Simultaneous Distributed Generation Allocation and Network Reconfiguration: A Review of Computational Intelligence

Iorkegh Samuel Tyolumun[1*], Ahmad Abubakar Sadiq[2], James Garba Ambafi,[3] Ademoh Agbogunde Isah[4]
[1]Ministry of Power. Renewable Energy and Transport Makurdi, Benue State
[2, 3,4] Department of Electrical & Electronics Engineering, Federal University of Technology, Minna, Nigeria
[*]sam.kegh@yahoo.com, 08062175865, 08082225602

ABSTRACT
Progressive load growth and variation on the distribution network prevents the network from optimally delivering safe and reliable power to the end users of electricity due to power loss and voltage deviations. Network reconfiguration (NR) and distributed generation (DG) allocation are two techniques that can improve the distribution network performance. To reduce the challenges on the distribution system in the presence of load growth, distribution Network Reconfiguration (DNR) and Distributed Generation (DG) are simultaneously employed using various Computational Intelligent Techniques (CITs). This review paper focuses on the role of CITs in addressing the optimisation challenge of simultaneous deployment of NR and DG. Fifty-two (52) articles were surveyed, where two (2) of which are review papers, the remaining fifty (50) were reviewed for over five (5) years from google scholar for various algorithms and techniques used in implementing NR and DG to reduce the distribution network challenges. Four (4) metrics were considered in the review which include: Case Scenarios, Fitness/Objectives, Test network and the Implementation platform. Each technique's strengths and weaknesses in handling the multi-objective nature of the problem and ensuring efficient convergence are analysed. Findings from the review indicate that the review for achieving single objective using NR only and DG only was 80% (40) and 54% (27) respectively while the review for various multiple objectives was 56% (28) and 8% (4) used the multi-objective variants of the CITs with only one (1) considering the conflicting objective of maximising load growth while minimising power loss or voltage deviations. This indicates that with the increasing penetration of DG into the distribution networks with increasing load, more work needs to be done in the simultaneous NR and DG planning.

Keywords: *Distributed Generation, Distribution network, Network Reconfiguration, Power loss reduction*

1. INTRODUCTION

Distribution networks are facing growing pressure to deliver reliable power while minimizing energy loss. Network reconfiguration (NR) and Distributed Generation (DG) allocation are two techniques that can improve distribution network performance. However, since the distribution system is the last stage of the power system that connects consumers' loads (Islam et al., 2019), it is responsible for providing the power demand in a reliable, secure, and safe form to satisfy the end users of the power grid (Mahdavi et al., 2023; Shaheen et al., 2021a). However, there is complexity in the operation and control of the distribution system due to high power loss, poor voltage profile, and high operational cost occasioned by the progressive load growth by the users (Shaheen et al., 2021a,b; Pegado et al., 2019). This load variation and growth introduce new challenges when reconfiguring distribution networks in the presence of DG, which are also intermittent.

One key cause of distribution systems complexity is attributed to the increasing usage of DG, which is driven by several factors. A key driver is the integration of carbon free energy sources like solar and wind power. These are well-suited to DG because they can be sited close to where the electricity is needed, reducing reliance on large, centralized power plants.

A study by Sambaiah and Jayabarathi (2019); Sayed et al., 2022) highlighted how DG from renewable sources can contribute to a more sustainable and environmentally friendly power grid. Another reason for the rise of DG is the focus on efficiency and reliability in traditional transmission and distribution systems. Local generation can help to reduce energy losses that occur when electricity travels long distances over power lines. Additionally, DG can improve grid resiliency with backup power during outages or peak demand periods. Hashim et al., (2012) examined how DG can be optimized to improve voltage profiles and reduce power losses in distribution networks.

However, Distributed Generation (DG) integration is presenting both opportunities and challenges for modern power systems. While DG offers benefits like renewable energy integration, accommodate load growth and reduced losses, its impact on network operation needs careful consideration. One of its impacts and challenge is maintaining efficient and reliable power flow.

On the other hand, Network Reconfiguration (NR) emerges as a critical tool to address these challenges posed by increased Dg integration. By strategically adjusting switching devices within the network, NR can optimize power flow, improve voltage regulation, and enhance overall grid stability to accommodate increased DG integration (Abdelaziz, 2017; Akrami et al., 2019; Thanh and Trung, 2019).

In order to tolerate the load growth and reduce the challenges in the control and operation of the distribution system, Distribution Network Reconfiguration (DNR) and Distributed Generation (DG) are simultaneously employed. Network Reconfiguration (NR) is a process of restructuring the topology of the distribution network by altering the normally open switches (tie) and normally closed switches (sectionalise) in a distribution system to ensure the transfer of load from the feeders with high loads to feeders with less loads. The deployment of Network Reconfiguration does not require additional investment. While DG – also called dispersed generation or decentralised generation – is a small generation unit with an output of a few kilowatts to megawatts installed at or close to the load point on an existing low-voltage distribution network. They include Photovoltaic (PV), Wind Turbines (WT), biomass, diesel generators and small gas turbines. The deployment of DG requires optimal planning to maximise its benefits. Simultaneous network reconfiguration and distributed generation placement guarantee optimal solutions to the challenges on the distribution network (Thanh et al., 2020)

Consequently, the growing complexity of power system planning due to DG integration has necessitated the exploration of advanced optimization techniques; where the conventional methods may struggle to handle the dynamic nature of DG and the intricate interactions within the network. Computational Intelligent Techniques (CITs) have emerged as promising tools to address these challenges. CITs encompass a range of algorithms inspired by natural phenomena, such as evolutionary processes or swarm behaviour. Studies published in (Mahdavi et al., 2023; Sambaiah and Jayabarathi, 2019; Shi et al., 2021; Monteiro et al., 2020), demonstrated the effectiveness of CITs in optimizing DG placement and Network Reconfiguration (NR) strategies. These techniques can efficiently search vast solution spaces to identify optimal configurations that minimize power losses, improve voltage profiles, and enhance overall grid stability, fostering a more efficient integration of DG into modern power distribution systems. However, several CITs have limitations in handling multiple objectives which characterize the operations of practical power systems (Sadiq et al., 2019). This paper presents a brief review of various Computational Intelligent Techniques (CITs) with the aim of identifying work done by the literal community in the area of simultaneous NR and DG allocation using multi-objective variants of CITs.

2. REVIEW OF INTELLIGENT COMPUTATIONAL TECHNIQUES

In this section, a total of fifty-two articles (52) were surveyed. Two (2) of which are also review papers. The reaming fifty (50) articles review the various algorithm and techniques used in the implementation of NR in the presence of DG aimed at different objectives, such as reducing power loss and enhancing the voltage profile of the distribution networks.

This survey systematically classified the reviewed articles into three classes based on number of objectives considered in the article. Thus, the classes are: titled Single, weighted multiple, and Multi-Objective Variants of the CITs deployed. Particularly, the review focuses on the simultaneous combination of Network Reconfiguration (NR) and Distributed Generation (DG) aimed at improving multiple objectives using multi-objective variants of Computational Intelligent Techniques (CITs). The review also identifies the complexity involved in considering load growth by the multi-objective variants of the CITs.

The fifty-two (52) articles reviewed were mainly sourced from Google scholar within 2019-2023. In reviewing the articles, metrics considered were based on four major categories: Case Scenarios, Fitness/Objectives, Test Networks, and Implementation platforms used. Two out of the fifty-two are reviewed articles, hence no metrics classification was considered, however, the focus of these review papers was contrasted with our focus herein.

Although various reviews were carried out by researchers, the focus are often not the aforementioned. For instance, Islam et al. (2019) reviewed the distribution network reconfiguration technique to reduce the distribution network's unbalance. Thakar et al. (2019) analysed and evaluated the various works done on reconfiguring microgrids to make them more efficient in reducing the microgrid's power loss and operational costs.

2.1 Fitness/Objective functions considered

Fitness functions, also known as objective functions, guide the optimization algorithms towards solutions that meet desired criteria in distribution network management. The application of different meta-heuristic optimization algorithms for simultaneous distribution network reconfiguration and Distributed Generation (DG) allocation are carried out by the literal community using different objectives. The focus is on enhancing distribution network performance by optimizing objectives such as power loss reduction, voltage profile improvement, Power Factor improvement, Voltage Stability Index, Reliability improvement, Loadability, various cost of maintenance or investment, and energy loss. The various fitness/objective functions employed are classified into single, weighted multiple and the use of multi-objective variants of the meta-heuristic optimization. Additionally, the advantages and disadvantages of single and multiple objective approaches are also explored

2.2 Single Objective

A repair schedule of the power system and natural gas system, which considers the reconfiguration of the power system and standalone operation of DG to enhance the operation of the two systems through the reduction of load shedding and repair time, was proposed(Lin et al., 2019).

Akrami et al. (2019) proposed a new strong probabilistic optimisation driven by data from µPMU to investigate the optimal network reconfiguration problem in the active distribution network with regard to the intermittency in generation and variability in load demand. The model, which aims to reduce power loss, was tested on bus 33 and Brazilian 135 test feeder to validate its functionality.

Teimourzadeh and Mohammadi-ivatloo (2019) provided a three–dimensional Group Search Optimisation (3D-GSO) approach for distribution network reconfiguration alongside distributed generation planning to reduce power loss in distribution networks. The model was investigated on bus 33 and 69 systems.

Akaber et al. (2019) presented a mathematical model that optimally minimised the cost of restoring service to energy consumers after a fault. The model takes power system data and reconfigures the networks to restore service to energy consumers after a fault in the presence of distributed energy storage. The model was tested on buses 14-, 30- and 57-.

Gerez et al. (2019) proposed a technique to solve the problem of power loss on a distribution system using the Selective Firefly Algorithm (SFA) and Load Flow Analysis Criterion (LFAC), which enhances the optimisation. The LFAC functionality was confirmed on 5 buses and 7 branch systems while the Selective Firefly Algorithm was modelled on buses 33, 70 and 84, and the findings were compared with Selective Particle Swarm Optimisation (SPSO) and Selective Bat Algorithm (SBAT) to validate its strength.

A distribution network reconfiguration to enhance the optimal radial structure of the distribution network to reduce power loss in a large distribution system was presented. The success of the model was investigated on bus 16-, 33-,70-,83-,136-,415-,880-,1760- and 4400-node distribution systems (Diaaeldin et al., 2019.b).

In work by Pegado et al. (2019), the problem of distribution network reconfiguration for power loss reduction was solved with the Improved Selective Binary Particle Swarm Optimisation (IBPSO) algorithm. The effectiveness of the model was validated on buses 33 and 94.

Improved Cuckoo Search Algorithm (ICSA) for power loss reduction using distribution network reconfiguration was also proposed by (Thanh and Trung 2019).

Krishna and Moger (2019) maximised the power output of photovoltaic (PV) modules by distributing the effect of partial shading on Photovoltaic modules leading to power loss using an enhancement version of suDoku reconfiguration pattern for 9 by 9 Total Cross-Tied (TCT) for PV array. Furthermore, the pattern was validated by comparing it with Global Maximum Power Point (GMPP), Mismatch Losses (ML), Fill Factor (FF) and efficiency. The NR here does not imply network reconfiguration but PV array reconfiguration.

Diaaeldin et al. (2019a) provided Discrete-Continuous Hyper Spherical Search (DC-HSS) to analyse optimal network reconfiguration alongside the placement of distributed generations at different cases in Distribution Networks (DNs) to provide the solution to mixed integer nonlinear problem of Soft Open Points (SOPs), and so reduce power loss in a

Distribution network. The model was validated on bus 33 and 83 test systems.

Sedighizadeh et al. (2019) presented a strategy that allowed for simultaneous optimal generation performance and distribution feeder reconfiguration in microgrids in a day-ahead period to reduce total system operation costs. The model's success, which was designed as a Mixed Integer Second –Order Cone Programming (MISOCP) problem, was tested on the IEEE 33-bus distribution network.

Zheng et al. (2020) presented a general robust method for distribution network reconfiguration that is free from the problem of uncertainty posed by active distribution networks produced by combining deep learning and robust optimisation.

A novel technique that formulates the radiality restrictions in the distribution network and enhances its structure and other features to optimise reconfiguration of microgrid after fault occurrence. Bus 33- and 123 were used to investigate the technique (Lei et al., 2020).

Li et al., (2020) also presented a linear programming model that checks the reliability of a distribution network and optimises its network reconfiguration after the occurrence of a fault on the network.

Nguyen et al. (2020) presented an effective Pathfinder Algorithm (PFA) to reduce power loss in a distribution network using network reconfiguration in the presence of distributed generation. The algorithm was tested on 33 and 18-node systems.

A Coyote Algorithm (COA) to reduce power loss in the distribution network was presented for network reconfiguration alongside distributed generation location and sizing on the network. The validity of the algorithm was confirmed on 69 and 119-node distribution systems (Thanh et al., 2020).

The reconfiguration of the distributed network for Photovoltaic distributed generation and energy storage was maximised to reduce power loss using Binary Particle Swarm Optimisation (BPSO) by (Monteiro et al.,2020).

A power loss reduction algorithm was developed using the Chaotic Stochastic Fractal Search Algorithm (CSFSA) in distribution network reconfiguration. The algorithm was verified on 33, 84,119 and 136 bus distribution systems (The et al., 2020).

Hemeida et al. (2021) presented the Mante Ray Foraging (MRFO) algorithm deployed to curtail power losses in the distribution network through optimal and appropriate determination of the capacity and position of renewable distribution generation integrated in the distribution network. The efficiency of the algorithm was further evaluated using the IEEE 33-bus, IEEE 69-bus, and IEEE 85-bus systems.

Mahdavi et al. (2021) presented a mathematical model to reconfigure distribution systems to reduce power loss efficiently.

Helmi et al. (2021) proposed the Harris Hawk Optimisation (HHO) algorithm as an optimisation strategy for the reconfiguration of modern distribution networks to reduce the overall power losses on the network. The model's efficiency was tested on 33, 85 and artificial 295 bus systems.

Salkuti (2022) proposed a NR algorithm to address the of NR problem, including DG and D-STATCOM allocation by considering techno-economic objectives. However, only power loss minimization was selected as an objective and a Gravitational Search Algorithm (GSA) was used to solve the problem, which was demonstrated in IEEE 33 bus.

A new chaotic search group algorithm (CSGA) was proposed by Huy et al., (2022) for simultaneous NR and allocation of DG with the objective of minimum real power loss in different test network 33-, 69-, 84- and 118-bus under three load levels.

Mahdavi et al. (2023) presented a deterministic reconfiguration model that does not change easily by a small load and DG power change. The model was used to reconfigure distribution networks, considering the possibility of an increase or decrease in load and DG power. Although the problem was formulated as an optimization problem, it was not clear why deterministic approach was employed.

2.3 Single Objectives: Advantages and Disadvantages

Out of a total of fifty-two (52) articles reviewed, 46% considered single objective. The prominent single objective considered is power loss minimization, which was considered by over 70% of the reviewed papers as counted from the meta–Table I in the appendix. Other objectives considered alongside power loss includes: voltage profile improvement or minimization of voltage deviation. While the power loss minimization aims to reduce energy wasted during power transmission within the network, voltage profile improvement ensures voltage levels stay within acceptable ranges at all points in the network for stable operation.

Although consideration of single objective function for simultaneous NR and DG allocation is simple to implement and computationally efficient, it often may not capture the entire spectrum of network performance considerations. Also, in real power systems operations, other key performance indicators are equally important hence, the results obtained for single objective becomes a local optimal in the presence of other conflicting objectives such as loadability improvement (Sadiq et al., 2019).

2.4 Weighted Multiple Objectives

An enhancement of the Elitist-Jaya Algorithm for network reconfiguration alongside distributed generation planning in a power distribution system to reduce power loss was presented by (Raut and Mishra 2019).

A model solved with the epsilon-constrained (EPC) method that considered the optimisation of many different objectives was used to investigate the optimal reconfiguration of the distribution system to enhance the quality service delivery of the distribution network through power loss reduction. The model was investigated in a general algebraic modelling system on the bus 33 test system (Jahani et al., 2019).

Veera et al. (2019) proposed an algorithm simulated on the IEEE 33 bus that can give the maximum results of microgrid reconfiguration and accommodation of distributed generation that are renewable in nature to reduce power loss and energy cost. The gravitational search algorithm determined the distributed generation's location, while the DG's capacity was determined using a general algorithm modelling system.

Novel Adaptive Shuffled Frogs Leaping Algorithm (ASFLA) was proposed to reduce power loss and voltage stability index in the distribution system via network reconfiguration and distributed generation planning. The algorithm was modelled in the 33 and 69 bus distribution networks (Onlam et al., 2019).

Particle Swarm Optimisation (PSO) algorithm in dynamic hourly and static seasonal network reconfiguration was used to optimise the planning of renewable-based DG and Battery Energy Storage System (BESS) in the distribution network to enhance load accommodation on the network, minimise power loss and voltage. Bus 69 was used for the investigation (Mukhopadhyay and Das, 2020).

Ajoulabadi et al. (2020) modelled the optimal reconfiguration of a microgrid-based distribution network, considering the demand response programme to optimise the scheduling dynamics of the network reconfiguration. The objective was to reduce losses and the operation cost of the system. The model was tested on IEEE 83-bus.

Bagheri et al. (2020) proposed the best way to combine distribution network reconfiguration and suitable DG location and determine DG capacities and operation while considering the cost of switching actions and losses. It was modelled using mixed integer nonlinear programming to reduce power loss and was solved by Tabu Search Algorithm (TSA). The obtained result was justified by Particle Swarm Optimisation (PSO). Further tests were conducted on IEEE 33 bus and 69 and compared with other algorithms' results.

Combined reconfiguration with optimal planning of capacitor and renewable-based distributed generation units in distribution networks using a New Thief and Police Algorithms to reduce power loss and operational cost and improve voltage stability was proposed. The algorithm was confirmed on IEEE bus 33, and further validation was done by comparing it with other algorithms.(Tolabi et al., 2020).

Water Cycle Algorithm (WCA) to be used in searching for optimal network reconfiguration and distributed generation sizing and placement on the distribution network to reduce power loss and improve power factor. The efficiency of the algorithm was compared with Harris Search Algorithm (HSA), Firework Algorithm (FWA) and Cuckoo Search Algorithm (CSA) for validation after it was tested on 33 and 69-Bus test systems (Muhammad et al., 2020).

Salau et al. (2020) presented an algorithm, modified Selective Particle Swarm Optimisation (SPSO) to optimise power loss in distribution systems through optimal network reconfiguration of distribution network. The model was programmed in MATLAB and implemented using a 33 radial bus distribution system.

Essallah and Khedher (2020) enhanced the maximum operation of the distribution system through power loss reduction by network reconfiguration and distributed generation accommodation using a Mixed Particle Swarm Optimisation (MPSO) algorithm where simulation was carried out on buses 33 and 69.

Power loss minimisation and voltage stability of the distribution network using an Improved sine-cosine algorithm (ISCA) for the network reconfiguration alongside distributed generation planning was tested on buses 33 and 69 to confirm the functionality of the model, and further comparison was made with other algorithms (Raut and Mishra, 2020).

Jafar-nowdeh et al. (2020) presented the Moth–Flame Optimisation (MFO) algorithm to be used in an optimal restructuring of the distribution network and the planning of renewable-based distributed generation for reliability, power loss reduction in the network, voltage profile improvement and stability of the system. The algorithm was modelled and simulated on the bus 33 radial distribution system.

Hemmati et al. (2020) presented a new optimal framework for performing reconfiguration on the reconfigurable microgrid with consideration to the capability of the microgrid to operate alone without being connected to the main grid. The technique was performed on a 10-bus radial test system with renewable sources using the probability of islanding (PIO) index. The techniques reduced the total operation cost of the microgrid using the Time-Varying Acceleration Coefficients Particle Swarm Optimization (TVAC- PSO).

Reduction of power loss and emission in automated distribution systems in the presence of daily load growth conditions, using Jellyfish Search Algorithm (JFSA) with the combination of distributed system reconfiguration, distributed generation units hoisting, and distribution Static VAr Compensator (SVCs) operation was suggested. The algorithm was validated on buses 33 and 69 (Shaheen, et al., 2021b).

A Modified Marine Predator Optimisation (MMPO) algorithm for network reconfiguration alongside distributed generation planning in a distribution system with varying load conditions was presented. The algorithm was compared with many other algorithms to validate its superiority (Shaheen et al., 2021a)

A power failure management framework, which comprises network reconfiguration and distributed energy scheduling that enables the distribution network to restore power to as much load as possible after a disaster affecting a line to reduce outage cost, was presented by (Shi et al., 2021).

Shaheen et al. (2020) proposed an improved equilibrium optimisation algorithm (IEOA) that combines network reconfiguration and Distributed Generation placement to enhance the power quality and effective operation of the distribution network through power loss and voltage stability improvement. The effectiveness of the algorithm was validated on bus 33 and 69 test systems.

Sambaiah and Jayabarathi (2019) presented an algorithm called the Salp Swarm Algorithm (SSA) for distribution network reconfiguration and renewable distributed generation planning to curtail power loss and voltage deviation on the network. The model was validated on 33 and 69 bus test systems. Although, two objectives were considered, they were also not weighted or combined.

Nguyen et al. (2022) presented an algorithm called the Wild Geese Algorithm (WGA) to enhance the successful reconfiguration of the distribution network alongside optimal DG placement to curtail power losses in the Distribution network system, considering the enhancement of voltage and current in the network without violating the distribution network barriers. The model was compared with PSO and PathFinder Algorithm (PFA).

Sayed et al., (2022) argued that network reconfiguration can help to increase the DG hosting capacity of a network. However, the intermittent nature of loads and DG were often neglected, thus their work proposed the SHADE optimization algorithm along with the switch open and exchange (SOE) reconfiguration method for solving the aforementioned optimization problem, considering uncertainty related to both the network load and the output power of the renewable DGs. The objectives considered are maximizing the hosting capacity (HC) of the DGs and reducing network power losses in addition to improving the voltage profile. Five different case studies have been conducted considering 33-bus and 59-bus distribution networks.

2.5 Multi-Objective Optimization Variants

Uniyal and Sarangi (2020) combined network reconfiguration and distributed generation to enhance voltage stability and reduce power loss in distribution networks in the presence of uncertainty in load low and DGs operating at different power factors using the Modified Whale Optimisation Algorithm (A-MWOA). The model was tested on 33 and 69 bus systems.

Azizivahed et al. (2020) studied the Electric Energy Not Supplied (EENS) and Voltage Stability Index (VSI) with consideration to renewable energy resources and energy storage systems in a balanced and unbalanced distribution network reconfiguration that changes to minimise operational cost and reduce power loss. This was tested on bus 119. The Shuffled Frog Leaping Algorithm (SFLA) was deployed to handle reliability voltage stability index and operational cost.

Annual energy loss reduction through meter placement oriented state estimation in a distribution network using a Multi-objective–Biased Random-Key Genetic Algorithm (MOBRKGA) in the presence of distribution network reconfiguration was proposed by Raposo and Rodrigues, (2020).

The Chaos Disturbed Beatle Antennae Search (CDBAS) algorithm was formulated to reduce the time to compute the multi-objectives of optimal active power loss reduction, load balancing index, and total sum of the minimum voltage deviation in a distribution network. The algorithm was validated on bus 33, 69 and 118 test radial distribution networks (Wang et al., 2020).

Considering current and voltage constraints, a model was formulated to maximise the hoisting of renewable-based distributed generation and power loss reduction in distribution networks through distribution network reconfiguration. The mathematical programming model was investigated on nodes 16,59,69,83 and 415 (Ali et al., 2021).

2.6 Multiple Objectives: Advantages and Disadvantages

Multiple objective optimizations are powerful tools that can be applied to NR and DG allocation simultaneously. It considers multiple goals at the same time, such as minimizing power loss, improving voltage profile, and enhancing reliability. This integrated approach can lead to more comprehensive solutions, compared to single-objective optimization (Sadiq et al., 2023; Wang et al., 2020).

For instance, a multiple objective optimization approach might minimize power loss as a primary objective, while also considering voltage profile as a secondary objective. The algorithm would search for solutions that achieve good performance on both objectives. This can be achieved by assigning weights to each objective, indicating their relative importance (Nguyen et al., 2022; Sayed et al., 2022). However, using weighted coefficient does not provide a correlation between objectives. More so, in real and practical applications, improvement in one objective result in deterioration of another objective. Thus, various multi-objective variants of different meta-heuristic optimization approaches are being developed by the literal community.

The weighted approach to multi-objective optimization which does not provide a clear understanding about the impacts of improving one objective on another objective.

Although the multiple objectives variant of the meta heuristics provides a more holistic approach to network optimization by addressing multiple performance aspects simultaneously, it can be computationally expensive and involve trade-offs between objectives. Hence the focus will be arriving a trade-off depending on the application, between accuracy of results and computations burden.

3. RESULTS AND DISCUSSIONS

The distribution of the fifty-two (52) reviewed articles is as outlined in Table 1.

3.1 Results for Single Objective

The number of articles reviewed over five (5) years for single objective is shown in Figure 1.

Table 1: Distribution of Reviewed Articles Over five (5) Years

Fitness Function Classification	2019	2020	2021	2022	2023	Total	(%)
Single Objective	11	7	3	2	1	24	46.15
Weighted Multiple Objective	4	10	5	2	0	21	40.38
Multi-Objective Variant	0	4	1	0	0	5	9.615
Review Papers	2	0	0	0	0	2	3.846
Total	17	21	9	4	1	52	100

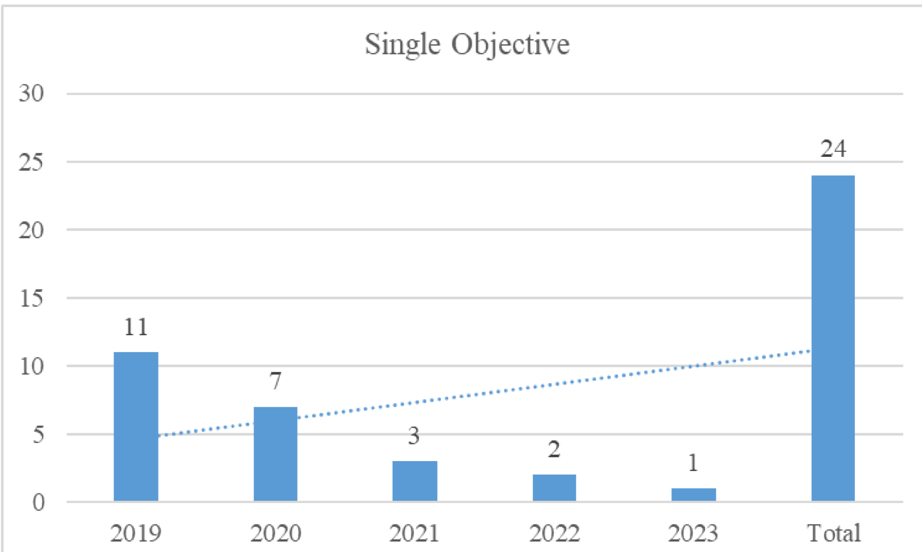

Figure 1: Single Objective articles over 5 years

From Table 1 and Figure.1, with a total of twenty-four (24) articles accounting for about 46% of the reviewed, in 2019 shows an increase in the development and application of various approaches to the implementation of NR – DG using single objective. However, as the modern distribution networks becomes active, a steady decline was observed by researchers over five years (2019 – 2023) on the need to consider other objectives aside the power loss minimization which was the prominent single objective.

3.2 Results for Weighted Multiple Objective

Figure 2 shows the review results for weighted multiple objectives.

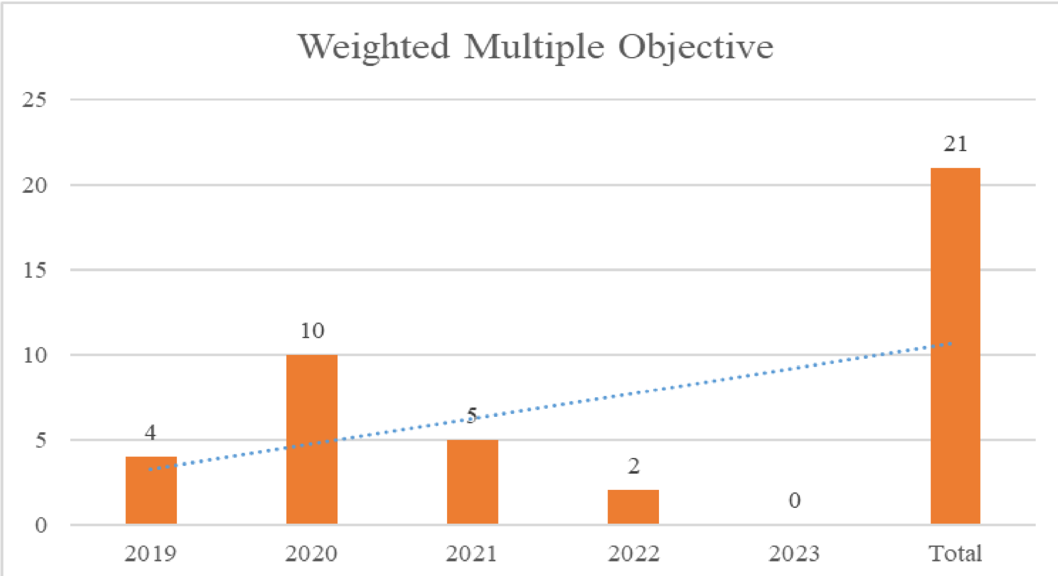

Figure 2: Weighted Multiple objectives over 5 years

From a total of twenty-one articles that considered weighted multiple objectives, year 2020 depicts the spike in the consideration of multiple objectives. This followed the 2019 spike of single objective. Noticeable also from Figure 2 was a decline in the formulation of NR – DG problem as a weighted multiple objectives starting from 2021 to 2023.

3.3 Results for Multi-Objective Variant

Figure 3 shows the results for the review of the multi-objective variant for over five years.

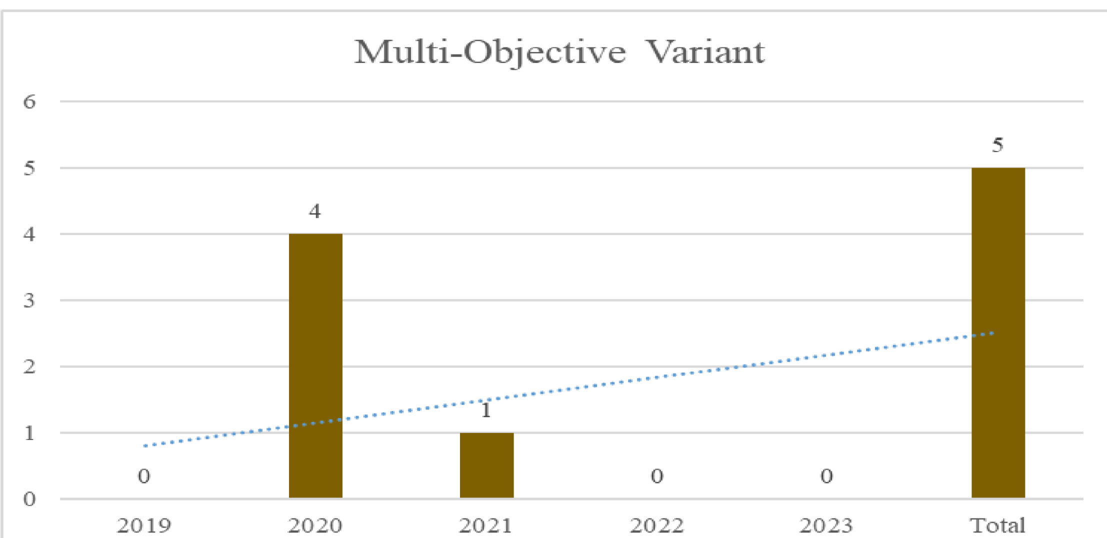

Figure 3: **M**ulti-Objective variant over 5 years

The development of multi-objective variant started from year 2020, it can be deduced from the reviewed literature that much work is still yet to be done on these research front. This is evident from only 5 articles or less than 10% of the reviewed articles considering multi-objective variants. This is attributable to the complexity and computational burden associated with the multi-objective variant implementation of the problem formulation of NR-DG simultaneous optimisation.

The distribution of the all the review based on fitness/objective function is shown in Figure 4

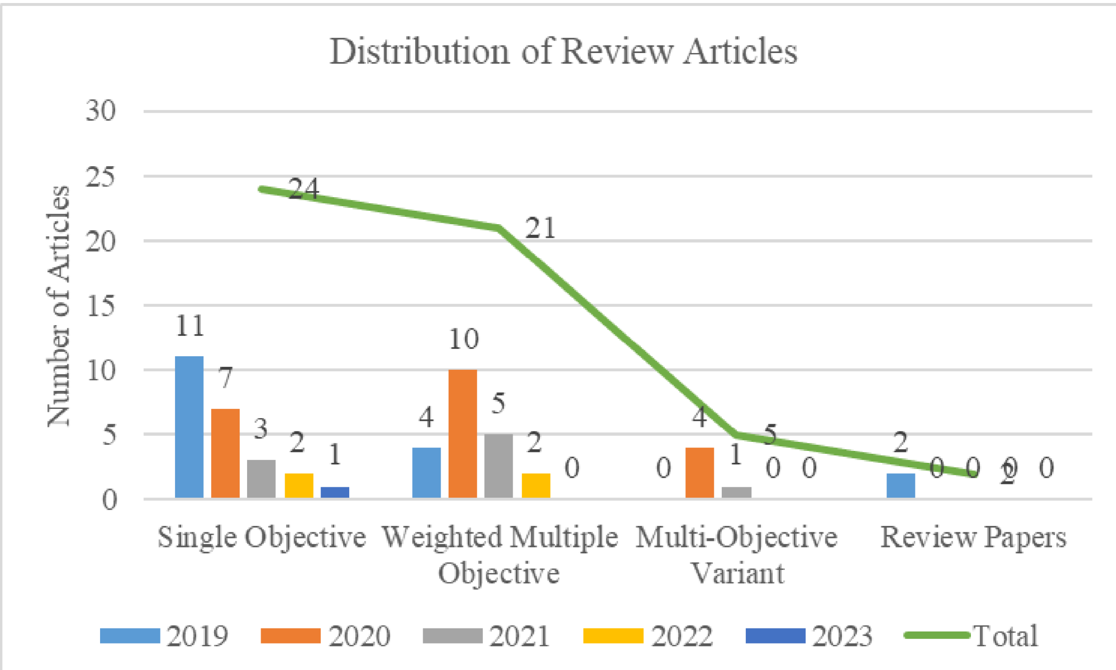

Figure 4: Distribution of Review Articles

3.4 Research Gaps

From the review the following gaps were identified:

- Mostly single objectives of power loss or voltage deviation were considered.
- Where multiple objectives were to be achieved, there was trade-off between the objectives which results in the attainment of an optimal result for an objective at the expense of another.
- Less research attention was given to the multi-objective variant of the CITs to handle conflicting objectives of power loss minimisation and load growth maximisation

3.5 Significant Findings

This review offers a thorough study of the incorporation of DG systems and NR techniques, with a unique emphasis on the utilization of computational intelligent-based approaches. This is to investigate the underlying reasons for the concurrent implementation of DG and NR.

From the Table 2, the statistics indicate that about 80% (40) of the reviewed articles considered NR only, 54% (27) considered DG only, while 46% (23) considered simultaneous NR and DG. This indicate that with the increasing penetration of DG into the distribution networks, more work needs to be done in the simultaneous NR and DG planning. Similarly, 56% (28) of the articles reviewed considered various multiple objectives, however, only 8% (4) uses the multi-objective variants of the CITs. Moreover, the multiple objectives can be conflicting such as maximizing load growth while minimizing power loss or sums of voltage deviation. Out of the 8% (4) only Wang et al., (2020) considered the two conflicting objectives.

This finding goes a long way in providing professionals and scholars with a comprehensive understanding of contemporary approaches and identifying potential areas for future research in this field as a way of knowledge transfer and consumption.

4 CONLUSION

In this paper, network reconfiguration and distributed generation planning have been reviewed, and the review highlighted the various computational models and intelligent algorithms adopted by different researchers alongside network reconfiguration and DG planning to optimise results that mitigate the challenges of power loss and voltage deviation on the distribution network with increasing load. Besides, it analyses the current body of academic research on computational intelligence methodologies, evaluates their efficacy in increasing the position of DG and network topology status, and offers useful knowledge toward the actual use of these methods in practical distribution systems.

In future works and with the comprehensive research data, more research is expected to be conducted in the simultaneous combination of network reconfiguration and DG allocation in distribution network to minimise network challenges and improve loadability.

REFERENCE

Abdelaziz, M. (2017). Distribution network reconfiguration using a genetic algorithm with varying population size. *Electric Power Systems Research*,*142*, 9–11. https://doi.org/10.1016/j.epsr.2016.08.026

Ajoulabadi, A., Ravadanegh, S. N., & Behnam Mohammadi-Ivatloo. (2020). Flexible scheduling of reconfigurable microgrid-based distribution networks considering demand response program. *Energy*, *196*. https://doi.org/10.1016/j.energy.2020.117024

Akaber, P., Moussa, B., Debbabi, M., & Assi, C. (2019). Automated Post-Failure Service Restoration in Smart Grid Through Network Reconfiguration in the Presence of Energy Storage Systems. *IEEE Systems Journal*, *PP*, 1–10. https://doi.org/10.1109/JSYST.2019.2892581

Akrami, A., Member, S., Doostizadeh, M., Aminifar, F., & Member, S. (2019). Optimal Reconfiguration of Distribution Network Using μ PMU Measurements : a Data-Driven Stochastic Robust Optimization. *IEEE Transactions on Smart Grid*, *PP*(c), 1. https://doi.org/10.1109/TSG.2019.2923740

Ali, Z. M., Diaaeldin, I. M., Aleem, S. H. E. A., El-rafei, A., Abdelaziz, A. Y., & Jurado, F. (2021). *Scenario-Based Network Reconfiguration and Renewable Energy Resources Integration in Large-Scale Distribution Systems Considering Parameters Uncertainty*.

Azizivahed, A., Arefi, A., Ghavidel, S., Shafie-Khah, M., Li, L., Zhang, J., & Catalao, J. P. S. (2020). Energy management strategy in dynamic distribution network reconfiguration considering renewable energy resources and storage. *IEEE Transactions on Sustainable Energy*, *11*(2), 662–673. https://doi.org/10.1109/TSTE.2019.2901429

Bagheri, A., Bagheri, M., & Lorestani, A. (2020). Optimal reconfiguration and DG integration in distribution networks considering switching actions costs using tabu search algorithm. *Journal of Ambient Intelligence and Humanized Computing*, *0123456789*. https://doi.org/10.1007/s12652-020-02511-z

Diaaeldin, I., Aleem, S. A., El-Rafei, A., Abdelaziz, A., & Zobaa, A. F. (2019a). Optimal network reconfiguration in active distribution networks with soft open points and distributed generation. *Energies*, *12*(21). https://doi.org/10.3390/en12214172

Diaaeldin, I. M., Aleem, S. H. E. A., El-Rafei, A., Abdelaziz, A. Y., & Zobaa, A. F. (2019b). A novel graphically-based network reconfiguration for power loss minimization in large distribution systems. *Mathematics*, *7*(12). https://doi.org/10.3390/MATH7121182

Essallah, S., & Khedher, A. (2020). Optimization of distribution system operation by network reconfiguration and DG integration using MPSO algorithm. *Reinforced Plastics*, *34*(00), 37–46. https://doi.org/10.1016/j.ref.2020.04.002

Gerez, C., Silva, L. I., Belati, E. A., Filho, A. J. S., Member, S., & Costa, E. C. M. (2019). Distribution Network Reconfiguration Using Selective Firefly Algorithm and a Load Flow Analysis Criterion for Reducing the Search Space. *IEEE Access*, *7*, 67874–67888. https://doi.org/10.1109/ACCESS.2019.2918480

Hashim, T. J. T., Mohamed, A., & Shareef, H. (2012). A review on voltage control methods for active distribution networks. *Przeglad Elektrotechniczny*, *88*(6), 304–312. http://www.red.pe.org.pl/articles/2012/6/71.pdf

Helmi, A. M., Carli, R., Dotoli, M., Member, S., & Ramadan, H. S. (2021). Efficient and Sustainable Reconfiguration of Distribution Networks via Metaheuristic Optimization. *IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING*, 1–17.

Hemmati, M., Behnam, M.-I., Abapour, M., & Amjad, A.-M. (2020). Optimal Chance-Constrained Scheduling of Operation Constraints. *IEEE Systems Journal*, *14*(4), 5340–5349. https://doi.org/10.1109/JSYST.2020.296463

Hemeida, M. G., Ahmed, A., Mohamed, A. A., Alkhalaf, S., & El-dine, A. M. B. (2021). Optimal allocation of distributed generators DG based Manta Ray Foraging Optimization algorithm (MRFO). *Ain Shams Engineering Journal*, *12*(1), 609–619. https://doi.org/10.1016/j.asej.2020.07.009

Huy, T. H. B., Tran, T. Van, Ngoc Vo, D., & Nguyen, H. T. T. (2022). An improved metaheuristic method for simultaneous network reconfiguration and distributed generation allocation. *Alexandria Engineering Journal*, *61*(10), 8069–8088. https://doi.org/10.1016/j.aej.2022.01.056

.Islam, H.Lu, M. Hossain, L. L. (2019). *Mitigating Unbalance Using Distributed Network Reconfiguration Techniques in distributed power generation grids with services for Electric Vehicle: A Review*.

Jafar-nowdeh, A., Babanezhad, M., & Arabi-nowdeh, S. (2020). Environmental Technology & Innovation 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*, *20*(101118), 1–12. https://doi.org/10.1016/j.eti.2020.101118

Jahani, M. A. T., Nazarian, P., Safari, A., & Haghifam, M. R. (2019). Multi-objective optimization model for optimal recon fi guration of distribution networks with demand response services. *Sustainable Cities and Society*, *47*(November 2018), 101514. https://doi.org/10.1016/j.scs.2019.101514

Krishna, G. S., & Moger, T. (2019). Improved SuDoKu reconfiguration technique for total-cross-tied PV array to enhance maximum power under partial shading conditions. *Renewable and Sustainable Energy Reviews*, *109*(December 2018), 333–348. https://doi.org/10.1016/j.rser.2019.04.037

Lei, S., Chen, C., Member, S., & Song, Y. (2020). Radiality Constraints for Resilient Reconfiguration of Distribution Systems : Formulation and Application to Microgrid Formation. *IEEE Transaction on Smart Grid*, *3053*(c), 1–13. https://doi.org/10.1109/TSG.2020.2985087

Li, Z., Wu, W., Zhang, B., & Tai, X. (2020). Analytical Reliability Assessment Method for Complex Distribution Networks Considering Post-Fault Network Reconfiguration. *IEEE*

Transactions on Power Systems, *35*(2), 1457–1467. https://doi.org/10.1109/TPWRS.2019.2936543

Lin, Y., Member, S., Chen, B., Wang, J., & Member, S. (2019). Transactions on Power Systems A Combined Repair Crew Dispatch Problem for Resilient Electric and Natural Gas System Considering Reconfiguration and DG Islanding. *IEEE Transactions on Power Systems*, 1–12. https://doi.org/10.1109/TPWRS.2019.2895198

Mahdavi, M., Alhelou, H. H., Hatziargyriou, N. D., & Al-hinai, A. (2021). An Efficient Mathematical Model for Distribution System Reconfiguration Using AMPL. *IEEE Access*, *9*, 79961–79993. https://doi.org/10.1109/ACCESS.2021.3083688

Mahdavi, M., Schmitt, K. E. K., & Jurado, F. (2023). Robust Distribution Network Reconfiguration in the Presence of Distributed Generation under Uncertainty in Demand and Load Variations. *IEEE Transactions on Power Delivery*, *38*(5), 3480–3495. https://doi.org/10.1109/TPWRD.2023.3277816

Monteiro, A., Paulo, J., Florentino, R., Suman, A., Power, E., Operation, S., & Grid, S. (2020). Electric distribution network reconfiguration optimized for PV distributed generation and energy storage. *Electric Power Systems Research*, *184*(January), 106319. https://doi.org/10.1016/j.epsr.2020.106319

Muhammad, M. A., Mokhlis, H., Naidu, K., Amin, A., & Franco, J. F. (2020). *Distribution Network Planning Enhancement via Network Reconfiguration and DG Integration Using Dataset Approach and Water Cycle Algorithm*. *8*(1), 86–93. https://doi.org/10.35833/MPCE.2018.000503

Mukhopadhyay, B., & Das, D. (2020). Multi-objective dynamic and static reconfiguration with optimized allocation of PV-DG and battery energy storage system. *Renewable and Sustainable Energy Reviews*, *124*(109777), 1–32. https://doi.org/10.1016/j.rser.2020.109777

Nguyen, T. T., Duong, T. L., & Ngo, T. Q. (2022). Wild Geese Algorithm for The Combination Problem of Network Reconfiguration and Distributed Generation Placement. *International Journal on Electrical Engineering and Informatics*, *14*(1), 76–92. https://doi.org/10.15676/ijeei.2022.14.1.5

Nguyen, T. T., Nguyen, T. T., Duong, L. T., & Truong, V. A. (2020). An effective method to solve the problem of electric distribution network reconfiguration considering distributed generations for energy loss reduction. *Neural Computing and Applications*, *2*. https://doi.org/10.1007/s00521-020-05092-2

Onlam, A., Daranpob, Y., Chatthaworn, R., Surawanitkun, C., Siritaratiwat, A., & Khunkitti, P. (2019). Power Loss Minimization and Voltage Stability in Electrical Distribution System via Network Reconfiguration and Distributed Generation Placement Using Novel Adaptive Shuffled Frogs Leaping Algorithm. *Energies*, *12*(553), 1–12. https://doi.org/10.3390/en12030553

Pegado, R., Ñaupari, Z., Molina, Y., & Castillo, C. (2019). Radial distribution network reconfiguration for power losses reduction based on improved selective BPSO. *Electric Power Systems Research*, *169*(December 2018), 206–213. https://doi.org/10.1016/j.epsr.2018.12.030

Raposo, A. A. M., & Rodrigues, A. B. (2020). Robust meter placement for state estimation considering Distribution Network Recon fi guration for annual energy loss reduction. *Electric Power Systems Research*, *182*(106233), 1–9. https://doi.org/10.1016/j.epsr.2020.106233

Raut, U., & Mishra, S. (2019). An improved Elitist – Jaya algorithm for simultaneous network reconfiguration and DG allocation in power distribution systems. *Reinforced Plastics*, *30*(00), 92–106. https://doi.org/10.1016/j.ref.2019.04.001

Raut, U., & Mishra, S. (2020). An improved sine – cosine algorithm for simultaneous network reconfiguration and DG allocation in power distribution systems. *Applied Soft Computing Journal*,*92*,106293. https://doi.org/10.1016/j.asoc.2020.106293

Sadiq, A. A., Adamu, S. S., & Buhari, M. (2019). Available transfer capability enhancement with FACTS using hybrid PI-PSO. *Turkish Journal of Electrical Engineering and Computer Sciences*, *27*(4). https://doi.org/10.3906/elk-1812-54

Sadiq, A. A., Buhari, M., Ambafi, J. G., Adamu, S. S., & Nwohu, M. N. (2023). Contingency constrained TCSC and DG coordination in an integrated transmission and distribution network: A multi-objective approach. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *4*(April), 100156. https://doi.org/10.1016/j.prime.2023.100156

Salau, A., Werkie, Y., & Bitew, D. (2020). Optimal network recon fi guration for power loss minimization and voltage pro fi le enhancement in distribution systems. *Heliyon*, *6*(June), e04233. https://doi.org/10.1016/j.heliyon.2020.e04233

Salkuti, S. R. (2022). An efficient allocation of D-STATCOM and DG with network reconfiguration in distribution networks. *International Journal of Advanced Technology and Engineering Exploration*, *9*(88), 299–309. https://doi.org/10.19101/IJATEE.2021.874812

Sambaiah, K. S., & Jayabarathi, T. (2019). Optimal reconfiguration and renewable distributed generation allocation in electric distribution systems. *International Journal of Ambient Energy*, *42*(9), 1018–1031. https://doi.org/10.1080/01430750.2019.1583604

Sayed, M. M., Mahdy, M. Y., Abdel Aleem, S. H. E., Youssef, H. K. M., & Boghdady, T. A. (2022). Simultaneous Distribution Network Reconfiguration and Optimal Allocation of Renewable-Based Distributed Generators and Shunt Capacitors under Uncertain Conditions. *Energies*, *15*(6), 1–27. https://doi.org/10.3390/en15062299

Sedighizadeh, M., Shaghaghi-shahr, G., & Esmaili, M. (2019). Optimal distribution feeder reconfiguration and generation scheduling for microgrid day-ahead operation in the presence of electric vehicles considering uncertainties. *Journal of Energy Storage*, *21*(June 2018), 58–71. https://doi.org/10.1016/j.est.2018.11.009

Shaheen, A. M., Elsayed, A. M., El-Sehiemy, R. A., & Abdelaziz, A. Y. (2020). Equilibrium optimization algorithm for network reconfiguration and distributed generation allocation in power systems. *Applied Soft Computing*, *98*(xxxx), 106867. https://doi.org/10.1016/j.asoc.2020.106867

Shaheen, Abdullah M, Elsayed, A. M., El-sehiemy, R. A., & Ghoneim, S. S. M. (2021a). A modified marine predators optimization algorithm for simultaneous network reconfiguration and distributed generator allocation in distribution systems under different loading conditions. *EngineeringOptimization*. https://doi.org/10.1080/0305215X.2021.1897799

Shaheen, Abdullah M, Elsayed, A. M., & Ginidi, A. R. (2021b). Effective Automation of Distribution Systems With Joint Integration of DGs / SVCs Considering Reconfiguration Capability by Jellyfish Search Algorithm. *IEEE Access*, *9*, 92053–92069. https://doi.org/10.1109/ACCESS.2021.3092337

Shi, Q., Li, F., Olama, M., Dong, J., Xue, Y., & Starke, M. (2021). Network reconfiguration and distributed energy resource scheduling for improved distribution system resilience ☆. *Electrical Power and Energy Systems*, *124*(June 2020),106355. https://doi.org/10.1016/j.ijepes.2020.106355

Teimourzadeh, H., & Mohammadi-ivatloo, B. (2019). Jo urn a. *Applied Soft Computing Journal*, 106012. https://doi.org/10.1016/j.asoc.2019.106012

Thakar, S., Vijay, A. S., & Doolla, S. (2019). Sustainable Energy , Grids and Networks System reconfiguration in microgrids. *Sustainable Energy, Grids and Networks*, *17*, 100191. https://doi.org/10.1016/j.segan.2019.100191

Thanh, T., & Trung, T. (2019). An improved cuckoo search algorithm for the problem of electric distribution network reconfiguration. *Applied Soft Computing Journal*, *84*(105720), 1–28. https://doi.org/10.1016/j.asoc.2019.105720

Thanh, T., Trung, T., Au, N., & Long, T. (2020). A novel method based on coyote algorithm for simultaneous network reconfiguration and distribution generation placement. *Ain Shams Engineering Journal*, *xxxx*. https://doi.org/10.1016/j.asej.2020.06.005

The, T. T., Ngoc, D. V., & Anh, N. T. (2020). Distribution Network Reconfiguration for Power Loss Reduction and Voltage Profile Improvement Using Chaotic. *Hindawi Complexity*, *2020*(2353901), 1–15.

Tolabi, H. B., Ara, A. L., & Hosseini, R. (2020). A New Thief and Police Algorithm and Its Application in Simultaneous Reconfiguration with Optimal Allocation of Capacitor and Distributed Generation Units. *Energy*, 117911. https://doi.org/10.1016/j.energy.2020.117911

Uniyal, A. & Sarangi, S (2020). Optimal network reconfiguration and DG allocation using adaptive modified whale optimization algorithm considering probabilistic load flow. *Electric Power Systems Research*, *April 2019*, 106909. https://doi.org/10.1016/j.epsr.2020.106909

Veera, V., Satya, V., Murty, N., & Kumar, A. (2019). Optimal DG integration and network reconfiguration in microgrid system with realistic time varying load model using hybrid optimisation. *IET Smart Grid*, *2*(2), 192–202. https://doi.org/10.1049/iet-stg.2018.0146

Wang, J. I. E., Wang, W., Yuan, Z. H. I., Wang, H., & Wu, J. (2020). A Chaos Disturbed Beetle Antennae Search Algorithm for a Multiobjective Distribution Network Reconfiguration Considering the Variation of Load and DG. *IEEE Access*, *8*, 97392–97407. https://doi.org/10.1109/ACCESS.2020.2997378

Zheng, W., Huang, W., & Hill, D. J. (2020). Electrical Power and Energy Systems A deep learning-based general robust method for network reconfiguration in three-phase unbalanced active distribution networks. *Electrical Power and Energy Systems*, *120*(December 2019), 105982. https://doi.org/10.1016/j.ijepes.2020.105982

Table 2: Meta-Table showing different cases, fitness functions considered and implementation platforms used.

REFERENCE	CON. APP.	CIT APP.	CASE SCENARIOS							FITNESS/OBJECTIVES/TEST NETWORKS									IMPLEMENTATION		
			NR	DG	ESS	NR – DG	LD VAR	GEN. VAR	FAULT	PL	PF	VSI	VP/D	RELI	COST	LD GT	E - LOSS	TEST NETW	MO	CIT-MO	SOFTWARE
Mahdavi *et al*. (2023)	AMPL					√	√	√									√	IEEE 33, 70 & 118			AMPL using CPLEX
Shaheen *et al*. (2021a)		IEOA				√				√		√						IEEE 33, 69	√	⊠	MatlabR2017b
Li et al., (2020)	L-Prog.		√											√				7, 38 & 54 nodes	⊠	⊠	CPLEX
Diaaeldin et al. (2019a)		HSS								√								IEEE 33 & 83	⊠	⊠	
Azizivahed *et al*. (2020)		SFLA	√	√	√			√						√	√			119-bus	√	√	MatlabR2011b
Sambaiah and Jayabarathi (2021)		SSA	√	√		√				√			√			√		IEEE 33, 69	√	⊠	
Pegado et al. (2019),		IS -BPSO	√							√								IEEE 33, 94	⊠	⊠	
Ajoulabadi *et al*. (2020)			√	√			√			√					√			IEEE 83	√	⊠	MATPOWER/MATLAB 2014
Sedighizadeh *et al*. (2019)			√	√			√	√							√		√	IEEE 33	√	⊠	GAMS
Helmi *et al*. (2021)		HHO	√	√						√								IEEE33,85&29	⊠	⊠	MATPOWER /MATLAB R2019
Muhammad et al., (2020).		WCA				√				√	√							IEEE 33, 69	√	⊠	
Shi, et al., (2021).	L-Prog.					√	√		√						√			IEEE 69, 123	√	⊠	Matlab-CPLEX
Olalekan *et al*. (2020)		SPSO	√							√			√					IEEE 33	√	⊠	MATLAB R2016b
Essallah and Khedher (2020)		MPSO	√	√		√				√			√					IEEE 33, 69	√	⊠	
Nguyen *et al*. (2020)		PFA				√	√	√									√	IEEE 18, 33	⊠	⊠	MATPOWER/MATLAB R2016a
Mahdavi *et al*. (2021)		MICP	√							√								7,12,16,28,30,33,49,59,69,70,119,136, etc.	⊠	⊠	CPLEX
Vitor *et al*. (2020).		BPSO	√	√	√			√		√								IEEE 37	⊠	⊠	
Thanh and Trung (2019).		ICSA	√							√								33, 69, 119	⊠	⊠	PSS/ADEPT
Thanh et al., (2020).		COA	√		√					√								69, 119	⊠	⊠	MATPOWER/MATLAB
Raut and Mishra (2019).		IEJAYA	√	√	√					√						√		33, 69	√	⊠	MatlabR2014a
Veera *et al*. (2019)		GSA/GA	√	√	√		√	√		√					√			33	√	⊠	MATLAB/GAMS
Raposo and Rodrigues, (2020).		MOBRKGA	√							√							√		√	√	
Ali et al., (2021).		NSGA - MOPSO				√	√	√		√								16, 59, 69, 83	√	√	MATLAB r2018a
The et al., (2020).		CSFSA	√	√			√			√			√					33,84,119,136	√	⊠	MATPOWER/MATLAB
Wang et al., (2020).		CDBAS	√	√			√	√		√			√			√		33, 69, 118	√	√	

Onlam *et al*., (2019).		ASFLA	√	√		√				√		√						33, 69	√	⊠	
Raut and Mishra, (2020).		ISCA	√	√		√				√		√						33, 69	√	⊠	MatlabR2014a
Diaaeldin *et al*., (2019b).	Graph-theory		√							√								136-, 415-, 880-, 1760-, 4400, etc.	⊠	⊠	
Teimourzadeh and Mohammadi-ivatloo (2019)		3D-GSO	√	√		√	√			√								33.69	⊠	⊠	
Uniyal and Sarangi (2020)		A-MWOA	√	√			√			√		√				√		33,69	√	⊠	
Shaheen *et al*., (2021b)		MMPO				√	√			√		√				√		33,69	√	⊠	
Gerez *et al*. (2019)		SFA	√							√								33,70,84	⊠	⊠	MATPOWER/MATLAB
.Tolabi et al., (2020).		TPA	√	√		√				√			√		√			33	√	⊠	/MATLAB
Jafar-nowdeh *et al*. (2020)		MFO				√				√		√	√	√				33	√	⊠	
Abdullah M Shaheen, Elsayed, & Ginidi, (2021).		JFSA	√	√		√	√			√								33,69	√	⊠	
Ghazi et al., (2019)		EPC/MMFF	√							√				√				33	√	⊠	GAMS
Mukhopadhyay and Das, (2020).		PSO	√	√	√	√				√			√			√			√	⊠	
Akaber *et al*. (2019)	Math-Model		√		√	√									√			14,30,57	⊠	⊠	CPLEX
Krishna and Moger, (2019)		I -SuDoKu	√	√						√									⊠	⊠	
Hemmati *et al*. (2020)		TVAC-PSO	√	√	√									√	√			10	√	⊠	MATLAB/CPLEX
Lei et al., (2020).	Linear - Prog		√	√											√			33,123	⊠	⊠	
Lin et al., (2019).		RCD	√			√									√			13,123	⊠	⊠	GUROBI
Akrami *et al*. (2019)		SRO	√	√			√	√							√			33, 135	⊠	⊠	
Zheng *et al*. (2020)		DNN	√	√			√	√							√			33, real	⊠	⊠	Matlab 2019a
Hemeida et al., (2021)		MRFO	√	√						√								33,69,85	⊠	⊠	MATLAB 2014b
Bagheri *et al*. (2020)		TSA	√			√									√			33,69	√	⊠	Matpower
Thakar *et al*. (2019)		Review paper focusing on MG NR with objectives considered, constraints considered, optimization techniques used, and methods of incorporating uncertainty inherent in renewable generation																			
Nguyen *et al*. (2022)		WGA				√				√			√						√	⊠	Matpower /Matlab 2016a
Salkuti, (2022)		GSA	√	√		√				√								33	⊠	⊠	
Huy et al., (2022)		CSGA	√	√		√	√			√									⊠	⊠	MATLAB R2019b
Sayed et al., (2022b)		SHADE	√	√		√				√			√						√	⊠	

CONV. APP. = Conventional Approach; **CIT APP** = Computational Intelligent Techniques Approach; **NR** = Network Reconfiguration; **DG** = Distributed Generation; **VAR** = Variation; **GEN. VAR** = Generation Variation; **PL** = Power loss; **PF** = Power Factor; **VPD** = Voltage Profile/Deviation; **RELi** = Reliability; **LDGT** = Load Growth; **E-LOSS** = Energy Loss; **TEST NETW** = Test Network; **MO** = Multiple Objectives; **CIT-Based MO =** CIT Multiple Objectives **AMPL** = A Mathematical Programming Language; **IEOA** = Improved Equilibrium Optimisation Algorithm; **HSS** = Hyper-Spherical Search Algorithm; **SFLA** = Shuffled Frog Leaping Algorithm; **SSA** = Salp Swarm Algorithm; **IS - BPSO** = Improved Selective Binary Particle Swarm Optimisation; **HHO** = Harris hawks optimization; **WCA** = Water Cycle Algorithm; **SPSO** = Selective