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Optimal Reconfiguration of Fully Automated Distribution System for Reliable and Resilient Operation using Hybrid Single Candidate Optimizer

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Abstract: Power systems around the world are transforming into automated networks for more efficient, secure, reliable, and resilient operations, while satisfying technological, economic, and environmental goals. This study addresses the optimal network reconfiguration (ONR) problem by developing a multi-objective function that targets loss reduction, voltage profile improvement, and reliability enhancement. It recommends merging renewable energy sources (RES) with energy storage systems (ESS) to improve resilience. The complex nonlinear multi-objective, multi-variable, and multi-constraint problem is simplified by an efficient single candidate optimizer (SCO). Further, a novel severity index of interruption (SII) is introduced for reducing the search space and thus, improving the computational efficiency of SCO in the proposed hybridization algorithm. In terms of statistical metrics and computing time, simulations on IEEE test systems show that the SCO-SII approach outperforms the basic SCO, grasshopper optimization algorithm (GOA), cuckoo search algorithm (CSA) and Pathfinder algorithm (PFA) in reconfiguration, RES integration, and robust mode augmentation. The capacity of the methodology to handle uncertainty in current electrical networks emphasises its importance.

Keywords: Electrical distribution system, Energy storage system, Renewable energy sources, Optimal network reconfiguration, Single candidate optimizer, Security, Severity index of interruption, Reliability, Resilient.

1. Introduction

Automation in electrical distribution systems provides advantages, such as increased operational efficiency, rapid problem detection, remote control capabilities, and data-driven decSIIon-making. It improves the load control, reduces outages, and facilitates the incorporation of renewable energy sources (RESs) [1]. Some hurdles include cyber security risks, device compatibility issues, large initial expenditures, and the need for experienced staff to successfully administer and maintain automated systems. On the other hand, changing the connections between feeders and switches to change the topology of power distribution networks is a reconfiguration of an electrical distribution system and one of the features of automated electrical distribution system (AEDS) with remote control switches (RCSs) [2]. It is used to promote energy efficiency and dependability and optimise the power flow. Among these issues are the development of complex algorithms, real-time monitoring, load balancing, voltage management, and the integration of RESs while ensuring a consistent supply and minimal outage interruption [3]. Identifying the optimal RCSs for changing their mode of operation (ON/OFF) is a difficult task because of the $2^{(b+t)}$ combinations, where b and t are the number of branches and tie lines, respectively [4].

In literature, the problem of optimal network reconfiguration (ONR) is handled by various meta-heuristics than conventional approaches [5]. Meta-heuristic algorithms (MHA) outperform conventional optimization. They thrive in difficult, non-linear, and multimodal optimisation problems without clear mathematical formulas. They efficiently search for enormous solution spaces and often find near optimal solutions owing to their versatility. They perform well for real-world problems with difficult analytical solutions. Genetic algorithm (GA), particle swarm optimisation (PSO), and simulated annealing (SA) are well-suited for parallel computing, improving their scalability and speed in solving complex optimisation problems across domains [6]. However, in last decade, various efficient and simple MHAs are introduced for solving complex optimization problems including ONR problem in EDS.

One of the key goals of the ONR problem is to improve its performance. Many researchers are working on reducing losses, improving voltage profiles, increasing voltage stability, and reducing voltage imbalance. In [7], improved selective binary particle swarm optimisation (IS-BPSO) was utilised in IEEE 33-bus and 94-bus practical systems to reduce losses using ONR. Using selective particle swarm optimisation (SPSO), ONR was solved to enhance network performance (in terms of loss reduction and voltage profile improvement) under varied loading situations in [8]. In [9], the sequential branch-exchange algorithm (SBEA), stochastic Kruskal's algorithm (KA), and GA are hybridized to manage the radiality constraint when solving ONR for loss reduction and achieving a lower loading index. In [10], an improved GA (IGA) and efficient GA (EGA) are proposed for loss reduction in the ONR problem. In [11], Harris hawks optimisation (HHO) is introduced for loss reduction in ONR by achieving a successive search space and initial feasible solutions to prevent convergence challenges in load flow solutions.

Another significant operational goal of current EDSs is to improve reliability. In [12], an exhaustive approach (EA), genetic algorithm (GA), and PSO were used to maximise the dependability index of the expected energy not served (ENS) for the ONR. In [13], the performance of an equilibrium optimiser (EO) was compared with that of other meta-heuristics while solving an ONR problem with the goal of reducing loss and improving dependability. The binary particle swarm optimization gravity search algorithm (BPSOGSA) is developed in [14] for the ONR issue with the goal of loss reduction and optimization of the dependability indices system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), and expected energy not served (ENS).

ONR is required to regulate RCSs, which include workforce management, switching yard management, and communication systems. This could result in investment and operational expenditure. While solving the ONR problem, a few researchers have also concentrated on this element. In [15], tabu search algorithm (TSA) was used to reduce loss and switching costs while tackling the ONR problem concurrently with RES allocation. In [16], an extended sine-cosine algorithm (ESCA) for the ONR problem was proposed to reduce the loss, substation power, DG power, and switching costs.

Although these studies have focused on performance optimisation, reliability enhancement, and economic operation, the impact of load variation, particularly new trends in electric vehicles, has been overlooked. In this regard, a few academics have recently attempted to solve the ONR problem while considering the EV fleet load changes. In [17], a non-linearly decreasing technique for constructing modified grey wolf optimisation (MGWO) while solving the ONR problem for loss reduction was proposed, considering the network load and electric vehicles (EVs) vehicle-to-grid (V2G) and grid-to-vehicle (G2V) scenarios. In [18], self-adaptive butterfly optimisation (SABOA) was developed to address the network variability caused by RES and EVs by solving the hourly ONR with a focus on loss reduction and voltage profile enhancement.

However, owing to recent harsh weather changes, predicting uncertainties and related corrective and preventive measures as well as service restoration after being subjected to defective conditions have become common and difficult duties for network operators. Resilience has become an unavoidable element in modern networks [19-20]. In [21], the integration of energy storage systems (ESSs) to boost the EDS resilience against hurricanes is investigated. In [22], coyote optimisation algorithm (COA) based photovoltaic (PV)-based DG with an ESS is integrated in a multilateral distribution network to handle the EV load penetration. The mayfly optimisation algorithm (MOA) was used in [23] to optimise the design of a hybrid PV/ESS/DSTATCOM unit for handling the islanding mode of operation. In [24], a dandelion optimiser (HDO) with loss sensitivity factors (LSFs) was used to handle hourly ONR to deal with load and PV penetration variations.

In light of the above reviewed works, as compared in Table 1 and as per the no-free-lunch theorem (NFL) [25], which inspires the researchers to introduce either new optimisation techniques like puzzle optimization algorithm (POA) [28], stochastic komodo algorithm (SKA) [29], or modifications, improvements or hybridization of existing algorithms like extended stochastic coati

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Table 1. Comparison of literature works on ONR application

Reference	Contributions focused on:
[7, 10, 11]	Only loss reduction (F_1)
[8]	Both loss reduction (F_1) and voltage profile improvement (F_2)
[9]	Both loss reduction (F_1) and loadability enhancement (F_5)
[12, 14]	Only reliability improvement (F_4)
[13]	Only reliability improvement (F_4 , F_5 , F_6)
[15]	Both loss reduction (F_1) and switching cost (F_7)
[16]	Multiple objectives: loss reduction (F_1) , switching cost (F_7) and DG cost (F_8)
[17]	Only loss reduction (F_1) considering variability in load (U_1) and EV load (U_2)
[18]	Both loss reduction (F_1) and voltage profile improvement (F_2) considering variability in load (U_1) and EV load (U_2) and RES generation (U_3)
[21, 22]	Both loss reduction (F_1) and resilience improvement by ESS (S_1)
Proposed	Multiple objectives: loss reduction (F_1), voltage profile improvement (F_2), switching cost (F_7), SAIFI (F_5) and resilience improvement by ESS (S_1) considering variability in load (U_1), EV load (U_2) and RES generation (U_3)
Where F_1: Loss; F_2: Voltage profile; F_3: Loadability; F_4: ENS; F_5: SAIFI; F_6: SAIDI; F_7: Switching cost; F_8: DG cost; U_1: Load variability; U_2: EV load variability; U_3: RES variability; S_1: ESS integration	

optimizer (ESCO) [30] and guided pelican algorithm (GPA) [31] for solving real problems.

In recent times, single candidate optimizer (SCO) [26] offers efficiency and consistency in optimization. Grasshopper optimization algorithm (GOA) excels in handling complex problems. Cuckoo search algorithm (CSA) provides versatility and scalability. Pathfinder algorithm (PFA) offers robustness in solving diverse optimization challenges. These algorithms outperform others by addressing specific problem domains effectively and delivering reliable solutions. This paper makes the following major contributions.

a) Addressing the ONR problem with multiple objectives, including technical, economic, reliability, and resilience considerations.
b) Integrating optimal Energy Storage Systems (ESS) to ensure uninterrupted power supply in islanded microgrids, even during faulty conditions.
c) Introducing a novel SCO approach, hybridized with a reduced search space using the Severity Index of Interruption (SII).
d) Conducting simulations on IEEE 33-bus and 69-bus test systems across multiple scenarios.
e) Demonstrating the computational efficiency of SCO compared to GOA, CSA, and PFA.

The major advantages of proposed methodology over cited works include a comprehensive approach considering various objectives, innovative use of ESS for resilience, and the introduction of a new SCO algorithm for ONR problem-solving.

The paper is organized as follows: Section 2 discusses net effective loading uncertainty using load, PV, WT generation, and EVs. The proposed multi-objective function is explained in section 3. The basic and hybrid SCO are described in section 4. Section 5 shows how SCO-SII solves ONR on IEEE 33-bus and 69-bus test systems. Section 6 concludes this study thoroughly.

2. Modelling of net-effective loading

This section explains the variability in EDS due to connected loads, EV fleets, PV and WT generations. The net-effective loading in the network includes regular connected load, PV an WT generation and EV fleets load, as given by:

$$P_{d(eff)} = \left(\sum_i \bar{P}_{d(i)} + \sum_j \bar{P}_{ev(j)}\right) - \left(\sum_m \bar{P}_{pv(m)} + \sum_n P_{wt(n)}\right) \quad (1)$$

$$Q_{d(eff)} = \left(\sum_i \bar{Q}_{d(i)} + \sum_j \bar{Q}_{ev(j)}\right) - \left(\sum_m \bar{Q}_{pv(m)} + \sum_n Q_{wt(n)}\right) \quad (2)$$

3. Problem formulation

The proposed multi-objective function is aimed to reduce losses, voltage deviation, reliability index SAIFI [14], resilience index (RI) [21], and is given by:

$$OOF = min\{f_1 + f_2 + f_3 + (1/f_4)\} \quad (3)$$

$$f_1 = P_{loss(t)} = \sum_{k=1}^{nbr} I_{br(k)}^2 \times r_{br(k)} \quad (4)$$

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$$f_2 = V_{dev(t)} = \frac{1}{nbus}\sqrt{\sum_{i=1}^{nbus}(|V_s| - |V_i|)^2} \quad (5)$$

$$f_3 = SAIFI_{(t)} = (\sum_k U_k N_k)/\sum_i N_i \quad (6)$$

$$f_4 = RI_{(t)} = N_{i(t)}/N_i \quad (7)$$

The following are the major operational and planning constraints for solving Eq. (16).

$$|V_{i,min}| \leq |V_i| \leq |V_{i,max}| \quad (8)$$

$$nbr + ntl = nbus - 1 \quad (9)$$

$$|A| = \pm 1 \quad (10)$$

4. Solution methodology

This section explains the new meta-heuristic single candidate optimizer (SCO) with reduced search space as a solution methodology for solving ONR problem considering performance, reliability and resilience as major objectives.

4.1 Single candidate optimizer

TM Shami et al. proposed the single candidate optimizer (SCO) in [26], a new method that uses a single candidate solution throughout the optimisation process to find better answers, unlike most existing algorithms that use a swarm of particles. The proposed technique divides the optimisation process of T-function evaluations or iterations into two phases, where the candidate solution updates its position differently. Single-solution-based algorithms and two-phase approaches have been established as meta-heuristic optimisation methods but have been applied individually. The robust algorithm combines a single-candidate technique and two-phase strategy. Crucially, the proposed technique uses a unique set of equations to update the position of the candidate solution based only on its present position.

The procedure begins by randomly selecting a candidate solution from the search space, assessing it for fitness, and then designating the candidate's position as the global best position, g_{best} and its ftness as the global best fitness, $f(g_{best})$. The initial potential solution is generated as follows:

$$s_{c,j} = lb_{c,j} + r_1(ub_{c,j} - lb_{c,j}) \quad (11)$$

The goal of the two-phase strategy is to balance and create a variety of exploration and exploitation. When the γ function evaluations are completed, the first phase of the SCO algorithm ends. In contrast, the λ function evaluations were performed in the second phase, where $\gamma + \lambda = k_{max}$. The candidate solution updates its location in the first stage of SCO as follows:

$$s_{c,j} = \begin{cases} g_{best,j} + \varphi|g_{best,j}| & if\ r_2 < 0.5 \\ g_{best,j} - \varphi|g_{best,j}| & else \end{cases} \quad (12)$$

$$\varphi = exp[-(ak/k_{max})^a] \quad (13)$$

The second stage of the SCO process is a deep search that begins by thoroughly examining the area surrounding the best spot discovered during the first stage. Phase Two's last stages help narrow the search area and concentrate primarily on potential areas. As the second phase progressed, the candidate solution updated its position as follows:

$$s_{c,j} = \begin{cases} g_{best,j} + r_3\varphi(ub_{c,j} - lb_{c,j}) & if\ r_3 < 0.5 \\ g_{best,j} - r_3\varphi(ub_{c,j} - lb_{c,j}) & else \end{cases} \quad (14)$$

As the function evaluations increase, φ decreases exponentially from Eq. (13). This behaviour is significant because a large value of w at the start of the search process effectively explores the search space, whereas a low value strengthens the exploitation at the end of the optimisation phase. The limitations of meta-heuristic algorithms include being stuck in local optima, particularly in the later stages of the search process. In other words, updating candidate solution positions does not increase the fitness.

SCO updates the candidate solution position differently in the second phase if no fitness improvement is achieved in m consecutive function evaluations. Counter c counts the number of function evaluations m that fail to enhance fitness sequentially. A binary parameter p determines whether the upgraded candidate may enhance fitness: 1 indicates success, and 0 indicates failure. In the second phase of SCO, a candidate solution changes its position based on Eq. (14); however, if m successive function evaluations do not enhance the fitness value, it updates as follows:

$$s_{c,j} = \begin{cases} g_{best,j} + r_4\varphi(ub_{c,j} - lb_{c,j}) & if\ r_4 < 0.5 \\ g_{best,j} - r_4\varphi(ub_{c,j} - lb_{c,j}) & else \end{cases} \quad (15)$$

where $lb_{c,j}$ and $ub_{c,j}$ are the lower and upper bounds of the search variables, $s_{c,j}$ is the jth candidate solution vector, r_1, r_2, r_3 and r_4 are the random numbers between 0 and 1, a is a constant, k and k_{max} are the present and maximum number of iterations, respectively.

The candidate solution can switch from exploitation to exploration in Eq. (15), which helps it escape the local optimum. When variable placements are changed, it is occasionally possible for their values to deviate from the expected range or bounds. The updated locations are set as follows in cases where the variable values are greater than their upper and lower bounds to prevent them from exceeding the boundaries:

$$s_{c,j} = g_{best,j} \quad for \quad lb_{c,j} < s_{c,j} < ub_{c,j} \tag{16}$$

If the updated location exceeds the bounds, the updated dimension of the candidate solution in Eq. (16) is given the same value as the global best value. The more explanation of SCO and its unique features in comparison to various other meta-heuristics can be realized in [26].

4.2 Proposed hybrid algorithm optimizer

In network reconfiguration, identification of optimal RCSs for altering their operating status is very crucial for avoiding non-convergence of load flow or islanding of any bus/ node (s) in the network. On the other hand, the reliability of the network is mainly dependent on network configuration. Thus, the search space for SCO is defined based on number of consumers affected or buses islanded under each RCSs opening condition. In this connection, this work proposes severity index of interruption (SII) for each RCS and is given by,

$$SII_{rcs(k)} = \frac{NCI_{rcs(k)}}{N_i}, k\forall 2: (nbr + ntl) \tag{17}$$

where $SII_{rcs(k)}$ and $NCI_{rcs(k)}$ are the SII and number of consumers interrupted for the opening of RCS-*k*, respectively.

The branches with less SII are used as reduced search space for SCO for improving its computational efficiency. Also this approach can ensure reliability improvement in the network.

5. Simulation results

Simulations are performed on MATLAB R2023a. In Scenario 1, ONR is performed on standard IEEE test systems and compared with literature. In Scenario 2, the data of test systems are modified for PV, WT and EV load penetrations.

5.1 Scenario – 1

In this section, ONR problem is solved for loss reduction (f_1) in the standard IEEE test systems. In addition, basic SCO, PSO, BOA, and GOA compared with proposed SCO-SII. For all algorithms, the maximum number of iterations is considered as 50.

***Case Study 1*:** The basic schematic diagram of IEEE 33-bus is given in Fig. 1. The feeder has 33 buses, 32 branches and 5 tie-lines and thus, it has $2^{(32+5)} = 2^{37}$ possible combinations as search space determining ONR. The feeder is operating at a voltage level of 12.66 kV and serving a total real and reactive power loads of 3715 kW and 2300 kVAr, respectively. Initially, all tie-lines i.e., # 33 (8-21), # 34 (9-15), # 35 (12-22), # 36 (18-33) and # 37 (25-29) are assumed to be open for basic radial configuration and correspondingly, the network has real and reactive power losses of 202.677 kW and 135.141 kVAr, respectively.

By implementing the proposed SCO-SII, the best configuration is obtained by opening branches # 7 (7-8), # 9 (9-10), # 14 (14-15) and # 32 (32-33) and a tie-line 37 (25-29). And the remaining 4 tie-lines i.e., # 33 (8-21), # 34 (9-15), # 35 (12-22), # 36 (18-33) are closed. The single-line diagram of reconfigured feeder is given in Fig. 2. By this configuration, the real and reactive power losses are decreased to 139.5513 kW and 102.305 kVAr, respectively.

Case Study 2: The basic schematic diagram of IEEE 69-bus is given in Fig. 3. The feeder has 69 buses, 68 branches and 5 tie-lines and thus, it has $2^{(68+5)} = 2^{73}$ possible combinations as search space determining ONR. The feeder is operating at a voltage level of 11 kV and serving a total real and reactive power loads of 3802.1 kW and 2694.7 kVAr, respectively. Initially, all tie-lines i.e., # 69 (11-43), # 70 (13-21), # 71 (15-46), # 72 (50-59) and # 73 (27-65) are assumed to be open for basic radial configuration and correspondingly, the network has real and reactive power losses of 225 kW and 102.165 kVAr, respectively. In addition, there are around 9 buses which are not satisfied low voltage limit (i.e., 0.95 p.u.) and results for voltage sag of 0.0313 p.u.

The best configuration suing SCO-SII is obtained by opening the branches # 14 (14-15), # 55 (55-56), and # 61 (61-62) and two tie-lines # 69 (11-43) and 70 (13-21). And the remaining 3 tie-lines i.e., # 71 (15-46), # 72 (50-59) and # 73 (27-65) are closed. The single-line diagram of reconfigured feeder is given in Fig. 4. By this configuration, the real and reactive power losses are decreased to

99.6192 kW and 114.6825 kVAr, respectively.

For 33-bus system, the optimized results of SCO-SII are compared in Table 2 with bench mark results given in bench mark results given in [4], AMPL [5], IS-BPSO [7], SBEA [9], EGA [10], HHO [11], PSO [12], EO [13], BPSOGSA [14], TSA [15], ESCA [16] and SABOA [18].

Similarly, for 69-bus system, the optimized results of SCO-SII are compared in Table 2 with bench mark results given in bench mark results given in [4], AMPL [5], EGA [10], EO [13], BPSOGSA [14], TSA [15], ESCA [16] and MGWO [17].

From Table 2, despite the optimization approach, the configuration and total power losses remain consistent at 139.5513 kW. For both the test systems, the results of SCO-SII are well agreement with literature. Interestingly, despite the use of various optimization techniques, they all converge to the same configuration and power loss value, indicating that this particular configuration represents an optimal or near-optimal solution for the given problem as defined in benchmark results in [4]. In addition, the effectiveness of SCO-SII is compared with PSO, BOA, GOA, and SCO. The statistical analysis of 50 independent iterations is given in Table 3.

In both the 33-bus and 69-bus cases, all algorithms achieved the same best value, with 139.55 and 99.62, respectively. However, there were variations in their worst values, where BOA had the highest worst value at 163.07 for the 33-bus case and 137.28 for the 69-bus case. Conversely, SCO had the lowest worst value at 130.69 for the 69-bus case. When evaluating mean values, which indicate optimization performance, SCO outperformed in both cases. It had the lowest mean value of 140.46 for the 33-bus case and 100.34 for the 69-bus case. Median values, a measure of central tendency, remained consistent among all algorithms in both cases, with values of 139.90 for the 33-bus and 99.05 for the 69-bus. Examining standard deviation (SD), a lower value signifies more consistent results. SCO-SII demonstrated the lowest SD in both cases, with 2.96 for the 33-bus and 5.66 for the 69-bus, indicating its consistent performance. Regarding computation time, all algorithms were relatively close in both cases, but SCO and SCO-SII were the fastest, completing their optimization tasks in 1.36 seconds for the 33-bus and 2.03 seconds for the 69-bus.

In summary, this table offers a comparative analysis of optimization algorithms across the 33-bus and 69-bus cases, considering key performance metrics such as best, worst, mean, median, standard deviation, and computation time. Notably, SCO-SII stands out for its efficient mean objective function values and speedy optimization while maintaining result consistency.

5.2 Scenario – 2

In this Scenario, ONR problem solved along with simultaneous optimal allocation of PV, WT, EV fleet and ESS using only SCO-SII. The maximum capacities of PV and WT systems are considered as 1 MW and 1.5 MW with power factor of 0.866 leading, respectively. The EV fleet load demand is treated as 1 MW with a power factor of 0.95 lagging. For ESS, the optimal location, required capacity and optimal power factors are optimized.

Case Study 1: At first, the impact of EV fleet load at bus-6 is evaluated without performing ONR. Later, by optimally integrating PV, WT and ESS, the results are compared. In Table 4, the results on IEEE 33-bus are presented. The real and reactive power losses are registered as 351.504 kW and 210.112 kVAr, respectively. The minimum voltage magnitude is observed at bus-18 as 0.8939 p.u. and the overall voltage deviation is determined as 0.0056. The reliability index SAIFI is estimated as 2.5741. Since, the network has only grid connectivity for serving the load, the overall resilience index is 0 because, it cannot able to restore power under faulty conditions.

However, by having optimized PV, WT and ESS system, the network performance is improved significantly. The real and reactive power losses are reduced to 65.93 kW and 48.5 kVAr, respectively. The minimum voltage magnitude is at bus-31 is raised to 0.9714 p.u. and the overall voltage deviation is reduced to 0.0038. The reliability index SAIFI is reduced to 2.1274. Since, the network has now equipped with multiple energy systems with storage, it can able to serve all the loads even under faulty conditions in upstream network. Thus, resilience index become 1.

Case Study 2: At first, the impact of EV fleet load at bus-61 is evaluated without performing ONR. Later, by optimally integrating PV, WT and ESS, the results are compared. In Table 4, the results on IEEE 33-bus are presented. The real and reactive power losses are registered as 499.49 kW and 217.88 kVAr, respectively. The minimum voltage magnitude is observed at bus-61 as 0.8599 p.u. and the overall voltage deviation is determined as 0.003. The reliability index SAIFI is estimated as 2.5778. Since, the network has only grid connectivity for serving the load, the overall resilience index is 0

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Table 2. Comparison of IPFA results with literature

IEEE 33-bus			IEEE 69-bus		
Ref	**Open branches**	**P_{loss} (kW)**	**Ref**	**Open branches**	**P_{loss} (kW)**
Base	33, 34, 35, 36, 37	202.677	Base	69, 70, 71, 72, 73	225
Bench Mark [4]	7, 9, 14, 32, 37	139.5513	Bench Mark [4]	14, 57, 61, 69, 70	99.62
AMPL [5]	7, 9, 14, 32, 37	139.5513	AMPL [5]	14, 57, 61, 69, 70	99.62
IS-BPSO [7]	7, 9, 14, 32, 37	139.5513	EGA [10]	14, 58, 61, 69, 70	99.62
SBEA [9]	7, 9, 14, 32, 37	139.5513	EO [13]	14, 56, 61, 69, 70	99.62
EGA [10]	7, 9, 14, 32, 37	139.5513	BPSOGSA [14]	14, 56, 61, 69, 70	99.62
HHO [11]	7, 9, 14, 32, 37	139.5513	TSA [15]	14, 56, 61, 69, 70	99.62
PSO [12]	7, 9, 14, 32, 37	139.5513	ESCA [16]	14, 56, 61, 69, 70	99.62
EO [13]	7, 9, 14, 32, 37	139.5513	MGWO [17]	14, 56, 61, 69, 70	99.62
BPSOGSA [14]	7, 9, 14, 32, 37	139.5513	**SCO-SII**	14, 56, 61, 69, 70	99.62
TSA [15]	7, 9, 14, 32, 37	139.5513			
ESCA [16]	7, 9, 14, 32, 37	139.5513			
SABOA [18]	7, 9, 14, 32, 37	139.5513			
SCO-SII	**7, 9, 14, 32, 37**	**139.5513**			

Table 3. Comparison of computational features with other algorithms

Item	IEEE 33-bus					IEEE 69-bus				
	PSO	BOA	GOA	SCO	SCO-SII	PSO	BOA	GOA	SCO	SCO-SII
Best	139.55	139.55	139.55	139.55	139.55	99.62	99.62	99.62	99.62	99.62
Worst	169.77	163.07	160.08	160.26	160.87	135.99	137.28	136.51	130.69	134.39
Mean	141.69	140.96	144.17	140.46	140.34	104.89	100.85	101.69	101.78	100.34
Median	139.90	139.90	139.90	139.90	139.90	99.05	99.18	99.05	99.05	99.05
SD	5.53	4.62	4.35	3.04	2.96	7.00	6.86	8.86	8.39	5.66
Time	1.47	1.46	1.38	1.36	1.36	2.22	2.10	2.29	2.11	2.03

Table 4. Results SCO-SII for Scenario – 2

Parameter	IEEE 33-bus		IEEE 69-bus	
	Base case	Optimized case	Base case	Optimized case
P_{pv} *(kW)/ bus*	–	775.3/ 22	–	490.3/ 64
P_{wt} *(kW)/ bus/ p.f.*	–	1285.8/ 25/ 0.866	–	1434/ 61/ 0.866
P_{ev} *(kW)/ bus/ p.f.*	1000/ 6/ 0.95	1000/ 6/ 0.95	1000/ 6/ 0.95	1000/ 61/ 0.95
P_{ess} *(kW)/ bus/ p.f.*	–	735.6/ 33/ 1	–	537.6/ 11/ 1
Open RCSs	33, 34, 35, 36, 37	7, 9, 14, 27, 30	69, 70, 71, 72, 73	14, 56, 61, 69, 70
$f_1 = P_{loss}$ *(kW)*	351.504	65.9354	499.4872	314.5485
Q_{loss} *(kVAr)*	210.112	48.4889	217.8805	226.992
V_{min} *(p.u.)*	0.8939 (18)	0.9714 (31)	0.8599/ 61	0.9377 (61)
$f_2 = V_{dev}$	0.0056	0.0038	0.003	0.0009
$f_3 = SAIFI$	2.5741	2.1274	2.5778	2.2437
$f_4 = RI$	0 (for main grid fails)	1	0 (for main grid fails)	1

because, it cannot able to restore power under faulty conditions.

However, by having optimized PV, WT and ESS system, the network performance is improved significantly. The real and reactive power losses are reduced to 314.5485 kW and 226.992 kVAr, respectively. The minimum voltage magnitude is at bus-61 is raised to 0.9377 p.u. and the overall voltage deviation is reduced to 0.0009. The reliability index SAIFI is reduced to 2.2437. Since, the network has now equipped with multiple energy systems with storage, it can able to serve all the

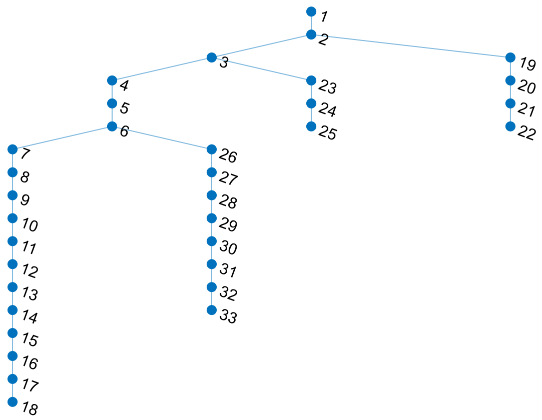

Figure. 1 Basic IEEE 33-bus feeder

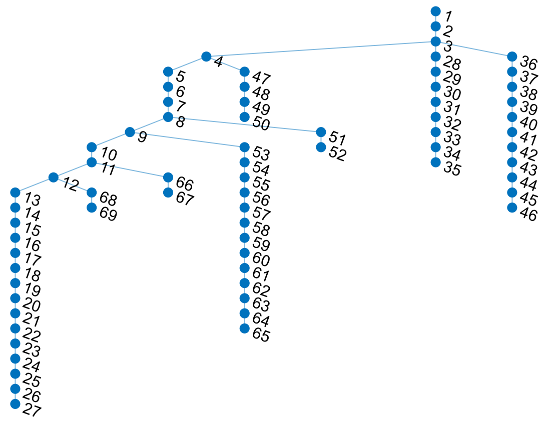

Figure. 3 Basic IEEE 69-bus feeder

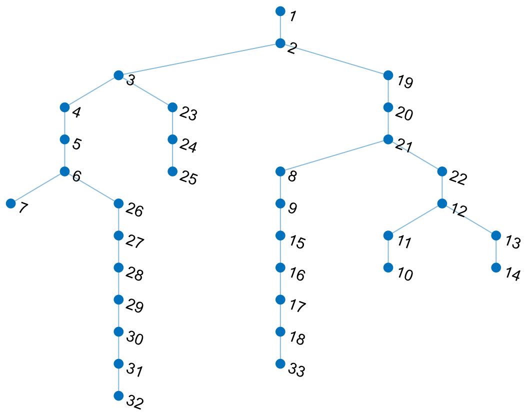

Figure. 2 Optimally reconfigured IEEE 33-bus feeder

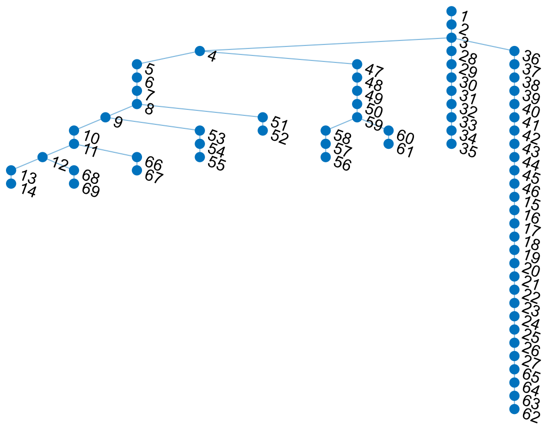

Figure. 4 Optimally reconfigured IEEE 69-bus feeder

loads even under faulty conditions in upstream network. Thus, resilience index become 1.

This work, the analysis is limited for only maximum loading conditions. However, the proposed mathematical model is more suitable for analyzing hourly variability in the network with load, RE generation and EV load penetration. This is treated as future scope of this work.

6. Conclusion

This study focuses on optimising the network reconfiguration (ONR) by developing a multi-objective function for loss reduction, voltage profile improvement, and reliability enhancement. It recommends merging renewable energy sources with energy storage systems to improve the resilience. An efficient single-candidate optimiser (SCO) simplifies the complex problem, and a novel severity index of interruption (SII) reduces the search space. Simulations on IEEE test systems show that the SCO-SII approach outperforms other algorithms in terms of reconfiguration, RES integration, and robust mode augmentation. In 33-bus, the losses are raised to 73.25% with EV load, however, they are reduced with proposed methodology by 67.51% in comparison to base case. Similarly, in 69-bus, the losses are raised to 121.22% with EV load, however, they are limited to 39.8 % with proposed methodology. These results are clearly indicating the adaptability of proposed methodology for real time applications.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, software and original draft preparation are done by V Sai Geetha Lakshmi and M Devika Rani; Supervision: P Muthukumar, review, and formal analysis are done by F Jeno Jasmine and Rathinam Muniraj.

Notations

$P_{d(eff)}$	Net-effective real loading
$Q_{d(eff)}$	Net-effective reactive loading
$\bar{P}_{d(i)}$	Connected real power load at bus-*i*
$\bar{Q}_{d(i)}$	Connected reactive load at bus-*i*
$\bar{P}_{ev(j)}$	EV fleet's real power load at bus-*j*

$\bar{Q}_{ev(j)}$	EV fleet's reactive load at bus-*j*
$\bar{P}_{pv(m)}$	Real generation of PV system at bus-*m*
$\bar{Q}_{pv(m)}$	Reactive power generations of PV system at bus-*m*
$P_{wt(n)}$	Real generation of WT system at bus-*n*
$Q_{wt(n)}$	Reactive power generations of WT system at bus-*n*
$r_{br(k)}$	Resistance of a branch-*k*
$I_{br(k)}$	Current flow in a branch-*k*
nbr	Number of branchs
$V_{dev(t)}$	Voltage deviation index
$\|V_s\|$, $\|V_i\|$	Voltage magnitudes of sub-station bus and bus-*i*, respectively;
$nbus$	Number of buses in the network
U_k	Unavailability or failure rate of a branch
N_k	Number of consumers affected due to failure or unavailability of a branch-*k*
N_i	Total number of consumers in the network
$RI_{(t)}$	*RI* at time-*t*,
$N_{i(t)}$	Number of consumers with power supply
$\|V_{i,min}\|$	Minimum voltage magnitude limit
$\|V_{i,max}\|$	Maximum voltage magnitude limit
$I_{br,max(k)}$	Current limit for branch-*k*
$\|A\|$	determinant of bus-incident matrix
ntl	Number of tie-lines

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