Behavior of the Social Spider Technique on Network Reconfiguration

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ABSTRACT

The goal of this paper is to offer a new strategy for solving the network reconfiguration problem with the aim of decreasing real power loss and enhancing the voltage profile in the distribution system. Social spider optimization (SSO), a new swarm algorithm, is employed to concurrently reconfigure and find the best network. The proposed method was tested on 30-bus mesh and 33-bus radial distribution systems at fixed load levels. To show the performance and efficacy of the suggested method, it was compared to optimization methodology, such as the genetic algorithm, harmony search algorithm, Kruskal's maximal spanning tree, discrete evolutionary programming, and cuckoo search algorithm. The findings reveal that SSO is a strategy worth investigating for tackling the network reconfiguration problem.

Keywords: Network Reconfiguration, Radial Network, Swarm Approaches, Nature-Inspired Algorithm

LIST OF SYMBOLS

SSO	Social Spider Optimization
NR	Network reconfiguration
GA	Genetic Algorithm
CSA	Cuckoo Search Algorithm
HSA	Harmony Search Algorithm
xd	Lower bound of switches
xu	Upper bound of switches
$dims$	Number of switches
$itern$	Number of iterations
$spidn$	Number of computation elements
fit	Fitness function
x	Vector
$V_{\min}$	Minimum voltage post reconfiguration
$spbest$	Best position of the spider
$spbesth$	Entire history of the switch configurations

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1. INTRODUCTION

Network reconfiguration may be used for reducing power loss, and enhancing voltage profiles. It entails altering the network's topology with the help of switches deployed throughout the network. Adjustment of the topological configuration is performed through network reconfiguration by opening or closing the tie and sectionalizing switches. Loss minimization enhances the improvement in voltage profile.

The preponderance of articles on the same simple approach have addressed distributed network reconfiguration across the years [1–11], with only the methodology and objective function changing. Several swarm algorithms are being developed to mimic the behavior of insect or animal groups in nature, using a combination of deterministic rules and randomization. The fundamental disadvantage of evolutionary optimization methods is the lengthy execution time necessary to solve the problem due to an enormous number of power flows being required. The cuckoo optimization algorithm, simulating the habitat of cuckoo birds [12], the bacterial foraging optimization algorithm for studying the communal foraging behavior of bacteria [13], the artificial bee colony approach which mimics the collaborative behavior of bee communities [14], and particle swarm optimization which mimics the social behavior of fish schools and bird flocks. [15]. One of the several features of these techniques is that even if there is no mathematical solution to a problem, it can still be solved [16]. Only a few studies have used binary versions of metaheuristic strategies to solve the network reconfiguration problem, and these mostly employ prominent methods, such as particle swarm optimization and the genetic algorithm [17–19]. When a male dominant spider discovers one or more female members within a specific range, the mating procedure begins. It reproduces by mating with all the females. [20]. Binary particle swarm optimization is implemented in [21] for reconfiguration in the case of reduced power loss. In this case, the binary particle swarm optimization response vector comprises all the system's switches. Closed switches are represented by one bit, while open switches are represented by a zero bit. Many academics have been drawn to the unique and exotic collective behavior of social insects. The execution of extremely complex tasks by insect swarms of relatively simple and 'unintelligent' individuals using only limited local knowledge and basic behavioral principles, are shown in these groups' cooperative swarming behavior [22]. Web production and interpersonal relationships are some of the few activities that members of a social spider colony engage in, depending on their gender. The web is a vital aspect of the colony because it offers all members a common environment as well as a means of communication. Through tiny vibrations, mating prospects are sent across the web.

Individuals use localized information to execute their own collaborative behavior, creating a simultaneous impact on the colony's social control [23–26]. The functional notions of a social spider colony are used in this study to build a revolutionary swarm optimization approach. All social spiders communicate through a shared web encompassing the entire environment. The proposed method yields a query space, representing a spider location in the collaborative web [27]. The social spider optimization technique is implemented in this paper for network reconfiguration. Although the social spider optimization algorithm has been well-developed for a variety of issues in various fields, the applicability of its binary equivalent for addressing issues in the power system, such as network reconfiguration, remains a concern.

Despite the fact that SSO is not a binary optimization technique, its objective function is written in such a way that it can be used for binary optimization to improve the chances of obtaining the goal of minimizing active power loss to address the network reconfiguration issue. Electric networks with 30-node and 33-node are chosen to reconfigure for power loss reduction, $V_{\min}$ and the voltage stability index to examine the efficacy of the SSO algorithm to meet the NR challenge. To demonstrate the importance of applying the proposed methodology, a detailed comparative analysis of indices, i.e., real power loss, $V_{\min}$ (p.u.), and voltage stability index is conducted to indicate the performance of the proposed the GA [41] and Kruskal's maximal spanning tree algorithm [38] for a 30-node system. A comprehensive comparative assessment of indices, i.e., real power loss and $V_{\min}$ (p.u.), reflecting the effectiveness of the proposed technique using discrete evolutionary programming [39], CSA [42], and HSA [17], is accomplished for a 33-node system to illustrate the significance of implementing the appropriate methodology. The suggested technique discovers the best topographical configuration of a power network for 30 and 33-node systems with the least amount of real power loss, $V_{\min}$ (p.u.), and voltage stability. The goal function and limitations are taken into consideration, and the suggested methodology successfully tested on IEEE 30 and IEEE 33-bus systems. Additionally, the effect of including additional branches to the 33-node system to address the NR problem is also examined in this paper. The binary domain for the NR problem is implemented through the SSO technique.

This paper is organized as follows. The articulation of the problem is presented in Section 2, while Section 3 describes the SSO in detail. Section 4 discusses the implementation of SSO to address the issue of NR. Sections 5 and 6 provide the numerical findings and concluding notes, respectively.

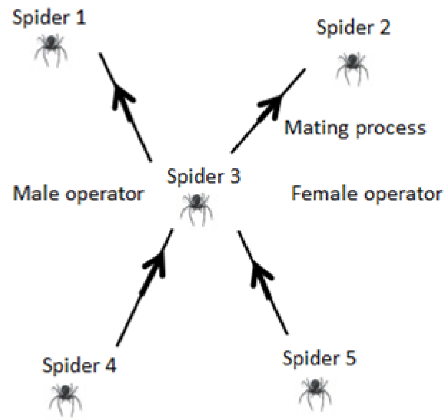

Fig. 1: *Schematic depiction of SSO.*

2. ARTICULATION OF THE PROBLEM

As shown in Fig. 1, each spider is associated with a weight and fitness parameters. In the proposed methodology, these parameters are dependent on the power loss of the evaluated network. The fitness parameters are updated based on the vibration intensity produced by the spiders. The mating process helps in optimizing the network and thus the power loss.

2.1 Circulation of Power

The condition of the switches is altered to reconfigure the network. The purposes of this system modification are to reduce power loss and enhance reliability.

$$Z = \Delta P_l^r + \Delta V_d \tag{1}$$

where ΔP_l^r, following restructuring, is the proportion of overall power dissipation in the branches. ΔV_d is the maximal voltage dip for all buses is computed by employing the proportions of bus voltages to create the voltage fluctuation index.

In Eq. (1), the variation in losses after the redesign along with the divergence from the base voltage are taken into account, with the aim of minimizing the quantities. The limitation is to keep the network's radial topology to provide all load locations.

System power losses are computed by summing the deficits of all operational system branches together as represented in Eq. (2).

$$P_l = \sum_{j=1}^{N_{ac}} R_j \frac{P_j^2 + Q_j^2}{V_j^2} \tag{2}$$

$$N_{ac} = N_b - 1 \tag{3}$$

where P_j and Q_j depict the 'j' real and reactive power of the bus. R_j is the line section's resistance, V_j portrays the voltage and N_{ac} is the number of operational branches.

The challenge of system reconfiguration is that the switches can only be in one of two states: open or closed. A binary vector can be used to represent the switch status by attributing a value of 1 to the 'close' state and 0 to the 'open' state. Every branch in the network requires a switch control to determine the number of sectionalizing switches N_s and tie switches N_t. The overall total of handled switches N_T is depicted in Eq. (4):

$$N_T = N_s + N_t \tag{4}$$

A binary character y represents the configuration of the switches, with zeros indicating open switches and one signifying closed switches.

MATPOWER is implemented in this work which is an open-source MATLAB power system simulation framework. It is extensively utilized in the pedagogy for optimal power flow (OPF) computation. It also comes with capabilities for managing OPF-based bidding platforms as well as co-optimizing inventories and power [32]. Computational load power flow modeling is employed through MATPOWER to calculate the system power loss of the objective function. The application is encountered during the objective function assessment procedure [33].

3. SOCIAL SPIDER ALGORITHM

The SSO was first introduced by Cuevas *et al.* [27]. The operative concepts of the social spider colony are employed to guide the development of a new swarm optimization algorithm in this research. The SSO represents the overall computational complexity of a common network in which all social spiders communicate. Therefore, every response symbolizes a spider location in the shared web inside the exploration area. Every spider is assigned a weight based on the strategic objective function, illustrated by the social spider. Male and female inquiry agents are represented by the technique. Every species is accompanied by a number of adaptive operators that the replicate various cooperative behaviors typically recognized throughout the colony, based on gender. The extremely female-influenced swarms of social spiders are an intriguing feature. The method begins by identifying the proportion of female and male spiders that will be characterized as individuals in the complex computation in an attempt to replicate this phenomenon. The proportion of females F_N is chosen arbitrarily from a limit of 65–90% of the overall population P. As a result, the accompanying equation is used to compute F_N:

$$F_N = floor\left[(0.9 - rand \cdot 0.25) \cdot P\right] \tag{5}$$

where $floor(\cdot)$ is a function that converts a real value to an integer value and rand represents the random number which varies from 0 to 1. The calculation of the number of male spiders M_N is depicted through the complement of P and F_N.

$$M_N = P - F_N \tag{6}$$

Binary event allocation is used in the proposed approach. It also has exclusivity and progressive adaptation depending on swarm heterogeneity. The exclusivity replenishes the first member in a freshly generated population with the fittest individual identified thus far, bypassing the choice and pairing methods and therefore preserving the individual throughout algorithm repetitions. The mean standardized variation of feasible solutions is used to calculate diversification. The preference technique employs the vector V of swarm cost factor parameters. The suggested computation cognitive approaches can be stated as mentioned earlier [37]:

Approach 1: Specify the proportion of male and female spiders in the overall community.
Approach 2: Compute the radius of mating by starting with the female and male individuals arbitrarily.
Approach 3: Estimate the mass of each spider.
Approach 4: Female spiders should be moved in accordance with the female collaborative operator's instructions.
Approach 5: The male spiders should be moved in accordance with the male collaborative operator's instructions.
Approach 6: Execute the mating procedure.
Approach 7: The procedure is complete if the final conditions are satisfied; otherwise, return to Approach 3.

3.1 Attributing Fitness

The spider size, in a physiological analogy, is a feature that assesses an entity's ability to adequately execute adequately its designated responsibilities. Each spider is assigned a weight w_s that symbolizes the optimal proposal correlating to the spider s of population P.

$$b_s = \max_{x \in \{1,2,\ldots,N\}} Z(s_x) \tag{7}$$

$$wor_s = \min_{x \in \{1,2,\ldots,N\}} Z(s_x) \tag{8}$$

where b_s and wor_s are the best and worst values for contemplating the minimization problem.

$$w_s = \frac{Z(p_i) - wor_s}{b_s - wor_s} \tag{9}$$

where $Z(p_i)$ denotes the fitness function generated from the spider positioning assessment p_i in relation to the optimization problem $Z(\cdot)$.

3.2 Reverberations Are Modeled Using the Collaborative Web

The communal net serves as a means for community individuals to exchange data. This message is encrypted as little oscillations; essential for the population's communal functioning. The vibrations are determined by the spider's mass and distance from the source. Since the distance between the individual who causes the vibrations and the individual who perceives them is relative, members who are closer to the member causing the vibrations sense higher vibrations than those further away. In order to emulate this progression, the vibrations perceived by member x and the consequences of the data sent by the member y are modeled using the following equation.

$$Osc_{x,y} = w_y \cdot e^{-d^2_{x,y}} \tag{10}$$

where $-d^2_{x,y}$ portrays the length of a line fragment connecting two locations in the Euclidean space among x and y as a result $d_{x,y} = \|s_x - s_y\|$. Despite the fact that any pair of individuals can be used to estimate the vibrations felt, the SSO technique takes into account the previously mentioned specific correlations.

Individual $x(s_x)$ perceives vibrations $Oscch_x$ as a consequence of evidence provided by individual $ch(s_ch)$, who is an entity with two essential attributes: it is the closest individual to x and has a heavier mass than $x(w_ch > w_x)$. The vibration $Oscbe_x$ felt by member x is a reaction of the circumstances provided by individual $be(s_{be})$ with 'be' representing the individual with the optimum weight of the overall population P and thus $w_{be} = \max_{x \in \{1,2,\ldots,N\}} w_x$. Individual $x(s_x)$ perceives vibrations $Oscfe_x$ as a consequence of evidence provided by individual $fe(s_{fe})$ with 'fe' becoming the closest female entity to x.

$$Oscch_x = w_{ch} \cdot e^{-d^2_{x,ch}} \tag{11}$$

$$Oscbe_x = w_{be} \cdot e^{-d^2_{x,be}} \tag{12}$$

$$Oscfe_x = w_{fe} \cdot e^{-d^2_{x,fe}} \tag{13}$$

3.3 Getting the Population Established

The SSO, like other optimization computations, is an evolving procedure in which the overall population is arbitrarily initialized. The initialization of the set T of M spider places is the first step in the process. Every other spider location, whether it be $female_x$ or $male_x$, is an m-dimensional matrix representing the attributing parameters that need to be optimized. The accompanying equations illustrate how such quantities are dispersed arbitrarily and equitably within the pre-specified significantly lower component limit p_y^{low} and the upper starting component limit p_y^{high}:

$$female^0_{x,y} = p_y^{low} + rand(0,1) \cdot \left(p_y^{high} - p_y^{low}\right) \tag{14}$$

$$male^0_{z,y} = p_y^{low} + rand(0,1) \cdot \left(p_y^{high} - p_y^{low}\right) \tag{15}$$

where $x = 1, 2, \ldots, M_{female}$, $y = 1, 2, \ldots, m$, and $z = 1, 2, \ldots, M_{male}$ denote the parameterization and corresponding indices, while zero denotes the starting population. $rand(0,1)$ is a function that creates an arbitrary range of between 0 and 1. As a result, the y-th component of the x-th female spider placement is $female_{x,y}$.

3.4 Controller for Mating

In a social spider community, prominent males and females execute mating. When a predominant male m_d spider ($d \in D_{dominant}$) uncovers a set E^d of female individuals along a particular radius R (mating range), it mates, establishing new offspring f_n produced by taking into account all the components of the set T^d created by the unification $E^d \cup m_d$. It should be noted that the mating process is cancelled if the set E^d is null. The radius of the spectrum R is determined by the size of the objective function. The radius R is computed using the appropriate framework:

$$R = \frac{\sum_{y=1}^{n} p_y^{high} - p_y^{low}}{2 \cdot n} \tag{16}$$

The mass of each participating spider (components of T^d) determines the possibility of each individual being influenced by the next offspring during the mating procedure. The spiders with a bigger mass have a greater chance of influencing the emerging product, while those with a lower mass are less likely to do so. The roulette technique assigns each member's impact likelihood $P_{s_{ip}}$, presented as specified in the following equation:

$$P_{s_{ip}} = \frac{w_{ip}}{\sum_{y \in T^k} w_y}, \quad y \in T^d \tag{17}$$

4. IMPLEMENTATION OF SSO TO ADDRESS THE ISSUE OF NETWORK RECONFIGURATION

The switching of activities necessitates the assignment of analysis and control to each branch in the system. The solutions are provided as binary characters to aid the analysis and investigation operations, with zero signifying no interconnection and one signifying closed connections. The set of alternative network topologies given $C(N_t, N_s)$ is huge and rises rapidly with both N_t and N_s. At the time, the set of radial arrangements is significantly lower, equivalent to the number of spanning trees $\varsigma(B)$ in graph structure B. As a result, it is advantageous to preserve the viability of the approach throughout the optimization process.

The network graph connection is verified initially. If the network is not linked, the following switches are locked until it is. Only certain switches that do not really create cycles can indeed be closed at this point. Eventually, new interconnections are established until the system topology transforms into a tree, corresponding to a radial network arrangement. The adjustments actually tested are saved while altering the individual to save unwanted repeats. Cost functions are set to equal the penalty value proportional to the number of isolated nodes or branches. Cost functions are considered equivalent to a penalty value proportionate to the number of closed loops in the existence of any closure loop. The next sequence of switches is computed by employing the proposed methodology if the maximal number of repetitions is not met.

4.1 The Penalty Functions

The efficacy target of the system reconfiguration approach in this paper is system power loss. The SSO algorithm searches for the optimal switch status to minimize system power loss. The position vectors of the particles in the SSO represent the switch state to address the system reconfiguration challenge. To ensure the viability of a set of switch configurations, the electrical connection from the source to the load must be established as a restriction enforced on each position vector. A fitness function must be constructed to analyze the appropriateness of the solution provided by the particles at each step of the recurrence. This fitness function is used to analyze a particle's individualized best position vector $spbest$ and the global optimal position vector $spbesth$. Penalty functions cope with restrictions more effectively using the proposed methodology. The objective function is formulated to retrieve the radial structure from the IEEE 30-bus mesh network and IEEE 33-bus system. The penalty function must meet load demand and should have no isolating node. Moreover, the conventional closed-loop configuration and open-loop function of a power distribution network necessitates radial power delivery following reconfiguration, with no loop produced. The following analytical procedures are proposed to address the network reconfiguration issue in the distribution system to reduce real power loss.

The goal of implementing the penalty function is to send 'feedback' proportional to the degree of unwanted behavior and contributes to the cost function (number of islands and closed loops) to obtain the fitness function. When an optimization algorithm attempts to reduce the cost function, it learns about the factors that cause a dramatic increase in error. Thus, the penalty functions ensures that the optimization algorithm maintains the constraints while generating an output. To remove the possibility of a network break, discover the islands, and calculate the least likelihood of power loss, the penalty function is implemented. If a cycle exists, the penalty function undertakes the task of determining the closed loop relevant to the network, resulting in a new penalty function.

With the proposed methodology, the SSO technique is implemented as a metaheuristic soft computing tool to achieve the objective functions: (i) minimized power loss (P_{loss}), (ii) configuring an optimal radial network, and (iii) removal of isolated points. SSO is applied as a search algorithm and the state relationship is maintained with the proposed methodology. The MATPOWER is used as a computational toolbox to examine the state of the switches for the IEEE 30 and IEEE 33-bus systems, respectively, while the switching configuration is considered by default, based on the MATPOWER knowledge. Analysis of the entire network of IEEE 30 and IEEE 33-bus systems is executed through MATPOWER. The constraint function is designed to verify the presence of isolated points or groups.

The fitness function is computed through the exclusion of isolated points or groups, followed by calculating the least amount of power loss. Each group and solitary point are depicted as an island, and there should only be one group and no isolated points in the ideal scenario. The second penalty function is used to check for the presence of closed loops or cycles. The penalty function introduced in this study is representational of the number of cycles because, in theory, the number of cycles should be equal to zero. This is a method for conveying feedback to the proposed methodology and summarizes the existence of a closed-loop system. The function is configured to remove open switches and represent bus data in graph terminology. The number of computational components in the spider is set at 70, and the number of iterations computed is 1000.

The implementation of the optimization technique results in the best spider position and fitness function. The local minima data is obtained through mathematical representation within the boundary conditions. The best spider position is crucial since it retains all the switching information. The proposed method presented in the form of a flow chart in Fig. 2 can be described according to the following steps:

- *Step 1*: Initialize the population size, lower bound, upper bound, iterations, and number of spiders as the basic parameters of the SSO algorithm.
- *Step 2*: Select the network and initialize the set of switches randomly, each with a value of either ON or OFF.
- *Step 3*: Evaluate the objective function based on a cost function that depends on real power loss, isolated nodes, and network cycles.
- *Step 4*: Repeat the process until maximum iterations are obtained.

Fig. 3 depicts the pseudo code of the proposed methodology. The convergence of the optimization process presented in Fig. 4 shows the iteration at which the radiality and minimal power loss are reached. The computational time required is 458 seconds considering the time complexity of the objective function.

5. NUMERICAL FINDINGS

5.1 The 30-Node System

The effectiveness of the SSO method is evaluated in this research using IEEE 30 test power systems. In [34, 35], the line and bus data of the IEEE 30-bus system are mentioned, while [29] provides the generating data. The voltage magnitude of load buses and generators is limited within the range of $0.95\,\text{p.u.} \leq V \leq 1.1\,\text{p.u.}$ [29].

As depicted in Fig. 4, the optimal solution has been found for the majority of iterations. The system's reactive and actual power demands are 283.40 MW and

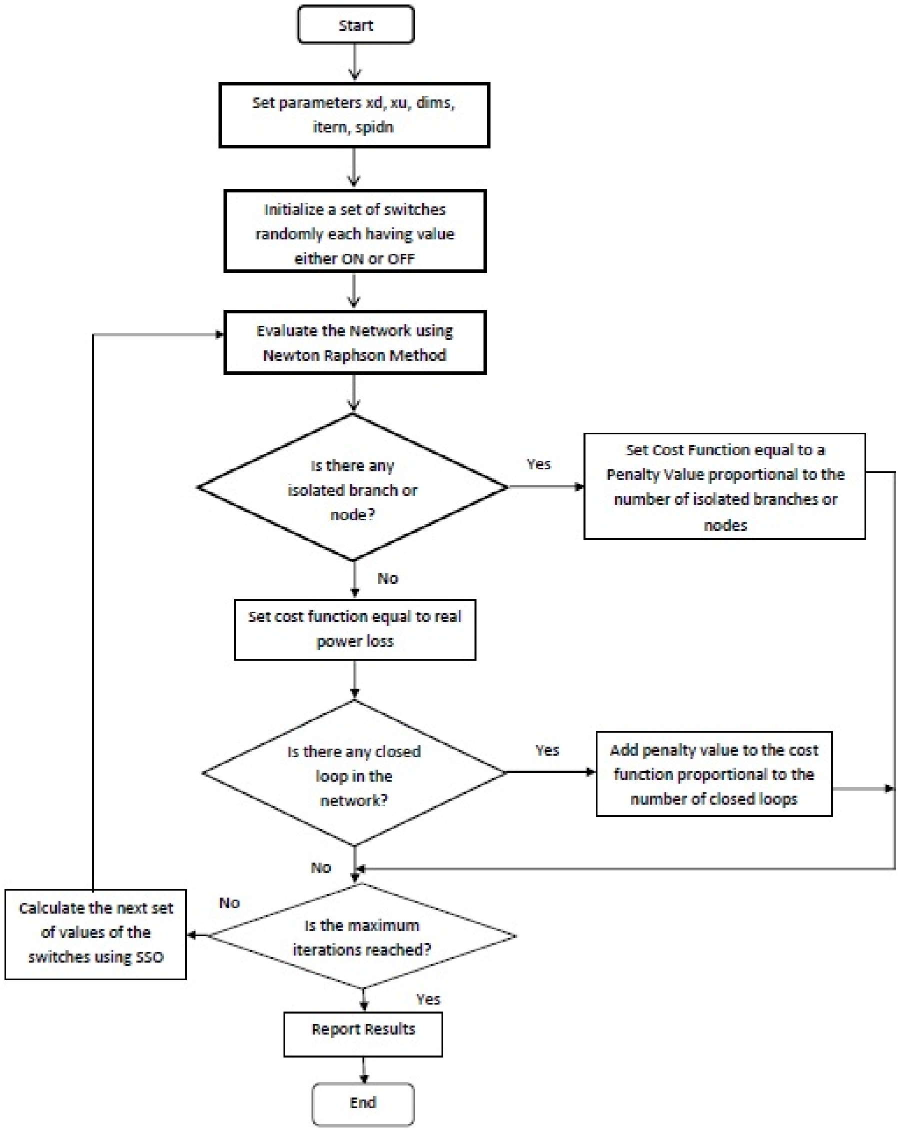

***Fig. 2**: The suggested approach predicated on a flow model.*

Pseudo codes for SSO:

1. Initialize population size, lower bound, upper bound, iterations, and number of spiders
2. Define the number of female and male spiders in the total population
3. For each vector, generate the randomized computation elements
4. **while** terminating the parameters not met do
5.   **for** each vector in the population do
6.   Assess the importance of fitness function
7.   **end for**
8.   **for** each spider in the population do
9.   Determine the vibration intensity produced by each spider
10.   Obtain the best position
11.   Update the fitness parameters
12.   Perform mating process
13.   **end for**
14. **end while**

***Fig. 3**: Pseudo code of the proposed algorithm.*

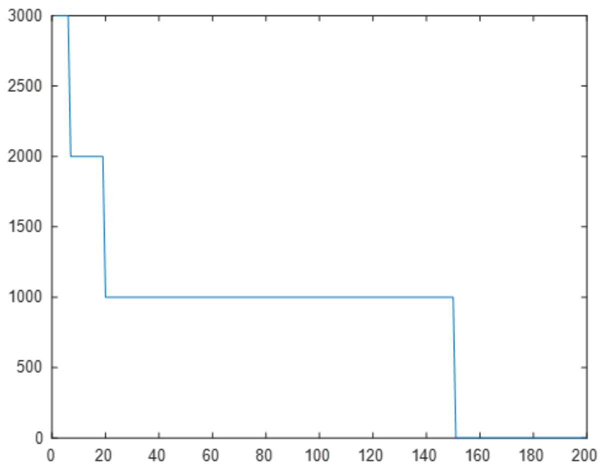

***Fig. 4**: IEEE 30-bus system convergence.*

***Table 1**: Switch layout information for the IEEE 30-bus system.*

Begin Bus	Terminate Bus	Switch
1	2	X1
2	3	X2
2	4	X3
3	4	X4
2	5	X5
2	6	X6
4	6	X7
5	7	X8
6	7	X9
6	8	X10
6	9	X11
6	10	X12
9	11	X13
9	10	X14
4	12	X15
12	13	X16
12	14	X17
12	15	X18
12	16	X19
14	15	X20
16	17	X21
15	18	X22
18	19	X23
19	20	X24
10	20	X25
10	17	X26
10	21	X27
10	22	X28
21	22	X29
15	23	X30
22	24	X31
23	24	X32
24	25	X33
25	26	X34
25	27	X35
28	27	X36
27	29	X37
27	30	X38
29	30	X39
8	28	X40
6	28	X41

***Table 2**: Change in voltage profile of the IEEE 30-bus system following reconfiguration.*

Bus	Voltage (p.u.)	
	Before Reconfiguration	After Reconfiguration
01	1.06	1
02	1.043	1
03	1.0207	1.0167
04	1.0139	0.9942
05	1.01	0.9962
06	1.018	1.01
07	1.0033	0.9982
08	1.01	0.9945
09	1.0798	1.0952
10	1.1288	1.0965
11	1.082	1.0756
12	1.0788	1.0985
13	1.071	1
14	1.0684	1.02
15	1.0708	1.0809
16	1.0897	1.092
17	1.1098	0.9936
18	1.0748	1.0836
19	1.0815	1.0825
20	1.0922	1.0847
21	1.1128	0.9945
22	1.1135	1
23	1.0779	1
24	1.0989	1.0875
25	1.0667	1.06
26	1.0429	1
27	1.0581	1.034
28	1.0171	1.01
29	1.0308	1.01
30	1.015	0.9936

126.20 MVAR, respectively [38]. To assess the cost of the test system's edges (feeder), a distribution load flow study was performed. The cost matrix for a 30-node network is 30 × 30. For each unique scenario on the test system, the Newton Raphson method was applied through the MATPOWER simulation tool to evaluate the initial voltage magnitudes and voltage angles of all buses. The explicit arrangement of switch configurations for the IEEE 30-bus system is shown in Table 1. The SSO is used to create the optimal radial network using penalty functions, resulting in the best global solution for an IEEE 30 node network. Between the lines, the switches X11(6–9), X12(6–10), X13(9–11), X14(9–10), X15(4–12), X16(12–13), and X36(28–27) experience almost no power loss. As a result, the lines containing the above-mentioned transformers are left unaltered while obtaining the best path.

For the explicit location of switches, the modified manuscript includes a switch configuration layout as presented in Table 1. The voltage profile of the 30-bus system before and after reconfiguration, resulting in the optimal path, is shown in Table 2. The results in Table 3 validate that the proposed algorithm is significantly better than the ones employed in GA [41], and Kruskal's maximal spanning tree algorithm [38], since it is capable of identifying even better optimal switching configurations with the minimal amount of power loss while witnessing the shortest calculation time. Fig. 5 shows the optimum graph achieved. As portrayed in Table 3, the least active power loss of 16.668 MW attained using SSO is 5.29% less than the previously published best result of 17.599 MW using the Kruskal's maximal spanning tree

***Table 3**: Analogy of the results for the multiple methodologies used in the IEEE 30-bus test system's P_{loss} function.*

Governing Parameter	Defined Techniques	Loss (MW)
Minimum Power Loss	Proposed Technique (SSO)	16.668
	GA [41]	17.542
	Kruskal's Maximal Spanning Tree Algorithm [38]	17.599

***Table 4**: Analogy of the results for the multiple methodologies used in the IEEE 30-bus test system's $V_{\min}$ function.*

Governing Parameter	Defined Techniques	$V_{\min}$ (p.u.)
$V_{\min}$	SSO	0.9936
	GA [41]	0.9931

***Table 5**: Analogy of the results for the multiple methodologies used in the IEEE 30-bus test system's voltage stability indicator function.*

Governing Parameter	Defined Techniques	Voltage Stability Index (p.u.)
Voltage Stability Index (p.u.)	SSO	0.2063
	Kruskal's Maximal Spanning Tree Algorithm [38]	0.2821

algorithm as explained in the literature. The proposed strategy achieves the greatest possible condition with the least amount of real power loss compared to existing approaches, such as GA [41] and Kruskal's maximal spanning tree algorithm [38]. The optimum topology for the IEEE 30-bus system derived using SSO is depicted in Fig. 6. Fig. 7 shows a significant augmentation in voltage over the basic configuration of the 30-node system. Although most of the node voltage amplitudes amended more favorably than before reconfiguration, the network topology does not break the voltage constraint. Fig. 8 shows a comparative graph of the proposed method with other established methodologies for a 30-node system with minimum power loss. Fig. 9 depicts a comparative graph of the proposed method with other established methodologies of a 30-node system with $V_{\min}$. The $V_{\min}$ of 0.9936 p.u. obtained using SSO is 0.05% lower than the previously published best result of 0.9931 p.u. obtained using GA [41], as shown in Table 4. According to the literature, the voltage stability index produced using SSO is 26.86% lower than the prior reported best value of 0.2821 p.u. acquired using Kruskal's maximal spanning tree [38], as shown in Table 5.

The performance indicators, P_{loss}, $V_{\min}$, and voltage

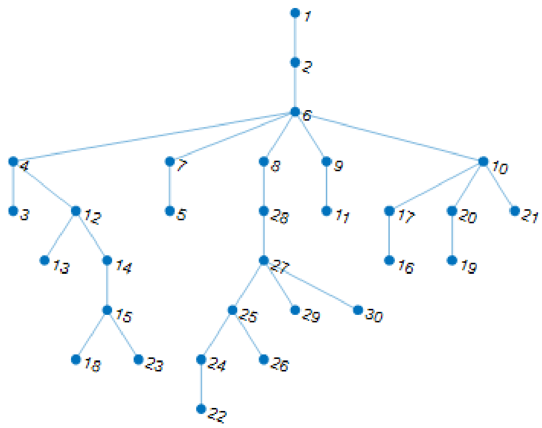

***Fig. 5**: Depiction of the optimum 30-node radial system as a biograph.*

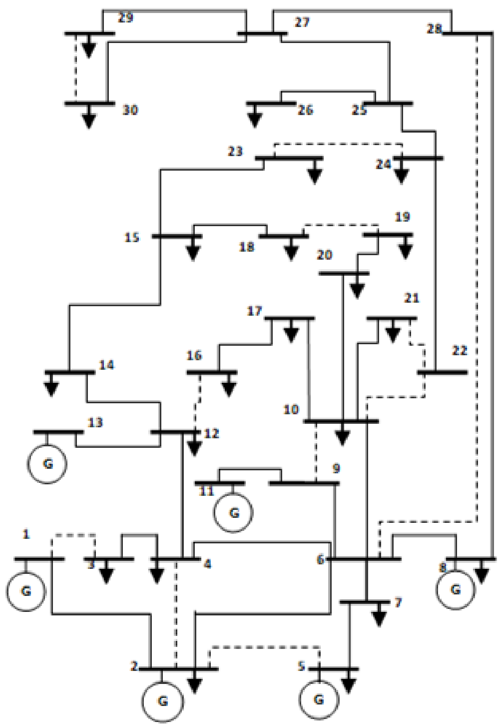

***Fig. 6**: Depiction of optimal configuration obtained through SSO.*

stability indicator as portrayed in Tables 3, 4, and 5, respectively, demonstrate the efficacy of the proposed technique. A comparison graph of the proposed method with other recognized methodologies for a 30-node system is shown in Fig. 10, delivering the optimal voltage stability index.

5.2 The 33-Node System

The suggested algorithm is applied on a 33-bus radial distribution test system of 12.66 kV. The network has 33 vertices. The system statistics are sourced from [17].

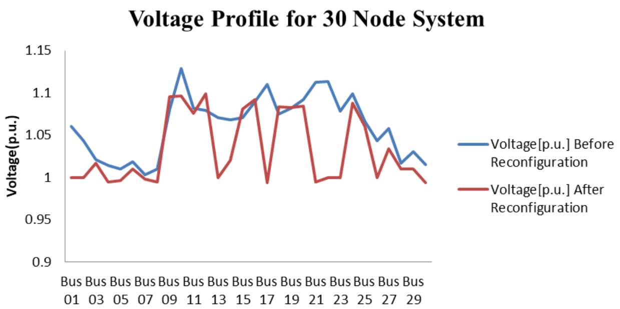

Fig. 7: *Voltage profile determination for a 30-node system.*

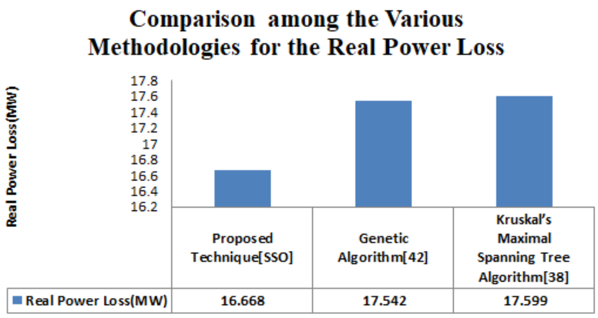

Fig. 8: *Assessment the SSO technique's efficacy applying various methodologies in a 30-node system for P_{loss}.*

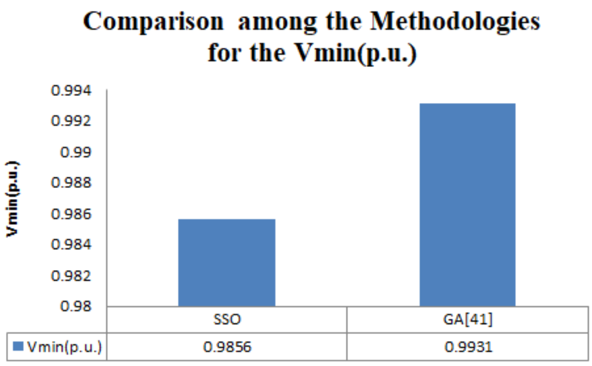

Fig. 9: *Assessment the SSO technique's efficacy applying various methodologies in a 30-node system for $V_{\min}$.*

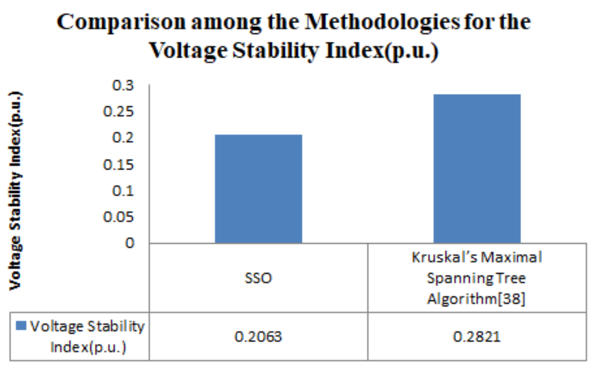

Fig. 10: *Assessment the SSO technique's efficacy applying various methodologies in a 30-node system for voltage stability index (p.u.).*

Table 6: *Change in voltage profile of the IEEE 33-bus system following reconfiguration.*

Bus	Voltage (p.u.)	
	Before Reconfiguration	After Reconfiguration
01	1.00	1
02	0.997	0.997
03	0.976	0.986
04	0.968	0.982
05	0.950	0.979
06	0.946	0.972
07	0.941	0.972
08	0.935	0.969
09	0.929	0.966
10	0.928	0.965
11	0.927	0.965
12	0.921	0.965
13	0.919	0.962
14	0.917	0.961
15	0.916	0.961
16	0.913	0.959
17	0.913	0.955
18	0.997	0.954
19	0.993	0.995
20	0.992	0.981
21	0.992	0.977
22	0.992	0.973
23	0.979	0.981
24	0.973	0.970
25	0.969	0.963
26	0.948	0.971
27	0.945	0.970
28	0.934	0.965
29	0.926	0.961
30	0.922	0.958
31	0.918	0.954
32	0.917	0.954
33	0.917	0.954

In the distribution system reconfiguration challenge, the switches can only be in one of two states: open or closed. A binary vector can be used to represent the switch status by attributing a value of 1 to the 'close' state and 0 to the 'open' state.

Table 6 shows the voltage profile of the 33-bus system before and after reconfiguration, resulting in the best path. Tables 7 and 8 show the performance measures P_{loss} (MW) and $V_{\min}$, respectively, illustrating the efficacy of the recommended strategies, i.e., the HSA [17] and discrete evolutionary programming [39].

Table 7 shows the findings of reconfiguration utilizing SSO, discrete evolutionary programming [39], and HSA [17] methodologies. Distribution load flow analysis was conducted to determine the cost of the test system's edges (feeder). The cost matrix of a 33-node network is 33 × 33. Newton Raphson was used to evaluate the initial voltage magnitudes and voltage angles of all buses

***Table 7**: Analogy of the results for the multiple methodologies used in the IEEE 33-bus test system's P_{loss} function.*

Governing Parameter	Defined Techniques	Loss (MW)
Minimum Power Loss	SSO	0.10973
	Discrete Evolutionary Programming [39]	17.599
	HSA [17]	0.13806

***Table 8**: Analogy of the results for the multiple methodologies used in the IEEE 33-bus test system's $V_{\min}$ function.*

Governing Parameter	Defined Techniques	$V_{\min}$ (p.u.)
$V_{\min}$	SSO	0.954
	CSA [42]	0.9378
	HSA [17]	0.9342

***Table 9**: Analogy of the results for various parameters with and without the additional branches.*

Governing Parameter	Defined Techniques	Loss (MW)
Additional Branches (8–12, 14–17)	SSO (without)	0.10973
	SSO (with)	0.1197
$V_{\min}$	SSO (without)	0.954
	SSO (with)	0.951

for each unique situation on the test system through the MATPOWER simulation program. Fig. 11 depicts the 33-node network. The convergence property of the SSO algorithm to achieve minimum real power loss is shown in Fig. 12 for the 33-node system.

The optimum graph obtained is depicted in Fig. 13 for the 33-node system. Many of the node voltage amplitudes show a more favorable improvement after reconfiguration than before, according to the voltage level produced by SSO in Fig. 14. Despite most node voltage amplitudes improving during reconfiguration, the network structure does not break the voltage constraint. The evaluation of the SSO technique's efficacy using various methodologies on a 33-node system for minimization of real power loss is depicted in Fig. 15. An assessment of the SSO technique's efficacy using various methodologies on a 33-node system shows that almost all the node voltage amplitudes demonstrate a greater improvement after reconfiguration than before, as depicted in Fig. 16. Table 7 indicates that the minimum real power loss of 0.10973 MW produced using SSO is 21.36%, lower than the previously published best result of 0.13955 MW obtained using discrete evolutionary programming [39]. According to the literature, the voltage profile generated using SSO is 2.11% lower than the previous best value of 0.9342 p.u. obtained using the HSA [17], as shown in

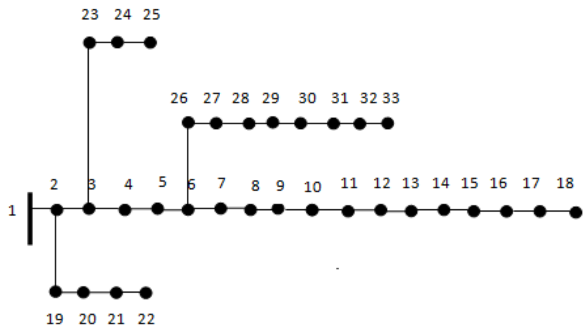

***Fig. 11**: Depiction of the 33-node system.*

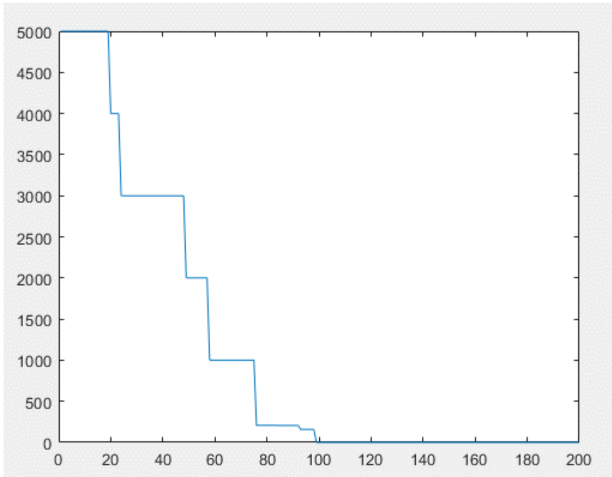

***Fig. 12**: IEEE 33-bus system convergence.*

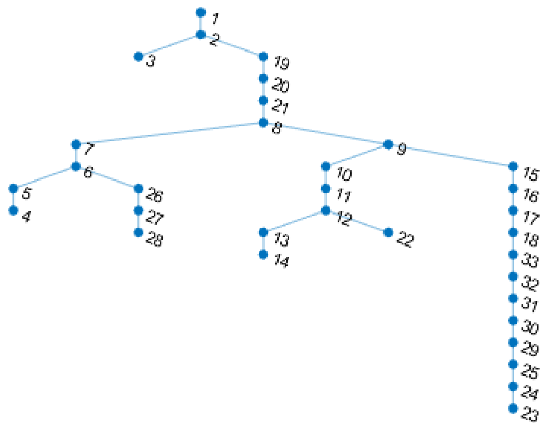

***Fig. 13**: Graphical representation of the optimal network for the IEEE 33-bus system.*

Table 8. The performance measures of real power loss and voltage profile demonstrate the efficacy of the proposed techniques, as shown in Tables 7 and 8, respectively.

5.2.1 Additional branches to the 33-node system

Additional branches over the existing laterals are implemented and their series impedance addressed. The

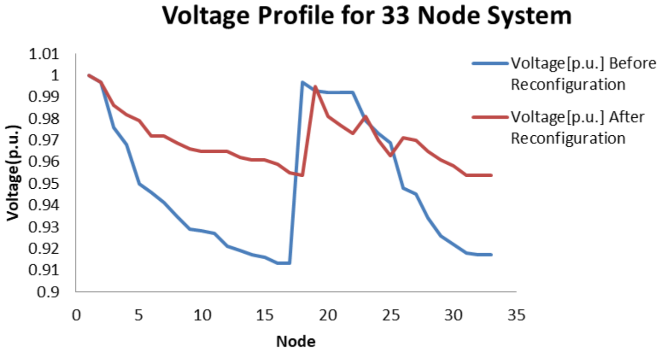

***Fig. 14**: Voltage profile determination for a 33-node system.*

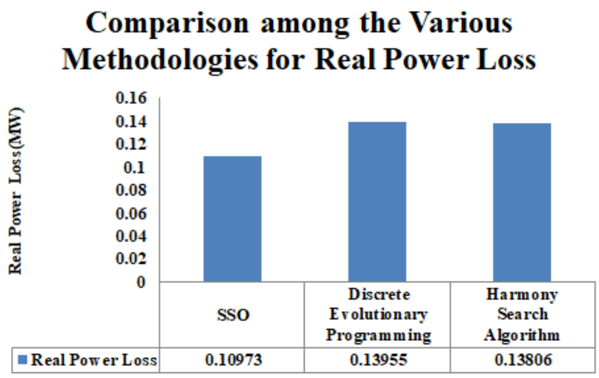

***Fig. 15**: Assessment the SSO technique's efficacy applying various methodologies in a 33-node system for P_{loss}.*

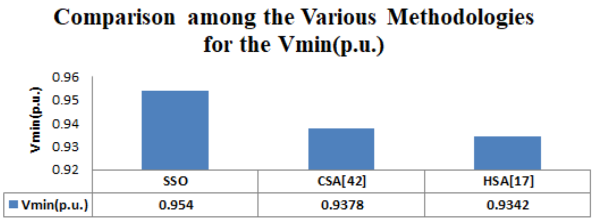

***Fig. 16**: Assessment the SSO technique's efficacy applying various methodologies in a 33-node system for V_{min}.*

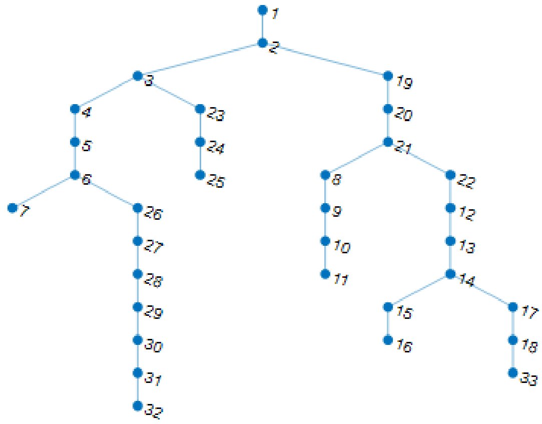

***Fig. 17**: Graphical representation of the optimal network for an IEEE 33-bus system with additional branches.*

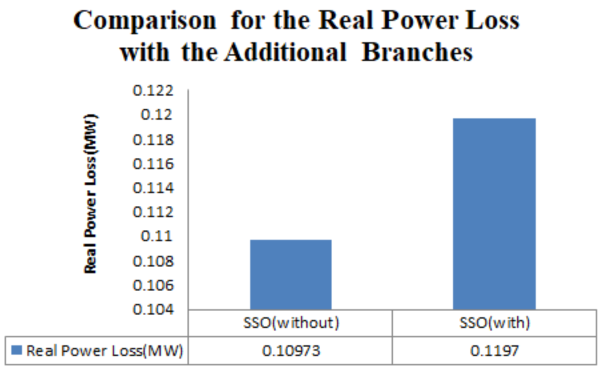

***Fig. 18**: Assessment of SSO efficiency with the inclusion of additional branches for P_{loss}.*

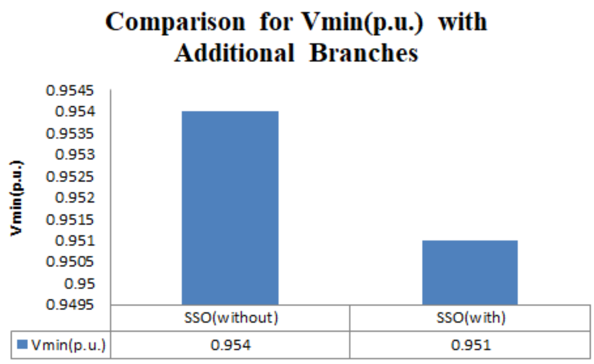

***Fig. 19**: Assessment of SSO efficiency with the inclusion of additional branches for V_{min}.*

additional branches appear between nodes 8 and 12 and nodes 14 and 17 accordingly (Fig. 17).

The real power loss obtained through the addition of the branches is 0.1197 MW. The minimum real power loss of 0.10973 MW acquired using SSO without the implementation of new branches is 8.68% lower than the previously reported best result of 0.1197 MW obtained using SSO with additional branches across 8–12 and 14–17, as shown in Table 9. As indicated in Table 9, the minimum voltage of 0.9954 p.u. achieved utilizing SSO without new branches is 0.44% lower than the formerly stated best result of 0.991 p.u. acquired using SSO with extra branches spanning from 8–12 and 14–17.

Fig. 18 depicts the evaluation of the SSO technique's efficacy with the inclusion of extra branches to minimize real power loss. As can be observed from Fig. 19, the node voltage amplitudes show greater enhancement without the extra branches than with, according to an assessment of the SSO technique's efficacy. Table 9 offers an overview of the superior result without lateral branches for a 33-node system.

6. CONCLUSION

This paper proposes an appropriate way of reconfiguration to minimize power loss by relying on SSO. The objective function is designed in such a way that the SSO optimization technique can be implemented in the binary domain for the indices of minimum real power loss, $V_{\min}$, and the voltage stability indicator, defining the performance statistics of the proposed technique for the 30-node system, 33-node system, and the inclusion of additional branches to the 33-node system. The results reveal that SSO outperforms Kruskal's maximal spanning tree algorithm and GA in terms of determining the ideal network architecture, as measured by the minimal power loss, $V_{\min}$, and voltage stability index for an IEEE 30-bus system. The SSO for the 30-node system shows a power loss reduction of 5.29%, while the $V_{\min}$ and voltage stability index demonstrate a reduction of 0.05% and 26.86%, respectively. In terms of establishing the best network architecture, as assessed by minimal power loss and $V_{\min}$ for an IEEE 30-bus system, SSO surpasses discrete evolutionary programming, CSA, and HSA. For a 33-node system, the power loss reduction in SSO is 21.36% and 2.11% for voltage stability index. Additionally, the inclusion of additional branches to the 33-node system for adopting the NR problem is also proposed. The power loss reduction in SSO with the inclusion of additional branches is 0.1197 MW and the $V_{\min}$ 0.951 p.u. The results show a better outcome for the 33-node system without the use of lateral branches. The findings suggest that SSO is a strategy worth investigating to address NR challenges.

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