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Finding optimal reactive power dispatch solutions by using a novel improved stochastic fractal search optimization algorithm

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Abstract

In this paper, a novel improved Stochastic Fractal Search optimization algorithm (ISFSOA) is proposed for finding effective solutions of a complex optimal reactive power dispatch (ORPD) problem with consideration of all constraints in transmission power network. Three different objectives consisting of total power loss (TPL), total voltage deviation (TVD) and voltage stabilization enhancement index are independently optimized by running the proposed ISFSOA and standard Stochastic Fractal Search optimization algorithm (SFSOA). The potential search of the proposed ISFSOA can be highly improved since diffusion process of SFSOA is modified. Compared to SFSOA, the proposed method can explore large search zones and exploit local search zones effectively based on the comparison of solution quality. One standard IEEE 30-bus system with three study cases is employed for testing the proposed method and compared to other so far applied methods. For each study case, the proposed method together with SFSOA are run fifty run and three main results consisting of the best, mean and standard deviation fitness function are compared. The indication is that the proposed method can find more promising solutions for the three cases and its search ability is always more stable than those of SFSOA. The comparison with other methods also give the same evaluation that the proposed method can be superior to almost all compared methods. As a result, it can conclude that the proposed modification is really appropriate for SFSOA in dealing with ORPD problem and the method can be used for other engineering optimization problems.

Keywords: *objective function, optimal reactive power dispatch, stochastic fractal search, transmission power network*

Nomenclature

$Q_{Geni}^{\min}, Q_{Geni}^{\max}$	Lower and upper bounds of reactive power of the generator *i*
$Vol_{Geni}^{\min}, Vol_{Geni}^{\max}$	Lower and upper bounds of voltage of the generator *i*
$Q_{ci}^{\min}, Q_{ci}^{\max}$	Lower and upper bounds of capacitor bank at the bus *i*
$T_{i}^{\min}, T_{i}^{\max}$	Lower and upper bound of tap changer
$Vol_{loadi}^{\min}, Vol_{loadi}^{\max}$	Lower and upper bound of voltage at bus *i*
$S_{ij}^{\max}$	Capacity of branch *ij*
No_{bus}, No_{Gen}, No_{load} , No_c No_t	Number of all buses, generators, load buses, capacitor banks and transformers
P_{di}, Q_{di}	Real and reactive power of the load bus *i*
Sol_{rd1}, Sol_{rd2}, Sol_{rd3}	Randomly chosen solutions in the current population
λ, ω	Random number between zero and one
Sol_{best}	The best solution in population
Iter	Current iteration

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1. Introduction

Optimal reactive power dispatch (ORPD) is a kind of separate problem of optimal power flow (OPF) and considered as a traditional VAR rearrangement problem in power system. The ORPD is a non-convex, non-linear, non-smooth optimization problem and contains many objectives such as power losses of transmission lines, voltage deviation, and voltage stability index. The perfect mission of ORPD is to optimize the three forenamed objectives by adjusting the optimal control variables such as voltage of generation buses, positions of transformer tap and reactive power of compensator. At the same time, some parameters consisting of voltage of load buses, apparent power flow of transmission lines and reactive power of generators must be operated within predetermined limits [1, 2].

In the beginning of the 20th century, a series of methods called deterministic methods such as Newton approach (NP) [3], linear programming (LP) [4], an efficient dual simplex linear programming (ELP) [5], a different version of LP [6, 7], interior point method (IPM) [8], an efficient interior point approach (EIPA) [9], successive quadratic programming approach (SQPP) [10, 11], and dynamic programming approach (DPA) [12] have been proposed for solving the ORPD problem. These methods could find solutions in a short time and good solution quality could not be assured. In some special situations associated with a large system or more complicated constraints, their applicability is limited.

The mentioned difficulties created motivations for researchers to search for different solutions for handling the ORPD problem. A huge number of methods based on particle swarm optimization (PSO) such as original Particle Swarm Optimization PSO [13], Multiobjective Particle Swarm Optimization (MOPSO) [14], Comprehensive Learning Particle Swarm Optimization (CLPSO) [15], Hybrid Particle Swarm Optimization and Tabu Search (PSO-TS) [16], and improved PSO based on Pseudo Gradient search (IPG-PSO) [17] have been applied for optimal reactive power dispatch. Among these algorithms, IPG-PSO is the latest version of PSO proposed by Dieu at el. in 2016. In [17], the authors proposed two improvements by using chaotic sequences and a linearly decreasing inertia weighting factor and pseudo gradient theory. As a result, the proposed method has become strong and defeated other versions of PSO method.

Besides, a lots of Differential Evolution methods have been launched for optimizing objectives of ORPD problem involving first made Differential Evolution approach (DE) [18, 19], a combination of Ant System and Differential Evolution method (CAS-DE) [20], and a corporation of Double Differential Evolution Technique and Modified Teaching Learning Technique (CDET-MLT) [21]. In CAS-DE, mutation and selection operation of DE have been improved, becoming new ones. In the comer, the mutation factor has been replaced by the variable scaling mutation (VSM) to enlarge the variety of individuals. In the latter, a probabilistic state transition rule of the ant system is applied to get the best solutions. CDET-MTLT has been established from double differential evolution technique and modified teaching learning technique. Through IEEE 14, IEEE 30 and IEEE 118-bus systems, the performance of CDET-MTLT is outstanding in term of the best active power loss, the worst active power losses, the standard deviation, and average execution times when compared to other methods.

Further, some of the recent evolutionary methodologies like as conventional Genetic Algorithm (CGA) [22], Modified conventional Genetic Algorithm (MCEGA) [23], Improved NSGA-II (INSGA-II) [24], applying the simulated binary crossover in real coded Genetic Algorithm (SBCRCGA) [25] have been developed for ORPD. In addition to these methods above, some of approaches such as gravitational search optimization algorithm (GSOA) [26], Ant lion optimization method (ALOM) [27], Quasi-oppositional teaching learning based optimization method (QOTLBOM) [28], Teaching learning based optimization (TLBO) [28], Pooled-neighbor swarm intelligence technique (PNST) [29], combined Nelder–Mead simplex based firefly technique (CFA-NMS) [30], Chaotic krill herd based technique (CKHBA) [31], Artificial Bee Colony behavior based method (ABCBM) [32], Exchange market method (EMT) [33], Backtracking search optimization method (BTSOM) [34], and harmony search algorithm (HSA) [35] have been also promulgated to address ORPD problem. The appearance of these algorithms makes the number of the meta-heuristic method family increasingly expand as well as provides more solutions for dealing not only ORPD problem but also different problems in many engineering fields.

In this article, we propose a novel improved Stochastic Fractal Search optimization algorithm (ISFSOA) for dealing with all constraints of ORPD problem and obtaining three objectives. The proposed method is developed based on standard Stochastic Fractal Search optimization algorithm (SFSOA) by modifying the first new solution generation technique, diffusion technique. SFSOA was constructed by three process, diffusion and two other update processes [36] in which diffusion uses more time because it generates many new solutions. The proposed method performance is demonstrated via the implantation on IEEE 30-bus system with three study cases and comparisons with SFSOA and other methods.

2. Optimal Reactive Power Dispatch Problem Formulation

ORPD problem is considered to be a complicated problem in power system filed due to the presence of set of complex constraints from transmission grid and different single objectives such as power loss of all branches, sum of voltage deviation of all load buses and voltage stability index, L-index. The mathematical formulation of the considered problem is consisting of the expression of such objectives and the set of constraints. They are as follows:

2.1. Three Single Objectives

The target of such ORPD problem is to optimize technical issues together with benefit in which minimization of power loss in all branches is related to the saving of energy and maximum of benefit while minimizing total voltage deviation of all load buses and minimizing L index are two issues regarding power quality. Three objective are respectively shown in the three following equations:

$$Minimize\,\Delta P_{loss} = \sum_{i=1}^{No_{bus}} \sum_{\substack{j=1 \\ j\neq i}}^{No_{bus}} g_{ij} \left[Vol_i^2 + Vol_j^2 - 2Vol_i Vol_j \cos\left(\varphi_i - \varphi_j\right) \right] \tag{1}$$

$$\text{Minimize } TVD = \sum_{i=1}^{No_{load}} \left|1 - Vol_{loadi}\right| \tag{2}$$

$$\text{Minimize } L\,index = \max(L_i); i = 1, \ldots, No_{bus} \tag{3}$$

where g_{ij} is conductance of branch ij; φ_i and φ_j are voltage phase of bus i and bus j, respectively; Vol_{loadi} is voltage of load bus i; and L_i is the L index value of bus i determined by [16].

2.2. The Set of Complex Constraints

ORPD problem takes all constraints of electric components and other issues into account in aim to retain the stable operation of transmission grid. Constraints of all electric components are expressed in inequalities, which are imposed on the lower bound and upper bound of operating values. On the contrary, equality constraints are about balance of active and reactive power at each bus. Inequality constraints aim to restrict all components within safe condition while equality constraints keep the balance between source side and load side. The balance of source side and load side can be observed by the meaning of the two following models:

$$P_{Gi} - P_{di} - V_i \sum_{j=1}^{No_{bus}} V_j \left[b_{ij} \sin\left(\varphi_i - \varphi_j\right) + g_{ij} \cos\left(\varphi_i - \varphi_j\right) \right] = 0 \tag{4}$$

$$Q_{Gi} + Q_{ci} - Q_{di} + Vol_i \sum_{j=1}^{No_{bus}} Vol_j \left[b_{ij} \cos\left(\varphi_i - \varphi_j\right) - g_{ij} \sin\left(\varphi_i - \varphi_j\right) \right] = 0 \tag{5}$$

where b_{ij} is unreal term of admittance of branch ij.

In addition, important constraints regarding generators, transformers, load, capacitors and transmission branches are also taken into account. Basically, such components are constrained by the lowest operating value and the highest operating value, which can be observed by the following inequalities:

$$Q_{Geni}^{\min} \le Q_{Geni} \le Q_{Geni}^{\max};\ i = 1,...,No_{Gen} \tag{6}$$

$$Vol_{Geni}^{\min} \le Vol_{Geni} \le Vol_{Geni}^{\max};\ i = 1,...,No_{Gen} \tag{7}$$

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max};\ i = 1,...,No_{c} \tag{8}$$

$$T_{i}^{\min} \le T_{i} \ \le T_{i}^{\max};\ i = 1,...,No_{t} \tag{9}$$

$$Vol_{loadi}^{\min} \le Vol_{loadi} \le Vol_{loadi}^{\max};\ i = 1,...,No_{load} \tag{10}$$

$$S_{ij} \le S_{ij}^{\max} \tag{11}$$

3. The Proposed Algorithm

3.1. Original Stochastic Fractal Search Optimization Algorithm

SFSOA was developed in 2014 by Salimi [36] by carrying out two more update processes on fractal search algorithm (FSA). FSA is the original algorithm with the contribution of diffusion process and election but its performance was considered to be low and insignificant for complex optimization problem with discontinuous variables in search spaces [36]. SFSOA is more complicated than FSA due to the presence of the first and the second update processes; however, the search ability of SFSOA is significantly improved because the two proposed techniques can both exploit large spaces and scan local zones for avoiding missing effective solutions.

The diffusion process is the first step of SFSOA and it can be executed by applying either (12) or (13) depending on the result of comparison between a random number (ε) and a predetermined value (Pre). The two factors have the same range from zero to one but ε is randomly produced while Pre is selected by experience. If ε < Pre, (12) is selected and otherwise, (13) is employed. Clearly, if Pre is set to 1, approximately all solutions are produced by the function of (12). On the contrary, if Pre is selected to be zero, (13) is used all the time.

$$Sol_{k}^{new} = Gaussian(Sol_{best}, \beta) + \lambda(Sol_{best} - Sol_{k}) \tag{12}$$

$$Sol_{k}^{new} = Gaussian(Sol_{k}, \beta) \tag{13}$$

$$\beta = \left| \left(Sol_{k} - Sol_{best}\right) \frac{\log(Iter)}{Iter} \right| \tag{14}$$

After obtaining the set of new solutions, fitness function of each one is calculated and comparison between old and new ones are made in aim to keep more effective ones and abandon others. Next, the first update is performed for achieving the second new solutions. There is only one way for the second search by using such considered solution and two other random solutions. The model below is employed.

$$Sol_{k}^{new} = Sol_{rd1} - \lambda\left(Sol_{rd2} - Sol_{k}\right) \tag{15}$$

Similar to the diffusion process, selection operation is also applied for keeping potential solutions. Then, the kept solutions are newly updated by using the two following methods:

$$Sol_{k}^{new} = \begin{cases} Sol_{k}^{new} + \lambda\left(Sol_{rd1} - Sol_{rd2}\right) & if\ \omega > 0.5 \\ Sol_{k}^{new} - \lambda\left(Sol_{rd3} - Sol_{best}\right) & else \end{cases} \tag{16}$$

3.2. Improved Stochastic Fractal Search Optimization Algorithm (ISFSOA)

In the proposed ISFSOA method, we suggest improving diffusion process of SFSOA due to the low performance of original diffusion, which is performed by using either (12) or (13). It can be pointed out that (13) is a random walk around considered solution *k* by using Gaussian random walk. The equation produce new solutions not based on available solutions but Gaussian distribution is the main method. In ORPD problem, control variables have different ranges. For instance, tap changer of transformers and voltage of generators are around 1.0 while capacitors can be from zero to tens of MVAR. For the difference, Gaussian distribution cannot generate an effective step size around current solution k and found solutions are not of high quality. Consequently, in the improved method, we propose (13) should be cancelled and another better one is employed. In (12) sees that Gaussian distribution together with a step size (Sol_{best}-Sol_k) produce a step size and one solution nearby the best solution Sol_{best} is found. Obviously, the search strategy aim to exploit local zone nearby the current best solution. So, we propose another way for exploring large zone around all current solutions based on the following model:

$$Sol_k^{new} = Gaussian(Sol_k, \beta) + \lambda(Sol_{best} - Sol_k) + \lambda(Sol_{rd1} - Sol_k) \tag{17}$$

Now, either (12) or (17) is used for diffusion and selection condition should be established. At the beginning, we calculate fitness function of solution k, called $Fitness_k$ and then we calculate average fitness function of all solutions, called $Fitness_{mean}$. In case that $Fitness_k$ > $Fitness_{mean}$, the solution k is of low quality and search strategy should exploit around the current best solution. Thus, (12) should be used. For another case, i.e. $Fitness_{mean}$ < $Fitness_k$, the solution k is of high quality and search strategy should exploit around itself by using (17).

4. The Application of ISFSOA for Solving ORPD Problem

4.1. Generation of Initial Population

Before generation of initial population, a very important task of ORPD problem is to determine control variables, which are included in each solution. For better understanding of the selection, matpower 4.1 programming should be mentioned as a major factor of ORPD problem. The program is used to determine remaining variables of transmission grid such as voltage of all loads (Vol_{loadi}), power flow of all branches (S_{ij}) and reactive power of all generators (Q_{Geni}). However, input data of the program consist of voltage of all generators (Vol_{Geni}), tap changer of all transformer (T_i) and reactive power of all shunt capacitors (Q_{ci}). Consequently, each solution Sol_k is represented by Sol_k=[$Vol_{Gen1,k}$,…, $Vol_{GenNoG,k}$, $T_{1,k}$,…., $T_{NoT,k}$, $Q_{c1,k}$, …., Q_{cNoc}] and is randomly produced by using the model below:

$$Sol_k = Sol_{\min} + \lambda(Sol_{\max} - Sol_{\min}); \;\; k = 1, ..., N_{pop} \tag{18}$$

where Sol_{min} and Sol_{max} are lower bound and upper bound of all selected control variables.

4.2. Evaluation Function of Solutions

Evaluation function of solutions has very important role in finding promising solutions for ORPD problem. It is established by using single objective and penalty term [17]. All control variables in sol_k are given to matpower program for running and then objectives in (1), (2) or (3) can be obtained. In addition, dependent variables obtained by using matpower program are checked and penalized in fitness function. The typical fitness function of ORPD problem is formulated as follows [17]:

$$Fitness_k = Objective_k + Penalty_k \tag{19}$$

where $Fitness_k$ is the fitness function of solution k; $objective_k$ is the objective of the solution *k*; $Penalty_k$ is the penalty factor for dependent variables of the solution *k*.

4.3. Condition of Stopping Search Algorithm

The search of solution will be terminated in case current iteration (*Iter*) is equal to the maximum predetermined iteration (*G*).

5. Numerical Results

The section presents comparisons of result obtained by the proposed method together with SFSOA and other methods on three objectives of IEEE 30-bus system. The system consists of 6 generators, 24 loads, and 41 branches, 9 VAR compensators and 4 transformers [37]. For implementation, population size (Pop) and the maximum iteration (G) are set to 100 and 20 for three study cases. SFSOA and ISFSOA are coded on Matlab program and run fifty trials for each case on a computer with a 2.2-GHz processor and a 3-GB RAM.

5.1. Results Obtained on TPL Objective of IEEE-30 Bus System

The results in terms of the best TPL (MW) and standard deviation of all runs from two implemented and other methods are reported in Table 1. In addition, improvement percentage (in %) of the proposed ISFSOA over other ones is also reported in the table. The value of improvement in final column can show the superiority of ISFSOA over all methods. The improvement is from 0.16 to 8.63% corresponding to the second best and the worst method. Compared to SFSOA, the proposed method can improve the performance about 1.39% and approximately all runs of ISFSOA have lower TPL than those from SFSOA as observed from Figure 1. On the other hand, ISFSOA is also faster than other methods because it use smaller values for *Pop* and *G*. Thus, ISFSOA is really effective for the study case.

Table 1. Comparison of TPL Objective Obtained by Different Methods

Method	Min.	Std. dev.	*Pop*	*G*	Improvement (%)
PSO [16]	4.6862	-	-	-	3.67
TS [16]	4.9203	-	-	-	8.25
PSO-TS [16]	4.5213	-	-	-	0.16
ALO [27]	4.59		-	100	1.65
QOTLBOM [28]	4.5594	0.037	50	100	0.99
TLBO [28]	4.5629	0.0564	50	100	1.07
SGA [35]	4.9408	-	-	30,000	8.63
PSO [35]	4.9239	-	-	30,000	8.32
HSA [35]	4.9059	-	-	30,000	7.98
SFSOA	4.5777	1.05	20	100	1.39
ISFSOA	4.5142	0.012	20	100	

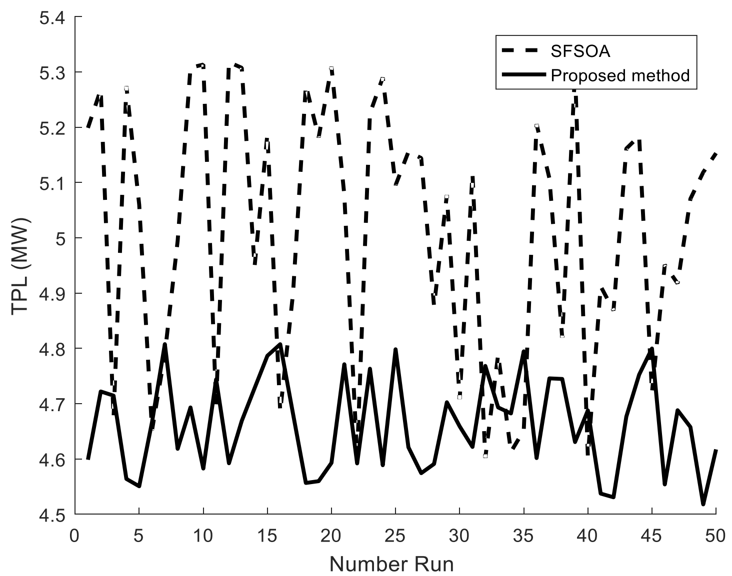

Figure 1. TPL of 50 runs obtained by SFSOA and the proposed method

5.2. Results Obtained on TVD Objective of IEEE-30 Bus System

Result comparisons for the case are shown in Table 2. The observation from final column can imply that the proposed method is the second best method, behind QOTLBOM [28]. The result improvement of ISFSOA over other ones can be from 0.22 to 56.88% and that is 27.05% for the comparison with SFSOA. The outstanding search of ISFSOA is also confirmed via Figure 2 of 50 runs. The standard deviation, Pop and G indicate that ISFSOA is more stable and faster than nearly all methods.

Table 2. Comparison of TVD Objective Obtained by Different Methods

Method	Min.	Std. dev.	Pop	*G*	Improvement (%)
PSO-TVIW [17]	0.1038	0.1112	20	200	14.26
PSO-TVAC [17]	0.2064	0.0153	20	200	56.88
SPSO-TVAC [17]	0.1354	0.0103	20	200	34.27
PSO-CF [17]	0.1287	0.0404	20	200	30.85
PG-PSO [17]	0.1202	0.0222	20	200	25.96
SWT-PSO [17]	0.1614	0.133	20	200	44.86
PGSWT-PSO [17]	0.1539	0.0656	20	200	42.17
IPG-PSO [17]	0.0892	0.0298	20	200	0.22
QOTLBOM [28]	0.0856	0.0314	10	200	-3.97
TLBO [28]	0.0913	0.0403	50	100	2.52
SFSOA	0.122	0.0155	20	100	27.05
ISFSOA	0.089	0.0031	20	100	0

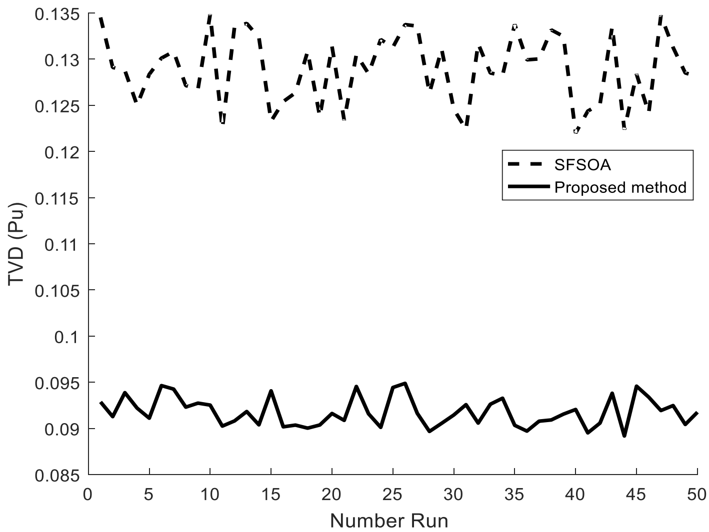

Figure 2. TVD of 50 runs obtained by SFSOA and the proposed method

5.3. Results Obtained on L Index Objective of IEEE-30 Bus System

Table 3 summarizes comparisons for L index objective. Improvement values indicate that there are some methods are superior to ISFSOA; however, the verification of optimal solutions in other studies confirmed that only IPG-PSO [17] and QOTLBOM [28] found better optimal solution. But, it should be noted that the two methods have used higher values for *Pop* and *G*. They are 20 and 200 for IPG-PSO [17] and 50 and 100 for QOTLBOM [28] but 20 and 100 for ISFSOA. Clearly, ISFSOA can be more effective than these methods. As compared to SFSOA, the proposed method can improve result up to 0.559% and all runs have better L index value as seen in Figure 3. All optimal solutions obtained by the proposed ISFSOA are reported in Table 4.

Table 3. Comparison of L index Objective Obtained by Different Methods

Method	Min.	Std. dev.	*Pop*	*G*	Improvement (%)
PSO-TVIW[17]	0.1258	0.0008	20	200	1.033
PSO-TVAC[17]	0.1499	0.0009	20	200	16.945
SPSO-TVAC[17]	0.1271	0.0006	20	200	2.046
PSO-CF[17]	0.1261	0.0008	20	200	1.269
PG-PSO[17]	0.1264	0.0008	20	200	1.503
SWT-PSO[17]	0.1488	0.0074	20	200	16.331
PGSWT-PSO[17]	0.1394	0.0081	20	200	10.689
IPG-PSO[17]	0.1241	0.001	20	200	-0.322
BA [27]	0.1191		40	100	-4.534
GWO [27]	0.118		40	100	-5.508
ABC [27]	0.1161		40	100	-7.235
ALOM [27]	0.1161	-	40	100	-7.235
QOTLBOM [28]	0.1242	0.0452	50	100	-0.242
TLBO[28]	0.1252	0.0454	50	100	0.559
SFSOA	0.1252	0.021	20	100	0.559
ISFSOA	0.1245	0.004	20	100	0

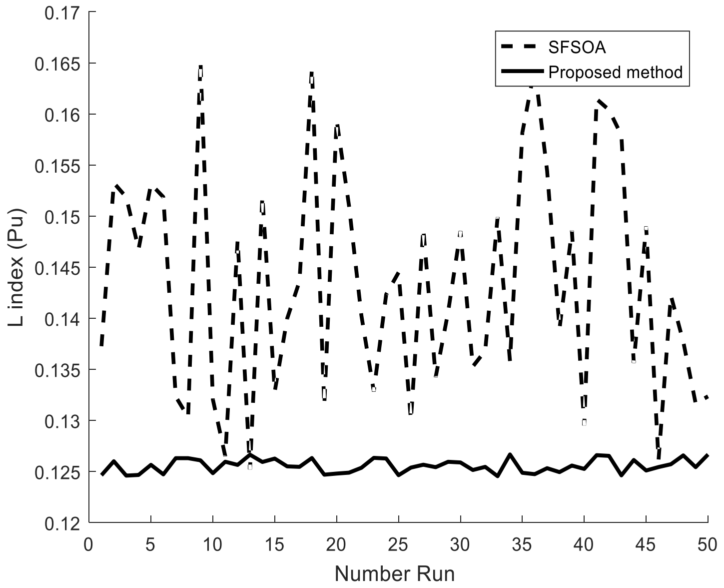

Figure 3. L index of 50 runs obtained by SFSOA and the proposed method

Table 4. Optimal solutions obtained by ISFSOA method

Control varialbes	TPL optimization case	TVD optimization case	L index objective
V_{g1}	1.1000	1.0182	1.1
V_{g2}	1.0942	1.0114	1.0952
V_{g5}	1.0750	1.0201	1.1
V_{g8}	1.0762	1.0091	1.1
V_{g11}	1.1000	0.9843	1.1
V_{g13}	1.1000	1.0093	1.1
$T_{6\text{-}9}$	1.0448	0.9979	1.1
$T_{6\text{-}10}$	0.9006	0.9017	0.9041
$T_{4\text{-}12}$	0.9790	0.983	0.9699
$T_{27\text{-}28}$	0.9685	0.9761	0.9659
Q_{c10}	5.0000	5	5
Q_{c12}	4.8187	3.1053	0.0723
Q_{c15}	4.4849	5	5
Q_{c17}	5.0000	0	2.1529
Q_{c20}	4.5755	4.99	5
Q_{c21}	4.9985	5	4.4906
Q_{c23}	2.6688	5	4.0909
Q_{c24}	4.9546	5	4.0361
Q_{c29}	2.3865	5	0

5. Conclusion

In the paper, we has proposed ISFSOA for finding optimal solutions of ORPD problem for different objectives of IEEE 30-bus system consisting of power loss, voltage deviation and L index. The obtained result comparisons between the two methods have indicated that the proposed method has found better solutions and its search stabilization has been superior to SFSOA. Thus, it can conclude that the proposed modification on diffusion process was highly effective. Comparisons with other methods available in other studies have shown potential search ability of the proposed method since it could obtain approximate or better results than other ones excluding some methods with invalid solutions and without reported solutions. As a result, the proposed method can be recommended to be an effective method for ORPD problem and it can be used for other problems in other engineering fields.

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