Enhancing the Voltage Profile and Net Profit of Reconfigured Distribution Networks with the Optimal Integration of EVCS and Capacitor Banks with Chaotic HBA

K. Asokan, and Madhubabu Thiruveedula

***Abstract*—Nowadays, plug-in electric vehicles (PEVs) are increasing very fast because people are worried about pollution caused by petrol and diesel vehicles. As the number of electric vehicles (EVs) is growing quickly, there is a need to provide proper and efficient charging stations. But installing many charging stations creates some problems in the distribution system, such as voltage becoming unstable and increase in power losses. In this paper, a complete optimization method is proposed to improve the voltage level and increase overall profit in radial distribution networks (RDNs). This is done by placing electric vehicle charging stations (EVCS), capacitor banks, and by changing the network connections (network reconfiguration) together at the same time. In this work, a Chaotic Honey Badger Algorithm (CHBA) is used to solve the complex optimization problem which has nonlinear and mixed-integer variables. By adding chaotic mapping, the search ability of the algorithm improves and it helps to avoid getting stuck at a wrong early solution. The objective function considers both technical and economic factors. It aims to reduce power loss, improve voltage condition, decrease installation and operating cost, and increase the benefit by reducing energy losses. The proposed method is tested on the IEEE 33-bus test system under different conditions. The results show good improvement in voltage level, reduction in power losses, and increase in net profit when compared with other existing methods like PSO, GWO, and AGWOPSO. The CHBA method behaves steadily and yields consistent results under various test situations, according to the statistical analysis. The results obtained indicate that the recommended strategy is appropriate for practical implementation in present-day power distribution systems, especially in networks where electric vehicles (EVs) are highly prevalent.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/10257

***Index Terms*— Capacitor banks, Chaotic HBA, Electric Vehicle Charging Stations, net profit maximization, Network reconfiguration (NR), Radial distribution system (RDS).**

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I. INTRODUCTION

VEHICLES using conventional internal combustion engines are among the largest emitters of greenhouse gases (GHGs). The growth of electric vehicles (EVs) reduces transportation system GHG emissions. Consequently, many countries are switching to electric vehicles. Therefore, for EV companies to grow sustainably, intelligent organization is needed to create an affordable and easily available EVCS apparatus. Large-scale EV integration also requires the correct installation of EVCS in the distribution network. Inadequate EVCS placement can result in a mismatch between generation and demand, an increase in actual energy loss, a weak voltage curve, and ultimately, a decline in voltage stability margin. It is crucial to place EV charging stations (CSs) in the right locations to alleviate these problems. The position of the EVCS influences the reliability and efficiency of the RDS. The implementation of EVCS has increased the burden on distribution networks. In addition, it leds to voltage oscillations and greater energy loss. In this research, the network is reconfigured using EVCSs and shunt capacitors placed properly to minimize these issues.

When an EVCS is integrated into the current grid infrastructure, it randomly causes an imbalance, low power factor, electrical harmonics, and voltage instability [1]. The distribution network is affected by several factors, such as charging methods and vehicle population at charging stations. The influence of EVCS on the distribution network was reviewed and verified by experimental studies [2] and [3], which depend on the objective function of power quality variables and starting cost. The progression of the energy grid towards renewable power, with EVs helping to promote future energy growth, was examined in relation to the effect of EVCS on a distributed system [4]. The load of the EV influences distribution system elements, such as the voltage profile, energy loss, and distortion of harmonics, as EV penetration increases. Therefore, EV fast-charging stations (FCSs) must be positioned properly for the distribution network to be reliable. A two-stage procedure [5] for FCS implantation is suggested to reduce this issue.

By reconfiguring the network, EVCS's effect on the distribution network is decreased. A fixed network structure and fluctuating load requirements result in significant energy loss in the distribution network. Therefore, prompt NR is crucial. Network rearrangement is typically preferred to alleviate overloaded feeders and lower the actual energy loss in the distribution network [6], [7]. To lower energy losses, the configuration of the distribution network is adjusted by switching on and off sectional and tie switches. The network must also retain its radial configuration and nodal voltage restrictions while providing electricity to all the connected loads [8]. PSO is a meta-heuristic approach [9] that uses specific technological restrictions to determine the best reconfiguration for decreasing active losses and voltage variations.

However, network reconfiguration may not achieve the intended decrease in power loss and power quality restrictions. Reconfiguring the network and using Shunt Capacitors (SCs) together increases the voltage profile and reduces energy losses and usage. Capacitors enhance the voltage profile and minimize losses, which makes the system more stable when used with an EVCS. In addition, the costs of EVCS installation and operation were considered to optimize the net profit [10]. The optimal positioning of capacitors in the distribution system results in a reactive energy adjustment, which enhances the voltage curve and lowers the loss [11].

The metaheuristic method can be used to solve various optimization challenges. The best way to set up charging stations (CS) and capacitors (CAP) was suggested by a novel approach [12]. A new approach to distribution network rearrangement (DNR) for PEVs is proposed [13]. Using network reorganization as a strategy option, a new MILP concept [14] was proposed for the organization of live distribution systems and non-utility-owned EVCS. To handle the financial goals of users and the EVCS owners independently, the method uses multi-objective optimization. For both Less-Voltage and Medium-Voltage Distribution Systems, a two-phase EV charging plan and network rearrangement method is suggested as a solution to the power loss minimization issue [15]. Using the BPSO algorithm [16], EV charging planning and network modification issues are resolved. To choose potential solutions for the distribution network rearrangement problem without having to resolve load flow or optimization-based methods, a quick and easy method is recommended [17]. [18] incorporates shunt capacitors into the RDG with stable and time-dependent load considerations to improve the voltage profile and annual net savings. This reduces energy loss and the overall annual costs. Simultaneous SCA and RDNR is a complicated and nonlinear optimization issue for which a unique adaptive particle swarm optimization (APSO) method has been suggested [19]. To reduce the overall power loss, the DE algorithm and queuing theory [20] are suggested as ways to optimize the distribution network's PEV charging and DG size. To improve system efficiency and reduce carbon emissions, fuzzy Pareto optimality was used to plan distribution systems with EVCS [21]. To optimize the positioning of EVCSs and HFC-DG units simultaneously, a unique SHOA [22] is recommended. The primary objective is to reduce the actual energy loss caused by the higher energy use EVCSs. The ideal placement of the DSTATCOM and EVCS in the DS was determined using a novel optimization approach based on the nature-inspired BESA [23].

The literature has documented a number of additional techniques in addition to metaheuristic approaches. While deterministic approaches like convex optimization and mixed-integer linear programming (MILP) [24], [25] offer globally best results under simplified assumptions, they have restrictions when it comes to solving nonlinear and combinational optimization issues. Artificial neural networks and support vector machines are two methods for machine learning that have been used for EV load prediction and charging coordination [26], [27]. Nevertheless, both techniques are not directly appropriate for discrete planning issues and require large training datasets. Although hybrid metaheuristic algorithms [28], [29] have demonstrated enhanced search capabilities, they frequently entail greater computing complexity. In contrast to existing methods, the recommended CHBA efficiently handles multi-variable optimization while striking a balance between exploration and exploitation.

Few attempts have been made to jointly optimize EVCS placement, capacitor placement, and reconfiguration under a single economic cost criterion, despite the fact that multiple studies have focused on these variables. Furthermore, existing approaches only employ traditional metaheuristic algorithms, which have insufficient exploration capability and a tendency to converge prematurely.

This study tries to solve these problems by using the CHBA method to find the best locations for EV charging stations, proper size of capacitors, and suitable network reconfiguration. The main aim is to improve voltage quality and increase the overall net income of the system. Thus, the novelty of this work is not the first occurrence of chaotic optimization in HBA but rather the first systematic incorporation of chaotic optimization into HBA for the combined problem, along with a practical cost–benefit framework. The statistical analysis shows that this integration provides non-incremental gains in terms of reliability of convergence and net profit.

The key contributions of this work are as follows:

1. Optimization of EVCSs installation locations, capacitor distribution, and power system network reconfiguration.
2. Proposed Chaotic Honey Badger Algorithm (CHBA) for convergence enhancement and escaping from local minima.
3. Incorporation of technical (loss reduction, voltage profile improvement) and economic (profit maximization) criteria.
4. Application to IEEE 33 bus system and comparative study.

II. Problem Formulations

For electric utility providers and their consumers, the effective implementation of EVCS is essential. Due to the narrow scope of all electric vehicles, recharging is required many times while driving. Due to the significant burden that EVCSs exert on distribution networks, they often cause power failures. Therefore, even with a slight raise in energy loss, the proper positioning of EVCS is essential. Capacitors boost the voltage profile and lower energy loss, which reduces the impact of EVCS installations on the DN.

A. Clarification of the Objective Functions

The key aim of this investigation is to determine the desirable locations for capacitors and EVCS within the distribution network. The voltage profile deteriorates, and system power losses increase when EVCS are adopted in the distribution network. To effectively reduce power failures, capacitors are positioned at ideal distribution network nodes. The capacitor allocation system effectively maintained the voltage curve within the preset limitations. Therefore, an objective function was developed to reduce power failures without violating the subject limitations. This reduces the total yearly power loss expenses, improves the consistency of the distribution network, and enhances the net profit. The integration of capacitors and EVCS into the distribution system is illustrated in Fig. 1. The objective functions for the proposed problem are mathematically expressed as follows:

Total active power loss $P_{T,loss} = \sum_{j=1}^{N_{br}} P_{loss,j}(m,n)$ (1)

Enhance net profit = Profit from reduced energy loss − operating expenditures for the system's components− the cost of installing the system components.

Profit from reduced energy loss =

$$K_{ep} * \left(P_{T,loss} - P_{T,loss}^{cap}\right) * T \quad (2)$$

the cost of installing the system components =

$$\beta[\ c_i^{cap} * N_{cap} + C_i^{EVCS} * N_{EVCS} + K_{cp} * \sum_{i=1}^{N_{cap}} Q_{cap}(i)\ ] \quad (3)$$

operating expenditures for the system's components =

$$C_O^{cap} * N_{cap} + C_O^{EVCS} * N_{EVCS} \quad (4)$$

All cost components, including installation cost, operating cost, and energy loss cost, are converted to annual values to maintain consistency in the objective function. Reliability studies under various operating conditions are required to update electrical distribution systems to accommodate present and growing loads. The energy not provided (ENS) is regarded as a sign to evaluate the system's reliability. The following procedures can be used to calculate the yearly cost of unsupplied energy:

$$C_{ENS} = \sum_{j=1}^{N_{br}} \left(\sum_{t=1}^{T=365} \left(\sum_h \left(\frac{E^d(h)}{T} F_h R_h\right) PC_t \right)\right) \quad (5)$$

The difference between the cost of power that was not supplied before and after the addition of EVs can be characterized as a reliability-advancement benefit. This difference can be expressed as follows:

$$C_{RE} = C_{ENS} - C_{ENS,V2G} \quad (6)$$

Here, the overall active loss of energy after capacitor integration is denoted by $P_{T,loss}^{cap}$, K_{ep} is the amount spent on energy per kilowatt-hour(kwh), β represents the depreciation factor, T represents the time in hours, installation expenses for each site's capacitor and EVCS are c_i^{cap} and C_i^{EVCS}, the capacitor purchase price per kVAR is denoted by K_{cp} the operating costs for EVCS and capacitors are C_O^{cap} and C_O^{EVCS}, respectively, N_{cap} and N_{EVCS} indicate the quantity of capacitors and CSs, the mean energy demand at hour h is represented by $E^d(h)$, $Q_{cap}(bs)$ indicates the sum of reactive power injection in bus bsth , at hour h, F_h stands for the failure percentage, the outage duration is R_h at hour h, PC_t is the penalty in $/kWh for not supplying energy on day t.

B. A Description of the Operational Constraints

The simulated objective functions are improved by taking into account the following limitations.

Limitations on Load Flow

The limits of the distribution system concerning load flow are as follows:

$$P^{substation} = \sum_{j=1}^{N_{br}} P_{loss}^{j}(m,n) + \sum_{bs=1}^{N_{bus}} P_{avail,bs} + P_{EVCS}^{bs} \quad (7)$$

$$Q^{substation} + \sum_{bs=1}^{N_{bus}} Q^{cap}(bs) = \sum_{j=1}^{N_{br}} Q_{loss}^{j}(m,n) + \sum_{bs=1}^{N_{bus}} Q_{avail,bs} \quad (8)$$

Bus Voltage Tolerance

The voltage of each bus, denoted by V(*b*s), must lie within the lowest V_{bs}^{min} and highest V_{bs}^{max} limits.

$$V_{bs}^{min} \leq V(bs) \leq V_{bs}^{max} \text{ bs= 1,2,3…}N_{bus} \quad (9)$$

Transmission Line Tolerance

Every line of power flow, $PF(j)$, must be within the bounds of the greatest value PF_j^{max} that is given.

$$\text{PF(j)} < PF_j^{max} \quad (10)$$

Capacitor Count Restriction

Capacitor placements are meant to be limited by this restriction. The number of fixed capacitors N_{cap} has to be less than or the same as the highest number of capacitors N_{cap}^{max}.

$$N_{cap} \leq N_{cap}^{max} \quad (11)$$

Capacitor Size Limit

The reactive power infusion Q_{cap} shall not exceed the permitted maximum Q_{cap}^{max} and minimum Q_{cap}^{min} values.

$$Q_{cap}^{min} \leq Q_{cap} \leq Q_{cap}^{max} \quad (12)$$

Capacitor's Maximum Compensation Limit

The reactive power of load $Q_{avail,bs}^{total}$ must be either equal to or less than the total reactive power discharge of capacitor Q_{cap}^{total}.

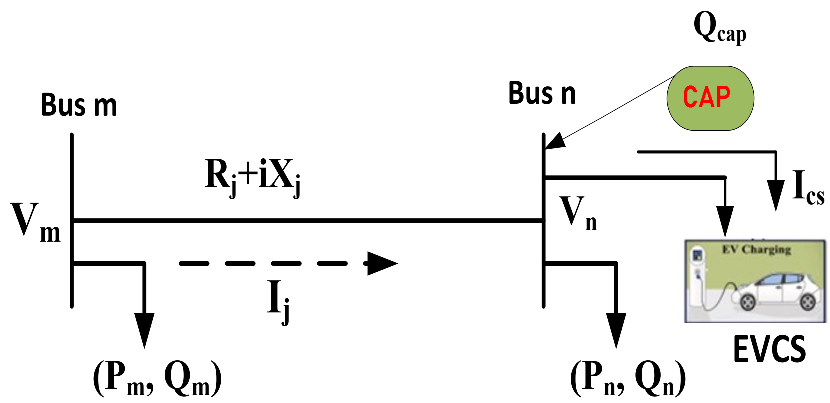

Fig.1. A distribution system's representation of an integrated EVCS and capacitor.

$$\sum_{p=1}^{N_{cap}} Q_{cap}(p) \leq \sum_{bs=1}^{N_{bus}} Q_{avail,bs} \tag{13}$$

Reactive power is indicated by $Q^{substation}$ and active energy by $P^{substation}$ on the substation bus, the bsth bus's valves might be as high as V_{bs}^{max} and as low as V_{bs}^{min}, the power flow is shown by PF(j) for the jth branch. Q_{cap}^{min} and Q_{cap}^{max} represent the lowest and greatest injected reactive power, respectively. The reactive power load at bus bsth is $Q_{avail,bs}$.

Capacitor placement is restricted to load buses to ensure effective reactive power compensation. Additionally, overcompensation is avoided by limiting total reactive power injection to the system reactive demand. Power factor constraints are implicitly maintained within acceptable limits (0.95-1.0) to ensure system stability.

C. EVCS Load Modelling

The distribution network is subject to additional loads from EVCSs. Eq. (14) may be used to assess the total load of the distribution system after the integration of the EVCS.

$$T_{load} = \sum_{bs=1}^{N_{bus}} P_{avail,bs} + P_{EVCS}^{bs} \tag{14}$$

Here, T_{load} represents the total system load, N_{bus} denotes the total number of buses, $P_{avail,bs}$ represents the load that is currently exists at bs^{th} bus, and P_{EVCS}^{bs} represents the EVCS load that is connected to bs^{th} bus.

The EVCSs capacity depends on several factors, including the charging rate (CR), the number of vehicles running in the grid-to-vehicle (G2V), and vehicle-to-grid (V2G) manners, the number of charging ports, discharging rate (DCR), and their respective rated power. Thus, the following expression is used for the EVCS capacity:

$$P_{EVCS}^{bs} = [N_{EV}(G2V) * C_R - N_{EV}(V2G) * DC_R] \tag{15}$$

The EVCS will simply apply the extra load exclusively to the bus where the CS is anticipated to be installed. The optimization is done for that bus number, or CS location, which is the decision variable.

Although the above formulation assumes a deterministic EV load representation, real-world EV charging demand is inherently time-varying and stochastic, influenced by:

- Vehicle arrival/departure patterns
- Charging behaviour diversity
- State-of-charge variations
- User preferences and queuing effects

To maintain computational tractability, a steady-state aggregated load model is adopted in this work. However. The following assumptions are considered:

- EVCS demand is constant during the analysis period
- Charging ports operate at rated capacity
- No queuing or waiting-time constraints are modelled

Despite these simplifications, the proposed framework provides valuable insights into planning-level optimization. Future work will extend this model to incorporate:

- Time-series EV load profiles (24-hour variation)
- Probabilistic and stochastic modelling
- Queue-based charging station dynamics

D. Capacitor Integration Modelling in the Distribution Network

Incorporating capacitor units into the distribution system at strategic points has multiple benefits, such as improving voltage curves, lowering line loss, correcting power factor, and more. The following are the general rules for including capacitors into the distribution system. Presented as the ultimate reactive power after a capacitor injection at bus n is

$$Q_N^{inj} = Q_n - Q_{cap} \tag{16}$$

Fig. 1 shows the actual power loss following the capacitor's connection at bus n, which is stated as

$$P_{loss(m,n)}^{cap} = \frac{P_n^2 + Q_N^{inj}}{|V_n|^2} * R_j \tag{17}$$

$$P_{loss(m,n)}^{cap} = \frac{\left(P_n^2 + \left(Q_n - Q_{cap}\right)^2\right)}{|V_n|^2} * R_j \tag{18}$$

$$P^{cap}_{loss(\mathrm{m,n})} = R_j * \frac{(P_n^2+Q_n^2)}{|V_n|^2} + \frac{Q_{cap}^2-2*Q_n*Q_{cap}}{|V_n|^2} * R_j \quad (19)$$

The decrease in power loss, indicated as $\Delta P^{cap}_{loss(\mathrm{m,n})}$, represents the disparity in power loss prior to and subsequent to the installation of the capacitor, and can be expressed as

$$\Delta P^{cap}_{loss(\mathrm{m,n})} = \frac{Q_{cap}^2-2*Q_n*Q_{cap}}{|V_n|^2} * R_j \quad (20)$$

$P^{cap}_{T,loss}$ is the overall reactive energy loss after capacitor integration, Q_N^{inj} is the net inserted reactive energy, and $Q_{cap}(bs)$ is the reactive energy inserted at the bs^th^ bus.
The number of capacitors in the distribution system may be increased to effectively decrease power losses.

III. Proposed Method

In this study, CHBA is used as a new and effective optimization method to find the best locations for EV charging stations (EVCS) and capacitors in the radial distribution network (RDN). Hashim et al. [30] developed this method by taking inspiration from the smart searching behavior of honey badgers when they look for food. HBA mainly works in two stages, called the hunting stage and digging stage, which help the algorithm to search better solutions. It is highly effective for solving mixed-integer and nonlinear optimization problems [31], [32].

A. A Computational Depiction of HBA

HBA is often categorized into two phases: digging and honey phases. The population of possible cures in HBA may be mathematically expressed as

$$Population\ of\ candidate\ solutions = \begin{bmatrix} x_{11} & x_{12}x_{13} & \dots x_{1D} \\ x_{21} & x_{22}x_{23} & \dots x_{2D} \\ & \dots\dots\dots & \\ x_{n1} & x_{n2}x_{n3} & \dots x_{nD} \end{bmatrix} \quad (16)$$

where x_i denotes i^{th} site of the honey badger

$$x_i=[x_i^1, x_i^2 \dots\dots\dots x_i^D] \quad (17)$$

To address non-linear optimization problems, the following steps are typically implemented:

Step 1: Initialization phase: First, set the initial population size N for the HBA utilizing the formula:

$$x_i = r_1 \times (ub_i - lb_i) + lb_i \quad (18)$$

Here the random number r_1 falls between 0 and 1.

Step 2: Defining Intensity: Next, to evaluate the intensity, the prey's focus rate is connected with its space through the honey badger. According to the inverse square law, the ability of the prey scent is determined as follows:

$$I_i = r_2 \times \frac{S}{4\pi d_i^2} \quad (19)$$

Here the random integer r_2 falls between 0 and 1.

$$d_i = x_{prey} - x_i\ , S = (x_i - x_{i+1})^2$$

Step 3: Updating Density factor: The density factor α regulates time-dependent variability, encouraging a flawless transition from investigation to production. The lowering factor α was altered using the following formula, which reduces unpredictability over time:

$$\alpha = C \times \exp(\frac{-t}{t_{max}}) \quad (20)$$

Here t_{max} is the highest count of repetitions, and $C \geq 1$

Step 4: Escaping from local optimum: This step is crucial for preventing the approach from being locked in local optima, alongside the subsequent two steps.

Step 5: Upgrading agent places: The agents places of residence were updated throughout this phase. Digging and honey are the two stages involved in updating the HBA position.

Digging phase: During this stage, the honey badger's movements followed a cardioid pattern. The formulas stated below can be used to depict these movements:

$$x_{new} = x_{prey} + \beta \times x_{prey} \times F \times I + \propto \times r_3 \times d_i \times F \times |[1-\cos(2\pi r_5)] \times \cos(2\pi r_4)| \quad (21)$$

$$f(x) = F = \begin{cases} 1, & if r_6 \leq 0.5 \\ -1, & else \end{cases} \quad (22)$$

Here the random integer r_6 falls between 0 to 1.

Honey phase: The successful approach of a honey badger to a hive, guided by a honey guide, may be stated as follows:

$$x_{new} = x_{prey} + F \times r_1 \times \alpha \times d_i \quad (23)$$

Here the r_1 falls between 0 to 1.

B. Proposed Chaotic HBA (CHBA) Algorithm

Similar to many metaheuristic algorithms, the Honey Badger Algorithm (HBA) may face challenges such as premature convergence and reduced population diversity, particularly in complex and high-dimensional optimization problems. To address these shortcomings, researchers have proposed various improvements, with one of the most effective being the Chaotic Honey Badger Algorithm (CHBA). CHBA is an enhanced version of HBA. It incorporates chaotic or Henon maps into the basic structure of the HBA to improve its search dynamics and global optimization capabilities. The performance of the basic HBA optimizer is improved by changing the C and β parameters of Eq. (29) using a two-dimensional Henon map [33]. The values of C and β were changed according to the following equation:

$$\beta(t) = 7 * x_{t+1}\ ,\ C(t) = 4 * y_{t+1} \quad (24)$$

Here t is the present iteration, $y_{t+1} = 0.3 * x_t$ and $x_{t+1} = 1 - 1.4 * x_t^2 + y_t$ are Henon map vectors. The 7 and 4 were utilized to alter the Henon map vectors so that they fell within the same range as set by the HBA developer. The quantities of C and β, chosen by the basic HBA developers, were 2 and 6, respectively. between the CHBA, the parameters C and β are chosen to exhibit a broad range of values between the ranges of [0 4] and [0 7], respectively, by means of the selection of 4 and 7. During implementation, a Henon map has an

initialization of 0 (x(1) = 0; y(1) = 0).
The excavation stage and density parameter will be written as

$$U_{new} = prey + F_g \times \beta(t) \times In \times prey + F_g \times r_3 \times (prey - U_i) \times (cos2\pi r_4) \times (1 - cos2\pi r_5) \quad (25)$$

$$\sigma = C(t) \times \exp(\frac{-Iter}{Iter_{max}}) \quad (26)$$

C. Implementation of CHBA Methodology for Network Reconfiguration based Optimal Positioning of EVCSs and Capacitors in RDS

The following steps are applied to optimize the position of EVCSs and Capacitors depending on network reconfiguration, and the CHBA technique is employed to tackle the MOVSO problem. Fig. 2 shows the recommended strategy, which includes two tactics for EV charging planning and capacitors with NR.

1. The line, bus and load data, reconfiguration tie-lines, capacity of capacitors and EVCSs units, Tolerance, Rating of charging points of EVs and Operating limits of RDS were studied.
2. The Distribution Load Flow technique was used to perform the base scenario load flow assessment and identify the minimum voltage, VSI, and network loss violations of the proposed test system.
3. Set the number of reconfiguration tie-line switches, Capacitors, EVCSs and Charging Points of EVs in the projected RDS.
4. The Population size, dimension, highest number of iterations, lower and upper bounds of CHBA, Chaotic map function, (location and size of tie-line switches, Capacitors, EVCSs, Charging Points and EV Power rating, respectively) are initialized.
5. The iteration and bus number were set to 1.
6. The multi-objective function's fitness value for each of the CHBA's digging and honey phases is obtained by reconfiguring the network and positioning the capacitors and EVCSs at suitable buses.
7. Evaluate the multi-objective functions that go along with each stage of honey and digging.
8. The greatest fitness metrics in the array should be saved once the placements for the honey and digging stages were revised.
9. Find out how the digging and honey periods are doing right now.
10. Upgrade the position of all phases with chaotic mapping (NR Switches, Capacitors and EVCSs).
11. The suitable switches are opened, capacitors and EVCS are placed and the DS load flow analysis is run.
12. Check whether all constraints have been fulfilled; if not, proceed to step 6; if so, continue to the next phase.
13. If there are as many iteration processes as iterations, proceed to the next step. If not, proceed to step 5.
14. When the optimal solution for ICI, AVDI, power loss, voltage profile, and VSI is offered globally, the program is completed.

D. Network Reconfiguration (NR)

Rearranging the open/closed positions of tie switches and sectionalizers to modify a system topology is called the NR process. Switching an open tie-switch leads to the formation of a loop at an actual radial DN. Hence, to restore the system's radiality, one of the loop's sectionalizers should be opened. Thus, the technique guarantees the DN's radial topology and avoids unsupplied buses.

IV. Results and Discussion

The effectiveness of the recommended CHBA was investigated to reduce power loss, enhance voltage stability, and net profit in various distribution networks. Using reconfigured networks with EVCS and capacitor banks, the suggested approach was applied to an RDS with 33 and 69 nodes. The simulations were run on a computer with 8 GB of RAM, an i5 Intel Core CPU, and a 4210U processor, which can reach speeds of up to 2.5 GHz.

For the present research work, EVCS demand is modeled using the data in Table I, which specifies EV types, individual power ratings, number of charging points, and the corresponding EVCS ratings (min and max). The total EVCS power ranges from 975 kW to 1674.5 kW, and net power injections for G2V and V2G modes are used in the optimization.

TABLE I
FEATURES OF ELECTRIC VEHICLES AND CHARGING STATIONS FOR THE SIMULATION

Type of EV	EV power rating (kW)	No. of CP's		CS's rating (kW)	
		Min	Max	Min	Max
BMW i3	44.00	10	20	440.00	880.00
Chevrolet volt	2.20	25	35	55.00	77.00
Tesla model X	13.00	15	25	195.00	325.00
SAE J1772 standard	7.00	30	40	210.00	280.00
Changan yidong Eado	3.75	20	30	75.00	112.50
CS's overall power rating (kW)				975	1674.50

Cost Parameters for EVCS and Capacitor Banks are shown in Table II. The total cost is calculated by combining the capital expenditure (CAPEX) for EVCS and capacitor bank installation with annual operation and maintenance (O&M) costs and energy consumption charges. Standard assumptions for unit costs, lifetimes, and tariffs have been adopted to ensure consistency and transparency, as summarized below:

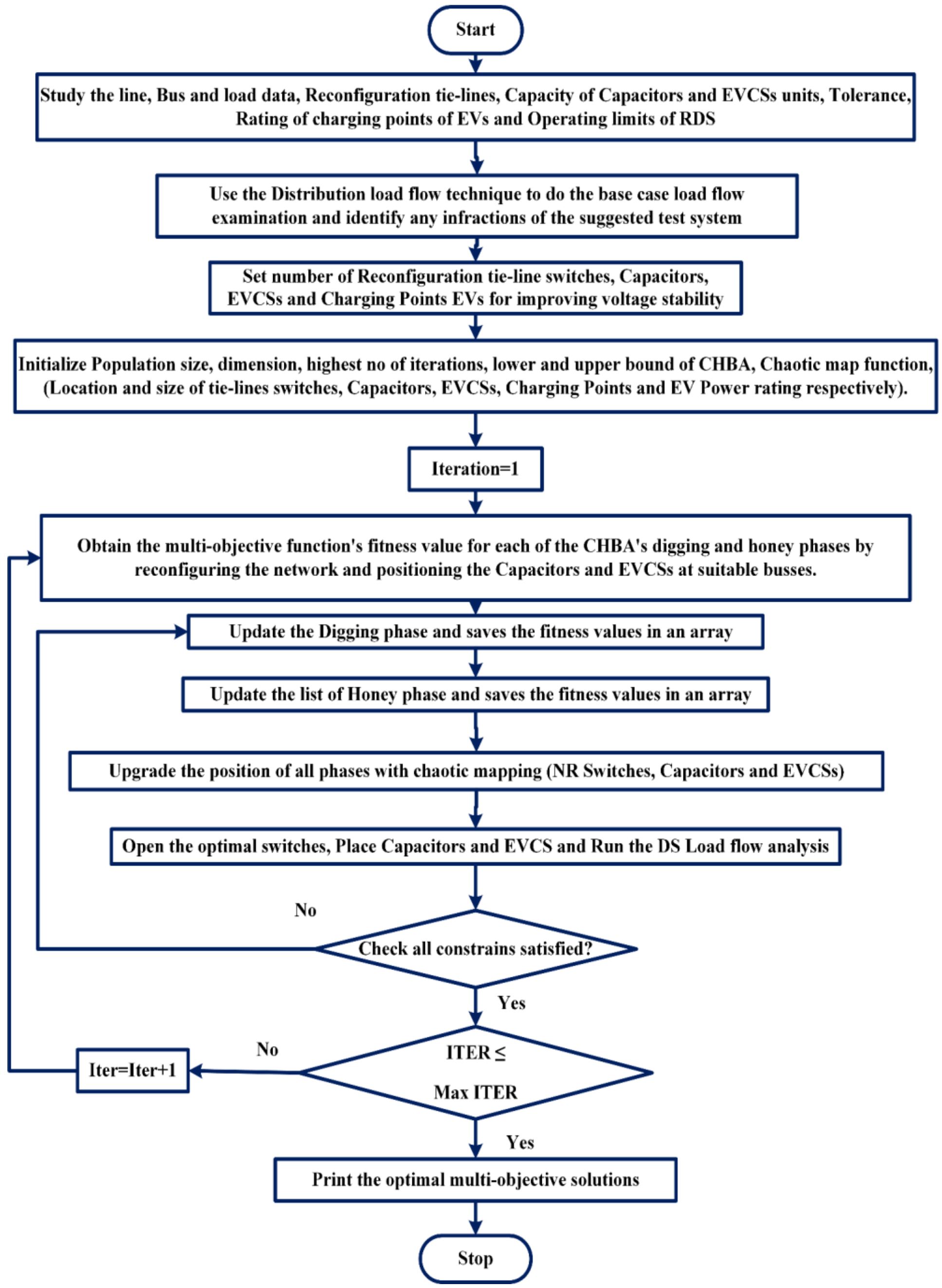

Fig. 2. CHBA's flow chart for network reconfiguration-based capacitor and EVCS optimum positioning.

TABLE II
ECONOMIC PARAMETERS USED FOR EVCS AND CAPACITOR BANK COST ANALYSIS

Component	Unit Cost	Lifetime	Notes
EVCS Installation	\$5000 / station	10 years	Average installation cost
Capacitor Bank Installation	\$1000 / KVAR	15 years	Standard industry value
Operation & Maintenance	2% of CAPEX/year	Annual	Includes labor & losses
Energy Cost	\$0.10 / kWh	—	Assumed electricity tariff

Various case studies are used to analyze the test systems, and the simulated findings are displayed both numerically and visually. The impact of the suggested CHBA strategy was further shown via a comparative study. Algorithm Parameters, Model Variables and Units of existing techniques are shown in Table III.

A. Test system: Radial Distribution System with 33 Nodes

One main feeder, thirty-two transmission lines, thirty-three buses, and three network laterals comprise this test system. The system's real power requirement was 3,715 kW, including 2300 kVAR of reactive power. All loads are modeled as constant PQ loads under steady-state conditions. Fig. 3 depicts the one-line diagram of the 33-node test system. The IEEE 33-

bus radial distribution system is considered with a base power of 100 MVA and base voltage of 12.66 kV. Bus voltage limits are maintained between 0.95 p.u. and 1.05 p.u. Three distinct test cases are used to analyze the bus and line impedance data from the source [34] and the recommended test system, including

Case 1: Without compensating devices, base case
Case 2: Capacitor and EVCS placement
Case 3: Network reconfiguration with Capacitor and EVCS placement

Case 1 involves performing a load flow analysis without capacitors or EVCS and using distribution power flow. The flow of reactive and active power, voltage violations, reactive and active power losses, and voltage profile were determined. Table I displays the findings. At 0.6951 (p.u.), the VSI is at its lowest at 0.9131 (p.u.), whereas the voltage is at its lowest. For the power flow in the basic scenario, the active power loss was 201.870 KW. The power flows, losses, voltage violations and variations, and week buses of the proposed system were determined from the base case research.

Installing capacitors and EVCS improves the system voltage profile and net profit; this is regarded as Case 2. Considering the power flow research, two EVCS and four capacitors with ratings ranging from 0 to 2 MVAr were charged with a power range of 975 kW.

To identify and ascertain the optimal location and size of capacitors and the optimal location of the EVCS, an effective optimization tool of the CHBA technique is used. The parameter settings of the CHBA were as follows: maximum number of iterations = 300, number of variables = 8, random number = 0 to 1, and population size = 40. The proposed CHBA successfully determined the optimal locations of the EVCS, which were 18 and 22. Additionally, 4, 8, 26, 30, and 207 kVAR, 294 kVAR, 426 kVAR, and 540 kVAR were the ideal locations and capacitor sizes, respectively.

The 33 nodes have the EVCS and capacitors placed at the best locations with optimal values. The outcomes of the distribution load flow utilizing the CHBA approach are displayed in Table IV and include the voltage at every bus and enhanced VSI, decreased network loss and voltage variations, and increased system net profit. The VSI and lowest voltage are 0.74194(p.u.) and 0.93809(p.u.), respectively, whereas the net profit and power loss are $ 19123 and 135.26 kW. Compared with the base scenario, the energy loss was reduced by 32.99%. In comparison to the base scenario, the lowest amount of voltage increased by 2.73%. Compared with the current PSO, GWO, and AGWOPSO approaches, the power loss reduction was improved by 5.06%, 4.62%, and 3.34%, respectively. Additionally, RDS's net profit is 30.14%, 36.06%, and 38.30% higher than that of the current techniques.

In Case 3, the proposed 33-node test system is restructured using five tie-line switches (T34, T35, T36, and T37) and fitted with the EVCS and capacitor banks. Here, five tie-lines, two EVCS and four capacitors are considered to enhance the voltage of each node and net profit of the RDS. This projected CHBA approach was implemented to restructure the 33-node and determine the open switches, proper location and sizing of the EVCS and capacitor units.

The structure of the IEEE 33-node test setup after NR with the placement of two EVCS and four capacitors is shown in Fig. 4. The honey and digging stages of the HBA successfully optimize the system parameters, such as the proper locations of two EVCS, location and sizes of four capacitors, and modification the structure of the existing RDS using tie-lines. The tuned best positions of the EVCS and capacitor were 2, 19 and 15, 11, 24, and 30, respectively. The optimal sizes of the EVCS and capacitors were 975 KW, 975 KW, 975 kW, and 248 KVAr, 166 KVAr, 352, KVAr, and 858 KVAr, respectively. The open and tie-line switches are 9, 32, 7, 14, and 34, 35, 36, and 37, respectively.

TABLE III
COMPARISON OF ALGORITHM PARAMETERS AND OPTIMIZATION VARIABLES OF EXISTING METHODS

Aspect	PSO	GWO	AGWOPSO	Model Parameter	Unit / Description
Population Size	50	30	50	ENS	kWh/year
Iterations	100	100	100	Real Power Loss	kW
c1 / α	1.5	0.5	Hybrid	Net Profit	$/year
c2 / β	1.5	0.5	Hybrid	Capital Cost	$
Inertia Weight (w)	0.7	—	Adaptive	Operating Cost	$/year
Control Strategy	Velocity update	Encircling prey	Hybrid PSO-GWO	Voltage (V)	p.u
Objective Basis	Annualized cost	Annualized cost	Annualized cost	Time Basis	Annual

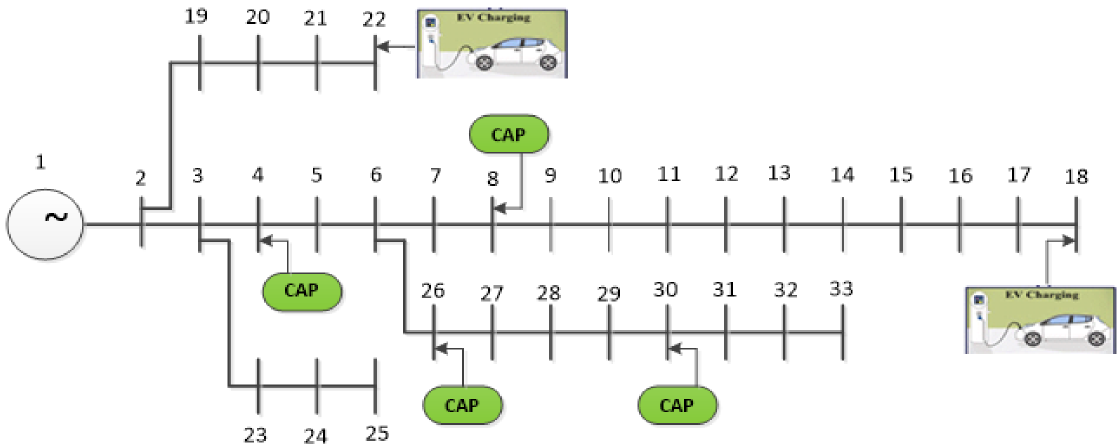

Fig. 3. A 33-node RDS single line layout with EVCS and capacitors.

To improve the net profit and voltage profile, the EVCS and capacitors are optimally sized in the RDS utilizing CHBA and distribution power flow. The EVCS and capacitor placement, base case, reconfiguration alone, reconfiguration with EVCS and capacitor placement, and reconfiguration with EVCS and capacitor placement were some of the test cases used to assess the enhanced voltage profile. Fig. 5 shows the voltage profile comparison for different operating cases of the RDS. The minimum VSI and minimum node voltage were calculated as 0.84244 (p.u.) and 0.95808 (p.u.), respectively.

The results of several test scenarios using the CHBA approach for the recommended IEEE-33 bus test setup are presented in Table IV. The simulation outcomes for the base scenario, EVCS and capacitor installation alone, and reconfiguration with the EVCS and capacitor arrangement are presented. In addition, the cost of installing system components, Real Power loss in kW, system components operating costs, total capacitor cost, net profit of RDS, and power-loss reduction benefit were included. The recommended CHBA decreased the active power loss to 106.98 kW while achieving a maximum net profit of $ 35,834. The proposed approach achieved an efficiency of 90% with a convergence time of 35 seconds. Table V presents the results achieved and compares them with other existing methods, such as GWO, AGWOPSO, and PSO. The table shows that the CHBA approach decreases active energy loss and maximizes RDS net profit compared with newly found soft computing strategies such as AGWOPSO, GWO, and PSO.

Fig. 6 shows a visual representation of the power loss of several methods using the suggested CHBA algorithm. According to the graph, the CHBA efficiently reduces the power loss by 47% compared to the base case strategy. Figure 7 compares the convergence curve of the CHBA with those of the current techniques. The CHBA requires 70–80 iterations with a processing time of 30–35 seconds to obtain optimal solutions.

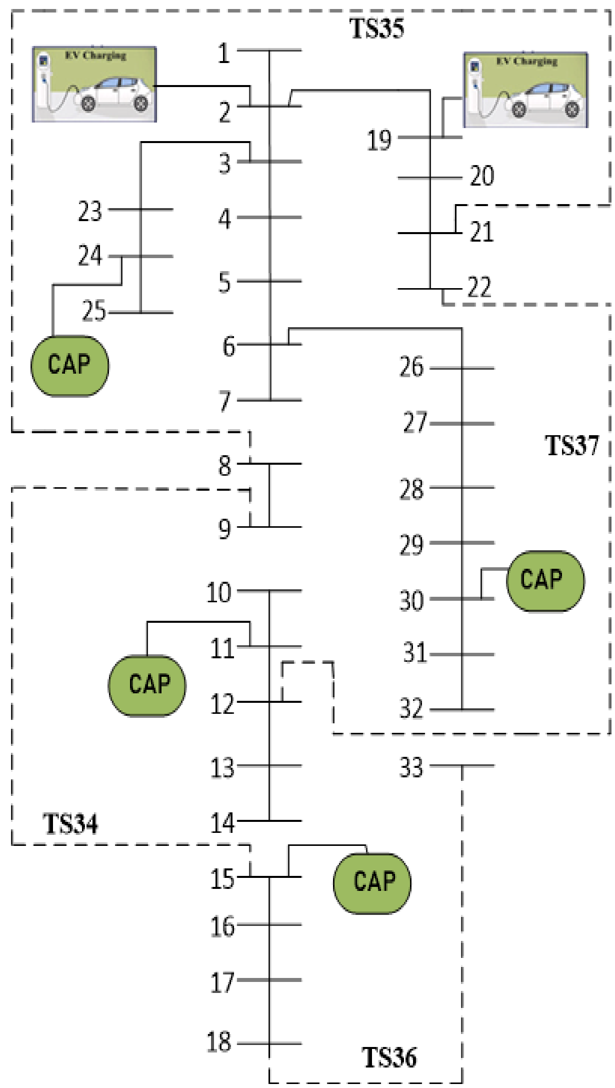

Fig. 4. Structure of 33 node test system after Network Reconfiguration with EVCS and Capacitors.

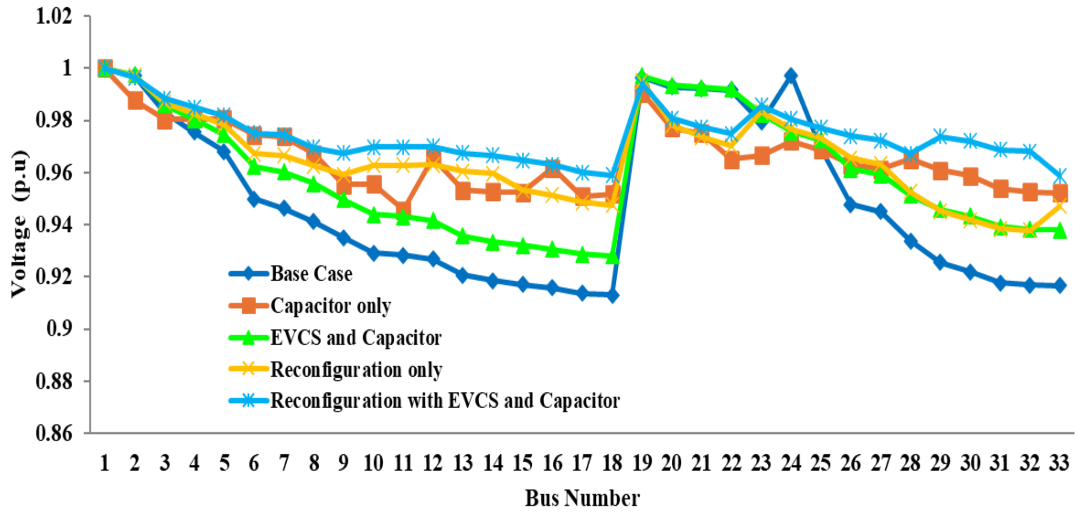

Fig. 5. 33-node RDS voltage profile comparison with various case studies.

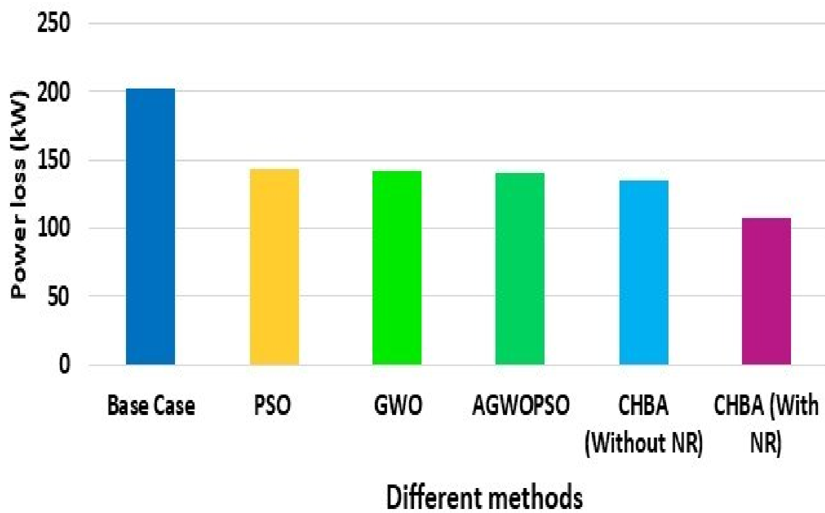

Fig. 6. Comparison of power loss in a 33-node system using the suggested and existing approaches.

Fig. 8 shows a bar chart that compares the net profit of the suggested techniques with those of other existing approaches. According to the graph, when compared with other approaches, the suggested CHBA with network reconfiguration, EVCS, and capacitors yielded the highest profit. In comparison with the other clever techniques of PSO, GWO, and AGWOPSO, the net gain was 67.07%, 65.07%, and 62.72% higher, respectively. To overcome the limited and nonlinear voltage stability issues in the RDS, the proposed CHBA approach is a practical optimization technique.

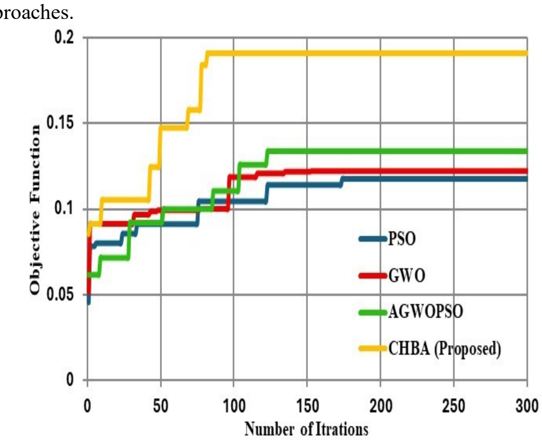

Fig. 7. Convergence curve of 33- node RDS with various methods.

TABLE IV
SIMULATION RESULTS OF IEEE 33-BUS SYSTEM UNDER VARIOUS OPERATING SCENARIOS

Parameters	Base Case (Case 1)	EVCS and Capacitor placement (Case 2)	Reconfiguration with EVCS and Capacitor placement (Case 3)
Open switches	-	-	9, 32, 7, 14
Tie-line switches	-	-	37, 36, 35,34
Optimal position and size of EVCS	-	18(975 KW), 22((975 KW)	2(975 KW), 19((975 KW)
Optimal location and size of Capacitor	-	4(207 kVAR), 8 (294 kVAR), 26 (426 kVAR), 30(540 kVAR)	15(248 KVAr), 11(166 KVAr) 24(352 KVAr), 30(858 KVAr)
Minimum VSI (p.u)	0.6951	0.74194	0.84244
Minimum Voltage(p.u)	0.9131	0.93809	0.95808
Real Power loss (KW)	201.870	135.26	106.98
Total capacitor cost ($)	-	1406	1624
System components operating costs ($)	-	2800	2800
Cost of installing system components ($)	-	10883	11668
Benefit of reducing energy loss ($)	-	32806	50302
Net Profit ($)	-	19123	35834
Convergence time in seconds	-	32	35
Efficiency	-	84	90

B. Statistical Analysis

Statistical analysis has been incorporated to evaluate the robustness of the results in terms of net profit. The mean and standard deviation values are computed for all considered methods. The results show that the proposed reconfiguration with EVCS and capacitor placement (Case 3) achieves the highest net profit, while also exhibiting higher variability due to improved solution space exploration. In comparison, existing methods provide lower profit with relatively higher uncertainty. Overall, the statistical evaluation confirms the effectiveness and comparative advantage of the proposed approach in improving economic performance. Table VI shows the statistical performance comparison of the proposed method with existing methods.

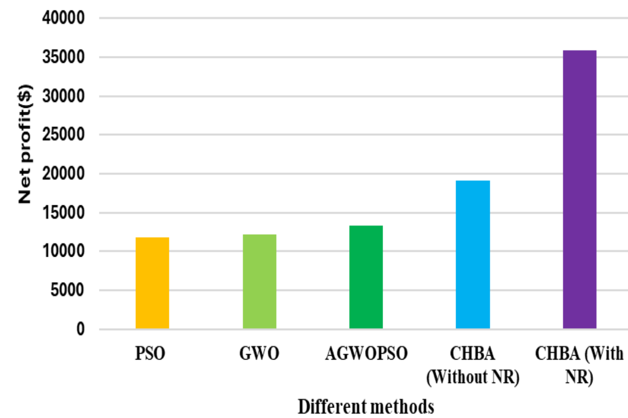

Fig. 8. Net profit comparison between the suggested and current approaches for a 33-node system.

TABLE VI
STATISTICAL COMPARISON OF NET PROFIT PERFORMANCE FOR VARIOUS METHODS

Method	Net Profit ($)	
	Mean	Standard Deviation
Existing Methods (AGWOPSO, GWO, PSO)	12457.43	3542.66
EVCS and Capacitor placement (Case 2)	13396.09	4853.62
Reconfiguration with EVCS and Capacitor placement (Case 3)	17605.53	7235.41

C. Computational Complexity Analysis of CHBA

The computational complexity of the recommended Chaotic HBA is analyzed to assess its scalability and suitability for large-scale distribution networks.

Let:

T_{max} = maximum number of iterations

N= population size

D = number of decision variables (EVCS locations, capacitor sizes, etc.)

The total computational complexity of CHBA can be expressed as:

$$O(T_{max} \times N \times D)$$

This is due to the fact that every iteration entails updating the places of each candidate solution and calculating the fitness function. The main computational demands of the proposed CHBA are associated with the population size, number of decision variables and the maximum number of iterations. The algorithm involves computing with all the candidate solutions in every

TABLE V
COMPARATIVE PERFORMANCE ANALYSIS OF PROPOSED CHBA AND EXISTING OPTIMIZATION APPROACHES

Parameter	Base Case	**PSO** [35]	**GWO** [35]	**AGWOPSO** [35]	**CHBA (Proposed)** Without NR	**CHBA (Proposed)** With NR
Active power loss (kW)	201.870	142.470	141.820	139.940	135.26	106.98
Total number of EVs	-	100.0	100.0	100.0	100.0	100.00
optimal nodes for EVCS	-	19,2	19,2	19,2	18, 22	2, 19
Capacitors Optimal nodes	-	9, 16, 27, 32	32, 30, 18, 7	7, 18, 30, 32	8, 30, 4, 26	15, 11, 24, 30
Capacitor sizes (kVAR)	-	450.12,519.45, 425.32, 740.56	425.18, 494.5, 353.8, 710.2	371.7, 473.7, 220.59, 608.13	294 540 207, 426	248, 166 352, 858
Total kVAR	-	2135.450	1983.680	1674.120	1467	1624
Energy loss cost ($)	106102.870	74882.230	74540.590	73552.460	32806	50302
% loss reduction in energy loss cost	-	29.420	29.740	30.670	69.08	52.59
Net profit ($)	-	11798.110	12215.640	13358.550	19123.00	35834.00
Efficiency	-	74.50	75.10	81.50	84.00	90.00

iteration, so the computational complexity is proportional to the number of candidate solutions and the dimension of the search. But because of the efficient exploration capability introduced with the chaotic mapping, CHBA is able to converge more quickly than it would without the chaotic mapping, and with fewer uncalled-for searches. The proposed method shows better convergence behavior than the conventional methods of PSO and GWO with good computational complexity for practical distribution system applications.

In the current study:

N=40

T=300

D=8(number of control variables)

As a result, the computing effort is still affordable and on line with other population-based optimization approaches like GWO and PSO.

D. Environmental Impact Analysis

By comparing the emission levels for the IEEE 33-node test system under various operation scenarios, the environmental impact has been determined. Without EVCS, capacitor placement, or reconfiguration, the system produces about 140 tons of CO_2 per year in the standard case. Emissions have decreased to roughly 118.5 tons yearly, or nearly 15%, using just EVCS and capacitor placement. Further improvement is observed when network reconfiguration is also applied along with EVCS and capacitors, where emissions decrease to approximately 93.8 tons per year, achieving an overall reduction of about 33% compared to the base case. These results clearly demonstrate that the proposed methods progressively enhance environmental performance, with the combined approach providing the most significant reduction in greenhouse gas emissions.

V. CONCLUSION

In this study, the effects of EVCS on radial distribution networks (RDN) were analyzed using a powerful and novel optimization tool based on the CHBA approach. The proposed CHBA simultaneously reconfigures the RDN and installs capacitors and EVCS to achieve optimal solutions (reduce the active power loss, improve the system voltage curve, and maximize the net profit). Three different scenarios were considered for the 33-node test system to examine the efficacy of the proposed CHBA. The case study included a base case without compensating devices, EVCS and Capacitor placement, and network reconfiguration with EVCS and Capacitor placement. Compared to the other tested scenarios, the concurrent implementation of Network Reconfiguration (NR) with capacitor and EVCS placement demonstrated superior success. This approach significantly minimizes active power loss and voltage variations, maximizes net profit, and effectively increases the VSI value.

In addition, the efficacy of the suggested CHBA strategy was assessed by comparing the results obtained using PSO, GWO, and AGWOPSO. The following are the main conclusions of this study:

- Simultaneous optimum NR, capacitor, and EVCS allocations on the RDN with various case studies significantly improved the system performance.
- The results showed that the CHBA technique had a shorter computational time, optimal outcomes, and better convergence than the other soft computing techniques.

- This technique enhances the voltage profile and VSI while minimizing the active power loss. The reduction in power loss was quantified as 47% for the 33-node system, marking a significant improvement over the base scenario.
- Furthermore, the CHBA approach offers the best cost-effective solutions in terms of installation and system component running costs, as well as the advantages of energy loss reduction and net profit of the RDN.
- The effectiveness of the CHBA approach was investigated, and the outcomes were compared with those of other popular meta-heuristic approaches, such as GA, HSA, ABC, ALO, AGWO-PSO, GWO, and PSO.

The potential future extensions of this study are as follows:

- The suggested CHBA was appropriately adjusted to allow for the simultaneous positioning of the DSTATCOM and DG with an EVCS and optimal NR.
- Scheduling of Shunt Capacitors and Solar Photovoltaic DG Optimally with Network Reconfiguration and EVCS to Enhance RDS Efficiency.
- The CHBA will be used to optimize the deployment of DSTATCOMs, RES, and capacitor banks to optimize the techno-economic benefits of an EVCS-loaded distribution network.
- The proposed CHBA will be further validated by benchmarking it with some recently published metaheuristics, such as the Dung Beetle Optimizer (DBO), Snow Ablation Optimizer (SAO), and Artificial Rabbit Optimization (ARO), in future work.

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