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An AQ-SCS Optimization Assisted Optimal Expansion Planning with Fixed and Switchable Capacitors for Distribution System

Abstract: - Distribution System has given renewable-based DGs like Solar PV and Wind turbines a lot of attention because of growing worries about global warming and the depletion of fossil fuels. This work proposes a unique hybridized optimization technique for a distribution system expansion plan utilizing an innovative theoretical framework. Two stages are used to tackle the issue with the distribution system expansion plan: master optimization and sub-optimization for every state of the system. The developed Aquila based Sand Cat Swarm (Aq-SCS) optimization method considers the distribution system factors, like DG type, size/capacity, location, PQ power, fixed capacitor, switchable capacitor, and the SPV/wind capacity with load demand uncertainties. The sub-algorithm is employed in conjunction with the DG allocation strategy produced by the master algorithm to deduce the state-dependent operating tactics for each individual DG unit with respect to active and reactive power. The suggested Aq-SCS optimization approach is created by combining the properties of the SCSO with the AOA models. The main objective of achieving the minimal possible cost for the DSEP is verified, and the cycle continues unless the best outcome (least cost) is reached. The analysis of the suggested approach is carried out in 4 cases, such as (i) Without DG and capacitor (ii) With capacitor and no DG (iii) With DG and no capacitor (iv) With both capacitor and DG. The analysis is made in IEEE 33 bus system. The Aq-SCS approach outperforms the conservative approaches SSI-CS, WHO, AQO, and SCSO, according to the analysis conducted in MATLAB/Simulink utilizing an IEEE-33 bus system with five system states.

Keywords: Distribution Generation systems; Distribution System Expansion Planning; Master Optimization; Sub-Optimization; Algorithms

I. INTRODUCTION

With dispatchable and non dispatchable generating patterns, renewable DG systems offer techno-economic advantages to many shareholders. The incorporation of dispatchable renewable DG units like biomass generators, into the grid has been viewed as an appealing solution to satisfy the rising needs for load, while also lowering total emissions and greatly enhancing customer reliability. A growing number of intermittently generating renewable DG units have been linked to the distribution grid in recent years. Because of power supply concerns, the incorporation of non dispatchable renewable DG units is unable to assure stable power output. As a result, it's critical to evaluate and measure the system performance in relation to the integration of non dispatchable renewable distributed generation units. Several approaches have been examined in the literature while examining the distributed network's DG units.

Thus, to meet the increasing demand in a centralized structure, Distribution System Expansion Planning (DSEP) systems have historically been utilized for estimating the type, capacity, positioning, and the timing of the installed new equipment [1]. The DSEP issue is a non-convex Mixed integer non -linear programming(MINLP) from a mathematical perspective three types of optimization systems are accessible in the DSEP literature, such as the mixed strategy, the heuristic technique, as well as the mathematical modeling approach. Several publications contain studies on the DSEP difficulties with various RES. For instance, a multistage DSEP model that takes into account both distributed and centralized Energy Storage Devices (ESD) was created in [2] and a MILP model was

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used to formulate this issue. An enhanced harmony search method was used to solve a DSEP model that took into account the unpredictability of the load, energy price, and pollution of DGs as given in [3]

To reduce the expenditures associated with DG incorporation, a heuristic strategy inspired by cost-benefit modeling has been developed in [4], which considers variations in the market price of energy as well as varied load levels. To optimize the overall cost throughout a scheduling period, a model of optimization for DSEP with DG is provided in [5]. The effects of growing DG saturation losses have been examined for various production sources. In [6], a technique for analysis is created to minimize the loss of energy in a distributed system by placing DG at the best possible location. In case of system restrictions including voltage constraints, DG penetration, and dependability, a GA-based technique is described in [7] to reduce system losses. To determine the finest location for DG units in distributed systems, an iterative approach that utilizes the system's voltage stability assessment is presented in [8]. In [9], the effects of deferral network investments on DG expansion are examined by taking into account DG at many potential sites. In order to reduce the overall system cost while taking system improvements into account, a sequential two-stage optimization method is devised in [10] along with a full scheme for DSP with the inclusion of DG units. In [11], an ordinal optimization (OO) method is utilized to maximize incentives related to DG links and losses with the objective to determine a perfect solution with least computing overhead. A PSO was suggested in [12], to distribute generation systems powered by biomass in DNs while considering the best possible capital expenses and advantages.

The following is an outline of the proposed study's principal contributions:

- Develops an innovative hybridized approach to determine the optimal DSEP by modifying parameters that include generator type, fixed capacitor, switchable capacitor, size/capacity, location, PQ power, SPV/wind capabilities with variable load demand.
- Presents a meta-heuristic strategy named Aq-SCS approach that effectively resolves optimization issues.
- The performance of the projected technique is examined and compared across many standardized schemes, demonstrating its superiority over traditional methods.

The article is structured in the following manner: Observations of the methods presently in operation are given in Section II. In Section III, Modeling on DG Capability and system Concerns is explained; Section IV portrays the parameter tuning process using the hybridized Aq-SCS technique. Section V provides an explanation of the system's outcomes while Section VI concludes the article.

II. LITERATURE REVIEW

A. Related Works

A co-optimization framework for the active DSEP system was established in 2020 by Shiwei Xie et al. [13]. It concurrently optimizes the methods of operation for dynamic network administration along with all constituent choices regarding investments. A two-stage strategy was created to crack the system optimally, and the mixed-integer nonlinear programming issue was relaxed using a second-order programming method in order to arrive at the final solution. Ultimately, an analysis of the case studies was conducted to showcase the efficacy of the suggested methodology.

A multiple stage, multi-scenario scheduling strategy for ADN with co-optimized investment decision-making and operation methods was suggested by Changsen Feng et al. [14] in 2018. The suggested model completely optimizes the following options: assigning VRs and/or SVGs, building the cable circuit, boosting substation capacity, and selecting DG connection sites. The ideal ADN design and the active management of DGs are generated together with the operating plan for each situation. Using an off-the-shelf solver, a MIQCP model is built to ensure the convergence to optimal performance. Research findings show that taking into account the DNP algorithm's various possibilities provides the best possible set of investment choices and operational tactics that can be put into practice at the lowest possible cost.

A novel multi-stage approach was created in 2020 by Majid Abdi-Siab et al. [15] utilizing bi-level optimization to extend the DN while accounting for plug-in electric automobiles. The investment and utilization choice factors can be determined at the upper level, where the intended functionality is the overall yearly investment cost plus the yearly projected manufacturing and service cost. This bilevel optimization was recast as a MILP issue employing primal-dual formulation, which may be solved with commercial solvers. The effectiveness, tractability, and financial benefits of the suggested technique were demonstrated using a 24-node network for distribution. The findings suggest that the DEP implementing the smart charging technique will conclude in lower investment costs in contrast to the scenario where the ineffective charged approach is employed.

The PDS was created in 2020 by M D Shahin Alam et al. [16], who also investigated the impact of several DERs on pollutants, transmission losses, operating costs, and the success of EM. The impact of combining EVs, ESSs, and RSs on system operational efficiency was also investigated. A novel dependability factor called RISR and Sensitivity assessments were also included. The numerical analyses were performed with a novel hybrid PSO-TS optimization technique on the widely used PG&E 69-bus system.

ToU-based DR was developed in 2019 by Reza Gholizadeh-Roshanagh and Kazem Zare [17], and it was integrated into electricity DEP together with cost elasticity of demand. The MILP approach was used to model the multi-stage DEP problem. The suggested method was used on a main distribution network with 18 nodes. The findings demonstrated that taking demand's cost elasticity into account can have a big impact on the overall cost of investments. Thus, the presented approach shows the accuracy of the demand model corresponded to DSEP outcomes.

In 2020, Saheed Lekan Gbadamosi et al.[18] conducted an assessment of the possible effects of RES and DR on the GTEP issue. To fulfill the intended energy demand, GTEP and demand response is taken into consideration and ultimately accomplish an ideal expansion strategy for power systems. To estimate the effect of DR penetration on system performance, the suggested model takes into account many tiers of penetration in the planning system. As a MIQP difficulty, a multi-period multi-objective GTEP approach was presented and developed. Analysis based on sensitivity was done and the findings show that a higher penetration of DR reduces power generation, emissions, and system costs by enhancing the availability of RES in the electrical system.

Employing DC, improved DC, and AC modeling techniques, Saheed Lekan Gbadamosi et al. [19] in 2021 addressed multi-objective optimization issues with regard to calculating power losses and their effects on the expansion planning process in a precise and effective manner. The CONOPT and CPLEX solvers, which are integrated within the Algebraic Modelling Language, were used to solve the MINLP problem in this study. Three scenarios are used to assess and validate the suggested techniques: an actual Nigeria Power System, the IEEE 24 bus test system, and the IEEE Garver's 6 bus system. The AC response technique, as opposed to the improved DC technique, provides a reliable estimation of power losses and an effective optimum plan tactics, according to a comparison of the three modeling strategies.

In 2022, Saheed Lekan Gbadamosi et al. [20] presented an expansion planning approach that integrates large-scale RES while considering harmonic emission regulations into account. This methodology minimizes the entire cost, active power loss and harmonic energy losses by merging the multi-objective optimization problems using a weighted sum approach. A systematic approach was used to compute and enumerate the harmonic pollutants from the RES elements. The developed AC mixed-integer nonlinear programming problem was addressed employing a mathematical model. The sensitivity evaluation findings determine the most significant way to minimize harmonic emissions from RES incorporation into the grid and ripple torque by utilizing ANFIS control, which helps determine the optimal drive location and forecasts the non-matching pulses.

B. Review

The features and limitations of several DSEP optimization techniques are illustrated in Table 1. To lower the cost of the distribution system while enhancing stabilization achievement, an iterative load shedding scheme was created in [13] But the limitations on reactive power are not taken into account. An MIQCP model was introduced in [14], which is better because of its increased precision and DNP's long-term characteristics. A major drawback is its uncertainty. Moreover, a bi-level optimization strategy was established in [15], which provides less computational complexity. However, ESS investment and DR are not considered here. According to [16], operational efficiency restrictions were not focused when creating the PSO-TS algorithm-based expansion plan. MILP technique was presented in [17], which provide more accurate load models. But planning techniques for expansion did not take load profile into account. A multi-period multi-objective GTEP model was presented in [18], which improves RES utilization and reduces generation and transmission investment. Nevertheless, it increases the GTEP problem's computational intractability and difficulty. MILP and MINLP methods were recommended in [19] which offer precise calculation of power losses and effective, ideal planning approach. However, it has to focus more on RERs and load demand uncertainties. A weighted sum approach was developed in [20] that regulate PQ properly and sustain oscillations within the selected bounds. However, small range of power loss has a large impact on the objective function.

The table 1 provides the feature and challenges of various DSEP plan optimization strategies.

Table 1. Features and challenges of existing DSEP optimization approaches

Author	Adopted Strategy	Advantages	Limitations
S. Xie *et al.* [13]	Iterative method	❖ Enhance the system steadiness ❖ The optimal direction of load shedding can yield the highest possible margin.	❖ Does not consider reactive steadiness power.
C.Feng *et al.* [14]	MIQCP model	❖ It is more desirable regarding the long-term properties of DNP and its superior precision level.	❖ A major drawback is its uncertainty.
M. Abdi-Siab *et al*. [15]	bi-level optimization strategy	❖ Computational complexity is minimum.	❖ However, ESS investment and DR are not considered here.
M.S.Alam *et al.* [16]	RISR + hybrid PSO-TS	❖ EMSR is much improved with regard to operating costs, loss avoidance, and decreases in emissions.	❖ An inability to take into account a number of operational and planned performance requirements, including system resilience.
R.Gholizadeh-Roshanagh and K.Zare [17],	MILP technique	❖ Produce more accurate load models.	❖ Load profiles were not considered by expansion planning techniques.
S.L. Gbadamosi *et al.*[18]	multi-period multi-objective GTEP model	❖ Improves utilization of RES. ❖ Reduce generation and transmission investment.	❖ Nevertheless, it increases the GTEP problem's computational intractability and difficulty.
S.L. Gbadamosi *et al.* [19]	MILP and MINLP methods	❖ Precise calculation of power losses and effective, ideal planning approach	❖ Have to focus more on RERs and load demand uncertainties.
S.L. Gbadamosi *et al.* [20]	weighted sum	❖ Control power quality appropriately and keep oscillations within permitted bounds.	❖ Minimal quantities of power loss have a significant impact on achieving the objective function.

III. MODELLING OF DG CAPABILITY AND SYSTEM UNCERTAINTIES

Numerous benefits come with adding various DG units to the electric grid, which includes support for voltage and increased reliableness. Though, the economic concerns are as significant when considering long-term planning. According to this investigation, the purpose of DG planning is to lower a utility's total cost once the planning time finishes. Figure 1 suggests that the total cost of a suggested allocation for energy-controlled DG units may be estimated using the capital cost of DG units along with additional variable costs that relate to DG functions coupled to appropriate network modes. Thus, an optimal planning throughout the prediction period may be evaluated by creating a master optimization along with sub-optimization.

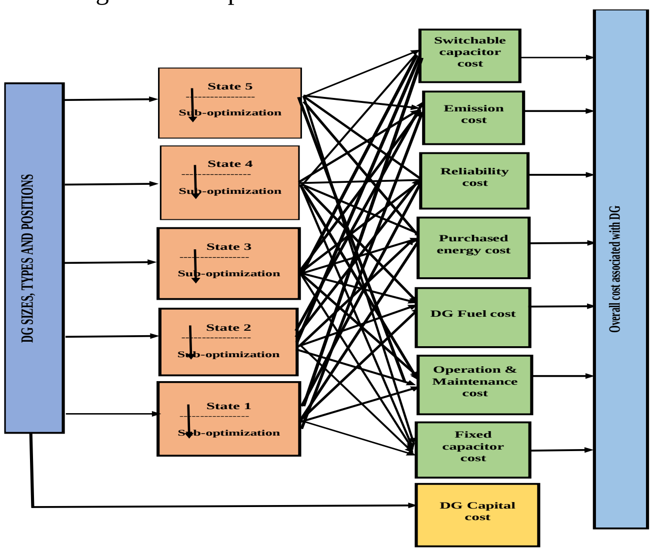

Figure 1. Assessed cost of a DG distributed system

A. Complications based on Master Optimization

By minimizing the overall cost throughout the course of the planning stage, the master optimizing issue determine the best distribution of DG units with regards to DG capacity, types, and positions. As stated in Equation (1), the total of the related state-dependent expenses and the DG capital expenses may be used to create the desired functionality for the master optimization dilemma. According to [21], the sub-optimization may yield the state-dependent expenses for the entire system state. The sub-optimization can harvest the state dependent cost for every state of the system.

$$C_{total} = \sum_{N=1}^{N_s} \left(C_{cpty}^{wd} U_N^{wd} + C_{cpty}^{SPV} U_N^{SPV} + C_{cpty}^{B_g} U_N^{B_g} \right) + \sum_{s=1}^{state} C_s^{st} \tag{1}$$

Where, N_s indicates the entire nodes of the system, C_{cpty}^{wd}, C_{cpty}^{SPV}, $C_{cpty}^{B_g}$ denotes the wind, SPV and biomass generator price factors that are utilized for determining the capital costs. In this study, the capitalized cost of C_{cpty}^{wd}, C_{cpty}^{SPV}, and $C_{cpty}^{B_g}$ is kept as \$1882/KVA, \$4004/KVA and \$2293/KVA. Similarly, the wind capacity (U_N^{wd}), PV capacity (U_N^{SPV}) and bio mass capacity ($U_N^{B_g}$) varies from 0 to 1500 KVA at node N, correspondingly. Furthermore, the recently established Aq-SCS optimization yields the ideal capacity values for PV, wind, and biomass output.

1) Saturated bounds for DG Units

In *accordance with the capacity factor and the peak load demand, DG saturation limit may be stated as:*

$$\sum_{N=1}^{N_s} \left(Cf_N^{SPV} Q_N^{SPV_r} + Cf_N^{wd_r} Q_N^{wd_r} + Q_N^{Bg_r} \right) \leq E_{\mathrm{lim}it} Q_p^{Ld} \tag{2}$$

Where, Cf_N^{wd} and Cf_N^{SPV} embodies the wind/SPV capacity factors; $Q_N^{SPV_r}$, $Q_N^{wd_r}$ and $Q_N^{Bg_r}$ signifies the rated real power of SPV/WT/biomass generator. Likewise, $E_{\mathrm{lim}it}$ and Pwr_p^{LD} denotes the saturated bound and peak load demand, respectively.

2) Overall DG Capacity installed at every node

The maximal permitted DG capacity on server capacity owing to land space along with network restrictions can restrict the total installation DG or hosting capacity at all system nodes$U_N^{\max}$.

$$\left(U_N^{wd} + U_N^{SPV} + U_N^{Bg} \right) \leq U_N^{\max} \tag{3}$$

3) Suboptimizing Scenario

To reduce the state-dependent expenses C_s^{st}, the optimal PQ power from DG units must be obtained in the sub-optimization scenario.

$$C_s^{st} = C_s^{OM} + C_s^{fuel} + C_s^{pu} + C_s^{e} + C_s^{r} \tag{4}$$

The total amount of active energy generated by the DG units may be used to calculate the DG O&M costs C_s^{OM} Which is specified as,

$$C_s^{OM} = \sum_{Pl=1}^{P} \sum_{N=1}^{N_s} \left(W_{Pl} T_{Pl,s} \left(C_{Pl}^{pvm} Q_{N,s}^{SPV} + C_{Pl}^{wdm} Q_{N,s}^{wd} + C_{Pl}^{bgm} Q_{N,s}^{Bg} \right) \right) \tag{5}$$

Here, Pl signifies the total scheduling for 5 years, W_{Pl} denotes current value cost feature, $T_{Pl,s}$ indicates the entire system state hours for a scheduled year; C_{Pl}^{wdm}, C_{Pl}^{pvm}, C_{Pl}^{bgm} declares the predictable O&M cost factors (in \$/kWh) that for wind is \$0.01/Kwh , SPV is \$0.01/Kwh and biomass generator is \$0.012/Kwh, correspondingly. The terms $Q_{N,s}^{SPV}$, $Q_{N,s}^{Wd}$ and $Q_{N,s}^{Bg}$ portrays the PV, wind and biomass capacity that will be generated via the proposed Aq-SCS optimization model. Therefore, it is possible to assess the entire fuel costs C_s^{fuel} of biomass generators and the overall energy cost produced over a planned horizon.

$$C_s^{fuel} = \sum_{Pl=1}^{P} \sum_{N=1}^{N_s} C_{Pl}^{fuel} \left(W_{Pl} T_{Pl,s} Q_{N,s}^{Bg}\right) \tag{6}$$

Where, C_{Pl}^{fuel} represents the predicted fuel cost aspect.

It is possible to determine the energy cost obtained from the grid in terms of the active power lost, injected active power by DG units along with the utilized active power loads as stated in,

$$C_s^{pu} = \sum_{Pl=1}^{P} C_{Pl}^{pu} W_{Pl} T_{Pl,s} \times \left(\sum_{B \in B^f} \left(\left| I_{B,s} \right|^2 r_B^f \right) + \sum_{N=1}^{N_s} \left(Q_{N,s}^{Ld} - Q_{N,s}^{wd} - Q_{N,s}^{SPV} - Q_{N,s}^{Bg} \right) \right) + F_c + S_c \tag{7}$$

where, C_{Pl}^{pu} determines the evaluated price factor of purchased energy cost from grid; B^f be the feeder set, $I_{B,s}$ signify the current of the branch; r_B^f denotes the feeder resistivity, $Q_{N,s}^{Ld}$ implies the load demand; F_c and S_c be the fixed as well as switchable capacitor cost.

The entire amount of energy received from the electrical grid as well as the energy generated by biomass-based generators may be used to assess the cost of emissions C_s^e, as shown in Equation (8),

$$C_s^e = \sum_{Pl=1}^{p} C_{Pl}^e W_{Pl} T_{Pl,s} \left(E_f C_{pu}^{-1} C_s^{pu} + E_{fuel} \sum_{N=1}^{N_s} Q_{N,s}^{Bg} \right) \tag{8}$$

Where, C_{Pl}^e represent the evaluated cost factor of the emission (\$/kg), E_f and E_{fuel} indicates the emission factors (kg/kWh) that are related with consumed real energy and total energy provided by the biomass generator.

System dependability costs C_s^r are assessed using the energy not supplied (ENS) cost, which is computed as,

$$C_s^r = \sum_{Pl=1}^{P} \sum_{B \in B^f} C_{Pl}^r W_{Pl} \delta_B \mu_{Pl,s} \times \left(\sum_{N \in N_{B,s}^m} \left(t_{B,s}^m Q_{N,s}^{Ld} \right) + \sum_{N \in N_B^r} \left(t_{B,s}^r Q_{N,s}^{Ld} \right) + \sum_{N \in N_{B,s}^a} \left(t_{B,s}^a Q_{N,s}^{Ld} \right) \right) \tag{9}$$

Where, C_{Pl}^r represents the reliability cost factor; δ_B implies the feeder failure rate; $\mu_{Pl,s}$ be the system probability rate; $N_{B,s}^a$, $N_{B,s}^m$ and $N_{B,s}^r$ signifies the system nodes that are restored after automatic, manual and repair switching, respectively. Likewise, $t_{B,s}^a$, $t_{b,state}^{manual}$ and $t_{b,state}^{repair}$ represents the time of automatic switching, manual switching and repair time accordingly.

B. Proposed Methodology of optimal Expansion Planning

The primary objective of the suggested investigation is the development of an innovative mathematical framework for the distributed framework's expansion planning through the implementation of an integrated optimization method. Two stages, like master optimization and sub-optimization are used to address the distributed system planning challenge across every state of the system [13]. The suggested Aq-SCS optimization algorithm uses the distribution system input variables, such as fixed and switchable capacitors, DG type, size and capacity, position, PQ power that are produced by system uncertainties, like load demand, solar, and wind power uncertainties.

The distributed system's expansion planning challenge is first defined as a MINLP issue that is addressed by employing the Master optimization technique. Sub-optimization for every state of the system is included in the master optimization process. The presented scheme employs the master technique to derive potential DG allocation schemes for fixed and switchable capacitors, as well as the sizes, types, and positions of DG units. The sub-

algorithm is employed in concurrence with the DG allocation scheme produced by the master technique to extract the state-dependent operating techniques for PQ power from each separate DG unit.
The combination of AOA [22] and SCSO [23] algorithms' distinguishing traits are combined to create the suggested Aq-SCS optimization strategy. The suggested approach is used to attain the goals of adjusting the variables, including fixed capacitors, switchable capacitors, DG type, size/capacity, position, PQ power. The process is terminated after confirming that the DSEP strategy's basic goal of obtaining the least feasible cost is met, otherwise the process continues unless the best result (least cost) is reached. Figure 2 displays the flow chart depiction of the suggested Distribution system Expansion plan model.

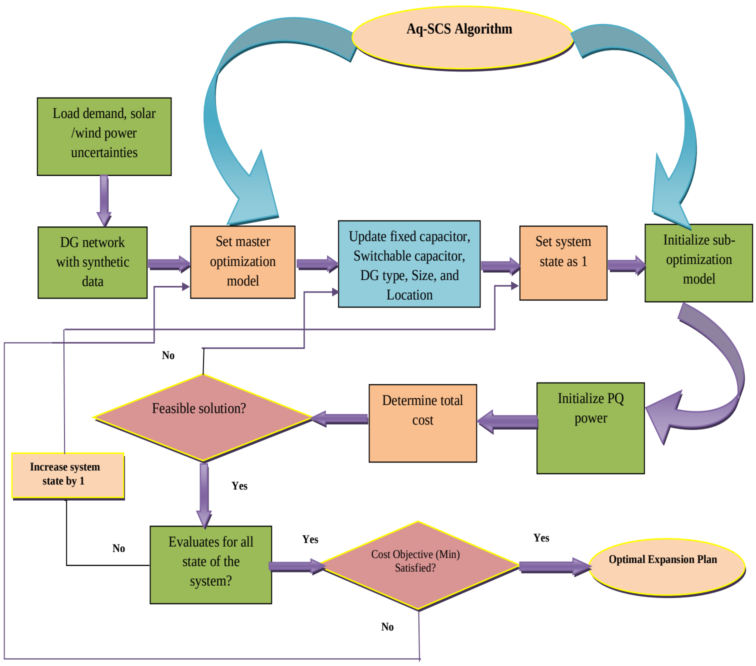

Figure 2. Schematic diagram of DSEP scheme

IV. PARAMETER TUNING BY HYBRIDIZED AQ-SCS TECHNIQUE

A. Objective Model

The primary goal of the research is to create an integrated methodology for optimum expansion planning for the distributed system by adjusting the factors, including DG type, size/capacity, fixed capacitor, switchable capacitor, position, PQ power, and the distribution system's wind/solar capacities. In the same way, maximizing the load that may be increased in a distribution system reduces costs. Here, 0 and 7 are taken to be the lowest and higher bounds for the type and position of wind turbines, SPV and biomass in which their capacity limits are maintained at 0 to 1500.

B. Aquila based Sand Cat Algorithm(Aq-SCS)

AQO an innovative population-based optimization approach [22] inspired by the Aquila's' instinctive hunting and feeding activities.

1) Aquila's fishing attitude and techniques:

Aquilas that move quickly are characterized by their powerful feet and long, sharp talons that they use to catch prey. This will defend its domain to an extent of 200km2. The Aquila mainly uses four foraging strategies, which it applied based on the circumstances: "stepping and seizing the prey," "poor soar with continuous descent attack," "contour flying with brief glide assault," and "high soar with a vertical stoop." The mathematically simulated hunting behavior of Aquila is briefly explained here.

2) Initialization

In simple terms, Aquila is a population-based methodology, where a list of population(J), which are generated arbitrarily within the space of search are displayed as in Equation (10),

$$J = \begin{bmatrix} J_{1,1} & \cdots & J_{1,q} & J_{1,\dim-1} & J_{1,\dim} \\ J_{2,1} & \cdots & J_{2,q} & \cdots & J_{2,\dim} \\ \cdots & \cdots & J_{p,q} & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ J_{N-1,1} & \cdots\cdot & J_{N-1,q} & \cdots\cdot & J_{N-1,\dim} \\ J_{N-1} & \cdots\cdot & J_{N,q} & J_{N,\dim-1} & J_{N,\dim} \end{bmatrix} \tag{10}$$

The ideal outcome is determined by selecting the best outcome from each iteration. J indicates the contemporary developed individual random solution as per eqn. (11), $J_p$characterize the p^{th}solution. N refers the overall count, and $\dim$ refers the dimensional size.

$$J_{p,q} = r \times (U_q - L_q) + L_q \\ p = 1, 2, \ldots N; \quad q = 1, 2 \ldots . d \tag{11}$$

Where, $r$defines the randomness count, $L_q$and $U_q$stipulates the bottom and uppermost limits of q.

C. Mathematical Modelling

The AO technique may use different behaviours to transition from the exploratory levels to the exploiting steps according to this situation. If $t_p \leq \left(\frac{2}{3}\right) * it_{\max}$ condition is met, then the exploratory level will be stimulated; or else, the exploited steps will be accomplished. Likewise, the presented approach depending on the four chasing stages of AQO is enlightened in the subsequent segments.

Step I: Prolonged exploring phase (J_1):

The finest location for hunting is designated by the Aquila by using a high soar with a vertical stoop to identify the food source area. In addition, the AO seeks a greater area, descends vertically, and investigates from a high altitude in order to locate the prey. In order to regulate the new optimal position in the searching area, SCSO is inhibited into the AQO optimization because SCSO is inexpensive to operate in an effective manner.

$$J_{new} = S_{range} * Pos_{bc}(p) - rnd(0,1) * J(p) \tag{12}$$

$$S_{range} = rnd * G_s \tag{13}$$

$$G_s = S - \left(\frac{2*S*t_p}{it_{max}}()\right) \tag{14}$$

Where, Pos_{bc} defines the optimal candidate position. S_{range} States the sensitive ranging; $G_s$be the generalized sensitive limit minimized from 2 to 0.

Step II: Narrowed exploration (J_2):

While hitting the victim's body, the Aquila extensively investigates the target solution space in this part utilizing a variety of speeds and directions. The technique is identified as quick glide attack during contour flying. In this instance, in order to be ready for an assault, AO prudently investigates the chosen region of the intended prey and is expressed as,

$$J_2 = J_{best} \times Lvy(d) + J_r + (u - v) * rnd$$
(15)

$$Lvy(d) = a * \frac{x*\rho}{y^{1/\alpha}}$$
(16)

where, J_2 implies the subsequent iterated value; $Lvy(d)$indicates the levy distributed flight; $J_r$defines the arbitrary populace of Aquila; rnd_2stipulates the randomized solution within [1,N]; a denotes the fixed constant equal to 0.01; x and y be the arbitrary counts in [0,1]; α be a constant equal to 1.5 and is calculated as,

$$\rho = \left(\frac{\Gamma(1+\alpha) * \sin\left(\frac{\phi\alpha}{2}\right)}{\Gamma\left(\frac{1+\alpha}{2}\right) * \alpha * 2^{\left(\frac{\alpha-1}{2}\right)}} \right)$$
(17)

$$\begin{cases} u = rnd \times \cos(\theta) \\ v = rnd \times \sin(\theta) \\ rnd = R_1 + 0.00565 \times \dim \\ \theta = -\lambda \times \dim + \dfrac{3 \times \varphi}{2} \end{cases}$$
(18)

Where, R_1 ranges between 1 and 20 for constant search count; dim is a integer count between 1 and dimensional searching space, $\lambda = 0.005$.

Step III: Prolonged exploiting level (M_3):

While the hunting site is being selected and the area to be struck has been carefully defined, the Aquila approaches vertically with a preemptive strike to gauge the prey's reaction before landing and engaging in battle. As a result, the phrase low flight with a slow descent attack is used. Equation (8) gives the position update of each sand cat and is given by

$$J_{new} = J_{best}(p) - S_{range} * Pos_{rnd} * cos(\delta)$$
(19)

Where, δ be the roulette wheel selection; Pos_{rnd}states the gap amongst the Aquila and the prey, and is given by

$$Pos_{rnd} = |rnd(0,1) * J_{best} - J|$$
(20)

Equations (12), (17) and (18) update each sand cat position in the explored and exploited stages and hence it is named as Aquila based Sand Cat Optimization (Aq-SCS) Algorithm.

Step IV: Narrated exploitation (J_4):

Finally, in this method, the Aquila follows the victim while paying attention to its chaotic escape path and then attacks it on the ground. This scientific behavior is specified by,

$$J_4 = Q_f * J_{best} - (E_1 * J * rnd) - E_2 * Lvy(d) + rnd * E_1$$
(21)

$$Q_f = t_p^{((2*rnd-1)/(1-it_{\max})^2}$$
(22)

$$E_1 = 2 * rnd - 1$$
(23)

$$E_2 = 2 * \left(1 - \frac{t_p}{it_{\max}}\right) \tag{24}$$

Where, Q_f represents the functional quality that is utilized to adjust the searching strategy. E_1 Corresponds to an integer value within -1 and 1 that represents the prey's tracking behavior; E_2displays the AO's flight slope surface that is decreased from 2 to 0. Algorithm 1 describes the proposed Aq-SCS pseudocode. Figure 3 depicts the Aq-SCS flowchart representation.

Algorithm 1: Pseudo code of Aq-SCS Model

Aq-SCSModel
Set populace J and its variables
while do
Assess the fitness functionality values
for $(p = 1, 2, ..., N)$ ***do***
Upgrade $u, v, E_1, E_2, Lvy(d)$ *and so on*
if $t_p \le \left(\frac{2}{3}\right) * it_{\max}$ then
If $rnd \le 0.5$ then
Step 1: Enhanced Exploring phase (J_1)
Upgrade the present resolutionby Equation (12)
If $Fit(J_1(t_p + 1)) < Fit(J(t_p))$ then
$J(t_p) = J_1(t_p + 1)$
if $Fit(J_1(t_p + 1)) < Fit(J_{best}(t_p))$
$J_{best}(t_p) = J_1(t_p + 1)$
end if
end if
else
Step 2: Narrated exploring phase (J_2)
Utilizing Equation (13), adjust the present value
If $Fit(J_2(t_p + 1)) < Fit(J(t_p))$ then
$J(t_p) = J_2(t_p + 1)$
if $Fit(J_2(t_p + 1)) < Fit(J_{best}(t_p))$
$J_{best}(t_p) = J_2(t_p + 1)$
end if
end if
end if
else
If $rnd \le 0.5$ then
Step 3: Prolonged exploiting phase (J_3)
Adjust the Current value by means of Equation (17)
If $Fit(J_3(t_p + 1)) < Fit(J(t_p))$ then
$J(t_p) = J_3(t_p + 1)$
if $Fit(J_3(t_p + 1)) < Fit(J_{best}(t_p))$
$J_{best}(t_p) = J_3(t_p + 1)$
end if
end if
else

Step 4: Narrated exploiting stage (J_4)
Update new value by employing Equation (19)
If $Fit(J_4(t_p+1)) < Fit(J(t_p))$ then
$J(t_p) = J_4(t_p+1)$
if $Fit(J_4(t_p+1)) < Fit(J_{best}(t_p))$
$J_{best}(t_p) = J_4(t_p+1)$
end if
end if
end if
end if
end for
end while
Return **the optimal value** (J_{best}).

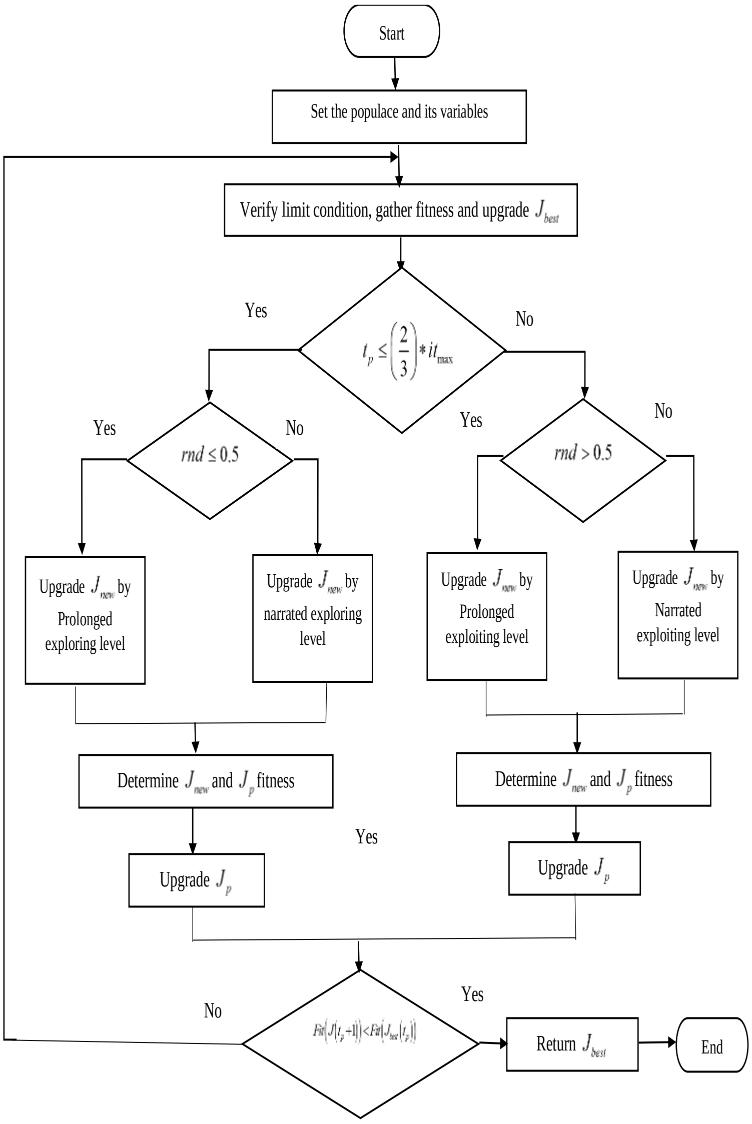

Figure 3. Aq-SCS flowchart representation

V. Results and discussions

A. Simulation Procedure

The empirical study was carried out utilizing the offered Aq-SCS technique for distributive system planning, which accounts for the uncertainties in the system and the reactive capabilities of numerous DG systems, with the aid of MATLAB/Simulink. Information on load demand is gathered from the "Hourly Load Data" dataset, which is utilized for the examination in this study [24]. The following comparison shows how the suggested approach for every instance of testing reduces total cost, capital cost, O&M cost, fuel cost, purchased cost, emission cost, reliability cost, fixed capacitor cost, and switchable capacitor cost in comparison to the typical techniques, like SSI-CS [25,26], WHO [27], AQO [20], and SCSO [21] respectively.

B. Capital Cost

The suggested over typical techniques' capital costs for optimum DG allocation systems are displayed in Figure 4. Therefore, in contrast with additional standard procedures, the suggested Aq-SCS approach achieves a low-cost value.

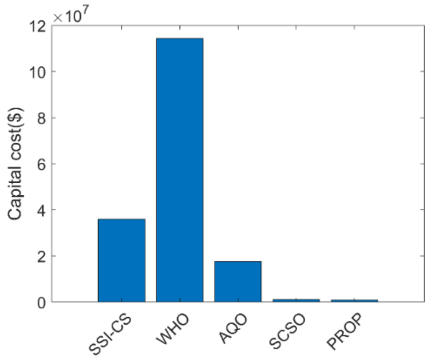

Figure 4: Analysis based on capital cost

C. Analysis based on Puchased Energy Cost

The ideal DG allocation techniques for the suggested against conventional approaches are shown by their purchased energy cost in Figure 5. Therefore, compared to current procedures, the suggested Aq-SCS method achieves a lower cost.

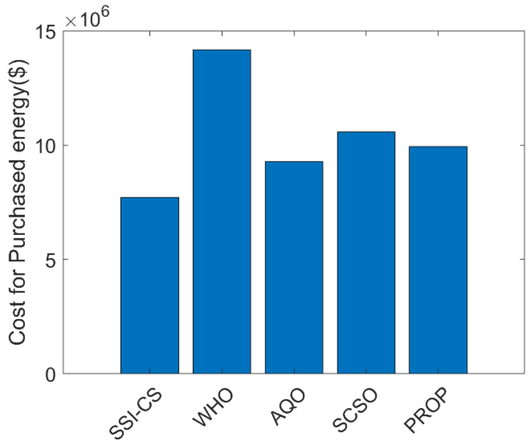

Figure 5: Purchased energy cost analysis

D. Evaluation based on Fuel Cost

The suggested Aq-SCS technique is contrasted with standard models, like SSI-CS, WHO, AQO, and SCSO depending on evaluation of fuel cost, as seen in Figure 6. As such, the suggested Aq-SCS approach achieves the lowest possible cost with regard to standard tactics.

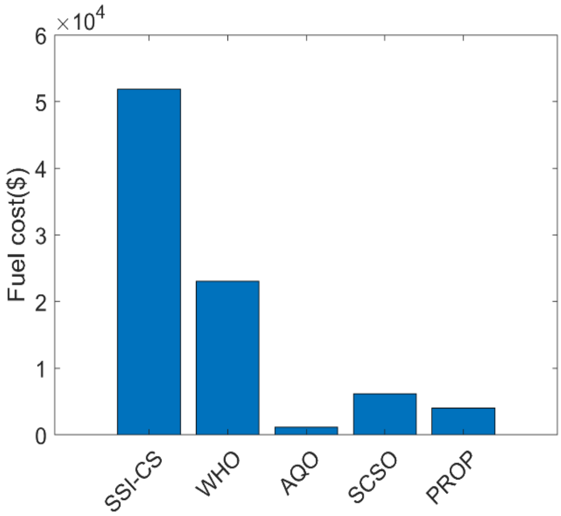

Figure 6: Comparative study based on fuel cost

E. Evaluation based on Emission Cost

Figure 7 displays the emission cost assessment, whereby the suggested Aq-SCS approach is compared to SSI-CS, WHO, AQO, and SCSO strategies. Therefore, in relation with different conventional models, the suggested AQ-SCS method achieves a lower cost.

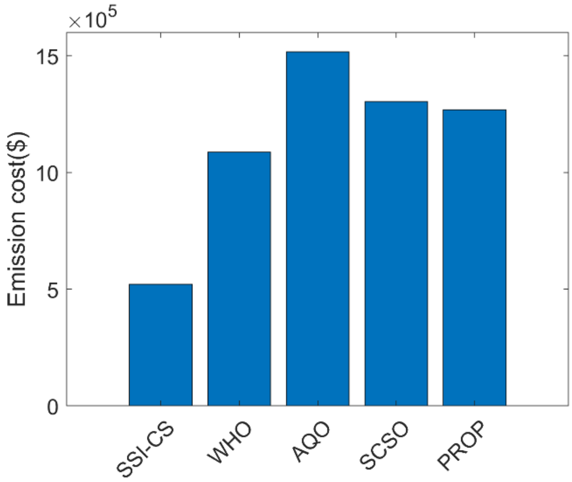

Figure 7: Comparative study based on emission cost

F. Evaluation based on O&M Cost

The suggested Aq-SCS approach is used to compare the operating and maintenance costs of several prevalent methods, including SSI-CS, WHO, AQO, and SCSO, as seen in Figure 8. As such, the suggested Aq-SCS approach achieves the lowest possible cost in comparison with existing strategies.

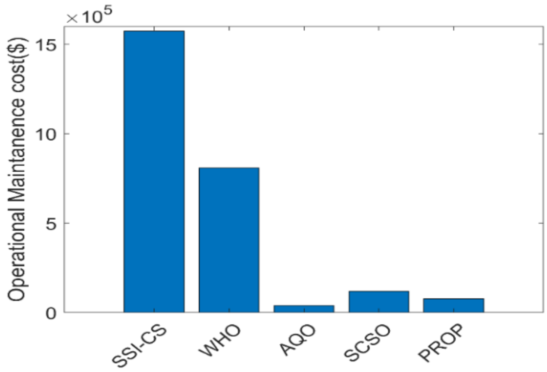

Figure 8: Comparative study based on O&M cost

G. Analysis based on Reliability Cost

The reliability cost evaluation of the suggested Aq-SCS approach was shown in Figure 9, with various other current methods, including SSI-CS, WHO, AQO, and SCSO, respectively. Consequently, as contrasted with traditional strategies, the suggested Aq-SCS approach achieves a minimal cost.

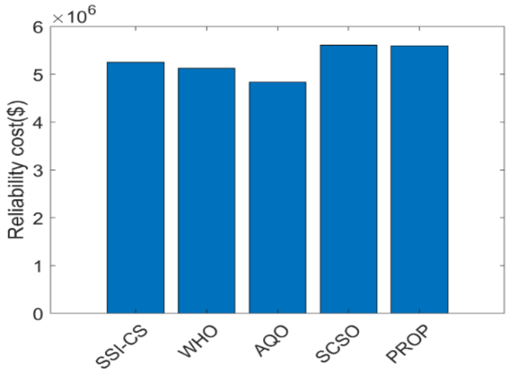

Figure 9: Comparative study based on reliability cost

H. Analysis based on Total Cost

The performance of Aq-SCS in comparison to current techniques is shown in Figure 10 based on the entire cost. In light of this, the suggested Aq-SCS approach achieves the lowest cost in contrast to traditional methods.

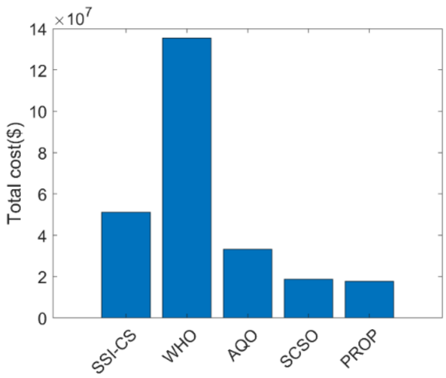

Figure10: Comparative study based on total cost

I. Analysis based on fixed capacitor cost

The reliability cost estimation of the suggested Aq-SCS approach is illustrated in Figure 11, along with various other conventional approaches, such as WHO, AQO, and SCSO accordingly. Consequently, as contrasted with traditional methods, the suggested Aq-SCS approach achieves reduced expense.

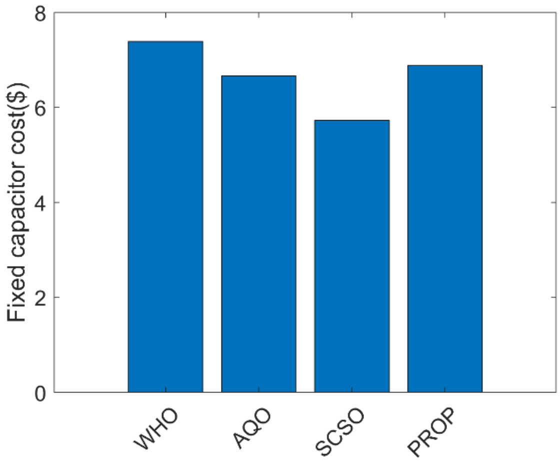

Figure 11: Comparative study based on fixed capacitor cost

J. Analysis based on Switchable Capacitor Cost

The suggested Aq-SCS method's switchable capacitor cost analysis was shown in Figure 12, along with various other prevailing approaches, including WHO, AQO, and SCSO models. Hence, in comparison to traditional methods, the suggested Aq-SCS approach achieves a minimum cost.

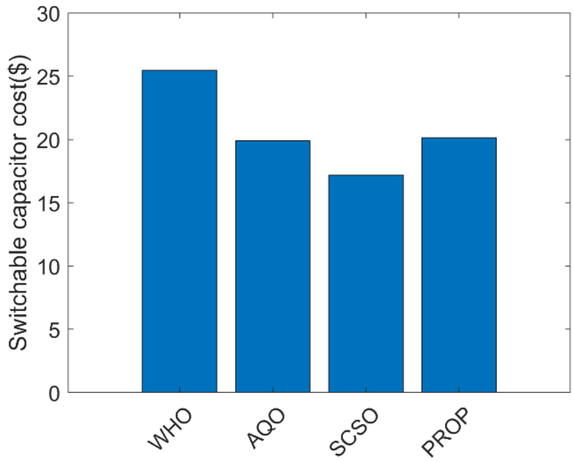

Figure 12: Comparative study on switchable capacitor cost

The expense associated with allocating DG optimally for the proposed techniques are compared to those of other standard approaches and depicted in Table 2.

Table 2. Comparative Analysis of Cost for the Ideal DG Allocation

	SSI-CS	WHO	AQO	SCSO	Proposed
Total cost	5.11E+07	1.36E+08	3.32E+07	1.88E+07	1.78E+07
Capital cost	3.60E+07	1.14E+08	1.76E+07	1.14E+06	8.95E+05
O&M cost	1.57E+06	8.09E+05	39310	1.18E+05	7.71E+04
Fuel cost	51855	23056	1176.3	6182.4	4049.1
Purchased cost	7.72E+06	1.42E+07	9.27E+06	1.06E+07	9.94E+06
Emission cost	5.21E+05	1.09E+06	1.52E+06	1.30E+06	1.27E+06
Reliability cost	5.25E+06	5.13E+06	4.83E+06	5.61E+06	5.60E+06

Fixed capacitor cost	-	7.386	6.659	5.728	6.883
Switchable capacitor cost	-	25.467	19.899	17.184	20.133

K. Evaluation based on Convergence

Figure 13 illustrates an iterative and entire cost comparison between the proposed technique and standard approaches. Investigation is done in this instance for a large range of iterations, involving 0, 5, 10, 15, 20, 25, and 30. It is evident that throughout the iterations, the suggested Aq-SCS design has consistently produced low-cost values as compared to the standard methods.

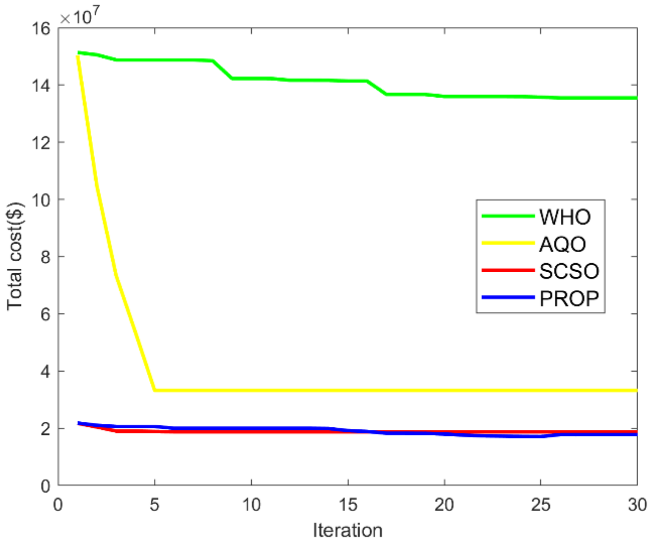

Figure 13: Convergence analysis

From the outcomes, it is revealed that Aq-SCS attains lowest cost in contrast with typical approaches, like WHO, AQO and SCS correspondingly.

Table 3, 4 and 5 shows the DG allocation schemes using wind turbine, PV and biomass based on size and location. Table 6 illustrates the optimal fixed and switchable capacitor types of the proposed Aq-SCS method over typical WHO, AQO and SCSO optimization techniques. Moreover, the computation time achieved Table 6 select the corresponding range of capacitors from Table 7 and 8 [28].

Table 3: DG Allocated Wind Turbine Model

WHO		AQO		SCSO		PROPOSED	
WT spot	WT size	WT Spot	WT size	WT Spot	WT size	WT Spot	WT size
1	670.34	2	64.069	1	200.12	2	8.1583
2	894.67	4	63.622	2	207.6	4	117.44
3	853.28	6	64.555	3	210.04	5	21.847
9	605	7	64.458	4	207.21	6	4.4773
10	1000	9	63.158	5	216.46	7	58.04
15	126.05	12	66.829	6	238.81	8	37.688
20	216.63	13	64.181	7	214.85	9	87.762
23	352.72	14	67.151	8	220.73	10	1.9255
24	529.68	15	64.988	9	229.14	12	14.467

25	327.99	17	63.137	10	209.84	14	101.31
30	444.86	21	67.133	11	207.82	15	39.433
32	1	23	63.686	12	209.99	17	4.9875
		25	65.479	13	204.59	20	31.026
		28	67.21	14	252.93	21	64.959
		29	63.233	15	217.48	23	63.567
				16	217.92	25	132.72
				17	220.93	26	418.61
				18	221.99	27	23.934
				19	218.34	28	10.798
				20	187.82	29	36.989
				21	234.88	30	129.26
				22	212.99	32	28.829
				23	219.81	33	4.7175
				24	233.48		
				25	220.52		
				26	198.05		
				27	220.69		
				28	178.06		
				29	227.31		
				30	224.22		
				31	224.6		
				32	201		
				33	222.41		

Table 4: DG Allocated PV Model

WHO		AQO		SCSO		PROPOSED	
PV spot	PV size	PV spot	PV size	PV spot	PV size	PV spot	PV size
2	627.91	1	65.144	1	205.18	1	588.82
5	210.9	2	67.029	2	220.88	2	63.899
10	1	3	65.592	3	210.27	3	11.701
11	918.27	6	64.157	4	209.97	4	795.19
18	937.28	7	66.663	5	223.74	7	4.2482
22	793.3	9	64.706	6	398.95	8	10.428
23	231.2	12	66.564	7	204.07	9	465.75
24	871.03	13	64.248	8	203.92	11	6.0825
26	464.65	14	64.147	9	214.91	13	877
30	787.28	15	65.445	10	322.96	14	1.8269
32	421.52	19	63.992	11	231.94	16	53.361
		22	63.154	12	204.74	17	8.5336
		25	66.805	13	220.23	18	21.253
		26	63.566	14	209.23	19	755.45

		27	64.088	15	211.23	21	187.42
		28	65.102	16	220.66	24	167.3
		29	64.132	17	228.45	27	32.083
		30	63.896	18	212.19	30	969.71
		31	63.48	19	233.7	31	494.44
				20	210.34	32	643.76
				21	211.79	33	2.1275
				22	224.2		
				23	214.37		
				24	201.65		
				25	207.54		
				26	216.81		
				27	198.92		
				28	192.05		
				29	201.63		
				30	219.53		
				31	222.93		
				32	200.14		
				33	209.37		

Table 5: DG Allocated Biomass Model

WHO		AQO		SCSO		PROPOSED	
Biomass Spot	Biomass size	Biomass Spot	Biomass size	Biomass Spot	Biomass size	Biomass Spot	Biomass size
2	734.87	2	63.569	1	205.12	1	47.012
5	1000	3	65.746	2	200.49	2	9.1167
10	685.71	4	65.998	3	200.36	12	72.794
14	1	8	65.838	4	209.1	15	9.1257
18	703.78	10	64.729	5	202.73	16	50.01
22	638.49	11	66.06	6	212.96	22	55.946
26	1	12	64.475	7	218.69	23	96.038
30	1	16	64.172	8	256.94	30	121.13
31	244.36	17	67.042	9	215.77	31	10.311
32	426.4	18	64.038	10	218.74	32	9.0052
		19	63.953	11	223.31	33	14.721
		20	64.85	12	220.87		
		23	63.358	13	223.24		
		24	65.993	14	204.5		
		30	64.834	15	212.69		
		32	64.336	16	205.38		
		33	66.933	17	220.88		
				18	222.68		
				19	281.42		
				20	220.93		
				21	213.29		
				22	221.13		

				23	277.6		
				24	212.44		
				25	225.49		
				26	216.51		
				27	211.02		
				28	220.23		
				29	194.34		
				30	216.58		
				31	219.43		
				32	220.83		
				33	211.95		

Table 6: Optimal Fixed and Switchable Capacitor Type

Fixed Capacitor				**Switchable Capacitor**			
WHO	**AQO**	**SCSO**	**PROP**	**WHO**	**AQO**	**SCSO**	**PROP**
27	11	4	4	1	13	4	4
8	8	7	4	9	15	2	3
5	13	3	7	27	13	4	6
22	13	1	4	7	2	2	3
27	12	5	3	1	8	6	4
24	8	7	3	24	6	3	4
13	12	5	1	1	21	6	2
20	20	2	2	27	27	6	2
1	6	2	2	1	22	7	4
6	24	2	1	1	26	3	4
24	10	5	5	12	4	2	7
15	12	5	3	19	6	3	2
2	7	2	4	2	24	3	5
15	11	5	3	1	21	5	3
27	15	5	5	8	7	5	2
1	22	3	3	18	6	4	1
6	17	7	3	12	11	5	3
5	14	7	1	27	12	7	4
27	8	1	2	13	9	5	3
1	17	2	4	1	11	6	2
27	21	2	1	2	13	2	2
27	3	6	5	27	26	6	2
27	13	4	5	5	24	5	2
14	14	2	3	1	18	6	2
2	21	5	1	27	25	3	3
9	10	5	1	14	22	4	3
6	13	3	4	1	17	1	4
27	17	5	4	27	8	3	3
10	18	1	4	11	20	6	3
12	25	6	2	1	12	7	2
27	15	2	1	17	14	2	4
1	2	2	5	11	2	7	2
21	17	1	2	24	3	5	5

Table 7: Annual Fixed Capacitor Cost

Capacitor size (KVAR)	150	300	450	600	750	900	1050	1200	1350	1500	1650
Capacitor cost ($/yr)	0.5	0.35	0.253	0.22	0.276	0.183	0.228	0.17	0.207	0.201	0.193
Capacitor size (KVAR)	1800	1950	2100	2250	2400	2550	2700	2850	3000	3150	3300
Capacitor cost ($/yr)	0.187	0.211	0.176	0.197	0.17	0.189	0.187	0.183	0.18	0.195	0.174
Capacitor size (KVAR)	3450	3600	3750	3900	4050						
Capacitor cost ($/yr)	0.188	0.17	0.183	0.182	0.179						

Table 8: Annual Cost of Switchable Capacitor

Capacitor size (KVAR)	135-165	270-330	405-495	540-660	675-825	810-990	945-1155
Capacitor cost ($/yr)	1.5	1.05	0.759	0.66	0.828	0.549	0.684
Capacitor size (KVAR)	1080-1320	1215-1485	1350-1650	1485-1815	1620-1980	1755-2145	1890-2310
Capacitor cost ($/yr)	0.51	0.621	0.603	0.579	0.561	0.633	0.528
Capacitor size (KVAR)	2025-2475	2160-2640	2295-2805	2430-2970	2565-3135	2700-3300	2835-3465
Capacitor cost ($/yr)	0.591	0.51	0.567	0.561	0.549	0.54	0.585
Capacitor size (KVAR)	2970-3630	3105-3795	3240-3960	3375-4125	3510-4290	3645-4455	
Capacitor cost ($/yr)	0.522	0.564	0.51	0.549	0.546	0.537	

L. Analysis under 4 cases

The analysis of the suggested approach is carried out under 4 cases. The analysis is made in IEEE 33 bus distribution network as depicted in Figure 14.

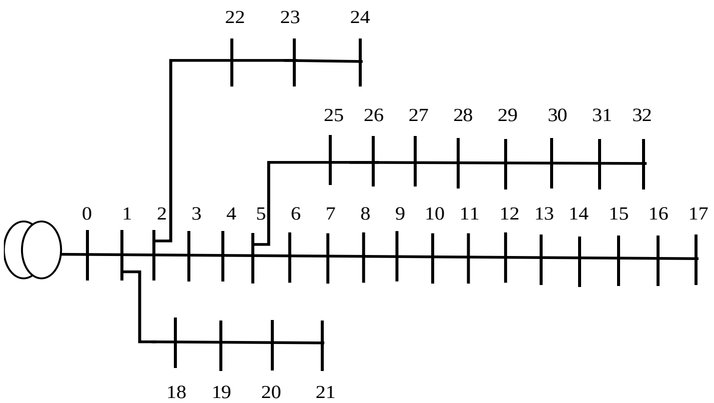

Figure 14: IEEE 33 bus distribution Network

The four cases under consideration are
(i) Without DG and capacitor
(ii) With capacitor and no DG
(iii) With DG and no capacitor
(iv) With both capacitor and DG

(i) Case 1: *Without DG and capacitor*

This is the base case load tested through the load flow method as stated below. In this case, there is no use of DG and capacitor. Table 9 depicts the line flow and losses without DG and capacitor.

Table 9: Analysis of Line Flow and Losses

Line		Power at bus &line flow		Line loss	
from	to	kW	kVAR	kW	kVAR
1	2	1954.7065	28.7598	100.8940	1.4845
2	1	-1853.812	-27.275	100.8940	1.4845
	3	833.558	31.0579	43.0856	1.6053
	19	324.047	8.2429	5.9400	0.1511
3	2	-790.4732	-29.4526	43.0856	1.6053
	4	469.5057	124.1295	1.6989	0.4492
	23	324.8714	14.9721	7.2292	0.3332
4	3	-467.8068	-123.6804	1.6989	0.4492
	5	-188.9624	-11.8587	1.1411	0.0716
5	4	190.1034	11.9303	1.1411	0.0716
	6	193.5974	60.0805	0.9519	0.2954
6	5	-192.6455	-59.7851	0.9519	0.2954
	7	59.8823	9.2248	0.1514	0.0233
	26	-503.5779	-14.9618	9.0712	0.2695
7	6	-59.7309	-9.2015	0.1514	0.0233
	8	-101.9682	-6.0398	0.4275	0.0253
8	7	102.3957	6.0651	0.4275	0.0253
	9	-86.3253	-9.8047	0.5034	0.0572
9	8	86.8287	9.8619	0.5034	0.0572
	10	-74.9986	-13.2428	0.2459	0.0434
10	9	75.2446	13.2862	0.2459	0.0434
	11	-168.9293	-7.6917	0.4103	0.0187
11	10	169.3396	7.7104	0.4103	0.0187
	12	-61.5174	-13.0853	0.0230	0.0049
12	11	61.5404	13.0902	0.0230	0.0049
	13	-87.0982	-13.7068	0.5703	0.0897
13	12	87.6685	13.7965	0.5703	0.0897
	14	-29.6441	-8.3341	0.0237	0.0067
14	13	29.6678	8.3408	0.0237	0.0067
	15	-36.8189	-5.2986	0.0498	0.0072
15	14	36.8688	5.3058	0.0498	0.0072
	16	8.5970	3.2926	0.0012	0.0005
16	15	-8.5959	-3.2921	0.0012	0.0005
	17	3.4070	1.3296	0.0006	0.0002
17	16	-3.4064	-1.3294	0.0006	0.0002
	18	-15.9346	-3.6800	0.0065	0.0015
18	17	15.9411	3.6815	0.0065	0.0015
19	2	-318.1071	-8.0918	5.9400	0.1511
	20	265.0413	116.6574	2.4622	1.0837
20	19	-262.5791	-115.5737	2.4622	1.0837
	21	165.6995	18.5277	1.1555	0.1292
21	20	-164.5441	-18.3985	1.1555	0.1292

	22	72.3268	67.0583	0.0969	0.0898
22	21	-72.2299	-66.9685	0.0969	0.0898
23	3	-317.6422	-14.6390	7.2292	0.3332
	24	572.0586	377.1005	5.3973	3.5579
24	23	-566.6613	-373.5426	5.3973	3.5579
	25	128.1627	12.0456	1.3464	0.1265
25	24	-126.8162	-11.9191	1.3464	0.1265
26	6	512.6492	15.2313	9.0712	0.2695
	27	-186.2944	-65.2790	0.1595	0.0559
27	26	186.4538	65.3349	0.1595	0.0559
	28	-459.5716	-68.1065	13.4527	1.9936
28	27	473.0243	70.1001	13.4527	1.9936
	29	-573.8950	-66.3353	18.8895	2.1834
29	28	592.7845	68.5187	18.8895	2.1834
	30	-269.6490	-126.9502	0.4269	0.2010
30	29	270.0758	127.1511	0.4269	0.2010
	31	-20.3022	-5.3493	0.0141	0.0037
31	30	20.3162	5.3530	0.0141	0.0037
	32	-7.2801	-2.2724	0.0006	0.0002
32	31	7.2807	2.2726	0.0006	0.0002
	33	-1.0040	-0.4540	0.0000	0.0000
33	32	1.0041	0.4540	0.0000	0.0000
Total cost				215.8269	14.3633

(ii) Case 2: *With Capacitor and no DG*

In this case, the analysis is tested through IEEE 33 bus system considering capacitor and there is no DG. The results as shown in table 10 illustrate the minimal purchased cost obtained by the proposed technique over standard WHO, AQO and SCSO models. Figure 15 depicts the comparison of the developed over typical techniques based on purchased energy cost and table 10 tabulates the corresponding values.

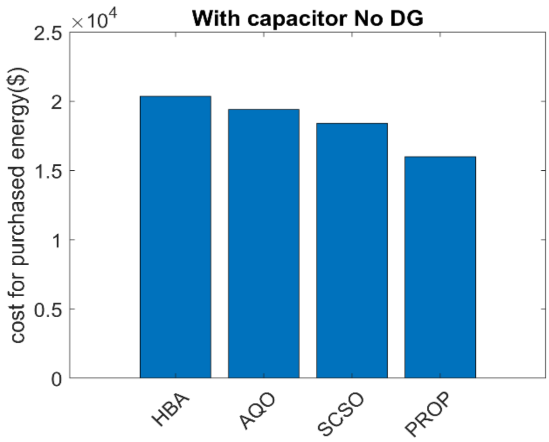

Figure 15: Comparative analysis based on purchased energy cost

Table 10: Purchased Energy Cost

	WHO	**AQO**	**SCSO**	**PROP**
purchased cost	20356	19417	18407	15991

***(iii) Case 3:** With DG and no Capacitor*

Here, the analysis is carried out by considering only DG and there is no use of capacitor. The results as described in table 11 depicts the corresponding total cost, capital cost, O&M cost, fuel cost, purchased cost, emission cost and reliability cost as stated in SSI-CS [23,24].

Table 11: Cost analysis

Total cost	5.11E+07
Capital cost	3.60E+07
O&M cost	1.57E+06
Fuel cost	51855
Purchased cost	7.72E+06
Emission cost	5.21E+05
Reliability cost	5.25E+06

***(iv) Case 4:** With both capacitor and DG*

In this case, the analysis is tested through IEEE 33 bus system considering both capacitor and DG as mentioned in our proposed methodology.

VI. Conclusion

A novel optimization methodology that takes system uncertainties and DG reactive capabilities into account for distribution system planning has been introduced in this research. When planning the development of the distributed network, the reactive capacities of renewable DG technologies, such as the SM-based biomass generator, the DFIG-based wind unit, and the VSI-based SPV unit were taken into consideration. Moreover, this research presented a newly integrated optimization technique termed as Aquila based sand Cat Swarm (Aq-SCS) Optimization that hybrid the standard AOA and SCSO algorithms for optimal tuning of DSEP. The recommended optimizing strategy is to lower the total system cost, which involves the cost of fuel, dependability, emissions, purchased energy, fixed and switchable capacitors, capital costs, and operations and maintenance. In order to assess where the DGs should be placed, this cost has been decreased. The results of the simulation also demonstrated that a reduction in total cost was achieved when the reactive abilities of distributed generation were included during the planning stage. Furthermore, it was found that the solar PV and wind-connected DG systems' reactive capacities enable them to equalize against the biomass-based generator. It is important to highlight that the framework for planning may easily be updated to include enhanced network management plans using the suggested technique. The advantages of load shedding in the best direction further demonstrate the value of our research, which closes the gap in research and merits more investigation in the future.

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