1. Introduction

Network reconfiguration (NR) and distributed generation placement (DGP) are the two most effective solutions to reduce power loss as well as improve technical indicators of the distribution system (DS). In the context of the modernly equipped switches (SW) with flexible switching capabilities and the strong development of distributed generation (DG) relied on renewable energy sources, the implementation of the above two solutions becomes even easier. In terms of definition, the NR problem is the process that search the radial network configuration of the DS to reach the technical or economical goals. It is implemented by altering the close/open status of switches installed on the DS. The obtained solution of the network reconfiguration problem has to satisfy the radial topology constraint and other technical ones. While, DG is power sources coupled directly within the DS or located near the energy consumption points. Based on the DG capacity, DG can be split into types including micro DG with capacity less than 5 kW, small DG with capacity in the range 5 kW to 5 MW, medium DG with capacity in the range 5–50 MW and large DG with its capacity in the range 50–300 MW [1]. While NR helps to share the load among the DS’s branches, DGP helps to reduce the capacity supplied from the main feeders. Both of NR and DGP contribute to improve the efficiency of the DS. Therefore, many studies have devoted attention to these two solutions.

For the NR problem, although it was proposed very early in the 1970s [2], it has still attracted the attention of researchers until now. There are a number of studies done recently such as [3–7]. In [3], the NR problem has been considered for power loss and voltage stability improvements. Wherein, modified particle swarm optimization (PSO) has been demonstrated for finding the optimal solution. In [4], selective particle swarm optimization (SPSO) has been successful applied to the NR problem to reduce power loss
and voltage improvement. In [5], selective firefly algorithm (SFA) has been presented for the NR problem with the goal of power loss reduction. In this work, the authors have shown the advantages of SFA compared to SPSO and bat algorithm. In [6], the NR problem has been considered to satisfy the multi-goal function consisting of losses, load balancing and voltage deviation using chaos disturbed beetle antennae search algorithm. The noted point of this work is that these indexes are validated in the 24 hours. In [7], the NR problem is solved to satisfy the goals of power loss reduction and reliability enhancing relied on epsilon method. Meanwhile, there are also many studies related to the DGP problem on the DS such as [8–12]. In [8], the DGP problem is considered to reduce power loss, voltage deviation and enhance the voltage stability of the DS using hybrid algorithm between elephant herding optimization (EHO) and PSO (EHOPSO). The noted point of this work is that the authors have shown the advantages of EHOPSO compared to EHO as well as PSO. In [9], the DGP problem is solved to reduce power loss, voltage deviation, the cost of DG and emission based on modified moth flame optimization (MMFA). In this work, MMFA has been demonstrated that it outperforms to moth flame optimization and other previous methods. In [10], hybrid method between GA and PSO (HGAPSO) is demonstrated for the DGP problem to reduce losses and voltage regulation improvement of the DS. In this work, HGAPSO has shown its high ability compared with the original GA and PSO. Similarly, in [11], the DGP problem for reducing power loss of the DS has been successfully solved by gravitational search algorithm. In [12], the DGP problem for reducing power loss considering signal stability constraint is also successfully validated by using GA.

Recently, a number of studies have combined both NR and DGP solutions to improve the efficiency of the DS. In [13], the NR and DGP are considered to enhance annual cost savings and reduce power loss. However, in this work the DGP problem is solved first and then the NR problem is carried out. In [14], genetic algorithm is proposed to solve the NR and DGP for minimizing power loss of the DS considering voltage controlled node in the DS. However, in this work the DGP problem is solved first based on sensitivity index of the DS and then the NR problem is considered. In [15], mixed PSO is presented for the NR and DGP problem for power loss reduction. However, the NR problem is solved first by using binary PSO and then the DGP problem is carried out by PSO. The common feature of the above methods is to optimize one of the two problems first and then the remaining solution will be optimized. The advantage of this technique is to narrow the problem size because it does not solve the problem of combining NR and DGP. However, it is clear that implementing each solution separately will not fulfill the potential of both solutions because a good radial structure of the DN that is reached after NR for a given goal may turn into a bad structure for that goal itself after DG installation. Meanwhile, an optimal DG installation for the given structure may not be appropriate when changing to another one. In [16], it has been pointed out that performing the DGP first then executing NR or performing NR first then executing DGP is not a smart choice. To overcome this situation, implementing two solutions at the same time is considered as the most effective solution to promote the effectiveness of the two problems of NR and DGP. However, combining two problems will make the association problem become extremely complicated due to the difference in the nature of the control variables and the larger search space. Therefore, the problem is that it is necessary to find strong algorithms to find the answer to the problem of combining NR and DGP.

Currently, there are a number of studies that has proposed methods based on new algorithms for the combined NR and DGP problem (NR-DGP). In [17], the stochastic method is proposed for finding the best network configuration and DG location for minimizing cost of distribution system and maximizing the profit of the DG. In [18], the NR and DGP problem is solved simultaneously to minimize power loss using water cycle algorithm (WCA). Wherein, WCA has been shown that it is better than cuckoo search algorithm and some previous methods. In [19], a thief and police algorithm (TPA) is first proposed for the NR and DGP problem for power loss and operational cost reduction as well as voltage stability improvement. In this study, TPA has also shown its superiority compared to PSO and GA. In [20], three-dimensional group search (3D-GS) optimization is proposed for the multi-goal simultaneous NR and DGP. The power loss reduction and voltage increasing are member objective functions considered in this study. In [21] improved shuffled frog leaping (ISFL) algorithm is proposed for finding optimal NR and DGP to minimize power loss, number of switching and voltage deviation. Wherein, weighting technique is used to incorporate the aforementioned functions. In [22] fuzzy multi-goal heuristic technique is proposed for finding optimal NR and DGP to satisfy goals consisting of power loss, branch current carrying, voltage limits and feeder balancing on the 70-node distribution system. However, the addition of new effective methods to the combined NR and DGP problem should still be encouraged to diversify the solving method and give more options in using the solving methods for operators.

In addition, the NR-DGP problem can affect to many factors of the DS. Thus, considering the multi-goal NR-DGP problem should also be promoted. There are popular methods in order to solve the multi-goal problem such as the weighted sum method, goal programming method, e-constraint method, TOPSIS method and the fuzzy decision-making relied on the max-min technique. By using the weight sum method, the multi-goal problem model can be usually formulated as multi-goal function with weights. In which, the multi-goal function is transformed into a single-goal function that is generated from the weighted sum of the component goals. However, the determination of accurate weights is one of the biggest drawbacks of this method and the obtained result is often a function of the weight coefficients [23]. Furthermore, the goal programming method can be also used to combine the membership goals by minimizing the deviations of the goal functions from their desired values [24]. In spite of reaching efficiency computation, selection of appropriate priorities to the goals is difficult that requires knowledge of the considered problem.
While using the \(\varepsilon\)-constraint method for the multi-goal problem, the multi-goal problem is formulated as the single-goal problem by considering one of goal as the primary goal function and the rest goals as the constraints bound by permissible levels [25]. However, selection of primary and slave goals can be affected to the obtained solution [26]. For using the TOPSIS method, the best compromise solution is selected based on the geometric distance between it with the positive and negative ideal solutions [27]. Although the calculation process is simple and easy to understand, the setting of weights for the objective functions for the decision matrix still needs to be considered. The aforementioned limitations can be overcome by the fuzzy decision-making technique. By using and the fuzzy decision-making relied on the max-min technique, the multi-goal problem is converted into a single-goal problem of maximizing the minimum satisfaction degree among the membership functions. By bringing all the goals to the same scale, the choice of priority for each goal function is eliminated. In addition, a set of optimal solutions known as Pareto Front can be obtained after solving the multi-goal optimization problem. However, there is only the best compromise solution from the Pareto Front is selected as the final result for the problem [28]. While and the fuzzy decision-making relying on the max-min technique is a method to select the best compromise solution. Futhermore, the fuzzy decision-making rely on the max-min technique has been also successful applied for some problems in the power system such as the optimal planning DS [29], DGP problem [30, 31] and NR problem [32].

Due to effect of NR and DGP to technical indicators and demand of finding new solving methods for the NR-DGP problem, this paper proposes a new method based on the improved moth swarm algorithm (IMSA) for the multi-goal NR-DGP problem. Wherein, the moth swarm algorithm (MSA) is taken idea of the movement of moths for food searching in the dark [33] and it has been successful used for many problems in power system such as power flow [33, 34], emission dispatch problem [35] and capacitor placement [36]. For searching the optimal solution, the population is split into three categories including of pathfinders, prospectors and onlookers. The first group helps to explore the search space, the second one ensures the balance between exploration and exploitation meanwhile the final group is responsible for the exploitation of the search space. In IMSA, the pathfinders are improved by applying the Lévy distribution for all of variables of candidate solutions in the pathfinder group. The goals of the NR-DGP problem is to reduce power loss and voltage deviation as well as enhance load balance and feeder balance with the least number of changing switches. These membership goals are combined by the fuzzy decision relied on the max-min technique. For investigating the effectiveness of IMSA, the 33 and 84 nodes systems are used to optimize the NR and DGP. The obtained results are compared with the MSA and other previous methods to show the efficiency of the improvement of IMSA. In summary, the work's highlights are as follows:

(i) The NR-DGP problem is considered for multi-goals consisting of power loss, voltage deviation, load balance, feeder balance and number of changing switches.

(ii) IMSA is first proposed for the multi-goal NR-DGP problem to enhance the exploration ability of the search space.

(iii) IMSA is compared to MSA on two test systems for both of the problems consisting of the NR and NR-DGP problems.

(iv) The NR-DGP method has gained the better improvement of the test systems’ technical indicators than the NR technique.

(v) IMSA outperforms to MSA for the NR and NR-DGP problems in terms of successful rates and the quality of the gained results.

The rest of the article includes the following sections: The fitness function of the problem is shown in Section 2. Section 3 presents the IMSA for the multi-goal NR-DGP problem. The evaluated results in the test systems are shown in Section 4; meanwhile, the final section presents the conclusion of the paper.

### 2. The Fitness Function for the NR-DGP Problem

The optimal NR-DGP can bring technical benefits such as reduction of losses, improvement of voltage profile and improvement of reliability as well as economic benefits like reduction of network costs, reduction of DG costs and profit-maximization, etc. [37–39]. In this work, the considered goals is to reduce power loss \(P_{\text{loss}}\) and voltage deviation (VD) as well as enhance load balance (LB) and feeder balance (FB) with the least number of switching change (NSC).

\[
\min (f_k); k = 1, 2, \ldots, n_k, \quad (1)
\]

where \(f_k\) is the membership objective functions defined as follows:

(i) Power loss: Power loss of the DN occupies a high part in the power system. While NR transfers the load among branches of the DN, DGP provides local power to the loads. Both of the methods reduce the branches’ current to reduce power loss. Power loss is determined as follows:

\[
f_1 = P_{\text{loss}} = \sum_{i=1}^{n_b} R_i |I_i|^2, \quad (2)
\]

where \(R_i\) and \(I_i\) depict the resistance and current of the branch \(i\). \(n_b\) is the number of branches.

(ii) Voltage deviation: The VD minimization is examined as another goal function of the NR-DGP to enhance the power quality of the DS. It is determined as follows:
\[ f_2 = VD = V_d - V_{\text{min}}, \]  

(3)

where, \( V_d \) is the voltage amplitude of the slack bus. \( V_{\text{min}} \) is the minimum voltage amplitude of the DS.

(iii) Load balance: In order to improve the capacity of the DN, the LB among branches is considered in the NR-DGP process. LB index is calculated as follows:

\[ f_3 = \text{LB} = \text{var}\left(\frac{I_i}{I_{\text{rate}}}\right); \quad i = 1, 2, \ldots, n_{\text{Fe}}, \]  

(4)

Where, \( \text{var} \) is the variance function. \( I_{\text{rate}} \) is the rate current of the branch \( i \). \( I_i/I_{\text{rate}} \) shows the load level of the branch \( i \) [40].

(iv) Feeder balance: Similar to the LB index, the FB index helps to enhance load balance among feeders to improve of the DN’s capacity. FB index is calculated as follows:

\[ f_4 = \text{FB} = \text{var}(I_{F,i}); \quad i = 1, 2, \ldots, n_{\text{Fe}}, \]  

(5)

where \( I_{F,i} \) is the current of the feeder \( i \). \( n_{\text{Fe}} \) is the number of feeders of the DS.

(v) Number of switching change: Changing the number of switches can bring technically benefits, but it may increase operating costs. Therefore, minimizing NSC is also considered as a goal of the NR-DGP problem. NSC is defined as follows:

\[ f_5 = \text{NSC} = \sum_{l=1}^{n_{\text{SC}}} |S_{0,i} - S_i|, \]  

(6)

where \( S_{0,i} \) and \( S_i \) are the initial status and status after reconfiguration of the switch \( i \).

By using the fuzzy decision relied on the max-min technique, the multi-goal problem is converted into a single-goal problem of maximizing the minimum satisfaction degree among the membership functions. The details of the method of finding the best compromise solution for the NR-DGP problem are presented as follows:

Firstly, the normalized membership vector \( (v_k) \) of the target function \( k \) that is calculated as follows:

\[
 v_k = \begin{cases} 
 0; & f_k \geq f_k^{\text{max}} \\
 \frac{f_k^{\text{max}} - f_k}{f_k^{\text{max}} - f_k^{\text{min}}}; & f_k^{\text{min}} < f_k < f_k^{\text{max}} \\
 1; & f_k \leq f_k^{\text{min}}, 
\end{cases} 
\]  

(7)

where \( f_k^{\text{max}} \) and \( f_k^{\text{min}} \) are the maximum and minimum values of the goal function \( k \). \( f_k \) is the value of the goal function \( k \).

Then, the max-min technique is used to combine the component goal functions by determining the goodness degree (deg) of each candidate solution as follows [31, 32]:

\[ \text{deg} = \min(v_k). \]  

(8)

In order to determine the \( f_k^{\text{min}} \) values with \( (k = 1, 2, 3, 4) \), the single-goal NR-DGP problem is solved for the objective functions consisting of power loss reduction, voltage deviation reduction, load balance improvement and feeder balance improvement. The value of \( f_k^{\text{min}} \) is chosen to 0. For the \( f_k^{\text{max}} \) values with \( (k = 1, 2, 3, 4) \), they are obtained from the initial network configuration. The load flow is executed for the initial network configuration, then the power loss, voltage deviation, load balance and feeder balance indexes are gained. The \( f_k^{\text{max}} \) value is set equal to twice the number of initial open switches.

For each network configuration, the load flow problem is carried out to find value of goal functions from \( f_1 \) to \( f_4 \). The value of \( f_5 \) function is calculated by comparing the status of switches in the DS before and after reconfiguration. Equation (7) is used to determine the normalized value of the objective functions. Then, the overall satisfaction degree of the candidate NR-DGP configuration is the minimum value of all of the membership values as shown in (8). An illustration for selection the overall satisfaction degree of the candidate network configuration is shown in Figure 1. In which, the normalized membership vector of power loss, voltage deviation, load balance, feeder balance and number of switching change that is shown in red color is 0.3, 0.55, 7.5, 0.65 and 0.4, respectively. Then, the overall satisfaction degree of this candidate NR-DGP configuration is selected based on (8) is 0.3 that is shown in blue color.

Then, the fuzzy decision that is defined by selecting maximizing of the overall satisfaction degree of the candidate NR-DGP configurations is used for choosing the best compromise solution as shown in Figure 2. In other words, the multi-goal NR-DGP problem is transformed into the single-goal problem of finding the NR-DGP configuration with the best degree as follows:

\[ \text{obj} = \max \text{deg}, \]  

(9)

where \( \text{obj} \) is the goal function value of the multi-goal NR-DGP problem.

Furthermore, the process of finding the optimal solution for the NR-DGP problem, the system should not violate the below constraints:

(i) Power balance:

\[
\begin{align*}
P_{d} + \sum_{j=1}^{n_{DG}} P_{DG,j} = P_{\text{load}} + P_{\text{loss}}, \\
Q_{d} + \sum_{j=1}^{n_{DG}} Q_{DG,j} = Q_{\text{load}} + Q_{\text{loss}},
\end{align*}
\]  

(10)
where \( P_s \) and \( Q_s \) are active and reactive power of the slack bus. \( P_{DG,l} + j Q_{DG,l} \) are power of the DG \( l \). \( P_{load} + j Q_{load} \) are the load demand of the DS. \( Q_{loss} \) is reactive power loss of the DS. \( n_{DG} \) is the number of DGs.

(ii) Limits of voltage and current:

\[
\begin{align*}
V_{lo} \leq V_j \leq V_{hi}; & \quad j = 1, \ldots, n_{node}, \\
I_i \leq I_{i,hi}; & \quad i = 1, \ldots, n_{line}.
\end{align*}
\] (11)

In which, \( V_{lo} \) and \( V_{hi} \) are the allowed minimum and maximum voltage magnitudes that are respectively set to 0.95 p.u and 1.05 p.u. \( V_j \) is the voltage magnitude of the node \( j \). \( n_{node} \) and \( n_{line} \) are the number of nodes and the number of lines of the system. \( I_i \) and \( I_{i,hi} \) are the current of the line \( i \) and its rated value.

(iii) Limit of DGs:

\[
P_{DG,l} \leq P_{DG,\text{max},l},
\] (12)

where \( P_{DG,l} \) and \( P_{DG,\text{max},l} \) are capacity and capacity limit of the DG \( l \).

(iv) In addition, the feasible network configuration must be radial [41]:

\[
|\text{det}(A)| = 1,
\] (13)

where \( A \) is the connected matrix of size \( (n_{line} \times n_{node}) \) wherein \( A(i,j) = 1 \) or \(-1\) if the line \( i \) bridges from or to the node \( j \) otherwise \( A(i,j) = 0 \).

The fitness function comprising of the objective function and the penalty function of violation constraints is formulated as follows:

\[
f = \text{obj} + K_p \left[ \max(V_{lo} - V_{\text{min}}), 0 \right] + \left( \max(V_{\text{max}} - V_{hi}), 0 \right) + \left( \max\left( \frac{I}{\text{rate}_{\text{max}}}, 1 \right), 0 \right),
\] (14)
where $V_{\text{max}}$ and $V_{\text{min}}$ is the maximum and minimum voltage amplitude of the system. $Cl_{\text{max}}$ is the maximum carrying factor of the system. $K_p$ is penalty coefficient.

3. Improved Moth Swarm Algorithm for the Multi-Goal NR-DGP Problem

In MSA, the population of solutions is split into three main groups: pathfinders, prospectors and onlookers. In particular, the pathfinder group accounts for about 20% of the population [33] that is responsible for exploring the search space. Pathfinders will find the location of the light sources to lead other individuals to move towards the light sources. Note that, in the MSA the position of the light source and its intensity are respectively examined as the solution and the adaptive value of the solution. The prospector group moves around the light sources created by the first group to explore and exploit the space around the light sources. Finally, the onlooker group moves toward the best light source obtained by the two above groups to exploit the space around the best light source. Each group of moths is created by using different mechanisms. While, the individuals in the first group are produced by the Lévy-mutation, the second group is created by spiral motion technique and the third group is generated by using Gaussian walks and associative learning mechanisms.

Based on the mechanisms of MSA, it can be seen that the role of the pathfinder group is very important for finding new light sources in the search space. Moreover, the solutions in this group are the best individuals in the population. However, in the Lévy-mutation mechanism of creating new solutions of this group, not all control variables of the individuals are created but only a few control variables are created based on the normalized dispersal degree of the control variables compared to their mean dispersal degree value. In particular, the normalized dispersal degree ($\sigma_j$) of the control variables $j$ of the pathfinders in the group is calculated as follows:

$$
\sigma_j = \sqrt{1/n_p \sum_{i=1}^{n_p} \left( S_{i,j} - 1/n_p \sum_{i=1}^{n_p} S_{i,j} \right)^2} / 1/n_p \sum_{i=1}^{n_p} S_{i,j},
$$

(15)

where $n_p$ is the size of the pathfinder group. $S_{i,j}$ is the variable $j$ of the solution $S_i$.

The number of control variables for updating by the Lévy mechanism is determined based on the comparison between the dispersal degree of each variable and their average dispersion value as follows:

$$
j \in \text{the variable group: if } \sigma_j < \frac{1}{d} \sum_{j=1}^{d} \sigma_j,
$$

(16)

where $d$ is the dimension of the optimization problem.

The result of the above technique is that the new solutions contains two information components including new information generated from Lévy mechanism and old information of the previous solutions.

Using this technique prevents MSA from creating entirely new solutions to explore the search space. Meanwhile, the advantage of Lévy mechanism is to create new solutions at a position far from the current solutions. Therefore, in this study, we propose that not only a portion of the control variables of pathfinders is renewed but all of the control variables of pathfinders are newly created. For example, the initial pathfinder consisting eleven variables in range of [0, 20] has the value of [1.6663, 16.3382, 17.9191, 7.6574, 16.5643, 14.6755, 3.1362, 8.1774, 0.6078, 0.7103, 0.3192]. The normalized dispersal degree vector $\sigma$ calculated by (15) is [0.5179, 0.8423, 0.2343, 0.6106, 0.8328, 0.4319, 0.6999, 0.6903, 0.6071, 0.3817, 0.5229] with the average dispersion of 0.5792. The new pathfinder generated by combination of (16) and the Lévy-mutation mechanism of MSA is [13.2848, 16.3382, 0.0, 7.6574, 16.5643, 5.5310, 3.1362, 8.1774, 0.6078, 19.7784, 20.0], meanwhile the new pathfinder generated by IMSA via using the Lévy mechanism for all variables is [10.5866, 10.7115, 20.0, 6.4160, 2.0010, 0.5625, 0.0, 10.5772, 19.5310, 0.0, 20.0]. The initial and new pathfinders generated by MSA and IMSA is shown in Figure 3. By comparing the normalized dispersal degree of each variable with the average dispersion as shown in equation (16), the variables consisting of the 2nd, 4th, 5th, 7th, 8th and 9th of the new pathfinder generated MSA are the same as those of the initial pathfinder. Meanwhile, the new pathfinder produced by IMSA is definitely different to the initial pathfinder. Details of the improved IMSA for the multi-goal NR-DGP are presented as follows.

Step 1. Initialization

The control variables of the NR-DGP problem are open switches, the DGs’ location and capacity. Wherein, switches and DGs’ locations are integer form. Therefore, the initial solutions are created randomly as follows:

$$
S_{i,j} = S_{l_{0,j}} + \text{rand}(0,1)(S_{h_{i,j}} - S_{l_{0,j}});
$$

(17)

$$
i = 1, 2, \ldots, n; j = 1, 2, \ldots, d,
$$

where $S_{l_{0,j}}$ and $S_{h_{i,j}}$ are the lower and upper boundaries of the variable $j$. $n$ is the population size.

Then, the variables represent for switches and DGs’ location are modified as follows:

$$
S_{i,j} = \text{round}(S_{l_{i,j}}); \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, n_{sw} + n_{DG},
$$

(18)

where $n_{sw}$ and $n_{DG}$ are number of open switches and DGs, respectively.

After the initial population generated, the fitness value of each individual is calculated by using equation (14) and the best so far individual is determined. Then, the population is arranged in descending order of the fitness function and $n_p$ best individuals are selected to become pathfinders.

Step 2. Production of new solutions of the pathfinder group.

$$
S_{p_{\text{new}}} = S_{p_1} + L_{p_1} (S_{r_2} - S_{r_3}) + L_{p_2} (S_{r_4} - S_{r_5});
$$

(19)

$$
p = 1, 2, \ldots, n_p,$$
where $S_{i}$ to $S_{5}$ are five individuals in the pathfinder group selected randomly. $L_{p1}$ and $L_{p2}$ are factors generated by the Lévy-flights as follows:

$$L_i = \text{step} \odot \text{levy}(\alpha),$$

where step is a scaling coefficient selected to 0.01, $\alpha$ is distribution factor in range of 0 and 2, $\odot$ is the entry-wise multiplications.

Then, the new individuals are modified by using (18) and calculated the fitness value by using (14). Then, individuals of the pathfinder group are updated as follows:

$$S_{\text{p,new}} = \begin{cases} S_{\text{p,new}}; & \text{if } f(S_{\text{p,new}}) < f(S_{p}), \\ S_{p}; & \text{otherwise.} \end{cases}$$

Step 3. Production of new solutions of the prospector group.

In this step, each member of the prospector group is produced using the spiral flight mechanism as follows:

$$S_{t,\text{new}} = S_{t} - i \odot \text{kei}(\alpha) \odot 2\pi i \odot \cos(2\pi \theta) + S_{p}; \quad i = 1, 2, \ldots, n_{r},$$

where $S_{p}$ is the solution in the pathfinder group. The probability for an individual $S_{p}$ in the pathfinder group is selected based on a roulette wheel technique. $\theta$ is a random number in $[-1 - \text{iter}/\text{iter}_{\text{max}}]$, $n_{r}$ is the size of the prospector group that is calculated as follows:

$$n_{r} = \text{round}\left(\left(n - n_{p}\right) \times \left(1 - \frac{\text{iter}}{\text{iter}_{\text{max}}}\right)\right).$$

Then, the new individuals are modified by using (18) and calculated the fitness value by using (14).

Step 4. Production of new solutions of the onlooker group.

The rest individuals in the current population are considered as onlooker moths. The number of individuals in the onlooker group are divided into two small group. Each individual in the first small group is produced by the Gaussian walks mechanism as follows:

$$S_{t,\text{new}} = S_{t} + GW + (\text{rand}(0, 1) \odot S_{\text{best}} - \text{rand}(0, 1) \odot S_{t}),$$

where $S_{\text{best}}$ is the best-so-far solution. $GW$ is the distribution vector created by the Gaussian walks mechanism as follows:

$$GW = rv \odot N\left(S_{\text{best}}, \frac{\text{iter}}{\text{iter}_{\text{max}}}(S_{t} - S_{\text{best}})\right),$$

where $rv$ is vector consisting of $d$ random number in $[0, 1]$. Each individual in the second small group is produced by the associative learning mechanism as follows:

$$S_{t,\text{new}} = S_{t} + 0.001 \odot \text{rand}\left([S_{t} - S_{\text{lo}}, S_{\text{hi}} - S_{t}]\right) + 2 \odot \frac{\text{iter}}{\text{iter}_{\text{max}}} \odot \text{rand}(0, 1) (S_{\text{best}} - S_{t}) + \left(1 - \frac{\text{iter}}{\text{iter}_{\text{max}}}\right) \odot \text{rand}(0, 1) (S_{p} - S_{t}),$$

where $S_{p}$ is the solution in the pathfinder group.

The new solutions in the onlooker group are modified by using (18) evaluated the fitness function by using (14). Based on the fitness value of the new solutions in the prospector and onlooker groups. The solutions with better fitness values are chosen to form the new population for the next iteration. The whole steps for IMSA for the multi-goal NR-DGP problem are described in Figure 4. From the figure, the stopping condition of IMSA for the multi-goal NR-DGP problem is set based on two criterions consisting of the maximum number of iterations (iter$_{\text{max}}$) and the number of iterations that the number of iterations that the best fitness value does not enhance (iter$_{\text{nip, max}}$).

4. Numerical Results and Discussion

The NR-DGP approach relied on IMSA is coded in Matlab and executed on personal computer with processor 2.4 GHz, RAM 4 GHz. The Newton method that is integrated in Matpower is used for load flow analysis [42]. Two test networks which consist of 33-nodes and 84-nodes systems are carried out to validate the efficacy of IMSA for the multi-goal NR-DGP problem. Wherein, the first system is a medium-scale system with 5 open switches whilst the second one is a large-scale system with 13 open switches. The number of DGs is chosen to three for both of the test systems. The maximum power of DGs installed on two systems is limited to 2 MW and 5 MW respectively. Thus, the number of variables of the first and second systems are 11 and 19, respectively. For each test system, two cases are considered consisting of NR and NR-DGP. The performance of IMSA is compared to the original MSA. The control parameters consisting of population size $n$, maximum number of iterations iter$_{\text{max}}$ and maximum number of iterations that the fitness value does not enhance iter$_{\text{nip, max}}$ for each case are presented in Table 1.

The lower and upper limits of member goal functions for the test systems are displayed in Table 2, wherein the maximum value of the member goal functions is determined from the initial system. The load flow is executed for the initial system, then the power loss, voltage deviation, load balance and feeder balance indexes are gained. The maximum value of
the $f_5$ is set equal to twice the number of initial open switches. The minimum value of the member goal functions consisting of power loss reduction, voltage deviation reduction, load balance improvement and feeder balance improvement is obtained from the single-goal NR and NR-DGP problems. The minimum value of the $f_5$ is chosen to 0.

### 4.1. The First Test System

The first system is considered to reconfigure consists of 33 nodes and 37 branches as shown in Figure 5 [43]. The branches’ rated current is 255 A. To gain the optimal topology, the IMSA is executed in 50 times, the obtained best topology is regarded as solution of the multi-goal NR problem.

The obtained results for the test network by IMSA are shown in Table 3. For the case of NR, the optimal radial topology (ORT) gained by IMSA is \{33, 34, 7, 36 and 37\}. This topology results three factors consisting of power loss ($P_{loss}$), minimum voltage amplitude ($V_{min}$) and load balance among branches (LB) being improved compared to those of...
the initial topology. Wherein, $P_{loss}$ has been decreased by 22.77%, $V_{min}$ has increased by 2.25% and LB index has been reduced by 31.08%. It is noted that the improvement of these indices is obtained with only 2 transfer switches through substituting the 7th switch for the 35th switch. From the table, the feeder balance (FB) is not evaluated due to taking power from only a feeder of this system. Compared with Fuzzy-SFL [44], $P_{loss}$ and LB gained by IMSA is 5.023 kW and 0.0016 higher than those of Fuzzy-SFL but $V_{min}$ obtained by IMSA is 0.0018 higher than that of Fuzzy-SFL and}

| Item | $f_1$ | $f_2$ | $f_3$ | $f_4$ | $f_5$ |
|------|------|------|------|------|------|
| The 33-node system | | | | | |
| Maximum value | 202.6863 | 0.0869 | 0.0414 | 1 | 10 |
| Minimum value for the NR | 139.5543 | 0.058757 | 0.022668 | 0 | 0 |
| Minimum value for the NR-DGP | 52.6462 | 0 | 0.0063 | 0 | 0 |
| The 84-node system | | | | | |
| Maximum value | 531.9924 | 0.0715 | 0.0944 | 1.4418 | 26 |
| Minimum value for the NR | 469.8762 | 0.046813 | 0.0793 | 0.44722 | 0 |
| Minimum value for the NR-DGP | 336.0678 | 0.0325 | 0.0568 | 0.0545 | 0 |

**Table 2:** The limited values of each membership functions for the test systems.

| Item | ORT | $P_{DG}$ ($I_{DG}$) | $P_{loss}$ (kW) | $V_{min}$ (pu) | LB ($I/I_{rate\_max}$) | FB | NSC |
|------|-----|---------------------|---------------|--------------|----------------|-----|-----|
| Initial | 33, 34, 35, 36, 37 | — | 202.6863 | 0.9131 | 0.0399 | 0.8250 | — | — |
| Case 1: The multi-goal NR | | | | | | | |
| IMSA | 33, 34, 7, 36, 37 | — | 156.5330 | 0.9336 | 0.0275 | 0.8163 | — | 2 |
| MSA | 33, 34, 7, 36, 37 | — | 156.5330 | 0.9336 | 0.0275 | 0.8163 | — | 2 |
| Fuzzy-SFL [44] | 6, 8, 12, 36, 37 | — | 151.51 | 0.9318 | 0.0259 | 0.8153 | — | 6 |
| MOIWO [32] | 6, 11, 32, 34, 37 | — | 144.41 | 0.9357 | 0.0262 | 0.8138 | — | 6 |
| 3D-GSA [20] | 7, 9, 14, 28, 32 | — | 139.26 | 0.9422 | 0.0290 | 0.8126 | — | 10 |
| ISFL [21] | 7, 9, 14, 32, 37 | — | 139.5 | 0.9378 | 0.0272 | 0.8123 | — | 8 |
| Case 2: The multi-goal NR-DGP | | | | | | | |
| IMSA | 33, 34, 35, 36, 28 | | 1.2934 (25), 0.7693 (33), 1.0476 (15) | 73.1387 | 0.9851 | 0.0104 | 0.4380 | — | 2 |
| MSA | 33, 34, 35, 36, 28 | | 0.7693 (33), 1.0476 (15) | 73.1387 | 0.9851 | 0.0104 | 0.4380 | — | 2 |
| 3D-GSA [20] | 7, 8, 14, 25, 36 | | 0.6 (18), 1.19 (30), 0.345 (13) | 73.4783 | 0.9647 | 0.0117 | 0.4873 | — | 8 |
| ISFL [21] | 7, 14, 9, 31, 28 | | 0.595 (18), 1.059 (25) | 57.3602 | 0.9702 | 0.0113 | 0.5255 | — | 10 |

**Table 3:** The compared results among IMSA with MSA and other approaches for the 33-node system.
number of switching change (NSC) obtained by IMSA is 4 less than that of Fuzzy-SFL. The $P_{\text{loss}}$, $V_{\text{min}}$ and LB obtained by IMSA are as few improvement as those of MOIWO [32] but NSC obtained by IMSA is 4 and 2 less than that of MOIWO. Compared with 3D-GSA [20], the its indexes consisting of $P_{\text{loss}}$ and $V_{\text{min}}$ are better than those of IMSA but it takes 10 times of NSC to reach that results. This trend also happens to ISFL [21] with 8 times of NSC to take the better indexes than those of IMSA.

For the case of NR-DGP, the obtained ORT is [33, 34, 35, 36 and 28] while the optimal parameters in MW (node) of DGs’ is respectively 1.2934 (25), 0.7693 (33) and 1.0476 (15).

By opening these switches and installing these DGs, $P_{\text{loss}}$ has been decreased by 63.92%, $V_{\text{min}}$ has increased by 7.89% and LB index has been reduced by 73.93% compared with the initial configuration. In addition, the maximum index of load carrying has been reduced from 0.825 to 0.387 corresponding to 46.91% of reduction. It is noted that these results obtained by changing two switches. Compared with 3D-GSA [20], the factors of $P_{\text{loss}}$, $V_{\text{min}}$, LB and NSC obtained by IMSA is more improve than those of the 3D-GSA meanwhile there is only $P_{\text{loss}}$ index obtained by ISFIL [21] is better than that of IMSA but the rest indexes of the ISFIL are worse than compared to those of IMSA.

The balance among membership functions except the $f_4$ function is shown in Figure 6. From the figure, the balance level of the NR-DGP problem based on IMSA is better than the previous methods. In comparison between case 1 and case 2 obtained by IMSA, the case 2 ensures the better balance among membership functions than the case 1. The obvious improvement of voltage and current of the system after performing NR and NR-DGP are presented in Figure 7. Also from Figure 7, NR-DGP achieves the better voltage improvement and branch current reduction than those of NR.

In the optimal solution searching process, similar to other metaheuristic algorithms, IMSA relies on randomization to search the optimal solution. The obtained solutions may be different for different runs. So, for comparison between IMSA and MSA, the test cases have been executed in fifty runs to gain the statistical results such as maximum fitness value ($f_{\text{best}}$), minimum fitness value ($f_{\text{worst}}$), mean fitness value ($f_{\text{mean}}$) and standard deviation (STD). In which, the STD is a statistic that evaluates the dispersion of the obtained fitness value set compared to its mean. It is determined by the square root of variance. The small STD value indicates the set of fitness values near to the mean fitness value. The simulation results achieved in 50 runs in Table 4 show that for the case 1, the best value of the fitness function in 50 trials of two methods is the same but and the worst value the mean value of the fitness function and STD gained by IMSA is better than those of MSA. Wherein, the $f_{\text{mean}}$ value gained by IMSA is 0.0321 higher than that of MSA and the $f_{\text{mean}}$ value of IMSA is closer to the $f_{\text{best}}$ value than that of MSA and the STD obtained by IMSA is 0.0121 lower than that of MSA. This better performance of IMSA is also achieved for the case 2 with the better values of $f_{\text{worst}}$, $f_{\text{mean}}$ and STD. The best fitness value achieved in each run for two cases is shown in Figure 8. For the case 1, as shown in

![Figure 6: Balance among membership functions.](image)

Figure 8(a), both of IMSA and MSA find the same $f_{\text{best}}$ value in 21 runs but there are 23 trials that the best fitness value obtained by MSA is worse than that of IMSA, whilst the best fitness value of IMSA is only less than that of MSA in 6 trials. For the case 2, as shown in Figure 8(b), the number of runs that the $f_{\text{best}}$ value gained by IMSA is greater than, equal and less than that of MSA is 28, 2 and 20 respectively. The mean convergence of both of the methods in Figure 9 shows that IMSA converges to better value than MSA. These results shown that the IMSA has better performance than MSA for the NR and NR-DGP problem.

4.2. The Second Test System. The second system is considered to reconfigure consists of 83 load nodes, 11 feeders, 96 branches as shown in Figure 10 [45]. The rated current is set to 250 A for all branches.

The obtained results for the network by the IMSA are shown in Table 5. For the case 1, the ORT gained by IMSA is [54, 7, 86, 87, 88, 89, 90, 91, 92, 34, 95 and 63] that causes the improvement of $P_{\text{loss}}$, $V_{\text{min}}$, LB as well as FB compared with the initial topology. Wherein, $P_{\text{loss}}$ has been decreased by 46.6791 kW corresponding to 8.77% reduction, $V_{\text{min}}$ has increased by 2.09% and LB index has been reduced from 0.0944 to 0.0847 corresponding to 10.28% reduction and FB index has been decreased from 1.4418 to 0.5922 corresponding to 58.93% reduction. These improvements are obtained with only 8 transfer switches through substituting the switches of [54, 7, 34 and 63] for the switches of [84, 85, 94 and 96]. For the case 2, the improvement of these indicators is even better with the improvement of $P_{\text{loss}}$, $V_{\text{min}}$, LB and FB compared with the initial topology are 30.39%, 3.38%, 32.52% and 77.43%, respectively.

The improvement of voltage and current of the system after performing NR and NR-DGP are presented in Figure 11. The voltage of nodes has been enhanced and current of branches has been reduced after NR and NR-DGP by IMSA. Wherein, the NR-DGP achieves the better improvement of voltage and current than NR only. As shown in Figure 12, the balance of 11 feeders of the system gained by the NR-DGP has been better than that of the case 1 and the initial topology. The balance among membership functions is displayed in Figure 13. The figure shows that the obtained
Figure 7: Improvement of voltage and current of the 33-node system after NR and NR-DGP using IMSA.

Table 4: The performance of IMSA and MSA for the 33-node system.

| Item          | IMSA Case 1: The multi-goal NR | MSA Case 2: The multi-goal NR-DGP |
|---------------|--------------------------------|----------------------------------|
| $f_{\text{best}}$ | 0.5631                         | 0.8                              |
| $f_{\text{worst}}$ | 0.4357                         | 0.5316                           |
| $f_{\text{mean}}$ | 0.5423                         | 0.7278                           |
| STD           | 0.0426                         | 0.0817                           |
| Run time (s)  | 5.4825                         | 19.3344                          |

Figure 8: The best fitness function value of IMSA and MSA for the 33-node system in 50 trials. (a) Case 1: only reconfiguration and (b) Case 2: reconfiguration and DG placement.

Figure 9: Mean curve of IMSA and MSA for the 33-node system. (a) Case 1: only reconfiguration and (b) Case 2: reconfiguration and DG placement.
solution by IMSA for the case 2 ensures the better balance among the target functions compared with the case 1 and the MSA’s case 2.

The performance of IMSA and MSA for the 84-node system in Table 6 shows that for the case 1, the \( f_{\text{best}} \) and \( f_{\text{worst}} \) values in 50 trials of two methods are the same but the \( f_{\text{mean}} \) and STD values gained by IMSA is better than those of MSA. Wherein, the \( f_{\text{mean}} \) value of IMSA is 0.0653 higher and closer to the \( f_{\text{best}} \) value than that of MSA. For the case 2, IMSA has obtained the better optimal result than the MSA with the greater \( f_{\text{best}} \) value. In addition the \( f_{\text{mean}} \) and STD values of IMSA are also better than those of MSA.

The best fitness value achieved in each run for two cases is shown in Figure 14. Figure 14(a) shows that, for the case 1 the number of runs that the \( f_{\text{best}} \) value gained by IMSA is greater than, equal and less than that MSA is 29, 8 and 13 respectively whilst Figure 14(b) presents that there are 28 trials which the best fitness value obtained by MSA is worse than that of IMSA, whilst the best fitness value of IMSA is only less than that of MSA in 21 trials. The mean convergence of both of the methods in Figure 15 shows that IMSA tends to converge to better value than MSA for both of the cases. The run time of IMSA is nearly the same as that of MSA. These results demonstrate that the IMSA has better performance than MSA for the NR and NR-DGP problem in the large-scale test system.
Table 6: The performance of IMSA and MSA for the 84-node system.

| Item                      | IMSA Case 1: The multi-goal NR | MSA Case 2: The multi-goal NR-DGP |
|---------------------------|--------------------------------|----------------------------------|
| $f_{best}$                | 0.6190                         | 0.6190                           |
| $f_{worst}$               | 0                              | 0                                |
| $f_{mean}$                | 0.4257                         | 0.3168                           |
| STD                       | 0.1154                         | 0.1909                           |
| Run time (s)              | 90.5891                        | 96.1606                          |

Figure 11: Improvement of voltage and current of the 84-node system for two cases.

Figure 12: Balance among feeders of the 84-node system.

Figure 13: Balance among membership functions for the 84-node system.
5. Conclusion

This paper presents the multi-goal NR-DGP method relied on IMSA. The technical indicators considered during performing NR-DGP are reduction of power loss and voltage deviation, improvement of load balance and feeder balance with the least number of changing switches. For searching the optimal solution for the NR-DGP problem, IMSA is improved based on the original MSA. In which all control variables of solutions in the pathfinder group are updated using the Lévy technique instead of only partially adjusted like MSA. The efficiency of the proposed NR-DGP method is assessed on the 33-node and 84-node systems in two cases of NR and NR-DGP. The calculated results show that NR-DGP method has gained the better improvement of the test systems’ technical indicators than the NR technique. The obtained results also show that IMSA has better performance for the NR and NR-DGP problems than the MSA in term the quality of the obtained optimal solution that is expressed in worst, best, mean and STD values of the fitness function as well as the convergence characteristic in 50 runs. Therefore, IMSA can be an effective approach for determining the optimal solution of the NR and NR-DGP problems. For future works, IMSA can be used to the NR as well as NR-DGP problem to satisfy the single goals or apply to other problems in the power system fields.

Data Availability

Data of the 33-node and 84-node distribution systems in this study are available from the literature.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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