Multi-Objective Power Distribution Network Reconfiguration using Chaotic Fractional Particle Swarm Optimization

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ABSTRACT

Optimization of power distribution system reconfiguration is addressed as a multi-objective problem, which considers the system losses along with other objectives, and provides a viable solution for improvement of technical and economic aspects of distribution systems. A multi-objective chaotic fractional particle swarm optimization customized for power distribution network reconfiguration has been applied to reduce active power loss, improve the voltage profile, and increase the load balance in the system through deterministic and stochastic structures. In order to consider the prediction error of active and reactive loads in the network, it is assumed that the load behaviour follows the normal distribution function. An attempt is made to consider the load forecasting error on the network to reach the optimal point for the network in accordance with the reality. The efficiency and feasibility of the proposed method is studied through standard IEEE 33-bus and 69-bus systems. In comparison with other methods, the proposed method demonstrated superior performance by reducing the voltage deviation and power losses. It also achieved better load balancing.

Keywords: Chaotic Fractional PSO, Multi-Objective Reconfiguration, Deterministic and Stochastic Structures, Loss Reduction, Voltage Profile Improvement

1. INTRODUCTION

In recent decades, many electrical engineering researchers have been focusing on distributed power generations and microgrid resilience enhancement and control, which are predicated on renewable power sources [1–15]. In a radial distribution network, some switches are normally open (NO) and some others are normally closed (NC). As the mode of these switches changes, the network maintains its radial structure and provides all loads simultaneously. The power distribution procedure in distribution networks can be changed so that several technical and economic objectives could be achieved. These objectives include power reduction, voltage profile improvement, feeder load balancing, etc. The main goal is to find the optimal point for the network by considering the load forecasting error of the network, and also taking into account all constraints and assumptions.

One of the deficiencies found in previous research and studies was that they were focusing on only one or two objectives in reconfiguration, such as reducing the power losses [1] or increasing load balance [2, 3]. In [4], as a part of a new compilation, a method based on the simulated annealing and tabu search algorithms was presented. The reconfiguration scenario is used to reduce the power losses in distribution networks. A modified genetic algorithm was also presented in [5] to reduce the network ohmic losses in the distribution network. In [6], an exploratory method based on graph theory techniques including semi-sparse flow-sensitive matrix transmission was used to find the optimal point of the distribution network in terms of active power loss reduction. In [7], an online method is investigated to solve the Distribution Feeder Reconfiguration (DFR) problem. A new method based on optimal load distribution for solving the DFR problem using an innovative algorithm is also proposed in [8]. In this paper, a heuristic method was used based on load distribution to use reconfiguration for network loss reduction. In [9], a new optimization-based method is presented to observe the effect of distributed products on the DFR problem. In [10], a new approach based on evolutionary programming was presented to provide optimal reconfiguration management to reduce network loss. A new approach based on an artificial neural network was proposed in [12] to solve the DFR problem. In [13], the DFR

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strategy was proposed to reduce the amount of power loss by reducing the ohmic losses in the network. In [14], an intelligence optimization method based on innovative patterns is proposed to reduce the search field of the DFR problem and then search for optimal resolution. A method based on the distance measurement technique was proposed in [15] to explore the effect of the DFR problem for increasing load balancing in the system. Particle Swarm Optimization (PSO) algorithm was first introduced as a model of local movement for a group of animals. It has been implemented well on a variety of problems [16, 17]. The algorithm contains a swarm of particles, in which each individual can be an optimal response to the problem under optimization. Since fractional calculus-based evolutionary algorithms have proved their highly desirable performance in various engineering applications [18–20], a modified version of the Fractional PSO algorithm (FPSO) [18] is proposed and used in this study, with chaotic fractional velocity to promote best-performing particles and improve global optimality.

Solving the DFR optimization problem has some benefits such as reducing power loss, correcting load balances, improving the voltage profile, etc. The authors in [21] have attempted to obtain a fuzzy power dissipation solution by considering the exceeding limit of reactive power at the voltage-controlled bus, the uncertainties in voltage-dependent load models, load forecasting, and system parameters. A powerful tool for solving nonlinear equations was introduced in [22]. In this paper, a multi-layer perceptron neural network trained by the second-order Levenberg-Marquardt method was used to calculate the size and angle of the power distribution voltage in the IEEE 33-bus standard system. An artificial neural network approach based on Lagrange multiplication was proposed in [23] to solve the problem of the economic load distribution in the power system.

The purpose of this study is to investigate and present a suitable method for determining the best structure for power distribution networks by using a network reconfiguration strategy to increase network loading capacity. Considering the multiplicity of the problem and the interaction of objective functions, this study uses the Pareto point's theory for objective function management. To reduce the active power loss, improve the voltage profile, and increase the load balance in the system through deterministic and stochastic structures, a multi-objective chaotic fractional PSO is proposed and utilized for power distribution network reconfiguration. In addition, in order to consider the prediction error of active and reactive loads in the network, it is assumed that the load behaviour follows the normal distribution function. Single-objective and multi-objective reconfigurations are applied on 33-bus and 69-bus standard test systems with deterministic and stochastic structures to show the efficiency of the proposed optimal method.

The rest of the paper is organized as follows. In Section 2, the proposed chaotic fractional particle swarm optimization algorithm is described. Section 3 expresses the formulation of the problem with constraints and objective function, and a method for obtaining fuzzy interactions is introduced. Simulation results on the 33-bus and 69-bus standard test systems in single-objective and multi-objective modes have been evaluated in Section 4. Finally, the paper ends with Section 5 which gives over conclusions.

2. CHAOTIC FRACTIONAL PARTICLE SWARM OPTIMIZATION

The fractional particle swarm optimization algorithm was introduced in [18] as a local search algorithm for a fractional memetic algorithm. If $x_i(t)$ is the position of the i^{th} particle at time t, the position of the particle is expressed as

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{1}$$

For each particle i the velocity consists of three components: the cognitive component, which is derived from the best position ever experienced by particle i; the social component, which is derived from the position of the best particle that particle i is aware of; and the inertia component, which results from the previous speed of the particle. All particles are evoked by the social component that results from the position of the best particle in the whole population. This component is $y(t)$ and calculates the fractional velocity as

$$\begin{aligned} v(t+1) = {} & \alpha v(t) + \frac{1}{2}\alpha(1-\alpha)v(t-1) \\ & + \frac{1}{6}\alpha(1-\alpha)(2-\alpha)v(t-2) \\ & + \frac{1}{24}\alpha(1-\alpha)(2-\alpha)(3-\alpha)v(t-3) \\ & + \varphi_1(t)(P_{best} - x_i) + \varphi_2(t)(G_{best} - x_i) \end{aligned} \tag{2}$$

where $v(t)$ is the fractional velocity of particle i in the j dimension at time t. Parameters α, $\varphi_1(t) = r_1(t)c_1(t)$ and $\varphi_2(t) = r_2(t)c_2(t)$ are the inertia weight, individual training coefficient and the global training coefficient, respectively, which are used to set up cognitive and social components. Parameters $r_1(t)$ and $r_2(t)$ are random numbers with intervals of (0,1), and $c_1(t)$ and $c_2(t)$ are predefined constant values.

In this paper, chaotic sequences are employed in determining $r_1(t)$, $r_2(t)$, $c_1(t)$, and $c_2(t)$, four parameter settings of the FPSO algorithm, to enhance exploitation capability which is called the CFPSO algorithm. These sequences are given as

$$
\begin{aligned}
r_1(t) &= \rho \cdot r_1(t-1) \cdot [1 - r_1(k-1)] \\
r_2(t) &= \rho \cdot r_2(t-1) \cdot [1 - r_2(k-1)] \\
c_1(t) &= \rho \cdot c_1(t-1) \cdot [1 - c_1(k-1)] \\
c_2(t) &= \rho \cdot c_2(t-1) \cdot [1 - c_2(k-1)]
\end{aligned} \tag{3}
$$

where ρ is a control parameter $0 \leq \rho \leq 4$. $r_1(t)$, $r_2(t)$, $c_1(t)$, and $c_2(t)$ are deterministic chaotic sequences distributed in the range (0,1), displaying chaotic dynamics when $\rho = 4$. Note that ($r_1(0)$, $r_2(0)$, $c_1(0)$, $c_2(0)$) $\notin$ (0,0.25,0.5,0.75,1).

3. PROBLEM DESCRIPTIONS

3.1 Objective Function

The objective function is used to reduce total ohmic loss given as

$$f_1(X) = P_{loss} = \sum_{i=1}^{N_{br}} R_i \times |I_i|^2 \tag{4}$$

where R_i is the strength of i^{th} branch. I_i is the flow of i^{th} branch. N_{br} is the number of branches in the network. X is the control vector, which includes the status of the divider switches and the connector switches of the network as

$$X = [Tie_1, Tie_2, ..., Tie_{N_{Tie}}, SW_1, SW_2, ..., SW_{N_{sw}}] \tag{5}$$

where Tie_1 is the i^{th} Tie switch position and SW_1 is i^{th} divider switch position. N_{Tie} is the number of connector switches in the network and N_{sw} is the number of divider switches in the network. It's obvious that the number of Tie_1 can range between 0 and 1 which illustrates open and closed modes. The voltage deviation function given in Eq. (6) is used to reduce the voltage deviation in the network.

$$f_2(X) = dev(X) = \max\left[|1 - V_{\min}|, |1 - V_{\max}|\right] \tag{6}$$

where $V_{\min}$ and $V_{\max}$ denote the lowest and highest voltages, respectively. The objective function given in Eq. (7) is defined to increase the load balance of the network.

$$
\begin{aligned}
f_3(X) &= Balance(X) \\
&= -\min_i \left| \frac{I_{i,rate} - I_i}{I_{i,rate}} \right| ; i = 1, 2, 3, ..., N_{br}
\end{aligned} \tag{7}
$$

where $I_{i,rate}$ is the rated capacity of i^{th} line, and I_i is the current of i^{th} line.

3.2 Problem Constraints

The security of the optimal power flow is pledged by respecting the following restrictions.

a) The bus voltages limits are defined as

$$V_i^{\min} < V_i^t < V_i^{\max} \tag{8}$$

where $V_i^{\min}$ and $V_i^{\max}$ denote the minimum and maximum voltages at bus i, respectively.

b) The maximum permissible load distribution per line is limited by

$$\left|S_{ij}^{Line}\right| < S_{ij,\max}^{Line} \tag{9}$$

where $S_{ij,\max}^{Line}$ is the maximum allowable complex power passing through the branch between i and j buses and S_{ij}^{Line} is the amount of complex power passing through the line between i and j buses.

c) The maximum permissible current of distribution feeder is limited by

$$\left|I_i^t\right| < I_i^{\max} \tag{10}$$

where $I_i^{\max}$ is the maximum permissible current of distribution feeders.

The distribution load dispatch equations can be considered as constraints in the optimization problem, and are given as

$$
\begin{aligned}
P_i &= \sum_{i=1}^{N_{bus}} |V_i| \, |V_j| \, |Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \\
Q_i &= \sum_{i=1}^{N_{bus}} |V_i| \, |V_j| \, |Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j)
\end{aligned} \tag{11}
$$

where P_i and Q_i are the active and reactive powers injected to i^{th} bus, respectively. V_i is the voltage range of i^{th} bus. δ_i is the voltage angle of the i^{th} bus. θ_{ij} is the admittance angle between the j and i buses.

3.3 Fuzzy Interactions

The purpose of this study is to investigate the multi-objective DFR problem. In general, each limited multi-objective function can be formulated as

$$
\begin{aligned}
&\min F = [f_1(X), f_2(X), ..., f_n(X)]^T \\
&\text{s.t. } g_i(X) < 0; i = 1, 2, ..., N_{ueq} \\
&\qquad h_i(X) = 0; i = 1, 2, ..., N_{eq}
\end{aligned} \tag{12}
$$

where $g_i(X)$ and $h_i(X)$ are non-identical and constrained. N_{ueq} and N_{eq} are numbers of inequality and the inequality is constrained. A fuzzy interactive satisfactory method is proposed, which allows the operator to select the most optimal solutions from the lower set. Thus, using the theory of the fuzzy sets, Eq. (13) is obtained.

Table 1: *Single-objective reconfiguration of 33-bus system in deterministic structure.*

Method	No Load Flow (kW)	Power Loss (kW)	Voltage Deviation	Minimum Voltage	Open Switches
GT [7]	139.551	139.53	0.0612031	0.93879681	7, 9, 14, 32, 37
MOS [8]	139.538	139.52	0.0612031	0.93879681	7, 9, 13, 32, 37
BF-SD [9]	*not provided*	139.58	0.0612031	0.93879681	7, 9, 13, 22, 37
SPSO [10]	*not provided*	139.45	0.0612208	0.93879681	7, 9, 14, 32, 38
BPSO [13]	139.68	139.53	0.0622809	0.93781902	7, 8, 14, 32, 37
MPSO [22]	139.57	139.50	0.0612763	0.93879681	6, 9, 12, 32, 37
CFPSO	139.16	139.11	0.0642750	0.93879046	7, 9, 14, 32, 37

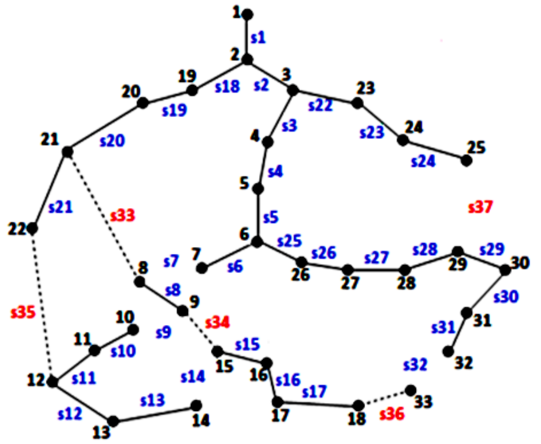

Fig.1: *33-bus system with s7, s9, s14, s32, and s37 open switches.*

Table 2: *Single-objective load balance comparison in 33-bus system in deterministic structure.*

Method	Load Balance	Open Switches
BPSO [13]	0.354716540	7, 11, 14, 36, 37
MPSO [22]	0.351584602	7, 10, 14, 36, 37
CFPSO	0.343774159	7, 9, 14, 36, 37

Table 3: *Multi-objective results of 33-bus system in deterministic structure.*

Method	Power Loss (kW)	Voltage Deviation	Load Balance	Open Switches
BPSO	143.761	0.06266	0.4037	6, 9, 14, 36, 37
MPSO	142.739	0.06218	0.3653	7, 34, 11, 32, 37
CFPSO	139.53	0.06524	0.3640	7, 9, 14, 32, 37

$$F(X) = \min_{x\in\Omega}\left\{\max_{i=1,\dots,n}|\mu_{ref,i} - \mu_{f,i}(X)|\right\} \tag{13}$$

where $\mu_{f,i}(X)$ is the fuzzy membership function $f_i(X)$. $\mu_{ref,i}$ is the degree of satisfaction $f_i(X)$. In this study, the trapezoidal membership function is used as a membership function. Thus, at the beginning of the optimization procedure, the operator can set the value of $\mu_{f,i}(X)$ at intervals of 0, 1.

4. SIMULATION RESULTS

To investigate the effectiveness and performance of the proposed method, IEEE 33-bus and 69-bus radial distribution systems with 12.66 kV voltage level are studied. Simulations for two single-objective and multi-objective modes with two structures have been implemented. The deterministic structure means no randomness is involved. The stochastic structure uses a random probability of distribution. The electric load is an uncertain parameter in a deregulated environment. In other words, an increase or decrease of this parameter directly affects the system. It is also assumed that the demand level is generally distributed around its specified expected value [13]. It is worth-mentioning that all of the results are obtained using fixed voltages throughout the process, where the values are considered from the load flow solution of the network with all the switches closed.

4.1 Deterministic single-objective structure for the IEEE 33-bus distribution system

In this section, a comparative study between the performance of the proposed method and other recent methods in deterministic single-objective structure for the IEEE 33-bus distribution system is investigated. Fig. 1 illustrates the 33-bus system reconfiguration with s7, s9, s14, s32, and s37 as open switches. Table 1 demonstrates the single-objective reconfiguration of a 33-bus system in deterministic structure, where the “No load flow” column shows the results achieved without the load flow method. As can be seen in Table 1, the optimal solution with regard to the power loss objective was found by the proposed method augmented with the load flow method. The load flow result illustrates the active power loss attained from the load flow after incorporating the algorithm result in the network.

According to Table 1, the proposed method is the best solution for voltage profile optimization. The initial voltage deviation of the system before reconfiguration was 0.0869092 p.u. The simulation results in Table 2 show that the CFPSO can bring

Table 4: *Single-objective reconfiguration of 69-bus system in deterministic structure.*

Method	No Load Flow (kW)	Power Loss (kW)	Voltage Deviation	Minimum Voltage	Open Switches
Initial network	233.384	225.0	0.079684	0.9092	11, 13–15, 17–21, 50, 57–65
GT [7]	105.37	102.6	0.051362	0.9321	11, 13–15, 18, 45–49, 57–65
MOS [8]	*not provided*	102.1	0.051362	0.9324	11, 13–15, 50, 58–65
BF-SD [9]	*not provided*	106.6	0.051362	0.9322	11, 17–18, 27–31, 49, 56–58
SPSP [10]	102.41	99.62	0.051362	0.9425	11, 13–19, 22–24, 49–51, 56–65
HAD [12]	102.39	99.62	0.051362	0.9420	11, 13–19, 22–25, 50–51, 57–58
CFPSO	101.84	99.04	0.054535	0.9428	11, 13–21, 58–59, 61–62

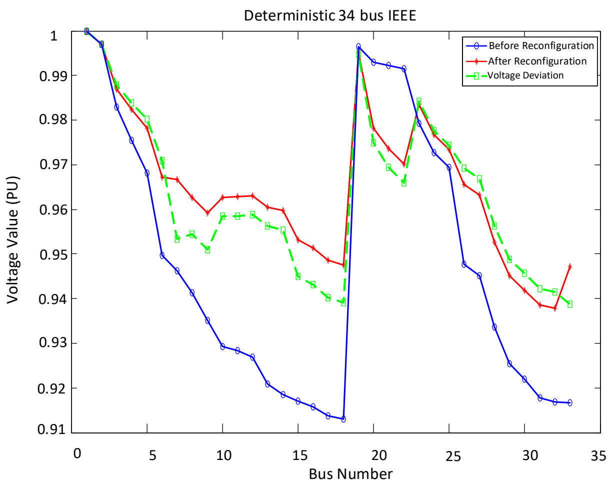

Fig.2: *33-bus IEEE network voltage improvement before and after multi-objective reconfiguration.*

a system load balance of 0.343774159, better than 0.354716540 and 0.351584602 obtained by BPSO [13] and MPSO [21], respectively. It should be taken into account that this amount of recovery of load balance can only be achieved by reconfiguration, and it is a significant success.

The load flow result illustrates the active power loss attained from the load flow after incorporating the algorithm result in the network.

4.2 Deterministic multi-objective structure for the IEEE 33-bus distribution system

In this section, practicability and efficiency of the proposed method in comparison with other recent methods in a deterministic multi-objective structure for the IEEE 33-bus distribution system is investigated.

As shown in Table 3, power losses in BPSO and MPSO are 143.76196 and 142.73916, respectively, while it is 139.5343 in CFPSO, which shows the better performance of the CFPSO. Also, the voltage deviation using CFPSO is less than the other two methods. The voltage equilibriums of 0.40372161 and 0.36531157 are obtained using BPSO and MPSO. It is 0.364086 in CFPSO, which shows the more favorable performance of CFPSO. Considering Fig. 2, it is clear that the 33-bus network voltage level has been improved optimally after multi-objective reconfiguration.

Table 5: *Single-objective feeder load balance comparison in 69-bus system in deterministic structure.*

Method	Load Balance	Open Switches
BPSO	0.754449	11–43, 20–21, 46–15, 58–59, 64–65
MPSO	0.750760	39–40, 16–17, 45–46, 58–59, 62–63
CFPSO	0.745811	11–43, 13–21, 14–15, 50–59, 61–62

4.3 Deterministic single-objective structure for the IEEE 69-bus distribution system

Similar to Section 4.1, this section investigates a comparison between the performance of the proposed method with other recent methods in deterministic single-objective structure for the IEEE 69-bus distribution system. According to Table 4, the power loss rate in the proposed method for single-objective optimization of a 69-bus system in deterministic structure is less than that of the other methods, which indicates better and more desirable performance by the proposed method. It should be noted that the total power loss before reconfiguration was 212/67 kW.

According to the results illustrated in Table 4, the proposed method has achieved the best solution. The initial voltage deviation of the system before reconfiguration was 0.079684 p.u.

The results shown in Table 5 indicate that the proposed method can change the system load balance from 0.5413236 to a better value of 0.74581189. It should be considered that this amount of recovery of the load balance can only be obtained by reconfiguration, and the results also show the performance of the proposed method with the value of 0.74581189 is more desirable in comparison with BPSO with value of 0.7544497 and MPSO with its value of 0.75076020.

Table 6: *Multi-objective reconfiguration of 69-bus system in deterministic structure.*

Method	Power Loss (kW)	Voltage Deviation	Load Balance	Open Switches
GA	115.944703	0.070062412	0.75367353	11–43, 13–21, 14–15, 58–59, 64–65
PSO	115.893236	0.058614557	0.74999069	11–43, 15–16, 15–46, 55–56, 62–63
CFPSO	104.750240	0.077260614	0.74810224	11–43, 20–21, 13–14, 58–59, 61–62

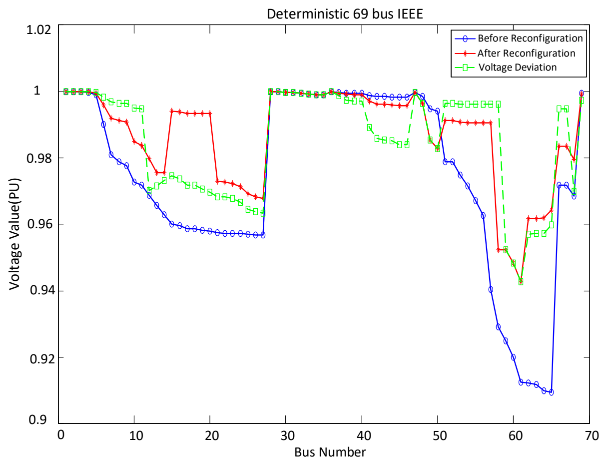

Fig.3: *69-bus IEEE network voltage improvement before and after multi-objective reconfiguration.*

4.4 Deterministic multi-objective structure for the IEEE 69-bus distribution system

Similar to Section 4.2, this section investigates a comparison between the performance of the proposed method with other recent methods in a deterministic Multi-objective structure for the IEEE 69-bus distribution system.

According to Table 6, a more desirable value for load balance objective is obtained by the proposed method (0.74810224) in comparison with BPSO and MPSO with 0.75367353 and 0.74999069, respectively. Considering Fig. 3, it is clear that the 69-bus network voltage level has been improved after multi-objective reconfiguration.

4.5 Stochastic single and multi-objective structures for the IEEE 33-bus and 69-bus distribution systems

In this section, 21 scenarios with high importance and high probability are selected from the literature [8,13,14]. Each scenario is applied on the network, and each one finds a best answer. Each answer has a probability, and each response is multiplied by the probability of its occurrence and eventually normalized.

According to Table 7, the power loss, voltage deviation, and load balancing in the stochastic structure are more optimal and lower than the deterministic structure, which indicates its better performance. Table 8 compares the multi-objective optimization results for stochastic and deterministic structures in 33-bus system with CFPSO algorithm and fuzzy framework. According to Table 8, power loss, voltage deviation, and load balancing in the stochastic structure are more optimal and lower than deterministic mode, which indicates its better performance.

Table 7: *Single-objective 33-bus system reconfiguration comparison in deterministic and stochastic structures by fuzzy framework and CFPSO algorithm.*

Framework	Power Loss	Voltage Deviation	Load Balance
Deterministic	139.11	0.0642750	0.3437741
Stochastic	139.5130	0.0642003	0.3437741
Max	141.8332	0.0652072	0.3453300
Min	138.9183	0.0611687	0.3437466
STD	0.631	0.0005312	0.0012000

Table 8: *Multi-objective 33-bus system reconfiguration comparison in deterministic and stochastic structures by fuzzy framework and CFPSO algorithm.*

Framework	Power Loss	Voltage Deviation	Load Balance
Deterministic	139.53	0.06524	0.3640
Stochastic	139. 5343	0.0641479	0.364086
Max	140.6871	0.0645000	0.365800
Min	138.9184	0.0620000	0.363000
STD	0.4458	0.0001364	0.000672

As is observed from Table 9, similar to the 69-bus system, in comparison with deterministic structure, objective functions are more optimal in stochastic mode. Table 10 shows a comparison of multi-objective power loss, voltage profile, and load balance objective of a 69-bus system in deterministic and stochastic structures using a fuzzy framework and the CFPSO algorithm. According to Table 10, better results of the objective function are achieved in a stochastic structure than with a deterministic structure.

5. CONCLUSIONS

In this paper, the problem of optimizing power distribution system reconfiguration was addressed as a multi-objective problem. The objective included

Table 9: *Single-objective 69-bus system reconfiguration comparison in deterministic and stochastic structures by fuzzy framework and CFPSO algorithm.*

Framework	Power Loss	Voltage Deviation	Load Balance
Deterministic	99.04	0.05453	0.745811
Stochastic	98.3656	0.05713	0.745757
Max	100.633	0.05780	0.750124
Min	97.4596	0.05671	0.742505
STD	0.8841	0.00032	0.002000

Table 10: *Multi-objective 69-bus system reconfiguration comparison in deterministic and stochastic structures by fuzzy framework and CFPSO algorithm.*

Framework	Power Loss	Voltage Deviation	Load Balance
Deterministic	104.75024	0.07726061	0.7481022
Stochastic	104.921596	0.057263585	0.747727
Max	106.7702	0.058424530	0.752504
Min	103.5279	0.056845345	0.745345
STD	0.8640	0.0004	0.001907

the system losses together with voltage profile improvement and load balancing in 33-bus and 69-bus standard IEEE systems. A multi-objective chaotic fractional fuzzy particle swarm optimization customized for power distribution network reconfiguration has been proposed and applied with deterministic and stochastic structures. In order to model the forecasting error of active and reactive loads and in order to reduce computer computations, a scenario-based approach was proposed that initially produced many scenarios by the roulette wheel, where among them, 21 possible and different scenarios were selected. To investigate the performance of the proposed algorithm, a comparison with BPSO [13] and MPSO [21] was performed. According to Tables 1–10, it was observed that the proposed method in deterministic structure mode in 33-bus and 69-bus standard systems demonstrated superior performance in reducing the voltage deviation and power losses, as well as load balancing compared to other methods in two single and multi-objective modes.

References

[1] P. Mehta, P. Bhatt, and V. Pandya, "Optimal selection of distributed generating units and its placement for voltage stability enhancement and energy loss minimization," *Ain Shams Engineering Journal*, vol. 9, no. 2, pp. 187–201, 2018.

[2] W. Meng, X. Wang, and S. Liu, "Distributed load sharing of an inverter-based microgrid with reduced communication," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 1354–1364, 2018.

[3] S. Lu, H. Fang, and Y. Wei, "Distributed clustering algorithm for energy efficiency and load-balance in large-scale multi-agent systems," *Journal of Systems Science and Complexity*, vol. 31, no. 1, pp. 234–243, 2018.

[4] B. de Andrade and N. R. Ferreira, "Simulated annealing and tabu search applied on network reconfiguration in distribution systems," in *2018 Simposio Brasileiro de Sistemas Eletricos (SBSE)*, Niteroi, 2018, pp. 1–6.

[5] O. Chocron, E. Vega, and M. Benbouzid, "Dynamic reconfiguration of autonomous underwater vehicles propulsion system using genetic optimization," *Ocean Engineering*, vol. 156, pp. 564–579, 2018.

[6] W. Dahalan and H. Mokhlis, "Simultaneous Network Reconfiguration and Sizing of Distributed Generation," in *Electric Distribution Network Planning*, F. Shahnia, A. Arefi, G. Ledwich, Eds., Singapore, Springer, 2018, pp. 279–298.

[7] S. Huang and V. Dinavahi, "Fast distribution network reconfiguration with graph theory," *IET Generation, Transmission & Distribution*, vol. 12, no. 13, pp. 3286–3295, 2018.

[8] J. Salehi, M. R. Jannati Oskuee, and A. Amini, "Stochastics multi-objective modelling of simultaneous reconfiguration of power distribution network and allocation of DGs and capacitors," *International Journal of Ambient Energy*, vol. 39, no. 2, pp. 176–187, 2018.

[9] M. R. Kaveh, R. Hooshmand, and S. M. Madani, "Simultaneous optimization of re-phasing, reconfiguration and DG placement in distribution networks using BF-SD algorithm," *Applied Soft Computing*, vol. 62, pp. 1044–1055, 2018.

[10] A. Parizad, H. R. Baghaee, A. Yazdani, and G. B. Gharehpetian, "Optimal distribution systems reconfiguration for short circuit level reduction using PSO algorithm," in *2018 IEEE Power and Energy Conference at Illinois (PECI)*, Champaign, IL, USA, 2018, pp. 1–6.

[11] A. Zarei, Y. Mousavi, R. Mosalanezhad, and M. H. Atazadegan, "Robust voltage control in inverter-interfaced microgrids under plug-and-play functionalities," *IEEE Systems Journal*, vol. 14, no. 2, pp. 2813–2824, 2019.

[12] H. Fathabadi, "Power distribution network reconfiguration for power loss minimization using novel dynamic fuzzy c-means (dFCM) clustering based ANN approach," *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 96–107, 2018.

[13] P. Raoni, Z. Ñaupari, Y. Molina, and C. Castillo, "Radial distribution network reconfiguration for power losses reduction based on improved selective BPSO," *Electric Power Systems Research*, vol. 169, pp. 206–213, 2019.

[14] A. Azizivahed, H. Narimani, M. Fathi, E. Naderi, H. R. Safarpour, and M. R. Narimani, "Multi-objective dynamic distribution feeder reconfiguration in automated distribution systems," *Energy*, vol. 147, pp. 896–914, 2018.

[15] A. Kavousi-Fard and M. R. Akbari-Zadeh, "Reliability enhancement using optimal distribution feeder reconfiguration," *Neurocomputing*, vol. 106, pp. 1–11, 2013.

[16] F. Pazhoohesh, S. Hasanvand, and Y. Mousavi, "Optimal harmonic reduction approach for PWM AC–AC converter using nested memetic algorithm," *Soft Computing*, vol. 21, no. 10, pp. 2761–2776, 2017.

[17] A. Arab and Y. Mousavi, "Optimal control of wheeled mobile robots: from simulation to real world," in *2020 American Control Conference (ACC)*, Denver, CO, USA, 2020, pp. 583–589.

[18] Y. Mousavi and A. Alfi, "A memetic algorithm applied to trajectory control by tuning of fractional order proportional-integral-derivative controllers," *Applied Soft Computing*, vol. 36, pp. 599–617, 2015.

[19] Y. Mousavi and A. Alfi, "Fractional calculus-based firefly algorithm applied to parameter estimation of chaotic systems," *Chaos, Solitons & Fractals*, vol. 114, pp. 202–215, 2018.

[20] Y. Mousavi, A. Alfi, and I. B. Kucukdemiral, "Enhanced fractional chaotic whale optimization algorithm for parameter identification of isolated wind-diesel power systems," *IEEE Access*, vol. 8, pp. 140862–140875, 2020.

[21] S. Ramanathan, R. Karthikeyan, and M. Gupta, "Development of processing maps for Al/SiCp composite using fuzzy logic," *Journal of Materials Processing Technology*, vol. 183, no. 1, pp. 104–110, 2017.

[22] 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, 2009.

[23] A. Heidari, V. G. Agelidis, J. Pou, J. Aghaei, and A. Ghias, "Reliability-worth Analysis of Distribution Systems Using Cascade Correlation Neural Networks," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 412–420, 2018.

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