

Article

Optimal Operational Reliability and Reconfiguration of Electrical Distribution Network Based on Jellyfish Search Algorithm

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Abstract: In this paper, the electricity network automation based on Power Network Reconfiguration (PNR) is implemented to improve the operational reliability of distribution systems using jellyfish search algorithm. For this purpose, system average interruption frequency index (SAIFI), system average interruption unavailability index (SAIUI) and total energy not supplied (TENS) are critical measures. In this paper, a new optimization technique of jellyfish search (JFS) algorithm is employed for distribution network reconfiguration for reliability improvement. It is concerned with the moving patterns of jellyfish. They are divided into three categories. The jellyfish could flow towards the ocean current or between its own swarm. Meanwhile, whenever the food supply is adequate, the jellyfishes are attracted to its location. It is formulated considering the three reliability indices of SAIFI, SAIUI and TENS, simultaneously in a multi-objective model based on the weight factors. The proposed methodology based on the JFS optimizer is implemented on an IEEE 33-node distribution network. According to the numerical results, the SAIFI, SAIUI and TENS is improved by 36.44%, 34.11% and 33.35%, compared to the initial condition. For comparison purposes, tuna swarm optimizer and tunicate swarm algorithm, besides the JFS algorithm, are implemented as well. The simulation results declare the significant outperformance of the JFS algorithm compared to TUNA and TSA in terms of the obtained improvements and the regarding convergence properties.

Keywords: distribution systems; operational reliability; network reconfiguration; jellyfish search algorithm



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1. Introduction

Power outages are irregular in developed countries; notwithstanding, they have severe consequences. A power system's reliability is characterized by two parameters: the frequency of outages and the duration of power outages [1]. A substantial amount of research has been conducted to reduce the frequency of power outages. However, more methods for reducing the duration of power outages by improving the distribution system performance must be identified [2,3]. Additionally, it is critical to employ distribution network reconfiguration to discover the optimum solutions according to the regulations and limits given by the operators in an attempt to provide a safe and economically optimal energy supply.

The Power Network Reconfiguration (PNR) is a method which helps mitigate the impacts of the power outages and enhance the reliability parameters in distribution networks [4]. In latest years, operational research has grown progressively in identifying the best PNR while considering a variety of objectives into care [5]. To reduce losses, the PNR issue was explored in [6] that used a harmony search method for radial balanced distribution networks. In [2], the PNR process was created by closing and opening switches using

a decision-making process to obtain the lowest possible losses. The distribution system was configured using a heuristic method based on intelligence-based algorithms to achieve the lowest possible losses [7]. All conceivable network modes are examined in the open and closed states of the switches in the PNR approach, which is based on mathematical optimization theory. As a result, they are more sophisticated than the heuristic technique and take longer to run.

The reliability of an electricity system to serve consumers with uninterruptible and adequate-quality electricity supply is defined as network reliability. Integrating additional devices for protection, exact specific fault location procedures, rapid switching and re-closing mechanisms, using more dependable equipment to avoid contingencies, and PNR are some approaches for improving the reliability [4]. PNR is viewed as a cost-effective and convenient method of increasing system reliability to solve these concerns. Currently, artificial intelligence methods and concepts have been employed to optimize the distribution power networks [8]. In [9], an electric field algorithm has been merged with pattern search approach and applied for the PNR in the distribution networks to enhance its performance. However, the total energy not supplied (TENS) to customers only the index utilized to represent the operational reliability in distribution networks.

In [10], power losses minimization and voltage profile improvement have been handled via PNR in distribution systems using a stochastic fractal search optimizer. Distribution systems, on the other side, are typically run radially, that needs to be retained during the PNR procedure [11]. In [12], a weight coefficient approach and cuckoo search optimizer has been applied for the balanced PNR as a multi-criteria optimization utilizing the power losses decrease, and voltage profile improvement. The described approach in [12] examines network radiality throughout the reconfiguration process. In [13], a discrete teaching-learning optimization has been carried out to handle the PNR of a distribution system using the weight coefficient approach to reduce the losses and voltage variations.

Additionally, in the presence of distributed generations (DGs), electricity network automation has been addressed based on the PNR and optimal operation of dispatchable and non-dispatchable DGs [14]. Numerous research have also been conducted using several objective features and optimization approaches such as Mixed-Integer Linear Programming [15], equilibrium optimizer [16], hybrid of analytical approach and particle swarm optimization [17,18], Water Cycle Algorithm [19] and Chaos Disturbed Beetle Antennae Search [20].

In [21], the PNR problem in the distribution networks was handled in order to optimally identifying its topology for minimizing the overall power losses. In this study, Harris hawk's algorithm was applied with higher performance contrasted to particle swarm optimization algorithm and cuckoo search algorithm under distributed generation and load variation. However, the operational reliability and voltage stability in distribution networks were completely ignored. In [22], an algebraic modeling language of CPLEX solver was applied for the PNR problem in the distribution networks. Despite the high robustness of CPLEX solver, the minimization of power losses has been utilized as a single objective task. In [23], the PNR problem of distribution networks with high wind power penetrations was treated and solved based on Bayesian learning-based evolutionary algorithm. In [24], a NoisyNet deep Q-learning network (DQN) has been carried out to the PNR issue for minimizing the system losses and improving the voltage profile. In [25], AMPL solver as a mathematical programming has been utilized for minimizing the active power losses of distribution systems via PNR issue. In this study, the considered objective function was conducted with uncertainty probability beside uncertain amounts in load demand. Despite the effective implementations of [21–25], the operational reliability and voltage stability in distribution networks were completely ignored.

Recently, a new optimization technique of JFS algorithm proposed in [26], is fascinated by the moving patterns of jellyfish. They are divided into three categories. To begin, the jellyfish could flow towards to the ocean current or between its own swarm. Meanwhile, whenever the food supply is adequate, the jellyfishes are attracted to their locations. Fur-

thermore, the numeric fitness function reveals the volume of food. The JFS was recently applied in effective manner for several engineering problems such as selective harmonic elimination in multilevel inverters [27], combined heat and power dispatching [28], maximum power point tracking (MPPT) of solar PV systems [29], design of a solar-powered thermoelectric air-conditioning system [30], control of superconducting magnetic energy storage system [31], PV parameter estimation [32], integration of renewable energy sources in power systems [33].

Hence, in this paper, the JFS algorithm is employed for distribution network reconfiguration for reliability improvement. In [14], the JFS algorithm was employed for addressing the PNR in the distribution networks considering the dispatching of distributed generation units and static Var compensators. The study in [14] was dedicated to the dynamic operation of distribution networks for the sake of minimizing the distribution losses and the emissions. On the other side, the operational reliability indices in distribution networks were not considered while its great importance of high impacts to guarantee the feeding continuity to consumers. In this paper, the JFS algorithm is formulated considering three reliability indices, simultaneously in a multi-objective model based on the weight factors. In this model, the system average interruption frequency index (SAIFI), the system average interruption unavailability index (SAIUI) and the total energy not supplied (TENS) are comprised. The proposed methodology based on the JFS optimizer is implemented on IEEE 33-node distribution network. According to the numerical results, the SAIFI, SAIUI and TENS is improved compared to the initial condition. For comparison purposes, Tuna swarm optimizer (TUNA) and tunicate swarm algorithm (TSA) besides the JFS algorithm are implemented as well. The simulation results declare the significant outperformance of the JFS algorithm compared to TUNA and TSA in terms of the obtained improvements and the regarding convergence properties

2. Distribution Network (DN) Reliability Indices

The reliability indices approved by Chilean law for a DN with multiple laterals and multi-feeding nodes are specified by the Inter-American Committee of Regional Electricity—CIER and are stated as follow [2]:

$$SAIFI = \frac{\sum_{n=1}^{N_n} S_n \tau_n}{\sum_{n=1}^{N_n} S_n} \quad (1)$$

$$SAIUI = \frac{\sum_{n=1}^{N_n} S_n U_n}{\sum_{n=1}^{N_n} S_n} \quad (2)$$

$$TENS = \sum_{n=1}^{N_n} ENS_n = \sum_{n=1}^{N_n} P_n \tau_n \quad (3)$$

$$SAIDI = \frac{\sum_{n=1}^{N_n} S_n r_n}{\sum_{n=1}^{N_n} S_n} \quad (4)$$

$$U_n = \tau_n \times r_n \quad n=1, 2, \dots, N_n \quad (5)$$

where *SAIFI* is the DN's average interruption frequency index, *SAIUI* is the DN's average interruption unavailability index, *SAIDI* is the DN's average interruption duration index and *TENS* is the total energy not supplied in the DN. *ENS_n* is the ENS related to each distribution node (*n*) to be not supplied. *S_n* and *P_n* are the apparent and active load demand

of the DN at the distribution node (n) to be not supplied; N_n is the number of DN nodes; τ_n and r_n are the failure rate and the repair time of each DN node (n). U_n is the unavailability of each distribution node (n).

3. Problem Formulation

Based on the three reliability indices of *SAIFI*, *SAIUI* and *TENS*, the problem formulation of reliability improvement in DNs is formulated to solve a multi-objective optimization function (*MOF*) as follows:

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

where, ω_1 , ω_2 and ω_3 are weighting factors to be specified by the DN operator according to their preference. In Equation (6), the parameters weighting factors are considered similar to each other and equivalent to (1/3) which represents the same priority for all indices. The superscript “max” indicates the maximum value to be specified.

The multi-objective model presented in Equation (6) seeks the best selection for the open links for reconfiguration. As a result, the vector of the independent variables (*VI*) looks like this:

$$VI = \{ \underbrace{O_{T1} O_{T2} \dots O_{TN_o}}_{Open\ Tie\ branches} \} \quad (7)$$

where, O_T is the tie lines to be open and No is their number.

The open tie links must always be assigned an integer value that is limited by the total number of DN lines, as shown below:

$$1 \leq O_{Tj} \leq No \quad j = 1, 2, \dots, No \quad (8)$$

The voltage at all DN nodes must be bounded by the permissible bounds related to the distribution code as follows:

$$V_n^{min} \leq V_n \leq V_n^{max} \quad n = 1, 2, \dots, N_n \quad (9)$$

where, V_n is the voltage magnitude at each DN node (n); N_n is the number of the DN nodes. The superscripts “min” and “max” refer to the minimum and maximum of each variable.

The current flow at all DN lines must be bounded by the permissible bounds related to the current capacity of each one as follows:

$$|I_{br}| \leq I_{br}^{max} \quad br = 1, 2, \dots, N_{br} \quad (10)$$

where, I_{br} is the current flow in the branch (br) which is limited by the regarding thermal capacity (I^{max}).

The power balance constraints at each distribution node must be maintained as equality constraints which guarantee the convergence of the load flow as follows:

$$P_j + Q_j = V_j [I_j]^* \quad n = 1, 2, \dots, N_n \quad (11)$$

where, P_j and Q_j are the real and reactive power at each DN node (j); V_j and I_j is the voltage magnitude and the current injected at each DN node (j).

Furthermore, the DN's radial structure is kept in operating service, with a branch-bus incidence matrix generated as regards:

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

This matrix has the dimensions of $N_n \times N_{br}$. The DN configuration is radial in form if their determinant is -1 or 1 , but the DN is not radial if the is zero [34].

4. JFS Optimizer

The JFS algorithm is a new optimization technique which is fascinated by the moving patterns of jellyfish. They are divided into three categories. To begin, the jellyfish could flow towards to the ocean current or between its own swarm. Meanwhile, whenever the food supply is adequate, the jellyfishes are attracted to their locations. Furthermore, the numeric fitness function reveals the volume of food [35,36]. The initial population could be arithmetically represented as follows [26]:

$$X_i(t+1) = 4P_0(1 - X_i), \quad 0 \leq P_0 \leq 1 \quad (13)$$

where $X_i(t+1)$ indicates the i th jellyfish chaotic counterpart, and P_0 is a randomized value within range $[0, 1]$ and does not equal to $\{0.0, 0.25, 0.75, 0.5, 1.0\}$. The value of the time control function $CF(t)$ is evaluated as described in Equation (14) which is changed from 0 to 1 over time [37]:

$$CF(t) = \left| \left(1 - \frac{t}{T^{\max}} \right) \times (2 \times r_1 - 1) \right| \quad (14)$$

where, t refers to the iteration number; $T^{\max}$ is the maximum number of iterations; r_1 is a randomized value within range $[0, 1]$.

If the CF value is greater than 0.5, the fresh place of each jellyfish could be developed, as shown in Equation (15) [26]:

$$X_i(t+1) = R \times (X^* - 3 \times R \times \mu) + X_i(t) \quad (15)$$

where μ symbolizes the mean of the jellyfishes; X^* is the best position of the jellyfishes in the population; R is a number chosen at random from the range $[0, 1]$. The best position of the jellyfishes of the population is extracted based on the minimum fitness value. Over all the jellyfishes of the population, the volume of food is evaluated, which is defined as the fitness function. They are sorted in an ascending order, and the first one is extracted as the best position. The considered fitness function of the PNR problem is formulated in Equation (6), comprising the three reliability indices of SAIFI, SAIUI and TENS as an MOF model. If the CF value is lower than 0.5, the fresh place of each jellyfish could be developed, depending on the moving inside the swarm, via either Equation (16) representing the passive type or Equation (17) following the active type as shown [26]:

$$X_i(t+1) = 0.1 \times R \times (U_b - L_b) + X_i(t) \quad (16)$$

$$X_i(t+1) = \begin{cases} X_i(t) + R(X_j(t) - X_i(t)) & \text{if } f(X_i) \geq f(X_j) \\ X_i(t) + R(X_i(t) - X_j(t)) & \text{if } f(X_i) < f(X_j) \end{cases} \quad (17)$$

where U_b and L_b signify the upper and lower limits of the control parameters, which are in between; and f symbolizes the quantity of food in aspects of the qualitative function associated with each jellyfish location. The upper and lower limits of the control parameters are related to the open links for reconfiguration which is formulated in Equation (7). Thus, the possibilities are regarding to the distribution lines which ranges from the first line to the maximum number of the lines as formulated in Equation (8).

Also, Equation (18) describes the checking model of each jellyfish location to be restored in the nearest boundary.

$$\begin{cases} X'_{i,d} = (X_{i,d} - U_{b,d}) + L_b(d) & \text{if } X_{i,d} > U_{b,d} \\ X'_{i,d} = (X_{i,d} - L_{b,d}) + U_b(d) & \text{if } X_{i,d} < L_{b,d} \end{cases} \quad (18)$$

where $X_{i,d}$ indicates the i th jellyfish place in d th dimension. The dimension for jellyfish place is the number of the control parameters which is defined as the open links for reconfiguration as in Equation (7). Figure 1 depicts the major stages of the JFS.

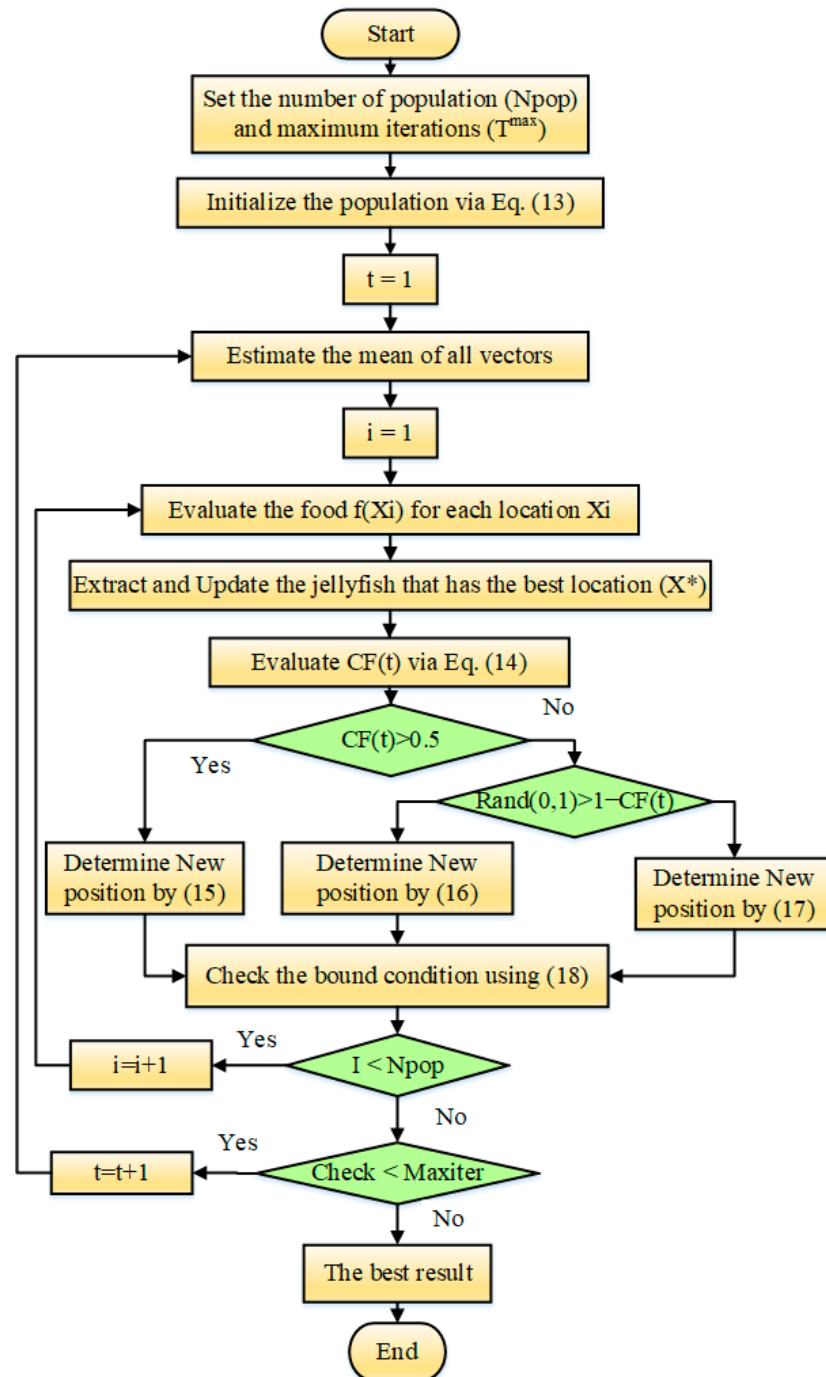


Figure 1. JFS Flowchart.

5. Simulation Results

The proposed methodology based on the JFS optimizer is implemented on a 33-node DN with 32 sectionalizing links and 5 open sections. Its single network diagram is depicted in Figure 2, where 12.66 kV is the base voltage of the 69-node DN [11]. For the nominal condition of this DN, the total apparent, active, and reactive power demands are, respectively, 4.6602 MVA, 3.802 MW and 2.6946 MVar [38]. The test DN is expected to perform under

balanced load circumstances. All loads are expected to have constant power in nature. The DN reliability data, comprising failure rates and lines repair time, is derived from [2].

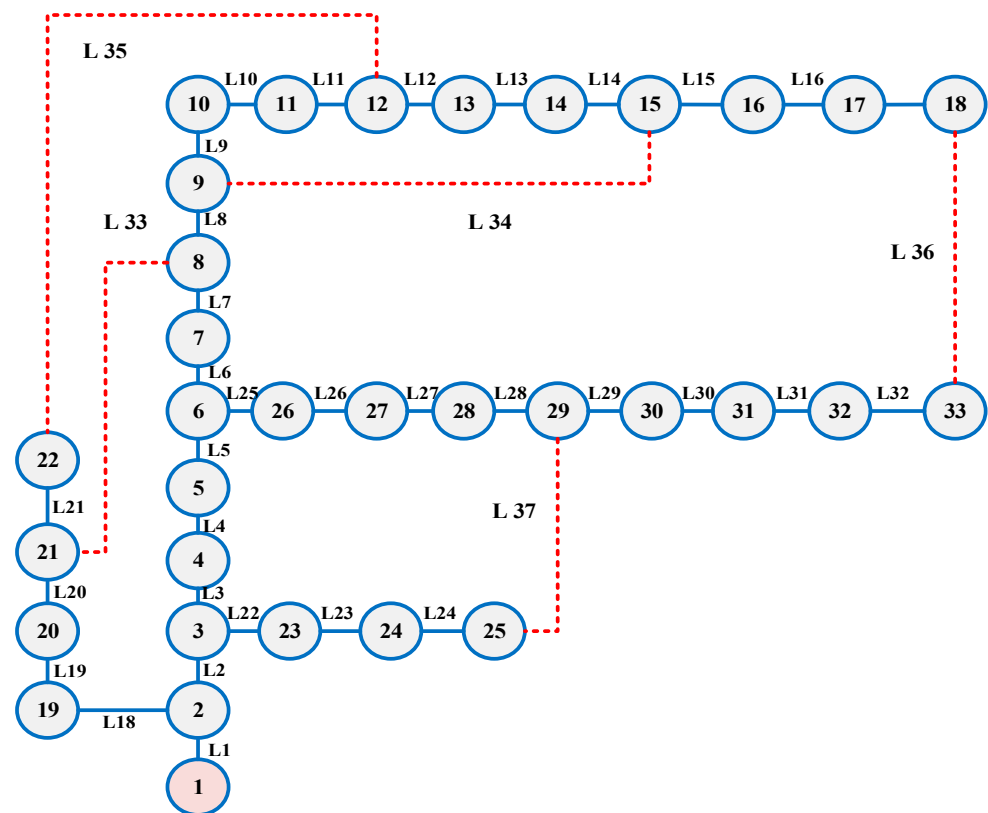


Figure 2. IEEE 33-node distribution system.

5.1. JFS Application for the Cases Studied

Four case studies are analyzed based on the objectives to be considered as follows:

Case 1 (Single objective model): Minimization of SAIFI described in Equation (1).

Case 2 (Single objective model): Minimization of SAIUI described in Equation (2).

Case 3 (Single objective model): Minimization of TENS described in Equation (3).

Case 4 (Multi-objective model): Minimization of MOF described in Equation (6).

In the multi-objective model of Case 4, $\text{SAIFI}^{\max}$, $\text{SAIUI}^{\max}$ and $\text{TENS}^{\max}$ are 8 times/year, 2.5 h/year and 10 MWh/year.

By applying the JFS algorithm on the four cases studied, Table 1 displays the must open tie lines which is optimally selected. Table 2 illustrates the related reliability measures.

Table 1. Optimal Tie Lines Based on The JFS Optimizer for The Cases Studied.

Items	Initial Case	Case 1	Case 2	Case 3	Case 4
Tie Lines	33	6	7	7	7
	34	10	9	9	9
	35	13	14	14	14
	36	17	16	16	16
	37	26	27	27	27

Table 2. Reliability Outcomes Based on The JFS Optimizer for The Cases Studied.

Items	Initial Case	Case 1	Case 2	Case 3	Case 4
SAIFI	6.4208	3.9681923	4.08061	4.08061	4.08061
SAIUI	1.9342	1.3169515	1.27448	1.27448	1.27448
TENS	7.0979	4.9605	4.7304	4.7304	4.7304
MOF	0.7620	0.5063	0.49763	0.49763	0.49763

From both tables, it can be clearly deduced that:

- In the first case, the SAIFI is minimized from 6.4208 times/year at the initial case to 3.968 times/year, which represents 38.2% improvement reduction.
- The same results are drawn for the second, third and fourth cases.
- SAIUI is minimized from 1.9342 h/year at the initial case to 1.27448 h/year, which represents 34.11% improvement reduction.
- TENS is minimized from 7.0979 MWh/year at the initial case to 4.7304 MWh/year, which represents 33.35% improvement reduction.
- TENS is minimized from 0.7620 at the initial case to 0.49763, which represents 34.7% improvement reduction.
- In the fourth case, the SAIFI is minimized from 6.4208 times/year at the initial case to 4.08061 times/year, which represents a 36.44% improvement reduction. In addition, the SAIUI is minimized from 1.9342 h/year at the initial case to 1.27448 h/year, which represents 34.11% improvement reduction. Also, the TENS is minimized from 7.0979 MWh/year at the initial case to 4.7304 MWh/year, which represents 33.35% improvement reduction.

5.2. Comparative Assessment for Solving the Cases Studied

In this sub-section, a comparative assessment is carried out for the three cases studied using three recent advanced algorithms. Tuna swarm optimizer (TUNA) [39] and tunicate swarm algorithm (TSA) [40], besides the JFS algorithm, are implemented as well. The three techniques are applied with population size of 30 individual and maximum number of 60 iterations. TUNA, TSA and JFS algorithms are implemented for 10 separate runs. The listing of technical details of the essential parameter settings in all techniques, i.e., TSA, TUNA, and JFS are shown in the Appendix A, Table A1.

For the four cases studied, the related average convergence curves are displayed in Figures 3–6, respectively, for minimizing the SAIFI, SAIUI, TENS and MOF. Added to that, Table 3 displays the related average objectives in terms of the SAIFI, SAIUI, TENS and MOF, respectively.

Table 3. SAIFI, SAIUI, TENS and MOF minimization using TUNA, TSA and JFS algorithms.

Optimizer	SAIFI Minimization		SAIUI Minimization		TENS Minimization		MOF Minimization	
	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Deviation
JFS	3.968192	9.36×10^{-16}	1.274482	0	4.7304	9.36×10^{-16}	0.4976	1.15×10^{-16}
TUNA	3.998131	0.0464	1.307449	0.05580	4.805	0.0969	0.504	0.008608
TSA	4.048725	0.0998	1.317488	0.03412	5.0403	0.3285	0.5071	0.0133

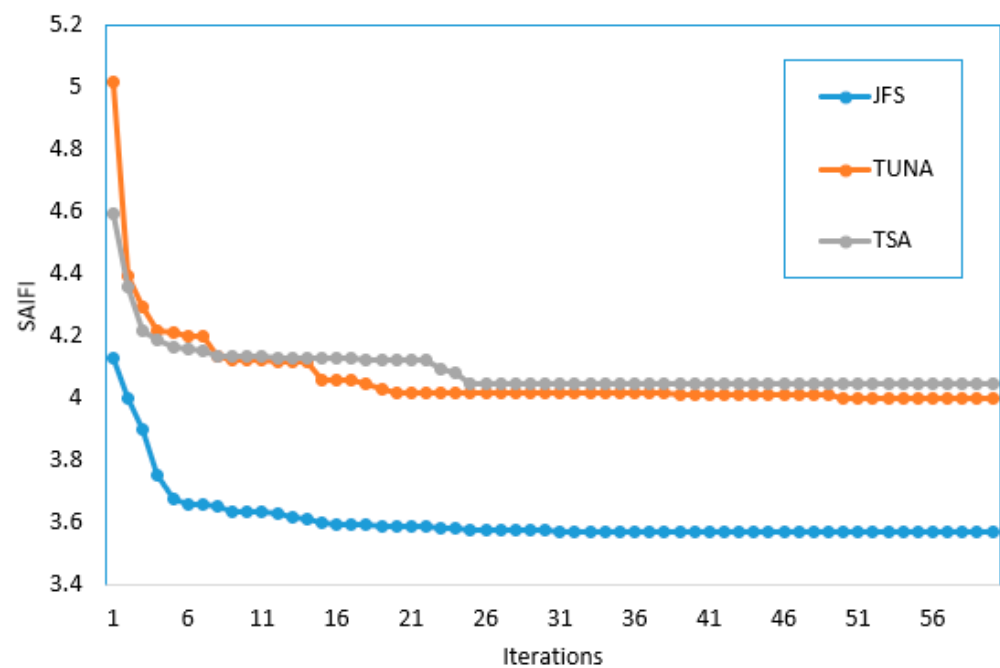


Figure 3. Convergence curves of TUNA, TSA and JFS algorithms for case 1.

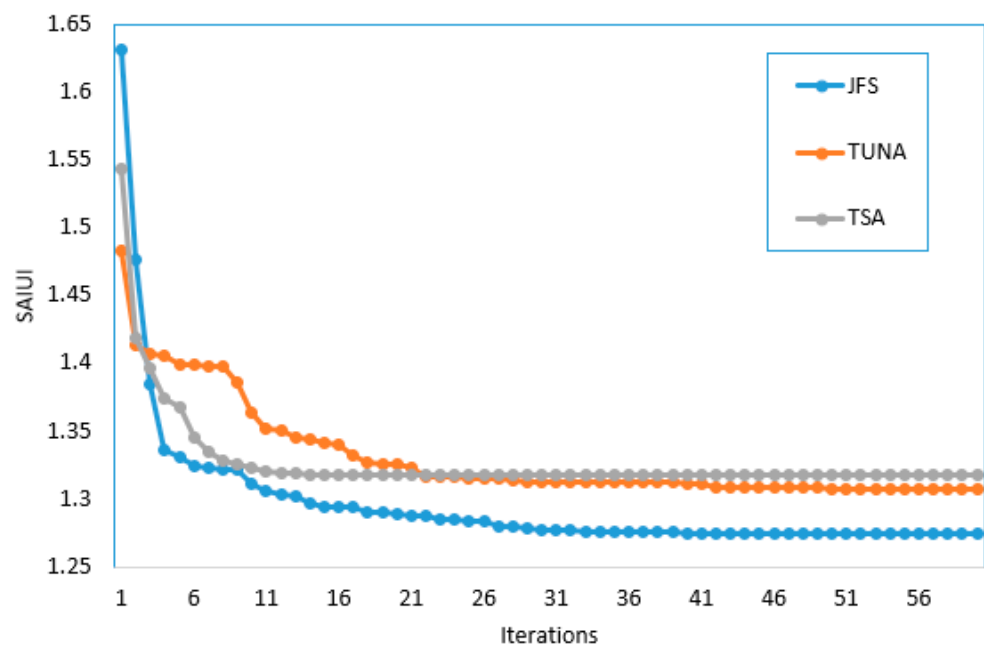


Figure 4. Convergence curves of TUNA, TSA and JFS algorithms for case 2.

In the first case, for minimizing the SAIPI, the JFS algorithm declares significant superiority over TUNA and TSA algorithms. It obtains the least average SAIPI with 3.9682 times/year, where TUNA and TSA algorithms obtains counterparts of 3.9981 and 4.0487 times/year. Also, the JFS algorithm obtains the least standard deviation with 9.36×10^{-16} , where TUNA and TSA algorithms obtains counterparts of 0.0464 and 0.0998.

In the second case, for minimizing the SAIUI, the JFS algorithm declares significant superiority over TUNA and TSA algorithms. It obtains the least average SAIUI with 1.22744 h/year, where TUNA and TSA algorithms obtains counterparts of 1.30744 and 1.3179 h/year. Also, the JFS algorithm obtains the least standard deviation with 0.00, where TUNA and TSA algorithms obtains counterparts of 0.0558 and 0.03412.

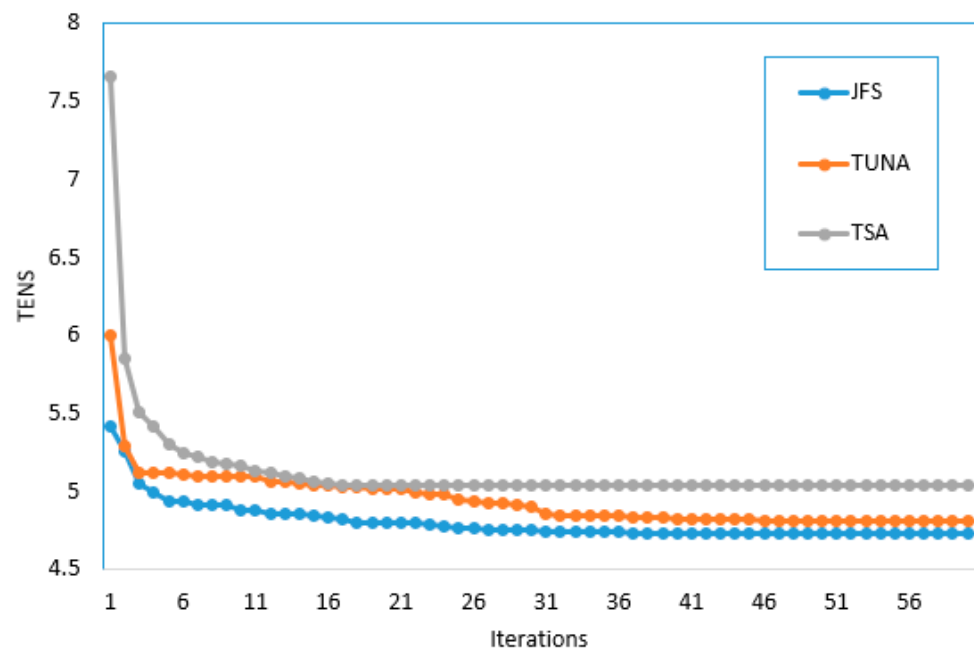


Figure 5. Convergence curves of TUNA, TSA and JFS algorithms for case 3.

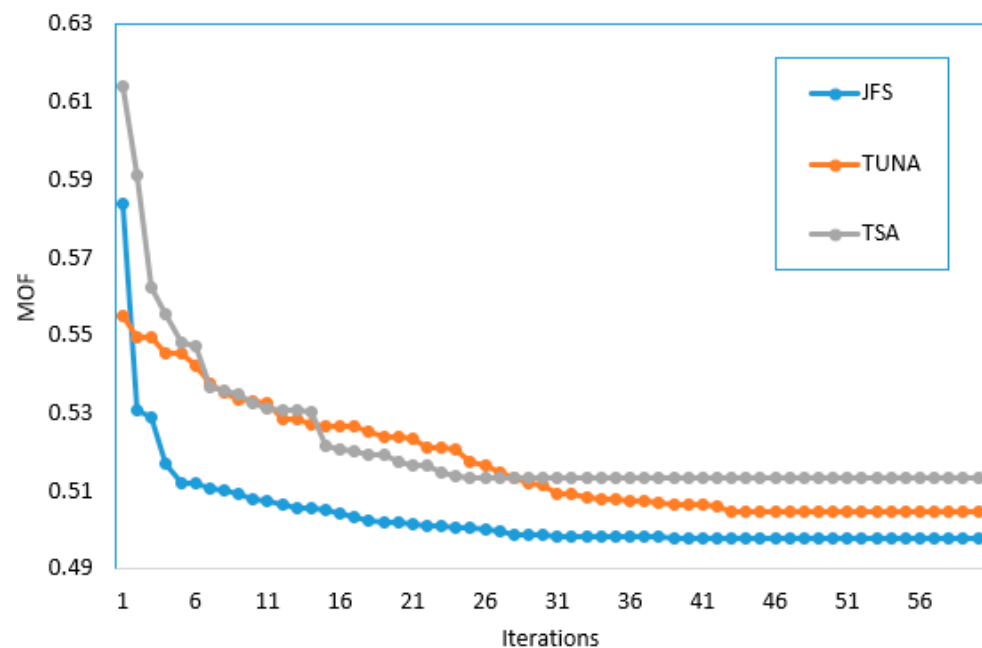


Figure 6. Convergence curves of TUNA, TSA and JFS algorithms for case 4.

In the third case, for minimizing the TENS, the JFS algorithm declares significant superiority over TUNA and TSA algorithms. It obtains the least average TENS with 4.7304 MWh/year, where TUNA and TSA algorithms obtains counterparts of 4.8049 and 5.04028 MWh/year. Also, the SNS algorithm obtains the least standard deviation with 9.36×10^{-16} where TUNA and TSA algorithms obtains counterparts of 0.0969 and 0.328.

In the fourth case, for minimizing the MOF, the JFS algorithm declares significant superiority over TUNA and TSA algorithms. It obtains the least average MOF with 0.4976, where TUNA and TSA algorithms obtains counterparts of 0.504 and 0.5071. Also, the JFS algorithm obtains the least standard deviation with 1.15×10^{-16} where TUNA and TSA algorithms obtains counterparts of 0.0086 and 0.0133.

The computational time of the proposed JFS, and of the proxy adopted (TUNA & TSA) are detailed in the Table 4 by recording the average time in seconds. As shown, the proposed JFS provides the least average computing time with 8.1775 s, while TUNA & TSA takes 13.94 and 11 s, respectively. The presented JFS shows convergence improvement with 41.33% compared to TUNA and 25.66% compared to TSA.

Table 4. Average computational time in seconds of the proposed JFS, TUNA & TSA.

Items	Case 1	Case 2	Case 3	Case 4	Average Time
JFS	8.21	7.92	7.75	8.83	8.1775
TUNA	13.29	13.37	14.2	14.9	13.94
TSA	10.54	10.7	11.69	11.1	11

To investigate the sensitivity analysis of the setting parameters for critical variables of different setting scenarios for the proposed jellyfish algorithm, different number of search agents and maximum number of iterations are considered, and the proposed jellyfish algorithm is applied for each scenario several times and the regarding indices are recorded in Table 5. As shown, great improvement is provided with higher reduction in the mean, maximum, standard deviation (Std), and standard error (Ste) with the increasing the number of search agents and maximum number of iterations. On the other side, the required computing time is increased. For that reason, the best settings are achieved at 30 search agents and 60 maximum number of iterations.

Table 5. Sensitivity analysis of different setting scenarios for the proposed JFS.

Indices	Number of Search Agents (Maximum Number of Iterations)								
	10 (30)	20 (30)	30 (30)	10 (60)	20 (60)	30 (60)	10 (90)	20 (90)	30 (90)
min	0.4976	0.4976	0.4976	0.4976	0.4976	0.4976	0.4976	0.4976	0.4976
mean	0.5027	0.4995	0.4982	0.4987	0.4977	0.4976	0.4983	0.4977	0.4976
max	0.5169	0.5036	0.4995	0.5014	0.4981	0.4976	0.5	0.4983	0.4976
Std	0.0055	0.0019	0.0007	0.0016	1.00×10^{-4}	1.15×10^{-16}	8.00×10^{-4}	2.00×10^{-4}	0
Ste	6.11×10^{-4}	2.11×10^{-4}	7.78×10^{-5}	1.78×10^{-4}	1.11×10^{-5}	1.28×10^{-17}	8.89×10^{-5}	2.22×10^{-5}	0

6. Conclusions

This paper presents an innovative application of the jellyfish search (JFS) algorithm to enhance the operational reliability of distribution systems. This application aims at improving the electricity networks automation via optimizing the Power Network Reconfiguration (PNR). In this regard, the system average interruption frequency index (SAIFI), system average interruption unavailability index (SAIUI) and total energy not supplied (TENS) are formulated, being considered simultaneously in a multi-objective model based on the weight factors. The proposed methodology based on the JFS optimizer is implemented on the IEEE 33-node distribution network. According to the numerical results, the SAIFI, SAIUI and TENS are improved by 36.44%, 34.11% and 33.35% compared to the initial condition. For comparison purposes, Tuna swarm optimizer and tunicate swarm algorithm besides the proposed JFS algorithm, are implemented as well. The simulation results declare the significant outperformance of the JFS algorithm compared to TUNA and TSA in terms of the obtained improvements and the regarding convergence properties. A comparative analysis based on sensitivity analysis at different parameters of population size and iteration number is carried out. Great improvement is provided with higher reduction in the mean fitness function, maximum fitness function, standard deviation (Std), and standard error (Ste) with increasing the number of search agents and maximum number of iterations.

In the future studies, as the mixed integer linear programming (MILP) can get an effective mathematical modelling to solve complex optimization problems. These points will be added future approach for solving the target problem for single and multi-objective frameworks.

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Appendix A

Table A1 describes the listing of technical details of the essential parameter settings in all techniques, i.e., TSA, TUNA, and JFS.

Table A1. Essential parameter settings in all techniques, i.e., TSA, TUNA, and JFS.

Algorithms	Proposed Time	Parameters Settings	Reference
Tuna swarm optimizer (TUNA)	2021	- Number of tuna population = 30 - Probability to regenerate the position in the space according to $z = 0.05$ - Constant to determine the extent to which the tuna follow the optimal individual and the previous individual in the initial phase $a = 0.7$	[39]
Tunicate swarm algorithm (TSA)	2020	- Jet propulsion behavior with number of search agents = 30 - Social forces between search agents are based on initial and subordinate speeds to make social interaction which are $P_{max} = 4$, $P_{min} = 1$	[40]
JFS	2020	- Number of search agents in population = 30 - maximum number of iterations = 60	[26]

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