Comparison of Algorithms to Solve Multi-objective Optimal Reactive Power Dispatch Problems in Power Systems with Nonlinear Models and a Mixture of Discrete and Continuous Variables

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Abstract: Optimal reactive power dispatch (ORPD) is a way to improve power system performance. Determination of the optimal value of the control variable can reduce the objective function to be achieved. The optimization of the two objective functions simultaneously is called multi-objective ORPD (MORPD). This research has a major contribution in proposing and utilizing original ideas from new algorithms and new ideas from the old algorithm to solve more complex variables and challenging ORPD problems. The ORPD problem is formulated as a nonlinear model with variables consisting of continuous and discrete. The proposed multi-objective algorithm is time-varying particle optimization (MOTVPSO), ant lion objective (MOALO), dragonfly algorithm (MODA), grey wolf optimizer (MOGWO), and multi-objective multi-verse optimization (MOMVO). To measure the effectiveness of those algorithms, testing is performed on the IEEE 57-bus. The simulation results show that the MOTVPSO algorithm can contribute more dominantly from the statistical tests conducted compared to previous studies and all four algorithms in this work to minimize real power loss. Whereas the MOMVO has an advantage in computational time efficiency.

Keywords: the IEEE 57-bus, multi-objective optimal reactive power dispatch, time-varying particle swarm optimization, ant lion optimizer, grey wolf optimizer, dragonfly algorithm, multi-verse optimization.

1. Introduction

An electric power system is required to realize the needs of electricity customers with the most economical costs, sustainable electricity supply, minimize real power loss, and total voltage deviation. Achieving those objectives requires setting a variable that affects the objectives to be achieved. The strategy is called the optimal power flow (OPF) [1]. Early in its development, the OPF problem was resolved by using the approximate approach [2]. But the OPF which is subject to constraints was applied in 1962 [3].

Because science related to power systems continues to develop, OPF consists of two parts, namely the optimization of real power flow and reactive power [4]. Research sub-section related to optimal reactive power dispatch (ORPD) [4-5] related to reactive power management. At alternating voltage and current, the phase difference between the two will cause the reactive power. The reactive power and voltage control are two aspects but are considered an activity. The control is solved by determining the variables that affect both. The ORPD aims to provide effective reactive power allocation. The objectives to be achieved in this work are to minimize real power losses and total voltage deviations. Determining the value of an appropriate control variable will contribute to minimizing the objective's function. The control variables referred to in this work are the voltage magnitude of the generator, reactive power compensators, and ratio tap transformers. None of the variables is permitted to exceed their abilities. By achieving the minimum objective function and without violating the variable limits, the security of the power system can be maintained as well as financial losses to the electricity supply company can be reduced as minimum as possible [6].

Received: March 30th, 2020. Accepted: July 27th, 2020
DOI: 10.15676/ijeei.2020.12.3.7

To date, research related to ORPD has been widely carried out and proven successful. All related research has advantages and disadvantages to get quality solutions and computational time efficiency. The quality of the solution is largely determined by the complexity of the ORPD problem being solved. Whereas the computational time efficiency is improved by simplifying the algorithm and increasing the specifications of the personal computer. Because the development of an increasingly complex power system requires researchers to continue to look for effective and efficient methods. Variations of the metaheuristic approaches have received much attention from researchers to date. The problems that cannot be solved by traditional methods can be solved using the approach.

In this work, the main contribution is to propose and utilize original ideas from four new algorithms and new ideas from the old algorithm to solve more complex and challenging ORPD problems. These multi-objective algorithms are the MOALO [7-8], multi-objective dragonfly algorithm (MODA) [9], grey wolf optimizer (MOGWO) [10-11], multi-verse optimization strategy (MOMVO) [12-13], and multi-objective time-varying particle swarm optimization (MOTVPSO). Incorporating ideas to improve PSO performance such as (i). The application of fine-tuning for inertia weight which decreases linearly will provide better accuracy [14], (ii). The application of fine-tuning to the 1st acceleration factor (c_1) aims to improve the exploration process at the beginning of time and decrease at the end of time [15], and (iii). The application of fine-tuning to the second acceleration factor (c_2) aims to decrease the process of exploitation at the beginning of time and increase at the end of time. These strategies will produce a diversity of local and global solutions that are tailored to the needs during the optimization process [15]. However, in this work, the adjustment is done nonlinearly so that the level of change becomes smoother.

All methods are used to solve ORPD problems with simultaneous multi-objective optimization by involving complex combinations of variables. To test the effectiveness and efficiency of the five algorithms tested on the IEEE 57-bus. The approach that has the most dominant contribution in producing statistical tests is seen as the most superior approach. The intended statistical test is the best objective value (*BOV*), the worst objective value (*WOV*), and mean objective value (*MOV*). The same statistical test is done to measure the computational time efficiency.

2. Related Works

An increasingly developed and complex power system requires researchers to find effective and efficient methods for solving existing problems. At the beginning of its development, the problems solving were carried out using traditional methods such as quadratic programming (QP) [16] and interior-point (IP) [17]. The traditional methods have the advantage of convergence speed [6]. However, the methods have disadvantages such as the need for differentiable and continuous objective functions, premature convergence, and tends to be problematic when handling a very large number of variables.

Currently, meta-heuristic optimization methods get a lot of attention from researchers who focus on optimization. The methods are inspired by the theory of evolution, physical phenomena, and swarm. The application of metaheuristic methods such as big-bang and big-crunch (BB-BC) and firefly optimization (FFO) [18], hybrid harrison hawk optimization based on differential evolution (HHODE) [19], a modified grasshopper optimization algorithm (MGOA) [20], an improved harmony search (HS) [21], a novel-efficient evolutionary-based multi-objective optimization (MOO) [22], an efficient cuckoo bird-inspired meta-heuristic algorithm (CBIA) [23], and symbiotic organisms search (SOS) [24] have been done to solve OPF and economic dispatch (ED) problems. However, the application of meta-heuristic approaches to solving other sub-research problems such as aging leader and challengers-particle swarm optimization (ALC-PSO) [6], seeker optimization algorithm (SOA) [25], mean-variance mapping optimization (MVMO) [26], gravitational search algorithm (GSA) [27], an intelligent water drop (IWD) [28], e-constraint differential evolutionary (EC-DE) [29], differential evolutionary (DE) [30], hybrid time-varying PSO and genetic algorithm

(HTVPSOGA) [31], hybrid PSOGSA [32], a novel improved ant lion optimization (IALO) [33], constriction factor based PSO (CFPSO) [34], and moth-flame optimization (MFO) [35] has also been proven successful in solving the ORPD problems. Those successes are done by adopting operators from other algorithms [6,29], the original idea of the algorithm used [25-28, 30, 34-35] and combining two different algorithms [31-32]. However, these methods have the disadvantage of solving the problems done only by optimizing the single-objective function and the control variable model that has continuous characteristics. Solving ORPD problems in this way is considered inefficient and not complex.

The resolution of more challenging ORPD problems has also been applied to the IEEE 57-bus. The hybrid artificial bee colony assisted DE (HDE-ABC) [36], hybrid modified imperialist competitive algorithm and invasive weed optimization (MICA-IWO) [37], improved DE (IDE) [38], gravitational search algorithm PSO (GSAPSO) [39], gravitational search algorithm-conditional selection strategies (GSA-CSS) [40], and improved GSA-CSS (IGSA-CSS) [40] methods have proven successful in solving problems of ORPD complexity. These successes are done by improving the performance of algorithms such as a combination of two different algorithms [36-37, 39], the development of operators used [38], and adopting other algorithm operators [40]. Although the methods have succeeded in solving more complex variable models (a combination of discrete and continuous), the optimization process is carried out with the only single-objective function. As a result, the method is considered inefficient to solve ORPD problems.

The different things are done to solve the ORPD problem by using methods such as the chaotic bat algorithm (CBA) [41], the hybrid PSO and imperialist competitive algorithms (PSO-ICA) [42], gaussian bare-bones water cycle algorithm (NGBWCA) [43], multi-objective ant lion optimization (MOALO) [44], and fractional-order Darwinian particle swarm optimization (FO-DPSO) [45]. The methods have proven their success in improving algorithm performance by a combination of two different algorithms [42], the utilization of other operators [43,45], and the original idea of the algorithm used [41,44]. The application of the methods is considered efficient because the optimization process is carried out with multi-objective simultaneously. However, all control variables are considered as continuous variables or non-complex variables.

The ORPD problem which is considered more efficient and more complex. The methods such as artificial bee colony (ABC) [46], the multi-objective PSO (MOPSO) [47], multi-objective enhanced PSO (MOEPSO) [47], and modified imperialist competitive algorithm (MGBICA) [48] have succeeded in solving these problems. The ABC algorithm [46] has solved the problems but does not consider bank capacitors as discrete variables. Improved the performance of the MOEPSO algorithm [47] is done by adding a mutation operator that has been proven successful in solving ORPD problems. Simultaneous multi-objective optimization and combination of variable types is a complex and challenging problem in the application of those three methods. Because these three studies have the same optimization models and types of variables (more complex and challenging ORPD problems), the simulation results in this work will be compared against the three.

To date, in this study, new metaheuristic algorithms discovered by Mirjalili such as ALO [7], DA [9], GWO [10], dan MVO [12], and the development of the PSO algorithm (TVPSO) are proposed and utilized to solve more complex and challenging ORPD problems. To measure the performance of the original ideas of the four new algorithms and new ideas from the PSO, all algorithms are tested on the IEEE 57-bus. A new idea from the TVPSO algorithm is the use of operators that are made adaptively. The adaptive change in operator value will have an impact on increasing the diversity of solutions based on the needs of the exploration and exploitation process. Both of these processes are carried out alternately with increasing and decreasing values. Besides, in this work, the computational time efficiency used from each algorithm is also investigated.

3. Mathematical Problem Formulation

A. MORPD Objective Functions

In this paper, two distinct objective functions are simultaneously optimized which are modeled on equation (1) and (2) without violating the equality and inequality boundaries. The two intended objective functions are as follows [6]:

A.1. The real power losses: this objective function is to minimize real power losses in the power system. The optimization stage is carried out without breaking the equality and inequality constraints. The objective function is expressed as:

$$\text{Min } J_1(P_L) = \sum_{k=1}^{N_E} g_k(V_r^2+V_s^2-2_rV_s cos\theta_{rs}) \quad (1)$$

where N_E is the bus number, P_L is the real power losses, g_k is the conductance on the k-channel, V_r is the voltage on the r-th bus, V_s is the voltage on the s-th bus, θ_{rs} is the phase angle between the r-th and s-th bus.

A.2. The total voltage deviation: this objective function is to minimize the total voltage deviation across the entire load bus in the power system. The objective function is expressed as:

$$\text{Min } J_2(TVD) = \sum_{i=1}^{N_{PQ}} |V_{PQ,r} - V_{PQ,r}^{\text{ref}}| \quad (2)$$

in which $V_{PQ,r}$: voltage on the load bus, $V_{PQ,r}^{\text{ref}}$: voltage reference on the load bus. The value is equal to 1.0 per unit (p.u.).

B. Constraints

B.1. Equality Constraints

The real and reactive power flow balances must be met in the optimization process. This implies that the amount of power supply from generation must be equal to the amount of power absorbed by the load (including real power losses). The power balances are modeled in the equations below.

$$P_{G,r} - P_{PQ,r} = V_r \sum_{r=1}^{N_B} V_s(G_{rs}cos\theta_{rs} + B_{rs}sin\theta_{rs}) \quad (3)$$

$$Q_{G,r} - Q_{PQ,r} = V_r \sum_{r=1}^{N_B} V_s(G_{rs}cos\theta_{rs} - B_{rs}sin\theta_{rs}) \quad (4)$$

Where: $P_{G,r}$ is the amount of real power supplied by the generator injected on the r-th bus, $Q_{G,r}$ is the amount of reactive power supplied by the plant injected on the r-th bus, $P_{PQ,r}$ is the amount of real power absorbed by the load on the r-th bus, $Q_{PQ,r}$ is the amount of reactive power absorbed by the load on the r-th bus, G_{rs} is the value of channel conductance from the r-th bus to the s-th bus, and B_{rs} is the value of the channel susceptance from the r-th bus to the s-th bus.

B.2. Inequality Constraints

The inequality constraints are stated in equation (5) - (10) with the following explanation:

i. Generator constraints: all voltage magnitudes of the bus generator and reactive power supply at the generator (including the slack bus) must be within the operational limits. Modeling of these variables and their limitations is shown below.

$$V_{G,r}^{\min} \le V_{G,ir} \le V_{G,r}^{\max},\ r = 1,2,..,N_G \quad (5)$$

$$Q_{G,r}^{\min} \le Q_{G,r} \le Q_{G,r}^{\max},\ r = 1,2,..,N_G \quad (6)$$

where: N_G is the number of generators, $V_{G,r}$ is the magnitude of the generator voltage injected on the r-th bus, and *min*/*max* is the equipment capability value limit.

ii. Transformer constraints: the utility value of the tap ratio on the transformer must meet the upper and lower limits. The boundary equation of this variable is stated below.

$T_r^{\min} \leq T_r \leq T_r^{\max}, \; r = 1,2,...,N_T$ (7)

where: N_T is the number of transformers and T_r is the tap ratio of the transformers on the r-th bus.

iii. Shunt compensator constraints: the utility value of the reactive power compensator must meet the upper and lower limits. The boundary equation of this variable is expressed below.

$Q_{c,r}^{\min} \leq Q_{c,r} \leq Q_{c,r}^{\max}, \; r = 1,2,...,N_c$ (8)

where: N_c is the number of utilities of the reactive power compensator injected on the i-th bus and $Q_{c,r}$ is the reactive power compensator injected on the r-th bus.

iv. Security constraints: all voltage magnitude values on the load bus must meet the upper and lower limits. While the distribution of power through the network which may not exceed the maximum capacity. The boundary equation of these variables is expressed below.

$V_{PQ,r}^{\min} \leq V_{PQ,r} \leq V_{PQ,r}^{\max}, \; r=1,2,..,N_{PQ}$ (9)

$S_{k,r} \leq S_{k,r}^{\max}, \; r = 1,2,...,N_k$ (10)

where: N_{PQ} is the number of load buses, N_k is the number of channels, $V_{PQ,r}$ is the voltage on the r-th load bus, and S_k is the power flow on the k-th channel.

3. Optimization Algorithms Description

The algorithm used to solve MORPD problems in this paper is introduced briefly. If the reader is interested in knowing more details about the algorithm used in this work, you can look at the original article in the references below.

A. Time-Varying PSO

The PSO algorithm is a population-based algorithm. The algorithm is very simple and has good robustness in controlling its parameters. The PSO algorithm only applies the concepts of position and velocity to each population. The utilization of leaders taken from secondary repositories [49] was also used in this study. The PSO algorithm with velocity and position is expressed below.

$v_i^j(t+1) = w(t).v_i^j(t) + c_1.r_1.[x_{pbest,i} - x_i^j(t)] + c_2.r_2.[rep_h - x_i^j(t)]$ (11)

$x_i^j(t+1) = v_i^j(t+1) + x_i^j(t)$ (12)

in which rep_h: the value taken from the repository that corresponds to a hypercube, $v_i^j(t)$: particle velocity, $x_i^j(t)$: the current particle position; $x_i^j(t+1)$: update of particle position; $x_{pbest,i}$: local solution, w: the inertia weight, $c_{1,2}$: acceleration factors 1 and 2, $r_{1,2}$: random values.

The time-varying inertia weight PSO (TVIW-PSO) performance has a very significant influence on parameter changes from linear inertia-weight [50]. In general, the problem of optimization that uses population, diversity of the population is needed alternately during the process of exploration and exploitation [51]. With this in mind, the PSO was further developed using the PSO-time varying acceleration (PSO-TVAC) method. This method aims to make time exchanges on local and global search [15].

To adopt the TVIW and TVAC strategies, this paper presents a modification of the two parameters on the PSO called TVPSO. The mathematical model of the three PSO parameters is expressed below. The flow chart of the first algorithm to solve the MORPD problem can be seen in Figure 1.

$w(t) = w_2 + [(t_{\max}-t)/t_{max}]^{t/t\max}(w_1-w_2)$ (13)

$c_1 = c_{1,i} + [(t_{\max}-t)/t_{max}]^{t/t\max}(c_{1,f}-c_{1,i})$ (14)

$c_2 = c_{2,i} + [(t_{\max}-t)/t_{max}]^{t/t\max}(c_{2,f}-c_{2,i})$ (15)

where: t is current iteration and $t_{\max}$ is the maximum number of iterations.

B. Ant Lion Optimization

The ALO [7] mimics the mechanism of the antlion in hunting and foraging interactions. The optimization process with this algorithm applies several strategies which are briefly explained as follows:

The random walk is the movement of ants looking for food in nature. The strategy is used the ALO algorithm which is formulated below.

$$X(t) = [0, Cum\_sum\,(2r(t_2)-1),\ldots,Cum\_sum(2r(t_{max})-1)] \quad (16)$$

where: $X(t)$ is random walk, *cum_sum* shows the cumulative amount, and t_{max} with $r = 1$ if $rand > 0.5$ and $r = 0$ if $rand \leq 0.5$.

The next strategies are trapping in antlion's pits, building traps, and ants sliding toward the antlion. These strategies are modeled with the following mathematical equations:

$$c^t = \frac{t_{max} \times c^t}{10^{\omega} \times t} \quad (17)$$

$$d^t = \frac{t_{max} \times d^t}{10^{\omega} \times t} \quad (18)$$

where: c^t is the minimum value of the variable in the t-iteration, d^t is the maximum value of the variable in the t-iteration, and w indicates the adaptive and conditional constant formulated below.

$$\omega = \begin{cases} 2 & \text{if} \quad t > 0.10\ t_{max} \\ 3 & \text{if} \quad t > 0.50\ t_{max} \\ 4 & \text{if} \quad t > 0.75\ t_{max} \\ 5 & \text{if} \quad t > 0.90\ t_{max} \\ 6 & \text{if} \quad t > 0.95\ t_{max} \end{cases} \quad (19)$$

Catching prey is the final stage of hunting for prey. While re-building the pit is done to find new prey. The final stage of hunting for prey is formulated below. Whereas operator elitism is used so that the best solution in each phase of optimization can be maintained. The flow chart of the second algorithm can be seen in Figure 2 to solve the MORPD problem in this work.

$$Antlion^t_j = Ant^t_i \text{ if } f(Ant^t_i) < f(Antlion^t_j) \quad (20)$$

where: $Antlion^t_j$ shows the j-th position of the antlion in the t-iteration and Ant^t_j shows the i-position of ant in the t-iteration.

C. Dragonfly Algorithm

DA algorithm [9] is taken from the uniqueness of dragonfly behavior. Static behavior is seen when dragonflies gather to find prey. While dynamic behavior is seen when dragonflies migrate, namely groups and in the same direction with great distances. The uniqueness of these two behaviors is very relevant to the two-optimization phases, namely the process of exploration and exploitation. The uniqueness is explained briefly with the following strategies:

The behavior of separation (S_i) is the behavior of dragonflies to avoid static collisions in their environment. The behavior of alignment (A_i) is the adjustment of position between dragonflies in their environment. Whereas the behavior of cohesion (C_i) is the tendency of dragonflies towards the center of mass. To survive, dragonflies must be interested in finding food sources (F_i) and overcome enemy interference from outside (E_i). The mathematical model of each behavior and Levy flight can be seen in full in reference [9].

To ensure convergence during the optimization process, each of these behaviors is applied to a weighting. The equations of inertia-weight and inertia on the behavior of each dragonfly are calculated as follows:

$$w = 0.9 - \frac{t(0.9-0.2)}{t_{max}}\ . \quad (21)$$

$$w_d = 0.1 - \frac{t(0.1-0.0)}{t_{\max}/2}. \quad (22)$$

where: w_d is the weight of dragonfly behavior with the adaptive weight requirements used, for t <0.75 $t_{\max}$, the weight value of each (except f) is the same as w_d. As for $t \geq 0.75t_{\max}$, the weight value (except f) is w_d/t. The weight value f for all iterations is twice the random value.

Renewal of the position and movement of the dragonfly uses two vectors namely the position vector (X) and the step vector (ΔX). When the optimization process is not found in the surrounding solutions, the Levy flight operator is used. The mathematical model of the dragonfly step is shown below.

$$\Delta X_{t=1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_i. \quad (23)$$

The position of the dragonfly is updated by using two strategies, namely if the dragonfly has at least one solution around it, then equation (24). But if not, equation (25) is used.

$$X_{t=1} = X_t + \Delta X_{t+1}. \quad (24)$$

$$X_{t+1} = X_t + \text{Levy}(d)X_t. \quad (25)$$

where Levy shows flights to areas that are not dense and the equation can be seen in references [9]. The flow chart of the third algorithm to solve the MORPD problem can be seen in Figure 3.

D. Grey Wolf Optimizer

The GWO algorithm [10] is taken from the unique behavior of the grey wolf namely dominant social leadership and hunting techniques. Unique behavior in hunting such as circling, attacking, and finding prey techniques. The GWO algorithm to solve the optimization problem that is explained as follows adopts the uniqueness of these behaviors:

Social leadership is social domination as long as the wolves interact. Alpha Wolf (α) is considered a first-best solution. Beta wolf (β) and delta (δ) are considered the second and third-best solutions. While the omega wolf (ω) is considered as the best solution. In hunting, wolves with types α, β, and δ have more ability to guide other wolves. Whereas omega (ω) wolves only follow orders from the other three wolves. The behavior when circling prey is a technique carried out by wolves to trap prey. Encircling prey (D) is s the behavior of wolves when they find prey where the wolves will renew their position $X(t+1)$. This behavior is modeled mathematically in equations below.

$$D = |C.X_p(t) - X(t)| \quad (26)$$

$$X(t+1) = X_p(t) - A.D \quad (27)$$

where D is the wolf's circular behavior, A and C are coefficient values, X_p is the position of prey, and X is the position of each wolf. Mathematical models of A and C are shown below.

$$A = 2a.r_1 - a \quad (28)$$

$$C = 2.r_2 \quad (29)$$

where: a is a value that decreases linearly from 2 to 0 during iteration and r_1/r_2 are random values in the range 0 and 1.

Hunting is the behavior of grey wolves looking for prey guided by alpha, beta, and delta wolves. These three best solutions are saved. Other wolves (including omega) are required to renew their position. The mathematical formula of wolf behavior in circling prey ($D_{\alpha,\beta,\delta}$) and the position of each best wolf ($X_{1,2,3}$) can be seen in reference [10]. While the position updates of other wolves are mathematically modeled below.

$$X(t+1) = (X_1 + X_2 + X_3)/3 \quad (30)$$

Attack prey (exploitation) is the final stage in hunting until the prey does not move anymore. To accommodate this strategy, component A is made to decrease so that component A also decreases. Component A is in the range of random values [-2a, 2a]. Component C is made does not decrease linearly. This component helps this algorithm in the exploration process so that it is not trapped in local optimization. The flow chart of the fourth algorithm to solve the MORPD problem can be seen in Figure 4.

E. Multi-verse Optimizer

The MVO algorithm [12] was discovered from the Big Bang theory related to multiverses that discuss the birth of the universe. In theory, there are three concepts used namely white holes, black holes, and wormholes. In this algorithm, the white hole is adopted as the first exploration process. The black hole is adopted as the second exploration process. Whereas wormholes are adopted as a process of exploitation. Every universe produces inflation. The higher the inflation value of the universe, the better the fitness value. Inflation is adopted as a function of objectives that will be minimized or maximized.

The MVO algorithm has the advantage that all solutions can contribute to generating new solutions. The elitism operator is used to store the best solution obtained by the algorithm during the optimization process. Whereas the mutation operator is not applied with one hundred percent random values. This is because where the best solutions are connected. The relationship between solutions is called a wormhole. This mechanism can improve the exploitation process of this algorithm. The MVO algorithm formula is shown below.

$$x_i^k = \begin{cases} \begin{cases} x_k + TDR \times (ub_k - lb_k) \times r_4 + lb_k) & \text{if } r_3 < 0.5, r_2 < WEP \\ x_k - TDR \times (ub_k - lb_k) \times r_4 + lb_k) & \text{if } r_3 \geq 0.5, r_2 < WEP \end{cases} \\ x_i^k & \text{if } r_2 \geq WEP \end{cases} . \tag{31}$$

where: x^k_i indicates the k variable in the i-th solution, x_k indicates the k-variable in the best solution, WEP is the probability of the existence of wormholes, TDR is the mileage rate, lb_k is the lower boundary of the k-th dimension, ub_k is the upper limit of the k-dimension, r_2 - r_4 are random values. The distribution of r_2 - r_4 values can be adjusted to emphasize the convergence of the exploration process. The formulas of WEP and TDR are shown in equations (32) and (33). The flow chart of the fifth algorithm can be seen in Figure 5 to solve the MORPD problem in this work.

$$WEP = WEP_{min} + t \times \left(\frac{WEP_{max} - WEP_{min}}{t_{max}} \right). \tag{32}$$

$$TDR = 1 - \left(\frac{t^{1/p}}{t_{max}^{1/p}} \right). \tag{33}$$

F. Multi-objective Strategy and Handling Constraints

Several strategies are used to solve multi-objective optimization problems simultaneously such as dominant and non-dominant Pareto. Pareto dominance [52] is a comparison of two solutions in which all objective function objective values are better when compared to other solutions. Whereas non-dominated [53] is a comparison of two solutions where none dominates. In other words, each solution only has one of the better objective function values. For the management of both solutions, an external repository [54] is used which consists of two parts:

a. An archived controller functions to determine the solution to be added and removed to/from the archive. The mechanism is based on the criteria for solutions that do not dominate each other.
b. Grid aims to produce a well-distributed Pareto front. The process of associating a new solution and removing an old solution is based on the probability value of the solution density. The mathematical formula of these mechanisms is shown below.

$P_i = c/N_i($ (34)

$P_i = N_i/c$ (35)

where c is a constant number that must be more than 1 and N_i is the number of solutions around the i-th solution.

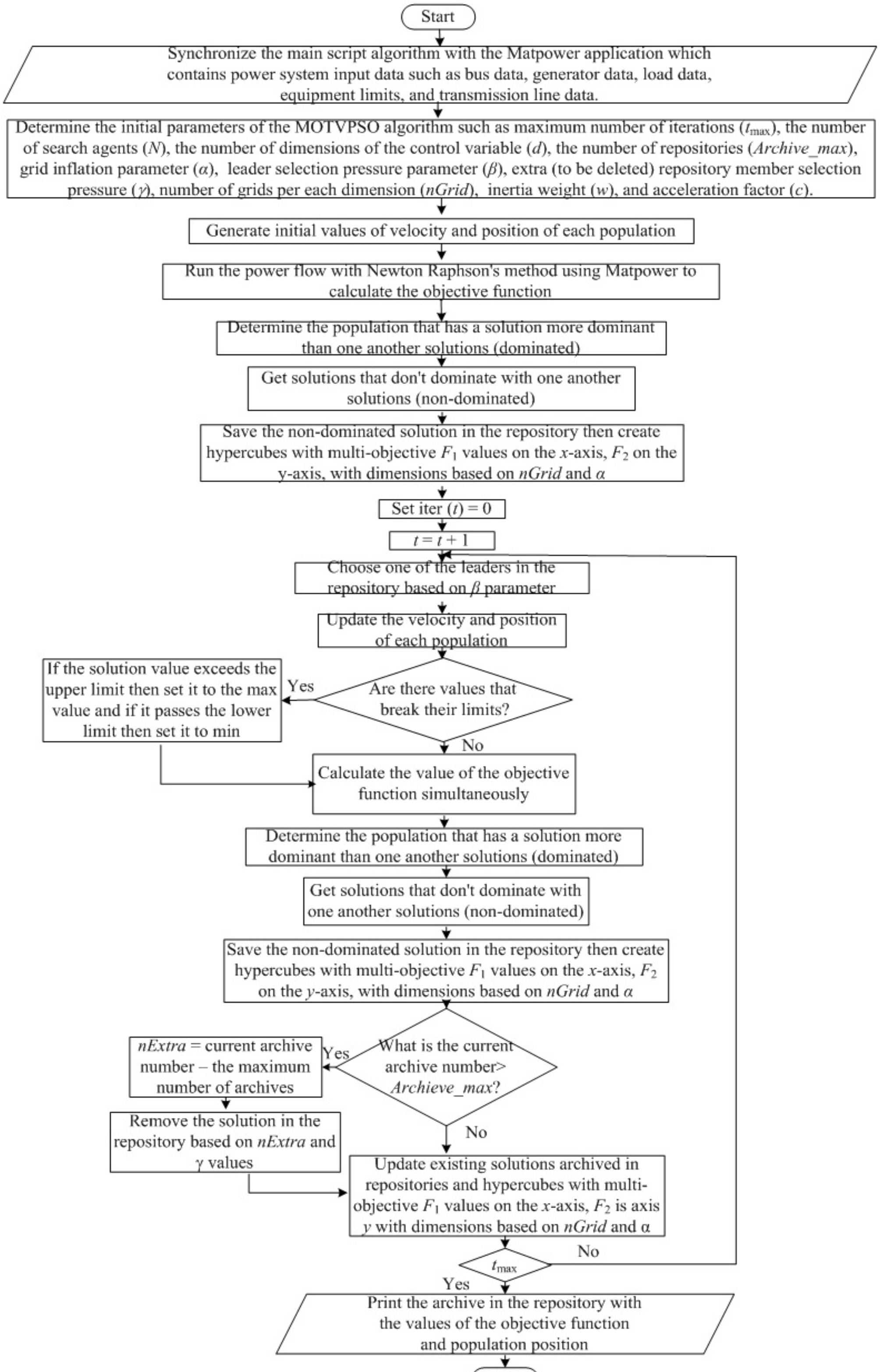


Figure 1. Flowchart of MOTVPSO algorithm

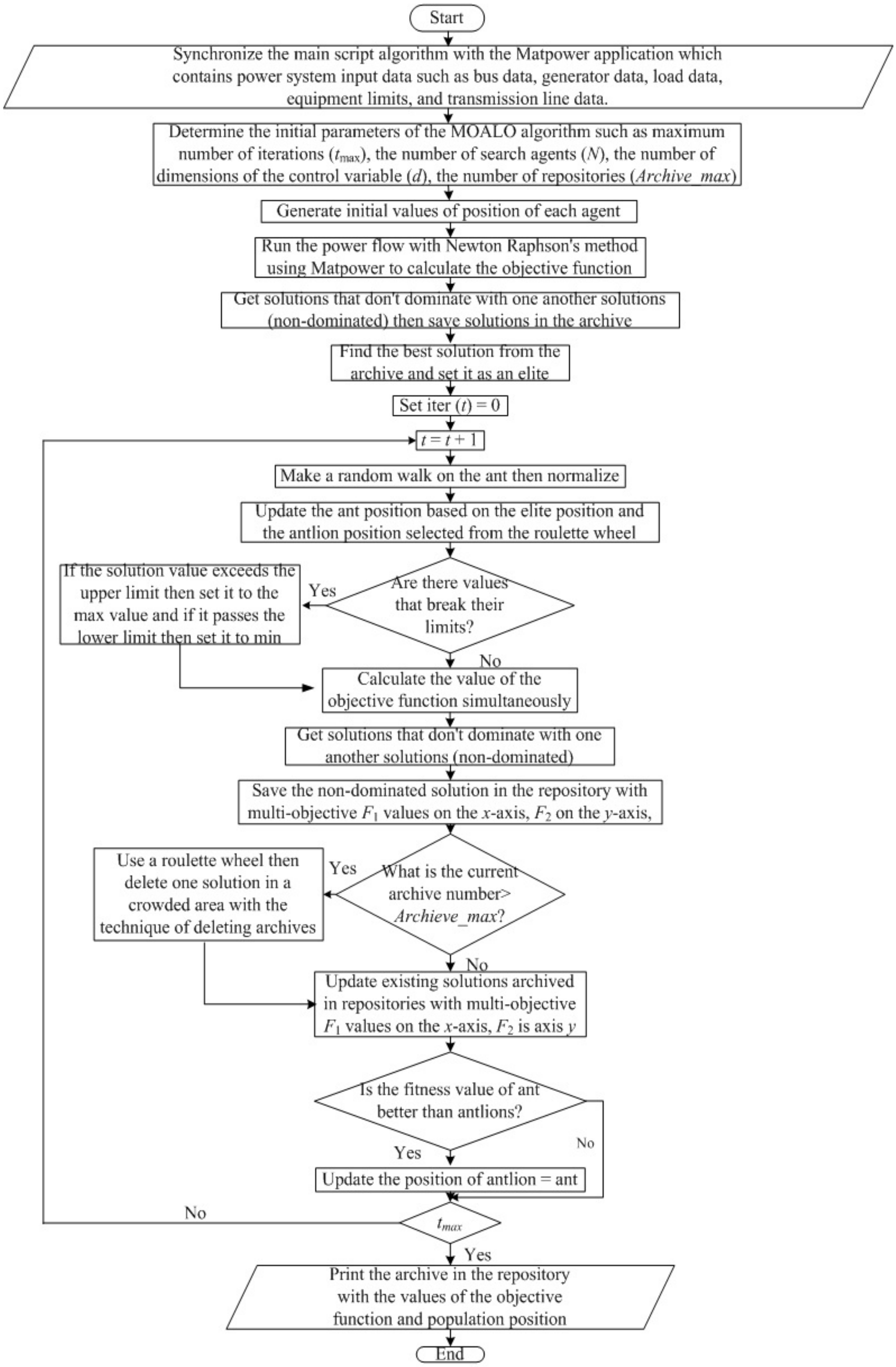


Figure 2. Flowchart of MOALO algorithm

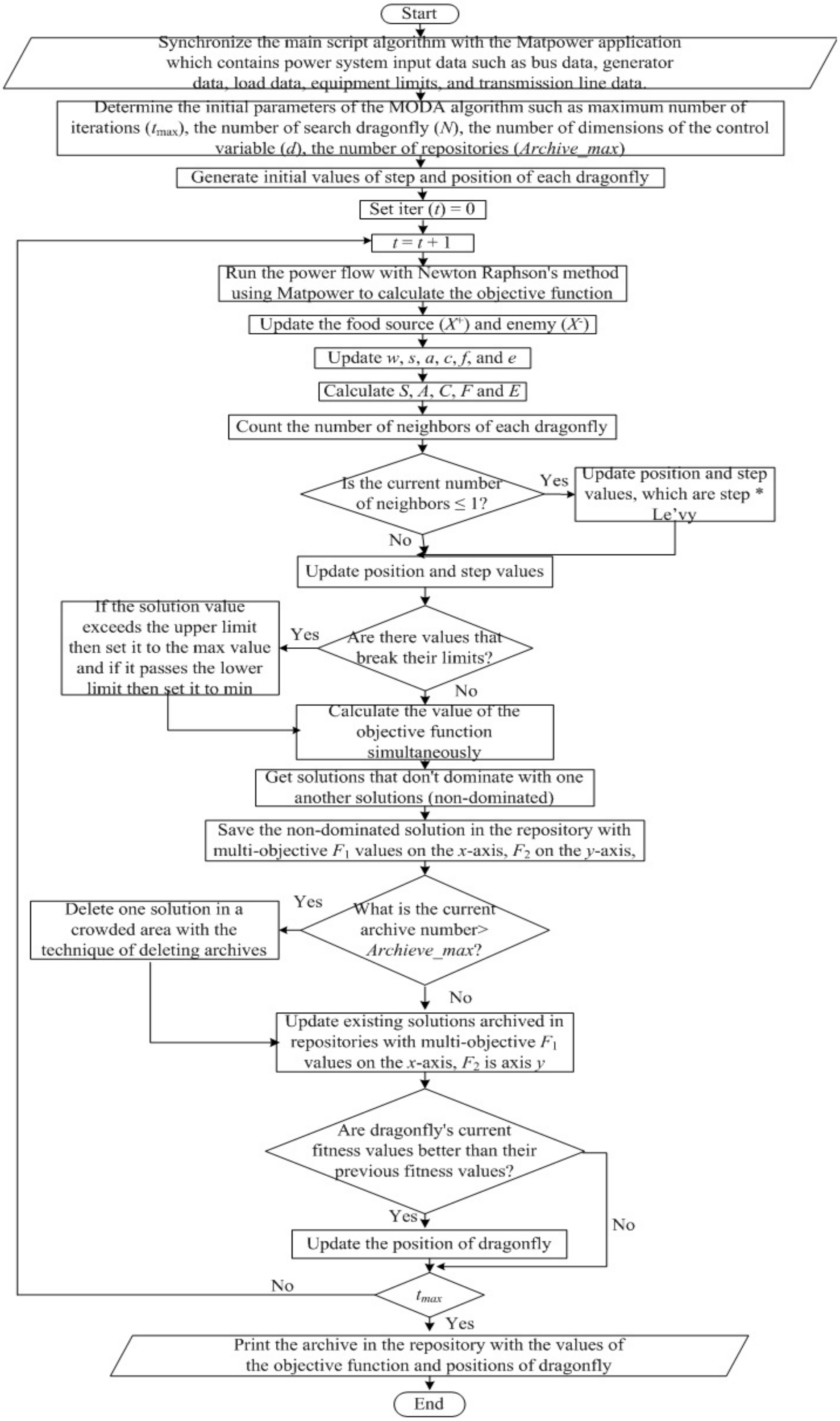


Figure 3. Flowchart of MODA algorithm

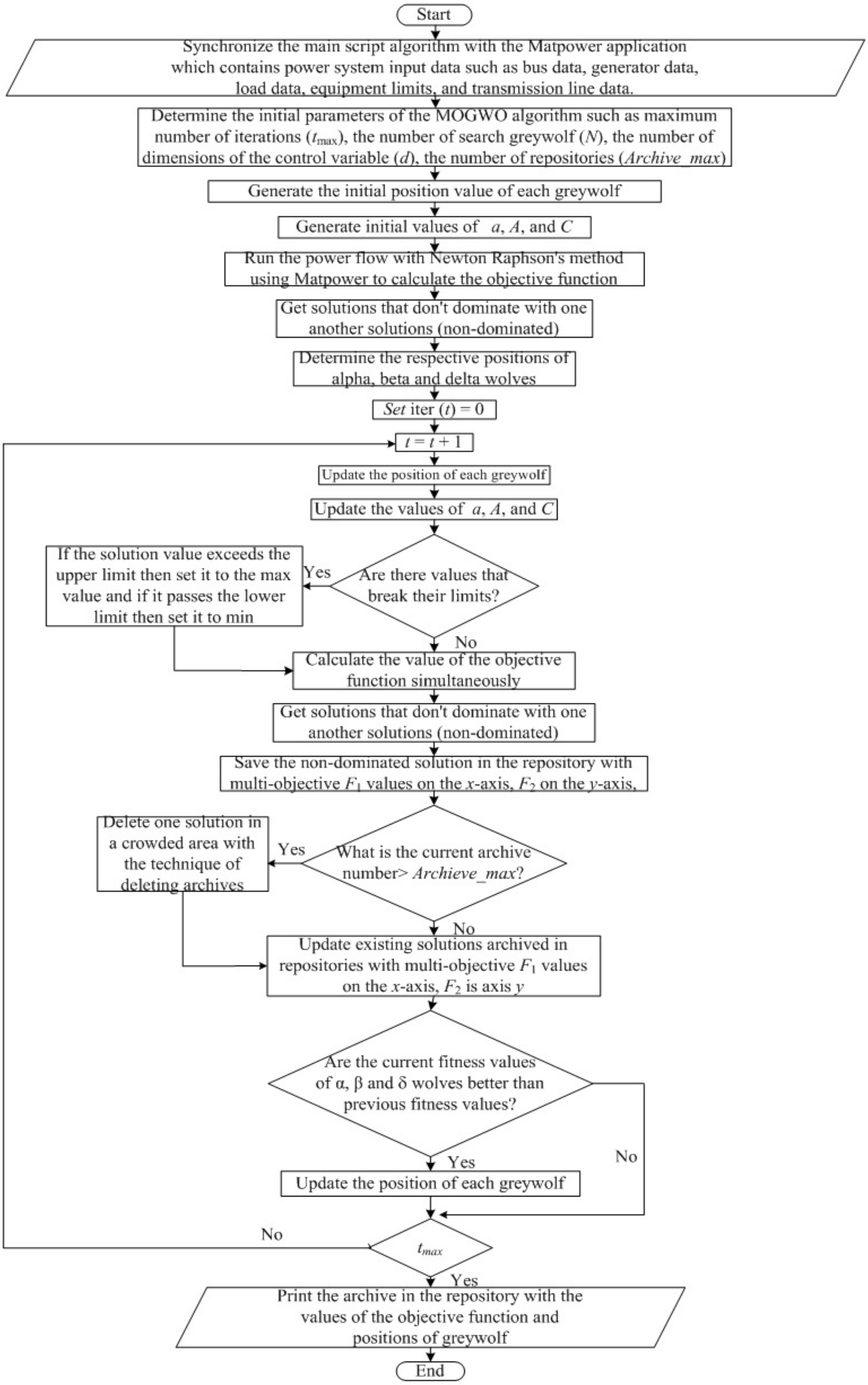


Figure 4. Flowchart of MOGWO algorithm

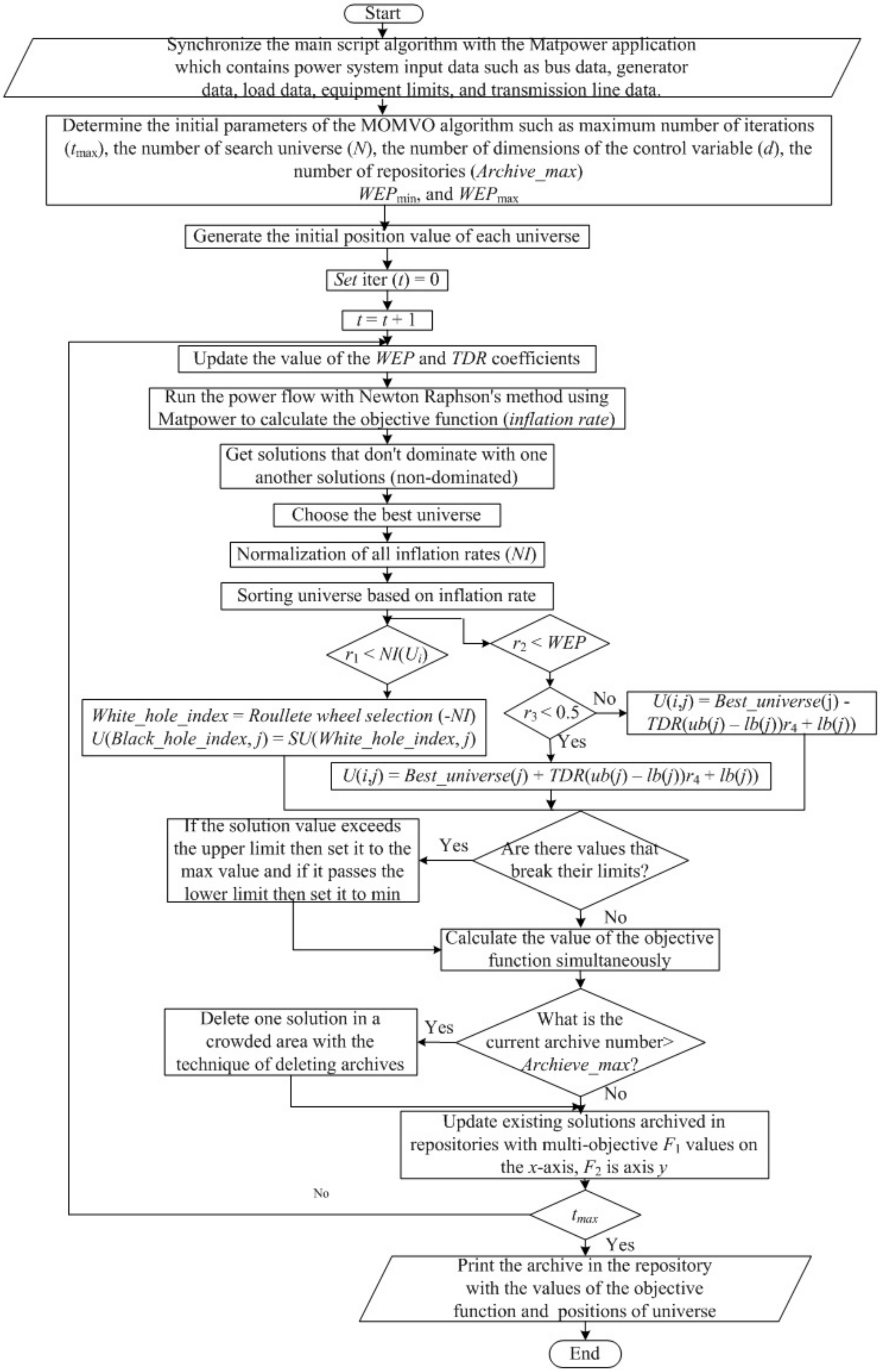


Figure 5. Flowchart of MOMVO algorithm

4. Simulation Results and Discussions

In this work, proposed algorithms are tested on the IEEE 57-bus [47]. A brief description regarding generator data, load data, transmission line data can be seen in Table 1, and the complete data can be seen in the Matpower application from reference [55]. The IEEE 57-bus system consists of 57 buses of which 7 are bus generators and 50 are load buses. Bus 1 is a slack bus while buses 2, 3, 6, 8, 9, and bus 12 are PV buses. The system has 80 transmission lines, 17 tap transformers, and 3 capacitor banks. 27 control variables are used in the case. 10 control variables consist of 7 control variables which are considered as continuous variables, namely the voltage magnitude on the bus generator and 17 ratio tap transformers (at lines 4-18, 4-18, 21-20, 24-25, 24-25, 24-26, 7-29, 34-32, 11-41, 15-45, 14-46, 10-51, 13-49, 11-43, 40-56, 39-57 and 9-55), and 3 capacitor banks (at buses 18, 25 and 53) considered a discrete variable.

The voltage magnitude limit on the generator bus and the tap transformers used are 0.9 - 1.1 per unit (p.u.). The step applied to the three-tap transformers is 0.02 p.u. The voltage magnitude limit on all load buses is 0.94 - 1.06 p.u. The limit of the reactive power compensator injected on bus 18 is 0.0 - 0.2 p.u. The reactive power compensator injected on buses 25 and 53 is 0.0 - 0.18 p.u. Each of the variables has a step of 0.02 p.u. Limitation and step data of variables can be seen in Table 2. The total loading is 1250.8 MW and 336.4 MVAr at 100 MVA base. Figure 6 shows a single-line diagram on the IEEE 57-bus. The parameters of the five algorithms can be read in Table 3.

Table 1. Description of Test Power System [47]

System data	Amount
Buses. N_B	57
Generators. N_G	7
Transformer. N_T	17
Shunts. N_C	3
Branches. N_E	80
Control variables	27
Discrete variables	20
Active power demands. MW	1250.8
Reactive power demands. MVar	336.4

Table 2. The Upper and Lower Limits of Variables [47].

Descriptions	Limits (p.u.)		Steps (p.u.)
	Lower	Upper	
Magnitude voltage generator, $V_{G,i}$	0.90	1.10	-
Tap transformer, T_i	0.90	1.10	0.02
Shunt compensator, $Q_{c,18}$	0.00	0.20	0.02
Shunt compensator, $Q_{c,25}$ and $Q_{c,53}$	0.00	0.18	0.02

Table 3. Parameter Settings of Algorithms.

Parameters of algorithm	Symbols	Values
Maximum number of iterations and population size $^{(1\text{-}5)*}$	t_{max}/N	300
Number of repositories$^{(1\text{-}5)*}$	$Archive_{max}$	100
Maximum and minimum values of the acceleration factor^{1*}	c	1.5 & 0.3
Maximum and minimum values of the inertia weight^{1}	w	0.9 & 0.4
Grid inflation parameter^{1,5}	*Alpha*	0.9
Leader selection pressure parameter^{1,5}	*Beta*	4
Extra (to be deleted) repository member selection pressure^{1,5}	*Gamma*	2
Number of grids per each dimension^{1,5}	*nGrid*	10
Maximum and minimum of wormhole existence probability^{5}	$WEP_{max/min}$	1.5/0.3

*1-5 = Algoritm number

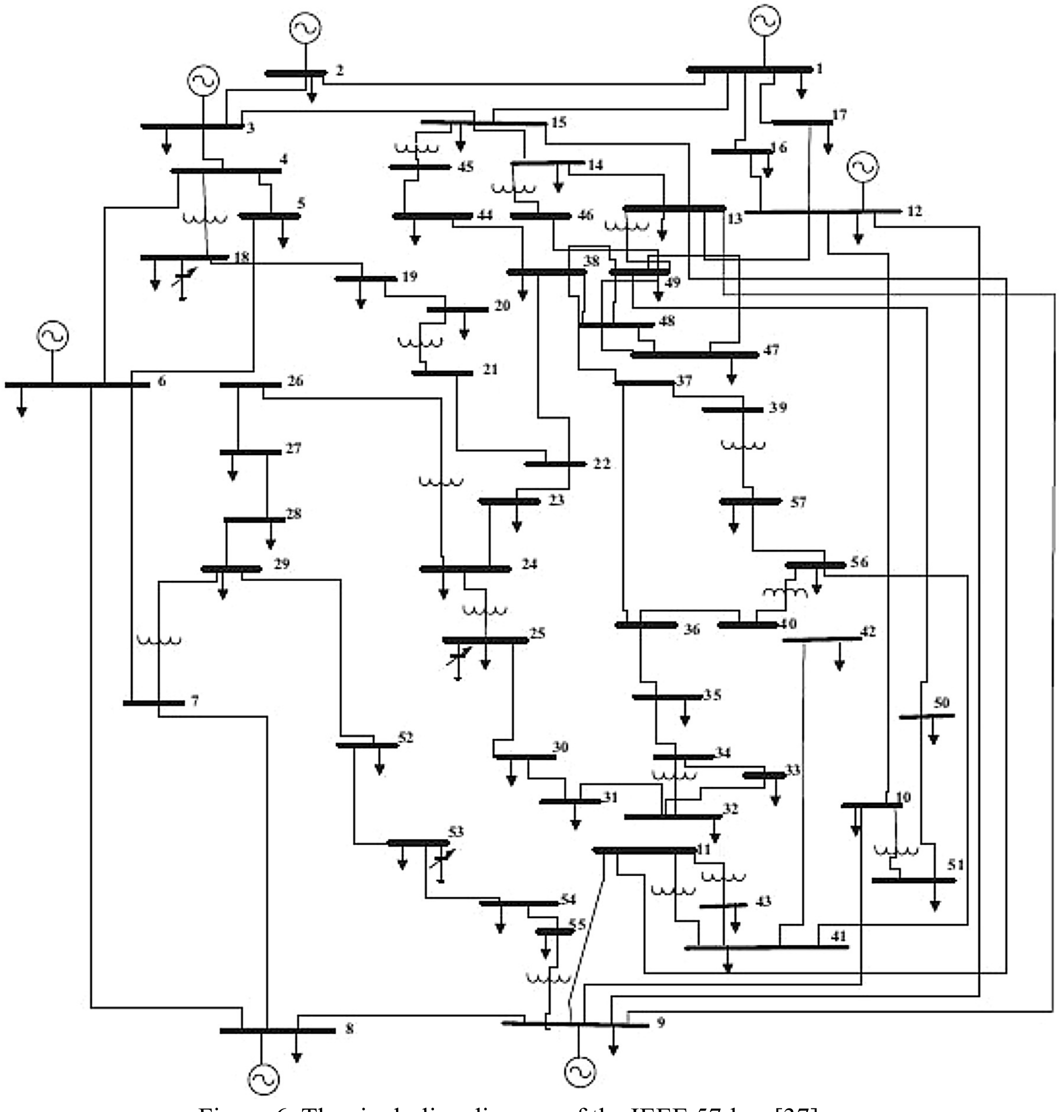


Figure 6. The single-line diagram of the IEEE 57-bus [37].

A. Quality of Solutions

A.1. Minimization of The Real Power Losses

The five algorithms are applied to minimize real power loss with simultaneous multi-objective optimization. Figure 7 – Figure 11 show the process of finding an optimal solution of five trials for each approach used. Each approach will produce the best *BOV* value. The best *BOV* values obtained from each of these approaches are then compared. From the simulation results, each of the MOTVPSO, MOALO, MODA, MOGWO, and MOMVO approach produces a *BOV* of 24.7106 MW, 24.9910 MW, 24.9108 MW, 25.0147 MW, and 25.0732 MW. The values produced by each MOEPSO [47], MGBICA [48], MOTVPSO, MODA, MOGWO, and MOMVO approach are 0.2744 MW (0.99 %), 2.7009 MW (9.79 %), 2.8766 MW (10.43%), 2.5962 MW (9.41%), 2.6764 MW (9.7%), 2.5725 MW (9.32 %), and 2.514 MW (9.11 %) lower than those of MOPSO approach [47]. The values of the control variables and *BOV* produced by these approaches can be seen in Table 4.

A.2 Minimization of The Total Voltage Deviation

The five algorithms are also applied to minimize the total voltage deviation on all load buses with simultaneous multi-objective optimization. Figure 7 – Figure 11 show the process of finding an optimal solution of five trials for each approach used. The simulation results obtained from those five approaches based on the minimum *BOV* sequence are MOTVPSO, MOALO, MODA, MOGWO, and MOMVO, respectively 1.9524 p.u., 1.9755 p.u., 1.9600 p.u., 1.9715 p.u., and 1.9681 p.u. The values of *TVD* produced by each of the MOEPSO, MOPSO, MGBICA, MOTVPSO, MODA, MOGWO, and MOMVO approach are 1.1295 p.u. (57.18%) [47], 1.0354 p.u. (52.41%) [47], 1.2009 p.u. (60.79 %), 0.0231 p.u. (1.17 %), 0.0155 p.u. (0.78 %), 0.0040 p.u. (0.2 %), 0.0074 p.u. (0.37 %), lower than those of the MOALO approach. The complete results of the optimal value of the control variables for each algorithm can be seen in Table 5.

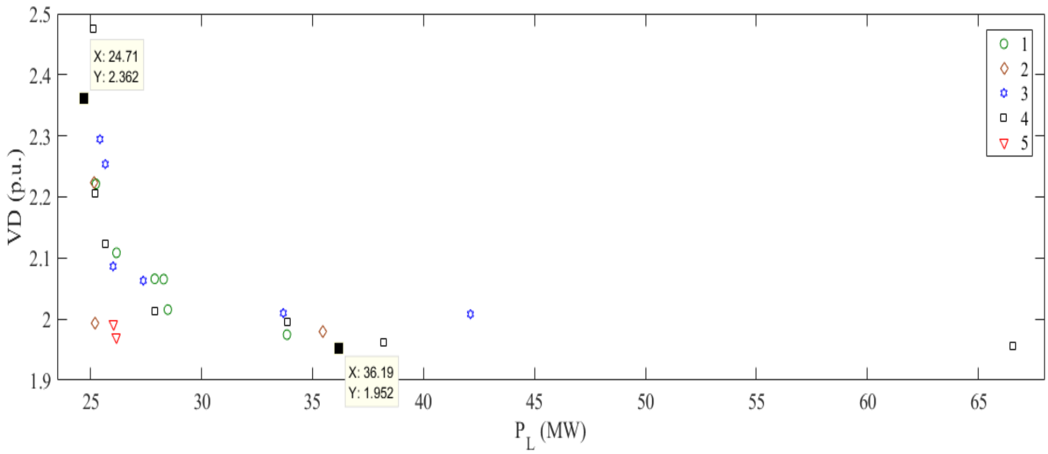


Figure 7. The search for optimal solutions with five trials using the MOTVPSO algorithm to solve MORPD problems

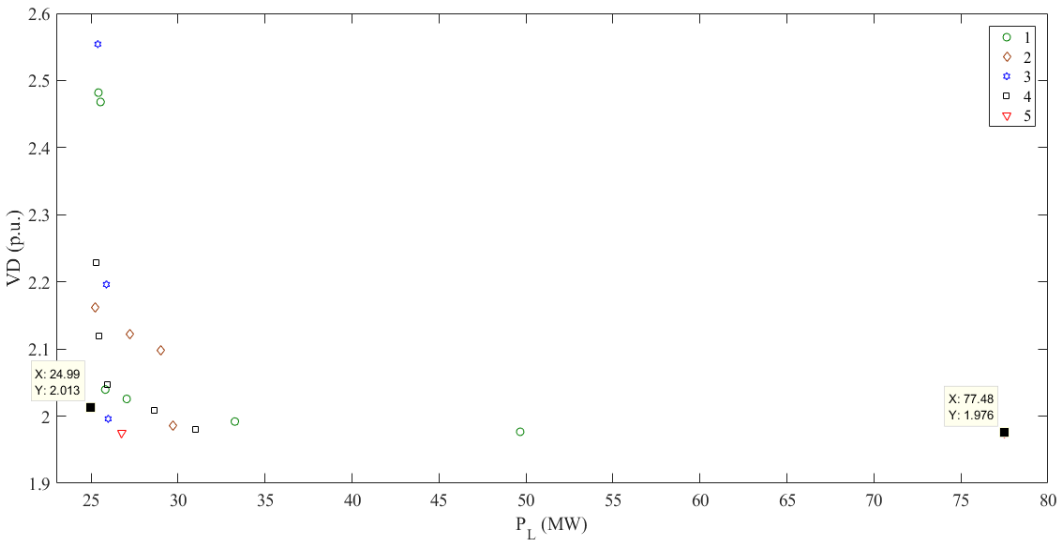


Figure 8. The search for optimal solutions with five trials using the MOALO algorithm to solve MORPD problems

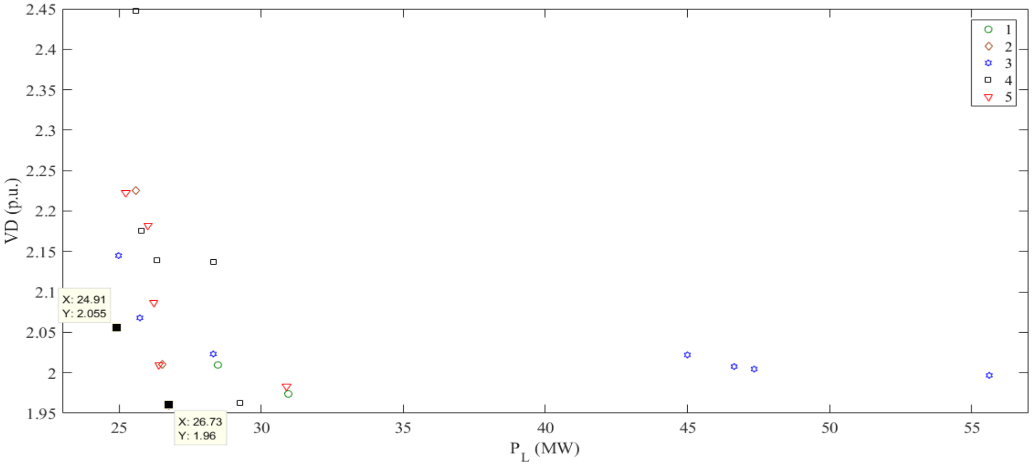


Figure 9. The search for optimal solutions with five trials using the MODA algorithm to solve MORPD problems

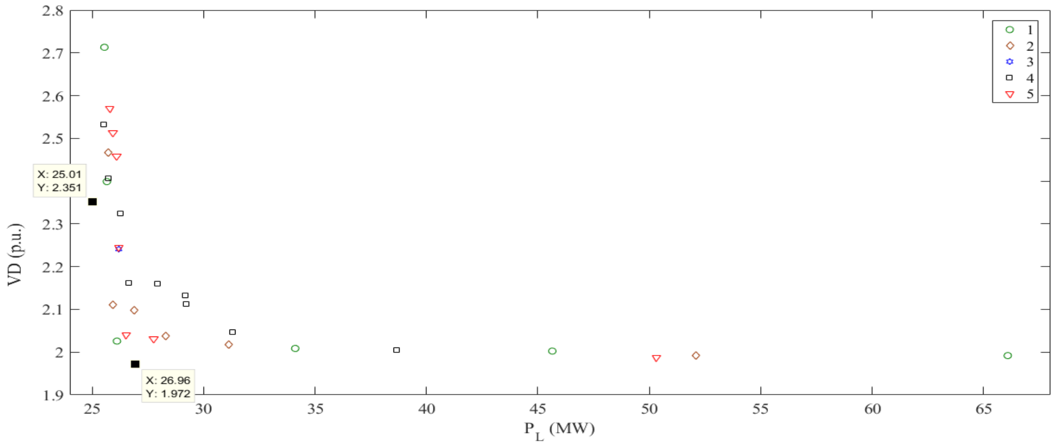


Figure 10. The search for optimal solutions with five trials using the MOGWO algorithm to solve MORPD problems

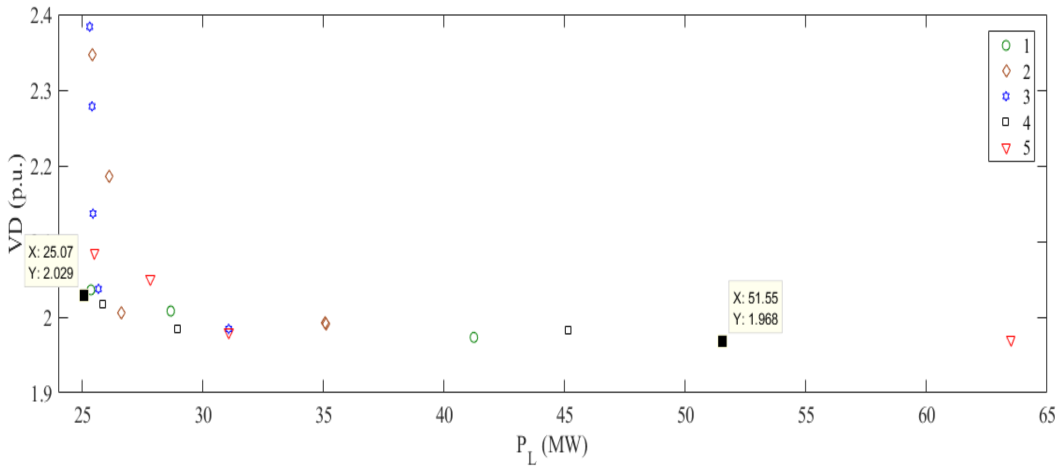


Figure 11. The search for optimal solutions with five trials using the MOMVO algorithm to solve MORPD problems

Table 4. Comparison of Simulation Results for The IEEE 57-bus with Real Power Losses Minimization Objective.

Variables (p.u.)	Algorithms			
	MOEPSO [47]	MOPSO [47]	MGBICA [48]	MOTVPSO
V_{G1}	0.931438	1.100000	1.0600	1.0923
V_{G2}	1.100000	1.100000	1.0492	1.0845
V_{G3}	0.900000	1.100000	1.0388	1.0683
V_{G6}	0.958431	1.100000	1.0353	1.0463
V_{G8}	0.900000	0.900000	1.0558	1.0692
V_{G9}	1.100000	0.911538	1.0212	1.0511
V_{G12}	0.900000	0.900000	1.0295	1.0647
$T_{4\text{-}18}$	1.10	1.10	0.95	1.10
$T_{4\text{-}18}$	0.90	0.90	1.00	1.10
$T_{21\text{-}20}$	1.02	1.04	1.01	1.02
$T_{24\text{-}25}$	0.90	1.10	-	0.98
$T_{24\text{-}25}$	0.98	1.10	-	1.04
$T_{24\text{-}26}$	1.02	1.10	1.02	0.98
$T_{7\text{-}29}$	0.96	0.98	0.99	1.06
$T_{34\text{-}32}$	0.90	0.90	0.93	1.06
$T_{11\text{-}41}$	0.90	0.90	0.91	1.02
$T_{15\text{-}45}$	0.94	0.94	0.97	0.92
$T_{14\text{-}46}$	0.92	0.92	0.96	0.94
$T_{10\text{-}51}$	0.94	0.94	0.96	1.10
$T_{13\text{-}49}$	0.90	0.90	0.92	0.94
$T_{11\text{-}43}$	0.94	0.96	0.95	0.96
$T_{40\text{-}56}$	1.10	1.10	1.03	1.06
$T_{39\text{-}57}$	0.96	0.98	0.98	1.10
$T_{9\text{-}55}$	0.96	0.96	0.99	1.02
Q_{c18}	0.10	0.00	0.04	0.20
Q_{c25}	0.00	0.18	0.06	0.04
Q_{c53}	0.08	0.00	0.05	0.10
P_L, MW	27.31280	27.58720	24.8863	24.7106
ΔP_L, %	0.99	-	9.79	10.43
TVD, p.u.	1.072430	1.313360	1.0283	2.3618

Table 4. Comparison of Simulation Results for The IEEE 57-bus with Real Power Losses Minimization Objective (Continued).

Variables (p.u.)	Algorithms			
	MOALO	MODA	MOGWO	MOMVO
V_{G1}	1.0968	1.0925	1.0950	1.0933
V_{G2}	1.0943	1.0969	1.0835	1.0828
V_{G3}	1.0905	1.0832	1.0685	1.0747
V_{G6}	1.0960	1.0458	1.0498	1.0901
V_{G8}	1.0689	1.0932	1.0815	1.0784
V_{G9}	1.0826	1.0733	1.0640	1.0867
V_{G12}	1.0793	1.0881	1.0376	1.0912
$T_{4\text{-}18}$	0.98	1.06	0.92	1.06
$T_{4\text{-}18}$	0.94	1.02	0.98	1.06
$T_{21\text{-}20}$	1.02	1.04	1.04	1.04
$T_{24\text{-}25}$	0.98	0.92	1.02	0.96
$T_{24\text{-}25}$	1.04	1.00	0.98	1.10
$T_{24\text{-}26}$	1.08	0.92	0.96	0.92
$T_{7\text{-}29}$	0.96	0.96	0.98	1.02
$T_{34\text{-}32}$	1.06	0.94	1.10	0.92
$T_{11\text{-}41}$	1.08	1.00	1.04	1.06
$T_{15\text{-}45}$	1.08	1.06	0.98	1.04
$T_{14\text{-}46}$	0.92	1.06	1.06	0.96
$T_{10\text{-}51}$	1.04	1.04	1.00	0.98
$T_{13\text{-}49}$	1.02	1.00	0.94	1.02
$T_{11\text{-}43}$	1.04	0.98	1.04	0.92
$T_{40\text{-}56}$	1.10	1.06	1.02	1.08
$T_{39\text{-}57}$	1.00	1.00	1.10	1.00
$T_{9\text{-}55}$	1.06	1.02	1.08	0.92
Q_{c18}	0.08	0.18	0.18	0.02
Q_{c25}	0.12	0.04	0.04	0.16
Q_{c53}	0.04	0.06	0.12	0.12
P_L, MW	24.9910	24.9108	25.0147	25.0732
ΔP_L, %	9.41	9.7	9.32	9.11
TVD, p.u.	2.0133	2.0553	2.3508	2.0290

Table 5. Comparison of Simulation Results for The IEEE 57-bus with Total Voltage Deviation Minimization Objective.

Variables (p.u.)	Algorithms			
	MOEPSO [47]	MOPSO [47]	MGBICA [48]	MOTVPSO
V_{G1}	0.9055	1.0479	1.0555	1.0665
V_{G2}	1.1000	1.1000	1.0339	1.0001
V_{G3}	0.9000	1.1000	1.0086	1.0992
V_{G6}	0.9061	0.9797	1.0067	1.0707
V_{G8}	0.9000	0.9882	1.0462	1.0830
V_{G9}	1.1000	0.9000	1.0067	1.0999
V_{G12}	0.9000	1.1000	1.0059	1.0824
$T_{4\text{-}18}$	1.10	1.10	0.93	0.98
$T_{4\text{-}18}$	0.90	0.90	1.01	0.94
$T_{21\text{-}20}$	0.98	0.98	0.98	0.96
$T_{24\text{-}25}$	0.90	1.10	-	0.96
$T_{24\text{-}25}$	1.10	1.10	-	0.98
$T_{24\text{-}26}$	1.02	1.10	1.07	1.04
$T_{7\text{-}29}$	0.96	0.96	0.96	1.02
$T_{34\text{-}32}$	0.90	0.90	0.91	0.94
$T_{11\text{-}41}$	0.90	0.90	0.90	1.02
$T_{15\text{-}45}$	0.94	0.94	0.95	0.94
$T_{14\text{-}46}$	0.92	0.98	0.95	0.92
$T_{10\text{-}51}$	0.98	0.98	0.98	1.04
$T_{13\text{-}49}$	0.90	0.90	0.94	0.92
$T_{11\text{-}43}$	0.92	0.96	0.97	0.92
$T_{40\text{-}56}$	1.10	1.10	1.04	0.92
$T_{39\text{-}57}$	0.90	0.90	0.93	1.02
$T_{9\text{-}55}$	0.96	0.94	0.98	0.96
Q_{c18}	0.04	0.00	0.03	0.18
Q_{c25}	0.00	0.18	0.06	0.14
Q_{c53}	0.10	0.00	0.03	0.08
TVD. p.u.	0.845954	0.94013	0.77461	1.9524
$\% \Delta TVD$	57.18	52.41	60.79	1.17
P_L. MW	27.7258	28.3395	26.4618	36.1927

Table 5. Comparison of Simulation Results for The IEEE 57-bus with Total Voltage Deviation Minimization Objective (Continued).

Variables (p.u.)	Algorithms			
	MOALO	MODA	MOGWO	MOMVO
V_{G1}	1.0758	1.0716	1.0758	1.0899
V_{G2}	0.9007	1.0893	1.0965	0.9633
V_{G3}	1.1000	1.0857	1.0899	1.0996
V_{G6}	1.0359	1.0446	1.0349	1.0401
V_{G8}	1.0819	1.0985	1.0964	1.0979
V_{G9}	1.0963	1.0948	1.0835	1.0968
V_{G12}	1.0873	1.0950	1.0917	1.0785
T_{4-18}	1.00	0.94	1.02	1.08
T_{4-18}	1.08	1.02	0.98	1.10
T_{21-20}	1.02	0.94	0.98	1.08
T_{24-25}	0.92	0.92	1.04	0.94
T_{24-25}	0.96	1.00	0.94	0.98
T_{24-26}	1.02	1.10	1.04	0.92
T_{7-29}	0.96	1.00	0.96	0.92
T_{34-32}	0.92	1.00	1.08	1.00
T_{11-41}	1.00	1.10	1.00	0.98
T_{15-45}	1.10	1.06	0.98	1.04
T_{14-46}	1.04	0.96	1.04	1.10
T_{10-51}	1.04	0.92	1.04	1.00
T_{13-49}	1.06	0.98	0.98	1.08
T_{11-43}	0.98	1.08	0.96	0.98
T_{40-56}	1.04	0.96	0.94	1.00
T_{39-57}	1.02	1.00	1.08	1.00
T_{9-55}	1.04	1.00	0.98	0.96
Q_{c18}	0.02	0.14	0.14	0.16
Q_{c25}	0.18	0.16	0.10	0.04
Q_{c53}	0.08	0.14	0.08	0.16
TVD, p.u.	1.9755	1.9600	1.9715	1.9681
ΔTVD, %	-	0.78	0.20	0.37
P_L, MW	77.4787	26.7349	26.9600	51.5468

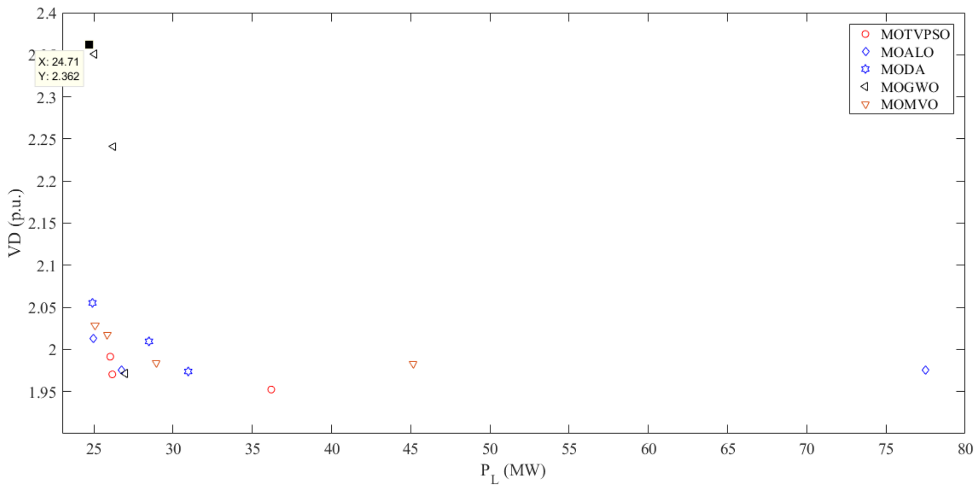
A.3 Statistical Tests

The MOTVPSO, MOALO, MODA, MOGWO, and MOMVO approaches are carried out for five trials on the power system mentioned earlier with aiming to minimize each P_L and TVD. The comparison of the process of finding a solution to minimize P_L and TVD on the IEEE 57-bus is shown in Figure 12 and Figure 13. The results of the statistical tests of each approach for the IEEE 57-bus are shown in Table 6.

The optimization stage in minimizing P_L on the IEEE 57-bus, Of 5 trials conducted in each approach, the MOTVPSO approach has the advantages of producing *BOV*, *WOV*, and *MOV* values compared to the other four approaches. The *BOV*, *WOV*, and *MOV* values for the MOTVPSO approach are respectively 24.7106 MW, 25.4222 MW, and 25.1332 MW. The optimization stage minimizes *TVD* on the IEEE 57-bus, the algorithm used in previous studies of MOEPSO and MOPSO is superior in producing *BOV*. However, the two algorithms do not present *WOV* and MOV values. So for the comparison of *WOV* and *MOV* conducted fellow approaches proposed in this work. The MOTVPSO approach has the advantage of producing *MOV* values of 1.9743 p.u. While the MOMVO algorithm is superior in producing *WOV* values, namely 1.9915 p.u. From the statistical tests, the ability of each algorithm to reduce the objective function is shown in Table 7. The table shows that the MOTVPSO approach has the most dominant contribution when compared to the four other approaches to solve MORPD problems on the IEEE 57-bus.

Some of the causes of the superiority of the MOTVPSO algorithm can be described qualitatively as follows:

1. The application of fine-tuning to inertia weight which decreases non-linearly so that optimal solutions can be produced with better accuracy [14]. Besides this strategy [56] can accelerate the convergence of PSO algorithms in finding optimal solutions.
2. The application of fine-tuning to the 1st and 2nd acceleration factors influences the exploration and exploitation process [15].



Figures 12. The best-obtained Pareto-fronts of MOTVPSO, MOALO, MODA, MOGWO, and MOMVO to minimize real power loss in the IEEE 57-bus.

Table 6. Detailed statistics based on *n* number of trials.

Algorithms	*BOV*		*WOV*		*MOV*	
	P_L (MW)	*TVD* (p.u.)	P_L (MW)	*TVD* (p.u.)	P_L (MW)	*TVD* (p.u.)
MOEPSO	27.3128	0.845954	NR	NR	NR	NR
MOPSO	27.5872	0.940126	NR	NR	NR	NR
MOTVPSO	24.7106	1.9524	25.4222	2.0081	25.1332	1.9743
MOALO	24.9910	1.9755	25.4233	1.9960	25.2729	1.9827
MODA	24.9108	1.9600	25.5996	1.9968	25.2627	1.9751
MOGWO	25.0147	1.9715	25.8032	2.0054	25.5262	1.9897
MOMVO	25.0732	1.9681	25.5084	1.9915	25.3319	1.9773

*NR=not reported

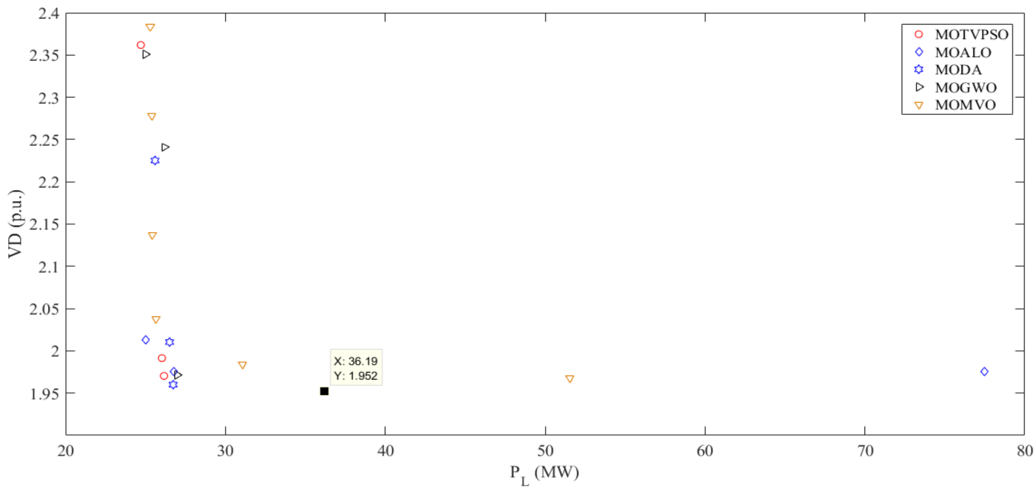


Figure 13. The best-obtained Pareto-fronts of MOTVPSO, MOALO, MODA, MOGWO, and MOMVO to minimize the total voltage deviation in the IEEE 57-bus.

Table 7. Comparison of The Number of Contributions in Reducing Objective Functions Based on Statistical Tests

Algorithms	ΔP_L (%)			ΔTVD (%)			Number of contributions
	BOV	*WOV*	*MOV*	*BOV*	*WOV*	*MOV*	
MOEPSO	0.99	NR*	NR*	57.18	NR*	NR*	1
MOPSO	0.00	NR*	NR*	52.41	NR*	NR*	0
MOTVPSO	10.43	1.48	1.54	1.17	0.00	0.77	4
MOALO	9.41	1.47	0.99	0.00	0.60	0.35	0
MODA	9.70	0.79	1.03	0.78	0.56	0.73	0
MOGWO	9.32	0.00	0.00	0.2	0.13	0.00	0
MOMVO	9.11	1.14	0.76	0.37	0.83	0.62	1

B. Computational Time

After the previous stages discussing the comparison of the quality of the solutions in each algorithm, the stage is examined in terms of the computational time used by each algorithm in solving MORPD problems. The computational time shows the efficiency of the algorithm. The quality of the solution and the computational time are two matters that are just as important as the optimization process. At this stage, we analyze the results of the statistical tests on the computation of time used, namely the best computing time (*BCT*), the worst computing time (*WCT*), *STDV*, and the mean computing time (*MCT*).

Table 8 shows the results of statistical tests on the computational time used by each algorithm to solve MORPD problems on the IEEE 57-bus. In the table, it can be seen that for five trials conducted by researchers, the MOMVO algorithm has the best computational efficiency if compared to the other algorithms. MOMVO algorithm produces a *BCT* value of 1786.535 s, a *WCT* value of 2071.983 s, and a *MCT* value of 1919.845 s. Although the MOMVO algorithm has a computationally efficient time, this algorithm has a weakness in producing quality solutions. Whereas the MODA algorithm has a weakness in the computational time used. The MOTVPSO algorithm has a fairly efficient computing time. Detailed computational time used by each algorithm which can be seen in Table 8.

Table 8. Comparison of Computational Time Based on Statistical Tests on Each Algorithm in Finding Optimal Solutions

Trials	Algorithms				
	MOTVPSO	MOALO	MODA	MOGWO	MOMVO
1	2483.479	1953.299	3779.785	2169.813	1984.133
2	2533.716	1952.369	3190.585	2156.664	1952.273
3	2500.900	2314.109	3194.499	2161.232	1804.299
4	2499.871	1909.604	3639.642	2164.531	2071.983
5	2506.568	1911.451	3215.298	2180.538	1786.535
BCT, (s)	2483.479	1909.604	3190.585	2156.664	1786.535
WCT, (s)	2533.716	2314.109	3779.785	2180.538	2071.983
STDV, (s)	18.257149	172.33185	283.63118	9.170628	121.91485
MCT, (s)	2504.9068	2008.1664	3403.9618	2166.5556	1919.845

Some of the causes of MOMVO algorithms tend to have highly efficient computing time are: (i). the local renewal solutions have relatively few processes, and (ii). the process of finding a solution that filters based on random values and *WEP*. While some of the causes of the MODA algorithm tend to be very long are: (i). the algorithm has many operators to determine the position of a search agent, and (ii). the algorithm provides different weight values for each operator so it takes time to update their weight values.

5. Conclusions and Future Works

In this work, five algorithms are proposed, namely MOTVPSO, MOALO, MODA, MOGWO, and MOMVO. All five algorithms are implemented to solve MORPD problems in the IEEE 57-bus. The problems solved in this work consist of simultaneous multi-objective optimization, handling constraints, and the characteristics of more complex control variables. All algorithms have never been used to solve MORPD problems. Based on the simulation results, the MOTVPSO algorithm has a more dominant contribution to the statistical test when compared to the four other algorithms and previous research in reducing real power losses. While reducing total voltage deviation, the MOTVPSO and MOMVO algorithms are superior based on statistical tests compared to the three algorithms proposed in this work. Whereas the MOMVO algorithm has an advantage in computational time efficiency. However, the algorithm has a weakness in producing sub-optimal solutions. In future research to improve the quality of solutions and reduce computational time, the MOTVPSO method can adopt several strategies used by the MOMVO algorithm. Besides, to improve model resolution and reduce uncertainty in the operation of power systems, future research needs to consider such things as the reactive power capacity of generators based on the capacity curve and the dynamic reactive power compensator technology.

6. Acknowledgment

The authors would like to appreciate and express great gratitude to the doctoral scholarship from the Indonesian Ministry of Research, Technology, and Higher Education (Grant No. 1405.27/E4.4/2015).

7. References

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