Reconfiguration of distribution networks with distributed generations using an improved neural network algorithm

Thanh Van Tran¹, Bao-Huy Truong¹, Tri Phuoc Nguyen², Thi Anh Nguyen², Thanh Long Duong³, and Dieu Ngoc Vo²,⁵
¹Institute of Engineering and Technology, Thu Dau Mot University, Binh Duong Province, Vietnam
²Department of Power Systems, Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, District 10, Ho Chi Minh City, Vietnam
³Faculty of Electrical Engineering Technology, Industrial University of Ho Chi Minh City, Ho Chi Minh City, Vietnam
⁴Vietnam National University Ho Chi Minh, Linh Trung Ward, Thu Duc District Ho Chi Minh City, Vietnam
Corresponding author: Dieu Ngoc Vo (e-mail: vndieu@hcmut.edu.vn).

The present research study was funded by Thu Dau Mot University (TDMU) under grant number DT.21.1-079.

ABSTRACT This study aims to suggest a new quasi-oppositional chaotic neural network algorithm (QOCNNA) for simultaneous network reconfiguration and distributed generations allocation (SNR-DG) in radial distribution networks (RDNs). The proposed QOCNNA is developed by combining original NNA with chaotic local search (CLS) and quasi-oppositional-based learning (QOBL) approaches. Integration of QOBL helps the algorithm improve exploration of the search space and convergence speed. Meanwhile, CLS can improve exploitation of the algorithm by performing local search around the current best solution. The objective of the SNR-DG problem is to define the network configuration, settings of distributed generations to optimize active power loss and voltage stability in RDNs. The performance of QOCNNA is tested on the SNR-DG problem with 33-, 69- and 118-bus RDNs considering different scenarios. The result analysis indicates that SNR-DG implementation is effective for power loss reduction and voltage stability improvement. Notably, QOCNNA yields active power loss reductions and voltage stability index improvements associated with case multi-objective SNR-DG at nominal load condition of {70.79%, 16.36%}, {84.02%, 8.59%}, and {57.79%, 10.10%}, respectively, for 33-, 69-, and 118-bus RDNs. In comparison with previous studies, QOCNNA is more effective in improving the performance of RDNs. Compared with other methods that we have applied, QOCNNA dominates the performance in solution accuracy, convergence speed, and robustness for all case studies. Also, QOCNNA finds effective and feasible solutions for daily variable load and generation scenario with the minimized total annual energy loss. Simulated outcomes in this scenario verify the superiority of QOCNNA over analytical-based approaches and the applied methods regarding total annual energy loss reduction and cost savings as well. There are hence simulation-based evidences to state that the CLS and QOBL help QOCNNA achieve a good trade-off between exploration and exploitation. Thus, QOCNNA has proved to be a favorable method in dealing with the SNR-DG problem.

INDEX TERMS Distributed generations; neural network algorithm; network reconfiguration; radial distribution networks

I. INTRODUCTION
Radial distribution network (RDN) plays a crucial role in the power systems, responsible for power supply from the transmission systems to the customer. However, the continuously growing load has posed challenges for power companies to operate RDN efficiently and reliably. Power loss significantly affects the operating efficiency of RDNs. Hence, it is imperative to reduce power loss for RDNs to operate efficiently and economically. In this regard, many approaches have been implemented to minimize the power losses of RDNs. Network reconfiguration (NR) and distributed generation (DG) integration are two prominent
techniques that attract much attention due to the development context of power sources and investment costs. NR is an effective method to minimize power loss in RDNs. RDNs are operated in the radial topology to decrease the fault level and protect coordination effectively. Tie-line switches (normally opened) and sectionalizing switches (normally closed) are two types of switches in RDNs. NR leads to a new network topology by altering the opened/closed status of switches while maintaining the radial topology of the system. NR is a vital grid strategy that decreases active power losses, improves voltage profile and system reliability [1]. Moreover, NR can transfer load from one branch to another to avoid overloading. Recently, distributed generations (DGs) have been swiftly integrated into RDNs due to electricity deregulation, fossil fuel depletion, and environmental concerns. Apart from NR implementation, the deployment of DG units is also a well-known grid strategy to decrease power losses and boost the voltage profile of RDNs. Therefore, the NR application in RDNs should be studied in the presence of DGs.

Since NR problem was firstly introduced by Merlin and Back [2], a large amount of research has also been done on the NR problem using various approaches from heuristic approaches like branch-and-bound method [2], modified branch exchange method [3], and switch exchange method [4] to metaheuristic approaches like particle swarm optimization (PSO) [5], [6], genetic algorithm (GA) [7], biased random key GA (BRKGA) [8], harmony search algorithm (HSA) [9], heuristic rules-based fuzzy multiple objectives [10], fireworks algorithm (FWA) [11], GA with varying population (GAVP) [12], and cuckoo search algorithm (CSA) [13]. In general, heuristic methods are characterized by fast convergence, but they lack the ability to handle large-scale systems with many constraints. Meanwhile, metaheuristic methods have robust searchability to discover optimal solutions or near-optimal solutions, which are well suited for large-scale networks. Hence, the applications of metaheuristic methods to NR problems are constantly evolving. Recently, many researchers have applied several artificial intelligence and analytical methods to solve the optimal DGs allocation problem in RDNs. In [14], comprehensive analytical expressions were suggested to define the allocation of PV units for maximizing the technical benefits in RDN. The objective functions include active and reactive power losses, voltage stability index, line congestion margin and voltage deviations. Mahmoud et al. [15] proposed generic closed-form analytical expressions to determine optimal locations and sizes of multi-type DGs and capacitors for optimizing reactive power loss in RDNs. Moreover, the proposed method incorporated an optimal power flow (OPF) algorithm to consider the constraints of systems. In [16], the authors utilized an efficient analytical (EA) method to obtain an optimal mix of different DG types with various generation capabilities to minimize power losses in RDNs.

Researchers have constantly proposed new methods to achieve a better performance for RDNs. One of those efforts is the simultaneous integration of NR and optimal DGs placement. Recent studies on the integration of these two effective strategies have been done using metaheuristic methods. Shaheen et al. [17] developed an improved equilibrium optimization algorithm (IEOA) to deal with the optimal integration of NR with DGs. Different load conditions of 33- and 69-bus systems were utilized to test IEOA method, and its superiority was confirmed. Onlam et al. [18] applied the adaptive shuffled frogs leaping algorithm to acquire optimal NR and DGs settings on several circumstances of 33- and 69-bus RDNs to minimize system losses and enhance voltage profile. Murty and Kumar [19] suggested NR and optimal renewable-based DGs placement considering load uncertainties. A hybrid fuzzy-bees approach was developed by Tolabi et al. [20] for NR with DG placement for reducing power losses, improving the feeder load balancing and voltage profile. In [21], an artificial bee colony was combined with a hybrid method of HSA and PSO to deal with the combined problem of NR with shunt capacitors and DGs allocation to optimize the power loss. In [22], a fuzzy multi-objective technique was utilized for handling NR. Afterwards, a heuristic approach was applied to obtain the optimal NR, which generated a solution based on the initial NR. In [23], an improved plant growth simulation method was proposed for NR with DGs presence for power loss reduction. Optimal DG locations were defined using sensitivity analysis. Bayat et al. [24] developed a heuristic approach for NR and DGs allocation to maximize loss reduction. In [25], levy flights embedded in sine–cosine algorithm to deal with NR and DGs allocation in 33-bus and 69-bus RDNs. The proposed problem considered power losses and voltage stability index objectives. Some other typical metaheuristic methods have also been applied to handle the combination of NR and DGs allocation, such as HSA [26], adaptive CSA [27], FWA [28], big-bang crunch algorithm [29], [30], hybrid grey wolf optimizer and PSO (GWO-PSO) [31], electromagnetism-like mechanism (ELM) [32], firefly (FF) [33], and three-dimensional group search optimization (3D-GSO) [34].

Based on the aforesaid literature survey, applying the metaheuristic algorithms to the integration of NR with DGs placement has several certain limitations. Most of the previous studies only focused on small- and medium-scale RDNs without considering large-scale RDNs. Moreover, integration of NR and DGs placement is a combined optimization problem, which poses a challenge to achieve optimal solutions due to its complexity. Although the powerful search capabilities of metaheuristic algorithms are well suited for achieving optimal solutions, there is no guarantee that they will be effective for all optimization problems [35]. Such methods may not yield reasonable quality solutions and may get stuck at a local optimum. Therefore, developing an appropriate algorithm is of interest.
to effectively solve the simultaneous NR and DGs placement, especially for large-scale systems.

Recently, a new meta-heuristic method inspired by biological nervous systems and artificial neural networks (ANNs), namely neural network algorithm (NNA), has been developed by Sadollah et al. [36]. Thanks to the ANNs structure, NNA has proven its high performance for benchmark functions. Furthermore, NNA is a parameter-free metaheuristic method; hence, algorithm parameters do not need to be fine-tune except for the population size and stopping criteria, making NNA easy to implement to solve optimization problems. Nevertheless, NNA has the notable disadvantage of converging prematurely and getting stuck in local minima due to its stochastic nature. Hence, improving the performance of NNA to efficiently solve the simultaneous NR and DGs placement problem is certainly worth further consideration.

Motivated by the above problems, this study proposes a new modified NNA called quasi-oppositional chaotic neural network algorithm (QOCNNA) to deal with the simultaneous NR and DGs integration (SNR-DG) problem in RDNs. The SNR-DG problem aims to minimize active power loss and maximize voltage stability index while sustaining system constraints, including power balance, feeder capacity limits, bus voltage limits, capacity and penetration limits of DGs, and radial topology constraints. QOCNNA was developed by integrating chaotic local search (CLS) and quasi-oppositional-based learning (QOBL) strategies into the structure of NNA. QOBL is a highly effective strategy that helps meta-heuristic algorithms improve global search ability to explore more promising regions on the design domain. In addition to QOBL, CLS is a strategy to boost the local search ability of algorithms to exploit promising regions (i.e., neighborhoods of best solutions). The incorporation of QOBL and CLS strategies aims to strike a good equilibrium between the exploration and exploitation tendencies of QOCNNA. The proposed QOCNNA was evaluated on 33-bus small-scale, 69-bus medium-scale, and 118-bus large-scale RDNs with different scenarios at different load conditions. Considering practical situation of daily variable load demand and generation, an effective methodology has been developed to determine the optimal network configuration and settings of DG according to a 24-h load curve and an hourly output curve of photovoltaic (PV) DG so that total annual energy loss is minimized. QOCNNA was compared with the original NNA, ant lion optimizer (ALO), whale optimization algorithm (WOA), sine cosine algorithm (SCA), and different intelligent algorithms in the literature, where its robustness and efficiency in solving the SNR-DG problem was proved.

The contributions of this study are presented as below:

- A new meta-heuristic algorithm, namely QOCNNA, is developed to deal with the SNR-DG problem, where real power loss and voltage stability index are simultaneously optimized.

- The QOCNNA is validated on the 33-bus, 69-bus, and 118-bus RDNs. Different scenarios at three load conditions are also investigated for the SNR-DG problem.

- The performance of RDNs is remarkably enhanced in terms of active power loss, voltage profile, and voltage stability after SNR-DG implementation using QOCNNA.

- A new effective methodology is developed to find the optimal network configuration and settings of a PV DG relative to daily variable load and generation scenario to minimize total yearly energy loss. Simulation results from QOCNNA are compared with NNA, ALO [37], WOA [38], SCA [39], and analytical-based methods [40] to demonstrate its effectiveness in this scenario.

- The comparisons of QOCNNA and other algorithms show that QOCNNA obtains better solution quality, convergence speed, and standard deviation of solutions in most case studies.

Section 2 defines the SNR-DG formulation. Then, the QOCNNA concept and its implementation for the SNR-DG problem are introduced in Sections 3 and 4, followed by the simulation results in Section 5. Lastly, Section 6 is the conclusion of this study.

II. PROBLEM FORMULATION

The aim of the SNR-DG problem is to define optimal network configuration, locations and sizes of DGs for minimizing active power loss and maximizing voltage stability index in RDNs while sustaining all operational constraints, which can be generally determined as follows:

A. ACTIVE POWER LOSS

Active power loss in an RDN can be determined as follows:

\[
OF_i = \min(P_L) = \min\left(\sum_{k=1}^{N_B} R_k I_k^2\right)
\]

(1)

where \(N_B\) signifies the total number of branches, \(P_L\) is the active power loss, \(R_k\) denotes the resistance of the \(k^{th}\) branch, and \(I_k\) represents the current of the \(k^{th}\) branch.

![FIGURE 1. A single line of an RDN.](image)

B. OVERALL VOLTAGE STABILITY INDEX

A single line of an RDN is portrayed as in Fig. 1. The voltage stability index (VSI) of the \((i + 1)^{th}\) bus is calculated as follows:
The overall voltage stability index (OVSI) of an RDN can be defined as following equation:

\[
OVSI = \sum_{i=2}^{N_B} VSI_i
\]

where \(N_B\) denotes the total number of buses.

The overall stability of the RDN is improved as the \(OVSI\) value increases. Hence, the objective to maximize \(OVSI\) can be given as follows:

\[
OF_2 = \text{Max}(OVSI) = \text{Min} \left( \frac{1}{OVSI} \right)
\]

**C. MULTI-OBJECTIVE FUNCTION**

In this study, active power loss and OVSI are simultaneously considered in a multi-objective function. The fitness function (FF) of the SNR-DG problem can be formulated as follows:

\[
FF = \text{Min} \left( w_1 \frac{P_L}{P_{L,\text{base}}} + w_2 \frac{OVSI_{\text{base}}}{OVSI} \right)
\]

where \(w_1\) and \(w_2\) are penalty coefficients, \(P_{L,\text{base}}\) and \(OVSI_{\text{base}}\) are values of active power loss and \(OVSI\) in initial case.

**D. SYSTEM CONSTRAINTS**

The SNR-DG problem must satisfy the following constraints:

1) **Power balance:** The power balance of RDNs must be balanced according to equations:

\[
P_S + \sum_{i=1}^{N_k} P_{DG,i} = \sum_{j=1}^{N_k} P_{D,J} + \sum_{k=1}^{N_k} P_{L,K}
\]

\[
Q_S + \sum_{i=1}^{N_k} Q_{DG,i} = \sum_{j=1}^{N_k} Q_{D,J} + \sum_{k=1}^{N_k} Q_{L,K}
\]

where \(P_S\) and \(Q_S\) denote the active and reactive power outputs at the slack bus, respectively; \(P_{DG,i}\) and \(Q_{DG,i}\) symbolize the active and reactive power outputs of the \(i^{th}\) DG, respectively; \(P_{D,J}\) and \(Q_{D,J}\) represent the active and reactive powers at the \(j^{th}\) bus, respectively; \(P_{L,K}\) and \(Q_{L,K}\) designate active and reactive power losses of the \(k^{th}\) branch, respectively; and \(N_DG\) represents the total number of DGs.

2) **Bus voltage and feeder capacity limits:** Limit of bus voltages and feeder capacity must be in the permissible ranges:

\[
V_{\text{min},i} \leq V_i \leq V_{\text{max},i}, \quad i = 1,...,N_B
\]

\[
|I_i| \leq I_{\text{max},k}, \quad k = 1,...,N_L
\]

where \(V_i\) denotes the voltage magnitude at the \(i^{th}\) bus, \(V_{\text{min},i}\) and \(V_{\text{max},i}\) represent the voltage limits of the \(i^{th}\) bus, respectively; and \(I_{\text{max},k}\) denotes the current limit of the \(k^{th}\) branch.

3) **DG capacity limits:** The DG capacities must be in the permissible ranges:

\[
P_{DG,\text{min},i} \leq P_{DG,i} \leq P_{DG,\text{max},i}, \quad i = 1,...,N_DG
\]

where \(P_{DG,\text{min},i}\) and \(P_{DG,\text{max},i}\) denote the power limits of the \(i^{th}\) DG, respectively.

4) **DG penetration limits:** The minimum and maximum DG penetration levels to a RDN are defined as 10% and 60% of total active power load demand of that network, respectively [25]. The threshold 10% chosen is to maintain the existence of DGs in the network for their impact evaluation while the selection of threshold 60% is to prevent the network from reverse power flow situation due to excessive penetration of DGs. These can be demonstrated by the following equation:

\[
0.1 \times \sum_{j=1}^{N_k} P_{D,J} \leq \sum_{i=1}^{N_k} P_{DG,i} \leq 0.6 \times \sum_{j=1}^{N_k} P_{D,J}
\]

5) **Radial configuration constraint:** After reconfiguration, the distribution network must ensure radial configuration and all loads are served [5], [41]:

\[
\text{det}(A) = \begin{cases} 
1 \quad \text{(radial system)} \\
-1 \quad \text{(not radial)} \\
0 
\end{cases}
\]

where \(A\) denotes a matrix indicating the connection of branches and buses in the network. \(A_{ij}\) is set to \(-1\) or \(1\) if the \(i^{th}\) branch is connected from/to the \(j^{th}\) bus; otherwise, \(A_{ij}\) is set to 0.

**II. QUASI-OPPOSITIONAL CHAOTIC NEURAL NETWORK ALGORITHM**

**A. NNA**

1) **INITIAL POPULATION**

In the search space, the initial population of pattern solutions \(X\) are randomly created as the following matrix:

\[
X = \begin{bmatrix}
X_1^1 & X_1^2 & \ldots & X_1^N \\
X_2^1 & X_2^2 & \ldots & X_2^N \\
\vdots & \vdots & \ddots & \vdots \\
X_N^1 & X_N^2 & \ldots & X_N^N
\end{bmatrix}
\]

where \(N_P\) is the population size and \(N\) is the number of decision variables. After initial population initialization, fitness function values of pattern solutions are defined. Then, the best pattern solution having the best fitness function value is determined as the target solution \((X_{\text{Target}})\).

2) **WEIGHT MATRIX**

In order to generate new candidate solutions, each pattern solution is assigned a corresponding weight vector, and initial weights are determined as follows:

\[
W = [W_1, W_2, \ldots, W_{N_P}] = \begin{bmatrix}
w_1^1 & w_1^2 & \ldots & w_1^N \\
w_2^1 & w_2^2 & \ldots & w_2^N \\
\vdots & \vdots & \ddots & \vdots \\
w_{N_P}^1 & w_{N_P}^2 & \ldots & w_{N_P}^N
\end{bmatrix}
\]
The theory of opposition-based learning (OBL) was first introduced by Tizhoosh [42]. The OBL strategy considers concurrently existing guesses and its opposite guesses to better approximate existing candidate solutions. Moreover, the theory of OBL was further developed into QOBL, showing that QOBL can be more effective than OBL for obtaining global optimal solutions [43]. The QOBL is

The pseudocode of NNA

Algorithm 2: Pseudocode of NNA

Initialize the initial parameters of the NNA ($N_t$ and $T_{max}$)
Randomly generate an initial population of pattern solutions
Calculate the fitness function values of initial pattern solutions
Randomly generate the weight matrix considering the imposed constraints in Eqs. (15) and (16)

Define target solution ($X_{Target}$) and its corresponding target weight ($W_{Target}$)

for $t = 1 : T_{max}$

Generate new pattern solutions ($X_t$) using Eqs. (7) and (18)
Update the weight matrix ($W_t$) using Eq. (19)

for $i = 1 : N_p$

if $	ext{rand} \leq \beta$

Perform the bias operator using Algorithm 1
else ($\text{rand} > \beta$)

Apply the transfer function operator using Eq. (21)
end if

end for

Calculate the fitness function values for all updated pattern solutions
Update the target solution and its corresponding target weight
Update the value of $\beta$ using Eq. (20)

end for

Return the target solution $X_{Target}$ and its corresponding fitness function value

where $W^t$ is a square matrix at the $t^{th}$ iteration that generates uniform random numbers from 0 to 1 over iterations.

To control the creation of new pattern solutions and bias of movement, the sum of the weights for a pattern solution is subject to the following constraint:

$$\sum_{j=1}^{N_p} W_{ij}^t = 1, \quad i = 1, 2, \ldots, N_p$$ (15)

where

$$W_{ij}^t \in [0, 1], \quad i, j = 1, 2, \ldots, N_p$$ (16)

This constraint is imposed to allow pattern solutions of NNA to control movement with slight bias (changing from 0 to 1). After creating initial weights, the weight corresponding to the target solution ($X_{Target}$), called the target weight ($W_{Target}$), is selected from the weight matrix $W$ in Eq. (14).

New pattern solutions at the $(t+1)^{th}$ iteration are generated and updated as follows:

$$X_{i,New}^{t+1} = \sum_{j=1}^{N_p} W_{ij}^t \times X_{j}^t, \quad j = 1, 2, \ldots, N_p$$ (17)

$$X_{i}^{t+1} = X_{i}^t + X_{i,New}^{t+1}, \quad i = 1, 2, \ldots, N_p$$ (18)

The weight matrix is then updated based on the target weight ($W_{Target}$) as the following equation:

$$W_{i}^{t+1} = W_{i}^t + 2 \times \text{rand}(0, 1) \times [W_{Target}^t - W_{i}^t], \quad i = 1, 2, \ldots, N_p$$ (19)

During the optimization process, the weight matrix must satisfy the imposed constraints in Eqs. (15) and (16).

3) BIAS OPERATOR

To explore the design domain, a bias operator is applied to adjust the probability of pattern solutions created in the new population and updated weight matrix. By virtue of its role, the algorithm is prevented from premature convergence (particularly in initial iterations). Table 1 gives the Pseudocode of bias strategy in NNA.

Modification factor $\beta$ defines the probability of the pattern solutions to be adjusted. The value of $\beta$ is initially set to 1, and the value of $\beta$ is reduced at each iteration as follows [36]:

$$\beta^{t+1} = \beta^t \times 0.99, \quad t = 1, 2, \ldots, T_{max}$$ (20)

When reducing operator bias adaptively, the algorithm tends to search for optimal solutions close to the target solution ($X_{Target}$) and avoids drastic changes in the pattern solutions in the last iterations.

4) TRANSFER FUNCTION OPERATOR

To create better quality solutions toward the target solution, the transfer function operator transfers the new pattern solutions from their current positions to new positions closer to the target solution ($X_{Target}$) in the search space. Hence, the proposed method for a transfer function operator ($TF$) is defined as follows:

$$X_{i,Updated}^{t+1} = X_{i}^{t+1} + 2 \times \text{rand}(0, 1) \times [X_{Target}^t - X_{i}^{t+1}], \quad i = 1, 2, \ldots, N_p$$ (21)

The bias operator has more opportunities to create new pattern solutions to explore unvisited pattern solutions in the first iterations. However, the chance for the bias operator is decreasing as the number of iterations goes up, and the transfer function operator has more opportunities to exploit towards target solutions. Table 2 presents the Pseudocode of NNA.

B. THE QOBL STRATEGY

The theory of opposition-based learning (OBL) was first introduced by Tizhoosh [42]. The OBL strategy considers concurrently existing guesses and its opposite guesses to better approximate existing candidate solutions. Moreover, the theory of OBL was further developed into QOBL, showing that QOBL can be more effective than OBL for obtaining global optimal solutions [43]. The QOBL is
TABLE 3. The pseudocode of QOBL approach.

| Algorithm 3: Pseudocode of QOBL strategy |
|-----------------------------------------|
| % $O_X$ is opposite point of $X_j$   |
| % $QO_X$ is the quasi-opposite point of $X_j$ |
| % $[L_B, U_B]$ is the search boundary |
| for $i = 1 : N_P$                     |
| for $j = 1 : N$                      |
| $O_X = L_B + U_B - X_j$              |
| $M_B = (L_B + U_B - L_B) / 2$        |
| if $(O_X < M_B)$                     |
| $QO_X = M_B + (O_X - M_B) \times \text{rand}$ |
| else                                 |
| $QO_X = O_X + (M_B - O_X) \times \text{rand}$ |
| end if                               |
| end for                              |
| end for                               |

In this study, QOBL is used in two phases of QOCNNA: population initialization and generation jumping. As for QOBL population initialization, the algorithm creates a quasi-oppositional population of the randomly generated initial population. Then, randomly created initial population and their quasi-oppositional population are considered simultaneously to define the best solutions for the initial population. As for QOBL generation jumping, the search process of the algorithm may be driven to jump to quasi-oppositional solutions that have better fitness function values. In this step, jumping rate $j_r$ is used to decide whether to jump to the quasi-oppositional solutions or keep current solutions. Table 3 depicts the Pseudocode of the QOBL approach.

C. THE CLS STRATEGY

Chaos is randomness created by simple deterministic systems. In QOCNNA, the chaotic sequence is employed to boost searchability and to prevent the algorithm from getting stuck into the local optimization. An initial chaotic value is defined as follows:

$$Z_0 = \text{rand}(0,1)$$

(24)

The following values of that chaotic sequence using a logistic map are given as the following equation [44]:

$$Z_{k+1} = \mu \times Z_k \times (1 - Z_k)$$

(25)

where $Z_k \in (0,1)$ \forall $k \in \{0,1,2,\ldots\}$ and $\mu \in (0,4]$.

The CLS strategy is integrated into QOCNNA to accelerate the search process by exploring the neighborhood of the current target solution (i.e., best solution). Hence, a new candidate solution is created as follows [45]:

$$X_{\text{NewTarget},k} = X_{\text{Target},k} + (Z_k - 0.5) \times (X_{i,k} - X_{j,k})$$

(26)

where $X_{\text{Target},k}$ and $X_{\text{NewTarget},k}$ are the current target solution and the new target solution created at the $k^{th}$ CLS iteration, respectively; $X_{i,k}$ and $X_{j,k}$ are the two solutions randomly selected from the current population, respectively; and $Z_k$ is the chaotic variable at the $k^{th}$ iteration. If fitness function value of $X_{\text{NewTarget},k}$ is better than that of $X_{\text{Target},k}$, $X_{\text{NewTarget},k}$ will replace $X_{\text{Target},k}$ in the population. The CLS strategy is executed until the CLS limit ($K$) is satisfied. The Pseudocode of the CLS strategy is given in Table 4.

D. THE PROPOSED QOCNNA

In this study, the original NNA is combined with QOBL and CLS strategies to develop an improved version of NNA called QOCNNA. Initially, QOCNNA randomly generates a population of pattern solutions $X$. The QOBL is then employed to create the quasi-oppositional population $QOX$ of the initial population. Afterwards, QOCNNA combines two sets of $X$ and $QOX$, and then the $N_P$ best solutions from the combined set $\{X, QOX\}$ are selected for the initial population. Next, the same search process as NNA is implemented to create a new population of pattern solutions and to update the weight matrix. Based on jumping rate $j_r$, QOBL may be used to help QOCNNA transition to better quasi-oppositional solutions of current pattern solutions. Lastly, the CLS is implemented to obtain a better target solution. The optimization process is executed until satisfying stopping criteria. QOCNNA pseudocode is presented in Table 5.

IV. APPLICATION OF QOCNNA TO SNR-DG PROBLEM

A. INITIALIZATION

Each pattern solution of the initial population in QOCNNA represents a solution vector for the SNR-DG problem consisting of opened switches, locations of sizes of DGs. Hence, the $i^{th}$ solution vector is expressed as follows:
TABLE 5. The pseudocode of QOCNNA.

| Algorithm 5: Pseudocode of QOCNNA |
|-----------------------------------|
| Initialize the initial parameters of the QOCNNA ($N_c$, $T_{min}$, $j$, and $K$) |
| % QOBL based population initialization % |
| Randomly generate an initial population $X$ |
| Generate quasi-opposite solutions $X$ of initial pattern solutions $X$ using Algorithm 3 |
| Calculate the fitness function values of combined set [$X$, $QOX$] and sort them |
| Select the $N_p$ best solutions from the set [$X$, $QOX$] as initial population |
| Randomly generate the weight matrix considering the imposed constraints in Eqs. (15) and (16) |
| Define target solution ($X_{target}$) and its corresponding target weight ($W_{target}$) |
| for $t = 1$ to $T_{max}$ |
| % Search process of NNA % |
| Generate new pattern solutions ($X_{new}$) using Eqs. (17) and (18) |
| Update the weight matrix ($W$) using Eq. (19) |
| for $i = 1$ to $N_p$ |
| if rand $\leq \beta$ |
| Perform the bias operator using Algorithm 1 |
| else (rand $> \beta$) |
| Apply the transfer function operator using Eq. (21) |
| end if |
| end for |
| Calculate the fitness function values for all updated pattern solutions |
| Update the value of $\beta$ using Eq. (20) |
| % QOBL based generation jumping % |
| if rand $< j_i$ |
| Generate quasi-opposite solutions $QOX$ of updated pattern solutions $X$ using Algorithm 3 |
| Calculate the fitness function values for quasi-opposite solutions $QOX$ |
| if $f_{new}(QOX) > f_{new}(X)$ |
| $X_{QOX} = QOX$ |
| $f(\overline{X}) = f(\overline{QOX})$ |
| end if |
| end if |
| % Chaotic local search % |
| Update the target solution and its corresponding target weight |
| Perform the CLS strategy to generate better target solution using Algorithm 4 |
| end for |
| Return the target solution $X_{target}$ and its corresponding fitness function value |

where $S$, $L$, and $P$ are opened switches, the locations and sizes of DGs, respectively, $N_{SW}$ denotes the number of opened switches.

To start QOCNNA, the initial population are randomly initialized within the design space as follows:

$$S_i = \text{round} [S_{i_{\text{min}}} + \text{rand} (0,1) \times (S_{i_{\text{max}}} - S_{i_{\text{min}}})],$$

$$L_j = \text{round} [L_{j_{\text{min}}} + \text{rand} (0,1) \times (L_{j_{\text{max}}} - L_{j_{\text{min}}})],$$

$$P_j = P_{j_{\text{min}}} + \text{rand} (0,1) \times (P_{j_{\text{max}}} - P_{j_{\text{min}}}),$$

where $S_{i_{\text{min}}}$ is equal to 1 and $S_{i_{\text{max}}}$ is the length of the $i$th fundamental loop vectors. The principle of the fundamental loop vectors can be found in [30]. $L_{j_{\text{min}}}$ is equal to 2, indicating that DGs may be integrated to all buses except the slack bus. According to Eqs. (28) and (29), values for opened switches ($S_i$) and locations of DGs ($L_j$) are rounded due to their integer nature.

B. FITNESS FUNCTION VALUE

The fitness function value ($FF$) of each pattern solution can be obtained as follows:

$$X_j = [S_1, ..., S_{N_{SW}}, L_1, ..., L_{N_{DG}}, P_1, ..., P_{N_{DG}}],$$

$$i = 1, ..., N_p$$

$$j = 1, ..., N_{DG}$$

**FIGURE 2.** Flowchart of QOCNNA for solving the SNR-DG problem.
\[ FF = OF + K \sum_{i=1}^{N_y} (V_i - V_{i,\text{lim}}) \]  
\[ + K \sum_{k=1}^{N_y} (I_k - I_{k,\text{lim}})^2 + K (PE_{DG} - PE_{DG,\text{lim}})^2 \]

where \( K \) embodies penalty constants for inequality constraint violations and is set to 10^3 in this study. The limit values of bus voltages \( (V_i) \), currents \( (I_k) \), and DG penetration \( (PE) \) are expressed as the following equation:

\[
    x_{\text{lim}} = \begin{cases} 
        x_{\text{max}} & \text{if } x > x_{\text{max}} \\
        x_{\text{min}} & \text{if } x < x_{\text{min}} \\
        x & \text{otherwise}
    \end{cases}
\]

where \( x \) signifies the values of \( V_i, I_k, \) and \( PE_{DG}, \) and \( x_{\text{lim}} \) signifies their limitations, respectively.

C. OVERALL PROCEDURE

QOCNNA implementation steps for the SNR-DG problem can be summarized as follows:

**Step 1:** Data acquisition for SNR-DG problem includes detailed data of test systems (load data and branch data), allowable limits for control variables (opened switches, locations and sizes of DGs), and operational constraints;

**Step 2:** Select the control parameters of QOCNNA \( (N_p, T_{\text{max}}, j_r, \) and \( K) \);

**Step 3:** Generate randomly initial population \( X \) of \( N_p \) pattern solutions as in Section 4.1. Implement the QOBL approach to create a quasi-opposite population \( QOX. \) Calculate fitness function values using Eq. (31) for all solutions in \( X \) and \( QOX. \) Select the \( N_p \) best solutions from the set \( [X, QOX] \) for the initial population;

**Step 4:** Create the initial weight matrix randomly as Eq. (14), satisfying the imposed constraint according to Eqs. (15) and (16);

**Step 5:** Define target solution \( (X_{\text{Target}}) \) having the best fitness function value and its corresponding target weight \( (W_{\text{Target}}). \) Set \( t = 0; \)

**Step 6:** Start the main loop, \( t = t + 1; \)

**Step 7:** Create new pattern solutions and update the pattern solutions as Eqs. (17) and (18);

**Step 8:** Update the weight matrix \( (W) \) via Eq. (19);

**Step 9:** If \( rand \leq \beta, \) perform the bias operator to update new pattern solutions and weight matrix using Algorithm 1. Otherwise, perform the transfer function operator to update the new position of pattern solutions according to Eq. (21);

**Step 10:** Update modification factor \( \beta \) using Eq. (20);

**Step 11:** Check the jumping rate condition. If \( rand < j_r, \) implement the QOBL approach to obtain quasi-opposite points of the current population. Evaluate fitness function values of quasi-oppositional solutions and select better solutions for new population;

**Step 12:** Update target weight corresponding to the target solution;

**Step 13:** Perform the CLS strategy to create a better target solution;

**Step 14:** If \( t \geq T_{\text{max}}, \) stop the optimization process; otherwise, back to Step 6.

Fig. 2 depicts the flowchart of QOCNNA for solving the SNR-DG problem.

V. SIMULATION RESULTS

This study validates the performance of the proposed QOCNNA on 33-bus, 69-bus, and 118-bus RDNs. In scenario 1, active power loss minimization is considered as a single objective function, where the weighting factors \( w_1 \) and \( w_2 \) in Eq. (5) are set to 1 and 0, respectively. For scenario 1, three cases at three load conditions are considered for an in-depth study. Cases 1 and 2 study NR and DGs installation problems separately, while case 3 investigates these two problems concurrently as a combined optimization problem. In scenario 2, active power loss minimization and voltage stability index maximization is considered as a multi-objective function, where \( w_1 \) and \( w_2 \) are set to 0.7 and 0.3, respectively, as proposed in Ref. [25]. Moreover, the considered load conditions are as follows: light load (0.5), nominal load (1.0), and heavy load (1.6). In addition, a practical scenario relative to daily variable load demand and generation has also been considered with the objective of total annual energy loss minimization. The voltage magnitudes at load buses must not exceed ±10% of the rated voltage for case studies. For 33-bus and 69-bus RDNs, the number of DGs is fixed to 3 with the size of each one ranging from 0 to 3 MW. Meanwhile, the number of DGs is 5 where the maximum size of each DG is 5 MW for 118-bus RDN.

QOCNNA is implemented on MATLAB 2019a, and Matpower 6.0 toolbox [46] is deployed to compute the load flow. The control parameters of QOCNNA contain a population size \( (N_p), \) a maximum number of iterations \( (T_{\text{max}}), \) jumping rate \( (j_r), \) and maximum iterations of chaotic local search \( (K), \) which are respectively set as follows: \( N_p = 50 \) (for 33- and 69-bus RDNs) and \( N_p = 100 \) (for 118-bus RDN), \( T_{\text{max}} = 200, j_r = 0.3, \) and \( K = 20. \) Moreover, QOCNNA is performed 30 times independently for each case study. To confirm the results of QOCNNA, the original NNA, ant lion optimizer (ALO) [37], whale optimization algorithm (WOA) [38], and sine cosine algorithm (SCA) [39] are also implemented for the SNR-DG problem. These methods also use the same population size and maximum number of iterations as QOCNNA for the same experimental system.

**FIGURE 3.** The IEEE 33-bus RDN.
TABLE 6. Simulation results of QOCNNA for scenario 1 of 33-bus RDN.

| Case study | Items                      | Load level       | Light (0.5) | Nominal (1.0) | Heavy (1.6) |
|------------|----------------------------|------------------|-------------|---------------|-------------|
| Initial case | Opened switches            | 33-34-35-11.66 kV | 33-34-35-36 | 33-34-35-36 | 33-34-35-36 |
|             | $P_{se}$ (kW)              | 47.07            | 202.68      | 575.36        |
|             | $V_{min}$ (p.u)            | 0.9583           | 0.9131      | 0.8528        |
| Case 1     | Opened switches            | 7-9-14-32-37     | 7-9-14-32-37| 7-9-14-32-37 |
|             | $P_{se}$ (kW)              | 33.2690          | 139.5513    | 381.2398      |
|             | $PLR$ (%)                  | 29.3213          | 31.1460     | 33.7391       |
|             | $V_{min}$ (p.u)            | 0.9608           | 0.9378      | 0.9027        |
| Case 2     | Opened switches            | 33-34-35-33-34-35| 33-34-35-36 | 33-34-35-36 |
|             | $P_{se}$ (kW)              | 0.3509/ (14)     | 0.7050/ (14)| 1.1180/ (14) |
|             | (MW)                       | 0.2875/ (25)     | 0.5702/ (25)| 0.8873/ (25) |
|             | $PLR$ (%)                  | 0.4761/ (30)     | 0.9538/ (30)| 1.5611/ (30) |
|             | $V_{min}$ (p.u)            | 0.9815           | 0.9622      | 0.9384        |
| Case 3     | Opened switches            | 11-28-31-33-34   | 11-28-31-34 | 11-28-31-34 |
|             | $P_{se}$ (kW)              | 0.2547/ (8)      | 0.4822/ (12)| 0.7318/ (12) |
|             | (MW)                       | 0.2982/ (18)     | 1.0153/ (25)| 1.8961/ (25) |
|             | $PLR$ (%)                  | 0.5616/ (25)     | 0.7315/ (33)| 0.9386/ (33) |
|             | $V_{min}$ (p.u)            | 0.9835           | 0.9674      | 0.9559        |

A. 33-BUS RDN

The 33-bus RDN is a small-scale system with a voltage level of 12.66 kV, 37 branches, 32 closed switches, and 5 opened switches [47]. The single line diagram of the 33-bus RDN is shown in Fig. 3. For base configuration, the total active and reactive loads of 33-bus RDN are 3.73 MW and 2.3 MVAr, respectively.

1) SCENARIO 1: ACTIVE POWER LOSS MINIMIZATION

In this scenario, QOCNNA is applied to minimize active power loss as a single objective function. Three different cases with three load conditions of light (0.5), nominal (1.0), and heavy (1.6) are considered. Table 6 details the numerical results found by QOCNNA for 33-bus RDN. Figs. 4 and 5 depict active power losses and voltage profiles for all cases of scenario 1 of 33-bus RDN at three load conditions, respectively. In the case of light load condition, the active power loss from the initial case is 47.07 kW, which is reduced to 33.2690 kW, 18.1929 kW, and 13.5084 kW for cases 1, 2, and 3, respectively. As a result, the power loss reduction (PLR) percentages associated with cases 1, 2, and 3 are 29.3213%, 61.3499%, and 71.3018%. Similarly, at nominal load condition, the active power loss of the initial case is reduced from 202.68 kW to 139.5513 kW, 75.4237 kW, and 54.6942 kW, which leads to PLR of 31.1460%, 62.7863%, and 74.8134% corresponding to cases 1, 2, and 3, respectively. Notably, in comparison with the initial case, PLR for cases 1, 2, and 3 at heavy load condition are 33.7391%, 64.8581%, and 74.8134%, respectively. Moreover, significant improvements in the voltage profile of the system for three cases at all load conditions are also obtained, as shown in Fig. 5.
In case 1, changing positions of opened and closed switches contributes to modifying the power flow paths, which is the main reason for such power loss reductions. As a result, distribution of power is realized through low resistance roots; therefore, power loss and voltage profile are improved. Meanwhile, in case 2, DG units provides local power supply, resulting in reduced power flows through the branches, which is the main reason for the improved system performance. From Table 1, improvement in PLR and voltage profile for case 2 are higher when compared to case 1. It shows that the DG installation offers more desirable results of maximum PLR compared to the NR implementation. Finally, a combination of NR and DG installation is studied in case 3. As shown in Table 1, Figs. 4 and 5, the optimal results in case 3 are better than cases 1 and 2 at all load conditions in terms of reduced power loss and improved voltage profile. Therefore, it shows that combining NR with the DGs installation in the SNR-DG problem would yield better results than considering each problem individually.

Table 7 presents comparisons between the proposed QOCNNA and other methods at all load conditions for case 3 of 33-bus RDN. At light load condition, QOCNNA yields opened switches {11-28-31-33-34}, DG locations at 8th, 18th, and 25th buses with the DG sizes of 0.2547 MW, 0.2982 MW, and 0.5616 MW. As a result, QOCNNA acquires an active power loss of 13.5084 kW, which is much lower than the values obtained by the other methods for all load conditions.

### Table 7: Comparative results of QOCNNA and other methods for case 3 of scenario 1 of 33-bus RDN.

| Load level | Methods | Opened switches | Sum $P_{inc}$ (MW) | $P_L$ (kW) | PLR (%) | Standard deviation |
|------------|---------|-----------------|---------------------|------------|---------|-------------------|
| Light (0.5) | Initial case | 33-34-35-36-37-38 | - | 47.07 | - | - |
|            | QOCNNA  | 11-28-31-33-34 | 1.1145 | 13.5084 | 71.3018 | 0.6772 |
|            | NNA     | 8-17-28-33-34  | 1.0595 | 18.1660 | 67.7804 | 0.7200 |
|            | ALO     | 7-9-28-32-35   | 1.1145 | 14.9030 | 68.3392 | 0.9015 |
|            | EOA [17] | 6-28-34-35-36  | 1.114 | 15.17 | 67.76 | - |
|            | IEOA [17] | 8-28-32-33-34 | 1.106 | 14.51 | 69.17 | - |
|            | ISCA [25] | 7-10-14-28-31 | 0.7867 | 16.24 | 65.49 | - |
|            | HSA [26] | 7-10-14-28-32 | 0.8898 | 17.78 | 62.22 | - |
|            | FWA [28] | 7-10-14-28-32 | 0.8607 | 16.22 | 65.53 | - |
| Nominal (1.0) | Initial case | 33-34-35-36-37-38 | - | 202.68 | - | - |
|            | QOCNNA  | 7-9-14-27-30 | 2.2290 | 54.6942 | 73.0141 | 2.5251 |
|            | NNA     | 10-14-28-32-33 | 2.2274 | 60.2994 | 70.2485 | 3.9668 |
|            | ALO     | 7-11-26-30-34 | 2.2290 | 59.0788 | 70.8508 | 6.9868 |
|            | EOA [17] | 8-27-33-34-36 | 2.229 | 61.48 | 69.66 | - |
|            | IEOA [17] | 7-10-13-27-31 | 2.228 | 57.40 | 71.67 | - |
|            | ISCA [25] | 7-9-14-28-31 | 1.6912 | 66.81 | 67.03 | - |
|            | HSA [26] | 4-7-10-28-32 | 1.6684 | 73.05 | 63.95 | - |
|            | GA [26]  | 7-10-28-32-34 | 1.9633 | 75.13 | 62.92 | - |
|            | RGA [26] | 7-9-12-27-32 | 1.774 | 74.32 | 63.33 | - |
|            | FWA [28] | 7-11-14-28-32 | 1.6841 | 67.11 | 66.89 | - |
|            | FF [33]  | 8-9-28-32-33 | 1.7738 | 73.95 | 63.51 | - |
| Heavy (1.6) | Initial case | 33-34-35-36-37-38 | - | 575.36 | - | - |
|            | QOCNNA  | 7-9-14-28-31 | 3.5664 | 144.9139 | 74.8134 | 7.0850 |
|            | NNA     | 7-8-9-17-28  | 3.5586 | 158.8140 | 72.3975 | 8.1438 |
|            | ALO     | 7-12-27-32-35 | 3.5664 | 158.8809 | 72.3859 | 10.7827 |
|            | EOA [17] | 10-28-30-33-34 | 3552 | 152.26 | 73.54 | - |
|            | IEOA [17] | 7-9-14-27-31 | 3566 | 148.42 | 74.19 | - |
|            | ISCA [25] | 7-9-14-28-31 | 2.9812 | 167.96 | 70.81 | - |
|            | HSA [26] | 7-10-14-28-32 | 2.7529 | 194.22 | 66.23 | - |
|            | FWA [28] | 7-10-14-28-32 | 2.7529 | 172.97 | 69.93 | - |
highlighting that the superiority of QOCNNA over NNA in terms of solution quality, proving the integrated improvement strategies contribute to enhance the search ability of NNA. Moreover, Fig. 6 presents the convergence curves provided by QOCNNA, NNA, and ALO for case 3 at all load conditions, which show that QOCNNA has better convergence characteristics than NNA and ALO. In initial iterations, NNA illustrates a slow convergence speed because bias values used in these iterations are sufficiently large to mainly perform exploration via the bias operator. In later iterations, NNA primarily implements exploitation as bias factor is reduced to lower values. Meanwhile, QOCNNA manifests a significant improvement in convergence speed in the initial iterations thanks to integrated CLS strategy, which enhances the exploitation of QOCNNA. Further, QOCNNA finds the final solution with a higher accuracy. This proves that adopting the QOBL strategy helps QOCNNA achieve a good balance between exploration and exploitation in the later iterations. Compared to ALO, QOCNNA performs the search more effectively for all cases of this scenario based on lower objective values obtained. Therefore, QOCNNA improves its performance compared to the original NNA and ALO for solution quality and convergence characteristics.

2) SCENARIO 2: ACTIVE POWER LOSS AND OVS

In scenario 2, QOCNNA is implemented to the SNR-DG problem (i.e., case 3) for the multi-objective scenario of active power loss and OVS, where loading levels of 0.5 (light), 1.0 (nominal), 1.6 (heavy) are investigated. Table 8 displays the optimal results obtained by QOCNNA. PLR for case 3 at light, nominal and heavy loadings are 71.5947%, 70.7981%, and 71.9608%, respectively. Meanwhile, the
improvement in OVSI for increasing load levels are 7.2037%, 16.3629%, and 30.0315%, respectively. It can be seen that active power loss and OVSI are better enhanced than the initial case. Hence, QOCNNA is capable of providing a good compromised solution for consideration of both active power loss and OVSI objectives. Fig. 7 presents the voltage profile of the system for light, nominal and heavy loadings for the initial case and after the SNR-DG, which shows bus voltages are completely improved. Accordingly, the minimum voltages are improved to 0.9870 p.u., 0.9732 p.u., and 0.9565 p.u. for light, nominal and heavy loadings, respectively.

The results yielded from the QOCNNA are compared to those from NNA, ALO, and ISCA [25] as in Table 8. QOCNNA yields a lower active power loss than that from NNA, ALO, and ISCA [25] for light load condition while the OVSI value obtained by the QOCNNA is slightly better than those from NNA and ALO, and much better than that from ISCA [25]. From the optimal results, QOCNNA has a better solution than NNA, ALO, and ISCA [25] for both active power loss and OVSI objectives for light load condition. For the nominal load condition, active power loss obtained by NNA, ALO, and ISCA [25] respectively are 59.1855 kW, 61.8983 kW, and 67.57 kW, which leads to PLRs being 70.7981%, 69.4597%, and 66.66%, respectively. Obviously, PLR obtained by QOCNNA is better than those obtained by other techniques. Likewise, the OVSI values (in p.u.) found by the QOCNNA, NNA, ALO, and ISCA [25] are 30.0893, 29.9359, 29.9176, and 29.97, respectively. Hence, QOCNNA can provide a better result for active power loss and OVSI objectives than NNA, ALO, and ISCA [25]. For heavy load condition, active power loss and OVSI value obtained by QOCNNA are 161.3266 kW and 29.0555 p.u., respectively. As a result, QOCNNA yields a significant enhancement in both two objective functions in comparison to NNA, ALO, and ISCA [25]. Moreover, standard deviations of optimal solutions found by QOCNNA are smaller than NNA and ALO, which shows QOCNNA is also more robust than other methods in solving multi-objective SNR-DG problem.

TABLE 8. Comparative results of QOCNNA and other methods for scenario 2 of 33-bus RDN.

| Load level | Methods | Opened switches | $P_{dc}$(Bus) | $P_L$ (kW) | PLR (%) | OVSI (p.u.) | OVSI (%) | Fitness function | Standard deviation | $V_{min}$ (p.u.) |
|------------|---------|----------------|---------------|-------------|---------|-------------|-----------|------------------|-------------------|-----------------|
| Light (0.5) | Initial case | QOCNNA | 7-9-14-28-31 | - | 0.2223/ (12) 0.3123/ (18) 0.5799/ (25) | 47.07 | 13.3706 | 71.5947 | 28.8819 | 30.9625 | 7.2037 | 0.4787 | 0.0087 | 0.9583 |
| NNA | 7-14-28-32-35 | 0.4514/ (9) 0.6341/ (29) 0.0290/ (33) | 15.0311 | 68.067 | 30.895 | 6.9697 | 0.504 | 0.016 | 0.9853 |
| ALO | 9-28-32-33-34 | 0.5938/ (25) 0.2214/ (26) 0.2993/ (13) | 14.5961 | 68.9911 | 30.8763 | 6.9053 | 0.4977 | 0.0265 | 0.9828 |
| ISCA [25] | 7-9-14-28-32 | 0.3397/ (30) 0.2054/ (18) 0.3241/ (20) | 17.68 | 62.44 | 30.93 | 6.49 | 0.5431 | - | - |
| Nominal (1.0) | Initial case | QOCNNA | 7-10-12-17-28 | 0.6521/ (32) 0.9343/ (25) 0.6426/ (15) | 202.68 | 59.1855 | 70.7981 | 25.8581 | - | 0.4622 | 0.0051 | 0.9131 |
| NNA | 6-10-14-17-28 | 0.1451/ (14) 1.2816/ (30) 0.8023/ (8) 0.5708/ (9) 1.1913/ (30) 0.4608/ (22) | 61.8983 | 69.4597 | 29.9359 | 15.7696 | 0.4729 | 0.0059 | 0.9672 |
| ALO | 7-11-14-28-32 | 60.8613 | 69.9713 | 29.9176 | 15.6991 | 0.4695 | 0.0225 | 0.9715 |
| ISCA [25] | 7-9-14-28-31 | 0.6217/ (30) 0.7266/ (18) 0.4362/ (20) | 67.57 | 66.66 | 29.97 | 14.51 | 0.4922 | - | 0.9678 |
| Heavy (1.6) | Initial case | QOCNNA | 7-9-17-28-34 | 1.1517/ (13) 0.9858/ (25) 1.4286/ (31) | 575.36 | 161.3266 | 71.9608 | 22.3449 | 29.0555 | 30.0315 | 0.427 | 0.0068 | 0.8528 |
| NNA | 11-14-17-27-33 | 1.0946/ (9) 0.5042/ (33) 1.9677/ (29) | 166.3376 | 71.0899 | 28.8648 | 29.1783 | 0.4346 | 0.0105 | 0.952 |
| ALO | 7-9-14-17-27 | 2.2617/ (30) 0.6558 / (12) 0.6489/ (9) 0.1097/ (30) 0.1154/ (18) 0.1018/ (20) | 166.1195 | 71.1278 | 28.8826 | 29.2579 | 0.4342 | 0.0149 | 0.9476 |
| ISCA [25] | 7-9-14-28-31 | 171.58 | 70.18 | 29 | 27.08 | 0.4399 | - | 0.9502 |
Therefore, QOCNNA is a more robust and effective method than others in reducing active power loss and enhancing OVSI of RDNs. Fig. 8 shows the convergence curves of QOCNNA and other methods for scenario 2 of 33-bus RDN at all load conditions. These figures show that QOCNNA obtains a faster convergence speed than NNA and ALO for all load conditions of this scenario.

From the obtained results, QOCNNA dominates the original NNA and other methods for solution accuracy and convergence rate in solving the SNR-DG problem for both scenarios of the 33-bus RDN. Therefore, QOBL and CLS are successfully integrated into QOCNNA to help the algorithm avoid local optimum trapping (exploration) and boost the convergence speed (exploitation) and hence improve QOCNNA performance.

**FIGURE 8.** Convergence characteristics of QOCNNA, NNA and ALO for scenario 2 of 33-bus RDN.

**TABLE 9.** Simulation results of QOCNNA for scenario 1 of 69-bus RDN.

| Case study | Items | Load level | Light (0.5) | Nominal (1.0) | Heavy (1.6) |
|------------|-------|------------|-------------|---------------|-------------|
| Initial case | Opened switches | 69-70-71 | 69-70-71 | 69-70-71 | 72-73 | 72-73 | 72-73 |
| P_L (kW) | 0.9567 | 0.9092 | 0.8445 |
| V_{min} (p.u) | 0.9754 | 0.9495 | 0.9165 |
| Case 1 | Opened switches | 14-56-61-69-70 | 14-57-61-69-70 | 14-57-61-69-70 | 98.6046 | 267.1102 | 267.1102 |
| P_L (kW) | 51.60 | 224.99 | 652.49 |
| PLR (%) | 54.2446 | 56.1741 | 59.0634 |
| V_{min} (p.u) | 0.9754 | 0.9495 | 0.9165 |
| Case 2 | Opened switches | 69-70-71-69-70 | 69-70-71-69-70 | 69-70-71-69-70 | 72-73 | 72-73 | 72-73 |
| P_L (kW) | 33.6118 | 98.6046 | 652.49 |
| PLR (%) | 66.5614 | 59.0634 | 59.0634 |
| V_{min} (p.u) | 0.9754 | 0.9495 | 0.9165 |
| Case 3 | Opened switches | 14-56-61-12 | 14-57-61-12 | 14-58-61-12 | 72-73 | 72-73 | 72-73 |
| P_L (kW) | 23.6118 | 98.6046 | 652.49 |
| PLR (%) | 66.5614 | 59.0634 | 59.0634 |
| V_{min} (p.u) | 0.9754 | 0.9495 | 0.9165 |
TABLE 10. Comparative results of QOCNNA and other methods for case 3 of scenario 1 of 69-bus RDN.

| Load level | Methods     | Opened switches | $\sum P_{inc}$ (MW) | $P_{L}$ (kW) | PLR (%)   | Standard deviation |
|------------|-------------|-----------------|----------------------|--------------|------------|--------------------|
| Light (0.5)| Initial case| -               | 51.60                | -            | -          | -                  |
|            | QOCNNA      | 14-56-61-69-70  | 1.1406               | 8.6804       | 83.1790    | 0.6475            |
|            | NNA         | 12-56-61-69-70  | 1.0333               | 9.6156       | 81.3667    | 0.7476            |
|            | ALO         | 9-13-56-64-70   | 1.1406               | 10.5353      | 79.5845    | 5.1837            |
|            | EOA [17]    | 12-55-62-69-70  | 0.970                | 9.4497       | 81.76      | -                 |
|            | IEOA [17]   | 12-55-62-69-70  | 1.098                | 9.03737      | 81.83      | -                 |
|            | ISC [25]    | 12-17-57-62-69  | 0.9721               | 10.02        | 80.58      | -                 |
|            | HSA [26]    | 10-14-16-56-62  | 1.0201               | 11.07        | 78.55      | -                 |
|            | FWA [28]    | 13-56-63-69-70  | 0.9399               | 9.58         | 81.43      | -                 |
| Nominal (1.0)| Initial case| -               | 224.99               | -            | -          | -                  |
|            | QOCNNA      | 14-55-61-69-70  | 2.2812               | 35.3683      | 84.2802    | 1.4818            |
|            | NNA         | 12-19-55-61-69  | 1.9751               | 39.1729      | 82.5892    | 1.5453            |
|            | ALO         | 9-13-20-53-62   | 2.2813               | 40.8180      | 81.8580    | 11.5016           |
|            | EOA [17]    | 12-18-56-63-69  | 2.263                | 37.5495      | 83.31      | -                 |
|            | IEOA [17]   | 10-13-57-61-70  | 1.831                | 36.9866      | 83.82      | -                 |
|            | ISC [25]    | 12-19-57-63-69  | 1.8731               | 39.73        | 82.34      | -                 |
|            | HSA [26]    | 13-17-58-61-69  | 1.8718               | 40.3         | 82.08      | -                 |
|            | GA [26]     | 10-15-45-55-62  | 2.0292               | 46.5         | 73.38      | -                 |
|            | RGA [26]    | 10-14-16-55-62  | 2.0654               | 44.23        | 80.32      | -                 |
|            | FWA [28]    | 13-55-63-69-70  | 1.8181               | 39.25        | 82.55      | -                 |
|            | FF [33]     | 12-19-57-61-69  | 1.9371               | 40.3         | 82.08      | -                 |
| Heavy (1.6)| Initial case| -               | 652.49               | -            | -          | -                  |
|            | QOCNNA      | 14-58-61-69-70  | 3.6399               | 92.6570      | 85.7996    | 5.8371            |
|            | NNA         | 12-18-58-63-69  | 3.5909               | 97.6747      | 85.0306    | 6.6672            |
|            | ALO         | 12-18-58-63-69  | 3.6500               | 99.4677      | 84.7558    | 40.9324           |
|            | EOA [17]    | 10-17-45-55-61  | 3.649                | 106.074      | 83.736     | -                 |
|            | IEOA [17]   | 10-12-13-57-62  | 3.649                | 100.4148     | 84.6       | -                 |
|            | ISC [25]    | 14-55-62-69-70  | 2.7449               | 104.5        | 83.92      | -                 |
|            | HSA [26]    | 10-13-18-58-61  | 3.3828               | 104.67       | 83.96      | -                 |
|            | FWA [28]    | 13-57-63-69-70  | 2.9613               | 102.97       | 84.21      | -                 |

B. 69-BUS RDN
The 69-bus RDN is a medium-scale system with a voltage level of 12.66 kV, 73 branches, 68 closed switches, and 5 opened switches [48]. Fig. 9 describes the single line diagram of 69-bus RDN. For base configuration, the total active and reactive loads of 69-bus RDN are 3.802 MW and 2.69 MVAr, respectively.

1) SCENARIO 1: ACTIVE POWER LOSS MINIMIZATION
Table 9 gives the simulation results found by the proposed QOCNNA for scenario 1 of 69-bus RDN. Figs. 10 and 11 depict active power losses and voltage profiles for all cases of scenario 1 of 69-bus RDN, respectively. For the light load condition, initial power loss of the system is 51.60 kW, which is reduced to 23.6118 kW (case 1), 17.2558 kW (case 2), and 8.6804 kW (case 3), respectively. The corresponding PLR percentages are 54.2446%, 66.5614%, and 83.1790% for cases 1, 2, and 3. Similarly, at nominal and heavy load conditions, PLR related to cases 1, 2, and 3 are {56.1741%, 68.5925%, and 84.2802%} and {59.0634%, 71.5085%, and 85.7996%}, respectively.

According to the optimal results, PLR in case 3 at all load conditions are the best values compared to cases 1 and 2. Furthermore, minimum voltage of the system for cases 1, 2, and 3 at light, medium, and heavy load conditions are improved to {0.9754 p.u., 0.9878 p.u., and 0.9904 p.u.}, {0.9495 p.u., 0.9760 p.u., and 0.9802 p.u.}, and {0.9165 p.u., 0.9597 p.u., and 0.9692 p.u.}, respectively. The voltage profiles in case 3 are better improved than in other cases for all load conditions, as shown in Fig. 11. This implies the solution of SNR-DG is more effective than the ones of merely NR or DG in improving voltage issues of the 69-bus network.

Table 10 shows comparisons between QOCNNA and other methods at all load conditions for case 3 of scenario 1 of 69-bus RDN. At light load condition, QOCNNA defines the optimal NR with opened switches [14-56-61-69-70], DG installations in 12th, 61st, and 64th buses with respective DG sizes of 0.2079 MW, 0.6963 MW, and 0.2364 MW. The active power loss attained by QOCNNA is 8.6804 kW, whereas the ones obtained by NNA, ALO, EOA [17], IEOA [17], ISC [25], HSA [26], and FWA [28], are 9.6156 kW, 10.5353 kW, 9.4497 kW, 9.03737 kW, 10.02 kW, 11.07 kW, and 9.58 kW, respectively. Accordingly, QOCNNA provides the lowest active power loss in comparison with other methods for this load condition. At normal load condition, opened switches obtained by QOCNNA are [14-55-61-69-70]. DGs are installed on 12th, 61th, and 64th buses with 0.4181 MW, 1.3805 MW, and 0.4827 MW DG sizes. The active power loss achieved by QOCNNA for this case is the best result compared to other methods. At heavy load condition, QOCNNA offers the optimal NR with opened switches [14-58-61-69-70], DG locations at 12th, 61th, and 64th buses with respective DG sizes of 0.5920 MW,
2.2781 MW, and 0.7698 MW. The active power loss by QOCNNA (92.6570 kW) is lower than NNA (97.6747 kW), ALO (99.4677 kW), EOA [17] (106.074 kW), IEOA [17] (100.4148 kW), ISCA [25] (104.5 kW), HSA [26] (104.67 kW), and FWA [28] (102.97 kW) for this load condition.

A comparative study in Table 10 shows that the proposed QOCNNA is an effective method for solving the SNR-DG problem. It is noted that QOCNNA is more robust than NNA and ALO in solving this scenario due to finding solutions with the lowest standard deviations for all load conditions. Fig. 12 portrays the convergence curves of QOCNNA, NNA, and ALO for scenario 1. From these figures, QOCNNA achieves better convergence than NNA and ALO for all case studies.

2) SCENARIO 2: ACTIVE POWER LOSS AND OVSI OPTIMIZATION

Multi-objective optimization of power loss minimization and voltage stability index maximization are investigated for the SNR-DG problem using QOCNNA in this scenario. Table 11 lists optimal results obtained by QOCNNA for this scenario. As for the consideration of active power loss and OVSI, the obtained PLRs are 82.7277%, 84.0223%, and 94.1823% for light, nominal and heavy loadings, respectively. Similarly, the OVSI values for the three loading conditions are effectively enhanced to 3.9261%, 8.5967% and 14.7118%, respectively. It is noted from the optimal results that SNR-DG application using QOCNNA shows a substantial improvement in both active power loss and OVSI objectives for all load conditions. Further, the voltage profile of the

**FIGURE 11.** Voltage profiles for scenario 1 of 69-bus RDN at three load conditions.

**FIGURE 12.** Convergence characteristics of QOCNNA, NNA and ALO for case 3 of scenario 1 of 69-bus RDN.
TABLE 11. Comparative results of QOCNNA and other methods for 69-bus RDN for scenario 2.

| Load level | Method      | Opened switches | \( P_{oc} \) (Bus) | \( P_L \) (kW) | \( PLR \) (%) | OVSI (%) | Fitness function | Standard deviation | \( V_{nom} \) (p.u.) |
|------------|-------------|-----------------|---------------------|----------------|--------------|-----------|------------------|---------------------|------------------|
| Light (0.5) | Initial case QOCNNA | - | - | 51.60 | 8.9133 | 82.7277 | 64.5966 | 3.9261 | 0.4096 | 0.0085 | 0.9567 |
|            | NNA         | 8-9-12-14-62    | 0.2046/ (66) 0.2730/ (27) 0.6663/ (61) | 10.2143 | 80.2066 | 66.6881 | 3.2377 | 0.4291 | 0.0228 | 0.989 |
|            | ALO         | 10-19-45-58-63  | 0.7333/ (61) 0.0666/ (68) 0.3401/ (24) | 10.2016 | 80.2312 | 66.8867 | 3.5453 | 0.4281 | 0.0691 | 0.989 |
|            | ISCA [25]   | 14-62-55-70-69  | 0.3593/ (60) 0.3015/ (61) 0.4019/ (65) | 11.02 | 78.64 | 67.39 | 4.16 | 0.4370 | - | 0.9879 |
| Nominal (1.0) | Initial case QOCNNA | 14-58-62-69-70 | 1.4113/ (61) 0.5167/ (27) 0.3533/ (12) | 224.99 | 84.0223 | 66.48 | 8.5967 | 0.3881 | 0.0038 | 0.9798 |
|            | NNA         | 10-16-58-63-71  | 1.3893/ (61) 0.0549/ (46) 0.8371/ (21) | 40.9018 | 81.8207 | 65.8789 | 7.6147 | 0.406 | 0.0045 | 0.9772 |
|            | ALO         | 10-13-19-53-61  | 1.3808/ (61) 0.0459/ (67) 0.4456/ (64) | 39.079 | 82.6309 | 65.5967 | 7.1537 | 0.4016 | 0.0345 | 0.9789 |
|            | ISCA [25]   | 14-55-62-70-69  | 0.8100/ (60) 0.7978/ (61) 0.5738/ (65) | 40 | 82.22 | 66.47 | 8.2 | 0.4007 | - | 0.9813 |
| Heavy (1.6) | Initial case QOCNNA | 14-58-62-69-70 | 0.5723/ (12) 0.8300/ (27) 2.2477/ (61) | 652.49 | 85.5659 | 65.5707 | 14.7118 | 0.3626 | 0.0039 | 0.8445 |
|            | NNA         | 12-58-64-69-70  | 2.6447/ (61) 0.4971/ (21) 0.5082/ (66) | 104.84 | 83.9325 | 65.4932 | 14.5761 | 0.3743 | 0.0042 | 0.9599 |
|            | ALO         | 12-19-55-62-69  | 0.8500/ (27) 0.5312/ (51) 2.2688/ (61) | 99.7307 | 84.7155 | 65.0262 | 13.7591 | 0.3707 | 0.0419 | 0.9672 |
|            | ISCA [25]   | 69-70-14-56-63  | 0.1061/ (60) 0.1108/ (61) 0.7720/ (65) | 105.76 | 83.79 | 65.09 | 13.22 | 0.3769 | - | 0.9615 |

The system is greatly enhanced after the SNR-DG as shown in Fig. 13. The minimum voltages are 0.9897 p.u., 0.9798 p.u., and 0.9668 p.u., respectively, for light, nominal and heavy load conditions after applying QOCNNA.

The results obtained by QOCNNA for scenario 2 of 69-bus RDN are compared to those obtained by other methods as presented in Table 11. For light load condition, QOCNNA obtains an active power loss of 8.9133 kW, which is lower than those of 10.2143 kW from NNA, 10.2016 kW from ALO, and 11.02 kW from ISCA [25]. Moreover, the OVSI values (in p.u.) achieved by QOCNNA, NNA, ALO, and ISCA [25] are 67.1327, 66.6881, 66.8867, and 67.39, respectively. QOCNNA obtains higher OVSI than NNA and ALO, and slightly lower than ISCA [25]. However, fitness value of QOCNNA is the lowest compared to the other methods. From the simulated results, the best solution found by QOCNNA is better than those obtained by NNA, ALO, and ISCA [25] for two considered objectives.

Moreover, QOCNNA gives the lowest active power losses and the highest OVSI values in comparison to NNA, ALO, and ISCA [25] for nominal and heavy load conditions. As can be observed in Table 11, QOCNNA obtains the best fitness function values as compared to NNA and ALO for all load conditions. Hence, QOCNNA has a better performance than the other techniques in finding a compromise solution among the objective functions. The standard deviation values achieved by QOCNNA are also much lower than those achieved by NNA and ALO for all load levels, which confirms its robustness in solving multi-objective SNR-DG problem.

Fig. 14 portrays the convergence characteristics of QOCNNA NNA, and ALO in terms of fitness function for three load conditions. It can be seen that QOCNNA can quickly converge to the minimum fitness value for all three load conditions. Generally, QOCNNA shows its superior performance over the original NNA and other methods in...
terms of solution accuracy and convergence speed in solving the SNR-DG problem of medium-scale 69-bus RDN.

C. 118-BUS RDN

The 118-bus RDN is a large-scale system with a voltage level of 11 kV, 132 branches, 118 closed switches, and 15 opened switches. For base configuration, the total active and reactive loads of 118-bus RDN are 22.709 MW and 17.041 MVAr, respectively.

1) SCENARIO 1: ACTIVE POWER LOSS MINIMIZATION

Similar to the above test systems, QOCNNA is also applied to 118-bus RDN for three cases at three load levels with objective of active power loss minimization in this scenario. Simulation results are reported in Table 12. Figs. 15 and 16 portray active power losses and voltage profiles for all cases at three load conditions of 118-bus RDN, respectively.

In the initial case, the power losses at the light, nominal, and heavy load conditions are 297.15 kW, 1298.09 kW, and 3799.70 kW, respectively. Table 12 shows that the PLRs for cases 1 to 3 at light load condition are {31.4740%, 53.3198%, 54.2760%}, respectively. Meanwhile, at nominal and heavy load conditions, PLRs for cases 1, 2, and 3 are {34.2087%, 55.7169%, 57.0241%} and {38.7237%, 59.4512%, 62.1732%}, respectively. Moreover, the minimum voltage magnitudes are improved from 0.9385 p.u., 0.8688 p.u., and 0.7673 p.u. (initial case) to 0.9764 p.u., 0.9541 p.u., and 0.9247 p.u., respectively, at the light, nominal and heavy loading conditions in case 3. From the optimal results, case 3 reduces power loss and improves minimum voltage remarkably compared to cases 1 and 2 at all load conditions.

FIGURE 13. Voltage profiles for scenario 2 of 69-bus RDN at three load conditions.

FIGURE 14. Convergence characteristics of QOCNNA, NNA and ALO for scenario 2 of 69-bus RDN.
The result comparisons of QOCNNA, NNA, and ALO for case 3 of scenario 1 of 118-bus RDN are reported in Table 13. The convergence curves of QOCNNA, NNA and ALO are depicted in Fig. 17. Obviously, the performance of QOCNNA is better than those of NNA and ALO in terms of solution quality and convergence characteristics in all case studies. QOCNNA also obtains lower standard deviations than NNA and ALO, which demonstrates the robustness of QOCNNA over the two methods. Therefore, QOCNNA shows its effectiveness in solving the large-scale SNR-DG problem.

2) SCENARIO 2: ACTIVE POWER LOSS AND OVSI OPTIMIZATION

In this scenario, the QOCNNA is applied to deal with the SNR-DG problem with the simultaneous optimization of active power loss and OVSI. Table 14 gives the optimal results for this scenario. From Table 14, QOCNNA not only obtains PLR of 56.8199%, 57.7960%, and 64.1986%, but it...
also enhances OVSI by 4.5563%, 10.1079%, and 18.7007% for light, nominal and heavy loadings, respectively. As depicted in Fig. 18, QOCNNA can effectively enhance the voltage profile of the system, with minimum voltages being improved to 0.9803 p.u., 0.9591 p.u., and 0.9345 p.u. for light, nominal and heavy loadings, respectively. It should be noted that the multi-objective SNR-DG problem on the 118-bus system is not documented in the literature and thus, comparing QOCNNA and previous studies is impossible. As seen in Table 14, the optimal solutions obtained by the QOCNNA for all load conditions are superior to those obtained by NNA and ALO for both active power loss and OVSI objectives. This proves that QOCNNA’s performance is better than those of NNA and ALO regarding the compromise among the two objective functions. The convergence characteristics shown in Fig. 19 demonstrate the excellent global search ability of the QOCNNA compared with NNA and ALO. Moreover, the standard deviation of solutions found by the QOCNNA is also the smallest among compared algorithms for all load conditions of this scenario.

Hence, QOCNNA can effectively solve the SNR-DG problem with a high-quality solution. The good performance of QOCNNA is due to the incorporation of two search strategies including CLS and QOBL. In QOCNNA, the QOBL approach is integrated to explore a more promising region; meanwhile, the CLS approach is used to locally exploit the neighborhood of the best solutions to enhance the solution accuracy. These approaches improve the exploration and exploitation capabilities of QOCNNA to avoid premature convergence and local optima stuck. Hence, QOCNNA can find the optimal solution with a faster convergence speed.

The QOCNNA, NNA, and ALO are implemented on a 3.5 GHz 8-core PC with 16 GB of RAM. Table 15 reports the average computational times of QOCNNA, NNA, and ALO for each case. Computational times of QOCNNA are longer than NNA and ALO for most case studies. However, QOCNNA has faster computational time than ALO for all cases of 118-bus large-scale system. The long computational speed of QOCNNA is due to the extra search time of QOBL and CLS strategies. Although QOCNNA does not dominate the computational time over NNA and ALO, QOCNNA outperforms the two methods for the solution quality, convergence characteristic, and robustness in all cases.

### D. Examination of Daily Load and Generation Variations on NR and DG Allocation Problem

From the above simulated results of three separate loading levels, the optimal solution of open switches, locations and sizes of DGs varies considerably in relation to different loading conditions. Therefore, the problem is to determine the optimal network configuration and settings of DGs when the actual load changes daily. To address this, a novel methodology has been developed for finding the optimal opened switches, locations, and sizes of DGs based on a load demand curve of a typical day.

Recalling that the object function of minimization of operational cost \((Co)\) in RDN usually comprises two factors, i.e., the cost of shifting switches \((Co_s)\) and the cost of active power loss as follows:

\[
Co = n_s \times Co_s + Co_a \times \sum_{k=1}^{n_s} P_{loss,k} \times T_k
\]  

### TABLE 13. Comparative results of QOCNNA and other methods for case 3 of scenario 1 of 118-bus RDN.

| Load level | Method | Opened switches | Sum \(P_{loss}\) (MW) | \(P_s\) (kW) | PLR (%) | Standard deviation |
|------------|--------|----------------|-----------------------|-------------|---------|-------------------|
| Light (0.5) | Initial case | 118-119-120-121-122-123-124-125-126-127-128-129-130-131-132 | - | 297.15 | - | - |
| QOCNNA | 11-23-38-42-53-58-70-117-122-125-127-128-129-130-132 | 6.8083 | 136.0566 | 54.2126 | 16.4666 | - |
| NNA | 8-12-23-34-43-61-71-74-87-95-121-122-129-130-131 | 6.6678 | 153.1411 | 48.4631 | 19.7526 | - |
| ALO | 11-21-32-39-42-43-50-55-60-66-108-127-128-129-130 | 6.1750 | 149.8976 | 49.5547 | 33.5727 | - |
| Nominal (1.0) | Initial case | 118-119-120-121-122-123-124-125-126-127-128-129-130-131-132 | - | 1298.09 | - | - |
| QOCNNA | 16-21-33-39-43-51-60-70-109-121-125-127-128-129-130 | 13.5176 | 519.3127 | 59.9941 | 63.4359 | - |
| NNA | 12-22-39-43-58-70-76-109-121-122-125-126-129-130-132 | 13.4878 | 605.1948 | 53.3781 | 88.1335 | - |
| ALO | 26-39-45-52-59-71-82-98-120-121-125-126-130-131-132 | 10.1101 | 611.3221 | 52.9061 | 90.7589 | - |
| Heavy (1.6) | Initial case | 118-119-120-121-122-123-124-125-126-127-128-129-130-131-132 | - | 3799.70 | - | - |
| QOCNNA | 22-26-33-39-42-52-58-70-121-125-126-128-129-130-131 | 19.8326 | 1373.3527 | 63.8563 | 134.5878 | - |
| NNA | 22-39-51-61-70-82-97-118-119-121-125-126-130-131-132 | 19.7210 | 1580.4894 | 58.4049 | 146.3508 | - |
| ALO | 23-25-34-39-45-50-61-69-98-107-109-123-125-127-130 | 16.9254 | 1512.6655 | 60.1899 | 193.5097 | - |
where \( C_{oa} \) is energy price; \( n_s \) is number of times shifting switches; \( T_k \) is operating time of configuration \( k \) and \( P_{loss,k} \) is active power loss induced by configuration \( k \).

However, some practical RDNs whose cost of shifting switches is too large when compared with the savings from power loss reduction. Also, the system of supervisory control and data acquisition has not been suitably developed yet, leading to the switches cannot be controlled remotely. Accordingly, the process of shifting the status of switches will result in a power outage since in this process, power from a path delivered to loads is first cut and power is then supplied to loads via another path. Hence, in this situation the switches will be remained unchanged for a long time by power suppliers and the prime objective of the NR process is therefore minimizing the cost of energy loss during variable load period. In other words, the problem of minimization of operational cost will be converted into the problem of finding a constant network configuration during the operating time so as to minimize energy loss. The object function of the NR problem for minimizing energy loss (\( EL \)) can be stated as follows:

\[
EL(S) = \sum_{i=1}^{24} P_{loss}(t) \times \Delta t
\]

(34)

Beside network reconfiguration, the allocation of photovoltaic (PV)-based DG has also been examined on the scenario of daily variable loads for minimizing energy loss. In this scenario, one PV DG is considered for allocation where the outputs of PV DG are estimated from the average output curve as in Fig. 20 [40]. Fig. 21 illustrates an hourly load demand curve of the 69-bus network which is similar to the one in [40]. To make a fair and efficient comparison with
The object function in [40] for the case of only PV DG, the object function $AEL$ has been modified for computing total annual energy loss ($AEL$) with an interval $\Delta t$ of 1 h. Precisely, the computation of $AEL$ is the summation of the active power losses of 24 loading levels over a day times 365 days a year. In addition, this object function has also been adopted to investigate two remaining cases including the case of only NR and the case of simultaneous NR and PV DG allocation. For the general case of simultaneous optimization, the function $AEL$ may be expressed as:

$$AEL(S, L, P, Q) = 365 \times \sum_{t=1}^{365} P_{loss}(t) \times \Delta t$$  (35)

### TABLE 14. Comparative results of QOCNNA and other methods for 118-bus RDN for scenario 2.

| Load level | Method  | Opened switches | $P_{inc}$/k(Bus) | $P_L$ (kW) | PLR (%) | OVS1 (%) | Fitness function | Standard deviation | $V_{con}$ (p.u) |
|------------|---------|-----------------|------------------|------------|---------|----------|-----------------|-------------------|-----------------|
| Light (0.5) | Initial case | 118-119-120-121-122-123-124-125-126-127-128-129-130-131-132 | - | 297.15 | - | 107.3935 | - | - | 0.9385 |
|            | QOCNNA  | 23-39-42-53-73-97-117-119-122-123-125-126-129-130-132 | 1.2344/(50) | 128.3092 | 56.8199 | 112.2867 | 4.5563 | 0.5892 | 0.0227 | 0.9803 |
|            | NNA     | 21-39-42-53-79-82-109-119-122-125-126-127-130-132 | 1.1881/(50) | 148.9972 | 49.8577 | 111.8196 | 4.1213 | 0.6391 | 0.0288 | 0.9738 |
|            | ALO     | 11-23-34-37-44-53-72-122-123-125-126-128-129-130-131 | 1.6784/(97) | 160.9496 | 45.8353 | 111.2229 | 3.5657 | 0.6688 | 0.395 | 0.9704 |
| Nominal (1.0) | Initial case | 118-119-120-121-122-123-124-125-126-127-128-129-130-131-132 | - | 1298.09 | - | 98.019 | - | - | 0.8688 |
|            | QOCNNA  | 1-22-34-39-44-51-61-70-86-97-123-125-129-130-131 | 3.5988/(73) | 547.8465 | 57.796 | 107.9267 | 10.1079 | 0.5679 | 0.0279 | 0.9591 |
|            | NNA     | 21-26-37-42-51-59-69-76-107-109-119-125-127-130-132 | 2.0913/(50) | 596.0247 | 54.0845 | 107.2264 | 9.3934 | 0.5956 | 0.0355 | 0.9329 |
|            | ALO     | 11-23-39-41-50-57-61-73-104-107-109-122-126-127-132 | 1.3689/(71) | 603.1019 | 53.5393 | 107.1996 | 9.3661 | 0.5995 | 0.1508 | 0.9396 |
| Heavy (1.6) | Initial case | 118-119-120-121-122-123-124-125-126-127-128-129-130-131-132 | - | 3799.7 | - | 86.9977 | - | - | 0.7673 |
|            | QOCNNA  | 16-21-39-51-61-72-75-108-118-122-125-127-129-130-132 | 4.5698/(47) | 1360.3474 | 64.1986 | 103.2669 | 18.7007 | 0.5033 | 0.0275 | 0.9345 |
|            | NNA     | 6-22-24-42-51-61-70-85-121-125-127-128-129-131-132 | 5.0000/(109) | 1538.8802 | 59.5 | 101.3394 | 16.4851 | 0.541 | 0.0347 | 0.9362 |
|            | ALO     | 21-26-34-39-44-52-59-76-85-116-121-125-126-127-129 | 4.4225/(72) | 1599.9892 | 57.8917 | 102.3773 | 17.6781 | 0.5497 | 0.0618 | 0.9281 |
For the test network, only is the 69-bus RDN with medium-size selected for the investigations. Bus voltage profile of the 69-bus network in a representative day before optimization is illustrated in Fig. 22. To validate the simulation results of the proposed QOCNNA for case studies, we have further run four different optimization methods including whale optimization algorithm – WOA [38], sine cosine algorithm – SCA [39], ALO [37], and original NNA [36] methods for each case study to compare results. The algorithm parameters of WOA, SCA, ALO and NNA are set the same as in their original studies [36]–[39]. The respective optimization results for the three cases of NR and PV DG allocation with the aim of minimizing the function $AEL$ in the 69-bus network are tabulated in Table 16 in which the step-by-step computation procedure in Appendix A is utilized.

For the case of only NR, the proposed QOCNNA obtains an optimal configuration with opened switches $\{14-57-63-69-70\}$, which is fixed during varying of loads. Hourly active power losses relative to this configuration are depicted in Fig. 23. This configuration achieves a reduced $AEL$ value of 617.69 MWh compared with an initial $AEL$ value of 1,381.97 MWh. Notably, this value is significantly lower than 760.65 MWh from WOA [38], 784.04 MWh from SCA [39], 790.06 MWh from ALO [37], and 738.60 MWh from NNA. Accordingly, the QOCNNA obtains the highest cost savings of 91,713.84 $ among the comparative optimizers. Also, the QOCNNA requires a CPU time of approximately 147.93 s to reach the final solution, which is faster than WOA and ALO, but slower than SCA and NNA. QOCNNA has a longer CPU time due to the extra time relative to the exploration process of QOBL and the exploitation process of CLS as well. It is noted that the extra search time makes a remarkable improvement in the performance of QOCNNA. Further, the voltage profiles of the network in a representative day after NR are plotted in Fig. 24. From the figure, the optimal solution of NR leads to a significant improvement in voltage magnitude at all buses compared with the initial case shown in Fig. 22. Convergence curves of five methods for minimizing $AEL$ function in Case 1 are depicted in Fig. 25. The QOCNNA shows a fast convergence to the optimal solution within 27 iterations while the remaining methods fail to approach the optimal solution. To further analyze the convergence of NNA, in the first iterations with sufficiently large modification factor (MF), the bias operator will be more likely activated to satisfy the exploration ability of NNA. This likelihood will gradually decrease as the MF decreases by iterations, meaning that in later iterations the transfer function operator may be activated to help NNA implement the local search in the designed space. In fact, with a decreasing step of 0.01, a MF value of 0.5 reached at the 50th iteration is large enough for NNA to remain the

For the test network, only is the 69-bus RDN with medium-size selected for the investigations. Bus voltage profile of the 69-bus network in a representative day before optimization is illustrated in Fig. 22. To validate the simulation results of the proposed QOCNNA for case studies, we have further run four different optimization methods including whale optimization algorithm – WOA [38], sine cosine algorithm – SCA [39], ALO [37], and original NNA [36] methods for each case study to compare results. The algorithm parameters of WOA, SCA, ALO and NNA are set the same as in their original studies [36]–[39]. The respective optimization results for the three cases of NR and PV DG allocation with the aim of minimizing the function $AEL$ in the 69-bus network are tabulated in Table 16 in which the step-by-step computation procedure in Appendix A is utilized.

For the case of only NR, the proposed QOCNNA obtains an optimal configuration with opened switches $\{14-57-63-69-70\}$, which is fixed during varying of loads. Hourly active power losses relative to this configuration are depicted in Fig. 23. This configuration achieves a reduced $AEL$ value of 617.69 MWh compared with an initial $AEL$ value of 1,381.97 MWh. Notably, this value is significantly lower than 760.65 MWh from WOA [38], 784.04 MWh from SCA [39], 790.06 MWh from ALO [37], and 738.60 MWh from NNA. Accordingly, the QOCNNA obtains the highest cost savings of 91,713.84 $ among the comparative optimizers. Also, the QOCNNA requires a CPU time of approximately 147.93 s to reach the final solution, which is faster than WOA and ALO, but slower than SCA and NNA. QOCNNA has a longer CPU time due to the extra time relative to the exploration process of QOBL and the exploitation process of CLS as well. It is noted that the extra search time makes a remarkable improvement in the performance of QOCNNA. Further, the voltage profiles of the network in a representative day after NR are plotted in Fig. 24. From the figure, the optimal solution of NR leads to a significant improvement in voltage magnitude at all buses compared with the initial case shown in Fig. 22. Convergence curves of five methods for minimizing $AEL$ function in Case 1 are depicted in Fig. 25. The QOCNNA shows a fast convergence to the optimal solution within 27 iterations while the remaining methods fail to approach the optimal solution. To further analyze the convergence of NNA, in the first iterations with sufficiently large modification factor (MF), the bias operator will be more likely activated to satisfy the exploration ability of NNA. This likelihood will gradually decrease as the MF decreases by iterations, meaning that in later iterations the transfer function operator may be activated to help NNA implement the local search in the designed space. In fact, with a decreasing step of 0.01, a MF value of 0.5 reached at the 50th iteration is large enough for NNA to remain the

| System | Scenario | Load level | QOCNNA | NNA | ALO |
|--------|----------|------------|--------|-----|-----|
| 33-bus | Light    | 34.4241    | 21.1106| 34.6392 |
|        | Nominal  | 33.7666    | 21.3928| 33.1026 |
|        | Heavy    | 33.6635    | 22.7201| 30.1585 |
| 2      | Light    | 34.9202    | 23.7738| 30.1680 |
|        | Nominal  | 35.4668    | 24.1679| 30.7914 |
|        | Heavy    | 37.0243    | 24.9710| 31.4698 |
| 69-bus | Light    | 40.9544    | 25.7319| 37.4283 |
|        | Nominal  | 40.6161    | 26.4172| 37.2397 |
|        | Heavy    | 44.0282    | 28.3895| 36.1827 |
| 2      | Light    | 41.9397    | 28.8032| 35.6665 |
|        | Nominal  | 43.3064    | 30.2412| 34.4542 |
|        | Heavy    | 46.8053    | 32.6261| 35.3223 |
| 118-bus| Light    | 57.8684    | 36.6683| 83.8207 |
|        | Nominal  | 61.8395    | 42.8737| 84.9837 |
|        | Heavy    | 68.3257    | 47.8329| 91.0057 |
| 2      | Light    | 58.2855    | 52.1114| 86.3282 |
|        | Nominal  | 64.8470    | 56.1389| 89.3360 |
|        | Heavy    | 69.5089    | 63.0611| 91.5608 |

FIGURE 19. Convergence characteristics of QOCNNA, NNA and ALO for scenario 2 of 118-bus RDN.
TABLE 16. Results of NR and PV DG allocation for daily variable load and generation scenario using different optimizers.

| Case study | Methods       | Opened switches | $S_{DG}$(Bus) | Optimal pf | Annual energy loss before optimization (MWh) | Annual energy loss after optimization (MWh) | Annual energy loss mitigation (%) | Cost savingsa ($) | Avg. CPU time |
|------------|---------------|-----------------|--------------|------------|----------------------------------------------|---------------------------------------------|----------------------------------|------------------|---------------|
| Case 1 – NR | QOCNNA        | 14-57-63-69-70  | -            | -          | 1381.97                                      | 617.69                                      | 55.30                             | 91,713.84        | 147.93        |
| Only NR    | NNA           | 5-11-55-62-70   | -            | -          | 1381.97                                      | 738.60                                      | 46.55                             | 77,204.91        | 65.17         |
| Only       | ALO           | 56-63-69-70-71  | -            | -          | 1381.97                                      | 790.06                                      | 42.83                             | 71,029.20        | 180.45        |
| Only       | WOA           | 20-42-44-56-63  | -            | -          | 1381.97                                      | 760.65                                      | 44.95                             | 74,558.56        | 151.78        |
| Only       | SCA           | 5-14-15-53-62   | -            | -          | 1381.97                                      | 784.04                                      | 43.26                             | 71,751.44        | 82.39         |
| Case 2 – NR | QOCNNA        | -               | 2.304/(61)   | 0.783      | 1381.97                                      | 569.78                                      | 58.77                             | 97,462.83        | 1524.85       |
| Only       | NNA           | -               | 2.446/(61)   | 0.807      | 1381.97                                      | 578.90                                      | 58.11                             | 96,368.62        | 971.52        |
| PVDG       | ALO           | -               | 2.361/(61)   | 0.801      | 1381.97                                      | 599.31                                      | 56.63                             | 93,919.82        | 744.30        |
| PVDG       | WOA           | -               | 3.498/(61)   | 0.86       | 1381.97                                      | 698.13                                      | 49.48                             | 82,061.40        | 698.62        |
| PVDG       | SCA           | -               | 2.661/(61)   | 0.857      | 1381.97                                      | 910.01                                      | 34.15                             | 56,635.02        | 994.51        |
| PVDG       | AM [40]       | -               | 3.618/(61)   | 0.83       | 1381.97                                      | 657.72                                      | 52.40                             | 86,910.00        | 0.10          |
| Case 3 – NR | QOCNNA        | 16-56-64-69-71  | 2.113/(61)   | 0.784      | 1381.97                                      | 369.08                                      | 73.29                             | 121,547.10       | 1012.16       |
| Only       | NNA           | 9-14-56-64-70   | 2.876/(61)   | 0.938      | 1381.97                                      | 454.07                                      | 67.14                             | 111,347.93       | 571.7         |
| Only       | ALO           | 14-56-64-69-71  | 2.984/(61)   | 0.872      | 1381.97                                      | 422.92                                      | 69.39                             | 115,086.73       | 753.22        |
| Only       | WOA           | 12-63-69-70-72  | 3.414/(61)   | 0.925      | 1381.97                                      | 707.19                                      | 48.82                             | 80,973.98        | 661.31        |
| Only       | SCA           | 9-15-56-62-71   | 0.391/(61)   | 0.875      | 1381.97                                      | 703.06                                      | 49.12                             | 81,469.82        | 387.75        |

pf denotes power factor of DG; The lowest object value is in bold; Tariff covers 0.12 $/kWh and cost savings in $ is equal to (AEL_{before} − AEL_{after})×10^4×0.12.

The hourly power output of PV DG in a representative day is plotted in Fig. 28. From the figures, it is observed that, after connecting one PV DG at bus 61, the output of PV DG related to each hour is as follows:

- Case 1: The output of PV DG is 617.69 MWh.
- Case 2: The output of PV DG is 569.78 MWh.
- Case 3: The output of PV DG is 369.08 MWh.

The hourly active power losses of the network obtained by the methods before and after PV DG connection are shown in Fig. 27. From the two figures, it is observed that, in the time range of 6 – 20 hours when network load demand tends to increase, the output of PV DG optimized by QOCNNA meets the load demand better than those optimized by the rest of methods. This leads to lower power losses in this period achieved by QOCNNA.
non-zero outputs of PV DG, the voltage profiles at nodes from 53 to 65 of the feeder where PV DG connected is remarkably improved. Moreover, convergence curves of five methods in solving the PV DG-only case of the network are shown in Fig. 29. The three ALO, NNA and QOCNNA methods have high competition in exploring the search space and the QOCNNA exhibits a strong search ability to approach the best solution among the three. For the convergence of NNA, in the first 50 iterations when the MF decreases from 1 to 0.5 by a step of 0.01, the MF values belonging to this range are large enough to activate the bias operator with a high probability for performing the exploration. In this phase, there are relatively large changes in the convergence curve. In later iterations, once the MF decreases to sufficiently small values, it is highly likely that the transfer function operator will be activated to execute the exploitation. Due to the local search at this stage, there are small changes observed in the convergence curve. For QOCNNA, thanks to the integrated CLS strategy, the exploitation aspect is noticeably enhanced in the first 50
iterations which leads to a better convergence profile as compared with NNA. In addition, the use of QOBL strategy also supports QOCNNA for the exploration ability in the later iterations, resulting in a better convergence trend observed. Clearly, the QOCNNA with integrated improvement strategies shows a faster convergence speed and higher solution accuracy for this case. This proves that QOCNNA achieves a better trade-off between the exploration and exploitation properties as compared with NNA. While the WOA and SCA methods fail to achieve an optimal solution for this case, showing a weak search capability.

Concerning the practical case of simultaneous NR and PV DG allocation, the QOCNNA settles at the optimal solution with the opened switches of \{16-56-64-69-71\} and the connection of one PV DG at bus 61 with maximum size of 2.113 MVA, which results in a reduced \textit{AEL} value of 369.08 MWh (i.e. 73.29\% reduction). This \textit{AEL} value is the lowest among those found by WOA, SCA, ALO and NNA methods. It means the highest cost savings of 121,547.10 $ is achieved.
by QOCNNA. Regarding CPU time, QOCNNA requires about 1012.16 s for the optimization process. Although it takes more time than the remaining methods, its solution quality is remarkably better. Also, the hourly optimized outputs of PV DG associated with the daily load demand of the network using other methods are depicted as in Fig. 30. The hourly active power losses of the network obtained by the methods before and after simultaneous NR and PV DG allocation are shown in Fig. 31. The combination of NR and PV DG allocation results in a more significant reduction in power loss at the hours of zero output of PV DG as compared with the solution of only PV DG allocation in Fig. 27. Moreover, most of the hourly power loss values obtained by QOCNNA are lower than those obtained by the comparative methods. Further, the voltage profiles of the network in a representative day after simultaneous NR and PV DG allocation are plotted in Fig. 32. The simultaneous solution of NR and PV DG leads to a significant improvement in voltage magnitude at all buses compared with the initial case shown in Fig. 22. Finally, convergence curves of the applied methods for minimizing AEL function in this case are illustrated in Fig. 33. The QOCNNA along with the ALO and NNA again shows high competition in the solution search process in this case and the QOCNNA is the unique method converging to the optimal solution. Compared with NNA, QOCNNA always shows the ability to search in the area of higher quality solutions and approaches the optimal solution with a faster convergence rate. This proves that the improvement strategies have helped QOCNNA achieve a better harmony between the exploration and exploitation. For the two WOA and SCA methods, they do not show the ability to efficiently explore the search space and suffer from a slow convergence speed when solving this case.

VII. CONCLUSION

In the paper, QOCNNA has been successfully proposed to solve the SNR-DG problem. Active power loss minimization and voltage stability index maximization in RDNs are the considered objective functions of the SNR-DG problem. The proposed QOCNNA is implemented to determine optimal configuration and positions and capacities of DGs for the 33-, 69-, and 118-bus RDNs at several scenarios with various case studies. For single-objective scenario, among three cases tested, the case of SNR-DG solved by QOCNNA is the most effective in reducing power loss in different load levels. Particularly, the PLRs at nominal load level after the SNR-DG by QOCNNA respectively are 73.01%, 84.28%, and 59.99% for the 33-, 69-, and 118-bus RDNs. Likewise, simulation results of multi-objective scenario also indicate that the optimal solution of SNR-DG found by QOCNNA leads to the significant improvement in network performance (i.e., power loss reduction and voltage stability index maximization) in all load conditions. Especially, as for case SNR-DG of the 33-, 69-, and 118-bus RDNs at nominal load condition, QOCNNA yields optimal solutions relative to PLR percentages of 70.79%, 84.02%, and 57.79%, respectively. At the same time, the OVSI improvement percentages are 16.36%, 8.59%, and 10.10%, respectively. The solutions offered by QOCNNA result in a better improvement in network performance than the ones found by NNA, ALO as well as previous methods in the literature in both scenarios. Further, QOCNNA shows a better convergence and lower standard deviation of solutions when compared with NNA and ALO for all case studies in two scenarios. Moreover, QOCNNA obtains the optimal network configuration and settings of PV DG satisfying the daily variable load demand and generation while minimizing total annual energy loss. The solution of QOCNNA in this scenario leads to more reduction in total annual energy loss than those of analytical-based approaches and other applied methods as well.

In conclusion, QOCNNA is capable of finding high-quality solutions with fast convergence speed and small standard deviation of solutions for the SNR-DG problem. In most cases, the optimized outcomes by QOCNNA are highly competitive and effective against the previous studies. This proves the improvement strategies help QOCNNA gain an excellent harmony between exploration and exploitation. For future researches, we will focus on expanding the SNR-DG problem as well as the QOCNNA algorithm in some aspects such as uncertainty in loads and renewable generations, combination of technical, economic, and reliability objectives, and development in multi-objective version of QOCNNA. It is noted that the application of QOCNNA for handling the uncertainty issues relative to the SNR-DG problem is discussed as in Appendix B below.

ACKNOWLEDGMENT

The present research study was funded by Thu Dau Mot University (TDMU) under grant number DT.21.1-079.

APPENDIX

A. EXAMINATION OF DAILY LOAD AND GENERATION VARIATIONS ON NR AND DG ALLOCATION PROBLEM

The procedure for NR and PV DG allocation considering daily variable load and generation is presented as:
1. Read the predicted data relative to the 24-h load.
2. Perform a 24-h load flow and calculate the total annual energy loss for the initial case using Eq. (35).
3. Randomly initialize the opened switches, location and sizes of one PV DG for each case study using the equations (A.1 – A.3) in which the numbers of control variables are 5, 49 and 54 corresponding to the NR-only, PV DG-only and simultaneous NR – PV DG cases:

   \[ X_i = \{ S_{1i}, \ldots, S_{N_{SW}} \}; \quad i = 1, \ldots, N_p \]  

   \[ X_i = \{ L_i, P_1, \ldots, P_n, Q_1, \ldots, Q_n \}; \quad i = 1, \ldots, N_p; \quad h = 24 \]  

   (A.1)
   (A.2)
\[ X_t = [S_1, \ldots, S_{N_{SW}}, L, P_1, \ldots, P_h, Q_1, \ldots, Q_h]; \]
\[ i = 1, \ldots, N_F; \quad h = 24 \]  \hspace{1cm} (A.3)

where \( P_1, \ldots, P_h \) and \( Q_1, \ldots, Q_h \) are respectively active and reactive power outputs of PV DG for a 24-h period. The control variables of \( S_i, L, P_i, Q_i \) are randomly initialized using the following equations:

\[ S_i = \text{round}[S_{i,\min} + \text{rand}(0,1) \times (S_{i,\max} - S_{i,\min})], \]
\[ i = 1, \ldots, N_{SW} \]  \hspace{1cm} (A.4)

\[ L = \text{round}[L_{\min} + \text{rand}(0,1) \times (L_{\max} - L_{\min})] \]
\[ P_t = P_{t,\min} + \text{rand}(0,1) \times (P_{t,\max} - P_{t,\min}), \]
\[ t = 1, \ldots, h \]
\[ Q_t = Q_{t,\min} + \text{rand}(0,1) \times (Q_{t,\max} - Q_{t,\min}), \]
\[ t = 1, \ldots, h \]  \hspace{1cm} (A.7)

This study assumes that PV DG adopts advanced technologies (i.e., using converters for connection) allowing operation at a desired power factor. With the non-dispatchable nature, the output of PV DG depends on the generation curve for 24-h a day as in [40]. Based on this generation curve, hourly output is equivalent to a daily peak output percentage of the DG unit. Therefore, the output range of PV DG for optimization at the hour \( t \) will be from 0% to 100% of the output at the hour \( t \) of the DG unit. Also, the location of PV DG may be determined by the geographic and resource factors. For a benchmark RDN, the nodes for DG allocation are not predetermined and so all nodes except slack node are considered as candidate nodes for DG placement. In other words, the search range for the PV DG placement will be from node 2 to node \( n \).

4. Execute the QOBL process to create the population QOX. Evaluate the fitness function for all candidate solutions in \( X \) and QOX according to Eqs. (A.8) and (A.9). Choose \( N_F \) best solutions from \( \{X, \text{QOX}\} \).

\[ FF_{AEL} = AEL + \sum_{h=1}^{24} \text{penal}_h \]  \hspace{1cm} (A.8)

where \( \text{penal}_h \) is a penalty function for controlling the violation of related constraints in the hour \( h \) of the day and is formulated as follows:

\[ \text{penal}_h = K \times \left( \sum_{i=1}^{N_F} (V_i^h - V_i^{\lim})^2 \right) \]
\[ + \sum_{i=1}^{N_F} \left( I_i^h - I_i^{\lim} \right)^2 + \left( PE_{DG,i}^{\lim,h} - PE_{DG,i} \right)^2 \]  \hspace{1cm} (A.9)

where \( K \) is penalty factor set to 10^4 for the investigations in this scenario and \( PE_{DG,i}^{\lim,h} \) is penetration limit of PV DG in the hour \( h \) depending on the total load demand of the network at that hour.

5. Define target items \( X_{\text{Target}} \) and \( W_{\text{Target}} \).

6. Assign \( t = 0 \) and \( \beta = 1 \).

7. while (\( t < T_{\text{max}} \) do

8. Generate new solutions and update the solutions via Eqs. (17) and (18). Update \( W \) using Eq. (19).

9. If \( \text{rand} \leq \beta \), execute the bias operator to update new solutions and weight matrix (Algorithm 1). Otherwise, apply the transfer function operator using Eq. (21) for solution update.

10. Update \( \beta \) using Eq. (20).

11. If \( \text{rand} < j \), perform the QOBL method to acquire quasi-oppositional points of the current population. These new solutions are only updated if their fitness values are better.

12. Update \( X_{\text{Target}} \) and \( W_{\text{Target}} \).

13. Implement the CLS strategy to find a better target solution;

14. \( t = t + 1 \)

15. end while

16. Return optimal solution of the opened switches, location, outputs of PV DG in relation to practical 24-h load variations. After acquiring the optimal hourly outputs of PV DG, the apparent power and the optimal \( pf \) of PV DG at hour \( t \) can be respectively computed using Eqs. (A.10) and (A.11):

\[
S_{DG,i} = \sqrt{P^2_{DG,i} + Q^2_{DG,i}} \]  \hspace{1cm} (A.10)

\[
pf_{DG,i} = \frac{P^2_{DG,i}}{\sqrt{P^2_{DG,i} + Q^2_{DG,i}}} \]  \hspace{1cm} (A.11)

B. DISCUSSION ON THE APPLICATION OF QOCNNA FOR HANDLING THE UNCERTAINTY ISSUES OF THE PROBLEM

For the optimization problem of NR and DG allocation in RDNs, the load-predicting errors along with PV and wind power generation considered as some main sources of uncertainty can be included in the mathematical modelling. To deal with these uncertainty parameters, there are three main approach groups in the literature including probabilistic approaches, possibilistic approaches and hybrid probabilistic-possibilistic approaches [49]. In this section, we will present the application of a commonly used probabilistic strategy of Monte Carlo simulation (MCS) belonging to the probabilistic approaches group for handling relevant uncertainties. Regarding the application, uncertain parameters are first modelled by probability density functions (PDFs) and are then dealt with MCS strategy. Electrical loads, PV and wind power generation can be modelled by using the common PDFs as follows:

**Electrical load**

Due to the errors in prediction, the loads are frequently modeled as a Gaussian PDF in which mean of the PDF is equal to the predicted load value. Most of the cases, a division of predicted value is taken as the PDF’s standard deviation [50], [51].

\[
PDF(S_L) = \frac{1}{\sqrt{2\pi\sigma}} \exp \left[ -\frac{(S_L - \mu)^2}{2\sigma^2} \right] \]  \hspace{1cm} (B.1)
where $L_t$ represents load’s apparent power; $\sigma$ and $\mu$ denotes mean and standard deviation of load power, respectively.

**PV power generation**

The power generated by a PV DG is primarily related to solar irradiation [50], [52], [53]. Solar irradiation is frequently modeled as a Beta PDF characterized by the following equation [50].

$$PDF(s) = \begin{cases} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \cdot \Gamma(\beta)} \cdot s^{\alpha-1} \cdot (1-s)^{\beta-1} & \text{if } 0 \leq s \leq 1 \\ \infty & \text{otherwise} \end{cases}$$  \hspace{1cm} (B.2)

where $s$ denotes solar irradiation (kW/m²); $\alpha$ and $\beta$ represent parameters relative to Beta distribution.

**Wind power generation**

The power generated by a wind turbine is primarily related to the wind speed [50], [54], [55]. Wind speed is frequently characterized by Weibull distribution as follows [50], [56], [57].

$$PDF(v) = \left( \frac{k}{c} \right) \left( \frac{v}{c} \right)^{k-1} \exp \left[ -\left( \frac{v}{c} \right)^{k} \right]$$  \hspace{1cm} (B.3)

where $k$ and $c$ are shape and scale factors of Weibull function, respectively.

The power generated by a wind turbine follows a function of wind speed and is estimated using Eq. (B.4).

$$P(v) = \begin{cases} 0 & \text{if } v < v_{in} \text{ or } v > v_{out} \\ \frac{v - v_{in}}{v_{rated} - v_{in}} & \text{if } v_{in} \leq v \leq v_{rated} \\ \frac{v_{rated} - v}{v_{rated} - v_{out}} & \text{if } v_{rated} < v \leq v_{out} \end{cases}$$  \hspace{1cm} (B.4)

where $P_{rated}$ is wind turbine’s rated power; $v_{rated}$ is rated speed of turbine (m/s); $v_{in}$ and $v_{out}$ are cut-in speed and cut-out speed of wind turbine (m/s), respectively.

After describing the uncertain parameters of the problem by PDFs, the probabilistic uncertainty handling technique of MCS is adopted for computations. Specifically, the input-output relationship of the problem is represented as follows:

$$y = f(X, U)$$  \hspace{1cm} (B.5)

where $X$ denotes the set of uncertain input parameters, i.e., loads, generation power of PV DG and wind DG; $U$ denotes the set of control variables, i.e., open switches and site of DGs and $y$ denotes the objective function to be minimized of the problem.

More specifically, in this case the opened switches and site of DGs will be found using the proposed QOCNNA so that the object function in Eq. (B.5) is minimized while considering the uncertainties of loads and generation power of PV and wind DGs. In the iteration process of MCS, for each pattern solution from population initialized by the QOCNNA, different samples of loads and generation power of PV and wind DGs are generated corresponding to each fixed value of $U$ using PDFs, the respective values of object function are then estimated for each sample based on input-output relation. Afterwards the mean of object function values is judged as the quality of that pattern solution. For this case, different pattern solutions are assessed at different iterations and the best pattern solution is chosen as optimal solution when the stopping condition is achieved. Below is the pseudo-code of MCS for handling the uncertain parameters.

for $i = 1 : n_{trial}$

Create sample $X_i$ of loads and generation power of PV and wind DGs.

Compute $y_i = f(X_i, Z)$

end for

$$\text{mean} = \frac{\sum_{i=1}^{n_{trial}} y_i}{n_{trial}}$$  \hspace{1cm} (B.6)

$$\text{std} = \sqrt{\frac{\sum_{i=1}^{n_{trial}} (y_i - \text{mean})^2}{n_{trial}}}$$  \hspace{1cm} (B.7)

where $n_{trial}$ is number of MCS trials; $\text{mean}$ and $\text{std}$ are mean and standard deviation of the $y$’s Gaussian PDF.

**REFERENCES**

[1] A. Ameli, A. Ahmadiifar, M.-H. Shariati, M. Vakilian, and M.-R. Haghipam, “A dynamic method for feeder reconfiguration and capacitor switching in smart distribution systems,” International Journal of Electrical Power & Energy Systems, vol. 85, pp. 200–211, Feb. 2017, doi: 10.1016/j.ijepes.2016.09.008.

[2] M. A and B. H., “Search for a minimal-loss operating spanning tree configuration in an urban power distribution system,” Power Syst Comput Conf, vol. 5th, no. 1, pp. 1–1, 1975.

[3] S. Ghasemi and J. Moshtagh, “A novel codification and modified heuristic approaches for optimal reconfiguration of distribution networks considering losses cost and cost benefit from voltage profile improvement,” Applied Soft Computing, vol. 25, pp. 360–368, Dec. 2014, doi: 10.1016/j.asoc.2014.08.068.

[4] D. Shirmohammadi and H. W. Hong, “Reconfiguration of electric distribution networks for resistive line losses reduction,” IEEE Transactions on Power Delivery, vol. 4, no. 2, pp. 1492–1498, Apr. 1989, doi: 10.1109/61.25637.

[5] A. Y. Abdelaziz, F. M. Mohammed, S. F. Mekhamer, and M. A. L. Badr, “Distribution Systems Reconfiguration Using a modified particle swarm optimization algorithm,” Electric Power Systems Research, vol. 79, no. 11, pp. 1521–1530, Nov. 2009, doi: 10.1016/j.epsr.2009.05.004.

[6] A. M. Othman, A. A. El-Fergany, and A. Y. Abdelaziz, “Optimal Reconfiguration Comprising Voltage Stability Aspect Using Enhanced Binary Particle Swarm Optimization Algorithm,” Electric Power Components and Systems, vol. 43, no. 14, pp. 1656–1666, Aug. 2015, doi: 10.1080/15325008.2015.1041623.

[7] J. Z. Zhu, “Optimal reconfiguration of electrical distribution network using the refined genetic algorithm,” Electric Power Systems Research, vol. 62, no. 1, pp. 37–42, May 2002, doi: 10.1016/S0378-7796(02)00041-X.

[8] H. de Faria, M. G. C. Resende, and D. Ernst, “A biased random key genetic algorithm applied to the electric distribution network reconfiguration problem,” J Heuristics, vol. 23, no. 6, pp. 533–550, Dec. 2017, doi: 10.1007/s10732-017-9355-8.

[9] R. Srinivas Rao, S. V. L. Narasimham, M. Ramalinga Raju, and A. Srinivas Rao, “Optimal Network Reconfiguration of Large-Scale Distribution System Using Harmony Search Algorithm,” IEEE Transactions on Power Systems, vol. 26, no. 3, pp. 1080–1088, Aug. 2011, doi: 10.1109/TPWRS.2010.2076839.
This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3134872, IEEE Access
[41] A. Y. Abdelaziz, F. M. Mohamed, S. F. Mekhamer, and M. A. L. Badr, “Distribution system reconfiguration using a modified Tabu Search algorithm,” Electric Power Systems Research, vol. 80, no. 8, pp. 943–953, Aug. 2010, doi: 10.1016/j.epsr.2010.01.001.

[42] H. R. Tizhoosh, “Opposition-Based Learning: A New Scheme for Machine Intelligence,” in International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC’06), Nov. 2005, vol. 1, pp. 695–701. doi: 10.1109/CIMCA.2005.1631345.

[43] S. Rahamayanan, H. R. Tizhoosh, and M. M. A. Salama, “Quasi-oppositional Differential Evolution,” in 2007 IEEE Congress on Evolutionary Computation, Sep. 2007, pp. 2229–2236. doi: 10.1109/CEC.2007.4424748.

[44] D. Jia, G. Zheng, and M. Khurram Khan, “An effective memetic differential evolution algorithm based on chaotic local search,” Information Sciences, vol. 181, no. 15, pp. 3175–3187, Aug. 2011, doi: 10.1016/j.ins.2011.03.018.

[45] J. Ji, S. Gao, S. Wang, Y. Tang, H. Yu, and Y. Todo, “Self-Adaptive Gravitational Search Algorithm With a Modified Chaotic Local Search,” IEEE Access, vol. 5, pp. 17881–17895, 2017, doi: 10.1109/ACCESS.2017.2748957.

[46] R. D. Zimmerman and C. E. Murillo-Sánchez, MATPOWER-manual-4.1.pdf. Cornell University, Ithaca, NY: Power Systems Engineering Research Center, 2011. Accessed: Sep. 19, 2020. [Online]. Available: https://matpower.org/docs/MATPOWER-manual-4.1.pdf

[47] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Transactions on Power Delivery, vol. 4, no. 2, pp. 1401–1407, Apr. 1989, doi: 10.1109/61.25627.

[48] M. E. Baran and F. F. Wu, “Optimal capacitor placement on radial distribution systems,” IEEE Transactions on Power Delivery, vol. 4, no. 1, pp. 725–734, Jan. 1989, doi: 10.1109/61.19265.

[49] A. Soroudi and T. Amrach, “Decision making under uncertainty in energy systems: State of the art,” Renewable and Sustainable Energy Reviews, vol. 28, pp. 376–384, Dec. 2013, doi: 10.1016/j.rser.2013.08.039.

[50] A. Soroudi, M. Aien, and M. Ehsan, “A Probabilistic Modeling of Photo Voltaic Modules and Wind Power Generation Impact on Distribution Networks,” IEEE Systems Journal, vol. 6, no. 2, pp. 254–259, Jun. 2012, doi: 10.1109/JSYST.2011.2162994.

[51] F. Liu, Z. Bie, S. Liu, and T. Ding, “Day-ahead optimal dispatch for wind integrated power system considering zonal reserve requirements,” Applied Energy, vol. 188, pp. 399–408, Feb. 2017, doi: 10.1016/j.apenergy.2016.11.102.

[52] M. N. Kabir, Y. Mishra, and R. C. Bansal, “Probabilistic load flow for distribution systems with uncertain PV generation,” Applied Energy, vol. 163, pp. 343–351, Feb. 2016, doi: 10.1016/j.apenergy.2015.11.003.

[53] B. R. Prusty and D. Jena, “A critical review on probabilistic load flow studies in uncertainty constrained power systems with photovoltaic generation and a new approach,” Renewable and Sustainable Energy Reviews, vol. 69, pp. 1286–1302, Mar. 2017, doi: 10.1016/j.rser.2016.12.044.

[54] G. Aquila, P. Rotela Junior, E. de Oliveira Pamplona, and A. R. de Queiroz, “Wind power feasibility analysis under uncertainty in the Brazilian electricity market,” Energy Economics, vol. 65, pp. 127–136, Jun. 2017, doi: 10.1016/j.eneco.2017.04.027.

[55] P. Xiong, P. Jinutitijareon, and C. Singh, “A Distributionally Robust Optimization Model for Unit Commitment Considering Uncertain Wind Power Generation,” IEEE Transactions on Power Systems, vol. 32, no. 1, pp. 39–49, Jan. 2017, doi: 10.1109/TPWRS.2016.2544795.

[56] S. H. Karaki, R. B. Chedid, and R. Ramadan, “Probabilistic performance assessment of autonomous solar-wind energy conversion systems,” IEEE Transactions on Energy Conversion, vol. 14, no. 3, pp. 766–772, Sep. 1999, doi: 10.1109/60.790949.

[57] J. Zhou, P. Lu, Y. Li, C. Wang, L. Yuan, and L. Mo, “Short-term hydro-thermal-wind complementary scheduling considering uncertainty of wind power using an enhanced multi-objective bee colony optimization algorithm,” Energy Conversion and Management, vol. 123, pp. 116–129, Sep. 2016, doi: 10.1016/j.enconman.2016.05.073.