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RESEARCH ARTICLE

Integration of Electric Vehicle Charging Stations and DSTATCOM in Practical Indian Distribution Systems Using Bald Eagle Search Algorithm

T. YUVARAJ[1], K. R. DEVABALAJI[2],
SUDHAKAR BABU THANIKANTI[3,4], (Senior Member, IEEE),
VIJAY BABU PAMSHETTI[3], (Member, IEEE), AND NNAMDI I. NWULU[4], (Senior Member, IEEE)

[1]Centre for Computational Modeling, Chennai Institute of Technology, Chennai 600069, India
[2]Department of Electrical and Electronics Engineering, Hindustan Institute of Technology and Science, Chennai 603103, India
[3]Department of Electrical and Electronics Engineering, Chaitanya Bharathi Institute of Technology, Hyderabad 500075, India
[4]Centre for Cyber-Physical Food, Energy and Water Systems, University of Johannesburg, Johannesburg 2006, South Africa

Corresponding author: Sudhakar Babu Thanikanti (sudhakarbabu66@gmail.com)

ABSTRACT Because of the increasing growth of Electric Vehicle (EV) in India, more electricity is required to power such vehicles. It is also gaining popularity because of its low maintenance, improved performance, and zero carbon impact. As the usage of electric vehicles grows, the distribution system's performance is impacted. As an outcome, the reliability of the distribution system (DS) is dependent on the position of the electric vehicle charging station (EVCS). The fundamental difficulty is the deterioration of the DS due to an incorrect EVCS location. The DS is linked to the charging station and works with the distribution static compensator (DSTATCOM) to minimize the impact of the EVCS. A new nature-inspired Bald Eagle Search Algorithm (BESA) based optimization technique was utilized to find the optimal allocation of DSTATCOM and EVCS in the DS. The proposed strategy for mitigating the real power loss has been tested on practical Indian 28-bus and 108-bus distribution networks. Power loss reduction optimizes the system's net savings, voltage stability, and bus voltage. The test case findings show that the BESA-based optimization is more accurate regarding power loss mitigation, bus voltage enhancement, and annual net saving improvement than the BA-based optimization in the DS.

INDEX TERMS Electrical vehicle (EV), bald eagle search algorithm (BESA), bat algorithm (BA), distribution STATicCOMpensator (DSTATCOM), voltage stability index (VSI), distribution system (DS), electric vehicle charging station (EVCS).

I. INTRODUCTION

Long-term development and poverty eradication depend heavily on energy. In India, 97.2% of the population has access to electricity. Natural gas and coal are the most frequent fuels utilized in the power sector. India has a total capacity for electricity generation of 388.134GW, with off-grid renewable energy (RE) accounting for 21.26% of that capacity. The lack of coal and natural gas might threaten the production of power. To address the nation's expanding electricity consumption, the Indian government has declared plans to construct 275 GW of renewable energy by 2027. The government plans to produce 356.681GW of energy from coal and nuclear power plants to meet demand, despite these technologies being bad for the environment and destroying our biosphere. This system necessitates using renewable energy, which emits less greenhouse gases (GHGs) than other conventional power-producing methods. To meet its long-term development objectives, India must offer reliable, high-quality power to its population [2].

India's transportation industry contributes considerably to GHG emissions. The bulk of these GHG emissions are

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attributed to CO_2. Also, CO_2 emissions from the energy and agricultural industries are rising. A concerning indicator of pollution and fuel consumption is the quick increase in the number of vehicles required to serve the nation's vast population [2].

Electric vehicle (EVs) is one of the most promising technologies for lowering emissions from transportation. EVs are designed to provide optimum performance while emitting low or no exhaust emissions. Compared to standard internal combustion (IC) engine vehicles, EVs offer several advantages, including lower fuel consumption and pollution. As a result, EVs are a critical solution for fossil fuel shortages, energy crises, and excess environmental pollutants caused by transportation [3]. Because of the incredible productivity of the electric/drive unit, EVs may drastically reduce gasoline costs. EV and charging station use in distribution networks can have significant systemic repercussions, such as higher electrical losses, changing voltage profiles, and congested lines [4].

Increasing electrical losses and decreasing bus voltage in some DS segments pose considerable challenges to power system operation. Increased peak load, higher system losses, a negative influence on bus voltage, lower power quality, and the danger of overloading distribution transformers, distribution lines, and cables are among the difficulties. The adoption of EVCS has a considerable negative influence on bus voltages and total system losses [5]. Yet, the appropriate deployment of EVCS is a difficult task for power system designers and operators [6]. DSTATCOMs are commonly installed by utility engineers to address the aforementioned distribution system difficulties. DSTATCOM allocation significantly impacts mitigating system power losses, enhancing voltage stability, and improving bus voltage. Utility engineers frequently place DSTATCOMs to address the DS, as mentioned above, issues. The allocation of DSTATCOM significantly influences reducing system losses, improving voltage stability, and increasing bus voltage.

Additionally, installing a DSTATCOM is generally well known as a technique for enhancing the economic value of the distribution system and improving its power quality. Because DSTATCOM provides reactive power to the distribution system regularly, it increases the voltage magnitude while minimizing system power loss [7]. Joint allocation of DSTATCOM and EVCS in the DS has benefits such as mitigated system loss, bus voltage enhancement, power factor improvement, power quality enhancement, reduced on-peak operating costs, the release of distribution line overloading, system stability improvement, pollutant emission reduction, and increased overall energy efficiency. A current study on the optimal placement of DSTATCOM has recommended reducing the charging impact of EVCS on DS. To address the effect of EVs on distribution networks, optimization techniques for the appropriate size and positioning of EVCS with DSTATCOM must be established. Figure 1 demonstrates the present methodology's layout.

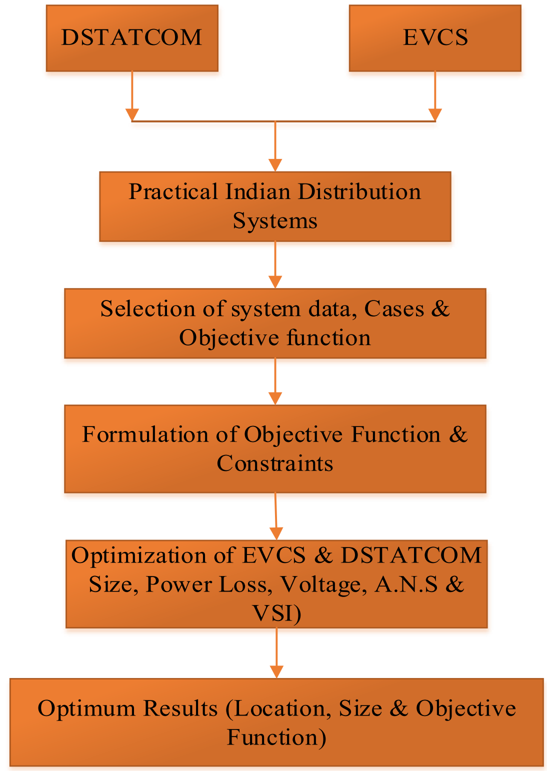

FIGURE 1. Outline of the proposed methodology.

II. RELATED WORKS

Several studies in the literature have attempted to solve the DSTATCOM allocation problem in distribution systems using various objective functions and optimization approaches [8]. Nevertheless, there needs to be more literature on EVCS allocation since research on EVCS is still in its early stages. Significantly few studies have addressed the EVCS allocation problem using real-time systems. Furthermore, there is a substantial body of literature on the simultaneous installation of EVCS with DGs and DSTATCOMs/capacitors. Table-1 [2], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36] provides a complete review of current research on EVCS planning using Distribution Generator (DG), Capacitor, Network Reconfiguration (NR), Battery Energy Storage System (BESS), and DSTATCOM for various types of distribution systems, optimization methodologies, and objective functions.

According to Table-1, using DSTATCOM allocation to reduce power loss and enlighten the bus voltage by incorporating EVCS into DS has yet to be included in planning studies.

Joint allotment of DSTATCOM and EVCS can mitigate power loss, increase the bus voltage and stability, power factor correction, balance the load, harmonic mitigation, and provide several other advantages. Moreover, most researchers

TABLE 1. Survey on EVCS placement in distribution system using various methods.

Reference No	Year of publication	Technique	Objective Function	Energy Sources	Test Systems	Outcomes/Findings/Limitations
[9].	2017	Fuzzy based optimization	Controlling the system loss and bus voltage deviation	DG	IEEE 33-bus	The presented approach is a powerful optimization technique that can be used to handle uncertainty and risk in decision-making problems. However, it is essential to be aware of its limitations to ensure that it is used appropriately and effectively.
[10].	2019	Bi-level programming based on Intelligent procedure	Maximization of the power supply company's yearly total earnings	DG	IEEE 33 & 69 buses	As the number of decision variables and constraints increases, the computational time and resources required to solve the optimization models increase exponentially. This limitation may make applying the models to larger-scale power distribution systems difficult.
[11].	2019	Real-time charging navigation technologies	The annualized societal cost of DGs and EVCSs	DG	Practical bus & IEEE 33-bus system	Real-time data on EV charging behavior, such as the state of charge of the EV battery and the location of available charging stations, may not be readily available, limiting the effectiveness of real-time charging navigation.
[12].	2019	Programming with mixed integer second-order system	The annualized societal cost of DGs and EVCSs	DG	Practical China 31 test system	Installing DG resources and EVCS in distribution systems with V2G interaction requires significant upfront investment costs. These costs can include the installation of new infrastructure, equipment, and control systems. The high investment costs may limit the implementation of coordinated allocation in some areas.
[13].	2020	Teaching learning based optimization	Loss reduction, AVDI & VSI enhancement	Grid	IEEE 33 & 69 buses	The optimization problem is based on a static representation of the distribution system, which does not consider the system's dynamic behavior under different operating conditions. This can lead to suboptimal solutions that may need to perform better in practice.
[14].	2020	Particle swarm optimization	Enhancement of the bus voltage and mitigation of actual loss	DG	IEEE 19 & 25 unbalanced buses	Unbalanced radial distribution systems have unequal phase loads, which can cause voltage imbalances and voltage drops. These issues can limit the optimal placement of charging stations and lead to technical challenges such as voltage instability.
[15].	2020	Hybrid Teaching-learning and Harries hawk based optimization.	Optimizing the active power losses, average voltage deviation index & VSI	DG	IEEE 33 & 69 buses	Multiobjective optimal allocation of EVCSs and DGs in RDS using metaheuristic optimization algorithms may not consider all relevant factors, such as changes in demand patterns or grid topology.
[16].	2020	Normal distribution crossover based optimization	Controlling the loss and nodal voltage	DG	IEEE 33 & 118 buses	The framework relies on simplified assumptions about the behavior of DGs and EVs, such as their output power and charging/discharging schedules. This may result in inaccurate predictions of their impact on the distribution system, especially in dynamic and uncertain scenarios.

TABLE 1. *(Continued.)* Survey on EVCS placement in distribution system using various methods.

[17].	2020	Grasshopper optimization algorithm	Increasing the substation power factor, mitigating loss, and enlightening the bus voltage	DG & Capacitor	51 & IEEE 69 buses	The convergence rate of the Grasshopper optimization algorithm can be slow when dealing with complex problems. This can result in longer computational times and may make the algorithm impractical for real-world applications
[18].	2021	Grey Wolf Optimization algorithm	Mitigation of active power loss	Grid	IEEE 33 bus	Smart charging technology can optimize the allocation of charging infrastructure by balancing the demand for charging with the availability of renewable energy sources. This technology can also allow EVs to be integrated into the grid, making them a part of the more extensive energy system.
[19].	2021	Stochastic Modeling and Grey Wolf Optimization	Improving the overall profit	Grid	Washington D.C.'s transportation infrastructure	The allocation of charging stations needs to be cost-effective. While the methodology can optimize the allocation of charging stations, it may need to consider the cost of installing and maintaining the charging stations, which can affect the economic viability of the network.
[20].	2021	Mixed-integer linear programming	Minimization of investment and operational costs, including CO2 emissions costs.	DG	24-node electrical distribution system	One of the main limitations is the high cost of implementing such a system. Installing renewable energy sources and charging stations can be expensive, and the additional costs of CO2 emissions reduction technologies further add to the overall cost.
[21].	2021	Hybrid of grey wolf optimization and particle swarm optimization	Minimization of active power loss reduction, Maximization of voltage profile and VSI	DG	IEEE 33 & 69 buses	The presented research has several limitations, such as using a stochastic approach to construct the EV load at charging stations to estimate the impact of increased EV demand on the distribution system. Furthermore, rather than conventional DGs, renewable-based DGs, may be included.
[22].	2021	Hybrid of grey wolf optimization and particle swarm optimization	Minimization of real power loss	Capacitor	IEEE 33 & 34 buses	The coordinated planning of EV charging stations and capacitors in distribution systems with V2G facilities is difficult to scale up to large distribution networks due to the complexity and uncertainty of the problem. This limits the applicability of the approach to small distribution networks.
[23].	2021	Hybrid of grey wolf optimization and particle swarm optimization	Minimization of active power loss, maximization of net profit, and improvisation of the reliability	Capacitor	IEEE 33 & 34 buses	Because of the limited range of all-electric vehicles, EVs must be recharged numerous times throughout the journey. When EVCS is installed wrongly in the distribution network, it causes an increase in power loss. As a result, the optimal position of EVCS is required for a slight increase in power loss.
[24].	2021	Hybrid soccer league competition-	Decreasing the power loss and increasing the minimum	BESS & DG	IEEE 33 & 85 buses	According to the findings, allocating the other energy sources is complicated using the proposed technique on the distribution systems.

TABLE 1. ***(Continued.)*** **Survey on EVCS placement in distribution system using various methods.**

		pattern search algorithm	voltage level and penetration rates			
[25].	2022	Combined loss sensitivity factor and Newton Raphson method	Analyzing the system voltage stability, reliability, and power losses	Grid	IEEE 33 bus	The method does not allow for flexibility in the placement of the charging stations, as it only considers fixed locations and assumes that all EVs have the exact charging requirements.
[26].	2022	Probabilistic load modelling	Minimization of power loss	Grid	IEEE 33 bus	The accuracy of the optimal allocation of EVCSs in an RDS using probabilistic load modeling depends on the quality and quantity of data available. In some cases, the necessary data may be general or complete, leading to inaccuracies in the model.
[27].	2022	Flower pollination algorithm	Minimization of investment, peak loss, and annual energy loss costs at different load factors	Network Reconfiguration (NR)	123 and 51 buses	The implementation of this method can require significant investment in the reconductoring of the electricity network. This cost may outweigh the benefits of load allocation in the long run, especially if the residential locations do not have a high density of EV owners.
[28].	2022	Political optimization algorithm	Minimizing the power loss and improving the voltage profile	DG	Indian 28 bus distribution system	The proposed algorithm may need to be more scalable for larger distribution systems with many distributed generators and electric vehicles. This is because the algorithm's complexity increases exponentially with the number of variables, making it difficult to solve for large systems.
[29].	2022	Stochastic second-order conic programming	Mitigation of network loss and bus voltage deviation	DG	Modified IEEE 15 bus	The presented approach is designed to solve problems that can be formulated as convex optimization problems. However, some issues in the field of energy systems, such as those involving non-convexities, may need to be more suitable for proposed modeling.
[30].	2022	Hybrid of genetic and particle swarm optimization techniques	Minimizing the losses, analyzing the cost and VSI	DG	IEEE 33 bus	The optimization approach may need to be more flexible to accommodate changes in the system over time. For example, suppose there is a change in the number of EVs in the microgrid or the availability of energy resources. In that case, the optimization model may need to be updated to reflect these changes.
[31].	2022	Particle swarm optimization technique	Reduction of total power losses	DG	IEEE 15, 33, 69 & 85 RDS	Particle swarm optimization is a single-objective optimization technique and may not be suitable for problems with multiple conflicting objectives, such as minimizing cost while maximizing reliability.
[32].	2022	Modified salp swarm algorithm	Reduction of total net present cost and leveled cost of energy	DG	The northwest region of Delhi, India	The environmental impact of electric vehicle charging stations can be challenging to quantify, as it depends on factors such as the source of electricity used, the efficiency of the charging station, and the emissions associated with the production of the charging station equipment.

TABLE 1. ***(Continued.)*** **Survey on EVCS placement in distribution system using various methods.**

[33].	2022	Marine Predator Algorithm	Loss reduction and bus voltage improvement	DG & Capacitor	Practical 83 Taiwan test system	Technical constraints, such as voltage stability and power quality issues, may limit the integration of DGs, SCs, and EVs in a DS. The marine predator algorithm may need to address these constraints adequately.
[34].	2022	Hybrid methodology	Minimizing active power loss costs, voltage deviations, and system costs.	DG & Capacitor	IEEE 118 bus	One of the primary limitations of using a multiobjective approach for allocating fast charging stations is the need for more data on electric vehicle usage patterns, charging behavior, and other related factors. With this data, it is easier to accurately model the behavior of electric vehicle users and determine the optimal locations for charging stations.
[35].	2023	Optimization using chaotic student psychology	Reducing active power loss, total voltage variation, energy loss costs, and overall operational costs	BESS & DG	IEEE 33-bus & practical Brazil 136-bus	The optimal allocation of EVCSs, DG, and BESS in an RDS is a complex problem that requires a multidisciplinary approach combining engineering, economics, and data science. While significant challenges are associated with this approach, addressing these limitations can lead to more efficient and sustainable energy systems that benefit consumers and the environment.
[36].	2022	Fuzzy-based optimization technique	Minimizing actual power loss, power factor correction, and bus voltage	DG & DSTATCOM	IEEE 69 bus	The optimal placement of EVCSs, DGs, and DSTATCOMs heavily depends on the demand and renewable energy sources in the distribution system. However, the market and renewable energy sources are still being determined, and the fuzzy logic-based approach may need to capture their variability fully.
[37].	2022	African vulture optimization algorithm	Decreasing the power loss index, voltage deviation index and VSI	DG & DSTATCOM	IEEE 33 & 85 buses	The African vulture optimization algorithm may only be applicable in some situations, and its effectiveness may depend on the specific characteristics of the problem being solved. Using other optimization algorithms or techniques in some instances may be necessary.
[38].	2022	Binary bat algorithm	Reduction of actual system loss	DG, NR & DSTATCOM	IEEE 33 bus	The algorithm may converge to an optimal solution very slowly, especially when dealing with large-scale problems. This can make it inefficient for optimizing the operation of radial distribution networks.

still need to consider cost analysis and real-time distribution networks when conducting their research study.

BESA is an innovative meta-heuristic optimization algorithm that imitates bald eagles' fish-hunting tactics or cunning social behavior [40]. Furthermore, some recent research show that BESA performs very well in identifying the best solution to engineering optimization issues [46], [47], [48]. Nevertheless, there has yet to be any mention of using BESA to solve the optimum installation of DSTATCOM and EVCS. As a result, the BESA was done on purpose to solve the optimization problem in this study.

The factors mentioned above motivated the author to use a revolutionary nature-inspired Bald Eagle Search Algorithm (BESA) to solve the issue of EVCS through efficient allocation of DSTATCOM in the DS. The research aims to decrease system losses and improve net savings. BESA is used to identify the position and size of the EVCS and DSTATCOM. Two real-time Indian distribution networks, with 28-bus and 108-bus DS, were utilized to show the efficiency of the suggested technique. Further, to demonstrate the effectiveness of the proposed approach, the authors constructed the objective function using five algorithms: the Bat Algorithm (BA) [41], the African vulture optimization algorithm (AVOA) [48], Binary bat algorithm (BBA) [49], Particle swarm optimization algorithm [50] and the proposed BESA [40]. Since there is no literature on distribution systems using EVCS and DSTATCOM for Indian 28-bus and 108-bus DS, the authors used the above algorithms to construct the same objective function. They compared the results to the proposed BESA. The reason behind choosing the above algorithms are:

(i) ***Bat Algorithm:*** It is a robust optimization algorithm that can be used to solve various complex problems.

(ii) ***African Vulture Optimization Algorithm:*** AVOA algorithm is a promising optimization technique that has shown good results in various applications, making it a reasonable choice for optimization problems.

(iii) ***Binary Bat Algorithm***: BBA can be a valuable tool for solving optimization problems that involve binary decision variables, particularly for those that require a fast and efficient solution.

(iv) ***Particle Swarm Optimization Algorithm:*** PSO algorithm is relatively simple to implement and can be easily modified or extended to incorporate additional features or constraints.

This research paper's primary contribution is as follows:

i. Novel integration of DSTATCOM and EVCS is proposed in the distribution system for real power loss mitigation.
ii. Two practical Indian distribution systems have been considered for EVCS and DSTATCOM allocation problems (28 and 108 buses DS).
iii. Cost analysis is considered for maximizing the net savings of the system using EVCS and DSTATCOM allocation problems.
iv. Five different algorithms (BESA, BA, AVOA, BBA, and PSO) are implemented to show the superiority of the proposed approach.
v. An integrated approach such as VSI and BESA is presented to resolve EVCS and DSTATCOM allocation problems in DS.
vi. The optimal siting of EVCS and DSTATCOM is determined using the VSI approach, and the nature-inspired Bald Eagle Search Algorithm determines optimal sizing.
vii. Different load levels (Light, Normal & Peak) are considered for EVCS and DSTATCOM allocation in the DS.

III. PROBLEM FORMULATION

A. POWER FLOW ANALYSIS

Since the transmission load flow is inappropriate for DS, the present study uses a specially designed direct distribution load flow (DLF) for DS to calculate base case values at each branch [37]. Figure 1 depicts a two-bus sample single-line design of a DS using presented DSTATCOM and EVCS.

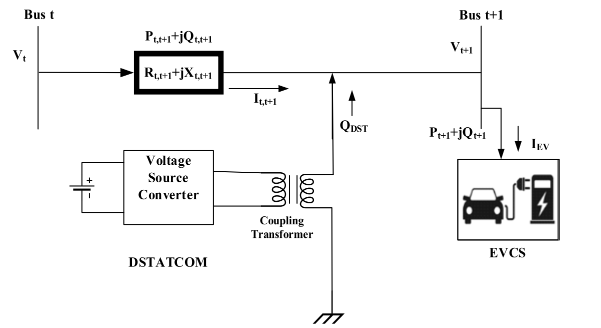

FIGURE 2. Sample distribution system.

The formulation of bus voltage at *t+1* is calculated as follows:

$$V_{t+1} = V_t - I(R_{t,t+1} + jX_{t,t+1}) \tag{1}$$

where V_{t+1} and V_t represent the magnitude of bus voltage of *t+1* and *t,* respectively, $R_{t,t+1}$ and $X_{t,t+1}$ represent the value of resistance and reactance of the link between *t* and *t+1* respectively.

The division current *I* is determined as:

$$I = [BIBC][i] \tag{2}$$

where *BIBC* indicated the Bus Current Injection to Branch Current matrix.

$$i_{t+1} = \frac{(P_{t+1} + jQ_{t+1})^*}{V_t} \tag{3}$$

where P_{t+1} and Q_{t+1} represent the real and imaginary load at bus *t+1,* respectively, and i_{t+1} represents the current injected at bus *t+1.*

The equations are used to compute the system's real and reactive power losses.

$$P_{loss}(t, t+1) = \left(\frac{P_{t,t+1}^2 + Q_{t,t+1}^2}{|V_t|^2}\right) R_{t,t+1} \tag{4}$$

$$Q_{loss}(t, t+1) = \left(\frac{P_{t,t+1}^2 + Q_{t,t+1}^2}{|V_t|^2}\right) X_{t,t+1} \tag{5}$$

The real and imaginary power flows between *t* and *t+1* are represented by $P_{t,t+1}$ & $Q_{t,t+1}$, respectively.

The system's total real and reactive power losses may be determined by summing all of the branch power losses.

$$P_{T,Loss} = \sum_{t=1}^{nb} P_{Loss}(t, t+1) \tag{6}$$

where nb is the number of branches.

B. MODELING OF DSTATCOM AND EVCS FOR DS

The proper placement of EVCS is critical for EV customers and power companies. Because all EVs have a limited range, they must be recharged many times throughout a trip.

Power loss increases when EVCS is placed incorrectly in the distribution network. As a result, the optimum position of EVCS is necessary for a minimum increase in system loss. By minimizing the power loss and enhancing the bus voltage, DSTATCOMs lessen the impact of integrating EVCS into the distribution network.

1) MODELING OF DSTATCOM

The deployment of DSTATCOM units in optimum positions across the distribution system provides several benefits, such as reduced line loss, improved bus voltage, power factor adjustment, and so on. The following are the governing equations for integrating DSTATCOM into the DS.

After injecting DSTATCOM at bus t, the net reactive power (Q_{NI}) may be defined as

$$Q_{NI} = Q_{t+1} - Q_{DST} \tag{7}$$

where Q_{DST} is the reactive power injected by DSTATCOM. In Figure 2, the actual power loss after placing the DSTATCOM at bus t is shown as:

$$P_{loss}(t, t+1) = \left(\frac{P_{t,t+1}^2 + Q_{NI}^2}{|V_t|^2}\right) R_{t,t+1} \tag{8}$$

$$P_{loss}(t, t+1) = \left(\frac{P_{t,t+1}^2 + (Q_{t+1} - Q_{DST})^2}{|V_t|^2}\right) R_{t,t+1} \tag{9}$$

$$P_{loss}(t, t+1) = \left(\frac{P_{t,t+1}^2 + Q_{t,t+1}^2}{|V_t|^2}\right) R_{t,t+1} + \left(\frac{Q_{DST}^2 - 2Q_{t+1} * Q_{DST}}{|V_t|^2}\right) R_{t,t+1} \tag{10}$$

The decrease in power loss, denoted by $\Delta \mathrm{P}_{T,Loss}^{\mathrm{DST}}$ is the change in system loss previously and afterward the deployment of a DSTATCOM and may be expressed as

$$\Delta \mathrm{P}_{T,Loss}^{\mathrm{DST}} = \left(\frac{Q_{DST}^2 - 2Q_{t+1} * Q_{DST}}{|V_t|^2}\right) R_{t,t+1} \tag{11}$$

Adding the number of DSTATCOMs is advantageous in lowering distribution network losses.

2) MODELLING OF EVCS

EVCSs increase the burden on the DS. Equation (12) may be used to determine the DS's overall load after incorporating EVCS.

$$\mathrm{P}_{Load} = \sum\nolimits_{t=1}^{nb} P_{avilable,t+1} + P_{EVCS(t+1)}) \tag{12}$$

where, P_{Load} denotes the system's overall load, $P_{available,t+1}$ is the already available load at $t+1$ bus and $P_{EVCS(t+1)}$ is EVCS load connected to $t+1$ bus.

As indicated in Table-2 [38], the energy required for battery charging is estimated using equations (13) and (14). The following are the EVCS models:

$$P_{EVCS} = n * B_c * S_c \tag{13}$$

$$S_c = 100 - \mathrm{SOCcurrentstatus} \tag{14}$$

TABLE 2. Energy demand of EVCS load during charging.

SOC current status (%)	Bc (kWh)	n	Sc (%)	Ec (kW)
20	10	20	80	160
30	16	30	70	336
50	20	50	50	500
		Total =100		Total= 996 kW

where P_{EVCS} denotes the total amount of power required from EVCS, Bc is the kWh rating of the battery, $Sc$is the needed amount of charging in SOC, and n denotes the number of EVs. Table-2 shows that EVs with different SOC levels are considered to be charged.

Simply said, the increased EVCS load will be placed solely on the bus where the EVCS is planned to be installed. The bus number, i.e. the EVCS location, is the decision variable for the optimization.

C. OBJECTIVE FUNCTION

The main goal of this research is to place the EVCS and DSTATCOM in the DS in the best possible positions. The DSTATCOM allocation technique maintains appropriate voltage levels on each bus. The bus voltage is impacted, and power loss is increased by the installation of EVCS in the DS. DSTATCOMs are installed at optimal distribution nodes to minimize the losses. As a result, the objective function aims to maximize net savings, enhance the voltage profile of the DS, and stay within the subject limitations while reducing power loss, which lowers overall annual energy loss costs.

The mathematical formulation of the objective function is provided by

$$Minmize(F) = Min(P_{T,Loss}) \tag{15}$$

where $P_{T,Loss}$ stands for the DS's overall power loss.

D. ANNUAL NET SAVINGS

Annual Net Savings (ANS) can be calculated by subtracting the Total Installation Cost (C_i) and Total Operating Cost (C_O) from the Reduction of Energy Cost(ΔE) of the system.

$$ANS = \Delta E - C_i - C_O \tag{16}$$

$$\Delta E = T * C_e(P_{T,Loss} - \mathrm{P}_{T,Loss}^{\mathrm{DST}}) \tag{17}$$

$$C_i = \alpha[(n_c * C_{DST}^i) + (n_{cs} * C_{CS}^i) + (C_{DST}^p * Q_{DST}^T)] \tag{18}$$

$$C_O = (n_c * C_{DST}^O) + (n_{cs} * C_{CS}^O) \tag{19}$$

Here, n_s&n_{cs} are the number of DSTATCOMs and EVCSs installed, $\mathrm{P}_{T,Loss}^{\mathrm{DST}}$ is the total real power loss after installing DSTATCOM, Q_{DST}^T is the total reactive power injected by DSTATCOM.

E. SYSTEM CONSTRAINTS

The optimal allotment of DSTATCOM/EVCS in DS is subjected to equality and inequality limitations.

1) POWER BALANCE

Constraints on power balance, often known as equality constraints, can be described as follows:

$$P_{T,Loss} + \sum P_{D(t)} + \sum P_{EVCS(t)} = \sum P_{DST(t)} \tag{20}$$

where $P_{D(t)}$ is the power demand at two buses of t, $P_{DST(t)}$ is the power production using DSTATCOM, and $P_{EVCS(t)}$ is the load by EVCS.

2) VOLTAGE LIMIT

$$V_{t,\min} \leq |V_t| \leq V_{t,\max} \tag{21}$$

The lower and upper voltage limitations at bus t are denoted by $V_{t,\min}$ and $V_{t,\max}$, respectively.

3) REACTIVE POWER COMPENSATION

$$Q_{DST(t)}^{\min} \leq Q_{DST(t)} \leq Q_{DST(t)}^{\max} \quad t = 1, 2, \ldots\ldots\ldots nb \tag{22}$$

where, $Q_{DST(t)}^{\min}$ and $Q_{DST(t)}^{\max}$ are the lowest and upper reactive power limitations of DSTATCOM adjusted at bus t, respectively.

F. OPTIMAL LOCATION

First, the Voltage Stability Index (VSI) is utilized to establish the ideal location for DSTATCOM. BESA will be utilized to calculate the ideal DSTATCOM size. The search space for the optimization process is reduced as a result of knowing the ideal place in advance.

G. VOLTAGE STABILITY INDEX

To measure the security of the power system, many indicators are employed. As shown in (23) [39], a new steady-state VSI is used in this section to determine the node with the most significant risk of voltage downfall. To function the distribution system properly, the VSI should be t $\geq$ 0. The VSI value at each node is determined from the DLF using an equation (23). DSTATCOM is likelier to be installed on the node with the lowest VSI value.

$$\begin{aligned} VSI\ (t+1) &= |V_{t+1}|^4 \\ &\quad - 4\left[P_{t,t+1} * X_{t,t+1} - Q_{t,t+1} * R_{t,t+1}\right]^2 \\ &\quad - 4\left[P_{t,t+1} * R_{t,t+1} + Q_{t,t+1} * X_{t,t+1}\right]\left|V_{t,t+1}\right|^2 \end{aligned} \tag{23}$$

IV. OPTIMIZATION ALGORITHMS

In the real Indian distribution systems, various algorithms and proposed Bald Eagle Search Algorithm (BESA) are utilized to find the ideal positions and sizes of the DSTATCOMs and EVCS.

A. BALD EAGLE SEARCH ALGORITHM

Bald eagles are foragers who choose fish (alive or dead) as their primary food source, particularly salmon. In 2020, Alsattar et al. [40] created a revolutionary meta-heuristic Bald Eagle Search Algorithm (BESA) that simulates bald eagle hunting behavior. Because it is challenging to capture fish in water, bald eagles frequently hunt from perches, but they can also track in the air and detect fish at considerable distances. When bald eagles begin foraging for food on a body of water, they fly in a particular direction and select a specific position. Bald eagles may be predatory due to their place at the top of the food chain.

Furthermore, bald eagles are said to be spirits that feast on essential, protein-rich foods. As a result, this method was broken into three steps. BESA's steps are as follows:

1) SELECT STAGE (STAGE-I)

During the selection stage, the bald eagle selects a rich food source for hunting. This procedure can be mathematically described using equation (24):

$$P_{new,i} = P_{best} + \alpha * r * (P_{mean} - P_i) \tag{24}$$

where α is the element that controls position changes and ranges from 1.5 to 2; r is a random value between [0, 1];

P_{best} is the best location recognized by bald eagles during their last search;; P_{mean} shows that the eagles have utilized all data from the prior points; P_i is the old eagle spot and $P_{new,i}$ is the new position.

2) SEARCH STAGE: (STAGE-II)

At this stage, the eagles are searching for fish inside the designated search zone while spiraling to speed up their search. The ideal swoop position is shown by (25):

$$P_{new,i} = P_i + y\,(i) * (P_i - P_{i+1}) + x\,(i) * (P_i - P_{mean}) \tag{25}$$

$$x(i) = \frac{xr(i)}{(max\,|xr|)} \tag{26}$$

$$y(i) = \frac{yr(i)}{(max\,|yr|)} \tag{27}$$

$$\mathrm{xr}\ (\mathrm{i}) = \mathrm{r}\ (\mathrm{i}) * sin\theta(i) \tag{28}$$

$$\mathrm{yr}\ (\mathrm{i}) = \mathrm{r}\ (\mathrm{i}) * cos\theta(i) \tag{29}$$

$$\theta\ (i) = \alpha * \pi * rand \tag{30}$$

$$r\ (i) = \theta\ (i) + R * rand \tag{31}$$

Equations (25)-(31) are involved in search stage. Where α is a parameter in the range of 5 to 10 for identifying the corner between the point search in the center point, R is a value in the range of 0.5 to 2 for determining the number of search cycles, and rand is a number between [0, 1].

B. SWOOPING STAGE (STAGE-III)

All points advance towards the best point as bald eagles swoop to their target fish from the best place in the search

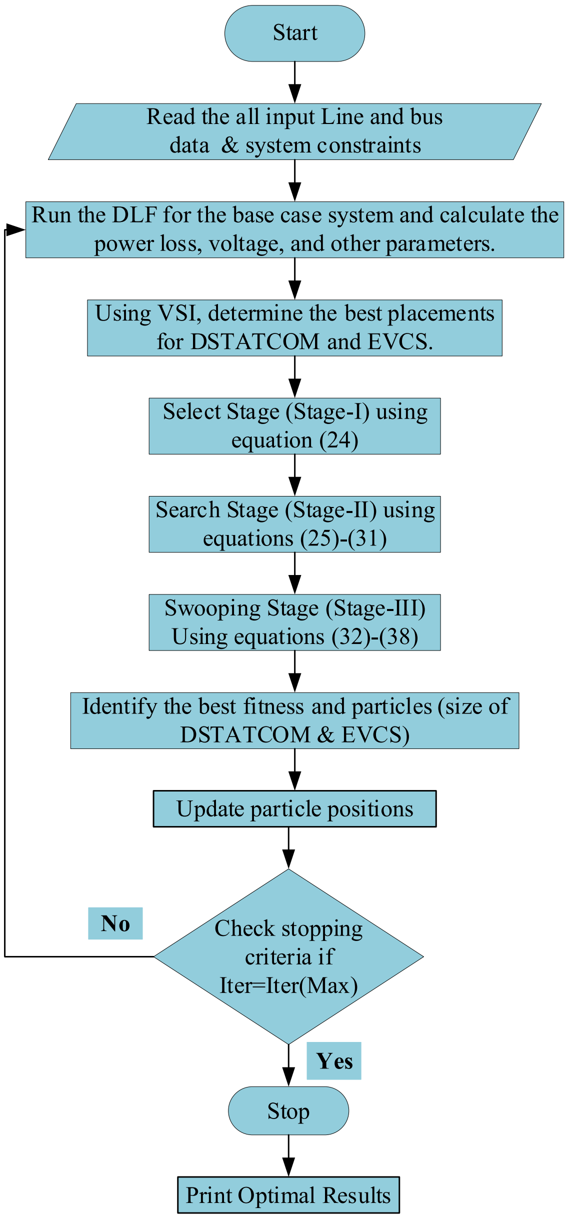

FIGURE 3. Flowchart for implementing BESA.

space. (32) is an example of this behavior:

$$P_{new,i} = rand{*}P_{best} + x1\,(i) *(P_i - (C_1{*}P_{mean})) + y1\,(i) *(P_i - (C_2{*}P_{best})) \quad (32)$$

$$x1(i) = \frac{xr(i)}{(max\,|xr|)} \quad (33)$$

$$y1(i) = \frac{yr(i)}{(max\,|yr|)} \quad (34)$$

$$\mathrm{xr}\,(\mathrm{i}) = \mathrm{r}\,(\mathrm{i}) * \sinh\theta(i) \quad (35)$$

$$\mathrm{yr}\,(\mathrm{i}) = \mathrm{r}\,(\mathrm{i}) * \cosh\theta(i) \quad (36)$$

$$\theta\,(i) = \alpha * \pi{*}rand \quad (37)$$

$$r\,(i) = \theta\,(i) \quad (38)$$

Equations (25)-(31) are involved in swooping stage. Where $C_1, C_2 \in$ [1], [2] and rand is the number within [0, 1]. Figure 3 depicts the entire flow chart of the proposed optimization using the BESA algorithm.

V. RESULTS AND DISCUSSION

The suggested method is utilized to optimize the placement and sizing of DSTATCOM and EVCS in an Indian 28-bus and 108-bus DS to validate its efficacy. MATLAB software was used to create the direct approach for the distribution system power flow algorithm, which was used to calculate the distribution network's base case real and reactive power losses as well as bus voltage values. To demonstrate the effectiveness of the suggested technique, the authors constructed the objective function using five different algorithms such as BA, AVOA, BBA, PSO, and proposed BESA. The above meta-heuristic optimization methods were utilized to identify the optimal position and size of DSTATCOM and EVCS.

TABLE 3. Objective Function parameters settings for net savings calculation [21], [42].

S.No	Parameter	Constant	Value	Unit
1	Energy Cost	Ce	0.06	\$/kWh
2	Depreciation factor	α	10	%
3	Time	T	8760	Hours per year
4	DSTATCOM Purchase Cost	C^{p}_{DST}	50	\$/kVAr
5	DSTATCOM Installation Cost	C^{i}_{DST}	1400	\$/ Placement
6	CS Installation Cost	C^{i}_{CS}	6070	\$/ Placement
7	DSTATCOM Operating Cost	C^{O}_{DST}	500	\$/Year/Placement
8	CS Operating Cost	C^{O}_{CS}	8400	\$/Year/Placement

This study explores three possible EV types to be positioned at a charging station, each with a battery energy of 20, 10, and 16kWh. The total number of EVs at a charging station is estimated to be 100, resulting in an additional power demand of 966kW on the system by one charging station. It is also assumed that EVs at charging stations have different State of charge (SOC) levels. To be deployed correctly in DS, a maximum of three EVCS with numerous charging ports and five DSTATCOMs are allowed. Table-3 [21], [42] shows the constants used to calculate net savings for both test systems.

The following cases have been considered for Indian 28-bus and 108-bus distribution systems.

Case (i): Without Compensation
Case (ii): With EVCS
Case (iii): With DSTATCOM
Case (iv): With DSTATCOM & EVCS

A. TEST SYSTEM-I (INDIAN 28-BUS DS)

To demonstrate the capacity of the present technique in a real-time system, an 11kV, 28-bus rural Indian DS was used. The network has 28 buses and is radial, with the substation connecting at the first bus, as indicated in Figure 4.

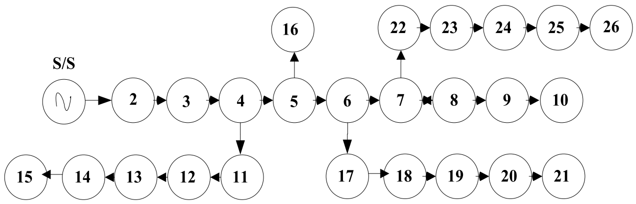

FIGURE 4. 28-bus Indian distribution network.

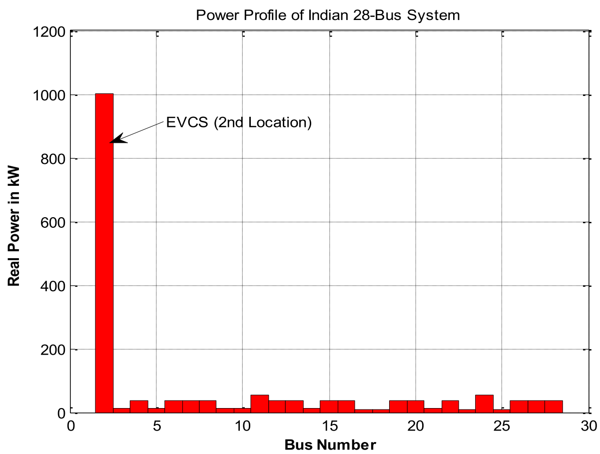

FIGURE 5. Power profile of 28-bus system.

Reference [43] provides the test system's essential load and bus data. To determine the base bus voltages and power flow across test system lines, the DLF method is used. In this scenario, one EVCS and three DSTATCOMs are ideally positioned in the DS with the assistance of VSI and BESA to attain lower objective values. A simple line schematic of a 28-bus Indian distribution system is shown in Figure 4.

The power profile of 28-bus system with EVCS installation on the distribution system is depicted in Figure 5. One 966kW EVCS is optimally placed at the 2nd bus on the 28-bus distribution system, which increases the actual power load to 1001.28kW from 35.28kW. This increase in power demand can cause voltage drops, especially during peak charging periods, which can impact the reliability and stability of the distribution system. If the demand exceeds the capacity of the distribution system, it can result in power outages or brownouts.

1) CASE (I): WITHOUT COMPENSATION

In this case, without the incorporation of DSTATCOM and EVCS, DLF analysis is conducted on DS with the existing load. After utilizing the DLF approach to compute the power flow algorithm, the bus with the minimum voltage of 0.9123p.u. The VSI value is 0.6927p.u. The system also has an actual power loss of 68.82kW and a reactive power loss of 68.82kVAr.

2) CASE (II): WITH EVCS

Table 4 demonstrates the effect of the EVCSs load on the performance of test system 1. Power loss increases from 68.82kW to 96.52kW when one EVCS is placed with the ideal position (2nd bus) on the DS owing to additional 966kW EVCS loading on the system. As a result, bus voltage profiles are influenced. The system's minimum voltage is decreased from 0.9123p.u to 0.9016p.u. Moreover, the EVCS's placement in the DS reduces voltage stability. The findings show that the optimum EVCS allocation strategy increases power loss and disturbs the bus voltage in DS, even when EVCS is placed close to the substation bus.

3) CASE (III): WITH DSTATCOM

Three DSTATCOMs are optimally located in the DS using BESA (11, 12 & 19 buses), BA (7, 12 & 19 buses), AVOA (6, 13 & 19 buses), BBA (9, 20 & 27 buses) and PSO (4, 13 & 21 buses). The base case for case-III is case-I. The base case (case-I) values are compared with case-III, and the results are tabulated in Table-4. Consequently, while using BESA, power loss is decreased from 68.82kW to 32.92kW. Moreover, BESA is used to improve the minimum bus voltage from 0.9123p.u to 0.9489p.u. DSTATCOM's appropriate locations and sizes, such as voltage profile, also affect VSI. The VSI value is determined to be 0.8061p.u, which is 0.6927p.u in the base case. Hence the VSI value is also improved.

Table-5 shows that BESA outperforms well in all aspects compared to other algorithms in case-III. When the BESA results are compared with other algorithms, the BESA approach reduces power loss by 52.16%, more significant than the BA's 43.79%, AVOA's 48.19%, BBA's 46.64% and PSO's 42.85%. Also, the BESA minimum bus voltage is 0.9489p.u, greater than the other algorithm's minimum voltage values. The annual net savings by proposed BESA ($13324) is high compared with other algorithms such as BA ($10497), AVOA ($12364), BBA ($12102), and PSO ($9655).

4) CASE (IV): WITH DSTATCOM & EVCS

In case-IV, multiple DSTATCOMs are combined with EVCSs are optimally positioned and sized on the DS using BESA and other algorithms to minimize the impact of EVCSs. The base case for case-IV is case-II. The base case (case-II) values are compared with case-IV, and the results are tabulated in Table-4. The installation of DSTATCOMs have reduced the power loss created by EVCSs on DS. The power loss decreases to 58.84kW from 96.52kW, the VSI enhances to 0.7701p.u from 0.6607p.u, and the minimum voltage enhances to 0.9371p.u. 0.9016p.u. The performance comparison of the Indian 28-bus system with different algorithms under different cases is depicted in Table-5.

This is the main case (Case-IV) compared to all other cases on DSTATCOM and EVCS allocation problem on DS. So, the comparison graphs of power loss and voltage profile for proposed and existing algorithms are considered only for case-IV. Figures 6 and 7 show the power loss and voltage profile comparisons of the 28-bus system (Case-IV) on the Indian 28-bus DS. From figures 6 and 7, it could be understood that the proposed BESA gives better loss reduction and voltage profile enhancement compared to other optimization

TABLE 4. Performance of Indian 28-bus system with different load factors under different cases.

Cases	Items	Light Load (0.5)	Medium Load (1.0)	Peak Load (1.6)
Case-I (Without Compensation)	Ploss (kW)	15.85	68.82	197.85
	Qloss (kVAr)	10.61	46.04	132.39
	Vmin (p.u)	0.9580	0.9123	0.8507
	VSImin (p.u)	0.8424	0.6927	0.5237
Case-II (With EVCS)	EVCS size in kW (Location)	483 (2)	966 (2)	1545.6 (2)
	Ploss (kW)	22.23	96.52	278.16
	Qloss (kVAr)	14.97	64.99	187.28
	Vmin (p.u)	0.953	0.9016	0.8317
	VSImin (p.u)	0.8249	0.6607	0.4784
Case-III (With DSTATCOM)	DSTATCOM size in kW (Location)	165 (7) 100 (12) 100 (19)	390 (7) 210 (12) 125 (19)	630 (7) 345 (12) 210 (19)
	Ploss (kW)	7.90	32.92	89.77
	% Ploss Reduction	50.15	52.16	54.62
	Qloss (kVAr)	5.22	21.81	59.47
	Vmin (p.u)	0.9746	0.9489	0.9136
	VSImin (p.u)	0.9022	0.8061	0.6929
Case-IV EVCS)	DSTATCOM size in kVAr (Location)	165 (7) 100 (12) 100 (19)	390 (7) 210 (12) 125 (19)	630 (7) 345 (12) 210 (19)
	EVCS size in kW (Location)	483 (2)	966 (2)	1545.6 (2)
	Ploss (kW)	14.09	58.84	160.37
	% Ploss Reduction	36.61	39.03	42.34
	Qloss (kVAr)	9.46	39.56	107.76
	Vmin (p.u)	0.9696	0.9371	0.8954
	VSImin(p.u)	0.8837	0.7701	0.6375

algorithms in 28-bus DS. The BESA approach results in better loss reduction (58.84kW), which is less than the BA (64.89kW), AVOA (61.73kW), BBA (62.87kW) and PSO (65.53kW) based approaches. Also, the BESA minimum bus voltage is 0.9371p.u, which is higher than the other algorithm results.

The Reduction of energy cost (ΔE), Total Installation cost (C_i)

Total Operating cost (C_O) are determined to calculate the Annual Net Savings ($) using DSTATCOM and EVCS on Indian distribution systems. BESA's ANS is $5253, BA's is $2272.73, AVOA's is $4209, BBA's is $3909, and PSO's is $1436. In this case, BESA provides a better reduction in power loss and voltage variation, as indicated in Table-5, as well as the most significant improvement in VSI.

Figure 8 compares real power loss values with other cases of the 28-bus system for various optimization algorithms. The bar chart shows that the BESA-based optimization technique produces better real power loss reduction than BA, AVOA, BBA, and PSO-based methods in all the cases.

To get near-global optimum solutions, the algorithm's convergence should be as steady as feasible. Figure 9 compares the convergence characteristic of BESA for a 28-bus test system with other known algorithms, such as BA, AVOA, BBA, and PSO, to anticipate the performance of the BESA. The BESA needs just ten iterations to converge to the optimal objective value. Furthermore, the BESA exhibits a steady and rapid convergence with a near-global searching ability to locate the ideal DSTATCOM sizes. BESA has a reasonably quick convergence speed in general. It converges the fastest and has the best convergence accuracy on both test systems.

5) PERFORMANCE ANALYSIS ON VARIOUS LOAD FACTORS

The performances of the Indian 28-bus system with various load factors under different cases utilizing the proposed BESA is depicted in Table 4. It shows how EVCS affects real power loss in a 28-bus system, and the effect of EV charging load on DS performance is evaluated using DSTATCOMs at three different load factors (0.5, 1.0, and 1.6). The proposed BESA-based DSTATCOM allocation and EVCS show better loss reduction, bus voltage enhancement, and stability improvement on the 28-bus system in all the load levels.

The real power loss and voltage profile of the 28-bus system using BESA are shown in Figures 10 and 11, respectively. Based on the figures, the proposed method minimizes the impact of EVCS on DS efficiently. It also can be said that the case-III gives better voltage profile enhancement and loss reduction compared to other cases.

B. TEST SYSTEM-II (INDIAN 108-BUS DS)

To validate the proposed method's performance, it is also used in the large-scale actual Indian 108 distribution system, which has 108 buses and 107 branches. This is an 11kV real-time

TABLE 5. comparison of Indian 28-bus system with different algorithms under different cases.

Cases	Items	BESA	BA	AVOA	BBA	PSO
Case-I (Without Compensation)	Ploss (kW)	68.82	68.82	68.82	68.82	68.82
	Qloss (kVAr)	46.04	46.04	46.04	46.04	46.04
	Vmin (p.u)	0.9123	0.9123	0.9123	0.9123	0.9123
	VSImin (p.u)	0.6927	0.6927	0.6927	0.6927	0.6927
Case-II (With EVCS)	EVCS size in kW (Location)	966 (2)	966 (2)	966 (2)	966 (2)	966 (2)
	Ploss (kW)	96.52	96.52	96.52	96.52	96.52
	Qloss (kVAr)	64.99	64.99	64.99	64.99	64.99
	Vmin (p.u)	0.9016	0.9016	0.9016	0.9016	0.9016
	VSImin (p.u)	0.6607	0.6607	0.6607	0.6607	0.6607
Case-III (With DSTATCOM)	DSTATCOM size in kW (Location)	390 (7) 210 (12) 125 (19)	210 (11) 125 (12) 350 (19)	170 (6) 150 (13) 310 (19)	160 (9) 180 (20) 230 (27)	460 (4) 150 (13) 175 (21)
	Ploss (kW)	32.92	38.68	35.65	36.72	39.33
	% Ploss Reduction	52.16	43.79	48.19	46.64	42.85
	Qloss (kVAr)	21.81	25.03	23.23	24.046	25.91
	Vmin (p.u)	0.9489	0.9387	0.9451	0.9447	0.9377
	VSImin (p.u)	0.8061	0.7764	0.7978	0.7959	0.7731
	Reduction of energy cost (ΔE)	18869	15842	17434	16872	15500
	Total Installation cost (C_i)	4045	3845	3570	3270	4345
	Total Operating cost (C_o)	1500	1500	1500	1500	1500
	Annual Net Savings ($)	13324	10497	12364	12102	9655
Case-IV (With DSTATCOM & EVCS)	DSTATCOM size in kVAr (Location)	390 (7) 210 (12) 125 (19)	210 (11) 125 (12) 350 (19)	170 (6) 150 (13) 310 (19)	160 (9) 180 (20) 230 (27)	460 (4) 150 (13) 175 (21)
	EVCS size in kW (Location)	966 (2)	966 (2)	966 (2)	966 (2)	966 (2)
	Ploss (kW)	58.84	64.89	61.73	62.87	65.53
	% Ploss Reduction	39.03	32.77	36.04	34.86	32.11
	Qloss (kVAr)	39.56	42.95	41.07	41.93	43.83
	Vmin (p.u)	0.9371	0.9281	0.9345	0.9341	0.9271
	VSImin(p.u)	0.7701	0.7419	0.7626	0.7601	0.7387
	Reduction of energy cost (ΔE)	19805	16625	18286	17686	16288
	Total Installation cost (C_i)	4652	4452	4177	3877	4952
	Total Operating cost (C_o)	9900	9900	9900	9900	9900
	Annual Net Savings ($)	5253	2272.73	4209	3909	1436

Indian radial distribution system with five significant feeds in urban India. This system's bus and line data are sourced from [44]. This system's overall actual and reactive power needs are 12132kW and 9099kVAr, respectively. Figure 12 is a sample line diagram of a 108-bus system. Four different cases are considered in the Indian 108-bus test system to study the efficiency of the existing technique.

When EVCSs are placed, they draw real power from the distribution grid. Figure 13 shows the real power demand profile of the Indian 108-bus distribution system. In this case, three 966kW EVCSs are optimally placed on the distribution system's 2nd, 3rd, and 64th buses. If three of EVCSs are placed simultaneously in an Indian 108-bus DS, the demand for power in that bus will increase, which could lead to an increase in real power loss. This can strain the distribution system, leading to voltage drops and potential power quality issues.

1) CASE (I): WITHOUT COMPENSATION

The distribution load flow technique on DS is used in the second test system Indian 108-bus, to calculate uncompensated system values. After running the power flow algorithm with the DLF, the system has a real power loss of 645.02kW and a reactive power loss of 359.43kVAr. 0.6397p.u and 0.8937p.u are the minimum VSI and voltage values, respectively. Table-6 demonstrates the performance of a 108-bus system with different load factors in different cases using the proposed BESA.

2) CASE (II): WITH EVCS

Three EVCS are optimally positioned (2nd, 3rd & 64th buses) at various positions in the 108-bus test systems on DS. Due to an additional power need of 2988kW imposed by three EVCSs, the test system loading condition is increased from 12132kW to 15030kW. The real power loss has grown from 645.02kW to 681.92kW. As seen in Table-4, the minimal VSI drops to 0.6413p.u from 0.6397p.u. The minimum bus voltage has been reduced from 0.8937p.u to 0.8987p.u. When case-II is compared to case-I, even with the ideal EVCSs location in both DS, the real power loss value is still large, but the VSI value is low.

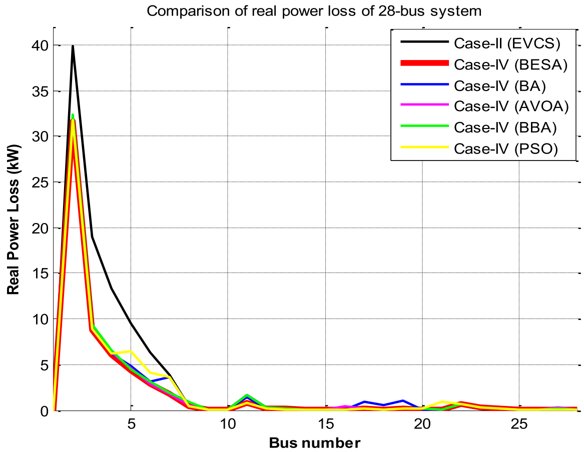

FIGURE 6. **Comparison of real power loss of 28-bus system (Case-IV).**

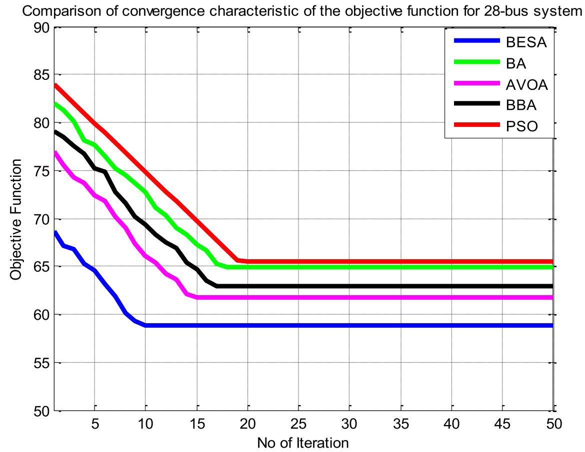

FIGURE 9. **Comparison of convergence characteristic of the Comparison of convergence characteristic of the objective function for 28-bus system.**

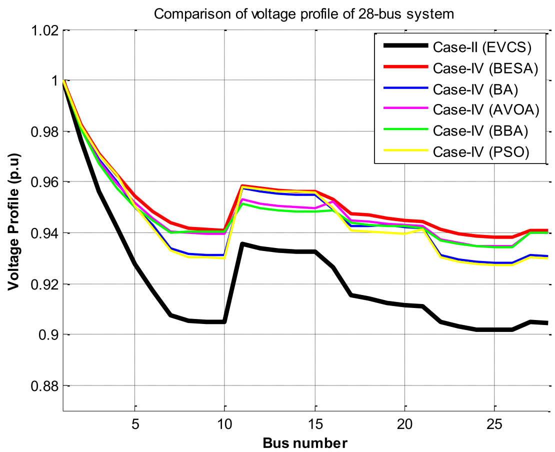

FIGURE 7. **Comparison of voltage profile of 28-bus system (Case-IV).**

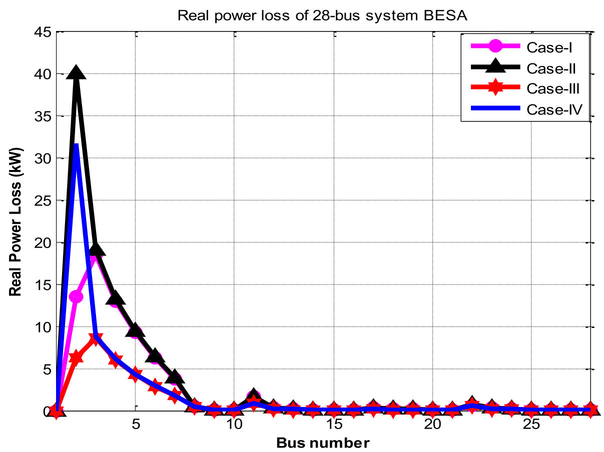

FIGURE 10. **Real power loss of 28-bus system using BESA.**

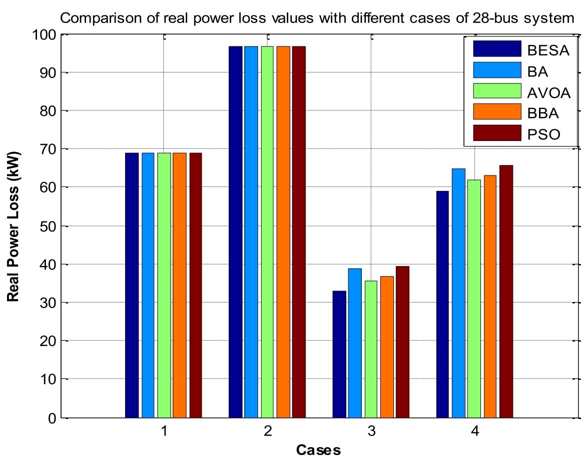

FIGURE 8. **Comparison of real power loss values with different cases of 28-bus system.**

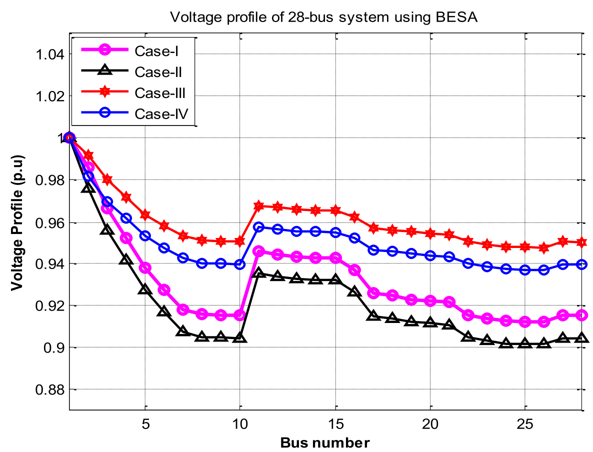

FIGURE 11. **Voltage profile of 28-bus system using BESA.**

3) CASE (III): WITH DSTATCOM

Five DSTATCOMs are ideally integrated into the test system-2 on the 23rd, 60th, 63rd, 84th, and 97th locations using BESA, 19th, 57th, 65th, 83rd, and 97th locations using BA, 22nd, 59th, 65th, 83rd, and 97th locations using AVOA, 6th, 59th, 68th, 83rd, and 96th locations using BBA and 14th, 24th, 65th, 83rd, and 95th locations using PSO. Using BESA, the

TABLE 6. Performance of Indian 108-bus system with different load factors under different cases.

Cases	Items	Light Load (0.5)	Medium Load (1.0)	Peak Load (1.6)
Case-I (Without Compensation)	Ploss (kW)	151.53	645.02	1802.8
	Qloss (kVAr)	85.05	359.43	992.81
	Vmin (p.u)	0.9497	0.8937	0.8158
	VSImin (p.u)	0.8143	0.6397	0.4458
Case-II (With EVCS)	EVCS size in kW (Location)	483 (2)	966 (2)	1545.6 (2)
		483 (3)	966 (3)	1545.6 (3)
		483 (64)	966 (64)	1545.6 (64)
	Ploss (kW)	160.39	681.92	1902.6
	Qloss (kVAr)	93.02	392.47	1081.6
	Vmin (p.u)	0.9537	0.8987	0.8238
	VSImin (p.u)	0.8233	0.6413	0.4494
Case-III (With DSTATCOM)	DSTATCOM size in kW (Location)	1230 (23)	2500 (23)	4080 (23)
		580 (60)	1175 (60)	1910 (60)
		900 (63)	1840 (63)	2975 (63)
		385 (84)	770 (84)	1230 (84)
		630 (97)	1290 (97)	2145 (97)
	Ploss (kW)	100.39	422.13	1157.3
	% Ploss Reduction	33.75	34.55	35.81
	Qloss (kVAr)	52.67	219.79	595.9
	Vmin (p.u)	0.9577	0.9138	0.8528
	VSImin (p.u)	0.8433	0.6956	0.5279
Case-IV (With DSTATCOM & EVCS)	DSTATCOM size in kVAr (Location)	1230 (23)	2500 (23)	4080 (23)
		580 (60)	1175 (60)	1910 (60)
		900 (63)	1840 (63)	2975 (63)
		385 (84)	770 (84)	1230 (84)
		630 (97)	1290 (97)	2145 (97)
	EVCS size in kW (Location)	483 (2)	966 (2)	1545.6 (2)
		483 (3)	966 (3)	1545.6 (3)
		483 (64)	966 (64)	1545.6 (64)
	Ploss (kW)	126.72	482.43	1277
	% Ploss Reduction	20	29.25	32.88
	Qloss (kVAr)	75.07	256.25	688.8
	Vmin (p.u)	0.9584	0.9138	0.8532
	VSImin(p.u)	0.8438	0.6954	0.5282
	N.S ($)	NA	36755.94	NA

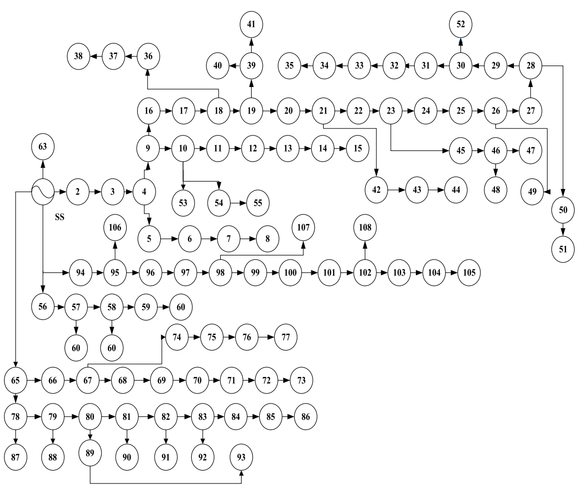

FIGURE 12. 108-bus Indian distribution network.

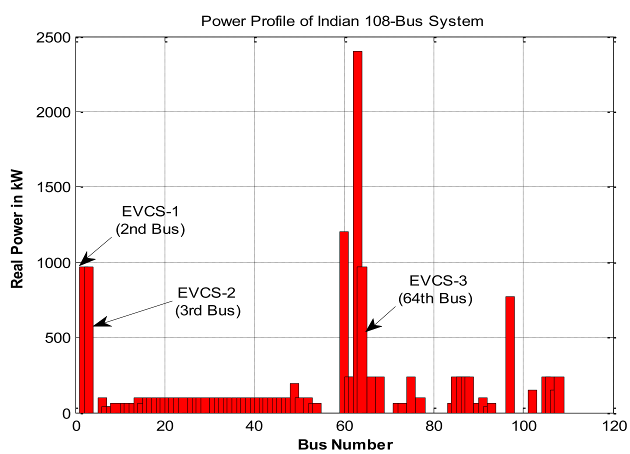

FIGURE 13. Power profile of 108-bus system.

power loss is mitigated from 645.02kW to 422.13kW, the minimum VSI is increased from 0.6397p.u to 0.6932p.u, and the least voltage is improved from 0.8937p.u to 0.9119p.u. When the BESA findings for 108-bus DS are compared to the other algorithm's results, it is discovered that the BESA technique leads to an actual power loss reduction, minimum

TABLE 7. Comparison of Indian 108-bus system with different algorithms under different cases.

Cases	Items	BESA	BA	AVOA	BBA	PSO
Case-I (Without Compensation)	Ploss (kW)	645.02	645.02	645.02	645.02	645.02
	Qloss (kVAr)	359.43	359.43	359.43	359.43	359.43
	Vmin (p.u)	0.8937	0.8937	0.8937	0.8937	0.8937
	VSImin (p.u)	0.6397	0.6397	0.6397	0.6397	0.6397
Case-II (With EVCS)	EVCS size in kW (Location)	966 (2) 966 (3) 966 (64)	966 (2) 966 (3) 966 (64)	966 (2) 966 (3) 966 (64)	966 (2) 966 (3) 966 (64)	966 (2) 966 (3) 966 (64)
	Ploss (kW)	681.92	681.92	681.92	681.92	681.92
	Qloss (kVAr)	392.47	392.47	392.47	392.47	392.47
	Vmin (p.u)	0.8987	0.8987	0.8987	0.8987	0.8987
	VSImin (p.u)	0.6413	0.6413	0.6413	0.6413	0.6413
Case-III (With DSTATCOM)	DSTATCOM size in kW (Location)	2500 (23) 1175 (60) 1840 (63) 770 (84) 1290 (97)	2890 (19) 1330 (57) 1075 (65) 650 (83) 1290 (97)	2620 (22) 1240 (59) 1060 (65) 675 (83) 1290 (97)	600 (6) 1220 (59) 550 (68) 710 (83) 1290 (96)	310 (14) 2230 (24) 1080 (65) 610 (83) 1380 (95)
	Ploss (kW)	422.13	482.43	476.25	513.54	553.27
	% Ploss Reduction	34.55	25.21	26.16	20.38	14.22
	Qloss (kVAr)	219.79	256.26	255.65	296.699	288.37
	Vmin (p.u)	0.9138	0.9119	0.9119	0.9114	0.9015
	VSImin (p.u)	0.6956	0.6932	0.6932	0.6915	0.6622
	Reduction of energy cost (ΔE)	117150	85457	88706	69106	48224
	Total Installation cost (C_i)	38570	36875	35125	22550	28750
	Total Operating cost (C_O)	2500	2500	2500	2500	2500
	Annual Net Savings ($)	76080	46082	51081	44056	16974
Case-IV (With DSTATCOM & EVCS)	DSTATCOM size in kVAr (Location)	2500 (23) 1175 (60) 1840 (63) 770 (84) 1290 (97)	2890 (19) 1330 (57) 1075 (65) 650 (83) 1290 (97)	2620 (22) 1240 (59) 1060 (65) 675 (83) 1290 (97)	600 (6) 1220 (59) 550 (68) 710 (83) 1290 (96)	310 (14) 2230 (24) 1080 (65) 610 (83) 1380 (95)
	EVCS size in kW (Location)	966 (2) 966 (3) 966 (64)	966 (2) 966 (3) 966 (64)	966 (2) 966 (3) 966 (64)	966 (2) 966 (3) 966 (64)	966 (2) 966 (3) 966 (64)
	Ploss (kW)	482.43	529.81	512.39	550.02	589.41
	% Ploss Reduction	29.25	22.31	24.86	19.34	13.56
	Qloss (kVAr)	256.25	296.15	288.01	329.46	320.73
	Vmin (p.u)	0.9138	0.9119	0.9119	0.9114	0.9015
	VSImin(p.u)	0.6954	0.6932	0.6932	0.6915	0.6622
	Reduction of energy cost (ΔE)	104850	79949	89105	69327	64391
	Total Installation cost (C_i)	40400	38696	36946	24371	30571
	Total Operating cost (C_O)	27700	27700	27700	27700	27700
	Annual Net Savings ($)	36760	13553	24459	17256	6120

bus voltage improvement, and stability enhancement. Table-7 displays the comparison of the Indian 108-bus system with different algorithms under different cases.

4) CASE (IV): WITH DSTATCOM & EVCS

In this case, five DSTATCOMs and three EVCSs are optimally placed using BESA on the Indian 108-bus system. After the optimization, BESA reduces the loss from 482.43kW to 645.02kW. In addition, the VSI is increased from 0.6413p.u to 0.6954p.u and the least voltage is improved from 0.8987p.u to 0.9138p.u. Figures 14 and 15 show the comparisons of power loss and voltage profile of the 108-bus system (Case-IV) on Indian 108-bus DS. From the figures (14 and 15) and discussions, it could be understood that the proposed BESA gives better loss reduction and voltage profile enhancement compared to other optimization algorithms in 108-bus DS.

Table-7 depicts the comparison of Indian 108-bus system with different algorithms under different cases. The presented approach has been tested with BA, AVOA, BBA and PSO in terms of loss reduction and voltage profile enhancement. Case-IV has a significant reduction in power loss and voltage variation, as indicated in Table-7, and the most significant improvement in VSI. BESA's ANS is $36760, BA's is $13553, AVOA's is $24459, BBA's is $17256, and PSO's is $6120. When the BESA and other algorithm findings are compared, the BESA technique results in a real power loss reduction of 29.25%, which is more than the BA's 22.31%,

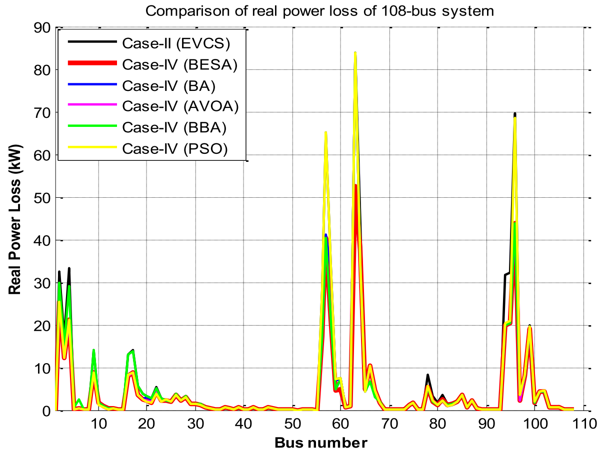

FIGURE 14. Comparison of real power loss of 108-bus system (Case-IV).

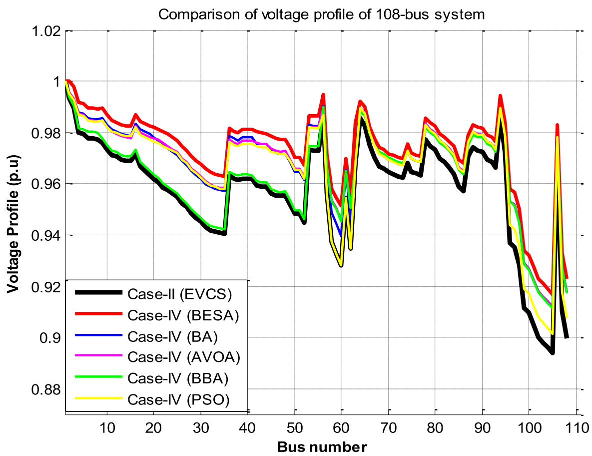

FIGURE 15. Comparison of voltage profile of 108-bus system (Case-IV).

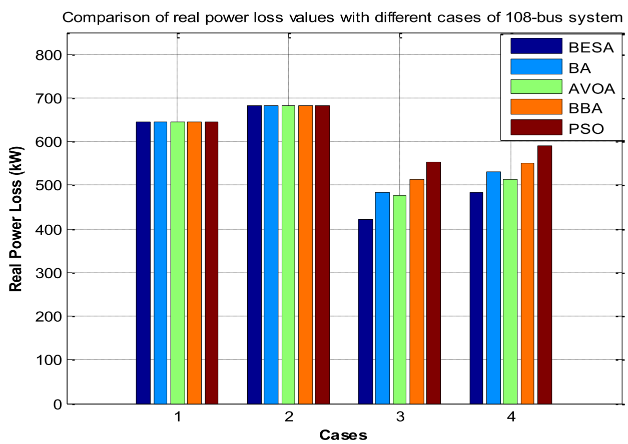

FIGURE 16. Comparison of real power loss values with different cases of 108-bus system (Case-IV).

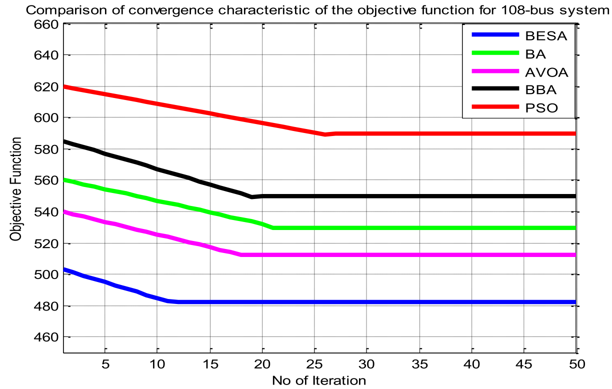

FIGURE 17. Comparison of convergence characteristic of the objective function for 108-bus system.

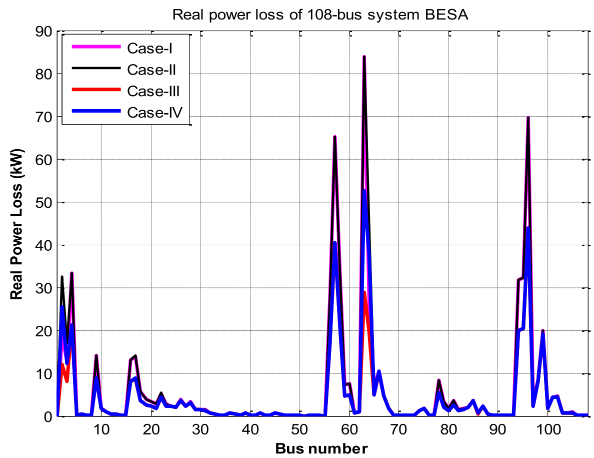

FIGURE 18. Real power loss of 108-bus system using BESA.

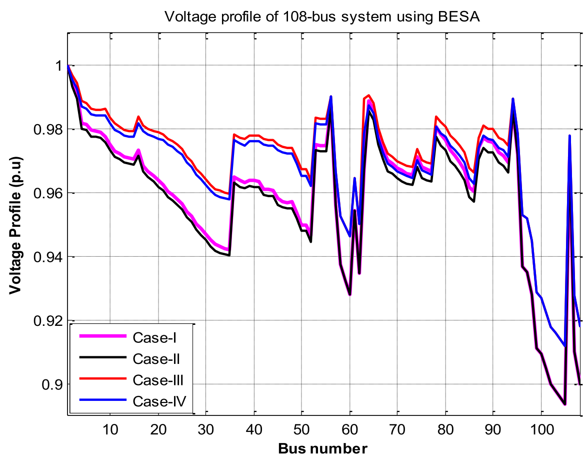

FIGURE 19. Voltage profile of 108-bus system using BESA.

AVOA's 24.86%, BBA's 19.34%, and PSO's 1356%, Additionally, the BESA minimum bus voltage is 0.9138p.u which is higher than other considered algorithm's minimum voltage.

Figure 16 depicts the comparison of real power loss values with different cases of 108-bus system for various optimization algorithms. From the bar chart, it can be observed that the BESA based optimization technique produces better real power loss reduction than BA, AVOA, BBA and PSO based techniques in all cases.

The convergence characteristic of BESA is compared with other known algorithms to anticipate its superiority in a 108-bus system, as illustrated in Fig. 17. The convergence diagram clearly shows that the BESA only needs 12 iterations to get the optimal objective function value. Furthermore, the

BESA algorithm has a steady and speedy convergence and a global searching capacity to locate the ideal DSTATCOM sizes.

5) PERFORMANCE ANALYSIS ON VARIOUS LOAD FACTORS

The performances of the Indian 108-bus system with various load factors under different cases utilizing the proposed BESA are depicted in Table-6. The various load factors (0.5, 1.0, and 1.6) have been considered to check the efficiency of the proposed BESA. In all the load levels proposed BESA based on DSTATCOM allocation along with EVCS show better loss reduction, bus voltage enhancement, and stability improvement on the 108-bus system. The real power loss and voltage profile of the 108-bus system using BESA are shown in Figures 18 and 19, respectively. In 108-bus also case-IV gives better results compared to the other cases. The attained simulation results demonstrated that the presented BESA can solve any complicated power system problem.

C. OVERALL ANALYSIS

Overall, the impact of EVCSs on power loss, voltage profile, and system stability in distribution systems will depend on several factors, including the size and location of the charging stations, the charging rate, the existing load on the system, and the availability of energy sources. Proper placing and sizing of EVCS will be essential to minimize the impact on the distribution system and ensure a reliable and efficient power supply and energy sources. DSTATCOM can be used to mitigate the effects of EVCSs on the DS. DSTATCOM can compensate for the reactive power, and provide additional power to the system, reducing the load on the grid and voltage fluctuations caused by EVCS. This combination of DSTATCOM and EVCS can help minimize the impact of EVCS on the Indian distribution system and improve its overall performance. In summary, using DSTATCOM can mitigate the impact of EVCSs on the distribution system. This combination can provide a more reliable and resilient grid, reduce the carbon footprint of EV charging stations, and help to ensure that the distribution system can handle the increased demand for electricity from EVCSs.

VI. CONCLUSION

Electric Vehicles are a feasible solution for lowering transportation pollution. Furthermore, the growing popularity of EVs has accelerated the creation of charging stations. Nevertheless, this increase would have a detrimental influence on DS, and it is vital to calculate the impact of appropriate EVCS sites. The current work explored a new technique for achieving optimal DSTATCOM-EVCS allocation for power loss mitigation. In this regard, a unique nature-inspired bald eagle search algorithm has been suggested and used to identify the best placements and sizes for the DSTATCOM and EVCS.

Furthermore, by adopting a BESA-based optimization technique, the effect of EVCS on DS is minimized. Using four different cases, two practical Indian 28-bus and 108-bus test systems were used to assess the feasibility and efficiency of the presented technique. The simulation results confirm that the major objective of this work was considerably attained with the assistance of BESA rather than other optimization algorithms. Power loss mitigation and net savings have been greatly improved in all three load factors by using BESA. In all cases investigated, optimum DSTATCOM allocation with EVCS provides improved power loss reduction and VSI enhancement in the DS. This proposed approach may be used successfully in developing real-time distribution networks with renewable DGs. The limitation of BESA is that it may only be suitable for solving some optimization problems. It best suits issues with a well-defined fitness function and a continuous search space.

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T. YUVARAJ received the B.E. degree in electrical and electronics engineering and the M.E. degree in power electronics and drives from Anna University, Chennai, India, in 2011 and 2013, respectively, and the Ph.D. degree from Vellore Institute of Technology, Vellore, India, in 2017. He is currently an Associate Professor with the Department of EEE, Chennai Institute of Technology, Chennai, where he is also a Research Member with the Centre for Computational Modeling. He has published more than 65 papers in the Web of Science-/Scopus-indexed journals. His research interests include the optimal allocation of compensating devices, electric vehicle charging stations in distribution networks using optimization algorithms, and power electronics applications in power systems. He is a member of IET and IAENG. He has also served as a Reviewer for various reputed journals, such as IEEE, Elsevier, Springer, Taylor and Francis, and Interscience journals.

K. R. DEVABALAJI received the bachelor's degree in electrical and electronics engineering and the master's degree in power electronics drives from Anna University, Chennai, India, in 2011 and 2013, respectively, and the Ph.D. degree from the Vellore Institute of Technology, Vellore, India, in 2016. He is currently an Assistant Professor with the Hindustan Institute of Technology and Science, India. He has authored or coauthored several research articles in reputed journals. He has over ten years of teaching and research experience. He has visited Thailand, Singapore, Indonesia, and the U.K. for presenting research papers, funded proposals, and collaborative research activities. His research interests include renewable energy systems, power systems, and power electronics and drives.

SUDHAKAR BABU THANIKANTI (Senior Member, IEEE) received the B.Tech. degree from Jawaharlal Nehru Technological University, Ananthapur, India, in 2009, the M.Tech. degree in power electronics and industrial drives from Anna University, Chennai, India, in 2011, and the Ph.D. degree from the Vellore Institute of Technology, Vellore, India, in 2017. He was a Post-Doctoral Research Fellow with the Department of Electrical Power Engineering, Institute of Power Engineering, University Tenaga Nasional (UNITEN), Malaysia. He is currently a Senior Research Associate with the Department of Electrical and Electronic Engineering Science, University of Johannesburg. He is also an Associate Professor with the Department of Electrical and Electronics Engineering, Chaitanya Bharati Institute of Technology, Hyderabad. He has authored or coauthored more than 140 research articles in various renowned international journals. His research interests include the design and implementation of solar PV systems, renewable energy resources, power management for hybrid energy systems, storage systems, fuel cell technologies, electric vehicles, and smart grids. He is acting as an Editorial Board Member and a Reviewer for various reputed journals, such as the IEEE and IEEE ACCESS, IET, Elsevier, and Taylor and Francis.

VIJAY BABU PAMSHETTI (Member, IEEE) received the M.Tech. degree in power system engineering from the National Institute of Technology (NIT), Kurukshetra, in 2014, and the Ph.D. degree in power system engineering from IIT (BHU) Varanasi, Varanasi, India, in 2019. He is currently an Assistant Professor with the Department of Electrical and Electronics Engineering, Chaitanya Bharathi Institute of Technology, Hyderabad, India. His research interests include distributed energy resources management systems (DERMSs), advanced distribution management systems (ADMSs), and optimization.

NNAMDI I. NWULU (Senior Member, IEEE) is currently a Full Professor with the Department of Electrical and Electronic Engineering Science, University of Johannesburg, and the Director of the Centre for Cyber-Physical Food, Energy and Water Systems (CCP-FEWS). His research interests include the applications of digital technologies, mathematical optimization techniques, and machine learning algorithms in food, energy, and water systems. He is a Professional Engineer registered with the Engineering Council of South Africa (ECSA), a Senior Member of the South African Institute of Electrical Engineers (SMSAIEE), and a Y-Rated Researcher by the National Research Foundation of South Africa. He is the Editor-in-Chief of the *Journal of Digital Food Energy and Water Systems* (JDFEWS) and an Associate Editor of *IET Renewable Power Generation* (IET-RPG) and *African Journal of Science, Technology, Innovation and Development* (AJSTID).