Solving the Problem of Optimal Reactive Power Dispatch Using Physical-Inspired Metaheuristic Algorithm

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Abstract. One of the methods for improving the efficiency of power system transmission is the Optimal Reactive Power Dispatch (ORPD). The ORPD technique has been used to minimize the transmission network's power loss by regulating the system control variables. The control variables regulated by ORPD control the reactive power generated sources, such as generator voltage, tap ratio setting for transformers, and reactive power injected by VAR compensator devices. On the other hand, ORPD is a non-linear and non-convex problem, so it needs an optimizer algorithm capable of solving its characteristics. This article discusses using a meta-heuristic algorithm (MA) to solve the ORPD problem. The MA used is one kind of physical phenomena-inspired optimizer called Archimedes optimization algorithm (AOA). The AOA tracks the best combination of all control variables, producing the maximum total active power loss. The performance of AOA tracking used in ORPD problem solving is tested using a standard IEEE 30 bus system. The AOA is compared to other MAs in comparison analysis to perform its superiority. AOA was also tested in correlation analysis to determine the best value of population size and the maximum number of iterations based-on its tracking accuracy, speed of convergence, and processing time. The results show that ORPD problem-solving with AOA has the advantage of reducing power loss by 11.9 %. The simulated results confirm the efficiency and robustness of AOA for solving the ORPD problem.

Keywords: Archimedes optimization algorithm, metaheuristic optimization, optimal reactive power dispatch, power system, transmission network.

1 Introduction

The increasing need for electrical energy will burden the power system network. Higher loading will affect voltage rise and fall. This will affect the stability of the electricity network system[1]. A power system network that continuously experiences instability will result in system collapse and reduced efficiency, which will, of course, result in damage and a decrease in electrical power quality[2]–[4]. Therefore, electricity service providers must always take effective and efficient steps to protect the distribution network system from stability problems. When planning and operating an electricity

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distribution system, voltage stability limitations must be considered[5]. Optimizing power system generation has challenges from load changes, impact on safety constraints, and generation scheduling. Electricity service providers must implement strategic steps in various optimizations to overcome these challenges and reach the desired limits. A single objective function must be handled within predetermined constraints: equality and inequality.

One technique to maintain system stability is optimal reactive power dispatch (ORPD). This ORPD controls reactive power distribution from the generation side to maintain stability and reduce power system losses[6]–[9]. The ORPD technique also has constraints set on the power system parameters. Constraints are also applied to control variables that affect system performance, namely power loss and voltage deviation. The control variables regulated by ORPD are generator voltage, transformer tap ratio, and reactive power injected by the compensator[10]–[12]. However, ORPD is a non-linear and non-convex technique. Therefore, ORPD requires optimization techniques that suit its character but can also solve problems with high performance.

Many non-linear optimization techniques have been developed based on metaheuristic algorithms (MA). Metaheuristic optimization provides random search performance and characteristics, accuracy in targeting global optima, and ease of implementation[13]. Many studies have used MA to solve ORPD problems, both ORPD for standard power systems and those integrated with distributed generation (DG). Some developments in ORPD solved with MAs categorized as conventional algorithms, such as Refs. [14]–[19], some research used MAs categorized as evolutionary algorithm (EA), such as Refs. [20]–[23]. Previous research conducted to ORPD which are used natural-inspired swarm algorithm (NSA), such as Refs. [24]–[29]. Finally, still there is no used of physical-inspired algorithm category in ORPD problem solving.

In this research, ORPD solution solutions for IEEE 30 standard bus system power system transmission networks are discussed. Solving the ORPD problem uses the Archimedes optimization algorithm (AOA), where this algorithm is still very newly implemented for this power system case. AOA is implemented to find the best combination of 12 control variables on the IEEE 30 bus consisting of generator voltage, tap ratio transformer, and reactive power injected by compensators.

2 Basic Theory

2.1 ORPD multi-objective functions

In order to determine the best reactive power dispatch technique, objective functions must be defined. These function sets usually comprise reactive power injection from VAR compensator devices, tap setting settings for transformers, and generator voltage minimization. These goals are to maximize system stability, reduce power losses, and optimize voltage levels. Through the simultaneous consideration of these variables, the ORPD technique aims to accomplish the power system's efficient and dependable operation.

Active power loss optimization. A major goal of reactive power optimization is to minimize power loss in the transmission network by using the best control variable settings while respecting system constraints. This approach reduces operational costs while increasing the power system's efficiency and reliability [30]–[35].

$$f_n = \sum_{k=1}^{Nb} \quad P_{kloss} = \sum_{k=1}^{Nb} \quad G_k\left(V_i^2 + V_j^2 - 2V_iV_j\,cos\delta_{ij}\right) \quad (1)$$

In each system network, P_{kloss} denotes the power loss, and *Nb* is the total number of system networks, also known as branches. Next, for every k^{th} branch, G_k represents its conductance. For each bus i and j, the voltage magnitudes are denoted by V_i and V_j, respectively, while the phase difference between V_i and $V_j$is represented by δ_{ij}.[36].

Constraints. The control variables in the ORPD problem are kept within nominal operation by using both equality and inequality constraints. While inequality constraints establish restrictions on variable values, equality constraints enforce particular connections among variables. In order to guarantee operational viability and system stability, these limitations work together to influence the optimization process.

Equality constraints. Equality constraints must constantly be applied, and they are linked to fulfilling particular correlations between variables. Usually, these restrictions stand in for load flow equations. [37], [38].

$$P_{gi} - P_{di} - V_i \sum_{k=1}^{Nb} \quad V_j\left(G_{ij}\,cos\delta_{ij} + B_{ij}\,sin\delta_{ij}\right) = 0 \quad (2)$$
$$Q_{gi} - Q_{di} - V_i \sum_{k=1}^{Nb} \quad V_j\left(G_{ij}\,cos\delta_{ij} + B_{ij}\,sin\delta_{ij}\right) = 0 \quad (3)$$

Assuming that Nb is the total number of system networks or branches, P_{gi} and Q_{gi} stand for the generator's active and reactive power. For each i^{th} bus, the active and reactive power of the loads are denoted by P_{di} and Q_{di}. The conductance and susceptance between the i^{th} and j^{th} buses are represented by G_{ij} and B_{ij} [39], [40].

Inequality constraints. However, factors like generator voltage, transformer tap settings, and VAR compensator devices are usually governed by inequality constraints. To combat the ORPD, the generator's initial active and reactive power outputs as well as the magnitude of its voltage are limited within predetermined bounds [41].

$$V_{gi}^{min} \leq V_{gi} \leq V_{gi}^{max}, \qquad i = 1, \dots, N_g \quad (4)$$

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max}, \qquad i = 1, \dots, N_g \quad (5)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, \qquad i = 1, \dots, N_g \quad (6)$$

In this case, N_g stands for the total number of generator buses. The generator voltages, active power, and reactive power minimum limits are V_{gi}^{min}, P_{gi}^{min}, and Q_{gi}^{min}. In addition, the maximum limits of the generator voltages, active power, and reactive power are denoted as V_{gi}^{max}, P_{gi}^{max}, and Q_{gi}^{max}. At the i^{th} bus, V_{gi}, P_{gi}, and Q_{gi} represent the generator voltages, active power, and reactive power, respectively.[42]–[45].

$$T_i^{min} \leq T_i \leq T_i^{max}, \qquad i = 1, \ldots, N_T \quad (7)$$

T_i is the tap setting of the transformer position at the i^{th} bus, T_i^{min} denotes its minimum limitations, and T_i^{max} denotes its maximum limits. These are the transformer restrictions. N_T is the total number of tap-changing transformers [46].

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max}, \qquad i = 1, \ldots, N_c \quad (8)$$

Reactive power injection is expressed as Q_{ci}, where Q_{ci}^{min} denotes the minimum and Q_{ci}^{max} denotes the maximum limits of the reactive power injection. N_c is the total number of shunt compensator devices.

3 Method To Problem-Solving

In earlier studies, meta-heuristic algorithms (MAs) have been used to answer a large number of ORPD problems. Given that the formulations of ORPD problems are non-convex and non-linear, MAs are especially well-suited because of their strong random searching powers. Voltage stability in power systems can be greatly enhanced and power loss can be much decreased by using MAs in ORPD. Furthermore, MAs work well at managing the multi-objective character of ORPD situations by striking a balance between a variety of restrictions and goals. Their adaptability to various load conditions and system configurations improves the overall dependability and efficiency of the power grid. Additionally, even greater performance and optimization outcomes for upcoming ORPD difficulties are promised by the ongoing development of advanced MAs.

3.1 Implementation of Mas

The meta-heuristic algorithms that are covered in this article are mostly nature-inspired swarm algorithms (NSAs) and evolutionary algorithms (EAs). These meta-heuristic methods handle the multi-objective functions of ORPD and the uncertainty of power generation from DGs in the ORPD problem with renewable-sourced DG integration. Meta-heuristic algorithms are durable and flexible, which enables them to efficiently address dynamic and complex optimization issues. They do have certain drawbacks, though, namely the possibility of becoming trapped in local optima and the requirement for meticulous parameter tweaking. Despite these difficulties, the development of hybrid techniques and the ongoing refinement of MAs offer hope for future ORPD problems that can be solved with greater efficiency and dependability.

3.2 Simulation Setup

The equality and inequality requirements outlined in subsections B.2.1 and B.2.2 apply to the modeling of the non-linear and non-convex ORPD problem. Equations (1) and (2) provide the foundation for the real power loss and voltage deviation goal functions. The control variables consist of the voltage of the generator, the tap-setting of the transformer, and the reactive power injected by the VAR compensator devices. The IEEE 30 bus system's single-line diagram can be seen in Figure 5.

Table 1 describes the simulation setup for the meta-heuristic methods used to address the ORPD problems AOA and PFA. A population size of 50 (*itMax*) and a maximum of 100 iterations (*nB*) are used by all MAs for ORPD. The number of populations indicates the search resolution in a meta-heuristic search, whereas the number of iterations influences the search range. As a result, while looking for the global optimum (*GBest*), more iterations and a larger population translate into increased accuracy.

Table 1. Standard IEEE 57 bus system test used for the implementation.

Items	System configurations	
	Quantity	**Details**
Buses	30	-
Branches	40	-
Thermal generators	6	Buses: 1, 2, 5, 8, 11 and 13
VAR compensator	2	Buses: 10 and 24
Transformer with tap changer	4	Branches: 6-9, 6-10, 4-12, and 28-27
Control variables	12	-
Bus voltage limits	40	[0.95 – 1.05] p.u.

Variations in constant types and values define each algorithm. The AOA is based on five constants that affect how quickly and where objects move. Table 2 presents the ORPD problem and how each optimization algorithm's tracking parameters are used

Table 2. Algorithm tracking parameters for ORPD problem solving with RE-sourced DG.

Parameters	AOA	PFA
Search agents	Object	Path
nB	48	48
itMax	100	100
Constants	d = 9; C1 = 1.4; C2 = 6; C3 = 1; C4 = 3;	N/A

The standard IEEE system bus is chosen in the first stage of the ORPD, as seen in Fig. 2, and the dataset array of buses, branches, and generators is then extracted. Matpower 7.0 provides all of these IEEE bus standard datasets. The Newton-Raphson method is then applied to the dataset in order to determine the power flow. The initial assessment for the power flow computation is the overall active power loss.

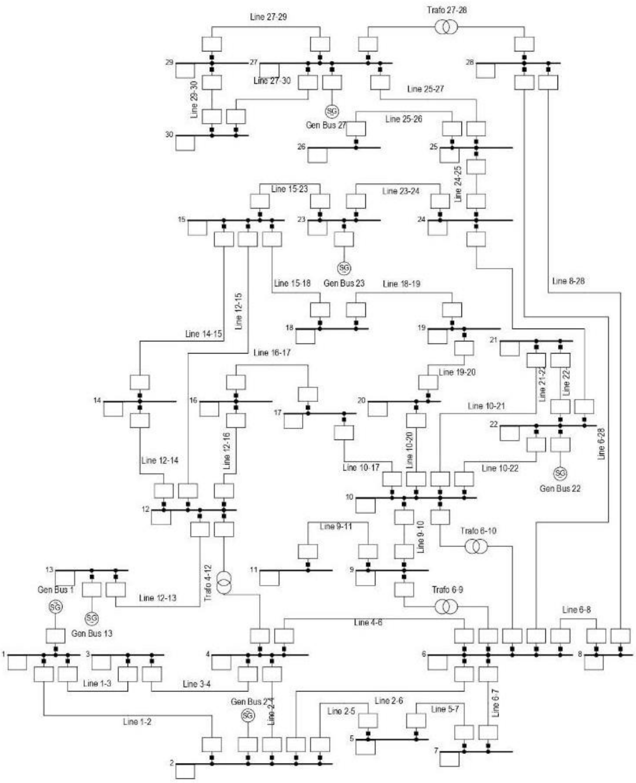

Fig. 1. Single line diagram of standard IEEE 30 bus system

The second stage involves defining the algorithm parameters for each optimization method, which are listed in Table 2; *nB* represents the total number of populations, and *itMax* denotes the maximum number of iterations. The first population is then created, with each member serving as a search or tracking agent and representing the problem's solution. Control factors, such as generator voltage, transformer tap settings, and reactive power injected by compensators, make up the ORPD's problem solution. To compute the power flow and determine the overall active power loss (PLoss), the control variable dataset is injected into the chosen standard bus system. This comprises the assessment phase.

Transforming the control variables dataset into search agent values is the third stage. In PFA, the pathfinder's distance serves as a proxy for the search agent. The location, density, and volume of the object within the fluid serve as the search agent's representation in AOA. Subsequently, each search agent is processed by its corresponding algorithm in order to identify the optimal local optima. An index contains the dataset of the top search agents (local optima/local best) from each loop, together with the parameters of the search agents, control variables, and output parameters (*Ploss*).

There are two ways to end an iteration loop: either by exceeding the maximum number of iterations (IT stop) or by meeting the convergence condition (CV stop). When the ideal point remains constant over the course of the next 100 repetitions, the CV stops. The global best optima (GBest) will be found by setting the least value of the output parameters, then the control variables dataset and algorithm's parameters, once the termination condition has been met. By acquiring the GBest, the optimization of ORPD problem-solving will be completed.

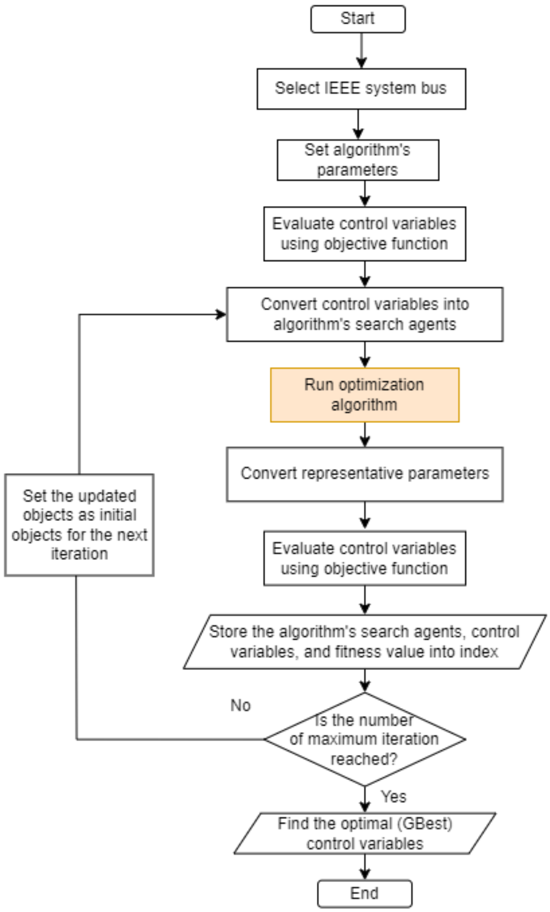

Fig. 2. Workflow diagram of meta-heuristic optimization technique used to solve ORPD.

3.3 ORPD optimization enhancement

A power system network's efficiency and performance can be enhanced by the ORPD technique, which modifies the system characteristics indicated by the control variables. Transformer tap ratio, generator voltage, and reactive power injected by VAR compensators are the control variables employed in ORPD. Numerous combinations of the three system parameters or control variables exist for each power system that is standardized in the IEEE bus system. As an illustration, Table 1 lists the parameter combinations for the 12 control variables included in a typical IEEE 30 bus system. However, in a power system network, the primary issue is system efficiency, which impacts power loss.

The random searching that characterizes MAs was discussed in the preceding section. MAs, such as ORPD, can solve the optimization problem because of their non-convex and non-linear formulation. As long as the limits specified throughout the operation are followed, the tracking or searching procedure of MAs can handle multi-objective and multi-input problems. Experience with applying MAs to the ORPD problem in both general and particular circumstances suggests that MAs can help keep all varieties of standard IEEE 30 bus system networks operating at peak efficiency and minimize power loss.

3.4 Archimedes optimization algorithm (AOA) enhancement

Optimizing swarm algorithms (PSA) influenced by physical phenomena, the Archimedes Optimization Algorithm (AOA) is a meta-heuristic algorithm with balanced convergence, exploration, and exploitation capabilities. Sophisticated optimization problems can be solved with the AOA. The Archimedes principle of physics serves as the foundation for AOA. The theory goes like this: if an object is submerged, whether completely or partially, the liquid will push it upward by the weight of the liquid that the object has displaced. It's known as the buoyant force, which is upward. The boundary force acting on an object submerged in liquid is equal to the weight of the liquid that has been displaced [47], [48].

Different accelerations are caused by variations in the density and volume of submerged objects [49]. When the weight of the item (W_o) equals the buoyant force (F_b) exerted by the fluid, these objects find equilibrium. Until the termination condition is satisfied, this procedure keeps repeating itself. An excellent solution or hitting a cap on the number of iterations are two examples of criteria that can be used to define termination conditions. To attain the intended balance, the object's density, volume, and acceleration are changed at each iteration[50], [51].

- Initialize the position of all objects.

$$O_i = lb_i + rand \times (ub_i - lb_i); i = 1, 2, \dots, N \quad (9)$$

Where O_i is the i object inside the amount of N population. lb_i and ub_i is the upper and lower limits of the searching range. Then (*vol)* is volume initialization and (*den)* is the density for each i- object.

$$den_i = rand;\ vol_i = rand \qquad (10)$$

Where *rand* is the dimensional vector which generate the number between 0 and 1 randomly. Acceleration (*acc*) from the object number *i.*

- Update the density and volume value. The *i* object's density and volume for iteration number *i* + *1* will be updated.

$$den_i^{t+1} = den_i^{t+1} + rand \times (den_{best} - den_i^1) \qquad (11)$$

$$vol_i^{t+1} = vol_i^{t+1} + rand \times (vol_{best} - vol_i^1) \qquad (12)$$

Where den_{best} dan vol_{best} is the density and volume of the best *i* object which is chosen by uniform *rand.*

- The density factors and transfer operators. After a while, items start to collide and attempt to find equilibrium or a balancing point. Transfer functions (TF) are required in the implementation of AOA in order to move search from exploration to exploitation.

$$TF = exp\ exp\ \left(\frac{t - t_{max}}{t_{max}}\right) \qquad (13)$$

Where TF increases over time until it reaches 1. Here, *t* and t_{max} are the number of iterations and the maximum number of iterations. The density decreasing factor (*d*) helps the AOA for global search to local search, which decreases in time.

$$d^{t+1} = exp\ exp\ \left(\frac{t_{max} - t}{t_{max}}\right) - \left(\frac{t}{t_{max}}\right) \qquad (14)$$

The regions that have been designated as promising can host meetings when d^{t+1} lowers over time. In AOA, a balance between exploration and exploitation can be ensured by managing these variables well.

- Exploration phase (a collision occurs between objects). If the *TF value* ≤ *0.5*, a collision between objects occurs, therefore a random material (*mr*) is selected and the object speed is updated.

$$acc_i^{t+1} = \frac{den_{mr} + vol_{mr} \times acc_{mr}}{den_i^{t+1} \times vol_i^{t+1}} \qquad (15)$$

Where den_i, vol_i, and acc_i are the density, volume, and velocity of the *i* object. Where $den_{mr}, vol_{mr}, acc_{mr}$ are the density, volume, and velocity of the random material. Note that TF ≤ 0.5 ensures exploration for one-third of the iterations. Using values other than 0.5 may change the usual exploration and exploitation.

- Exploitation phase Exploitation phase (no collisions on objects). If *TF* > *0.5*, no collisions occur between objects, at *t* + *1* the object velocity is updated.

$$acc_i^{t+1} = \frac{den_{best} + vol_{best} \times acc_{best}}{den_i^{t+1} \times vol_i^{t+1}} \qquad (16)$$

Where acc_{best} is the best object's velocity

Step 4.3. Normalizing speed to calculate percentage change

$$acc_{i-norm}^{t+1} = u \times \frac{acc_i^{t+1} - min(acc)}{(acc) - min(acc)} + l \qquad (17)$$

Where i and l are normalization terms which are set to 0.9 and 0.1. acc_{i-norm}^{t+1} determines the percentage of moves that will be changed by each agent. The speed value will grow if object I is distant from the global optimal value, indicating that it is either in the exploration or exploitation phase. This demonstrates the transition of the search process from the phase of exploration to that of exploitation. Typically, the speed factor begins at a high value and gradually drops. In this approach, searching agents will be assisted in moving away from local solutions and toward the greatest global options at the same time. Some search agents, however, stay in the exploration phase longer than is typical. As a result, in AOA, exploration and exploitation can coexist in equilibrium.

- Update the position. In the exploration phase ($TF \leq 0.5$) the position of the i object in the next iteration $t + 1$.

$$x_i^{t+1} = x_i^t + C_1 \times rand \times acc_{i-norm}^{t+1} \times d \times (x_{rand} - x_i^t) \qquad (18)$$

Where C_1 is a constant value of 2. However, if $TF > 0.5$ (exploitation phase) the object updates its position.

$$x_i^{t+1} = x_{best}^t + F \times C_2 \times rand \times acc_{i-norm}^{t+1} \times d \times (T \times x_{best} - x_i^t) \qquad (19)$$

Where C_2 is a constant value of 6. The value of T increases over time and is proportional to the transfer operator and can be defined as $T = C_1 \times TF$. The T value increases with time in the term $[C_3 \times 0.3, 1]$ and takes a certain percentage of the best position. Starting with a low percentage, it results in a big number of journey steps in the random search since there is a significant disparity between the optimum position and the current position. The percentage gradually rises as the search goes on in an effort to close the gap between the current and ideal positions. A balance between exploration and exploitation may result from this. The sign to change the direction of movement can be symbolized by F, where $P = 2 \times rand - C_4$.

$$F = \{+1 \; if \; P \leq 0.5 \;\; -1 \; if \; P > 0.5 \qquad (20)$$

- Evaluation. Each object calculated its own fitness value by the objective function F, then entered the best optima found in the variables x_{best} , den_{best}, vol_{best}, acc_{best}. Then the optima can be set as the solution for the optimization problem[52].

Due to its multi-objective and meta-heuristic characteristics, AOA can be applied to ORPD problems. The swarm idea is a feature of AOA, a kind of EA. Figure 3 illustrates the process flow of the ORPD problem-solving program employing AOA.

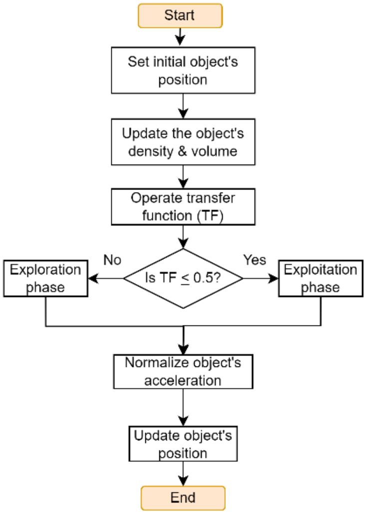

Fig. 3. Workflow diagram of AOA enhancement for ORPD

Initializing algorithm parameters, such as the number of populations, number of iterations, and algorithm constants, is the first step in the optimization procedure. Selecting the IEEE bus system and then extracting the dataset from it are the first steps in initializing the ORPD parameters. Generator, bus, branch, and VAR compensator device parameters are all included in the dataset.

The first population is formed randomly, adhering to the MAs rule, and each individual has an initial density, volume, and position. The ORPD control variables are reflected in the individual's parameters. The fitness value which is the sum of the power loss and voltage deviation is then calculated for each individual utilizing the objective fitness function provided by equation (1). The first iteration's starting circumstances are then determined by the individual parameters and fitness levels.

The ORPD control variables must be translated into volume and density values in order to run the optimization method because the AOA will use these. The best person and their best fitness value (*GBest*) are then found or tracked using the optimization procedure.

4 Result and Discussion

4.1 Optimization performance comparison and analysis

The analysis technique was conducted to determine the performance comparison of the four evolutionary algorithms represented in this research: PFA representing the conventional meta-heuristic algorithm, and AOA representing the physical swarm-inspired algorithm. Each algorithm has different characteristics in this ORPD case. Tables 3 display the running results of the two optimization algorithms. Each algorithm is executed with the parameter setup described in Table 3. The comparison of the algorithms is based on the parameters of the ORPD results, including control variables, power loss. Meanwhile, the parameters resulting from tracking include the best iteration and processing time.

Table 3. Running result AOA and FOA for ORPD control variables

Control variable	Base case	AOA	FOA
Vg1	1.0600	1.0592	1.0596
Vg2	1.0450	1.0568	1.0309
Vg5	1.0100	1.0518	1.0337
Vg8	1.0100	1.0544	0.9986
Vg11	1.0820	1.051	0.95921
Vg13	1.0710	1.0575	1.0145
T11	0.9780	1.0181	0.91105
T12	0.9690	1.0243	1.092
T15	0.9320	1.0251	0.97888
T36	0.9680	1.0253	1.0116
Q10	19	15.9681	11.49
Q24	4.3	3.6033	3.1146

Table 4 shows the result of optimization process of AOA as the implementation on ORPD problem solving of IEEE 30 bus system. The tracking process shows that AOA has superiority in tracking the best combination of control variables which produce minimum power loss 1.11 % lower than FOA did. The voltage deviation produced by AOA 42.86 % lower than FOA, also the result of VSI is 17.9 % higher that FOA.

Table 4. Running result AOA and FOA for ORPD parameters

Parameters	AOA	PFA
Power loss (MW)	15.1849	15.3559
Voltage deviation (p.u.)	0.78375	1.3718
VSI (p.u.)	0.21415	0.17581
No. under voltage bus	0	12
No. over voltage bus	6	1
No. convergence	77	57
Processing time (s)	99.0765	141.616

From the result of number of buses which experienced undervoltage, can be concluded that the system regulate by AOA is more stable, looked from zero value. Different with AOA result, the FOA experienced 12 buses are undervoltage due to voltage drop. AOA also has superiority in processing time which has 30 % faster tracking process that FOA. But in the term of convergence speed, the AOA is slower that FOA.

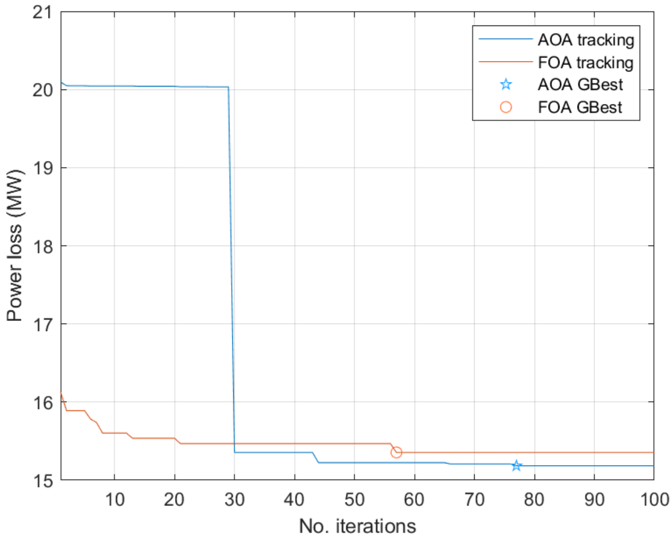

Fig. 4. Convergence curve of ORPD tracking process

Fig. 4 shows the process of AOA and FOA in searching the best combination of ORPD control variables which produce the minimum power loss. It shows that AOA can accurately minimize power loss rather than FOA which represent by *GBest* variable. In the other hand, the FOA experienced convergence early than AOA.

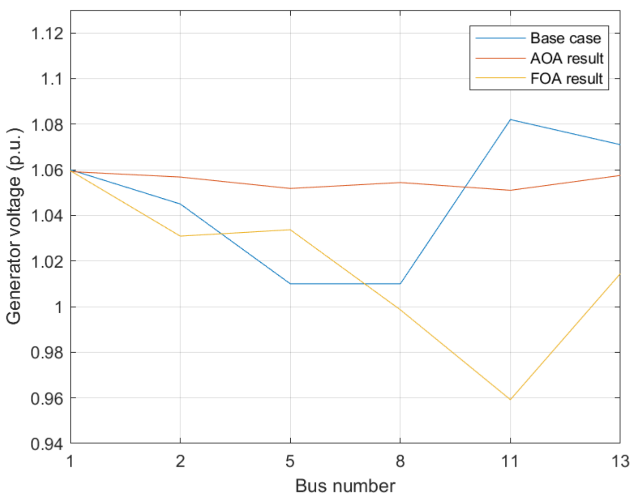

Fig. 5. Comparison test result for tracking the best combination of voltage generators

Voltage generator is part of the solution which optimized in ORPD problem solving. Fig. 5 shows the values of voltage generators tested in IEEE 30 bus system. From the graphic shows that AOA tracking tend to search in higher generator voltage mostly near the upper limit, such as 1.06 p.u. and FOA tend to search the generator voltage in lower value.

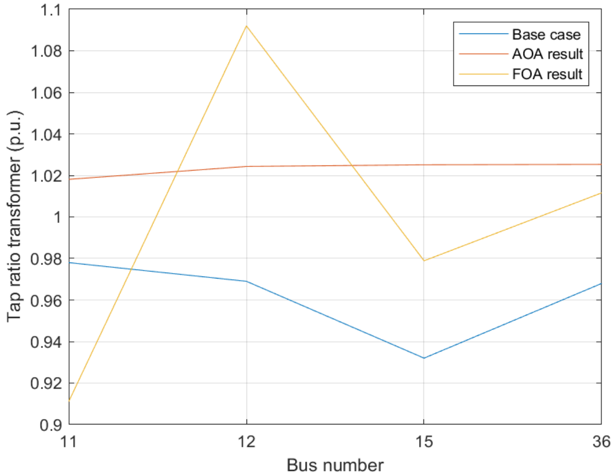

Fig. 6. Comparison test result for tracking the best combination of voltage generators

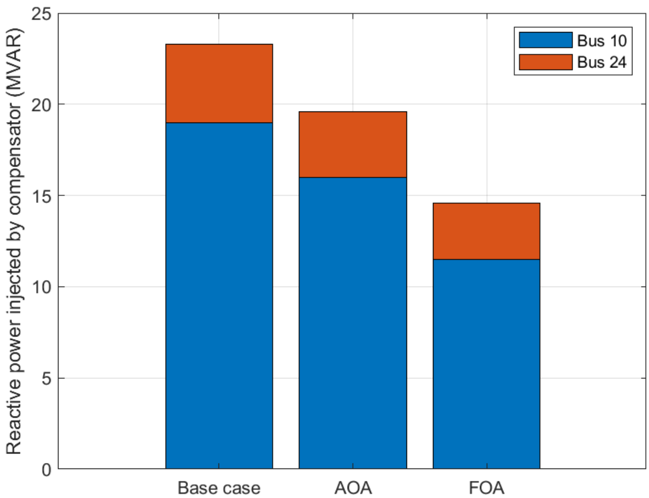

Fig. 7. Comparison test result for tracking the best combination of voltage generators

Almost exactly with the tracking process of generator voltage, the tracking process of AOA to search the tap ratio value always keep in the higher value than FOA and base case. Fig. 5 shows that the value of all tap ratios are between the upper and lower limits of their standard values. Then Fig. 6 shows the reactive power injected in bus number 10 and 24. Both AOA and FOA tracked the reactive power injected higher in bus number 10. The combination value of voltage generator, tap ratio transformer, and reactive power inject are significantly affects the active power loss in IEEE 30 bus system.

The statistical analysis showed in Table 5 also shows the superiority of AOA in the term of minimizing active power loss. AOA always produce the power loss2 % lower than FOA in average. Also, the running result of 33 tracking process, AOA always superior in both best result and worst result.

Table 5. Comparison test result between AOA and FOA tracking ORPD process

Parameters	AOA	PFA
Best result	15.1165	15.1322
Worst result	15.3445	16.1963
Average result	15.1874	15.5126
Std. deviation	0.0521	0.3507

The correlation test conducted to know the relationship between algorithm parameters and ORPD objective parameter. The algorithm parameters considered in AOA are population size, number of iterations, and processing. Also, the ORPD objective parameters considered is only power loss. It is significant to occur the correlation of the parameters because it can be used to optimizing the tracking process. It means if population size and number of iterations are increased, the accuracy could be higher, but will time-consuming, and vice versa. The negative value represents the both parameters are inversely correlated. The positive value means that the both parameters are directly correlated. The test results showed in

Table 6. Correlation test result between AOA parameters and ORPD parameters

Parameters	Power loss (MW)	Speed of convergence
Population size (nB)	-0.9678	15.1322
No. iterations (ItMax)	0.9240	16.1963
Processing Time (s)	-0.5185	0.3507

Table 6 obtained that there is significant correlation between population size and number of iterations to the value of power loss. It means the value of nB and ItMax will significantly affect to the tracking accuracy of minimum power loss. And also, the nB is showed significantly affects the convergence speed.

5 Conclusion

In this article AOA optimization method is employed to the problem of ORPD in standard power system. The IEEE 30 bus system is used as test environment to obtain the performance of the AOA compared with another kind of metaheuristic algorithm. The performance test is conducted in term of searching the best combination of control variables which produce minimum power loss as a single-objective function in a standard power system network. The control variables which being tracked by the optimization method including; voltage generators, tap ratio transformers, and reactive power injected by compensators. The optimization results confirm that the effectiveness of AOA in the case of standard IEEE 30 bus explain the superiority and robustness in solving ORPD problem. It was found that AOA has higher accuracy in tracking the global optima, such as minimum power loss. AOA also has faster processing time, but when it considered with speed of convergence AOA will lose to FOA. Consequently, the AOA optimization method can be advised as a highly promising algorithm to solve complex and non-linear issues in engineering, especially in power system.

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