and the prey, and accelerates the attack process. As a result of this integration, significant improvements are achieved in the exploration ability, positional accuracy, movement speed, and convergence rate of the hawks within the algorithmic model. Thus, to overcome this issue the HHO has been integrated with the framework of SCA to form a hybrid HHO-SCA that enhances its performance in the phases of exploration and exploitation. In this research, HHO-SCA is developed to simultaneously determine the optimal location and capacity of RES and EVCS, while integrating optimal EV charging scheduling, as a flexible resource to effectively minimize the system real power losses, cost of EVs charging voltage deviations, and cost in battery degradation.

1.1. Contribution

1. A comprehensive multi-objective function is developed to minimize the system's real power losses, EV charging cost, system voltage fluctuations, power supply cost, and battery degradation cost
2. Formulation of a novel hybrid optimization approach with the amalgamation of Harris Hawk Optimization and Sine Cosine Algorithm to form an enhanced HHO-SCA method minimize the system

real power loss, EV charging cost, power supply cost, voltage fluctuations, and battery degradation cost.

3. The HHO-SCA has been tested on standard benchmark functions to highlight its performance efficiency and has been applied to IEEE 33 bus system to optimize the research objectives. The HHO-SCA has been compared with recent Optimization techniques in terms of system real power loss, EV charging cost, power supply cost, voltage fluctuations, and battery degradation cost demonstrating improved performance in terms of computational efficiency and solution quality

2. Problem Formulation

2.1. Solar Photo Voltaic

Photovoltaic (PV) technology enables the direct transformation of sunlight into electrical energy and is one of the most prevalent approaches for solar power generation. The power output of a solar PV module is affected by solar irradiance (G), ambient temperature, and the output current and voltage. The temperature of the PV cells is typically estimated based on environmental and operational conditions:

2.2. Wind Energy System

A wind farm is a collection of wind turbines in a specific geographic area that work together to harness the kinetic energy of the wind and convert it into electrical energy. Wind farms are a sustainable and environmentally friendly method of generating electricity, contributing significantly to the global shift toward renewable energy.

2.3. EV Model

It is important to accurately model three key aspects related to EVs: the per mile energy consumption, the anticipated daily travel distance, and the time lapsed by the EVs while parked at the charging station. The anticipated daily distance—referring to how far EVs typically travel each day—can be effectively represented using a log-normal distribution. This statistical distribution describes random variables whose logarithms follow a normal distribution, making it suitable for modeling positively skewed data such as daily mileage. The log normal distribution can be represented as:

$$p = \begin{cases} p = 0 & for\ v_i < v\ and\ v > v_o \\ p = p_r * \dfrac{(v - v_i)}{(v_r - v_i)} & for\ v_i \le v \le v_r \\ p = p_r & for\ v_r \le v \le v_o \end{cases} \quad (1)$$

The Weibull PDF is represented as:

$$f_p(p) = \frac{k(v_r - v_i)}{c^k * p_r}\left[v_i + \frac{p}{p_r}(v_r - v_i)^{k-1}\right] \exp\left[-\left[\frac{v_i + \frac{p}{p_r}(v_r - v_i)}{c}\right]^k\right] \quad (2)$$

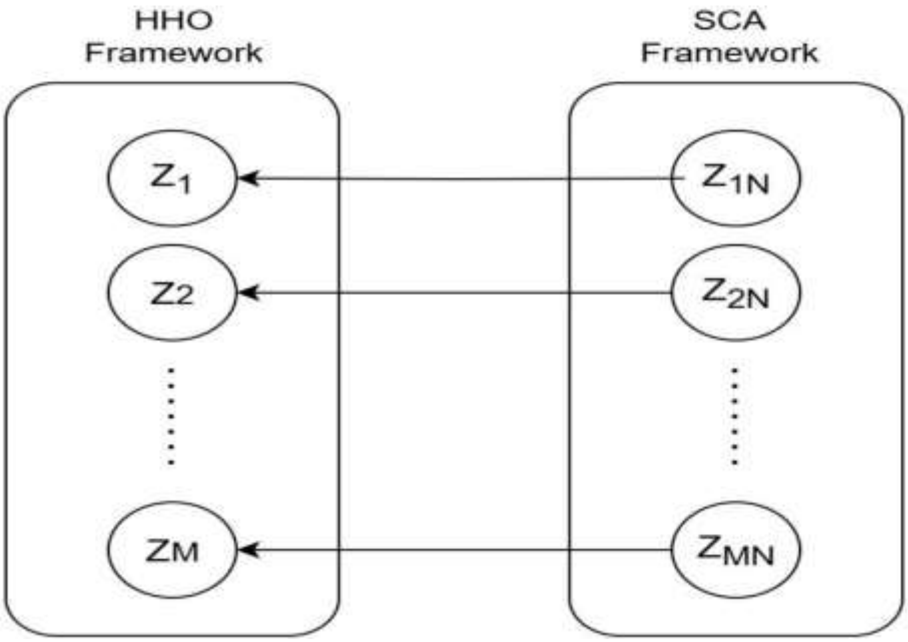


Fig1. Framework for HHO-SCA.

2.4. Objective function formulation

This section presents the mathematical formulations and models used to jointly optimize the siting and sizing of RES and EV charging stations, considering two distinct viewpoints. The first focuses on the system operator's objective to minimize power losses and voltage deviations, while the second emphasizes the perspective of consumers and EV owners aiming to lower their associated costs. Considering the above objectives the objective function can be represented as:

$$\min F_t = \alpha f_1 + \gamma f_2 + \beta f_3 + \tau f_4 \quad (3)$$

Here α=0.4, γ=0.3, β= 0.2, τ=0.1 are the coefficients for each of the objective functions considered based upon their importance.

In the objective function the system real power loss can be represented as:

$$F_1 = P_{loss} \quad (4)$$

3. Hybrid Harris-Hawk Optimization-Sine Cosine Algorithm (HHO-SCA)

3.1. Sine-cosine Algorithm (SCA)

The framework of Sine Cosine Algorithm (SCA) has been initially developed by Mirjalili, drawing upon mathematical concept of the periodic characteristics inherent in sine and cosine functions [16]. This algorithm employs these mathematical functions as a foundational mechanism for producing random candidate solutions, which are subsequently guided toward convergence with the optimal solution. The dynamics of exploration and exploitation within this framework can be illustrated as follows:

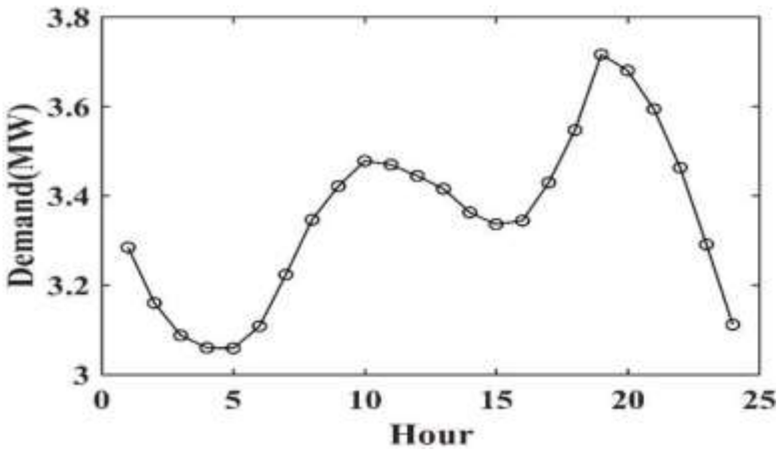


Fig2. Load profile for IEEE 33 bus system.

3.2. Harris-Hawk Optimization (HHO)

The HHO is inspired by the distinctive collaborative hunting strategies exhibited by Harris hawks in their pursuit of prey. These birds demonstrate coordinated behaviour characterized by vigilant observation, tracking, and an eventual assault on the target—typically a rabbit. This hunting tactic, commonly referred to as a "surprise pounce," exemplifies the exploitation phase of the algorithm. Initially, the hawks survey and explore the entire area in search of the prey, representing the exploration phase. Subsequently, the sudden and strategic attack signifies the shift to exploitation. The comprehensive operational structure of the HHO algorithm is presented as follows:

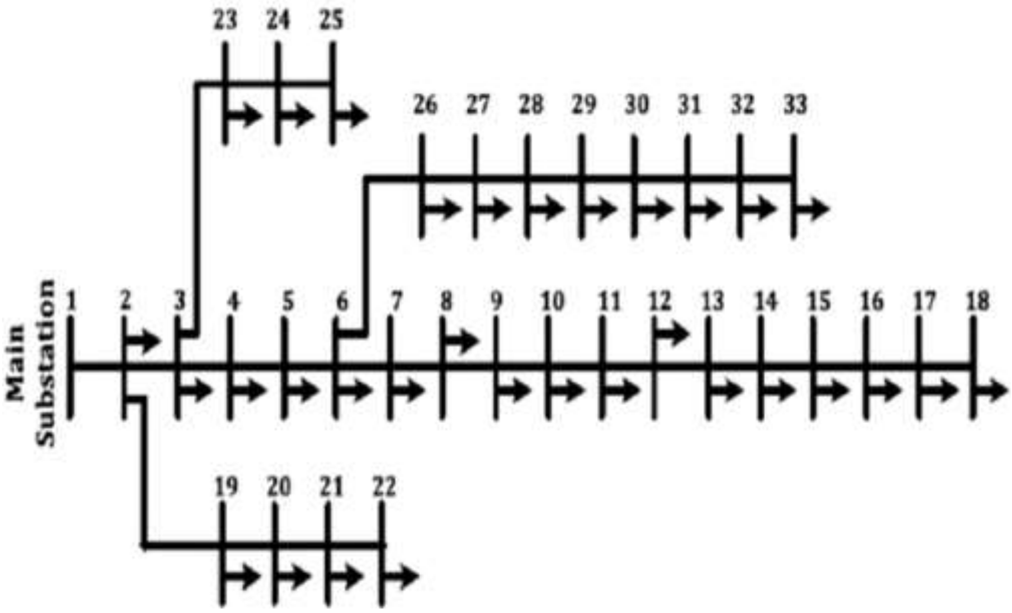


Fig3.Representation of IEEE 33 bus system framework.

3.3. Formulation of HHO-SCA

The Harris Hawks Optimization (HHO) algorithm, while effective, sometimes faces challenges in consistently locating the optimal solution for complex optimization problems. To address these limitations and enhance performance, a hybrid approach integrating HHO with the Sine Cosine Algorithm (SCA) is employed, resulting in the hybrid HHO-SCA (HHO-SCA) algorithm. As illustrated in Equation, during the exploration phase, hawks randomly perch on trees within the search space in preparation for the hunt.

However, the efficiency of this process can be hindered by long distances and extended waiting times. By embedding SCA-based mechanisms into Equation, both convergence speed and exploration capability are significantly improved. The mathematical formulation of the HHO-SCA hybrid model is expressed as follows:

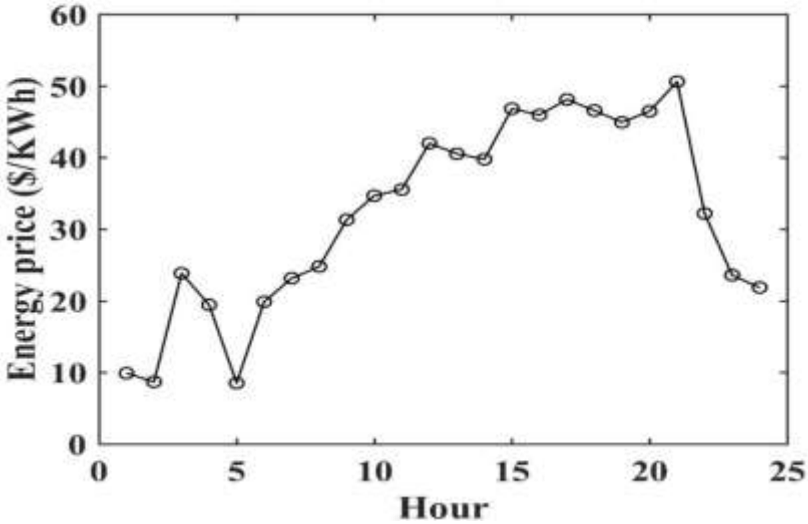


Fig4.Energy price for 24 hrs for the network.

4. Results and Discussions

4.1. IEEE 33 bus system

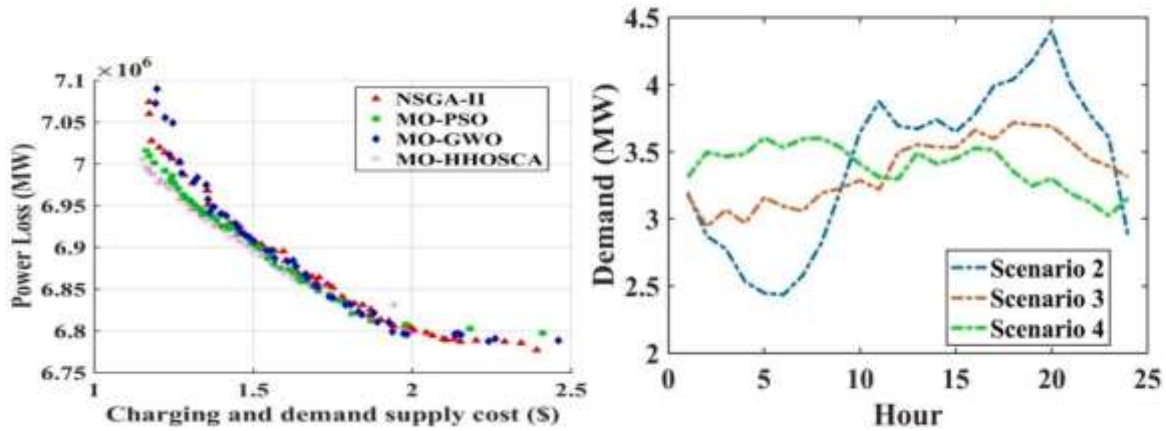
The proposed HHO-SCA has been successfully implemented for the optimal position and sizing of the RES and EV in the distribution network with the aims to optimize the loss reduction, voltage deviation, EV charging cost and battery depreciation cost. The complete execution of this research work has been conducted on MATLAB 2021(a) having a system configuration of 8 GB of RAM, a 3.10 GHz processor. The proposed approach has been validated with the application of HHO-SCA on IEEE 33 bus system which is represented in Figure 3 and its power demand for 24 hrs has been represented in Figure 3. In this research work, the maximum capacity of the RES and the EV charging station are considered to be 1.5MW and 1 MW respectively. The energy price for 24 hrs has been represented in Figure 5. To establish an effective performance comparison of HHO-SCA, the same proposed research has been solved with most recent optimization techniques like BOA, GBO, SCA, HHO. The parameters of these optimization algorithms are listed in To assess the effectiveness of the proposed HHO-SCA for the operation of the power system with RES and EVs, comparative analysis.

This research has been conducted considering five scenarios that have been illustrated in Table 1. The base case scenario is to assess the system's operational characteristics prior to any reconfiguration. In the first scenario, the focus is on identifying the optimal locations and capacities of RES within the grid to evaluate their effects on network performance metrics. The second and third scenarios explore the integration of EVs into the grid, specifically examining the influence of random and controlled charging strategies of V2G technology on system operations respectively. The fourth scenario investigates the impact of real-time pricing on consumer behavior, employing dynamic pricing as an indirect demand-side management tool.

`Table 1 Scenarios considered for the optimal operation of the IEEE 33 bus distribution system

Scenarios	Framework
Base case	Operation of IEEE 69bus system under fossil fuel
First	Operation with RES near the load centres
Second	Operations with optimal placement and sizing of RES and EV(V2G random charging)
Third	Operations Optimal placement and Sizing RES and EV(V2G controlled charging)

The proposed HHO-SCA has been applied to IEEE 33 bus system to achieve the optimal placement and the sizing of the RES and EV charging station. The optimized values of the objective variables are presented in Table. It can be observed that with HHOSCA for the fourth scenario, the power loss, voltage fluctuations index, EVs charging and demand supply cost, and battery depreciation cost are 1.076520 MW, 22.09p.u, 6,512,482$, and 135,051$ respectively. Among these scenarios, with the application of HHO-SCA the fourth scenario/configuration demonstrates superior performance based on the objective function criteria. Specifically, with HHO-SCA it yields lower values for the objectives F1, F2, and F3 relative to the other scenarios. The only additional component in this scenario is F4, which accounts for the battery depreciation cost associated with EV participation in the V2G scheme; an element not considered in the first and second scenarios.



It has been observed that in energy transactions the consumers seek to minimize their electricity expenses. The pricing mechanism implemented in the fourth scenario imposes a high energy pricing framework during the peak load condition. This enables the consumers to shift their EV charging from the high pricing interval to a low pricing interval thereby contributing to demand side management and alleviating potential overloading of the distribution network caused by simultaneous charging activities during the peak load hours. As illustrated in Figure 15 , the second scenario demonstrates significant demand volatility resulting from the uncoordinated and random charging behaviour of EVs, which imposes overload on the network during peak demand periods. In contrast, the third scenario employs the time of use pricing during the 24 hrs to manage EV charging behaviour, thereby smoothing the demand profile and reducing fluctuations. In contrast to this the implementation of a real-time pricing strategy in the fourth scenario further enhances demand-side efficiency by facilitating load shifting and peak shaving. Moreover, it can be observed from the graph that the 24 hrs demand curve is much favourable than the third scenario. Consequently, the resulting demand curve in this scenario exhibits improved characteristics compared to that of the third scenario.

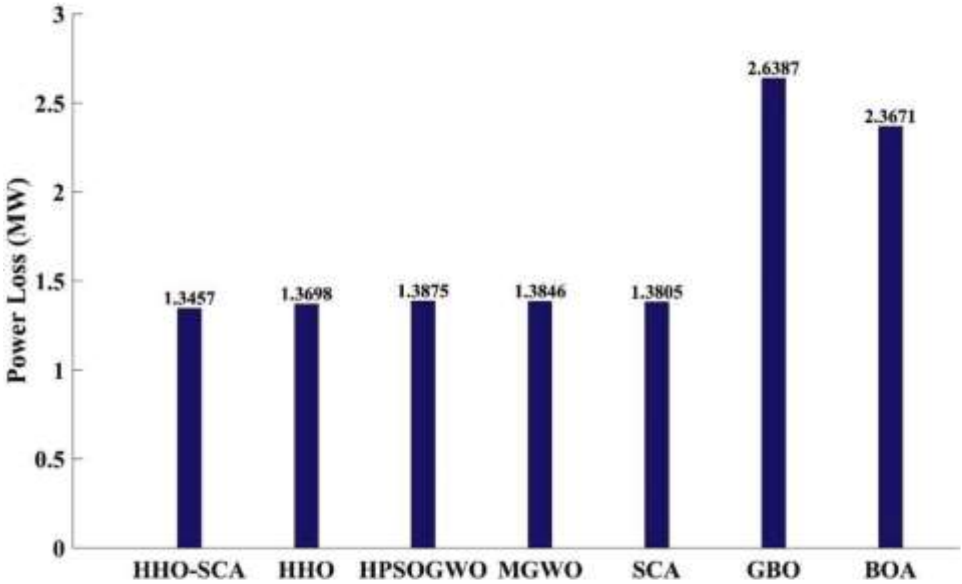


Fig 5. Power loss with HHO-SCA, GBO, SCA, HPSOGWO, MGWO, BOA.

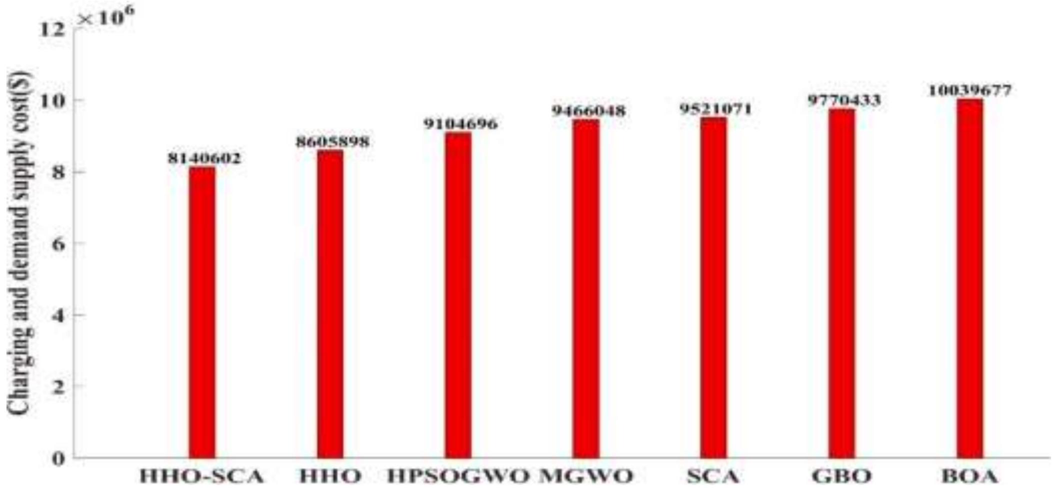


Fig 5Cost of Charging and demand supply with HHO-SCA, HPSOGWO, MGWO, GBO, SCA, BOA.

5. Conclusion

This research work proposed an efficient methodology for optimal placement and sizing of RES and EV charging stations in distribution networks. To support grid operations, it incorporates EV charging/discharging control via dynamic pricing reflecting hourly demand. A multi-objective optimization framework minimizes power losses, voltage deviations, energy procurement costs, and EV battery degradation, solved using a weighted sum method. An efficient HHO-SCA has been proposed to deliver optimal outcomes for the research objectives. The proposed HHO-SCA has been efficient in delivering optimal output for the objective functions considered. The proposed methodology with HHO-SCA has been validated on the IEEE 33-bus standard distribution network. Validated on the IEEE 33-bus system under various scenarios, the results showed improved voltage profiles, reduced losses, and enhanced demand shaping through strategic siting and sizing of RES and EV charging infrastructure. The approach also accounts for input uncertainty, aiding robust and cost-effective decision-making for network operators.

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