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The Impacts of Distributed Energy Sources on Distribution Network Reconfiguration

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***Abstract*—Thanks to the recent improvements in renewable energy technologies throughout the world, distributed energy sources are now playing an undeniable role in supplying the electricity in distribution networks. This paper studies the impacts of utilizing distributed generation units on the task of network reconfiguration in distribution systems. Considering the importance of reducing voltage drops and voltage sags in distribution systems, network reconfiguration is formulated as a multiobjective optimization problem in this study to minimize these two objective functions. A Pareto-based metaheuristic optimization algorithm is proposed to identify a Pareto frontier representing the alternative high-quality suboptimal configurations. The proposed optimization method is tested on a 69-bus distribution system to demonstrate the performance of the algorithm.**

***Index Terms*—Distributed generation (DG), distribution network reconfiguration, shuffled frog leaping algorithm (SFLA), voltage drop, voltage sag.**

I. Introduction

THE GROWING trend of installing distributed energy resources, including renewable energies, has dramatically changed the structure of power systems. That is the reason researchers have shown interest to rely on smart grids as an approach to increase the hosting capacity for distributed resources [1], [2]. This new paradigm of electrical grids proposes the adoption of two-way flows of electricity and builds a distributed energy delivery network. As a result, utilities are enforced to evolve their classic topologies to accommodate distributed generation (DG). DG units are categorized in two main groups: (1) conventional generation resources such as gas turbines, diesel generators, fuel cells, and battery banks; (2) renewable energy resources such as wind turbines, solar cells, hydro power, and hybrid wind-PV-battery system. The idea of decentralized generation suggests the generation of electricity from many small energy resources with the purpose of improving the security of supply and decreasing the environmental impacts of excessive burned fossil fuels in central plants. The motivation of this study is to analyze a potential smart grid solution for the problem of distribution network reconfiguration.

Distribution network reconfiguration is a critical issue in distribution systems management. Network reconfiguration is the process of changing the status of sectionalizing and tie switches to satisfy the objective functions defined by the system operator. This concept was proposed in 1975 by Merlin and Back with the purpose of identifying the optimal configuration representing the minimum power loss [3]. Considering the potential industry applications of this concept, researchers extended this field of study to apply it for the objective functions of optimizing the balance of feeder's load [4], restoration procedure of power grids [5], operation of switching devices [6], voltage deviations [7], and power quality [8].

The main challenge of implementing this idea is the high number of different possible switching combinations in a network to be considered and analyzed. For this reason, researchers have proposed different meta-heuristic intelligent optimization algorithms to simulate and solve this NP-hard combinatorial non-differentiable optimization problem [9]–[15]. However, it should be emphasized that heuristic methods do not guarantee to identify the actual optimal solution. By improving its structure, one can be hopeful to develop a heuristic optimization algorithm which is able to find high-quality suboptimal solutions which are close enough to the global optimum [16].

Considering the noticeable growing trend of on-site generation units in distribution systems over the last years, researchers have shown interest to solve the problem of network reconfiguration in the presence of DGs. In [17], a particle swarm optimization (PSO) algorithm is presented to solve network reconfiguration problem with the purpose of maximizing DG integration and minimizing total power loss. A meta-heuristic harmony search algorithm (HSA) is employed in [18] to simultaneously solve the optimal DG placement and network reconfiguration problems to optimize power loss and voltage profile. Optimal locations of DG units are recognized by sensitivity analysis in this study. A genetic algorithm (GA) is utilized in [19] to reconfigure distribution system so that it maximizes the penetration of DG units while it optimizes voltage profile and thermal constraints (i.e., total loading of the branches). In [20], operation strategies are taken into account to utilize network reconfiguration of automated distribution systems in the presence of DGs as a real-time operation to optimize power loss and service restoration. An artificial bee colony (ABC) algorithm is presented in [21] to reconfigure a distribution network containing hybrid renewable systems (wind turbines and solar cells) as DGs so that the total power loss, the total electrical energy cost, and the total reduced emission of atmospheric pollutants are optimized.

Shuffled frog leaping algorithm (SFLA) is presented in this paper to simulate the problem of network reconfiguration. SFLA is a meta-heuristic search model which provides a frog leaping rule for local search and a memetic shuffling rule for global

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information exchange [22]. Despite of its more complicated implementation, SFLA has three main advantages over the more classic meta-heuristic optimization algorithms (e.g., GA and PSO), which is the main reason it is employed in this work: (A) It is less sensitive to parameter settings. For example, in GA, the inappropriate determination of P_c (probability of crossover) and P_m (probability of mutation) leads to the identification of low-quality solutions. In SFLA, there is no "sensitive parameter" which should be tuned by the operator. Once the algorithm is developed, it can simply be employed for any case studies without the necessity of updating its parameters. (B) Because of the parallel-based local optimization in its structure, it can identify the solutions with higher quality which will be discussed in Section III. (C) It has a higher convergence speed [23].

The objective functions which are addressed by this optimization tool are voltage sag and voltage drop. Instead of assigning weights to the objective functions and defining a single objective function for the algorithm, the concept of Pareto dominance is utilized for the algorithm to search for the non-dominated sub-optimal solutions. Developing this Pareto-based optimization technique, the system operator will not have to rely on only one single solution. The algorithm will identify a set of high-quality suboptimal solutions on the Pareto frontier which are unable to dominate each other. Any of the recognized solutions on the Pareto frontier might be adopted as a candidate network configuration based on the situation of system. A Pareto dominance approach is presented in the structure of SFLA to update an Archive Set (i.e., a set of non-dominated solutions) as the optimization algorithm proceeds.

The focus of this paper is to present a new study which analyzes the quality of solutions (i.e., network configurations) identified by the proposed algorithm while new distributed energy sources are being installed in the network. The classic SFLA is improved in this work to develop a Pareto-based optimization method which performs based on a fuzzy logic. The reconfiguration model is tested on a 69-bus radial system to verify the performance and effectiveness of the presented method. Simulation results demonstrate that the developed algorithm is able to identify the solutions with higher quality compared to the classic SFLA, GA, and PSO.

The rest of this paper is organized as follows: problem formulation is provided in Section II; the methodology is elaborated in Section III; simulation results and discussions are described in Section IV; and Section V outlines the conclusion.

II. Problem Formulation

In this paper, the objective functions of optimal feeder reconfiguration problem are voltage drop and voltage sag which are calculated for each possible solution to perform the optimization process:

A. Voltage Drop

Voltage drop is a significant factor in distribution networks since its reduction not only causes the voltage profile improvement but it also decreases the network power loss. This variable indicates how the energy supplied by substation is reduced through the system. The total voltage drop in a network is formulated as follows:

$$F1 = \sum_{i=1}^{N} |V_{\mathrm{ref}} - V_i| \tag{1}$$

where, V_i, V_{ref}, and N stand for the voltage value of bus i, the rated voltage of substation (1 p.u.), and the number of nodes (i.e., buses) in the network, respectively.

B. Voltage Sag

Voltage sag is one of the main factors representing the power quality level in distribution systems. This variable is caused by short-circuit study and is defined as a decrease to between 0.1 and 0.9 p.u. in root mean square voltage at the power frequency for durations of 0.5 cycle to 1 min [24]. To calculate voltage sag, three-phase faults are studied to take into account the worst case scenario. The buses the sagged voltage is considered for are the points of common coupling (PCC). The total voltage sag in a distribution system is formulated as follows:

$$F2 = \sum_{i=1}^{N_{\mathrm{PCC}}} \sum_{j=1}^{N} \left| \frac{z_{ij} + z_f}{z_s + z_{ij} + z_f} \right| \tag{2}$$

where, z_{ij} signifies the impedance between bus i and fault location j. z_f and z_s refer to the fault impedance and the source impedance at bus i. N and N_{PCC} are the number of buses and the length of PCC, respectively.

The constraints that should be checked for each configuration to consider it as a feasible topology are as follows.

Bus voltage limits:

$$V^{\min} \leq |V_i| \leq V^{\max} \quad i \in \{1, 2, \ldots, N\} \tag{3}$$

where, V_i, $V^{\min}$ and $V^{\max}$ represent the voltage of bus i, the minimum and maximum allowed voltage values of the network, respectively.

Feeder capacity limits:

$$|I_k| \leq I^{\max} \quad k \in \{1, 2, \ldots, L\} \tag{4}$$

where, I_k, $I^{\max}$, and L refer to the current passing through branch k, the maximum allowed current value of each branch, and the total number of branches in the system, respectively.

Radial configuration: There should be only one possible path between each bus and the substation.

It should be emphasized that voltage sag is utilized as a criterion of power quality in this study. A lower value of F2 for a network configuration means that the system has a higher power quality so that the possibility of happening voltage sag for that network is lower. If a possible solution does not meet the three constrains of the problem formulation for any reasons (e.g., non-radial network), a noticeable penalty factor is considered for the configuration so that it will be automatically removed from the optimization process after a number of iterations.

III. Methodology

SFLA is a meta-heuristic optimization model that mimics the memetic evolution of a group of frogs looking for the stone

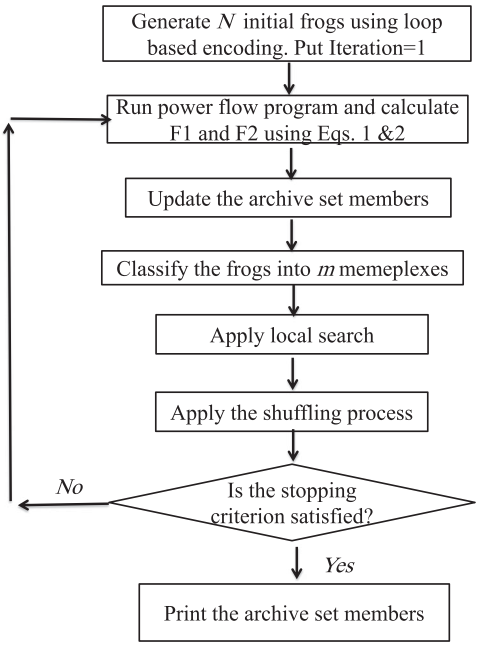

Fig. 1. The flowchart of algorithm.

containing the maximum food in a swamp. The structure of this algorithm is on the basis of "frog leaping rule" and "shuffling rule" which, respectively, bring about local search and global information exchange during the optimization process. In this study, the concept of Pareto dominance is considered within the structure of SFLA to develop a multi-objective optimization model discovering a set of non-dominated solutions located on the optimal Pareto frontier. Fig. 1 shows the flowchart of the presented reconfiguration optimization algorithm.

The main processors of the presented hybrid algorithm are loop-based encoding, updating the archive set members, classifying, local search, and shuffling process, which are elaborated at the rest of this section. The first operator presents a strategy to encode each possible configuration to a unique frog. The second operator saves the non-dominated configurations, which are found during the optimization process, to add them to an archive set. It also removes the members of this set that are dominated by the new identified solutions. The third operator classifies the frogs into different memeplexes to prepare them for local search. The fourth operator improves the worst frogs in different memeplexes in parallel. At the end of each iteration, the last operator combines the different improved memeplexes to build a united population.

A. Encoding

The main coding techniques to encode distribution networks are loop-based [25], node-based [26], branch-based [27], and binary switch-based strategies. Since the number of loops in a radial network is less than the number of nodes and branches, that will be more computationally efficient to rely on the loop-based method to encode distribution systems.

In order to implement the loop-based encoding, it should be considered that in a radial network (i.e., tree) the number of

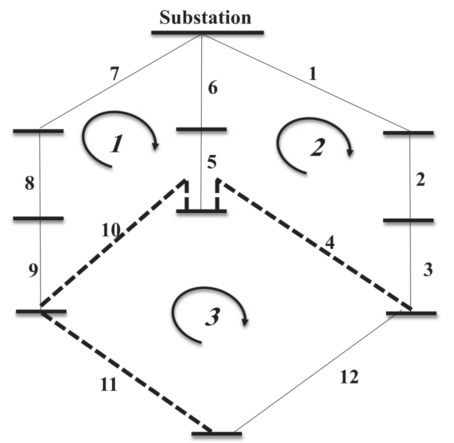

Fig. 2. A radial network with three loops.

closed branches is one unit less than the number of nodes. Also, the number of open branches should be equal to the number of loops in the system. Each encoded network configuration using this technique contains *P* bits where *P* is the number of loops. Only one open branch should be assigned to each loop. The loops are not allowed to consist of less than or greater than one open branch. It means that each bit of an encoded configuration indicates the branch number of the corresponding loop which is open. For instance, the encoded individual (i.e., frog) for the network topology shown in Fig. 2, which contains ten nodes, nine closed branches and three loops, is $F = \{10, 4, 11\}$. If node-based or branch-based encoding approaches were adopted, the number of bits of each encoded configuration would be associated with the number of nodes or branches. This difference for larger distribution networks will be more considerable which dramatically increases the computational burden of the optimization process.

B. Updating the Archive Set Members

A unique pair of voltage drop (F1) and voltage sag (F2) distinguishes each configuration (frog) from the others. The two network configurations *x* (Fx1, Fx2) and *y* (Fy1, Fy2) are considered as an example. *x* is dominated by *y* if and only if $Fy1 \leq Fx1$ and $Fy2 \leq Fx2$. But *x* and *y* are two non-dominated configurations if $Fy1 \geq Fx1$ and $Fy2 \leq Fx2$ or $Fy1 \leq Fx1$ and $Fy2 \geq Fx2$.

An archive set (*AS*) contains the set of the best non-dominated solutions identified during the optimization process. For example, Fig. 3(a) shows the *AS* members found at iteration *T*. As it can be seen, no frog in this set is able to dominate any other members of *AS*. At each iteration, *AS* members should be updated in two steps: (A) The new generated frogs, which are not dominated by the current *AS* members, should be added to the Pareto frontier. As it can be realized from Fig. 3(b), the frogs *z*, *m*, and *n* are the new *AS* members which are identified at iteration $T + 1$. (B) The old *AS* members, which are dominated by the new *AS* members, will be removed from the Pareto frontier at the next iteration. As it can be gathered from Fig. 3(c), the

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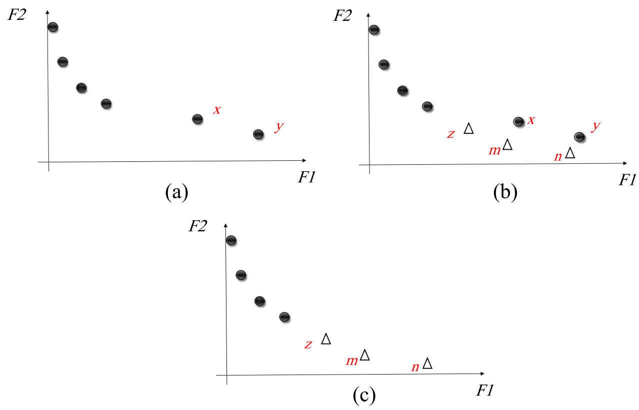

Fig. 3. Updating the archive set members. Circles: The AS members at Iteration T Triangles: The new identified AS members (a) AS at Iteration T (b) Adding the new non-dominated frogs (c) Removing the dominated frogs.

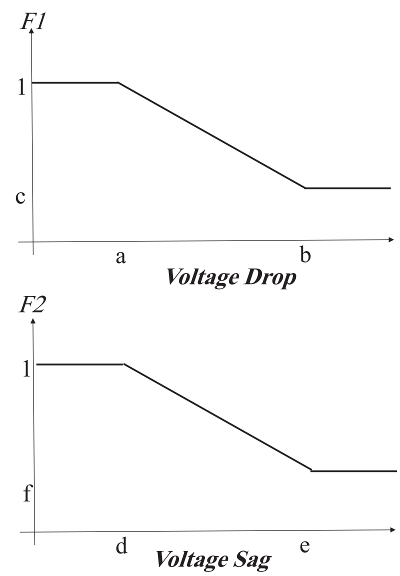

Fig. 4. Determining the fitness fuzzy value for classification.

frogs *x* and *y*, which are dominated by the new members *z, m*, and *n*, are deleted from the archive set.

C. Classifying

The purpose of this step is to prepare different groups of frogs to be improved in parallel by *Local Search*. Different methods can be adopted to classify the encoded frogs (i.e., network configurations) into *m* memeplexes. In this work, a fuzzy-based strategy is presented to assign one single fitness value to each frog as a criterion of selection for classifying. Two objective functions of voltage drop and voltage sag are calculated for each frog using (1) and (2). As it is shown in Fig. 4, two fuzzy values are assigned to these objective values using the trapezoidal fuzzy functions. The multiplication of these fuzzy values ($\mathrm{F} = \mathrm{F1} \times \mathrm{F2}$) will yield the fitness value of the corresponding frog. Using a trial-and-error approach, the parameters in Fig. 4 (i.e., *a*, *b*, *c*, *d*, *e*, and *f*) are determined so that they bring about more accurate classifications (i.e., a process that puts a range of high-quality and low-quality configurations in each class).

In the next step, the frogs should be classified in different memeplexes. Roulette wheel method [28] is employed for this purpose. All the memeplexes should contain the same number of frogs and they should be prepared fairly consisting of less fertilized and more fertilized frogs. That is the reason at the beginning step the first member of each memeplex should be selected from the roulette wheel so that, most likely, the frogs with higher fitness values will be chosen. When the first members of all of the memeplexes are selected, this process will be repeated to determine the second member of each memeplex, and so on. It should be emphasized that each selected frog should be taken out and it will not be put back in the roulette wheel for further selections.

D. Local Search

This step is an evolutionary method that is repetitively applied to each memeplex to improve the worst frogs of the corresponding memeplex. Using (5) and (6), the best and worst frogs in the memeplex are used to generate a new frog

$$D = \mathrm{rand}().(X_b - X_{w,\mathrm{old}}) \tag{5}$$

$$\begin{aligned} X_{w,\mathrm{new}} &= X_{w,\mathrm{old}} + D; \\ -D_{\max} &\le D \le D_{\max} \end{aligned} \tag{6}$$

where, rand() is a random value between zero and one. X_b, $X_{w,\mathrm{old}}$, and $X_{w,\mathrm{new}}$ refer to the best frog, the current worst frog, and the new frog in the corresponding memeplex, respectively. D and $D_{\max}$ stand for the step size and the maximum allowed step size.

If the worst frog is dominated by the new frog, it will be replaced by $X_{w,\mathrm{new}}$. Otherwise, this process will be repeated with the difference that instead of (5), (7) is used in which the best frog among all of the memeplexes (i.e., X_g) will be employed to generate the new frog. If the new developed frog cannot still dominate the older worst frog (i.e., $X_{w,\mathrm{old}}$) in the memeplex, this old frog will be replaced by another frog that is randomly generated. It is notable that the worst frog is dominated by the new one when its voltage drop and voltage sag values are higher than that of the new frog. Repeating this evolutionary process for each memeplex, the frogs will be improved locally in all the memeplexes

$$D = \mathrm{rand}().(X_g - X_{w,\mathrm{old}}). \tag{7}$$

E. Shuffling Process

At the end of each iteration, this step is applied to make the cultural evolution free from any bias. After applying the local search to each memeplex in order to improve the worst frogs locally, the shuffling processor will combine all of the frogs located in different memeplexes to develop a united population.

IV. Simulation Results and Discussions

In order to simulate the proposed optimization algorithm, MATLAB software is employed on a computer with the processor of Intel(R) Xeon(R) CPU E5-2603 0 at 1.80 GHz. The

TABLE I
THE DESCRIPTION OF DIFFERENT SCENARIOS

	No. DG Units	Bus No.	Power (KVA)
Sc #1	0	–	–
Sc #2	5	11, 21, 50, 55, 61	80, 50, 150, 10, 500
Sc #3	10	7, 11, 12, 21, 49, 50, 55, 61, 64, 65	15, 80, 80, 50, 150, 150, 10, 500, 100, 30

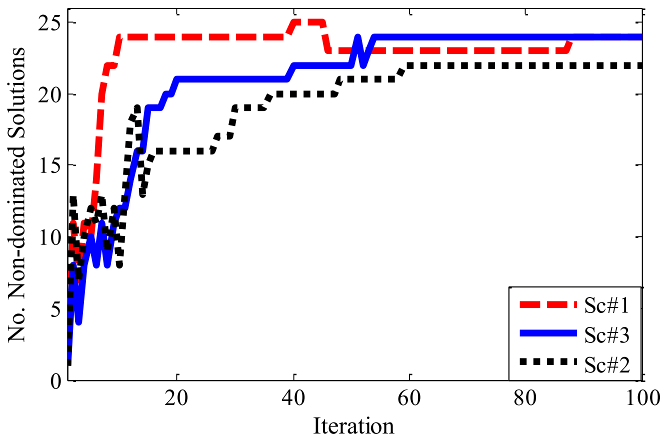

Fig. 5. The number of *AS* members found by the algorithm.

reconfiguration model is tested on a 69-bus radial distribution system [29] which contains 68 sectionalizing switches and five tie switches. The main transformer is connected to a substation with the nominal voltage of 12.66 KV and the MVA base is assumed at 100 MVA. As it can be found in [29], in the initial topology the Branch #69, 70, 71, 72, and 73 are open (i.e., Encoded Frog = {69, 70, 71, 72, 73}). The stopping criterion of algorithm is to reach Iteration #100 while the local search process is repeated 10 times for each memeplex in each iteration. Newton–Raphson is utilized as the power flow program. The PCC for voltage sag calculation are assumed to be Bus #12, 20, 24, and 28. *a*, *b*, *c*, *d*, *e*, and *f* are 0.8, 3.5, 0.1, 22, 43, and 0.15, respectively (see Fig. 4).

The main concentration of this study is to study the impact of distributed energy sources integration on the task of optimal network reconfiguration. For this purpose, the proposed optimization method is implemented in three different scenarios (described in Table I) and its efficiency in identifying high-quality solutions is compared for the three scenarios. It is notable that the power factor of all of the installed DG units is 0.8 lag.

As the optimization algorithm proceeds, the number of non-dominated solutions (i.e., the archive set's frogs) increases since it identifies a higher number of non-dominated configurations located on the Pareto frontier. This growing trend for different scenarios is compared in Fig. 5. As it is observed from the figure, approximately, the same number of non-dominated solutions is identified by the algorithm after 100 iterations for the three scenarios.

As it is discussed in Section II, the first defined objective function is voltage drop. In order to present the fluctuations of this fitness value during the optimization process, the average

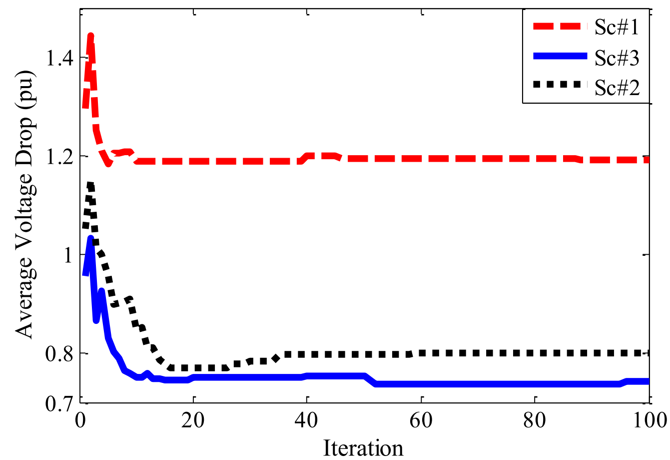

Fig. 6. The declining trend of average voltage drop.

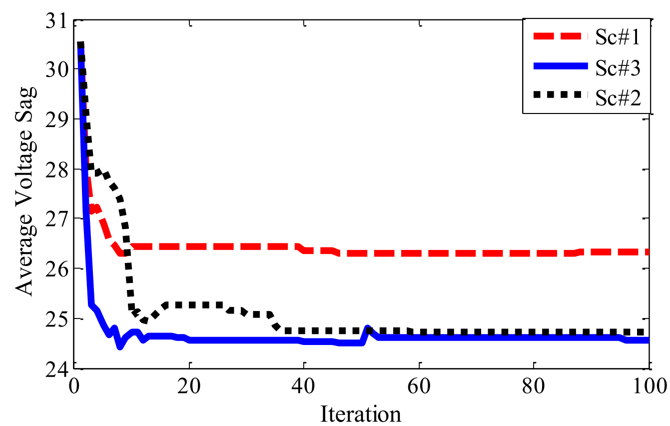

Fig. 7. The declining trend of average voltage sag (no unit).

voltage drop of all of the non-dominated solutions is recorded as the voltage drop representative of the corresponding iteration. Equation (8) clarifies how the average voltage drop is calculated for each iteration:

$$AveF1 = \frac{\sum_{i=1}^{M} F1(i)}{M} \tag{8}$$

where, $AveF1$, M, and $F1(i)$ refer to the average voltage drop, the number of solutions on the Pareto frontier, and the voltage drop (see (1)) of the ith solution (i.e., configuration), respectively.

Fig. 6 provides a comparison among the declining trends of average voltage drop for the three scenarios. This observation simply verifies that the integration of DG units to the network will bring about higher qualified solutions (i.e., the candidate configurations with lower voltage drop values) identified by the reconfiguration algorithm.

The second objective function defined for the algorithm is voltage sag formulated in (2). As there are different non-dominated solutions found in each iteration, the average voltage sag of the identified solutions is recorded to stand for the second fitness value of the relevant iteration. The declining trends of average voltage sag for the three scenarios during the optimization process are compared in Fig. 7. As it is demonstrated, the

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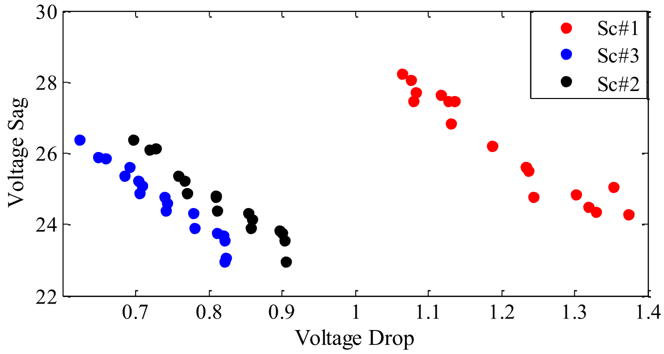

Fig. 8. The Pareto frontiers identified by the algorithm.

TABLE II
THE CONFIGURATIONS WITH THE LOWEST VOLTAGE DROP

	Configuration	Voltage Drop (After)	Voltage Drop (Before)
Sc #1	10, 20, 13, 58, 26	1.0637	1.8460
Sc #2	69, 20, 13, 58, 64	0.6961	1.4621
Sc #3	69, 19, 13, 58, 64	0.6236	1.3382

higher penetration of DG units in the network will lead to the identification of configurations with lower voltage sag values.

As it is presented in Fig. 5, the algorithm finds approximately the same number of solutions as the archive set members after 100 iterations for different scenarios. These identified network configurations are located on the Pareto frontiers which are illustrated together in Fig. 8. Any of these AS members can be employed by the system operator for a unique purpose depending on the situation of network. As it was expected, this study, by focusing on the problem of network reconfiguration, verifies that the more utilization of distributed energy sources in a distribution network results in the recognition of Pareto frontiers with higher quality presenting the configurations with lower values of voltage drop and voltage sag.

Table II presents the configurations with the lowest value of voltage drop on the identified Pareto frontiers shown in Fig. 8. The second column of this table indicates the open switches of each identified topology through the optimization. The words "Before" and "After" in this table refer to before and after running the optimization algorithm. The topology of the network before optimization is the initial configuration (i.e., Frog = {69, 70, 71, 72, 73}). For Sc #2 and Sc #3, five and ten DG units (described in Table I) are added to this initial network topology.

The voltage profiles of the network topologies presented in Table II are depicted in Fig. 9. The green line shows the voltage profile of the network before optimization when no DGs are yet installed in the system. The red line presents the network voltage profile after optimization (i.e., Sc#1). As it can be noted, the total voltage drop of the network has been improved after the network reconfiguration. The black and blue lines show the voltage profile of the network after optimization when 5 (Sc#2) and 10 (Sc#3) DG units are added to the system. The other observation of this comparison is the considerable voltage drop of Sc#1 at Bus# 27 although running the optimization for this scenario has led to a better overall voltage profile compared to the initial configuration. It means that running the optimization will not guarantee the improvement of voltage at every bus of the network. This issue can be resolved by adding DG units to the network. As it can be seen in Fig. 9, after adding DG units in different locations of the distribution system (see Table I), the optimization algorithm has identified the configurations which have a better overall voltage profile and also lower voltage drops at every bus of the network compared to the initial configuration.

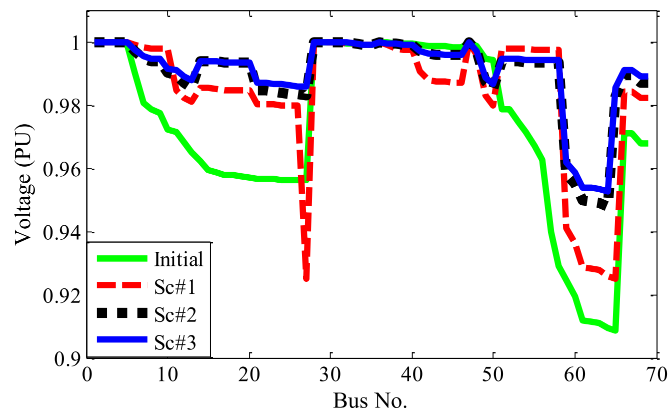

Fig. 9. The voltage profile of configurations presented in Table II.

TABLE III
THE CONFIGURATIONS LOCATED AT THE CENTER OF PARETO FRONTIERS

	Configuration	Voltage Drop	Voltage Sag
Initial	69, 70, 71, 72, 73	1.8460	30.9650
Sc #1	10, 19, 12, 58, 25	1.1305	26.8401
Sc #2	69, 19, 12, 58, 26	0.7693	24.8758
Sc #3	69, 19, 12, 58, 25	0.7406	24.3895

TABLE IV
COMPARISON OF SFLA, GA, PSO AND THE PROPOSED METHOD FOR SCENARIO #1

	Ave. Volt. Drop	Ave. Volt. Sag	Computational Burden (Second)
Initial	1.8460	30.9650	–
Proposed Model	1.1305	26.8401	10283
Classic SFLA	1.1491	28.0624	9612
Classic GA	1.5703	28.7523	13671
Classic PSO	1.6138	29.1191	12714

As it was explained in Section I, the advantage of employing a Pareto dominance-based optimization algorithm is that the system operator will have a higher flexibility in making decision in the process of network reconfiguration. It means that the operator will have the opportunity to pick any of the identified solutions on the Pareto frontier based on the situation of network. If the operator decides to consider an equal importance for voltage drop and voltage sag, the solution located at the center of Pareto frontier will be a desired topology for the network. Table III shows the corresponding fitness values of the configurations located at the center of Pareto frontiers for each scenario. As it is demonstrated, the higher number of DG units in the network leads to an improved solution identified by the optimization algorithm.

In Table IV, the performance of the proposed algorithm is compared with that of the classic SFLA, GA, and PSO for Sc #1 (i.e., no DG unit). In order to present a fair comparison, the same Pareto-based technique is applied to the corresponding classic methods so that, instead of only one single solution, they can find Pareto frontiers as well.

As it was expected, the SFLA related methods have a less computational burden compared with the other two methods (i.e., GA and PSO). Although the implemented classic SFLA is faster than the corresponding improved model, the proposed algorithm can identify high-quality solutions (i.e., the configurations with lower values of voltage drop and voltage sag).

The case study in this work is a system with only 69 buses; however, the real-world networks contain thousands of buses. For the implementation of distribution system reconfiguration task in larger networks, the utilization of distributed computing methods should be explored.

V. Conclusion

A Pareto-based meta-heuristic optimization algorithm is proposed in this paper to solve the multi-objective problem of distribution system reconfiguration with the purpose of optimizing voltage profile and voltage sag. The optimization method utilizes a Pareto dominance technique to recognize the non-dominated solutions identified by an improved SFLA. A fuzzy logic is introduced in the partitioning step of SFLA based on the values of voltage drop and voltage sag in order to provide a more accurate criterion for the classification of frogs. The proposed optimization algorithm is implemented in the presence of DGs to step toward the integration of smart grids embedded in the structure of power systems. The simulation results verify that the reconfiguration model is able to recognize the solutions with higher quality when a higher number of distributed energy sources are installed in the distribution network.

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