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 required 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]. Yapici 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 effectivenes 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.

\[
\begin{align*}
\text{Min} & \quad f(x,u) \\
\text{Subject to} & \quad g(x,u), \\
& \quad h(x,u)
\end{align*}
\]

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:

\( \text{a- } P_P \) is the active power output of the generator.
\( \text{b- } P_{T1} \) is the slack bus
\( \text{c- } V_P \) is the generator bus voltages
\( \text{d- } T \) is the transformer tap setting.
\( \text{e- } Q_L \) is the reactive power compensation value.

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

\[
u^T = \begin{bmatrix} \sum_{i=1}^{N_{pq}} P_{Tg} \cdot T_{pq} \cdot V_{pq} \cdot V_{pq} \cdot T_{pq} \cdot Q_{Cl} \cdot Q_{Ctc} \end{bmatrix},
\]

In here, \( T_{pq} \), \( T_{pq} \), and \( T \) 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:

\( \text{a- } P_{T1} \) is the active power output of the slack bus
\( \text{b- } V_L \) is the voltage of load bus
\( \text{c- } Q_P \) is the reactive power of the generator
\( \text{d- } S_L \) is the value of the transmission lines

\[
x^T = \begin{bmatrix} P_{T1}, V_{L1} \cdot V_{L1} \cdot T_{pq}, Q_{Cl} \cdot Q_{Ctc}, S_{L1} \cdot S_{L1} \cdot T_{pq} \end{bmatrix},
\]

\( T_{pq} \) 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.

\[
f_1 = \min(P_{RL}) = \sum_{k=1}^{N_{pq}} G_k \left( V_i^2 + V_j^2 - 2V_i V_j \cos(\phi_i - \phi_j) \right),
\]

In here, \( P_{RL} \) is the real power loss. \( G_k \) represents the line conductance between lines \( i \) and \( j \). \( V_i \) and \( V_j \) respectively show the voltage degrees at bus \( i \) and bus \( j \). \( \phi_i \) and \( \phi_j \) 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:

\[
f_2 = \sum_{i=1}^{N_{pq}} |V_i - 1|, \quad (4)
\]

In here, \( N_{pq} \) represents the total of the load buses. \( V_i \) 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:

\[
\begin{align*}
&\begin{bmatrix} I_P \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{pp}, Y_{pl} \\ Y_{lp}, Y_{pp} \end{bmatrix} \begin{bmatrix} V_P \\ V_L \end{bmatrix},
\end{align*}
\]

\[
\begin{align*}
&\begin{bmatrix} V_L \end{bmatrix} = \begin{bmatrix} Z_{LL}, F_{LP} \end{bmatrix} \begin{bmatrix} I_L \end{bmatrix},
\end{align*}
\]

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

\[
L_{ij} = 1 - \sum_{i=1}^{N_{pq}} \frac{F_{ij} V_i}{V_j} \angle(\delta_i - \phi_i - \phi_j), \quad (7)
\]

Hereby, \( V_i \) and \( V_j \) respectively represent the magnitudes of voltage values of \( i \) and \( j \) buses (generator buses), \( \delta_i \) and \( \phi_i \) 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:

\[
f_3 = L = \max(L_{ij}) \quad j = 1, 2, 3, \ldots, T_{pq},
\]

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 described below the OPF equations are described below:

\[
P_{Pi} - P_{Ki} - V_i \left( R_{ij} \cos(\phi_i - \phi_j) + B_{ij} \sin(\phi_i - \phi_j) \right) = 0, \quad i = 1, 2, 3, \ldots, T
\]

\[
Q_{Pi} - Q_{Ki} - V_i \left( R_{ij} \sin(\phi_i - \phi_j) + B_{ij} \cos(\phi_i - \phi_j) \right) = 0, \quad i = 1, 2, 3, \ldots, T
\]

\( P_{Ki} \) is the active and \( Q_{Ki} \) is reactive power load point of the \( i \). \( R_{ij} \) 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 \( j \); \( \phi_i \) and \( \phi_j \) respectively are the voltage angles of bus \( i \) and bus \( j \).

2.3.4.2 Disparity Constraints

Generator constraints: The generator active power \( (P_i) \), generator reactive power \( (Q_i) \) and voltage magnitude \( (V_i) \) are limited by their lesser and higher constraints:

\[
P_{Pi,\min} \leq P_i \leq P_{Pi,\max} \quad i = 1, 2, 3, \ldots, N_T,
\]

\[
Q_{Pi,\min} \leq Q_i \leq Q_{Pi,\max} \quad i = 1, 2, 3, \ldots, N_T,
\]

\[
V_{Pi,\min} \leq V_i \leq V_{Pi,\max} \quad i = 1, 2, 3, \ldots, N_T
\]

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

\[
T_{i,\min} \leq T_i \leq T_{i,\max} \quad i = 1, 2, 3, \ldots, N_T
\]

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

\[
Q_{ci,\min} \leq Q_c \leq Q_{ci,\max} \quad i = 1, 2, 3, \ldots, N_c
\]

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

\[
V_{Li,\min} \leq V_L \leq V_{Li,\max} \quad i = 1, 2, 3, \ldots, N_{pq}
\]

\[
S_{Li,\min} \leq S_{Li,\max} \quad i = 1, 2, 3, \ldots, N_{1}
\]

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 inspiriting 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.

\[
P_i = \left( \frac{2(n+1-i)}{n(n+1)} \right) \quad i = 1, \ldots, n
\]

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-memeplex (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.
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 ($P_s$) in the sub-memplex 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.

\[
X_{w}^{t+1} = P_w^t + \text{rand}(P_g^t - P_w^t), \quad (20)
\]

\[
X_{w}^{t+1} = P_w^t + \text{rand}(P_g^t - P_w^t), \quad (21)
\]

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 dimension is updated according to Eq. (23).

ii. The ParentTree represents the tree which is getting update; $i$ is index of the seed created from the ParentTree. BestTree indicates the best tree in population. Trees represent the tree-population as a whole; $v$ value represents the index of the tree selected randomly and the rand value shows a random value between zero and one.

\[
\text{Seed}_{ij} = \text{ParentTree}_i + 2(\text{BestTree}_j - \text{Trees}_{i,j})(\text{rand} - 0.5), \quad (22)
\]

\[
\text{Seed}_{ij} = \text{ParentTree}_i + 2(\text{ParentTree}_j - \text{Trees}_{i,j})(\text{rand} - 0.5), \quad (23)
\]

#### 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 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 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

#### 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 | 1.0956 |
| V2                    | 1.0615 | 1.0221 | 1.0876 | 1.0963 | 1.0940 |
| V3                    | 1.0711 | 1.0400 | 1.0658 | 1.0789 | 1.0724 |
| V4                    | 1.0849 | 1.0507 | 1.0700 | 1.0774 | 1.0735 |
| V5                    | 1.1000 | 0.9771 | 1.0669 | 1.0955 | 1.1000 |
| V6                    | 1.0665 | 0.9676 | 1.0995 | 1.0929 | 1.0992 |
| Transformer tap ratio   |     |     |          |     |     |      |
| T6-9                  | 0.97 | 0.9984 | 0.9937 | 1.0060 | 0.9845 |
| T6-10                 | 1.05 | 0.9824 | 0.9269 | 0.9867 | 0.9796 |
| T4-12                 | 0.99 | 1.0959 | 0.9996 | 1.0214 | 0.9980 |
| T28-27                | 0.99 | 1.0595 | 0.9648 | 0.9867 | 0.9745 |
| Capacitor banks (MVAR) |     |     |          |     |     |      |
| Qc-10                 | 5   | 1.6537 | 1.0303 | 3.1695 | 2.8322 |
| Qc-12                 | 5   | 4.3722 | 3.2628 | 2.0477 | 3.8728 |
| Qc-15                 | 5   | 0.1199 | 4.4982 | 2.9596 | 4.8250 |
| Qc-17                 | 5   | 2.0876 | 4.6258 | 2.6782 | 4.5574 |
| Qc-20                 | 4.1 | 0.3577 | 1.4852 | 4.8116 | 4.5596 |
| Qc-21                 | 3.3 | 0.2602 | 4.5480 | 4.8163 | 4.4670 |
| Qc-23                 | 0.9 | 0.0000 | 3.5751 | 3.5739 | 4.1538 |
| Qc-24                 | 5   | 1.3839 | 4.6527 | 4.1953 | 4.0072 |
| Qc-29                 | 2.4 | 0.0003 | 3.2407 | 2.0009 | 3.0106 |

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 Variables for IEEE-30 Bus Test System

| Variable Constraints | 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 $Q_s$ | 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-118 bus 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 Variables for IEEE-118 Bus Test System

| Variable Constraints | 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 $Q_s$ | See in [34] |

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

| Variables | OGSA | ABC | GWO | ALO | TSA | SFLA |
|-----------|------|-----|-----|-----|-----|------|
| Generator Voltage (p.u) | | | | | | |
| V1 | 1.0550 | 1.0250 | 0.9960 | 1.0164 | 1.0140 | 1.0001 |
| V4 | 1.0554 | 1.0440 | 1.0510 | 0.4299 | 0.3355 | 0.2520 | 0.3221 |
| V6 | 1.0301 | 1.0320 | 0.4800 | 0.3355 | 0.2520 | 0.3221 |
| V8 | 1.0175 | 0.2240 | 0.9880 | 0.2477 | 0.4777 | 0.3653 |
| V10 | 1.0250 | 0.6000 | 0.6250 | 0.4669 | 0.5000 | 0.5041 |
| V12 | 1.0410 | 0.3200 | 0.2100 | 0.2529 | 0.2021 | 0.1826 |
| V15 | 0.9973 | 0.9950 | 0.9800 | 0.5250 | 0.5000 | 0.5000 |
| V18 | 1.0477 | 0.7170 | 0.7200 | 0.5820 | 0.5000 | 0.9999 |
| V19 | 0.9899 | 0.9830 | 0.9820 | 0.5065 | 0.5000 | 0.9969 |
| V24 | 1.0287 | 0.0300 | 0.1030 | 0.5219 | 0.1826 |
| V25 | 1.0600 | 0.3000 | 1.0600 | 0.3000 | 0.3000 | 0.4023 |
| V26 | 1.0655 | 1.0077 | 1.0140 | 0.4977 | 0.4977 | 0.4977 |
| V27 | 1.0081 | 1.0060 | 0.2024 | 0.5832 | 0.5000 | 0.9998 |
| V31 | 0.9948 | 0.9920 | 0.9980 | 0.5073 | 0.5000 | 0.9924 |
| V32 | 0.9993 | 0.9030 | 0.1090 | 0.4610 | 0.0000 | 0.0017 |
| V34 | 0.9998 | 0.9031 | 0.9200 | 0.5363 | 0.2025 | 0.1096 |

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

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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.

7 REFERENCES

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