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# Reliability Improvement Based Reconfiguration of Distribution Networks via Social Network Search Algorithm

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***Abstract*—Power system's reliability is a decisive operational characteristic for distribution companies. Three key measures are considered for this intent. These measures are the system average interruption unavailability index, average interruption frequency index and total energy not supplied that are denoted SAIUI, SAIFI and TENS, respectively. In this research, a novel optimization approach based on social network search (SNS) is used for reconfiguration the distribution networks to enhance reliability. It is inspired by the social networking sites where people behave with different attitudes of emulation, dialogue, argumentation, and innovation. It is developed in a multi-objective framework using weighting attributes, considering the SAIFI, SAIUI, and TENS at the same time. The suggested approach is accomplished on an IEEE 69-node distribution system using the SNS optimizer. The computational findings show that the SAIFI, SAIUI, and TENS are enhanced by 23.9%, 27.63%, and 27.66%, respectively, as contrasted to the initial status. In addition to the SNS technique, the grey wolf optimizer (GWO) and tunicate swarm approach (TSA) are incorporated for comparative reasons. The simulated research findings show that the SNS algorithm outperforms the GWO and TSA algorithms in respect of achieved efficiencies and convergence features.***

***Keywords— reconfiguration, reliability, social network search algorithm, distribution systems.***

***List of symbols:***

| | |
|---|---|
| ***TENS*** | ***Total not supplied energy in the system*** |
| ***$ENSI_n$*** | ***ENS related to each node (n) to be not supplied*** |
| ***$S_n$*** | ***Apparent load at node (n) to be not supplied*** |
| ***$P_n$*** | ***Active load demand at node (n) to be not supplied*** |
| ***$N_n$*** | ***Number of system nodes*** |
| ***$\tau_n$*** | ***Failure rate of each node (n)*** |
| ***$r_n$*** | ***Repair time of each node (n)*** |
| ***$U_n$*** | ***Unavailability of each node (n)*** |
| ***$\omega_1$, $\omega_2$, and $\omega_3$*** | ***The specified operator weighting factors according to his preference*** |
| ***"max"*** | ***A superscript indicates the maximum of the associated variable*** |
| ***"min"*** | ***A superscript refers to the minimum of the associated variable*** |
| ***$O_T$*** | ***Tie lines to be open*** |
| ***No*** | ***the system tie lines number*** |
| ***$V_n$*** | ***Voltage magnitude at each system node (n)*** |
| ***$N_n$*** | ***Number of the system nodes*** |
| ***$I_{br}$*** | ***Current flow in the branch (br)*** |
| ***$I^{max}$*** | ***Thermal capacity the branch*** |
| ***$P_j$*** | ***Real power at each system node (j)*** |
| ***$Q_j$*** | ***Reactive power at each system node (j)*** |
| ***$V_j$*** | ***Voltage magnitude at each system node (j)*** |
| ***$I_j$*** | ***Current injected at each system node (j)*** |
| ***$X_i$*** | ***Solution related to each person's view (i)*** |
| ***LB*** | ***Lower limits of the independent variables*** |
| ***UB*** | ***Upper limits of the independent variables*** |
| ***$X_i$ and $X_j$*** | ***Two different person's solutions that are selected randomly*** |
| ***$m_1$ and*** | ***random vector within the range [-1, 1]*** |
| ***$m_2$*** | ***random vector within the range [0, 1]*** |
| ***$X_k$*** | ***A randomly selected solution*** |
| ***$m_3$*** | ***A random vector within the range [0, 1]*** |
| ***$r_1$ and $r_2$*** | ***Random values*** |
| ***round*** | ***An expression adjusts the direct insight to the nearest integer value*** |
| ***Nr*** | ***Size of the group*** |
| ***$r_3$ and $r_4$*** | ***Random values with an interval of [0, 1]*** |
| ***d*** | ***Superscript indicates the $d^{th}$ variable inside the solution vector which ranges within [1, Dim]*** |
| ***Dim*** | ***Dimension of the problem studied*** |
| ***$x_i$*** | ***The $i^{th}$ variable of (new idea)*** |

## I. Introduction

Electrical interruptions are uncommon in affluent nations, yet they have serious effects. The duration and frequency of power outages are the main items which describe the reliability of electrical power networks. In this context, innovative strategies for declining the power outages periods by enhancing distribution system performance must be developed [1], [2]. Furthermore, to guarantee a techno-economic benefits of the power supply, the reconfiguration process of electrical distribution grids is considered as an important task [3].

The mechanism for mitigating the effects of power interruptions and improving distribution system reliability characteristics is called Reconfiguration of Power Networks (RPN) [4], [5]. In recent times, operation science has evolved steadily in determining the optimum RPN while taking into account a range of service objectives [6]. In [7], several intelligent techniques merged with a heuristic approach has been developed to structure the distribution network to obtain the minimum power losses. The RPN problem has been investigated [8] that employed a harmony searching approach for minimizing the distribution losses in balanced radial feeders. The RPN mechanism in [1] has been built by opening and closing switches to achieve the lowest potential losses.

Network reliability has been regarded as the capacity of a power circuit to provide customers with an uninterrupted and acceptable electrical quality supply. Incorporating extra protective elements, accurate particular fault detection processes, quick changeover, reclosing devices, employing more reliable technology to minimize emergency states, and RPN are several techniques for boosting reliability [9]. On the other side, the typical nature of Distribution systems is the radial that retained during the RPN procedure [10]. In [11], the minimization of power losses in transmission grids and the improvement voltage profile have been handled via RPN in distribution systems using a stochastic fractal search optimizer. To address these problems, RPN is considered as a cost-effective and efficient technique of boosting system dependability. Nowadays, artificial intelligence approaches and concepts are being used to optimize electricity network distribution [12]. In [13], a backtracking search algorithm has been used to address the RPN problem in order to minimize energy losses considering differing loading situations. In addition to that, the applied technique in [13] has been validated via ETAP (the Electrical Transient Analyzer Program) to analyze the impacts of active and reactive power losses with RPN changes. The discontinuous teaching-learning learning optimizer was performed in [15], to manage the RPN of a delivery network utilizing the weighted factor technique to decrease losses and voltage fluctuations. In [14], ETAP has been dedicated as well to assessing the economic and technical views of the RPN process with capacitors switching in medium voltage ring reconfiguration.

Furthermore, with optimal incorporation of distributed energy resources (DERs), electrical distribution automating was therefore treated using RPN and optimal management of DERs [16]. Multiple kinds of studies were furthermore executed that used a variety of goal attributes and metaheuristic methods, including the equilibrium optimization method (EOM) [17], Water Cycle technique [18], hybridized particle swarm algorithm with analytical strategy [19], artificial ecosystem algorithm [20], strength Pareto evolutionary technique [21] and Beetle Antennae Searching method [22]. S. Talatahari et al. has introduced a new optimization approach for social network search (SNS) [23]. It is inspired by the social networking sites where people behave with different attitudes to share their new thoughts about an event. These attitudes and sharing strategies are distinct in order to communicate people's fresh viewpoints on a changed occurrence such as emulation, dialogue, argumentation, and innovation [24].

As a result, the SNS algorithm is used for distribution network reconfiguration, in this article, to improve the power system reliability. It is developed using three reliable indexes at the same time in a multi-objective framework that employs weighting factors. The SAIFI, SAIUI, and TENS are all included in this model. The suggested approach is tested on an IEEE 69-node distribution network using the SNS optimizer.

The numerical findings show that the SAIFI, SAIUI, and TENS are enhanced by 23.9%, 27.63%, and 27.66%, respectively, as in comparison to the initial situation. In addition to the SNS technique, the GWO (Grey wolf optimization algorithm) and tunicate swarm algorithm (TSA) are incorporated for comparative reasons. The simulated outcomes show that the SNS algorithm outperforms the GWO and TSA techniques in terms of achieved improvements and convergence features.

## II. Reliability Indexes of a Distribution System

The reliability indexes recognized by Chilean legislation are specified by the CIER (Inter-American Committee of Regional Electricity) for a DN with numerous laterals and multi-feeding nodes, which are as in Equations (1)-(4) as [1]:

$$SAIFI = \frac{\sum_{n=1}^{N_n} S_n \times \tau_n}{\sum_{n=1}^{N_n} S_n} \tag{1}$$

$$SAIUI = \frac{\sum_{n=1}^{N_n} S_n\, U_n}{\sum_{n=1}^{N_n} S_n} \tag{2}$$

$$TENS = \sum_{n=1}^{N_n} ENS_n = \sum_{n=1}^{N_n} P_n\, \tau_n \tag{3}$$

$$SAIDI = \frac{\sum_{n=1}^{N_n} S_n\, r_n}{\sum_{n=1}^{N_n} S_n} \tag{4}$$

$$U_n = \tau_n \times r_n \qquad n=1,2,.....,N_n \tag{5}$$

## III. Reliability Enhancement Model

A multi-objective minimization function (MOF) utilizes the three weighted normalized reliability indices, SAIFI, SAIUI, and TENS, is stated in Eq. (6) for reliability enhancement in DNs as:

$$MOF = \omega_1 \frac{SAIFI}{SAIFI^{max}} + \omega_2 \frac{SAIUI}{SAIUI^{max}} + \omega_3 \frac{TENS}{TENS^{max}} \tag{6}$$

*A. Constraints of the control variables*

The set of independent variables (IV) is the optimum choice for open lines for re-configuration, as seen below:

$$IV = \{ [ \underbrace{O_{T1}\ O_{T2} ...... O_{TNo}}_{Open\ Tie\ branches} ] \} \tag{7}$$

$$1 \le O_{Tj} \le No \qquad j = 1\ ,\ 2\ ,\ .......\ No \tag{8}$$

*B. Nodes Voltage constraints*

$$V_n^{min} \le V_n \le V_n^{max} \quad n = 1\ ,\ 2\ ,\ ....\ N_n \tag{9}$$

*C. Current capacity limits*

$$\left| I_{br} \right| \le I_{br}^{max} \quad br = 1\ ,\ 2\ ,\ ....\ N_{br} \tag{10}$$

*D. Power balance constraints*

$$P_j + Q_j = V_j I_j^* \quad n = 1\ ,\ 2\ ,\ ....\ N_n \tag{11}$$

*E. Radiality constraint*

The radiality constraint must be maintained with the aid of a branch-bus incidence matrix:

$$A_{ij} = \begin{cases} 1 & \text{if the line i exits from bus j} \\ 0 & \text{if line i isn't connected to bus j} \\ -1 & \text{if the line i enter to bus j} \end{cases} \quad (12)$$

Its dimension is $N_n \times N_{br}$. The system topology seems to be radial if its determinant is 1 or −1 [25], [26].

# IV. SNS Optimizer for Reliability Improvement via DN Reconfiguration

People in socially connecting networks are driven by the SNS technique, where they attempt to be appealing across multiple attitudes such as innovation, emulation, dialogue, and argumentation [23], [27].

Persons with a dialogue attitude can communicate with others and benefit from one of their different viewpoints. Others in an argumentation attitude can dispute with a set of people and examine their points of view. People in the spirit of innovation share a subject on social media generally founded on their fresh ideas and observations. These attitudes are mathematically modeled and explained.

## A. Initialization

To implement the SNS algorithm, the starting view for each individual may be constructed using Eq. (13):

$$X_i = LB + rand(0,1) \times (UB - LB) \quad (13)$$

The objective function for each person's perspective of view is then calculated. Figure 1 displays the key stages of the SNS.

## B. Emulation Attitude

The emulation attitude could be stated numerically as regards:

$$X_{i,new} = X_j + m_1 \times m_2 \times (X_i - X_j) \quad (14)$$

## C. Dialogue Attitude

The dialogue attitude could be stated numerically as regards:

$$X_{i,new} = X_k + m_3 \times [sign(f_i - f_j) \times (X_i - X_j)] \quad (15)$$

The expression (*sign*) represents the sign function, whereas the expression ($sign(f_i$-$f_j)$) represents a comparative assessment between the two objective values $f_i$ and $f_j$, which represents the movement direction of $X_k$. It is worth noting that the person's perspective on the event shifts as a result of talks with the $j^{th}$ user, where generated opinion reflects a new thought to communicate effectively with other people. Modifying the person's perspective about the occurrences is regarded as occurrence replacement [28].

## D. Argumentation Attitude

In the argumentation attitude, the perspective impacts may be described in the mathematical form as regards:

$$X_{i,new} = X_i + r_1 \times \left(\frac{\sum_{m=1}^{N_r} X_m}{N_r} - ((1 + round(r_2)) \times X_i)\right) \quad (16)$$

## E. Innovation Attitude

In the innovation attitude, a new notion will emerge, and the new influenced viewpoint can be numerically expressed as follows:

$$X_{i,new}^d = tX_j^d + (1 - r_3) \times (LB^d + r_4 \times (UB^d - LB^d)) \quad (17)$$

## F. Rules Related to Network

Every social networking site defines a number of duties for its members, and all such roles are regarded by all participants in common perspectives. People's perspectives are limited according to:

$$x_i = min(x_i, UB_i) \;\&\; x_i = max(x_i, LB_i), i = 1,2,....Dim \quad (18)$$

## G. Rules for Publishing

Various attitudes are considered based on user's viewpoint and the employed fresh views are dependent on their benefits. The new concept value may be assessed by the objective function of $X_{inew}$ that can be contrasted to the existing concept ($X_i$) as regards:

$$X_i = \begin{cases} X_i & f(X_{i,new}) > f(X_i) \\ X_{i,new} & f(X_{i,new}) < f(X_i) \end{cases} \quad (19)$$

# V. Simulation Results

In this section, the SNS based method is implemented on a 69-node DN with 68 sectionalizing links and 5 open sections. Fig. 2 shows the single line diagram is shown for 12.66 kV- 69-node DN [29]. For the normal condition of this 69-node DN, the total power demand is 3.802 +j 2.6946 MVA [30]. All loads are expected to have constant power in nature. According to [9], the typical repair time for a fuse is 1 hour and 0.5 hour for a switch. The reliability data of the tested DN, comprising failure rates and lines repair time, is taken from [1].

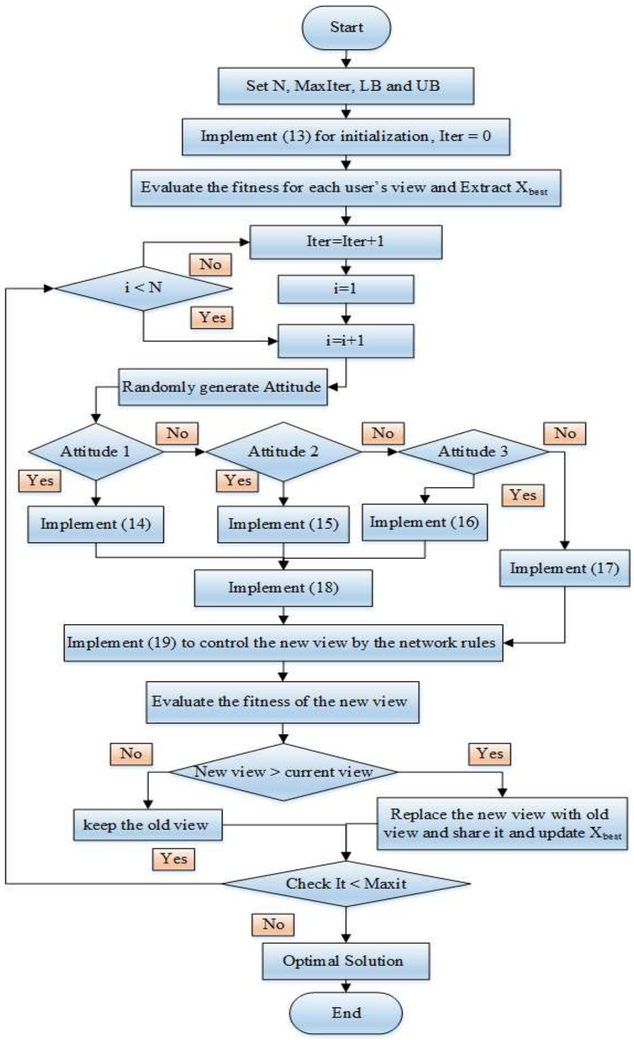


Fig. 1. SNS Flowchart.

## A. SNS application for the cases studied

The values of the weighting factors are used to examine four case studies, as indicated in Table I. The goal aim is considered based on the supplied values of the weighting factors. As shown, in the first case, SAIFI minimization (Eq. (1)) is considered as single objective model. In the second case, SAIUI minimization (Eq. (2)) is considered as single objective model. In the 3rd case, TENS minimization (Eq. (3)) is considered as single objective model. In the fourth case, MOF minimization (Eq. (6)) is considered as multi-objective model. In this case, $TENS^{max}$, $SAIUI^{max,}$ and $SAIFI^{max}$ are10 MWh/year, 2.5 h/year, and 14 times/year.

TABLE I. CASES STUDIED AND THE ASSOCIATED WEIGHT FACTORS

| Weighting Factors | Case 1 | Case 2 | Case 3 | Case 4 |
|---|---|---|---|---|
| $\omega_1$ | 1 | 0 | 0 | 0.333 |
| $\omega_2$ | 0 | 1 | 0 | 0.333 |
| $\omega_3$ | 0 | 0 | 1 | 0.333 |

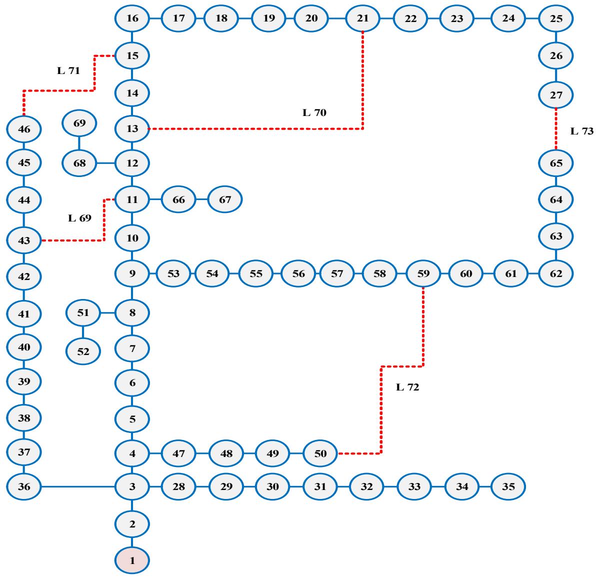


Fig. 2. IEEE 69-node distribution system

Table II depicts require organized tie lines and corresponding reliability results after implementing the SNS method to the four situations analyzed.

TABLE II. APPLICATION OF SNS OPTIMIZER FOR THE CASES STUDIED

| Items | Initial Case | Case 1 | Case 2 | Case 3 | Case 4 |
|---|---|---|---|---|---|
| Tie Lines | 69 | 42 | 69 | 69 | 42 |
| | 70 | 18 | 18 | 18 | 16 |
| | 71 | 45 | 14 | 14 | 71 |
| | 72 | 56 | 58 | 57 | 57 |
| | 73 | 64 | 64 | 64 | 64 |
| SAIFI | 9.1860 | 6.967522 | 7.264196 | 7.264196 | 6.990343 |
| SAIUI | 1.7864 | 1.313175 | 1.285865 | 1.285865 | 1.292803 |
| TENS | 6.7951 | 5.013195 | 4.899 | 4.899 | 4.9277 |
| MOF | 0.683404 | 0.508098 | 0.507705 | 0.507705 | 0.50306 |

This table obviously shows that: In Case 1, the SAIFI is reduced from 9.186 times/year to 6.967 times/year, representing a 27.09% improvement decrease. The findings are typical for both the 2nd and 3rd cases. The SAIUI in Case 2 is reduced by 28.19% compared and achieves to 1.2859 h/year. The TENS in Case 3, is reduced to 4.899 MWh/year, a reduction of 27.9% compared with the initial case. The minimum MOF in Case 4's multi-objective model is 0.50306, while the recorded MOFs in the initial case, Case 1, Case 2, and Case 3 are 0.683404, 0.508098, 0.507705, and 0.507705, correspondingly. The SAIFI in the 4th scenario is reduced by 23.9% to 6.9903 times per year compared with the original one. Also, the SAIUI is improved by 27.63% to 1.292803 h/year. Furthermore, the TENS is improved by 27.66% from 6.7951 MWh/year in the first instance to 4.9277 MWh/year

## B. *Case 1: SAIFI minimization*

For comparison purposes, GWO [31] and TSA [32] are applied. For the target of SAIFI minimization, Fig. 3 displays the average convergence properties of GWO, TSA, and SNS techniques. Also, Fig. 4 plots the average obtained SAIFI and the standard deviation over the 10 separate run times. As shown, the SNS algorithm has a significant superiority over optimization algorithms GWO, and TSA. It achieves the lowest mean SAIFI with 6.9761 times per year, whilst GWO and TSA techniques have equivalents of 7.193 and 7.3354 times per year, respectively. Furthermore, the SNS technique has the lowest standard deviation of 0.0115, while the GWO and TSA methods have equivalents of 0.6295 and 0.7117.

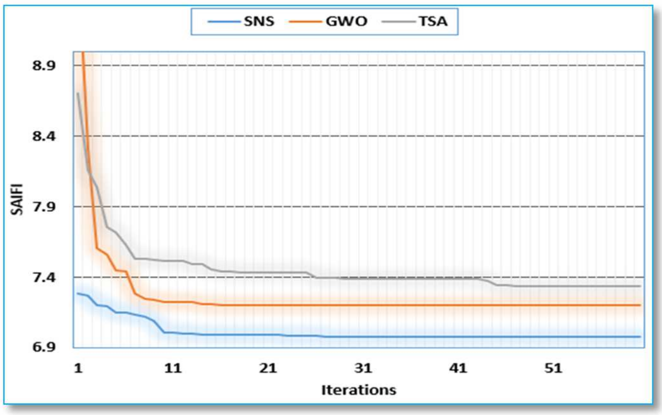


Fig. 3. Convergence rates of GWO, TSA, and SNS techniques for case 1

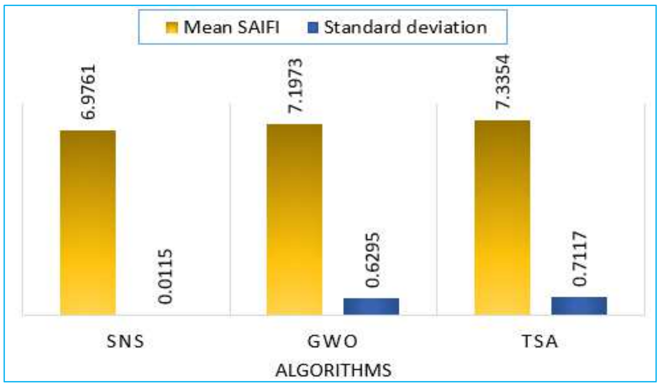


Fig. 4. SAIFI minimization using GWO, TSA, and SNS techniques

## C. *Case 2: SAIUI minimization*

For SAIUI minimizing, Fig. 5 displays the average convergence properties of GWO, TSA, and SNS techniques. Also, Fig. 6 plots the average obtained SAIUI and the standard deviation over the separate run times. As shown, the SNS algorithm has a significant enhanced performance over GWO, and TSA techniques. The SNS algorithm has the lowest mean SAIUI with 1.2926 h/year where GWO, and TSA techniques achieve counterparts of 1.3117 and 1.3432 h/year. It attains the smallest standard deviation, as well, with 0.0062 while GWO, and TSA techniques achieve standard deviations of 0.0477 and 0.1236.

## D. *Case 3: TENS minimization*

For TENS minimizing, Fig. 7 displays the average convergence properties of GWO, TSA, and SNS techniques. Also, Fig. 8 plots the average obtained TENS and the standard deviation over the separate run times. As shown, the SNS algorithm declares significant superiority over GWO, and

TSA techniques. It has the lowest mean TENS of 4.9324 MWh/year, whilst GWO and TSA methods have equivalents of 4.9611 and 4.9427 MWh/year, respectively. Furthermore, the SNS method has the lowest standard deviation of 0.0194, while the GWO and TSA procedures have equivalents of 0.0388 and 0.0524, respectively.

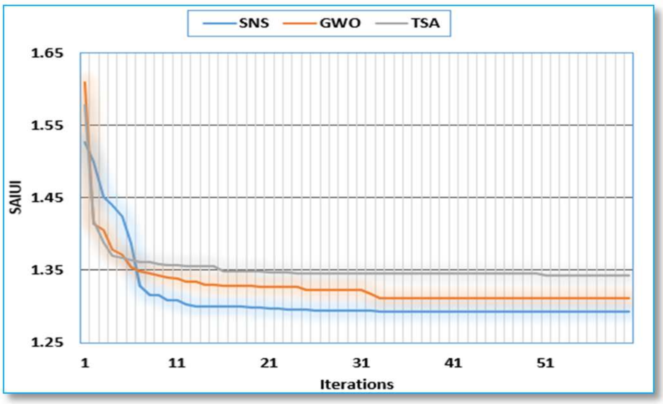


Fig. 5. Convergence rates of GWO, TSA, and SNS techniques for case 2

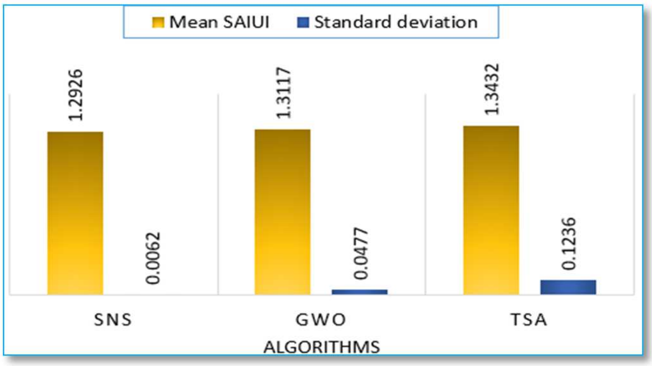


Fig. 6. SAIUI minimization using GWO, TSA, and SNS techniques

### *E. Case 4: MOF minimization*

For minimizing the MOF, Fig. 9 displays the average convergence properties of GWO, TSA, and SNS techniques. Also, Fig. 10 plots the average obtained MOF and the standard deviation over the separate run times. As demonstrated, the SNS algorithm outperforms the GWO and TSA approaches. It yields the lowest mean MOF of 0.50364, however GWO and TSA yield 0.50506 and 0.51461, respectively. Likewise, the SNS method has the lowest standard deviation of 0.00108, meanwhile the GWO and TSA procedures have equivalents of 0.00203 and 0.01637, respectively.

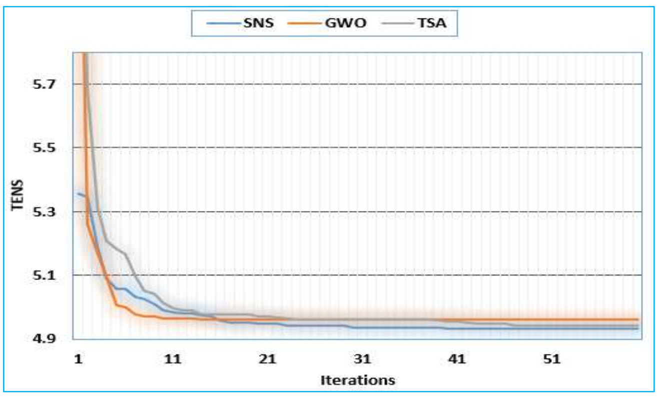


Fig. 7. Convergence rates of the three competitive optimizers GWO, TSA, and SNS techniques for case 3

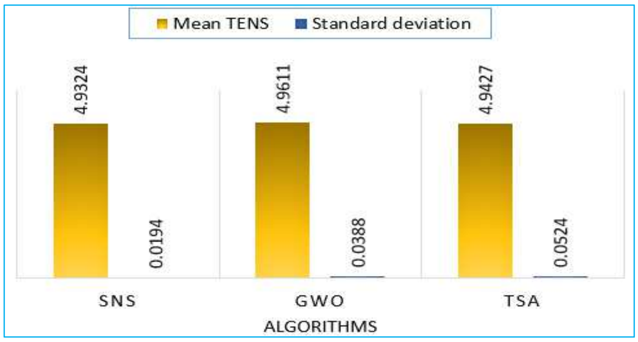


Fig. 8. TENS minimization using GWO, TSA, and SNS techniques

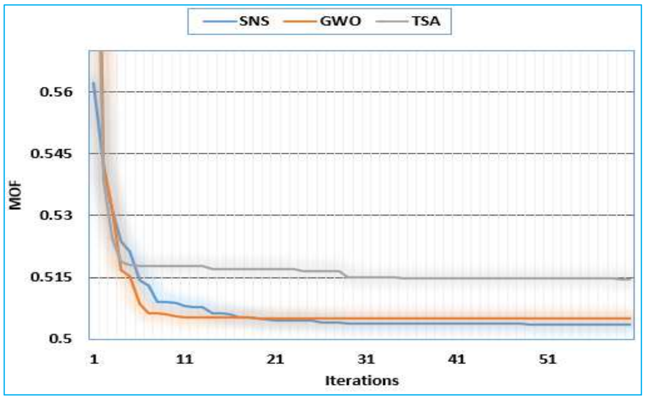


Fig. 9. Convergence rates of GWO, TSA, and SNS techniques for case 4

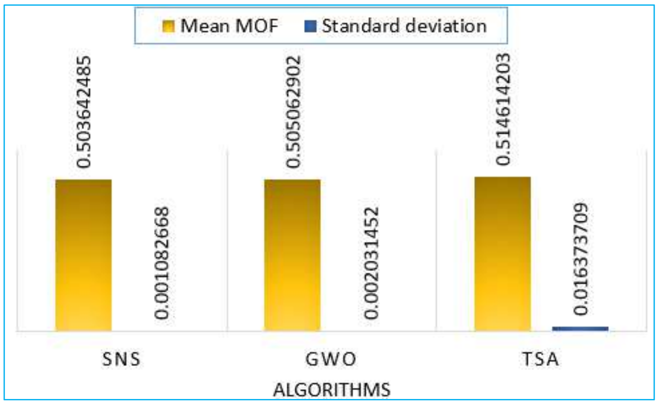


Fig. 10. MOF minimization using GWO, TSA, and SNS techniques

## VI. CONCLUSION

The current study developed the social network search algorithm for distribution network reconfiguration in order to improve the system reliability. Three reliability indices are simultaneously handled in a multi-objective framework. The proposed procedure based on the social network search algorithm is carried out on a standard IEEE 69-node distribution system. Numerical findings show that the SAIFI, SAIUI, and TENS are significantly enhanced with 23.9%, 27.63%, and 27.66%, respectively, as comparing to the initial situation. In addition to the social network algorithm, the grey wolf and tunicate swarm optimizers are incorporated for comparative reasons. The simulation results show that the social network search algorithm outperforms the grey wolf method and tunicate swarm approach in terms of achieved improvements and convergence features.

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