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Original scientific paper

New Metaheuristic Algorithms for Reactive Power Optimization

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Abstract: Optimal reactive power dispatch (ORPD) is significant regarding operating the practice safely and efficiently. The ORPD is beneficial to recover the voltage profile, diminish the losses and increase the voltage stability. The ORPD is a complicated optimization issue in which the total active power loss is reduced by detecting the power-system control variables, like generator voltages, tap ratios of tap-changer transformers, and requited reactive power, ideally. This study offers new approaches based on Shuffled Frog Leaping Algorithm (SFLA) and Tree Seed Algorithm (TSA) to solve the best ORPD. The results of the approaches are offered set against the current results studied in the literature. The recommended algorithms were tested by IEEE-30 and IEEE-118 bus systems to discover the optimal reactive power control variables. It was observed that the obtained results are more successful than the other algorithms.

Keywords: energy management; heuristic algorithms; load flow; optimization methods; reactive power control

1 INTRODUCTION

The problem of optimal power flow (OPF) is important and has been studied on through long ages. This issue needs to be developed for power system operators between OPF planning and operating. Several different methods have been used to figure out this problem. Reactive energy cost could be minimized by using optimal energy flow algorithms. It is possible to analyze the power dispatch under two titles such as ORPD and optimal real power dispatch. ORPD is a particular research item within the OPF. The primary target of ORPD is to determine the optimal settings of all control variables like generator reactive power outputs that minimize the loss of transmission line, transformer load tap changers and the output of shunt capacitors. Apart from this, the absolute value of total voltage fluctuations (TVD) or also voltage stability index (VSI) need to be changed during performance of the system restrictions.

Until today, many studies have been done in the literature to figure out the ORPD problem. Meta-intuitive algorithmic solutions are commonly seen in recent years besides mathematical programming techniques. Several classical methods such as gradient-based algorithms and various mathematical programming techniques are offered to resolve ORPD problems [1-3]. The hybrid approaches are used for the solution of ORPD besides the algorithms frequently utilized like ABC, GA, DE etc. [4-7]. Yapıcı et al., [8] proposed a new solution using the firefly (FF) algorithm. Ayan et al., [9] offered a new hybrid approach by adapting chaos theory to the ABC algorithm. A local search called Nelder-Mead (NM) algorithm is integrated with SFLA in [10] numbered study. The Gravity Search Algorithm (GSA) and GSA-based hybrid solutions are shown in [11-12] numbered studies. Chaotic Krill Herd Algorithm (CKHA) was obtained from [13] numbered article. The proposed algorithm in [13] achieves better results than other successful techniques in terms of the effectiveness and convergence rate. Khazali et al. mentioned that the results of harmony search algorithm (HSA) [14] are more reliable in comparison with other algorithms. Brett et al., [15] proposed the Alternating Direction Method of Multipliers method, which was used in conjunction with Quadratic Programming to remove voltage fluctuations in unbalanced situations. Several new methods are given in literature based on PSO [16-18].

The history of science is full of studies aimed at finding previously untried methods and improving the methods that have been tried before. Therefore, researchers are serving to enhance science by adding new techniques and methods to the scientific world. Now we will emphasize some of the techniques developed for the solution of ORPD. We have already mentioned that several techniques are discussed about the matter of ORPD solution. However, the multi-objective solution techniques [19-20] are frequently observed in recent years besides single-objective methods [21]. Numbered study point out the NSGA-II procedures for solving ORPD. PSO based multi-objective resolution methods, and the new understandings are given to literature via [22-23] numbered studies. A new Pareto multi-group search optimizer (SPMGSO) approach is presented as a new method in the study [24].

In addition to all the methods mentioned above, the studies that have been recently introduced in the literature have given different perspectives for the solution of the ORPD problem. According to the study in [25] the problem is solved by a nonlinear interval optimization (NIO) model in a microgrid where the wind turbine is integrated. Here, not only the optimum distribution target but also the deviation of it are taken into consideration. Therefore a multi-objective solution has been implemented. Hu et al. mentioned a distributed adaptive droop control method for optimal power dispatch on a DC micro-grid [26]. Kiefer-Wolfowitz procedure and Robbins-Monro algorithm combined with Truncated Algorithms have been proposed in another study [27].

Optimal reactive dispatch is also important for energy management strategies. Cimen et al. [28] propose a method to mitigate voltage unbalance by using demand side management. They use reactive power dispatch equations to find optimum bus for voltage sensitivity.

2 PROBLEM FORMULATION
2.1 ORPD

The ORPD is a linear and non-convergent optimization problem. The main objective of the ORPD problem is to reduce the active power value of the system;

to keep the value of the voltage within certain limits, and also to provide equality and inequality limits.

2.2 ORPD Problem Formulation

The ORPD problem is expressed as shown below.

$$\begin{array}{ll} \text{Min} & f(x,u) \\ \text{Subject to} & g(x,u), \\ & h(x,u) \end{array} \tag{1}$$

From the above expression, f is the aim function, g equality constraint and h is the power system operation limitation. In addition, u is a vector which is expressed as follows, independent control variable:

a- P_P is the active power output of the generator.
b- P_{P1} is the slack bus
c- V_P is the generator bus voltages
d- T is the transformer tap setting.
e- Q_c is the reactive power compensation value.

So, the u vector can also be stated as shown below:

$$u^T = \left[P_{P2} ... P_{PTg},\ V_{P1} ... V_{PTg},\ T_1 ... T_{Tt},\ Q_{C1} ... Q_{CTc} \right], \tag{2}$$

In here, T_g, T_t, and T_c respectively are the numbers of generating a system, transformer tap setting, and reactive shunt compensators. Besides, x is a vector and includes the dependent variables below:

a- P_{P1} is the active power output of the slack bus
b- V_L is the voltage of load bus
c- Q_P is the reactive power of the generator
d- S_L is the value of the transmission lines

$$x^T = \left[P_{P1},\ V_{L1} ... V_{LTpg},\ Q_{P1} ... Q_{PTg},\ S_{L1} ... S_{LT1} \right], \tag{3}$$

T_{pq} is the total of PQ buses and T_1 is the sum of the transmission lines.

2.3 Objective Functions

There are various target operations in various kinds of literature. However, the best accepted objective functions are discussed in this study.

2.3.1 Real Power Loss Reduction

The purpose of this process is to reduce the system's real power loss and the purpose is also defined as follows.

$$f_1 = \min(P_{RL}) = \sum_{k=1}^{N_{tl}} G_c \left(V_i^2 + V_j^2 - 2 V_i V_j \cos(\varphi_i - \varphi_j) \right), \tag{4}$$

In here, P_{RL} is the real power loss. G_c represents the line conductance between lines i and j. V_i and V_j respectively show the voltage degrees at bus i and bus j. φ_i and φ_j represent the bus voltage angles of bus i and bus j.

2.3.2 Recovering Voltage Profile

Voltage values of the system should not exceed the limits for the dependable activity of the power system. It is accepted just under these circumstances that the voltage deviation is acceptable constraint. The objective function is shown below:

$$f_2 = \sum_{i=1}^{N_{pq}} \left| V_i - 1{,}0 \right|, \tag{4}$$

In here, N_{pq} represents the total of the load busses. V_i represents the bus voltage of bus i.

2.3.3 Recovering the VSI

Increasing the losses of active and reactive power affects adversely the voltage of the system. The change in reactive power in the system causes a change in voltage stability. There is an inverse ratio between the L-index and the voltage stability. One of them is increasing, the other one is decreasing. The collapse point of the system is defined by the L-index. For this reason, it is very important to reduce the L-index. This is one of the main objectives of ORPD. L-index is defined as below:

$$\begin{bmatrix} I_P \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{PP} & Y_{PL} \\ Y_{LP} & Y_{PP} \end{bmatrix} \begin{bmatrix} V_P \\ V_L \end{bmatrix}, \tag{5}$$

I_P, I_L, and V_P, V_L are the current and voltage values of the generators and the load buses.

$$\begin{bmatrix} V_L \\ I_P \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LP} \\ K_{GL} & Y_{PP} \end{bmatrix} \begin{bmatrix} I_L \\ I_G \end{bmatrix}, \tag{6}$$

In Eq. (7) $F_{LP} = -\left[Y_{LL}\right]^{-1}\left[Y_{LP}\right]$ is expressed. The L-index of the j node is as below:

$$L_j = \left| 1 - \sum_{i=1}^{Tg} F_{ij} \frac{V_i}{V_j} \angle\left(\delta_{ij} + \varphi_i - \varphi_j \right) \right|, \tag{7}$$

Hereby, V_i and V_j respectively represent the magnitudes of voltage values of i and j buses (generator buses), δ_{ij} and φ_i respectively represent the phase angle of F_{ij} and phase angle of i generator voltage. T_{pq} is the PQ bus number. L-index is figured out for all load buses. As is stated above, the L-index value varies between 0-1 for load buses. Thus, L-index defines the voltage stability of the system. It can be explained as follows:

$$f_3 = L = \max(L_j) \qquad j = 1, 2, 3, ..., T_{pq}, \tag{8}$$

The smaller the rate of the L-index, the greater the value of the voltage stability. Consequently, L can be used as the voltage stability indicator. L-index should be increased for keeping the power system away from the negative events and balancing the voltage stability.

2.3.4 Constraints

The constraints acknowledged for ORPD problem are parity constraints and disparity constraints.

2.3.4.1 Parity Constraints

The parity constraints g and Eq. (10) - Eq. (11) which are one of the OPF equations are described below:

$$P_{Pi} - P_{Ki} - V_i \left(R_{ij} \cos(\varphi_i - \varphi_j) + B_{ij} \sin(\varphi_i - \varphi_j) \right) = 0, \quad i = 1, 2, 3, \ldots\ldots\ldots\ldots, T \tag{10}$$

$$Q_{Pi} - Q_{Ki} - V_i \left(R_{ij} \sin(\varphi_i - \varphi_j) + B_{ij} \cos(\varphi_i - \varphi_j) \right) = 0, \quad i = 1, 2, 3, \ldots\ldots\ldots\ldots, T \tag{11}$$

P_{Ki} is the active and Q_{Ki} is reactive power load point of the i. bus. R_{ij} is the real and B_{ij} is imaginary section of component i, j admittance bus matrix. V_i and V_j respectively are the voltage magnitudes of bus i and bus j; φ_i and φ_j respectively are the voltage angles of bus i and bus j.

2.3.4.2 Disparity Constraints

Generator constraints: The generator active power (P_P), generator reactive power (Q_P) and voltage magnitude (V_P) are limited by their lesser and higher constraints:

$$P_{Pi,\min} \le P_{Pi} \le P_{Pi,\max} \qquad i = 1, 2, 3, \ldots\ldots\ldots, N_T , \tag{12}$$

$$Q_{Pi,\min} \le Q_{Pi} \le Q_{Pi,\max} \qquad i = 1, 2, 3, \ldots\ldots\ldots, N_T , \tag{13}$$

$$V_{Pi,\min} \le V_{Pi} \le V_{Pi,\max} \qquad i = 1, 2, 3, \ldots\ldots\ldots, N_T , \tag{14}$$

Transformer restrictions: The transformer taps have maximum and minimum setting limits:

$$T_{i,\min} \le T_i \le T_{i,\max} \qquad i = 1, 2, 3, \ldots\ldots\ldots, N_t , \tag{15}$$

Adjustable VAR sources: The adjustable VAR sources have constraints below:

$$Q_{ci,\min} \le Q_{ci} \le Q_{ci,\max} \qquad i = 1, 2, 3, \ldots\ldots\ldots, N_c , \tag{16}$$

Security constraints: These constraints involve the load bus voltage angles and the limits on transmission line flow:

$$V_{Li,\min} \le V_{Li} \le V_{Li,\max} \qquad i = 1, 2, 3, \ldots\ldots\ldots, N_{pq} , \tag{17}$$

$$S_{Li,\min} \le S_{Li,\max} \qquad i = 1, 2, 3, \ldots\ldots\ldots, N_1 , \tag{18}$$

3 PROPOSED ALGORITHMS

Optimization problems are divided into two basic categories: continuous and discrete. In this study, shuffled frog leaping algorithm and tree seed algorithm which are continuous optimization methods are proposed. Aslan et al. [29] have mentioned in detail discrete optimization method. All algorithms run under the same conditions and the stopping criterion is determined as the number of function evaluations (FEs).

3.1 Shuffled Frog Leaping Algorithm (SFLA)

Eusuff et al. [30] offered a memetic-based approach in their SFLA study by inspiring from the movements of the frogs in nature. The SFLA is a population-based meta-heuristic algorithm influenced by the natural memetics. This algorithm provides exchange information from one individual to another in the local search space by using the memetic evolutions. Eusuff et al. pointed out in their research that they reached general best with the information change between the individuals via the shuffling feature in SFLA.

A specific number of frogs in memeplex are included in the memetic evolution in each iteration of memetic evolution phase. The triangular probability distribution equality in Eq. (19) was used to decide on which frogs need to be selected in memetic evolution phase.

$$P_i = \left(\frac{2(n+1-i)}{n(n+1)} \right) \qquad i = 1, \ldots\ldots\ldots, n , \tag{19}$$

Step 1. Set the parameters of algorithms
Set the number of memeplex (m) and frogs in an memeplex(n)
Set the number of the frogs in the sub-memepex (q)
Generate a population in solution space (P)
Calculate fitness for every individual in P
Sort the population with their fitness by descending order
Select the best solution (Gbest)
Step 2. Searching process
Divide the population into m memeplex
FOR every memeplex
FOR j=1 to sub-iteration
Select the q frog from the current memeplex to the sub-memeplex
Find the best and worst frogs in the sub-memeplex
Calculate a new position for the worst frog with best frog in sub-memeplex
IF the new position of he frog is better than current
Update the worst frog
ELSE
Calculate a new position for the worst frog with Gbest
IF the new position of the frog is better than current frog
Update the worst frog
ELSE
Generate a random frog
Update the worst frog
END IF
END IF
END FOR
END FOR
Step 3. Shuffled population
Combine the memeplexes into P
Sort the population with their fitness by descending order
Select the best solution (Gbest)
Step 4. Check the termination condition
IF termination condition is met
Report the best solution
ELSE
Then go to step 2.
END IF

Figure 1 Shuffled Frog Leap Algorithm pseudo code

The number of q frogs were selected for the sub-memeplex based on the selection probability with a roulette wheel. After the memetic evolution step is completed for each memeplex group, the frogs are shuffled in one population. The cost values of each frog were recalculated and the population was ranked from the best frog to the worst one. In SFLA, All frogs are sharing the information in both the memeplex group and at the end of the iteration. This feature of SFLA provides both local and global search. The pseudo code of the SFLA is shown in Fig. 1.

Eq. (20) or Eq. (21) were used for update the position of the worst frog (P_w) in SFLA. Firstly, Eq. (20) was used as the base when the new status of the P_w was computed. The cost is accounted for the new frog created. If the best frog (P_b) in the sub-memlex cannot find a better position for P_w, the location of the worst frog is revised with the parity Eq. (21). If the global best frog (P_g) cannot find a better position for the worst frog, a random frog is generated instead of P_w within bound values.

$$X_w^{i+1} = P_w^i + rand(\ )\left(P_b^i - P_w^i\right), \tag{20}$$

$$X_w^{i+1} = P_w^i + rand(\ )\left(P_g^i - P_w^i\right), \tag{21}$$

In another study, Aslan [31] modified the original SFLA algorithm to solve discrete optimization problems. Aslan used two-point crossover and single mutation operators of the GA instead of Eq. (20) and Eq. (21) in original SFLA structure when updating the position of the worst frog. Here, a similar approach of original SFLA is being used. Firstly, for position update process Eq. (20) is used and if the new position is better than P_w, then it is replaced by the new position. Otherwise, Eq. (21) is used for position update process of P_w. But if position update process with P_g does not reach a better position for the worst frog a random individual has been generated instead of P_w.

3.2 Tree Seed Algorithm (TSA)

The Tree seed algorithm is a nature-influenced meta-heuristic algorithm by Kiran [32] to answer the continuous optimization questions. Tree Seed Algorithm code was shown in Fig. 2.

In Tree seed algorithm, each tree represents a parent individual. Each seed represents the child individual consisting the parent tree. In TSA, if the quality of the information of the seed is better than its own tree, the position of the tree is updated by putting the seed instead of the position of the parent tree. In TSA, in each iteration, the number of seed ( ) was selected randomly between 1 and the number of population. The global best individual and the parent individual which is the randomly chosen candidate solution from the population other than the tree current itself, are used for generating positions for the seeds. The Eq. (22) and Eq. (23) were used to create process of seeds. Each dimension of the seed was updated with Eq. (22) or Eq. (23). The Search Tendency (ST) parameter was used for determining which equation would be used for the dimension update process.

The selection process for each dimension was realized as follows;

i. Firstly, a random value was generated between zero and one. If the random value is smaller than the ST, the relevant dimension is updated according to Eq. (22). If the random value is bigger than the ST, this relevant dimension is updated according to Eq. (23).
ii. The *ParentTree* represents the tree which is getting update; *i* is indis of the seed created from the *ParentTree, BestTree* indicates the best tree in population. *Trees* represent the tree-population as a whole; *r* value represents the index of the tree selected randomly and the *rand* value shows a random value between zero and one.

$$Seed_{i,j} = ParentTree_j + 2\left(BestTree_j - Trees_{r,j}\right)\left(rand - 0,5\right), \tag{22}$$

$$Seed_{i,j} = ParentTree_j + 2\left(ParentTree_j - Trees_{r,j}\right)\left(rand - 0,5\right), \tag{23}$$

Step 1. The initialization of the algorithm
Set the number of population size (N).
Set the ST parameter for the method
Set the dimensionality for the method (D).
Decide the termination condition
Generate N random tree location on the D-dimensional search space
Evaluate the tree location using objective function specified for the problem
Select the best solution (B)
Step 2. Searching with Seeds
FOR all trees
Decide the number of seeds produced for this tree.
FOR all seeds
FOR all dimension
IF (rand<ST)
Update this dimension using Eq. (22) (S)
ELSE
Update this dimension using Eq. (23) (S)
END IF
END FOR
END FOR
Select the best seed and compare it with the tree
If the seed location is better than tree location, the seed substitutes for this tree
END FOR
Step 3. Selection of Best Solution
Selection of the best solution of the population
If new best solution is better than the previous best solution, new best solution is substituted for the previous best solution
Step 4. Testing Termination Condition
If the termination condition is not met, go to Step 2.
Step 5. Reporting
Report the best solution

Figure 2 Algorithmic framework of TSA

4 IEEE-30 BUS TEST SYSTEM

The IEEE-30 bus test system is utilized to confirm and compare the efficiency and productivity of the algorithms suggested.

Table 1 Comparisons of Simulation Results of Different Algorithms for IEEE-30 Bus Power System

Variables	ABC	GSA	PSO-TVAC	WOA	**TSA**	**SFLA**
Generator Voltage (p.u)						
V1	1,1000	1,0716	1,0971	1,1000	1,1000	1,0956
V2	1,0615	1,0221	1,0876	1,0963	1,0940	1,0912
V5	1,0711	1,0400	1,0658	1,0789	1,0724	1,0795
V8	1,0849	1,0507	1,0700	1,0774	1,0735	1,0703
V11	1,1000	0,9771	1,0669	1,0955	1,1000	1,0848
V13	1,0665	0,9676	1,0995	1,0929	1,0992	1,0998
Transformer tap ratio						
T6-9	0,97	1,0984	0,9757	0,9936	1,0060	0,9845
T6-10	1,05	0,9824	0,9269	0,9867	0,9796	1,0205
T4-12	0,99	1,0959	0,9996	1,0214	0,9980	0,9876
T28-27	0,99	1,0585	0,9648	0,9867	0,9745	1,0083
Capacitor banks (MVAR)						
Qc-10	5	1,6537	1,0303	3,1695	2,8322	3,9654
Qc-12	5	4,3722	3,2628	2,0477	3,8728	3,6506
Qc-15	5	0,1199	4,4982	4,2956	4,8250	3,9852
Qc-17	5	2,0876	4,6258	2,6782	4,5574	4,4745
Qc-20	4,1	0,3577	1,4852	4,8116	4,5596	4,0074
Qc-21	3,3	0,2602	4,5480	4,8163	4,4670	4,7678
Qc-23	0,9	0,0000	3,5751	3,5739	4,1538	3,1475
Qc-24	5	1,3839	4,6527	4,1953	4,0072	4,2052
Qc-29	2,4	0,0003	3,2407	2,0009	3,0106	3,9546
Results						
Ploss (MW)	4,602	4,514	4,646	4,594	**4,572**	**4,686**
Reduction (%)	20,81	22,33	20,06	20,95	**21,33**	**19,37**

Comparison of simulation results of different algorithms is shown in Tab. 1 and Tab. 2 shows the range of variable constraints. There are 6 generators, 4 transformers and 9 shunt reactive compensation buses in the 30 bus system. There are 19 control variables in IEEE-30 bus test system. The penalty function approach is utilized to control the parameters in max and min limits. The max or min limits of the parameters are brought together to convert the discontinuous variables to continuous variables.

The results obtained by using TSA and SFLA algorithms were compared with other results in the literature. When the system operates without using any optimization method, the power loss is 5,812 MW. The goal is to minimize this loss with optimization methods.

The first four algorithms were shown in Tab. 1 above (ABC, GSA, PSO-TVAC, WOA) were taken from [33]. When the obtained results were examined, it is seen that TSA and SFLA algorithms give successful results. The reduction values are compared to the value of 5,812 MW. The constraints variables for IEEE-30 bus test system were given in Tab. 2.

Table 2 Constraints of Varıables for IEEE-30Bus Test System

Variable Costraints	Minimum Limit(pu)	Maximum Limit(pu)
Voltages for generator bus V_g	0,9	1,1
Voltages for load bus V_L	0,9	1,1
Tap setting T	0,9	1,1
Shunt compensators Q_c	0	0,05

5 IEEE-118 BUS TEST SYSTEM

In this study, a larger power system was required to test the performance of the developed algorithms. A standard IEEE-118bus test system was used for this purpose.

There were 186 transmission lines, 64 load buses, 54 generator buses, 14 reactive power supply, 9 transformers in this system. Here, 77 control variables, including generator buses, reactive power sources and transformers tap settings were used for comparison purposes. In Tab. 3 the maximum and minimum limits of control variables were given.

Table 3 Constraints of Varıables for IEEE-118 Bus Test System

Variable Costraints	Minimum Limit(pu)	Maximum Limit(pu)
Voltages for generator bus V_g	0,95	1,05
Voltages for load bus V_L	0,95	1,05
Tap setting T	0,9	1,1
Shunt compensators Q_c	See in [34]	

Table 4 Comparisons of Simulation Results of Different Algorithms for IEEE-118 Bus Power System

Varibles	OGSA	ABC	GWO	ALO	**TSA**	**SFLA**
Generator Voltage (p.u)						
V1	1,0350	1,0250	0,9960	1,0164	1,0140	1,0001
V4	1,0554	1,0440	1,0510	1,0299	1,0355	1,0242
V6	1,0301	1,0320	1.0480	1,0355	1,0250	1,0321
V8	1,0175	1,0240	0,9880	1,0247	1,0477	1,0365
V10	1,0250	1,0600	1,0250	1,0469	1,0500	1,0541
V12	1,0410	1,0320	1,0210	1,0259	1,0201	1,0186
V15	0,9973	0,9950	0,9860	1,0526	1,0000	0,9996
V18	1,0047	0,9710	0,9720	1,0580	1,0005	0,9999
V19	0,9899	0,9830	0,9820	1,0565	1,0000	0,9969
V24	1,0287	1,0050	1,0310	1,0549	1,0219	1,0186
V25	1,0600	1,0300	1,0600	1,0600	1,0500	1,0423
V26	1,0855	0,9770	1,0140	1,0457	1,0498	1,0500
V27	1,0081	1,0060	1,0240	1,0583	1,0070	0,9998
V31	0,9948	0,9920	0,9980	1,0573	1,0000	0,9924
V32	0,9993	1,0030	1,0190	1,0455	1,0002	1,0017
V34	0,9958	1,0310	1,0200	1,0322	1,0205	1,0196

Table 4 Comparisons of Simulation Results of Different Algorithms for IEEE-118 Bus Power System (continuation)

Varibles	OGSA	ABC	GWO	ALO	**TSA**	**SFLA**
V36	0,9835	1,0270	1,0130	1,0264	1,0190	1,0214
V40	0,9981	0,9850	1,0390	1,0124	0,9998	1,0024
V42	1,0068	0,9770	1,0210	1,0321	1,0060	1,0035
V46	1,0355	1,0230	0,9930	1,0446	1,0212	1,0183
V49	1,0333	1,0350	1,0420	1,0572	1,0369	1,0451
V54	0,9911	1,0080	1,0490	1,0313	1,0080	1,0110
V55	0,9914	0,9980	1,0340	1,0305	1,0055	1,0100
V56	0,9920	1,0040	1,0430	1,0292	1,0070	1,0015
V59	0,9909	1,0350	1,0450	1,0269	1,0355	1,0239
V61	1,0747	1,0360	0,9870	1,0373	1,0400	1,0306
V62	1,0753	1,0370	0,9910	1,0217	1,0360	1,0400
V65	0,9814	1,0410	1,0230	1,0582	1,0498	1,0480
V66	1,0487	1,0600	1,0540	1,0591	1,0500	1,0475
V69	1,0490	1,0120	1,0060	1,0600	1,0486	1,0414
V70	1,0395	1,0520	0,9780	1,0577	1,0075	0,9999
V72	0,9900	1,0150	1,0070	1,0592	1,0080	1,0000
V73	1,0547	1,0390	1,0360	1,0348	1,0028	1,0203
V74	1,0167	1,0140	0,9730	1,0533	0,9985	1,0046
V76	0,9972	1,0360	0,9980	1,0382	0,9995	1,0095
V77	1,0071	1,0230	0,9830	1,0395	1,0240	1,0312
V80	1,0066	1,0280	1,0090	1,0508	1,0380	1,0400
V85	0,9893	1,0180	0,9930	1,0529	1,0470	1,0325
V87	0,9693	1,0240	1,0540	1,0510	1,0215	1,0178
V89	1,0527	1,0250	1,0380	1,0600	1,0500	1,0452
V60	1,0290	0,9960	1,0070	1,0382	1,0095	1,0223
V91	1,0297	1,0380	1,0060	1,0223	1,0105	1,0092
V92	1,0353	1,0130	1,0130	1,0532	1,0390	1,0238
V99	1,0395	1,0160	1,0170	1,0447	1,0295	1,0385
V100	1,0275	1,0300	1,0020	1,0445	1,0305	1,0263
V103	1,0158	1,0530	1,0050	1,0385	1,0211	1,0156
V104	1,0165	1,0210	1,0000	1,0218	1,0082	1,0298
V105	1,0197	1,0080	1,0000	1,0376	1,0278	1,0157
V107	1,0408	1,0240	0,9750	1,0285	1,0150	0,9994
V110	1,0288	0,9800	1,0120	1,045	1,0125	1,0200
V111	1,0194	0,9980	0,9990	1,0254	1,0052	1,0210
V112	1,0132	1,0050	1,0020	1,0275	1,0065	1,0000
V113	1,0386	1,0010	0,9780	1,0567	1,0055	0,9997
V116	0,9724	1,0190	1,0190	1,0577	1,0500	1,0423
Transformer Tap Ratio						
T8–5	0,9568	0,97	0,96	1,00	0,9998	0,99
T26–25	1,0409	0,95	1,01	0,99	1,0500	1,00
T30–17	0,9963	1,00	0,92	1,00	1,0198	1,03
T38–37	0,9775	1,02	1,02	1,01	1,0050	1,01
T63–59	0,9560	1,02	0,98	1,03	0,9995	1,00
T64–61	0,9956	0,93	1,02	1,02	1,0182	1,01
T65–66	0,9882	0,94	0,96	0,97	0,9605	0,94
T68–69	0,9251	0,95	1,01	0,94	0,9698	0,94
T81–80	1,0661	0,99	0,94	1,00	1,0015	1,00
Capacitor Banks (MVAR)						
QC-5	-5	-33	19,32	-9	-0,1	-15
QC-34	4,8	8	10	6	9	10
QC-37	-24,9	0	-13	-19	-0,1	-15
QC-44	3,28	7	6	3	10	6
QC-45	3,83	7	7	6	10	7
QC-46	5,45	4	6	5	6	4
QC-48	1,81	9	6	9	8,5	8
QC-74	5,09	10	6	7	5,8	8
QC-79	11,04	12	6	6	20	12
QC-82	9,65	11	13	12	19,9	12
QC-83	2,63	8	4	6	10	6
QC-105	4,42	4	7	4	4	4
QC-107	0,85	2	4	3	1	2
QC-110	1,44	3	2	3	1	2
Results						
Ploss (MW)	126,99	120,42	131,26	119,78	**119,54**	**121,72**

The results obtained using TSA and SFLA algorithms are compared with other results in the literature. The first four algorithms shown in Tab. 4 (OGSA, ABC, GWO, and ALO) were taken from [35]. When the obtained results are examined, it is seen that TSA is most successful and powerful algorithm The TSA algorithm, with an active power loss value of **119,543 (MW)**, achieved more successful results than the algorithms which we compared. The SFLA algorithm gave a satisfactory result, but not better than TSA. It can be said that TSA is useful algorithm to analyze IEEE-118 bus system.

6 CONCLUSION

ORPD is an important problem that must be solved to reduce the active power loss value. Until now, many methods and algorithms have been used to solve this problem. As the possible methods of literature come out, best solutions for the ORPD problem will be tried. In this study, new algorithms, TSA and SFLA algorithm were adapted for this problem. The success of these algorithms was evaluated by assessing in IEEE-30 and IEEE-118 bus systems. The conclusions obtained were compared with different algorithms which are frequently used in literature. The shuffled frog leaping algorithm and tree seed algorithms are firstly used for this problem. Despite giving the best result with GSA in the IEEE-30 bus test system, TSA gave the second best result. According to the results obtained in the IEEE-118 bus test system, the best result belongs to TSA algorithm with a loss value of 119,543 MW. SFLA has shown successful results in both test systems. According to the results, it can be said that the TSA algorithm is more successful in larger systems. Each algorithm has been run twenty times. The final result is given by averaging the results obtained from twenty runs. It is found about these conclusions that the most fruitful and new one for the literature is the TSA. New methods can be developed to solve this problem to reduce active power losses.

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