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ANALYSIS OF ADVANCED POWER DISTRIBUTION SYSTEM CONFIGURATION FOR SMART GRID WITH THREE TIE SWITCHES AND USING AI TECHNIQUE

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Abstract: The electrical power system has now grown into a more complex, integrated network that is continually expanding. As a result, the power system is afflicted by a variety of problems, including increasing power losses, voltage volatility, line overloads, and so on. The optimization of actual and reactive power by placing energy resources at appropriate buses can minimize losses and improve voltage profiles, especially in congested networks. As a result, the optimal renewable energy allocation (ODGA) issue is viewed as a more relevant tool for power system planning and operation operations, as the power grid rapidly changes dependent on the type and penetration level of renewable energy sources (RESs). In this article, the Aquila optimizer is utilized to alleviate this issue and reduce stress on the primary grid, making the grid more resilient. The Aquila optimizer (AO) is also employed in the optimization of distributed network. The approach proposed in this work has many objectives, including minimizing power loss and overall voltage fluctuation in a distribution system while keeping system operational and security restrictions in mind

***Index Terms* - Tie switches, Aquila optimizer, binary Aquila optimizer, power loss**

I. INTRODUCTION

The distribution network (DN) is critical in power systems since it is responsible for power supply from transmission systems to customers. However, the ever-increasing load has made it difficult for power providers to run DN effectively and dependably. Power loss has a severe impact on DN operational efficiency. As a result, reducing power loss is critical for DNs to run efficiently and inexpensively. Many ways have been developed in this area to reduce DN power losses. Due to the development context of power sources and investment prices, network reconfiguration (NR) and renewable energy integration are two notable strategies that have received a lot of attention. NR is an efficient way for reducing power loss in DNs. DNs are operated in a radial topology to reduce fault levels and efficiently safeguard coordination. In DNs, there are two types of switches: tie-line switches (usually open) and sectionalizing switches. (typically closed). NR creates a new network topology by changing the open/closed status of switches while retaining the system's radial topology. NR is an important grid approach that reduces active power losses while also improving voltage profile and system dependability.[1]

Furthermore, to minimize overloading, NR can redistribute weight from one branch to another. Due to energy deregulation, fossil fuel depletion, and environmental concerns, renewable energy has been rapidly integrated into DNs. Aside from NR implementation, the deployment of renewable energy units is a well-known grid method for reducing power losses and improving RDN voltage profiles. As a result, the use of NR in RDNs should be investigated in the presence of renewable energy. Since Merlin and Back first introduced the NR problem, a large amount of research has been done on the NR problem using a variety of approaches ranging from heuristic approaches such as the branch-and-bound method, modified branch exchange method, and switch exchange method to metaheuristic approaches such as particle swarm optimization (PSO), genetic algorithm (GA), biased random key GA (BRKGA), harmony search algorithm (HSA), heuristic rules-based fuzzy multiple objectives. Heuristic approaches, in general, have quick convergence, but they are incapable of dealing with large-scale systems with multiple restrictions. Meanwhile, metaheuristic approaches, which are best suited for large-scale networks, offer robust searchability to uncover optimum or near-optimal solutions. As a result, metaheuristic approaches' applicability to NR issues are continually developing. Many academics have recently used a variety of artificial intelligence and analytical methodologies to tackle the optimum renewable energy allocation problem in RDNs. Comprehensive analytical expressions were proposed to describe PV unit allocation for maximising technological benefits in RDN. Active and reactive power losses, voltage stability index, line congestion margin, and voltage deviations are among the goal functions. Mahmoud and Lehtonen provided general closed-form analytical equations for determining appropriate positions and sizes of multi-type REs and capacitors in RDNs in order to minimize reactive power loss [2-8]. Furthermore, the suggested technique included an optimum power flow (OPF) algorithm to account for system restrictions. Researchers are continually proposing new strategies to improve RDN performance. One of these initiatives is the merging of NR and optimum RE deployment at the same time. Recent metaheuristic research on the merging of these two effective tactics have been conducted. Shaheen et al. created an enhanced equilibrium optimisation algorithm (IEOA) to cope with optimum NR-RE integration. The IEOA approach was tested under various load situations on 33- and 69-bus systems, and its superiority was validated. Onlam et al. used the adaptive shuffled frogs jumping method to get optimal NR and renewable energy settings on a variety of 33- and 69-bus DNs in order to minimize system losses and improve voltage profile.

Murty and Kumar proposed NR and optimum renewable-based RE deployment in the face of load uncertainty. Tolabi et al. created a hybrid fuzzy-bees technique. To cope with the coupled problem of NR with shunt capacitors and renewable energy allocation, an artificial bee colony was merged with a hybrid approach of HSA and PSO. For dealing with NR, a fuzzy multi-objective method was used. Following that, a heuristic technique was used to determine the ideal NR, which resulted in a solution based on the original NR. For NR with REs present, a better plant growth modelling approach was presented to reduce power loss. Sensitivity analysis was used to determine the best RE placements. Bayat et al. created a heuristic strategy for allocating NR and renewable energy in order to minimize loss. To deal with NR and REs allocation in 33-bus and 69-bus REs, levy flights are integrated in a sine-cosine algorithm. The suggested problem took power losses and voltage stability index targets into account. HAS, adaptive CSA, FWA, big-bang crunch algorithm, hybrid grey wolf optimizer and PSO (GWO-PSO), electromagnetism-like mechanism (ELM), firefly (FF), and three-dimensional group search optimization (3D-GSO) are some other typical metaheuristic methods that have been used to handle the combination of NR and renewable energy allocation. According to the aforementioned literature review, employing metaheuristic algorithms to the integration of NR with renewable energy placement has various disadvantages.[9-11]

Most earlier research has concentrated on small and medium-scale DNs, with little regard for large-scale DNs. Furthermore, the integration of NR and RE placement is a combined optimisation issue, which is difficult to solve due to its complexity. Although metaheuristic algorithms' tremendous search capabilities are ideally suited for obtaining optimum solutions, there is no assurance that they will be beneficial for all optimization issues. Such procedures may not produce satisfactory results and may become trapped at a local optimum. As a result, establishing a suitable method to successfully address the simultaneous NR and REs placement is of importance, particularly for large-scale systems.

Motivated by the aforementioned issues, this paper introduces a novel binary Aquila optimizer for dealing with the simultaneous NR and DGs integration (SNR-RE) problem in REs. The goal of the SNR-RE issue is to minimize active power loss and maximize voltage stability index while maintaining system restrictions such as power balance, feeder capacity limits, bus voltage limits, renewable energy capacity and penetration limits, and radial topology constraints.

II. TYPES OF AI OPTIMIZATION IN POWER SYSTEM

Many power system planning, operation, and control challenges have been solved using mathematical optimization (algorithmic) approaches throughout the years. Real-world mathematical formulations are generated under particular assumptions, and even under these assumptions, the solution of large-scale power systems is not straightforward. On the other hand, because power systems are huge, complicated, and geographically dispersed, there are numerous uncertainties in power system problems. Deregulation of electricity utilities has lately added new concerns into the mix of old difficulties. It is preferable that solutions to power system issues be optimal worldwide, although solutions found by mathematical optimisation are usually optimal locally. Because of these realities, it is difficult to properly address many power system problems by pure mathematical formulation alone. As a result, in recent years, artificial intelligence (AI) techniques such as expert systems (ES), artificial neural network (ANN), genetic algorithm (GA), and fuzzy logic have evolved as a supplementary tool to mathematical approaches in power systems. The true start of AI is commonly cited as 1958. Various optimization strategies have been used to address the power systems problem, and a considerable number of articles in this subject have been published since 1950. Kothari et al. offered a review of several power system difficulties.

1. Genetic Algorithm (GA):

To find an optimized solution, GA employs the principles of genetics and natural selection. Genetic algorithms have been the subject of substantial work by David Goldberg (1989). Darwin's idea of evolution serves as the foundation for the genetic algorithm search technique. Search techniques based on populations include genetic algorithms. The many solutions produced by a genetic algorithm are referred to as chromosomes. The chromosomes are made up of a variety of control variables with random values whose values must be optimized. These chromosomes move because of the fluctuation in their values, which is used in the search process. The objective function of the chromosomal population is assessed. For the following iteration, the selection process selects and keeps the chromosomes with the best values of objective function. [12-13]

The crossover and mutation of the chromosomes from the previous iteration produces the chromosomes for the subsequent iteration. The chromosomes created for the following iteration are referred to as the kid, while the chromosomes from the prior iteration are referred to as the parents. A child chromosome is created during the crossover process, which involves combining a portion of one parent chromosome with a portion of another parent chromosome. Some parent chromosome values are changed throughout the mutation process to create a child chromosome. The objective function of the fresh pool of kid chromosomes is then assessed. When the stopping requirement is reached, these kid chromosomes take on the role of parent chromosomes again. The stopping criterion may be based on number of iterations or convergence of control variable values stored in chromosomes. GA is a rugged optimization technique with simple methodology. The demerit of GA is it getting trapped in local minima.

2. Particle Swarm Optimization:

The most popular artificial intelligence optimization method is called particle swarm optimization (PSO). It is based on how fish in a pool or a flock of birds behave when looking for food. Shi and Eberhart have reported the preliminary research on PSO. A population-based search approach is PSO. In PSO, a population is created by generating a large number of particles at random. PSO does not waste the particles like GA does. The particles travel around the multidimensional space in quest of the best answer

The particle considers its most recent individual best location and the best position reached by any of the particles as it travels across the multidimensional space. A big inertia weight makes it easier to search globally, whereas a lower inertia weight makes it easier to search locally. The PSO tends to have greater global search capability at the start of the run while having more local search capability near the conclusion of the run by linearly lowering the inertia weight from a reasonably big number to a small value during the PSO run. The PSO termination criterion may be a predetermined amount of iterations, particle convergence, or if the global best remains unchanged for a predetermined number of iterations. For PSO to operate at its best, the inertia weights and constants must be chosen properly. [14-15]

3. Ant Colony Optimization:

Ant Colony Optimization (ACO) was first presented by Dorigo in 1992. ACO is based on how actual ant colonies forage. A population-based search method called ACO uses ants to find food, or an optimized solution. Artificial ants build solutions through a stochastic process. Iteratively adding the elements of a solution to incomplete solutions while taking into account (i) any heuristic knowledge about the issue being addressed and (ii) pheromone trails results in a solution. Ants leave behind pheromone trails when they go along a path.

These traces disappear over time to make searching in fresh, untouched places easier. Ants adopt a building policy that is a function of the problem constraints rather than moving randomly on the construction graph. Ants often work to create workable solutions, but they are also capable of creating unworkable ones when necessary. The ant colony in ACO builds routes to travel between nearby solutions to the optimization issue. The way ants walk contributes to the optimization problem's resolution. The ants carry out daemon acts to carry out centralized actions that can only be carried out by a group of ants. ACO's poor computing performance is this technique's fundamental flaw.[16-19]

4. Simulated Annealing:

The thermodynamics-based Simulated Annealing (SA) approach takes its cues from the crystallization of materials during cooling. A solid can achieve a low energy state through the thermodynamic process of annealing. In annealing, the temperature of the solid is raised until it melts, and then the temperature is lowered until the solid's particles are arranged in a condition with the least amount of energy. The objective function of the issue is comparable to the solid's energy state. Another form of neighborhood search is SA. The answer with the highest (or lowest) value of the goal function triggers the search. If the new location has a lower (or higher) value for the goal function, the solution shifts to the new position. A move is considered to be a negative move if it causes the solution to move to a place with a greater (or lower) value of the goal function. Depending on how far along the search is, bad movements are permitted. At first, more mistakes could be permitted, but at the conclusion of the search process, fewer mistakes are allowed. At freezing point, the lowest temperature, bad behavior is not tolerated. Hill climbing refers to bad manoeuvres adopted by solutions to escape a local confinement. [20-21]

Until a predetermined number of iterations or the freezing point, the search algorithm keeps running. SA's flexibility in implementing various optimization issues, its ease of programming, and its capacity to avoid local optima trapping are its benefits.

5. Differential Evolution:

In 1995, Storn and Price established the concept of differential evolution. The difference between DE and GA is that the former can effectively handle both continuous and floating point numbers. A random beginning population is created by DE, which iteratively applies mutation, crossover, and selection processes to modify and enhance the population. The selection procedure and the mutation strategy that enables DE self-adaptive are the two primary distinctions between the genetic algorithm and DE algorithm. The present solution is modified during the mutation process using a scaled mutation factor. A parent and a random solution or two parents' components are combined in a crossover. The selection process, selects the parent or child solution through tournament selection process or any other similar process. The stopping criteria applied in DE is similar to that of GA, it may be a certain number of iterations, or convergence of solutions or if the best solution does not change for a specific number of iterations.

6. Tabu Search:

An example of a neighborhood search is Tabu Search (TS). Fred Glover has been the principal spokesperson for it. The neighborhood of the present solution is then searched by TS after starting with a random solution. A move is the modification of the solution value between iterations. Every time the current solution iterates, the neighborhood also shifts. The limitations of the optimization problem's restrictions and quantity of solutions limit the neighborhood search options. The Tabu List also places limitations on a solution's ability to move.

A list of movements that are forbidden is called the tabu list. The list is typically used to stop cycling and eliminates the possibility of looking for a solution that has already been found. The tabu list keeps changing as the search process progresses. The older entries in the tabu list are eliminated with newer entries. An aspiration criterion may also be introduced to override the tabu list, which helps achieve better results. The search process can be stopped after some predefined number of iterations or if the optimum result does not change for a certain number of iterations. TS on its own in not efficient to solve power optimization problem, it should be combined with some other search process to enhance the capability of the search process.

III. AQUILA OPTIMIZER (AO)

The Aquila optimizer (AO) is a recently suggested algorithm that mimics the natural Aquila hunting process. Four phases make up the hunting process: broadened exploration by soaring high with a vertical stoop, focused exploration by gliding with a contour flight, broadened exploitation by low-flying descending assault, and focused exploitation by strolling and seizing prey. The AO algorithm employs a range of behaviors to go from the exploration stage to the exploitation stage. The first two-thirds of repetitions replicate the exploration stage, while the latter third of iterations represent the exploitation stage. The AO method is shown mathematically as follows. [22]

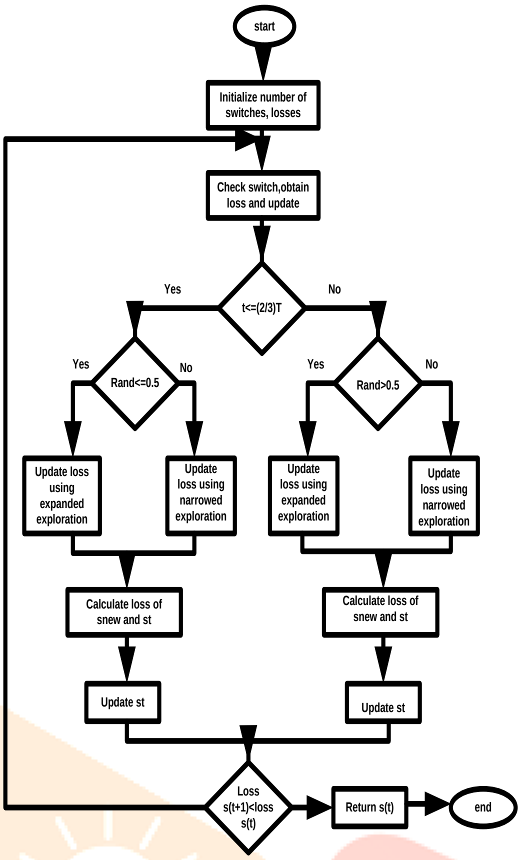

Figure.1 Flowchart-of-Aquila-Algorithm

Step 1: Initialization

In this first phase, the population of solutions has been generated at random and AO's other parameters are initialized. Initializing: The AO algorithm begins by spreading N solutions in a D-dimensional search space across a present range [L, U] by applying Equation.

$$S_{i,j} = L_j + r \times (U_j - L_j) \qquad (1)$$

where Xi,j is the j-th dimension of the i-th solution, Lj and Uj refer to the lower and upper bound value of the j-th dimension in the search space, and r is chosen at random from the range of 0 to 1. The position of solutions is kept in matrix XN×D. Then, by f(Xi), the fitness value of each solution is calculated.

Step 2: Expanded Exploration

Expanded exploration: An Aquila first determines the prey region and picks the optimal hunting location by high-soaring while stooping vertically. This behavior leads to the search space being explored from high altitudes to estimate where the prey can be located. In AO, this behavior is simulated to expand the exploration by Equation (2) and is executed when iter < (2/3 × MaxIter) and randomly generated value < 0.5,

$$S_1(iter+1) = S(iter) \times \left(1 - \frac{iter}{MaxIter}\right) + (S_M(iter) - S_{best}(iter) \times r) \qquad (2)$$

where S1(iter + 1) is the solution given by the prime method to use in the subsequent iteration and Xbest(iter) is the best solution found until the current iteration and approximates the position of prey. The (1 − iter Max Iter) term is utilized to regulate the extent of the exploration based on the number of iterations, where iter denotes the current iteration and MaxIter is the number of iterations that can be performed. In the iter-th iteration, SM (iter) indicates the mean of currently available solutions, as determined by

$$\left(S_M(iter) = \frac{1}{N} \sum S_i(iter)\right) \qquad (3)$$

Step 3: Narrowed Exploration

The second hunting method used by Aquila, the contour combat with brief glide, is intended for the third phase, or Narrowed Exploration, in which Aquila organizes the ground in order to circle the target animal to attack.

Detailed exploration: The second stage is the hunting technique known as contour flight of a brief glide assault. Aquila soars above the intended prey, gets ready to dive, and strikes when it is seen from a great height. This behavior enables the Aquila to narrowly examine a given area. When iter (2/3 MaxIter) and the randomly generated value > 0.5, this behavior is replicated in AO to limit the investigation.

$$S_2(iter+1) = S_{best}(iter) x Levy(D) + S_R(iter) + (y - x) x r \qquad (4)$$

where S2(iter + 1), SR(iter), and Levy(D) represent the solutions produced by the narrowed exploration strategy, a randomly selected solution from entire solutions in the iter-th iteration, and the Levy flight distribution function calculated by Equation

$$Levy(D) = sx\frac{ux\sigma}{v^{1/\beta}} \quad (5)$$

where s = 0.01, β = 1.5, and u and v are random integer numbers ranging in [0, 1].

$$y = p\cos\theta, x = p\sin\theta \quad (6)$$

$$p = r_1 + uD_1 \quad (7)$$

$$\theta = -wD_1 + \theta_1, \theta_1 = \frac{3\pi}{2}$$

(8)

Step 4: Expanded Exploitation

The principle behind the third hunting mechanism is essentially depicted in the fourth phase, dubbed Expanded Exploitation, where Aquila gradually descends into the targeted area and moves closer to the victim to strike. During the enlarged exploitation process, Aquila pursues its target using the third tactic. The Aquila is ready to take flight and launch an assault after carefully locating the prey zone. The Aquila descends vertically and makes the initial stroke to gauge how the prey would react to the attack. Low-flying descent attacks occur when iter > (2/3 MaxIter) and a randomly generated value produced by Equation 0.5.

$$S_3(iter + 1) = \left(S_{best}(iter) - S_M(iter)\right)\alpha - \gamma + ((U - L)Sr + L) \quad (9)$$

Step 5: Narrowed Exploitation

Finally in the fifth and the final step, the idea is taken from last attacking method of Aquila widely known as walk and grab attack to frame the last step known as Narrowed Exploitation

The fourth hunting strategy is used during the narrower exploitation step when the Aquila approaches the prey and attacks randomly. This behavior is called walking and grabbing the prey and is done when iter > (2/3 × MaxIter) and randomly generated value > 0.5 by Equation

$$S_4(iter + 1) = \left(QF(iter)S_{best}(iter)\right) - G_1S(iter)r - G_2Levy(D) + rG_1 \quad (10)$$

where S4(iter + 1) denotes the generated fourth search solutions, S(iter) is the iter-th iteration's current solution, and to balance the search strategy, a quality function called QF is calculated by Equation

$$QF(iter) = t^{\frac{2(r-1)}{(1-maxite)^2}} \quad (11)$$

G1 and G2 are values to represent the Aquila's prey tracking movements such that the G2's value is decreasing from 2 to 0.

$$G_1 = 2(r - 1) \quad (12)$$

$$G_2 = 2(1 - \frac{iter}{maxiter}) \quad (13)$$

3.1 Binary Aquila Optimizer (BAO) Algorithm

The search space of a binary optimization problem may be seen as a hypercube, where a point can be moved by changing one or more bits of its position. Continuous techniques are unable to update positions for binary optimization problems like feature selection because binary space only has two possible values, "0" and "1". One of the essential elements of metaheuristic-based feature selection algorithms, which translate the continuous search space to the discrete space, is the transfer function. Transfer functions are used to assess the probability of altering the elements of a position vector to 0 or 1 based on the value of the i-th solution's vector in the d-th dimension. S-shaped and V-shaped transfer functions are the two most prevalent forms of transfer functions such that continuous metaheuristic algorithms can be discretized and utilized to solve binary optimization problems by converting a real vector into a binary vector. [23]

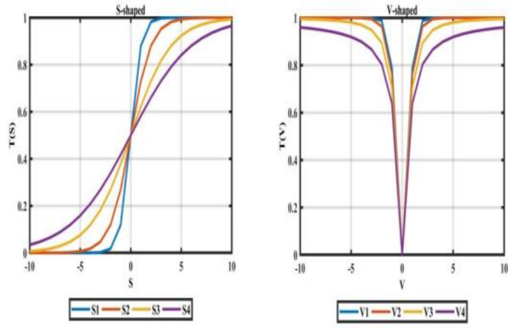

Figure.2. S-shaped and V-shaped transfer functions

Algorithm
1. The binary Aquila optimizer (BAO)
Input: loss, switch combination MaxIter (maximum number of iterations)
Output: The best solution (Sbest)
1 : Begin
2 : Initializing iter = 1, $\alpha = 0.1$, $\delta = 0.1$.
3 : Generating a initial loss S.
4 : While it $\leq$ MaxIter
5 : Evaluating the Loss values and set the Sbest(it).
6 : If iter < (2/3) × MaxIter
7 : If rand < 0.5
8 : Calculating S1 (iter + 1) using Equation (2).
9 : Updating S(iter + 1) and Sbest(iter).
10 : else
11 : Calculating S2 (iter + 1)
12 : Updating S(iter + 1) and Sbest(iter).
13 : End if
14 : else
15 : If rand < 0.5 then
16 : Calculating S3 (iter + 1) using Equation (9).
17 : Updating S(iter + 1) and Sbest(iter).
18 : Else
19 : Calculating S4 (iter + 1)
20 : Updating S(iter + 1) and Sbest(iter).
21 : End if
22 : End if
23 : Calculating the probability values
24 : Updating binary position.
25 : iter = iter + 1.
26 : End while
27 : Return the best solution -loss minimization (Sbest).
28 : End

3.2 MATLAB implementation of proposed method with AI

Distribution System 69-bus test system with the reclosure of 3 tie switches

In the default setup of the system, 69–73 tie switches are generally open while 1-68 sectionalize switches are normally closed. For every tie switch, there are five loops. There are 2.69 MVAR and 3.8 MW of total actual and reactive power demands, respectively. 12.66 KV is the system base voltage. [24-28]

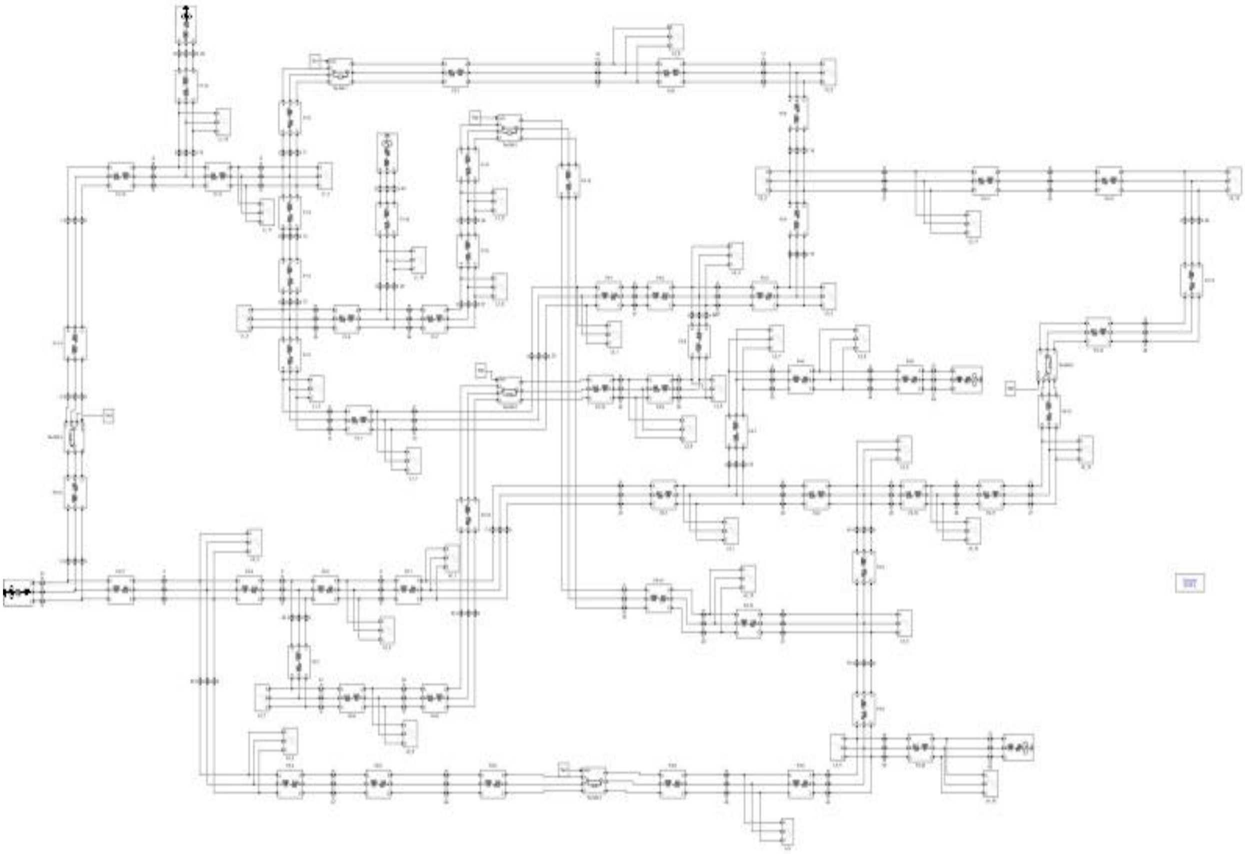

Table 1 Test Cases for Case Study

Case	Closed Tie SW	Opened Tie SW
Case1	No	All
Case2	1,2,6	3,4,5
Case3	2,3,5	1,4,6
Case4	3,4,6	1,2,5

Each feeder provides electricity to a variety of loads for household, business, and industrial clients. The majority of load profiles vary by client type. The test model's feeder load profiles are shown in Fig. Feeder 3 has a daylong load that is comparatively light. Feeders 1 and 2, on the other hand, exhibit a significant load.

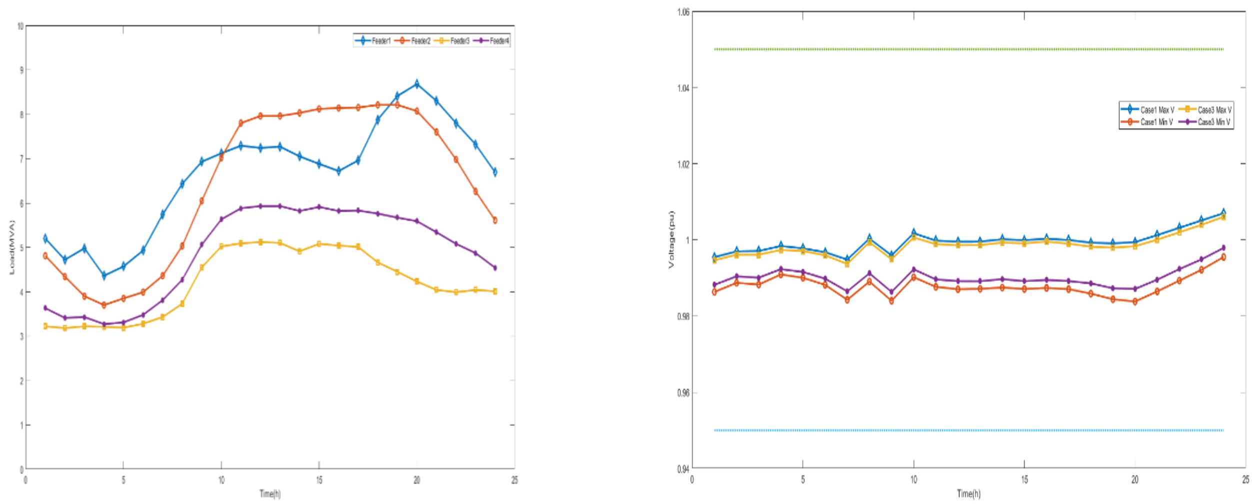

Figure.3 Load profile , Maximum and minimum voltage of each feeder in the test distribution system model

Power distribution systems with several linked REs that regulate voltage might malfunction. As a result, we contrasted examples 1 and 3's voltage regulation's robustness. At line sections F2-5, F3-6, and F4-14, the REs were linked together. The generation capacity was then changed from 1 to 10 MW. Fig. 10 displays the highest and minimum voltages in the test power distribution system. In Case 1, the 24 MW produced by the REGs caused the LDC technique to fail, resulting in undervoltage. However, in instance 3, the power distribution system could supply the 30 MW produced by the REs within a range of acceptable voltages.
The losses accrued during a 24-hour period for each scenario are shown in Fig.4. The optimal course of action for loss minimization is to upgrade to example 3, where the loss is decreased from 6.74 to 6.42 MWh. Power flow analysis needs to be done for each case, though, in order to assess loss reduction between scenarios. However, the processing time will lengthen if there are more tie changes.

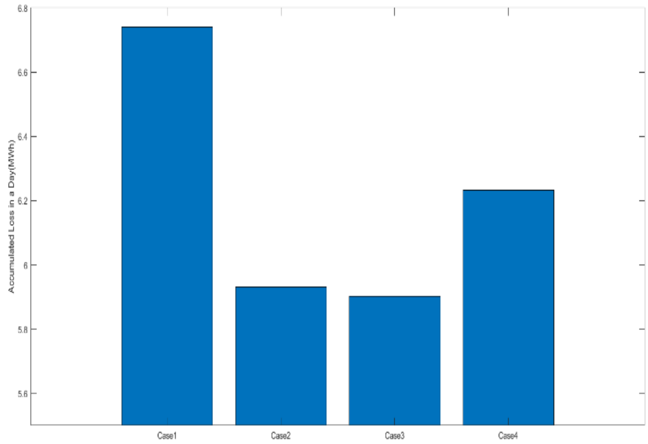

Figure 4. Losses during 24 h in the test distribution system model.

Table 2 Test Cases for Case Study

Case	Closed Tie SW	Opened Tie SW
Case1	No	All
Case2	2,3,5	1,4,6
Case3	1,2,6	3,4,5
Case4	3,4,6	1,2,5

The total ASV is highest in case 3. Therefore, this case is the best loop-upgrading solution for loss minimization. This shows that we can select a loop-upgrading path without conducting power flow analysis for each case.

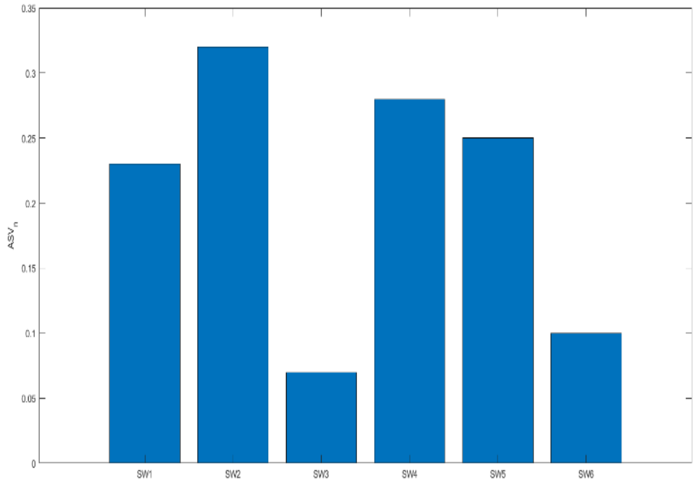

Figure.5 ASV for each tie switch

As seen in Fig5., the suggested switching significantly affects busbar voltage. Following reconfiguration, the minimum bus bar

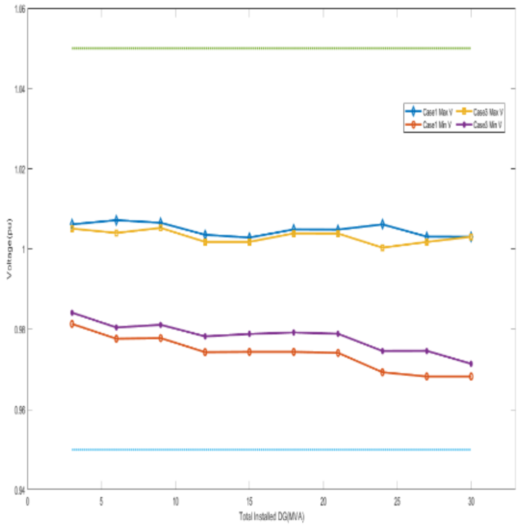

Figure.6 Maximum and minimum voltages with REGs of case 1 and case 3

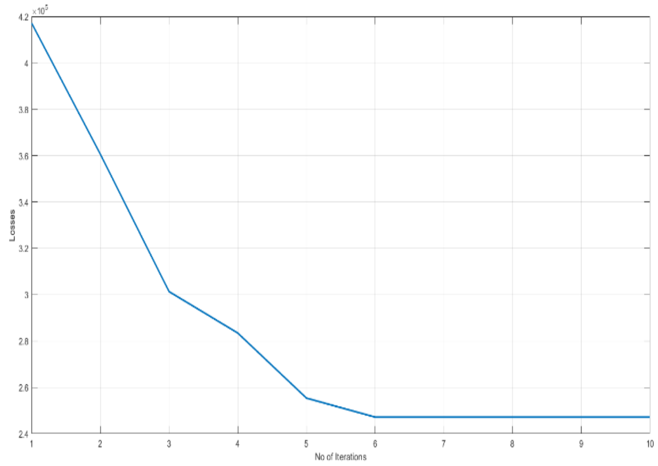

Figure.7 Initial Losses in the 69-bus system

voltage for the 69 Distribution network increases from 0.95 to 1.01 at bus 61.
The proposed switching has reduced the initial losses in the 69-bus system from 4.2 to 2.45 kW saving 1.75 kW.

Table 2 Results Comparison For 69 Bus Network

Operation	Losses	Switch combination	Switches closed	Switches opened
Reclosure of 2 tie switches	6.42 MWh	Case 3	2,5	1,3,4,6
Reclosure of 3 tie switches	5.93 MWh	Case 3	1,2,6	3,4,5

Operation	Minimum voltage	Maximum voltage
Reclosure of 2 tie switches	0.973	1.01
Reclosure of 3 tie switches	0.975	1.02

The above tables gives the comparison between 2 tie switches closed and 3 tie switches closed in terms of losses, ASV, minimum voltage and maximum voltage where 3 tie switches combination gives better performance in terms of losses by 7.6% approximately.
According to Figure, the system's default setup has 69-73 tie switches that are generally open and 1-68 sectionalize switches that are normally closed. For every tie switch, there are five loops. There are 2.69 MVAR and 3.8 MW of total actual and reactive power demands, respectively. 12.66 KV is the system base voltage. The REs' actual and reactive power injection limitations are equivalent to those of the Distribution 33-bus test system.
According to Figure, the biggest improvement in power loss reduction is for the scenario employing the suggested approach. Power loss for PQ+ type RE installation after reconfiguration is not smaller than RE installation before reconfiguration.

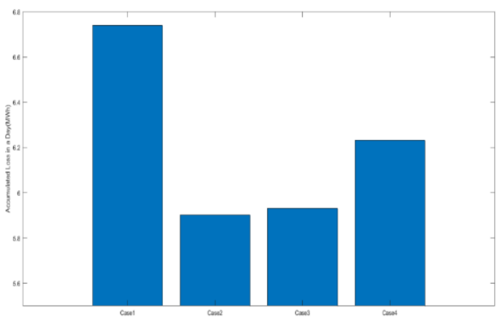

Figure.8 Accumulated losses vs different combinations with proposed approach

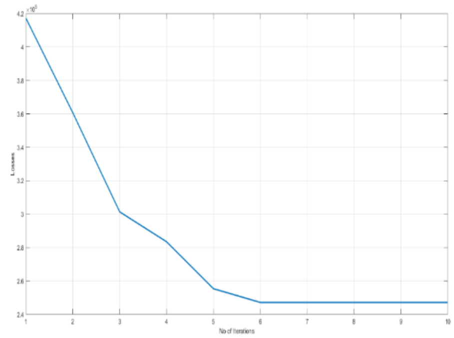

Figure.9 Initial Losses in the Distribution 69-bus system with proposed approach

Table 3: Results Comparison For Distribution 69 Bus Network

Operation	Losses
Reclosure of 2 tie switches	6.42 MWh
Reclosure of 3 tie switches	5.93 MWh
Binary Aquila Optimizer Algorithm	5.89 MWh

From the above analysis, it is clear that 69 bus system with Binary Aquila Optimizer Algorithm with Artificial Intelligence has shown better performance when compared with 69 bus system without Artificial Intelligence.

Conclusion

In this work, two binary variations of the Aquila optimizer (AO) were introduced and utilized to discover the wrapper approach's effective features. S-shaped and V-shaped transfer functions are utilized to alter the continuous version of Aquila optimizer into two binary algorithms, SBAO and VBAO. The Binary Aquila optimizer's performance over numerous iterations indicates its ability to find effective features while balancing exploration and exploitation. Binary Aquila Optimizer Algorithm with Artificial Intelligence has shown better performance when compared with Distribution 69 bus system without Artificial Intelligence.

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