Received: September 15, 2023. Revised: October 5, 2023.

INASS

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

An Improved Northern Goshawk Optimization for Optimal Reconfiguration of Modern Electrical Distribution System for Loadability Enhancement

Shaikh Sohail Mohiyodin[1] **Rajesh Maharudra Patil[1]*** **M. S Nagaraj[2]**

[1]*Visvesvaraya Technological University (VTU), Belagavi, Karnataka-590018, India*
[2]*Bapuji Institute of Engineering & Technology, Davanagere-577004, Karnataka, India*
* Corresponding author's Email: rajeshmaharudrapatil@gmail.com

Abstract: The prevalence of renewable energy sources (RESs) and electric vehicles (EVs) is significant in modern electrical distribution systems (EDS). Although these technologies undoubtedly contribute to environmental improvement, they also pose considerable challenges for power system operators owing to their intermittent and unpredictable nature. To address these concerns, EDSs prioritise efficiency and reliability, which can be achieved through optimal network reconfiguration (ONR). The ONR problem addresses the challenge of incorporating varying levels of RESs and EVs into the system by considering the distribution losses and line loadability index (LLI). To overcome convergence issues in load flow and identify the optimal branches and tie lines for switching on/off, thus significantly improving network performance, a novel optimisation methodology that combines the northern goshawk optimisation algorithm (NGO) and LLI is proposed in this study. To enhance the search capabilities of the original NGO algorithm, a Levy Flight distribution and a new adaptive parameter were introduced, resulting in an improved version called Improved NGO (INGO). Simulations were conducted on a modified east delta network (EDN) of the unified Egyptian network (UEN), covering various scenarios. By having photovoltaic (PV) penetration, the network loss reduced to 698.46 kW from 723.85 kW, but by having EV penetration, the losses are raised to 848.15 kW, however, by having both PV and EV load penetration, the losses are reduced to 764.53 kW. However, by implementing ONR, the network loss was reduced to 739 kW. Furthermore, the computational efficiency of INGO is compared to that of the basic NGO, as well as other algorithms such as the stochastic fractal search (SFS), harmony search algorithm (HAS), and artificial rabbits algorithm (ARO). The results obtained from INGO surpassed those of all other algorithms in terms of the target function and computation time. Furthermore, the reduction in losses and enhanced loadability demonstrated the adaptability of the proposed methodology for real-time applications.

Keywords: Electrical distribution system, Loss reduction, Voltage stability enhancement, Reactive power compensation, War strategy optimization.

1. Introduction

Renewable energy sources (RES) mainly as photovoltaic (PV) and wind turbine (WT) and also electric vehicles (EV) are being increasingly integrated into modern electrical distribution networks (EDS), posing both benefits and challenges. Intermittency from RESs can affect grid stability and dependability. Energy storage devices, such as energy storage systems (ESS) and pumped hydro storage, can help stabilise the electricity supply. Smart charging methods and vehicle-to-grid (V2G) technology can optimise charging schedules and reduce grid loads. Modern monitoring and control technologies, such as a demand side management (DMS) with advanced metering infrastructure (AMI), can provide real-time energy generation, consumption, and grid status data. These solutions aim to integrate RESs and EVs into distribution systems to achieve a more sustainable future.

Optimal network reconfiguration (ONR) of EDS can be useful for managing the penetration of renewable energy and electric vehicles by optimising the distribution system topology. It minimises power losses, enhances voltage profiles, and improves grid flexibility to accommodate the fluctuating nature of RESs and charging demands of EVs. Many researchers have contributed various solution techniques to solve ONR problem.

A hybrid optimisation technique that combines particle swarm optimisation (PSO) and harmony search (HS) solves the ONR problem in EDSs [1]. The goal is to reduce power loss and enhance the voltage profile within operational and technological limits. In [2], a guided initialisation technique was used to simplify the search space, reduce computational time, improve consistency in finding the optimal solution, improve the meta-heuristic algorithm efficiency, and minimise power loss while improving the EDS voltage profile. In [3], the sigmoid function of selective binary particle swarm optimisation (SBPSO) was modified to optimise the distribution network configuration and reduce the power losses. The method focuses on the particle rate of change control, search space exploration, and population convergence. The runner root algorithm (RRA), a modern metaheuristic algorithm inspired by plant runners and roots, was introduced in [4] to solve ONR problems. The approach was tested on two systems and was shown to be effective for the ONR problem. In [5], PSO, genetic algorithm (GA), and exhaustive search (ES) were used to optimise power distribution networks. This study analyzes the success rates of several strategies for solving the ONR problem with minimum power loss. In [6], efficient initial topology formation, bus injection-branch current (BIBC) matrix use, and GA modification were used to optimise the distribution network topologies. Optimising radial unbalanced distribution networks to reduce power losses, improve the voltage profile, and increase the system's voltage stability index (VSI) as described in [7]. It also uses the harmony search (HS) method to determine the best EDS distribution generation (DG) unit position. In [8], BPSO optimized EDS topology used an ANN to estimate PV generation and ESS performance, and reduced power losses. The proposed strategy optimises PV-based DG ESS operation. In [9], the ONR considered numerous objectives for better EDS operations and suggested a deep reinforcement learning (DRL)-assisted multi-objective bacterial foraging optimisation (MBFO) to tackle the non-convex, non-linear, many-objective optimisation problem. To improve the EDS operation, the PV power curtailment, voltage variation, power loss, line loading, and generator cost were optimised simultaneously. The goal of [10] is to minimise real power losses by proposing a new technique for tackling the ONR problem for loss reduction. To narrow the search space, a selective firefly algorithm (SFA) and load flow analysis criteria were used. Using the stochastic fractal search (SFS), a novel technique for tackling the ONR problem towards loss reduction in the presence of DG is presented [11]. In [12], an optimal distribution network reconfiguration and DG integration is suggested. The goals are maximum DG penetration, voltage profile improvement, and loss reduction. The model considers the switching action costs, losses, and DG reactive power generation. The solution addresses DG siting, sizing, and operation concurrently with DNR issues. In [13], modified manta ray foraging optimization algorithm (MRFOA) suggested for optimal control and operation of fully automated distribution networks. The recommended method reduces the power losses while satisfying equality and inequality requirements in Taiwan power company (TPC) distribution system. The purpose of [14] is to provide a novel way to solve ONR as well as DG sizing and placement by employing an improved shuffled frog leaping algorithm (ISFLA). The goal is to reduce power loss while remaining within the operating restrictions. In [15], an optimisation strategy for ONR and DG allocation problem is described based on modified sequential switch opening and exchange (MSSOE). Its primary contribution is to improve the efficiency and reliability of smart-grid power distribution systems. A hybrid optimisation technique for dynamic and multi-objective distribution network reconfiguration was presented with performance-enhancing loop matrix (LM) [16]. It uses the exchange market algorithm (EMA) and wild goat algorithm (WGA), adjustable population size, and parallel processing to improve convergence speed and accuracy. In [17], an improved tunicate swarm intelligent algorithm (ITSA) is introduced for simultaneous ONR with capacitor banks (CBs) and DGs allocation and control. The primary goals include energy loss reduction, voltage profile improvement, and load balancing. In [18], a new approach for ONR and DG allocation using the ant lion optimiser (ALO) is presented to reduce network losses and increase power quality indices. Simulations of the proposed technique on an imbalanced IEEE 33-bus grid with and without DGs and CBs demonstrated considerable gains. In [19], an efficient mathematical model for a distribution system reconfiguration that minimises power losses was proposed. The model is formulated as a mixed-integer nonlinear programming (MINLP) problem and solved using a mathematical programming language (AMPL) solver. Further, it also provides a comprehensive literature survey and a comparison study of various approaches for the ONR problem in various EDSs.

The aforementioned works show that the ONR problem is heavily addressed to improve various techno-economic benefits in EDS. However, reliability has emerged as a new study dimension for modern EDSs, considering load changes and uncertainties in RESs and EVs, and has been addressed in some recent studies on the ONR problem. In [20], a new strategy proposed to increase the reliability of EDS in the presence of DGs. The deep reinforcement learning (DRL) approach determines the best switches to adjust the power flow, resulting in less loss and greater reliability. A meta-heuristic moth-flame algorithm (MMFA) for ONR and placement of PV and WT based DGs while reducing power losses, improving the voltage profile and stability, and increasing dependability is shown in [21]. Further, graph theory-based modified particle swarm optimization (MPSO) [22], hybrid plant growth simulation (PGS)-particle swarm optimization (PSO) [23], and iterative branch exchange (IBE) [24] are proposed for solving simultaneous allocation of DGs and ONR problems.

Despite the emphasis in the literature on multiple techno, economic, environmental and reliable objectives when tackling ONR and DG allocation challenges, security margin enhancement in light of the emerging high EV load penetration has not been addressed considerably. In this regard, the following key contributions set this study apart from the literature.

1) A multi-objective optimization focusing on technical, reliable and security aspects in solving ONR problem considering RESs and EVs penetration.
2) Improved variant of northern goshawk optimization (INGO) by enhancing search capabilities using Levy Flight distribution and a new adaptive parameter.
3) Simulations are performed on a real-time 30-bus east delta network (EDN) of unified Egyptian network (UEN) for different scenarios.
4) The computational features of INGO are quantified and compared with basic NGO and stochastic fractal search (SFS), harmony search algorithm (HAS), and artificial rabbits algorithm (ARO).
5) For different scenarios, simulations are performed and highlighted the superiority of INGO and applicability of proposed method for real-time applications.

Additionally, the document is structured as follows. The methodology for evaluating network maximum loadability using the line loadability index is described in section 2. The suggested multi-objective functions and their restrictions are presented in section 3. The mathematical modelling of the suggested INGO and its implementation are provided in section 4. The simulation results and validation are presented in section 5. Finally, section 6 concludes the study.

2. Development of line loadability index

The line loadability index (L_{LI}) [25] is formulated considering a single branch between buses p and q, as shown in Fig. 1. The impedance, power flow in the branch, bus voltages are given in the figure.

The power at receiving bus-q can be determined by:

$$P_{pq} + jQ_{pq} = V_q\angle\delta_q \left(\frac{V_p\angle\delta_p - V_q\angle\delta_q}{r_{pq}+jx_{pq}}\right)^* \quad (1)$$

By separating real and imaginary parts of Eq. (1), the resultants are given by:

$$r_{pq}P_{pq} + x_{pq}Q_{pq} = -V_q^2 + V_p\, V_q cos(\delta_{qp}) \quad (2)$$

$$r_{pq}Q_{pq} - x_{pq}P_{pq} = V_p\, V_q sin(\delta_{qp}) \quad (3)$$

By squaring both sides of Eqs. (2) and (3) and summing, the resultant is given by:

$$V_q^4 + 2\left(r_{pq}P_{pq} + x_{pq}Q_{pq} - \frac{V_p^2}{2}\right)V_q^2 + \left(r_{pq}^2 + x_{pq}^2\right)\left(P_{pq}^2 + Q_{pq}^2\right) = 0 \quad (4)$$

By considering the parameters given in Eq. (5), the Eq. (4) can be reformulated as Eq. (6).

$$\left.\begin{array}{l} x = V_q^2 \;\; \& \;\; a = 1 \\ b = 2\left(r_{pq}P_{pq} + x_{pq}Q_{pq} - \frac{V_p^2}{2}\right) \\ c = \left(r_{pq}^2 + x_{pq}^2\right)\left(P_{pq}^2 + Q_{pq}^2\right) \end{array}\right\} \quad (5)$$

$$ax^2 + bx + c = 0 \quad (6)$$

The possible solutions for the newly formulated quadratic Eq. (6) can be realised only when its discriminant i.e., $(b^2 - 4ac)$ is greater than or zero and is given by:

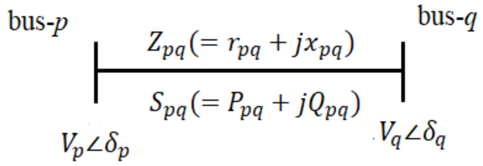

Figure. 1 A simple two-bus distribution network

$$\frac{V_q^2}{2} - \left(r_{pq}P_{pq} + x_{pq}Q_{pq} - \frac{V_p^2}{2}\right) + \sqrt{\left(r_{pq}^2 + x_{pq}^2\right)\left(P_{pq}^2 + Q_{pq}^2\right)} \geq 0 \quad (7)$$

If $P_{pq} + jQ_{pq}$ is increased to become left term of the Eq. (7) to become zero, then the possible two solutions can become equal that means, the loading point reached to critical loading point or nose point of the PV curve. By replacing $P_{pq} + jQ_{pq}$ as $L_{LI(pq)} \times \left(P_{pq} + jQ_{pq}\right)$, and then Eq. (7) made equals to zero, the resultant is:

$$L_{LI(pq)} = \frac{V_q^2}{2\left[\left(r_{pq}P_{pq} + x_{pq}Q_{pq} - \frac{V_p^2}{2}\right) + \sqrt{\left(r_{pq}^2 + x_{pq}^2\right)\left(P_{pq}^2 + Q_{pq}^2\right)}\right]} \geq 1 \quad (8)$$

The index $L_{LI(pq)}$ varies from ∞ (i.e., no loading) to 1 (i.e., critically loading). The maximum loading level of a branch can be evaluated by:

$$L_{LI(pq)}\left(P_{pq} + jQ_{pq}\right) \quad (9)$$

For generalizing for this loadability index for a network considering total branches of nbr, then, overall loadability of the network is given by:

$$L_{\overline{LI}} = min\left\{L_{LI(pq)}\left(P_{pq} + jQ_{pq}\right), \ \forall pq = nbr\right\} \quad (10)$$

By finding the minimum of $L_{LI(pq)}$ among all branches, the overall loadability index can be determined as defined in Eq. (10), consequently, by multiplying its basic power flow the maximum loadability (ML) can be evaluated and is given by:

$$ML = L_{\overline{LI}}\left(P_{\overline{pq}} + jQ_{\overline{pq}}\right) \quad (11)$$

By performing NR load flow [26], the bus voltages and thus, overall loadability index can be estimated for any distribution feeder using Eq. (11).

3. Problem formulation

The multi-objective function in this work is formulated to minimize distribution losses, reliability index i.e., system average interruption frequency index (SAIFI) and to maximize network loadability. Mathematically, it is given by.

$$F = P_{loss} + SAIFI + \frac{1}{ML} \quad (12)$$

The above multi-objective function constrained by the following aspects:

$$V_{i,min} \leq V_i \leq V_{i,max}; i \in nbus \quad (13)$$

$$\overline{nbr} + \overline{ntl} = (nbus - 1) \quad (14)$$

4. Solution methodology

In this section, the proposed solution methodology using northern goshawk optimization (NGO) [27] and its improvement variant is discussed.

4.1 Northern goshawk optimization

This section describes the process for the suggested solution using an effective and straightforward optimisation technique known as NGO, which was motivated by the hunting habits of the northern goshawk (NG), which is typically found in Eurasia and North America. Small and large birds, other birds of prey, small mammals such as mice, rabbits, and squirrels, as well as even larger species such as foxes and raccoons, are all consumed by the Accipiter-genus NG. The NG locates its prey, moves quickly in its direction, and then engages in a brief tail chase. The two phases comprise NG's pursuit of its prey: a swift approach and a quick tail-chase. Before hunting, NGs ponder carefully, and this trait serves as an inspiration for the development of the NGO algorithm. NGO is mathematically described in this section. The suggested NGO has initialisation, exploration, exploitation as well as termination phases, which are similar to those of any metaheuristic algorithm.

4.1.1. Initialization

At the beginning of the operation, a random initialisation of the population members is performed in the search space. Eqs. (15) and (16), which are used in the proposed NGO algorithm, calculate the population matrix.

$$N = [N_1, N_2, \ldots, N_i]_{p\times q}^T \quad (15)$$

$$N_n = [n_1, n_2, \ldots, n_i]_{q\times 1}^T \quad (16)$$

Each person is a potential solution, as mentioned previously. Consequently, the attributes of each population member can assess the objective function of the issue. These values are the vectors in Eq. (17) yields.

$$F(N) = \left[F_1 = f_1(n_1), \dots, F_n = f_n(n_n), \dots, F_j = f_j\left(n_j\right)\right]^T_{j\times 1} \quad (17)$$

An ideal solution was selected based on the fitness function value. When limiting or maximising, the proposed solution is more effective. The fitness function values vary with each iteration; therefore, the optimal solution should be updated.

4.1.2. Exploration

In this initial stage of exploration, the recognition of the prey and the attack by the NG were modelled. An NG will randomly choose a target prey and attack it immediately. The NGO's exploration capacity is increased in this phase because it can choose random prey from the search area. The search space was exhaustively explored to identify the ideal area. Eqs. (18-20) are used to mathematically model the first-step concepts.

$$P_n = N_n, n = 1{:}p, k = 1{:}p \quad (18)$$

$$N_{n,m(n,P1)} = \begin{cases} n_{n.m} + r\left(p_{m,n} - In_{n,m}\right) & F_{Pn} < F_n \\ n_{n.m} + r\left(In_{n,m} - p_{m,n}\right) & F_{Pn} \geq F_n \end{cases} \quad (19)$$

$$N_n = \begin{cases} N_{n(n,P1)} & F_{n(n,P1)} < F_n \\ N_n & F_{n(n,P1)} \geq F_n \end{cases} \quad (20)$$

4.1.3. Exploitation

After the NG attacks, the prey ran away. The northern goshawk continued to pursue its prey. The quickness of the NGs allows them to hunt in practically anyplace. This method can perform in-depth local searches of the search space by simulating this behaviour. The NGO algorithm advises scouting a target area with a radius of R. Eqs. (21-23) are used to mathematically model the notions of the second phase.

$$N_{n,m(n,P2)} = n_{n,m} + R(2r - 1)n_{n,m} \quad (21)$$

$$R = 0.02\left(1 - \frac{t}{T_{max}}\right) \quad (22)$$

$$N_n = \begin{cases} N_{n(n,P2)} & F_{n(n,P2)} < F_n \\ N_n & F_{n(n,P2)} \geq F_n \end{cases} \quad (23)$$

An iteration is completed after updating every member of the population using the first and second stages of the proposed NGO algorithm. At this stage, the ideal solution, fitness value, and new population size are chosen. Then, the algorithm keeps updating the population members based on Eqs. (18-23) until the end of the program. The best suggested solution from the algorithm iterations is offered as a quasi-optimal solution for the optimisation problem once the NGO technique is fully applied.

4.2 Improved northern goshawk optimization

The basic NGO algorithm is stuck in a local minimum. This frequently occurs in complex high-dimensional optimisation problems. Levy flight (LF) is added to the NGO algorithm to boost the search capabilities for difficult real-world issues. LF has improved resource search efficiency hence they have been included in the improved NGO (INGO) [28]. The second portion of Eqs. (19), (21), and (22) are updated using levy flight distribution [29] as follows:

$$N_{n,m(n,P1)} = n_{n.m} + LF\left(In_{n,m} - p_{m,n}\right) \quad F_{Pn} \geq F_n \quad (24)$$

$$N_{n,m(n,P2)} = n_{n,m} + \alpha\beta(2r - 1)n_{n,m} + K \quad (25)$$

The exploitation parameter α can be set to 0.0001. The adaptive parameter β is added to the smooth transition from exploration to exploitation, can be computed as follows:

$$K = \beta \times I \quad (26)$$

$$\beta = 1.99\left(0.99 - \frac{t}{T_{max}}\right) \quad (27)$$

By having these modifications, the performance of basic NGO is improved significantly [28].

5. Results and discussion

Simulations are performed on a real-time 30-bus east delta network (EDN) of unified Egyptian network (UEN) [30] for different scenarios using programming in MATLABR2023a. The PC has 16 GB RAM and Intel Core i3 Processor.

Two scenarios are simulated. In Scenario, ONR problem is solved using basic NGO [27] and stochastic fractal search (SFS) [31], harmony search algorithm (HAS) [32], and artificial rabbits algorithm (ARO) [33] and compared with INGO [28]. In Scenario-2, three case studies are compared

Received: September 15, 2023. Revised: October 5, 2023.

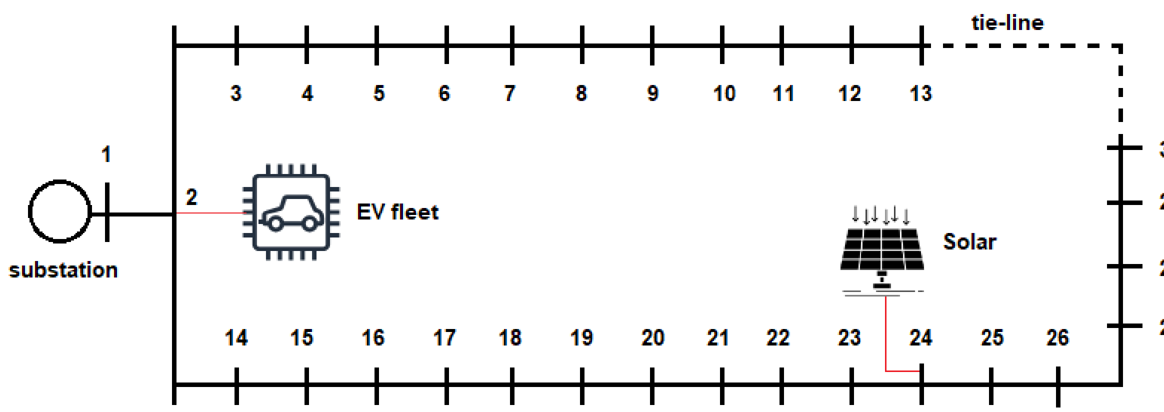

Figure. 2 Schematic diagram of EDN of UEN with assumed PV system and EV fleets

Table 1. Comparison of different case studies in Scenario-1

Case	**Branches**		**P_{loss} (kW)**	**Q_{loss} (kVAr)**	**V_{min} (p.u.)**	**SAIF1**	$L_{\overline{LI}}$
	Open	Close					
Base [30]	30	1 to 29	805.73	361.18	0.9463 (30)	3.148	1.73101
ONR by INGO	24	1 to 23 & 25 to 30	768.37	360.86	0.9511 (25)	3.001	1.73903

Table 2. Comparison of different algorithms for ONR problem in Scenario-1

Algorithm	**Branches**		**Worst**	**Best**	**Mean**	**Median**	**S.D.**	**Time (min)**
	Open	Close						
SFS [31]	24	1 to 23 & 25 to 30	932.422	768.370	778.220	768.370	30.366	3.546
HAS [32]	24	1 to 23 & 25 to 30	895.614	768.370	774.176	768.370	25.355	3.136
ARO [33]	24	1 to 23 & 25 to 30	879.220	768.370	791.848	808.977	23.914	3.286
NGO [27]	24	1 to 23 & 25 to 30	880.180	768.370	771.462	768.370	16.699	3.327
INGO [28]	24	1 to 23 & 25 to 30	883.541	768.370	770.767	768.370	16.281	3.122

Table 3. Comparison of different case studies in Scenario-2

Case	**Branches**		**P_{loss} (kW)**	**Q_{loss} (kVAr)**	**V_{min} (p.u.)**	**SAIF1**	$L_{\overline{LI}}$
	Open	Close					
Case 1 (base)	30	1 to 29	723.85	326.88	0.9514 (30)	3.1476	1.7982
Case 1 (ONR)	25	1 to 24 & 26 to 30	698.46	323.92	0.9582 (26)	2.9800	1.7998
Case 2 (base)	30	1 to 29	848.15	384.75	0.9454 (30)	3.1476	1.6431
Case 2 (ONR)	24	1 to 23 & 25 to 30	810.66	384.39	0.9502 (25)	3.0014	1.6449
Case 3 (base)	30	1 to 29	764.528	349.496	0.9505 (30)	3.1476	1.6979
Case 3 (ONR)	25	1 to 24 & 26 to 30	739.048	346.506	0.9573 (26)	2.9803	1.6993

considering: (a) only RESs penetration, (b) only EVs penetration and (c) both RESs and EVs penetration.

5.1 Simulations on real-time system

The standard east delta network (EDN) of unified Egyptian network (UEN) data is taken from [30]. The modified system by considering solar photovoltaic (SPV) system of 1 MW at bus-24 and EV fleet of 1.5 MW at bus-2 is shown in Fig. 2. The tie-line data which is not provided in [30] is assumed as (0.5 + j 1.0) ohm.

The standard EDN of UEN has total real and reactive power loads of 22441.3 kW and 14162.2 kVAr, respectively. The network is operating at 11 kV. The NR load flow [26] is used to compute bus voltage profile and branch power flows as well as total distribution losses.

For the radial configuration, without considering tie-line, the system has total of real and reactive power losses of 805.73 kW and 361.18 kVAr, respectively [30]. The network has lowest voltage magnitude of 0.9463 p.u. is observed at bus-29 and 30. Further, the SAIFI and $L_{\overline{LI}}$ are determined as 3.148 and 1.73101, respectively.

For ONR, the tie-line 30 is closed and INGO is used to identify the branch which is to be opened for formulating again best configuration. As per the results of INGO, the optimal branch for opening is 24 and correspondingly, the network performance is

 DOI: 10.22266/ijies2023.1231.77

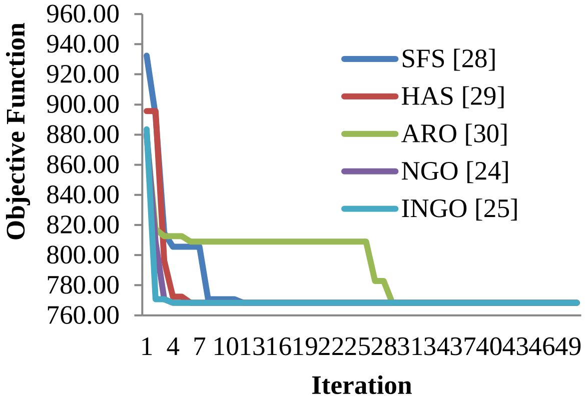

Figure. 3 Convergence of compared algorithms

evaluated and given in Table 1. The total real and reactive power losses are of 768.37 kW and 360.86 kVAr, respectively. The network lowest voltage magnitude at bus-25 is raised to 0.9511 p.u. Further, the SAIFI is decreased to 3.001 and $L_{\overline{LI}}$ is raised to and 1.73903. These figures are clearly indicating that the performance of system is improved significantly by reducing losses, improving reliability and enhancing loadability index.

The performance of INGO is further compared with other meta-heuristics namely SFS [31], HAS [32], ARO [33] and basic NGO [27]. The case study is repeated for 25 independent runs and the results are quantified with statistical measures and given in Table 2. As per the low standard deviation (S.D), mean, median and computational times, INGO is outperformed other algorithms, though the best result is same. This indicates the enhancement in search characteristics of basic NGO with the proposed modifications as described in Section 4.2. The convergence characteristics of all the algorithms for best results are given in Fig. 3.

5.2 Simulations on modified system

In the modified system, SPV and EV fleets are considered. The simulations in this scenario are performed only using INGO and the results are compared for all cases in Table 3.

5.2.1. Case 1 (Only SPV penetration)

By having 1 MW SPV system at bus-24, the results are discussed for base case (i.e., original radial configuration) and optimal configuration. The total real and reactive power losses are determined as 723.85 kW and 326.88 kVAr, respectively. The system has lowest voltage magnitude at bus-30 as 0.9514 p.u. Further, there is no change in SAIFI due to same configuration, however, $L_{\overline{LI}}$ is raised to 1.7982 due to the presence of SPV in the network.

As per the results of INGO, the optimal branch for opening is 25 and correspondingly, the network performance is evaluated. The total real and reactive power losses are reduced to 698.46 kW and 323.92 kVAr, respectively. The network lowest voltage magnitude at bus-26 is raised to 0.9582 p.u. Further, the SAIFI is decreased to 2.980 and $L_{\overline{LI}}$ is raised considerably to 1.7998.

5.2.2. Case 2 (Only EV fleet penetration)

By having 1.5 MW EV fleet at bus-2, the results are discussed for base case (i.e., original radial configuration) and optimal configuration. The operating power factor of EV fleet is treated as 0.85 lagging. Thus, the total network load is raised to 23941.3 kW and 14655.23 kVAr, respectively. Consequently, the total real and reactive power losses are registered as 848.15 kW and 384.75 kVAr, respectively. The system has lowest voltage magnitude at bus-30 as 0.9454 p.u. Further, there is no change in SAIFI due to same configuration, however, $L_{\overline{LI}}$ is decreased to 1.6431 due to the presence of EV fleet load in the network.

As per the results of INGO, the optimal branch for opening is 24 and correspondingly, the network performance is evaluated. The total real and reactive power losses are reduced to 810.66 kW and 384.39 kVAr, respectively. The network lowest voltage magnitude at bus-24 is raised to 0.9502 p.u. Further, the SAIFI is decreased to 3.0014 and $L_{\overline{LI}}$ is raised considerably to 1.6449. In comparison to base case, ONR resulted for improvement in performance.

5.2.3. Case 3 (Both SPV and EV fleet penetration)

In this case, by having both SPV and EF fleet, the results are discussed for base case (i.e., original radial configuration) and optimal configuration. The total real and reactive power losses are registered as 764.528 kW and 349.496 kVAr, respectively. The system has lowest voltage magnitude at bus-30 as 0.9505 p.u. Further, there is no change in SAIFI due to same configuration, however, $L_{\overline{LI}}$ is decreased to 1.6979 due to the presence of EV fleet load in the network.

As per the results of INGO, the optimal branch for opening is 24 and correspondingly, the network performance is evaluated. The total real and reactive power losses are reduced to 739.048 kW and 346.506 kVAr, respectively. The network lowest voltage magnitude at bus-26 is raised to 0.9573 p.u. Further, the SAIFI is decreased to 2.9803 and $L_{\overline{LI}}$ is raised considerably to 1.6993. In comparison to base case, ONR resulted for improvement in

Received: September 15, 2023. Revised: October 5, 2023.

Table 4. ONR comparison in IEEE 33-bus EDS

Ref.	Open Switches	P_{loss} (kW)
Base	33, 34, 35, 36, 37	202.677
SPSO [1]	7, 11, 28, 32, 34	112.58
FA [2]	7, 9, 14, 32, 37	139.551
IS-BPSO [3]	7, 9, 14, 32, 37	137.08*
GA, PSO [5]	7, 9, 14, 32, 37	139.551
GA [6]	7, 9, 14, 32, 37	139.2*
MPSO [22]	7, 9, 14, 32, 37	139.551
Proposed	7, 9, 14, 32, 37	139.551

* Answer is not accurate as per load flow [26]

performance.

5.3 Comparative study

In this case study, simulations are performed on standard IEEE 33-bus test system. The network has a total load of 3.715 MW and 2.3 MVAr, respectively. By performing the NR load flow [26], total distribution loss are estimated as 202.6771 kW and 135.141 kVAr, respectively. By implementing INGO, the best open switches for reconfiguration are determined as 7, 9, 14, 32 and 37, respectively. The new distribution losses with the optimal configuration are 139.5513 kW and 102.3050 kVAr, respectively. The results of INGO are compared with literature works in Table 4. It is observed that the results of INGO are fairly competitive with literature works SPSO [1], FA [2], IS-BPSO [3], GA, PSO [5] and GA [6]. This comparative study indicates the accuracy of INGO and suitability to solve real-time complex optimization problems.

6. Conclusion

To manage RESs and EV fleet loads in EDSs, this paper proposes a multi-objective optimisation that focuses on technical, reliable, and security aspects when solving the ONR problem based on the penetration of RESs and EVs. To solve the optimisation problem, a variant of northern goshawk optimisation (INGO) with enhanced search capabilities using the levy flight distribution and a new adaptive parameter was presented. Different scenarios were simulated on a 30-bus real-time east delta network (EDN) of the unified Egyptian network (UEN). INGO's computational characteristics are quantified and compared with those of NGO, SFS, HAS, and ARO. Simulations were performed for various scenarios, demonstrating the superiority of INGO and viability of the proposed method for real-time applications.

7. Future scope

As seen in literature, many heuristics have been employed for solving complex optimization problems. However, as per no free lunch (NFL) theorem [34], there is no single algorithm which can solve all kinds of optimization problems and thus, researcher are still inspiring to introduce new algorithms or modifications to the existing one. Some of such recent metaheuristics are puzzle optimization algorithm (POA) [35], stochastic komodo algorithm (SKA) [36], extended stochastic coati optimizer (ESCO) [37], guided pelican algorithm (GPA) [38], swarm magnetic optimizer (SMO) [39], walk-spread algorithm (WSA) [40] and four directed search algorithm (FDSA) [41] etc. Thus, the proposed work can be extended to utilize the above mentioned new algorithm and perfrom comparative study. Further the work has considered only PV system, it is also possible to extend to WT and their combinations in larger networks.

Notations

Z_{pq}	Impedance
r_{pq}	Resistance
x_{pq}	Reactance
S_{pq}	Complex power flow
P_{pq}	Real power flow
Q_{pq}	Reactive power flow
V_p & V_q	Voltage magnitudes
δ_p & δ_q	Voltage angles
$\overline{pq}$	Branch of lowest loadability index
$L_{\overline{LI}}$	Lowest loadability index
$nbus$	Number of buses
ntl	Number of tie-lines
nbr	Number of branches
$\overline{nbr}$	Number of branches in ON position
$\overline{ntl}$	Number of tie-lines in ON position
$V_{i,min}$	Minimum voltage limit
$V_{i,max}$	Maximum voltage limit
P_{loss}	Distribution real power loss
t	Current iteration number
T_{max}	Maximum iteration number
N	initial population of NGs
N_n	nth solution vector
$n_{m\times n}$	mth variable value by nth solution vector,
p and q	number of population and search variables
F	Vector of achieved objective function values
F_n	Fitness value obtained by nth suggested solution
P_n	Prey position for the nth NG
F_{Pn}	Fitness value,

k	Real number between 1 and q
r	Uniformly distributed random number between 0 and 1
$N_{n(n,P1)}$	New position for the nth solution
$N_{n,m(n,P1)}$	mth position at exploration phase
$F_{n(n,P1)}$	Fitness value at the first phase or exploration phase
I	Random number that can be either 1 and 2
$N_{n(n,P2)}$	New position for the nth solution at exploitation phase
$N_{n,m(n,P2)}$	mth position at exploitation phase
$F_{n(n,P2)}$	Fitness value at exploitation phase

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, software and original draft preparation are done by Shaikh Sohail Mohiyodin; supervision, review, and formal analysis are done by ajesh Maharudra Patil and M.S Nagaraj.

References

[1] A. O. Salau, Y. W. Gebru, and D. Bitew, "Optimal network reconfiguration for power loss minimization and voltage profile enhancement in distribution systems", *Heliyon*, Vol. 6, No. 6, 2020.

[2] M. A. Samman, H. Mokhlis, N. N. Mansor, H. Mohamad, H. Suyono, and N. M. Sapari, "Fast optimal network reconfiguration with guided initialization based on a simplified network approach", *IEEE Access*, Vol. 8, pp. 11948-11963, 2020.

[3] R. Pegado, Z. Ñaupari, Y. Molina, and C. Castillo, "Radial distribution network reconfiguration for power losses reduction based on improved selective BPSO", *Electric Power Systems Research*, Vol. 169, pp. 206-213, 2019.

[4] T. T. Nguyen, "Electric distribution network reconfiguration for power loss reduction based on runner root algorithm", *International Journal of Electrical and Computer Engineering*, Vol. 10, No. 5, pp. 5016-5024, 2020.

[5] O. Kahouli, H. Alsaif, Y. Bouteraa, N. B. Ali, and M. Chaabene, "Power system reconfiguration in distribution network for improving reliability using genetic algorithm and particle swarm optimization", *Applied Sciences*, Vol. 11, No. 7, p. 3092, 2021.

[6] D. Jakus, R. Čađenović, J. Vasilj, and P. Sarajčev, "Optimal reconfiguration of distribution networks using hybrid heuristic-genetic algorithm", *Energies*, Vol. 13, No. 7, p. 1544, 2020.

[7] A. Roosta, H. R. Eskandari, and M. H. Khooban, "Optimization of radial unbalanced distribution networks in the presence of distribution generation units by network reconfiguration using harmony search algorithm", *Neural Computing and Applications*, Vol. 31, pp. 7095-7109, 2019.

[8] R. V. Monteiro, J. P. Bonaldo, R. F. D. Silva, and A. S. Bretas, "Electric distribution network reconfiguration optimized for PV distributed generation and energy storage", *Electric Power Systems Research*, Vol. 184, p. 106319, 2020.

[9] Y. Li, G. Hao, Y. Liu, Y. Yu, Z. Ni, and Y. Zhao, "Many-objective distribution network reconfiguration via deep reinforcement learning assisted optimization algorithm", *IEEE Transactions on Power Delivery*, Vol. 37, No. 3, pp. 2230-2244, 2021.

[10] C. Gerez, L. I. Silva, E. A. Belati, A. J. S. Filho, and E. C. Costa, "Distribution network reconfiguration using selective firefly algorithm and a load flow analysis criterion for reducing the search space", *IEEE Access*, Vol. 7, pp. 67874-67888, 2019.

[11] T. T. Tran, K. H. Truong, and D. N. Vo, "Stochastic fractal search algorithm for reconfiguration of distribution networks with distributed generations", *Ain Shams Engineering Journal*, Vol. 11, No. 2, pp. 389-407, 2020.

[12] A. Bagheri, M. Bagheri, and A. Lorestani, "Optimal reconfiguration and DG integration in distribution networks considering switching actions costs using tabu search algorithm", *Journal of Ambient Intelligence and Humanized Computing*, Vol. 12, pp. 7837-7856, 2021.

[13] E. E. Elattar, A. M. Shaheen, A. M. E. Sayed, R. A. E. Sehiemy, and A. R. Ginidi, "Optimal operation of automated distribution networks based-MRFO algorithm", *IEEE Access*, Vol. 9, pp. 19586-195601, 2021.

[14] J. Siahbalaee, N. Rezanejad, and G. B. Gharehpetian, "Reconfiguration and DG sizing and placement using improved shuffled frog leaping algorithm", *Electric Power Components and Systems*, Vol. 47, No. (16-17), pp. 1475-1488, 2019.

[15] V. Vai, S. Suk, R. Lorm, C. Chhlonh, S. Eng, and L. Bun, "Optimal reconfiguration in distribution systems with distributed

generations based on modified sequential switch opening and exchange", *Applied Sciences*, Vol. 11, No. 5, p. 2146, 2021.

[16] A. Jafari, H. G. Ganjehlou, F. B. Darbandi, B. M. Ivatloo, and M. Abapour, "Dynamic and multi-objective reconfiguration of distribution network using a novel hybrid algorithm with parallel processing capability", *Applied Soft Computing*, Vol. 90, p. 106146, 2020.

[17] T. Fetouh and A. M. Elsayed, "Optimal control and operation of fully automated distribution networks using improved tunicate swarm intelligent algorithm", *IEEE Access*, Vol. 8, pp. 129689-129708, 2020.

[18] M. J. Moghaddam, A. Kalam, J. Shi, S. A. Nowdeh, F. H. Gandoman, and A. Ahmadi, "A new model for reconfiguration and distributed generation allocation in distribution network considering power quality indices and network losses", *IEEE Systems Journal*, Vol. 14, No. 3, pp. 3530-3538, 2020.

[19] M. Mahdavi, H. H. Alhelou, N. D. Hatziargyriou, and A. A. Hinai, "An efficient mathematical model for distribution system reconfiguration using AMPL", *IEEE Access*, Vol. 9, pp. 79961-79993, 2021.

[20] S. Malekshah, A. Rasouli, Y. Malekshah, A. Ramezani, and A. Malekshah, "Reliability-driven distribution power network dynamic reconfiguration in presence of distributed generation by the deep reinforcement learning method", *Alexandria Engineering Journal*, Vol. 61, No. 8, pp. 6541-6556, 2022.

[21] A. J. Nowdeh, M. Babanezhad, S. A. Nowdeh, A. Naderipour, H. Kamyab, Z. A. Malek, and V. K. Ramachandaramurthy, "Meta-heuristic matrix moth–flame algorithm for optimal reconfiguration of distribution networks and placement of solar and wind renewable sources considering reliability", *Environmental Technology & Innovation*, Vol. 20, p. 101118, 2020.

[22] A. E. Maksoud, A. H. Ahmed, and S. Hasan, "Simultaneous Optimal Network Reconfiguration and Allocation of Four Different Distributed Generation Types in Radial Distribution Networks Using a Graph Theory-Based MPSO Algorithm", *International Journal of Intelligent Engineering & Systems*, Vol. 16, No. 2, pp. 291-306, 2023, doi: 10.22266/ijies2023.0430.24.

[23] S. S. Parihar and N. Malik, "Network reconfiguration in the presence of optimally integrated multiple distributed generation units in a radial distribution network", *Engineering Optimization*, pp. 1-21, 2023.

[24] E. C. Pereira, C. H. Barbosa, and J. A. Vasconcelos, "Distribution network reconfiguration using iterative branch exchange and clustering technique", *Energies*, Vol. 16, No. 5, p. 2395, 2023.

[25] J. Yu, W. Li, and W. Yan, "A new line loadability index for radial distribution systems", *Electric Power Components and Systems*, Vol. 36, No. 11, pp. 1245-1252, 2008.

[26] R. D. Zimmerman, C. E. M. Sánchez, and R. J. Thomas, "MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education", *IEEE Transactions on Power Systems*, Vol. 26, No. 1, pp. 12-19, 2010.

[27] M. Dehghani, Š. Hubálovský, and P. Trojovský, "Northern goshawk optimization: a new swarm-based algorithm for solving optimization problems", *IEEE Access*, Vol. 9, pp. 162059-162080, 2021.

[28] H. T. Sadeeq and A. M. Abdulazeez, "Improved Northern Goshawk Optimization Algorithm for Global Optimization", In: *Proc. of 2022 4th International Conference on Advanced Science and Engineering (ICOASE)*, Zakho, Iraq, pp. 89-94, 2022.

[29] E. H. Houssein, M. R. Saad, F. A. Hashim, H. Shaban, and M. Hassaballah, "Lévy flight distribution: A new metaheuristic algorithm for solving engineering optimization problems", *Engineering Applications of Artificial Intelligence*, Vol. 94, p. 103731, 2020.

[30] A. A. A. E. Ela, R. A. E. Sehiemy, A. M. Kinawy, and M. T. Mouwafi, "Optimal capacitor placement in distribution systems for power loss reduction and voltage profile improvement", *IET Generation, Transmission & Distribution*, Vol. 10, No. 5, pp. 1209-1221, 2016.

[31] H. Salimi, "Stochastic fractal search: a powerful metaheuristic algorithm", *Knowledge-based Systems*, Vol. 75, pp. 1-8, 2015.

[32] X. S. Yang, "Harmony search as a metaheuristic algorithm", *Music-Inspired Harmony Search Algorithm: Theory and Applications, Studies in Computational Intelligence*, Vol. 191, pp. 1-14, 2009.

[33] L. Wang, Q. Cao, Z. Zhang, S. Mirjalili, and W. Zhao, "Artificial rabbits optimization: A new bio-inspired meta-heuristic algorithm for solving engineering optimization problems", *Engineering Applications of Artificial Intelligence*, Vol. 114, p. 105082, 2022.

[34] S. P. Adam, S. A. Alexandropoulos, P. M.

Pardalos, and M. N. Vrahatis, “No free lunch theorem: A review”, *Approximation and Optimization: Algorithms, Complexity and Applications*, Vol. 145, pp. 57-82, 2019.

[35] F. A. Zeidabadi and M. Dehghani, “POA: Puzzle Optimization Algorithm”, *International Journal of Intelligent Engineering & Systems*, Vol. 15, No. 1, pp. 273-281, 2022, doi: 10.22266/ijies2022.0228.25.

[36] P. D. Kusuma and M. Kallista, “Stochastic Komodo Algorithm”, *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 4, pp. 156-166, 2022, doi: 10.22266/ijies2022.0831.15.

[37] P. D. Kusuma and A. Dinimaharawati, “Extended Stochastic Coati Optimizer”, *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 3, pp. 482-494, 2023, doi: 10.22266/ijies2023.0630.38.

[38] P. D. Kusuma and A. L. Prasasti, “Guided Pelican Algorithm”, *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 6, pp. 179-190, 2022, doi: 10.22266/ijies2022.1231.18.

[39] P. D. Kusuma and F. C. Hasibuan, “Swarm Magnetic Optimizer: A New Optimizer that Adopts Magnetic Behaviour”, *International Journal of Intelligent Engineering & Systems*, Vol. 16, No. 4, pp. 264-275, 2023, doi: 10.22266/ijies2023.0831.22.

[40] P. D. Kusuma and A. L. Prasasti, “Walk-Spread Algorithm: A Fast and Superior Stochastic Optimization”, *International Journal of Intelligent Engineering & Systems*, Vol. 16, No. 5, pp. 275-288, 2023, doi: 10.22266/ijies2023.1031.24.

[41] P. D. Kusuma and A. Dinimaharawati, “Four Directed Search Algorithm: A New Optimization Method and Its Hyper Strategy Investigation”, *International Journal of Intelligent Engineering & Systems*, Vol. 16, No. 5, pp. 598-611, 2023, doi: 10.22266/ijies2023.1031.51.