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RESEARCH ARTICLE

A Two-Archive Harris Hawk Optimization for Solving Many-Objective Optimal Power Flow Problems

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ABSTRACT To improve power system operation and management and accomplish modern power system requirements, a new algorithm named two-archive harris hawk optimization (TwoArchHHO) is proposed to solve many-objective optimal power flow (MaOOPF) problems in this work. For modern power systems, only single-objective and multiobjective (2-3 objectives) optimal power flow problems (MOOPF) are inadequate. So, the problems become many-objective (more than 3 objectives) optimal power flow problem which is more complicated to be solved. Although several metaheuristic algorithms have been proposed to solve MOOPF problems, very few algorithms have been introduced to solve MaOOPF problems and high-performance algorithms are still required to solve MaOOPF problems which are more complicated. To solve the complicated MaOOPF problems, TwoArchHHO is proposed by adding the two-archive concepts of the improved two-archive algorithm into the harris hawk optimization (HHO) in order to enhance the searchability and eventually provide superior solutions. The objective functions considered to be minimized include fuel cost, emission, transmission line loss, and voltage deviation to improve power systems in the economic, environmental, and secure aspects. Several sizes of IEEE standard systems, which are IEEE 30-, 57-, and 118-bus systems, are tested to evaluate the performance of the proposed TwoArchHHO. The simulation results comprise Pareto fronts, best-compromised solutions, and hypervolume analysis are generated and compared with results from several algorithms in the literature. The data provided by the experimental trials and the hypervolume performance metric were examined using statistical testing methods. The results indicate that the TwoArchHHO obtained better optimal solutions than those of the compared algorithms including its traditional algorithms, especially in large systems. Based on the best-compromised solutions, the TwoArchHHO provided one best objective aspect among the compared algorithm for most cases. Based on the hypervolume, the TwoArchHHO generated better hypervolume values than those of the compared algorithms around 33.96% to 99.59% in the tested systems.

INDEX TERMS Harris Hawk optimization, metaheuristic algorithms, many-objective optimal power flow, two-archive algorithm.

I. INTRODUCTION

The introduction of the optimal power flow (OPF) problem has emerged as an essential instrument for the planning and management of power system operations [1], [2]. The OPF efficiently achieves the improvement of power system operation by optimally minimizing or maximizing considered objective functions and fulfilling system constraints [3]. In a power system, a large number of generating units are generally required to appropriately generate electricity at minimum

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operation costs and transmission loss in order to reach a maximum benefit for power companies [4], [5], [6]. Moreover, with the huge increase in environmental awareness, thermal plants are also required to operate at the minimum emission [7]. In addition, voltage deviation enhancement is required to enhance the voltage profile as well as system security [8], [9], [10]. From the stated problems, single-objective OPF and multiobjective OPF (MOOPF), which consider 2-3 objectives, are insufficient for present power system operation and management as it can optimize only few objectives at a time. Many-objective functions (more than three objective functions) will then be considered to be optimized in the OPF problem referred to as many-objective OPF (MaOOPF) problems in order to simultaneously improve power systems in all terms of the stated problems. So, four objective functions including fuel cost, emission, transmission line loss, and voltage deviation will be considered to be optimized in the MaOOPF problem in this work.

With many successful proposed algorithms for solving MOOPF problems; however, very few algorithms have been proposed to solve MaOOPF problems, and high-performance algorithms are still needed to solve MaOOPF problems as they are more difficult to provide superior tradeoff solutions when more than 3 objectives are considered. Moreover, the "No Free Lunch" theorem states that a single algorithm cannot be the most suitable for solving every optimization problem in every field [11], the improvement of optimization algorithms is still necessary to more efficiently solve optimization problems. Harris hawk optimization (HHO) is a recent optimization algorithm proposed by Ali Asghar Heidari, et.al [12]. HHO has been effectively utilized to address a variety of optimization challenges across various fields [13], [14], [15], [16], [17], and its performance is greater than many algorithms in the literature. However, the traditional HHO cannot solve more than one objective problem. The improved two-archive algorithm (Two_Arch2) is an efficient algorithm that can solve more than one objective function problem proposed by Wang, Handing, et al. [18], and it has been adopted to provide optimal solutions in several aspects [19], [20]. Thus, this research aims to propose a new robust algorithm to enhance the performance of the HHO by adopting the method from the Two_Arch2 algorithm to efficiently solve the MaOOPF problem. The contributions of this study are presented below.

1) A new algorithm named TwoArchHHO is proposed by adding the two-archive concept of the Two_Arch2 algorithm into the HHO algorithm in order to improve the searchability of the original algorithms.

2) The proposed TwoArchHHO is applied to solve MOOPF and MaOOPF problems by considering four objective functions comprising cost, emission, transmission loss, and voltage deviation in the IEEE 30-, 57-, and 118-bus systems.

3) The Pareto fronts of the TwoArchHHO are generated and compared with other algorithms in terms of hypervolume values, and the best-compromised solutions are found and compared with those of several algorithms in the literature. The performance of the TwoArchHHO is confirmed by statistical analysis.

The remainder of the paper is as follows: The formulations of the MaOOPF problem are given in section II. Section III presents the formulations of the related optimization algorithms. The concept of the proposed TwoArchHHO for solving the MaOOPF problem is explained in section IV. Section V provides the simulation results and discussions of this work. Finally, the conclusion of this work is concluded in section VI.

II. RELATED STUDIES

To solve the OPF problems, various traditional algorithms [21], [22], [23] have been proposed; however, the nonlinear characteristics of the traditional algorithms lead the system solutions to be stuck in the local searching area, and extensive computational resources and time are needed. Thus, several metaheuristic algorithms presented in [24], [25], [26], and [27] and the following algorithms have been proposed to cope with these weaknesses;

- [28] ant colony optimization (ACO)
- [29] grey wolf optimizer (GWO)
- [30] shuffle frog leaping algorithm (SFLA)
- [31] moth swarm algorithm (MSA)
- [32] harmony search algorithm (HSA)
- [33] teaching-learning-based optimization (TLBO)
- [34] improved colliding bodies optimization (ICBO)
- [35] adaptive lightning attachment procedure optimizer (ALAPO)
- [36] modified RUNge kutta optimizer (MRUN) [34]

The above listed metaheuristic algorithms have been introduced to solve single-objective OPF problems with different objectives such as fuel cost, emission, transmission loss, voltage stability index, and voltage deviation. However, with various improvement needs of power system operation and management, solving single-objective OPF problems does not meet a modern power system requirement.

To meet the requirement of modern power systems, many metaheuristic algorithms have been introduced to effectively provide solutions for multiobjective (2-3 objective functions) and many-objective (more than 3 objective functions) OPF problems.

In [37], hybrid modified particle swarm optimization-shuffle frog leaping algorithm (HMPSO-SFLA) was proposed to solve MOOPF problem by using cost and emission as the objectives in the three system sizes.
Modified sine-cosine optimization algorithm (MSCA) was introduced to solve MOOPF problem by selecting cost, active power loss and voltage deviation to be objectives in two IEEE systems [38].

In [39], multiobjective harmony search algorithm (MHSA) was presented to generate solutions for MOOPF problem which considered cost and L-index to be the objectives in the IEEE 30-bus system.
Multiobjective modified imperialist competitive algorithm (MOMICA) was shown in [40] to solve MOOPF problem with cost, emission, voltage deviation and active power losses as the objective functions in the IEEE 30- and 57-bus systems.
In [41], K. Abaci and V. Yamacli applied DSA on solving MOOPF problem in the IEEE 9-, 30-, and 57-bus test system by considering cost, power loss, emission, and L-index as the objective functions.
Multiobjective quasi-oppositional teaching learning-based optimization (QOTLBO) was proposed to solve MOOPF problem with four different objectives including cost, emission, power loss, and L-index as the objectives in the IEEE 30-, 62-, and 118-bus systems [42].
In [43], improved strength Pareto evolutionary algorithm (ISPEA2) was introduced to solve MOOPF problem by using cost and emission objectives in the two system sizes.

In addition, various other algorithms have been proposed to solve MOOPF problems with different 2-3 objective functions in several IEEE system sizes [44], [45], [46], [47]. For the MaOOPF problems, some algorithms were proposed by considering different objective functions including fuel cost, emission, transmission loss, L-index, and voltage deviation, and a few algorithms were also used to solve real-world problems as follows;

In [48], an enhanced genetic algorithm integrated with adaptive elimination strategy (NSGA-III) was introduced to solve MaOOPF problems by considering fuel cost, emissions, voltage deviation and line loss as the objective functions in the IEEE 30-, 57-, and 118-bus systems.
A novel hybrid salp swarm optimization and particle swarm optimization (SSOPSO) was proposed to solve MaOOPF problems by selecting cost minimization, emission reduction, transmission loss reduction, voltage profile improvement, and voltage stability enhancement as part of the objective functions in the IEEE 30-, 57-, and 118-bus systems [49].
J. Zhang, X. Zhu, and P. Li presented multiobjective evolutionary algorithm based on decomposition (MOEA/D) with many-stage dynamical resource allocation strategy to solve MaOOPF problems by using fuel cost, emission, voltage deviations, line losses and voltage stability index as part of the objective functions in the IEEE 30-, 57-, and 118-bus systems [50].
In [51], many-objective marine predators algorithm was introduced to solve MaOOPF problems by considering cost, emission, transmission loss, and voltage stability index as part of the objective functions in the IEEE 30- and 118-bus systems.
Multi-objective grasshopper optimization algorithm (MOGOA) was proposed to solve MaOOPF problems including voltage source converter-based multi-terminal high-voltage direct current systems and renewable energy sources by considering cost, cost with the valve-point effect and cost with emission and carbon tax, voltage deviation, and power loss as part of the objective functions [52].
S. Duman, M. Akbel, and H. T. Kahraman presented multiobjective adaptive guided differential evolution algorithm for real-world problem: multiobjective-alternating current OPF problem involving wind/PV/tidal energy sources by considering cost, power loss, voltage stability index, and voltage deviation as the objective functions in the IEEE 30-bus system [53].
In [54], a unified space approach-based dynamic switched crowding (DSC) was introduced to solve multimodal multiobjecitve optimization problems and real-world engineering problems incorporating both alternating current optimal power flow (AC-OPF) and alternating current/direct current optimal power flow (AC/DC-OPF) by selecting cost, power losses, voltage stability index, voltage deviation, and emission as part of the objective functions in modified IEEE 30-bys system.

III. MANY-OBJECTIVE OPTIMAL POWER FLOW (MAOOPF) PROBLEM

OPF was first proposed by Carpentier for optimizing power system operation and management [55]. With the development of OPF in the years after, single-objective OPF and MOOPF problems have been introduced. In the single-objective OPF problems, the objective function is normally an economic purpose such as fuel cost or transmission line loss whereas MOOPF problems simultaneously aim two or three objectives such as a pair of fuel cost and emission or transmission line loss or three of them [56], [57], [58], [59]. However, power system reliability and security have also been considered necessary awareness in modern power systems. So, MOOPF problems consisting of economic and environmental objectives are insufficient for the modern power system operation and management, and the problems become MaOOPF which considers more than three objective functions including objective functions for security. The many-objective optimization problem can be generally formulated as presented below [44].

$$\min f = \left\{f_1(x,u), f_2(x,u), \ldots, f_{Nobj}(x,u)\right\} \tag{1}$$

$$\text{subject to } g(x,u) = 0 \tag{2}$$

$$h(x, u) \leq 0 \tag{3}$$

where f is an objective function vector to be optimized, $g(x, u)$ is the equality constraints, $h(x, u)$ is the inequality constraints, x is a vector of state variables, and u is a vector of control variables.

Many-objective optimization is aimed to provide optimal variables in order to optimize more than three objective functions where each objective conflicts with each other. The best feasible solutions from all objective functions cannot be provided at the same time, and the optimal solutions are a tradeoff between each objective. Hence, more than one optimal solution called Pareto fronts is obtained. The objective functions and constraints of the MaOOPF problems are described in this section.

A. OBJECTIVE FUNCTIONS

In this research, four objective functions are aimed in the MaOOPF problems for economic, environmental, and secure developments.

1) FUEL COST

To maximize benefits for power companies, total fuel cost is mainly aimed to be minimized in the MaOOPF problem. It is calculated as the equation below.

$$f_{Cost}(x, u) = \sum_{i=1}^{N_{gen}} (c_i + b_i P_{gi} + a_i P_{gi}^2) \tag{4}$$

where f_{Cost} is the total fuel cost function (\$/h), N_{gen} is the generator number, P_{gi} is the real power generation of the i^{th} generators (MW), and a_i, b_i, and c_i are the fuel cost coefficients of the i^{th} generators.

2) EMISSION

To respond to environmental awareness, the emission objective is considered to be minimized and can be found in the following equation.

$$f_{Emission}(x, u) = \sum_{i=1}^{N_{gen}} (\gamma_i P_{gi}^2 + \beta_i P_{gi} + \alpha_i + \xi_i \exp(\lambda_i P_{gi})) \tag{5}$$

where $f_{Emission}$ is the total emission function (ton/h), $\gamma_i, \beta_i, \alpha_i, \xi_i$ and λ_i are the emission coefficients of the i^{th} generators.

3) TRANSMISSION LINE LOSS

A large number of generating units are generally required to appropriately generate electricity at minimum transmission loss in order to reduce generation cost. It can be found in the equation below.

$$f_{Loss}(x, u) = \sum_{L=1}^{N_L} g_L \left(V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_{ij})\right) \tag{6}$$

where f_{Loss} is the total transmission loss function (MW), N_L is the number of branches, g_L is the conductance of the L^{th} branch, V_i and V_j are the voltage at the i^{th} and j^{th} buses, and θ_{ij} is the voltage phase angle difference between the i^{th} and j^{th} buses.

4) VOLTAGE DEVIATION

Voltage deviation is aimed to be minimized in order to improve the voltage profile of a power system and assure the security of devices. The voltage deviation is computed as the provided equation.

$$f_{VD}(x, u) = \sum_{i=1}^{N_{pq}} |V_i - V_r| \tag{7}$$

where f_{VD} is the voltage deviation function, N_{pq} is the number of PQ buses, V_r is the reference voltage magnitude which is 1.0 p.u.

B. CONSTRAINTS

In the MaOOPF problem, the objective functions are aimed to be optimized while satisfying the following equality and inequality constraints.

1) EQUALITY CONSTRAINTS

The active and reactive power balance equations expressed below constitute the equality constraints in the MaOOPF problem.

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_{bus}} V_j (G_{ij} \cos(\theta_{ij}) + B_{ij} \sin(\theta_{ij})) = 0 \tag{8}$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{N_{bus}} V_j (G_{ij} \sin(\theta_{ij}) - B_{ij} \cos(\theta_{ij})) = 0 \tag{9}$$

where P_{di} is the active load demand at the i^{th} bus, N_{bus} is the number of buses, G_{ij} and B_{ij} are the transfer conductance and susceptance between buses i and j, respectively, and Q_{di} is the reactive load demand at the i^{th} bus.

2) EQUALITY CONSTRAINTS

To assure the security of system devices in power systems, the inequality constraints are set as follows:

$$P_{gi\,\min} \leq P_{gi} \leq P_{gi\,\max}; \quad i = 1, 2, \ldots, N_g \tag{10}$$
$$Q_{gi\,\min} \leq Q_{gi} \leq Q_{gi\,\max}; \quad i = 1, 2, \ldots, N_g \tag{11}$$
$$V_{gi\,\min} \leq V_{gi} \leq V_{gi\,\max}; \quad i = 1, 2, \ldots, N_g \tag{12}$$
$$Q_{ci\,\min} \leq Q_{ci} \leq Q_{ci\,\max}; \quad i = 1, 2, \ldots, N_c \tag{13}$$
$$T_{i\,\min} \leq T_i \leq T_{i\,\max}; \quad i = 1, 2, \ldots, N_t \tag{14}$$
$$V_{Li\,\min} \leq V_{Li} \leq V_{Li\,\max}; \quad i = 1, 2, \ldots, N_L \tag{15}$$
$$|S_{Li}| \leq S_{Li\,\max}; \quad i = 1, 2, \ldots, N_L \tag{16}$$

where subscripts min and max are minimum and maximum values, respectively, V_{gi} is the generator voltages at the i^{th} bus, Q_{ci} is the shunt compensation capacitor at the i^{th} bus, T_i

is the tap-ratio of transformers at the i^{th} bus, V_{Li} is the load bus voltages at the i^{th} bus, S_{Li} is the complex power flow at the i^{th} branch, N_c is the number of shunt compensation capacitors, and N_t is the number of transformer tap-ratios.

3) CONSTRAINT HANDLING

A penalty function technique is used as the constraint handling for the MaOOPF problem as formulated in the equation below. The objective function value will be penalized if the solution is infeasible.

$$F(x,u) = f(x,u) + K_p(P_{gslack} - P_{gslack}^{\lim})^2 + K_Q \sum_{i=1}^{N_g}(Q_{gi} - Q_{gi}^{\lim})^2 + K_V \sum_{i=1}^{N_L}(V_{Li} - V_{Li}^{\lim})^2 + K_S \sum_{i=1}^{N_{br}}(S_{bri} - S_{bri}^{\lim})^2 \tag{17}$$

where $F(x, u)$ is the penalized function, K_p, K_Q, K_V, and K_s are the penalty factors, and $x^{\lim}$ is the state variable limit, which is defined as follows:

$$x^{\lim} = \begin{cases} x & \text{if } x^{\min} < x < x^{\max} \\ x^{\max} & \text{if } x > x^{\max} \\ x^{\min} & \text{if } x < x^{\min} \end{cases} \tag{18}$$

where $x^{\max}$ and $x^{\min}$ are the maximum and minimum limits of the state variable, respectively.

C. MAOOPF PROBLEM

In order to solve the MaOOPF problem, which involves considering four independent objective functions and finding solutions that are a trade-off between these objectives, the approach applied is the Pareto dominance method. The objective of this method is to identify a non-dominated solution that represents the trade-off and store it in an archive commonly referred to as Pareto optimal fronts. The formulation of the Pareto dominance method is presented below [60].

$$\begin{aligned} &\forall i = \{1, 2, \ldots, N_{obj}\}, \quad F_i(X_1) \le F_i(X_2) \\ &\exists j = \{1, 2, \ldots, N_{obj}\}, \quad F_j(X_1) < F_j(X_2) \end{aligned} \tag{19}$$

where the vector X_1 dominates X_2 when satisfying both conditions.

When dealing with MaOOPF problems that involve more than three objective dimensions, generating an accurate graph of Pareto fronts becomes challenging. In such cases, an alternative approach is to utilize the fuzzy decision method to determine a best-compromised solution that considers optimal trade-offs across all objectives. This method assists system operators in selecting the most suitable choice from several available solutions. To implement the fuzzy decision method, fuzzy membership functions are initially computed for each dimension of all non-dominated solutions. The calculation process is given below:

$$\mu_i^j = \begin{cases} 1, & f_i^j \le f_{\min}^j \\ \dfrac{f_{\max}^j - f_i^j}{f_{\max}^j - f_{\min}^j}, & f_{\min}^j \le f_i^j \le f_{\max}^j \\ 0, & f_i^j \ge f_{\max}^j \end{cases} \tag{20}$$

where μ is the fuzzy membership function, $1 \le i \le N_S$, $1 \le j \le N_{obj}$, N_S is the number of non-dominated solutions, $f_{\min}^j$ and $f_{\max}^j$ are the minimum and maximum values of the j^{th} objective, respectively.

Then, the calculation of the combined fuzzy membership function values across each dimension is performed, followed by normalization using the following equation:

$$\mu_i^j = \frac{\sum_{i=1}^{m} \mu_i^j}{\sum_{j=1}^{NF}\sum_{i=1}^{m} \mu_i^j} \tag{21}$$

where the non-dominated solution with the greatest total normalized function value is recognized as the best-compromised solution.

IV. RELATED OPTIMIZATION ALGORITHMS

The concept of the proposed TwoArchHHO algorithm is improved from the concepts of HHO and Two_Arch2 methods. So, the brief description of the original HHO and Two_Arch2 methods are described in this section.

A. HARRIS HARK OPTIMIZATION

Harris hawk optimization (HHO) algorithm is a population-based optimization technique proposed by Ali Asghar Heidari, et.al, based on the hunting behaviors consisting of exploring prey, surprising pounce, and different attacking strategies of Harris hawks [12]. The HHO process comprises 3 main phases including exploration phase, transition from exploration to exploitation, and exploitation phase with different strategies as follows:

In the exploration phase, the hawks (candidate solutions) detect and track the prey (best solution) with their eyes. However, because of the hard detected prey (rabbit for the HHO), the hawks must first observe for the prey for a while by perching on the random locations based on two strategies having an equal chance (q). The hawks perch at random locations around their group (for $q \ge 0.5$), or perch by referring to the rabbit together with their group (for $q < 0.5$) as the given equation below [12].

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1 \left|X_{rand}(t) - 2r_2X(t)\right| & q \ge 0.5 \\ (X_{rabbit}(t) - X_a(t)) - r_3\,(LB + r_4(UB - LB)) & q < 0.5 \end{cases} \tag{22}$$

In Eq. (22), the hawks consist of N-individuals with the position (X) at iteration t and $t+1$, the best position

($X_{\text{rabbit}}(t)$), the randomly chosen candidate ($X_{\text{rand}}(t)$), and the average position of the hawks ($X_{\text{a}}(t)$). r_1, r_2, r_3, r_4, and q are randomly generated numbers between 0 and 1 changed every iteration, LB and UB are lower and upper limits of variables. The average position of the hawks can be calculated by the following equation.

$$X_a(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \tag{23}$$

After the exploration phase, HHO goes to the phase of transition from the exploration phase to the exploitation phase. It is assumed to refer to the rest energy of the prey to escape that is sharply reduced according to the escaping duration (iteration). The energy of the prey to escape (E) can be formulated according to the maximum iteration ($Iter_{\max}$) as follows [12]:

$$E = 2E_0(1 - \frac{t}{Iter_{\max}}) \tag{24}$$

In Eq. (24), E_0 is the initial energy of the prey randomly generated between [0,1] and changed every iteration. The exploration phase proceeds if the energy to escape $|E| \geq 1$. If the energy to escape $|E| < 1$, it is then the exploitation phase.

In the exploitation phase, hunting strategies are different according to the escaping styles of the prey. In this regard, four operations are modeled based on the hunting duration.

Parameter r is assumed to be the chance of the prey to escape where $r < 0.5$ represents the success to escape and $r \geq 0.5$ shows the failure to escape before getting snatched. In both cases, the hawks will perform a hard or soft besiege to catch the prey depending on the remaining energy (E) of the prey.

Soft besiege: The condition is $r \geq 0.5$ and $|E| \geq 0.5$. The position can be mathematically calculated as expressed [12].

$$X(t+1) = \Delta X(t) - E\,|JX_{rabbit}(t) - X(t)| \tag{25}$$

$$\Delta X(t) = X_{rabbit}(t) - X(t) \tag{26}$$

In Eq. (25), $\Delta X(t)$ is the distance between the rabbit and hawk positions, $J = 2(1\text{-}r_5)$ is the random jump power of the rabbit when it tries to escape, and r_5 is randomly generated between 0 and 1.

Hard besiege: If the rabbit has low energy and is tried, i.e., $r \geq 0.5$ and $|E| < 0.5$. The following equation represents the updated hawk positions of this situation [12].

$$X(t+1) = X_{rabbit}(t) - E\,|\Delta X(t)| \tag{27}$$

Soft besiege with progressive rapid dives: If the rabbit contains adequate energy and it can successfully dodge, i.e., $r < 0.5$ and $|E| \geq 0.5$, the hawks operate a soft besiege by the equation presented below [12].

$$Y = X_{rabbit}(t) - E\,|JX_{rabbit}(t) - X(t)| \tag{28}$$

Then, the hawks will rapidly dive to the rabbit if the previous dive was unhelpful based on the Levy flight as presented below [12].

$$Z = Y + S \times LF(D) \tag{29}$$

where D is the number of problem variables, S is a random vector by size 1 x D, and LF is the Levy flight function computed by the given equation [12].

$$LF(x) = 0.01 \times \frac{u \times \sigma}{|v|^{1/\beta}}, \sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \tag{30}$$

where u and v are randomly generated between 0 and 1, β is equal to 1.5 in this work and $\Gamma(x) = (x-1)!$.

So, in this situation, the position of hawks can be updated as follows [12]:

$$X(t+1) = \begin{cases} Y & \text{if} F(Y) < F(X(t)) \\ Z & \text{if} F(Z) < F(X(t)) \end{cases} \tag{31}$$

where Y and Z are computed by (28) and (29).

Hard besiege with progressive rapid dives: If the energy of the rabbit is inadequate to escape, but it can successfully escape, i.e., $r<$ 0.5 and $|E| < 0.5$. The hawks' position is mathematically formulated as follows [12]:

$$X(t+1) = \begin{cases} Y & \text{if} F(Y) < F(X(t)) \\ Z & \text{if} F(Z) < F(X(t)) \end{cases} \tag{32}$$

where Y and Z are calculated by (33) and (34) as presented below [12].

$$Y = X_{rabbit}(t) - E\,|JX_{rabbit}(t) - X_a(t)| \tag{33}$$

$$Z = Y + S \times LF(D) \tag{34}$$

B. IMPROVED TWO-ARCHIVE ALGORITHM (TWO_ARCH2)

The Two_Arch2 algorithm was introduced by Wang, Handing, et al. [18] inspired by the concept of the two-archive algorithm (Two_Arch) utilizing two types of archives [61]. In the traditional Two_Arch, one archive is used for improving the exploitation phase while the other is used for enhancing the exploration phase. The first archive is the Pareto archive, which can be called a convergence archive (CA). The other archive is generated to improve the diversity of the solutions, so it is called a diversity archive (DA). The concept of the two-archive method is that the non-dominated solutions which can dominate any solution in CA or DA are stored in the CA while the non-dominated solutions which cannot dominate any solution in CA and DA are kept in the DA. Then, the dominated solutions in CA and DA are removed. The total size of CA and DA is fixed while the sizes of CA and DA are flexible. When the DA is full, the extra solutions are deleted from DA according to their distances to CA.

In Two_Arch2, the concept of the original Two_Arch is used; however, CA and DA are independently updated, and the sizes of CA and DA are individually fixed. The indicator-based and Pareto-based principles are applied to the two archives, and a L_p-norm-based ($p< 1$) is proposed to maintain the diversity for the many-objective optimization problems. The quality indicator $I_{\varepsilon+}$ in IBEA [62] is adopted as the selection principle for CA. This indicator can indicate the minimum distance required for one solution to dominate another solution in the objective space which can be mathematically formulated in the following equation [18].

$$I_{\varepsilon+}(x_1, x_2) = \min_{\varepsilon}(f_i(x_1) - \varepsilon \leq f_i(x_2), 1 \leq i \leq N_{obj}) \tag{35}$$

The fitness is assigned to individuals as presented in (36) which is a determination of $I_{\varepsilon+}$ if x_1 is removed from the population [18].

$$F(x_1) = \sum_{x_2 \in P\backslash\{x_1\}} -e^{-I_{\varepsilon+}(x_2,x_1)/0.05} \tag{36}$$

To update the CA, the population is added to CA, and the extra solutions are removed according to the fitness. The solution with the least value of $I_{\varepsilon+}$ is deleted from CA in each iteration, and the $I_{\varepsilon+}$ values of the rest population in CA are then updated.

V. TWO-ARCHIVE HARRIS HAWK OPTIMIZATION (TWOARCHHHO) FOR SOLVING MAOOPF PROBLEM

The traditional HHO cannot solve MOOPF or MaOOPF problems by itself. Instead of only applying the Pareto method to the traditional HHO in order to solve MaOOPF problems, the performance of the HHO is also enhanced in this work. To enhance the effectiveness of the HHO, a new algorithm called TwoArchHHO is proposed by applying the concept of the two-archive method from Two_Arch2 into the traditional HHO, and a probability parameter is computed to improve the selection process of the Two_Arch2. In the proposed TwoArchHHO, the position of the rabbit (the prey or the near global position) in each iteration is alternatively selected from CA or DA to increase the diversity of the stored solutions and avoid being trapped in the local area of solutions. To alternatively randomly choose the rabbit position from CA or DA, the probability operation is used. As stated, CA focuses on the exploitation phase whereas DA focuses on the exploration phase. The probability parameter $S_p(t)$ which has a lower value at the initial iteration and gets higher according to the higher iterations is adopted to proceed with the two-archive method [63]. So that the algorithm will emphasize the exploration phase at the lower values of the iteration, and the exploitation phase will be more emphasized according to the higher iterations. The $S_p(t)$ can be calculated as given below.

$$S_p(t) = C_1 e^{C_2 t} \tag{37}$$

where

$$C_2 = \frac{\ln(S_{p,f}) - \ln(S_{p,s})}{Iter_{\max} - 1} \tag{38}$$

$$C_1 = \frac{S_{p,s}}{\exp(C_2)} \tag{39}$$

where $S_{p,s}$ and $S_{p,f}$ are the starting and ending values of S_p which are equal to 0.15 and 0.8 in this work, respectively.

The implementation of the TwoArchHHO for solving the MaOOPF problem is explained in the following steps.

Step 1. Initialize system data consisting of the number of populations, maximum iteration and Pareto archive size;

Step 2. Initialize data of HHO comprising location and energy of the rabbit and location of hawks;

Step 3. Evaluate the fitness of each initialized hawk;

Step 4. Find non-dominated solutions by Pareto dominance concept from (19) and keep in the initial CA and DA;

Step 5. Calculate S_p by (38);

Step 6. Uniformly randomly generate number between [0,1];

Step 7. If the generated number is more than the calculated S_p, select X_{rabbit} from CA. Then go to Step 9;

Step 8. If the generated number is less than the calculated S_p, select X_{rabbit} from DA. Then go to Step 9;

Step 9. Update the initial energy (E_0) and jump strength (J);

Step 10. Update the energy of the prey (E) by (24);

Step 11. If the energy of the prey is more than 1, update the position of hawks by (22). Then go to Step 16;

Step 12. If E is between 0.5 and 1 and r is more than 0.5, update the position of hawks by (25). Then go to Step 16;

Step 13. If E is less than 0.5 and r is more than 0.5, update the position of hawks by (27). Then go to Step 16;

Step 14. If E is between 0.5 and 1 and r is less than 0.5, update the position of hawks by (31). Then go to Step 16;

Step 15. If E and r are both less than 0.5, update the position of hawks by (32). Then go to Step 16;

Step16. Update CA by using (19) where the non-dominated solutions which can dominate any solution in CA or DA are stored in the CA and, the dominated solutions are removed. If the CA is full, $I_{\varepsilon+}$ is calculated by (35) and the fitness is found by (36). The extra solutions are removed according to the fitness where the solution with the least value of $I_{\varepsilon+}$ is deleted from CA in each iteration, and the $I_{\varepsilon+}$ values of the rest population in CA are then updated;

Step 17. Update DA by using (19) where the non-dominated solutions which cannot dominate any solution in CA and DA are kept in the DA and the dominated solutions are removed. If the DA is full, the extra solutions are deleted from DA according to their distances to CA.

Step 18. If the maximum iteration is reached, go to step 19; otherwise, go to step 5;

Step 19. Find the best-compromised solutions.

The flowchart of the proposed TwoArchHHO for solving the MaOOPF problem is presented in Fig 1.

VI. SIMULATION RESULTS AND DISCUSSIONS

The performance of the proposed TwoArchHHO was investigated in solving the MOOPF and MaOOPF problems in the IEEE 30-, 57-, and 118-bus systems where the objective functions include cost, emission, transmission loss, and voltage deviation (VD). Several case studies as in

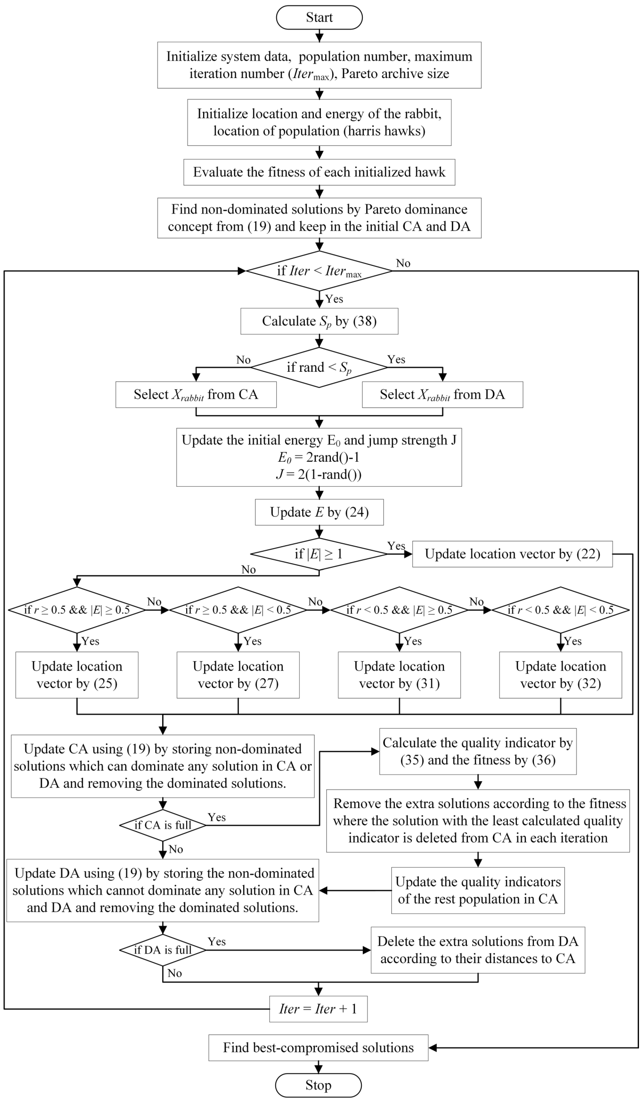

FIGURE 1. The implementation of the Two-Archive Harris Hawk Optimization (TwoArchHHO).

Table 1 were evaluated for each problem. Various algorithms consisting of multiobjective HHO (MOHHO), evolutionary algorithm for large-scale manyobjective optimization (LMEA) [64], NSGA-III, SPEA2, and TwoArch2 were simulated to compare with the proposed TwoArchHHO on solving the MOOPF and MaOOPF problems. The proposed TwoArchHHO and the compared algorithms were operated for 30 independent runs for each case study. The Pareto solutions and the best-compromised solutions of all algorithms are presented for the MOOPF and MaOOPF, respectively. The hypervolume values of all algorithms were then generated to compare the Pareto fronts of each algorithm.

A. IEEE 30-BUS SYSTEM

The performance of the proposed TwoArchHHO was evaluated on solving the MOOPF and MaOOPF problems in the IEEE 30-bus system as in cases 1-7. This system comprised 6 generators, 4 transformers, and 41 transmission lines. The total demands of the system were 283.4 MW and 126.6 MVAR, and the data of this system can be found in [65]. The number of populations, maximum iteration, and the Pareto archive size of the TwoArchHHO and the compared algorithms were all set at 100.

TABLE 1. Illustrative cases examined within this work.

Case study	Cost	Emission	Loss	VD	System
1	✓	✓			IEEE 30-bus
2	✓		✓		
3	✓			✓	
4		✓	✓		
5	✓	✓	✓		
6	✓	✓		✓	
7	✓	✓	✓	✓	
8	✓	✓			IEEE 57-bus
9	✓		✓		
10		✓	✓		
11			✓	✓	
12	✓	✓	✓		
13	✓		✓	✓	
14	✓	✓	✓	✓	
15	✓		✓		IEEE 118-bus
16	✓			✓	
17	✓	✓	✓		
18	✓	✓		✓	
19	✓	✓	✓	✓	

1) MULTIOBJECTIVE OPTIMAL POWER FLOW (MOOPF) PROBLEMS

In the IEEE 30-bus system, the proposed TwoArchHHO was first applied to solve the 2-objective problems which include cases 1-4 and 3-objective problems consisting of cases 5-6. The Pareto optimal fronts generated by the TwoArchHHO algorithm, and the compared algorithms are presented in Figs 2 and 3 for the 2-objective problems and 3-objective problems, respectively.

For the 2-objective problems, it can be noticed that the Pareto fronts of the TwoArchHHO are better than those of its traditional algorithms which are MOHHO and TwoArch2; however, they are very close to those of the other compared algorithms. The proposed TwoArchHHO also well provided 3-objective Pareto fronts with good diversity compared with the other algorithms.

2) MANY-OBJECTIVE OPTIMAL POWER FLOW (MAOOPF) PROBLEM

The TwoArchHHO was used to solve the MaOOPF problem in the IEEE 30-bus system which is case 7. The Pareto optimal fronts were obtained; however, they could not be presented in a proper plot. Instead, the best-compromised solutions were found compared to the other algorithms as shown in Table 2.

From Table 2, it is observed that all considered algorithms gave very close values to each other in all aspects of the objective values. The proposed TwoArchHHO generated the

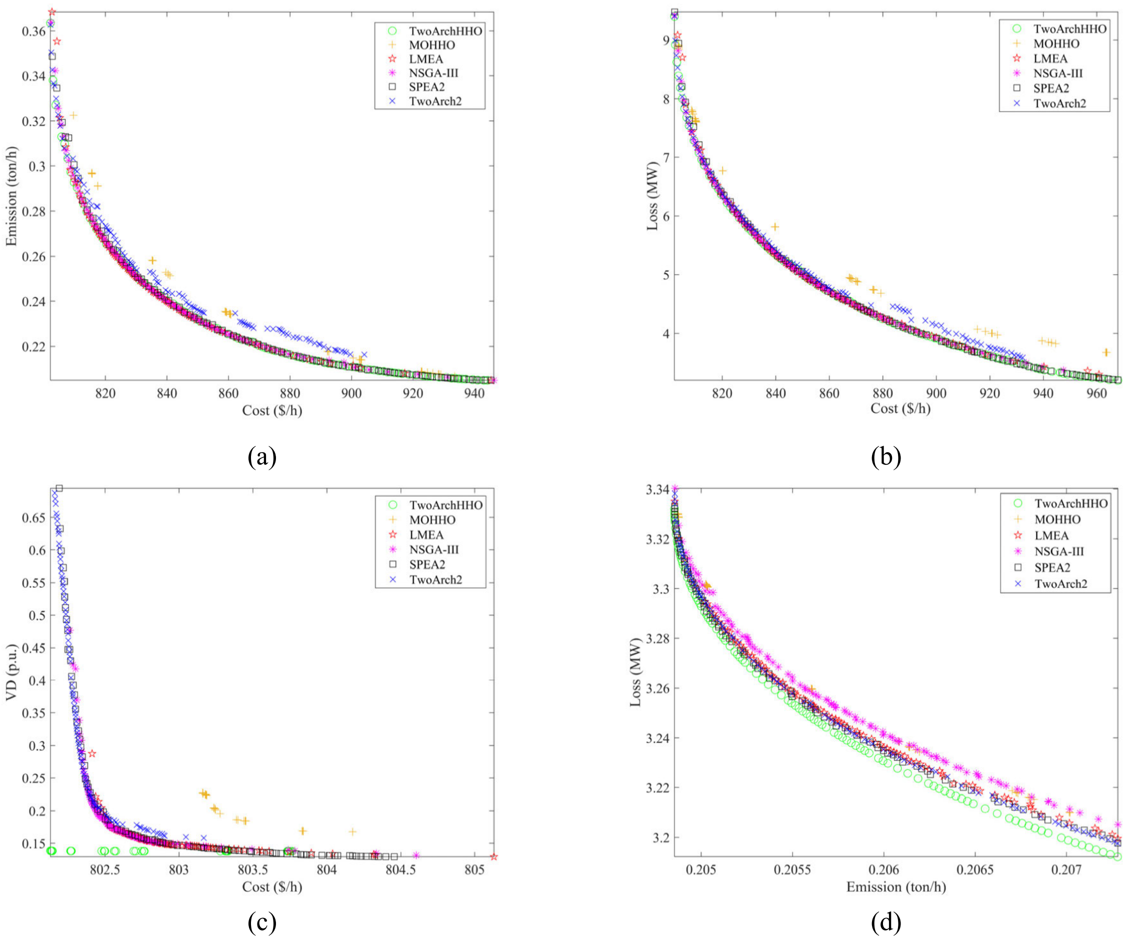

FIGURE 2. The comparison of Pareto optimal fronts for a) case 1, b) case 2, c) case 3, d) case 4.

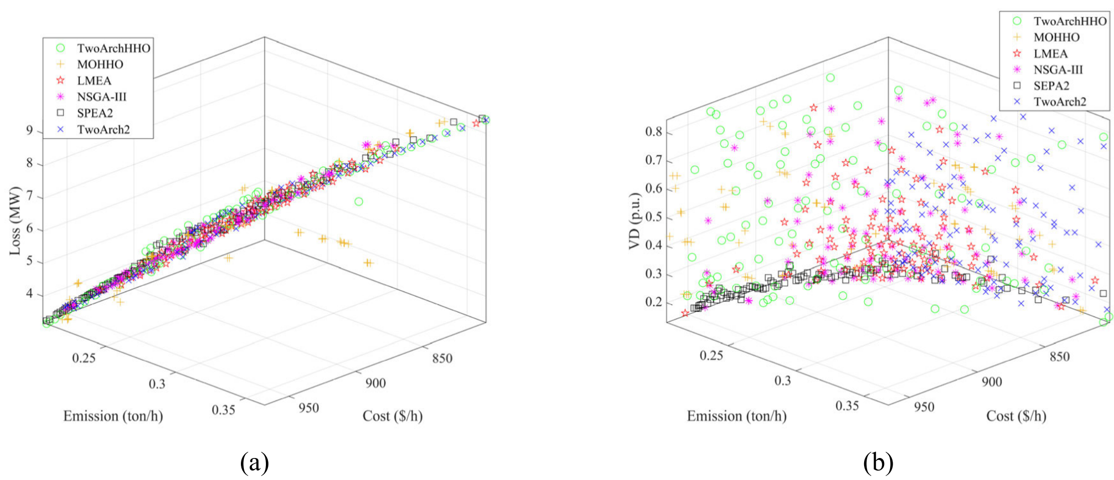

FIGURE 3. The comparison of Pareto optimal fronts for a) case 5, b) case 6.

best cost whereas SPEA2 provided the best emission and loss, and NSGA-III obtained the best VD. However, from the best-compromised solutions, it could not be concluded which algorithm has the highest performance in solving the MaOOPF because these solutions are one of the generated Pareto fronts. So, the hypervolume was calculated to exactly compare the algorithm performance as in the next subsection.

3) PERFORMANCE COMPARISON

To obviously compare the performance of the generated Pareto optimal fronts from all considered algorithms, the hypervolume values for cases 1-7 of the IEEE 30-bus system were calculated as expressed in Table 3 where the more hypervolume value means the greater Pareto optimal fronts.

TABLE 2. Best-compromised solutions for case 7.

	Cost ($/h)	Emission (ton/h)	Loss (MW)	VD
TwoArchHHO	**856.8454**	0.2374	5.2350	0.1663
MOHHO	869.9212	0.2296	5.6108	0.2431
LMEA	860.4901	0.2308	5.1041	0.1429
NSGA-III	865.4874	0.2259	5.1058	**0.1380**
SPEA2	863.1607	**0.2255**	**4.9807**	0.1549
TwoArch2	867.7745	0.2258	5.0473	0.2570

TABLE 3. Hypervolume comparison in the IEEE 30-bus system.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
TwoArchHHO	**0.0599**	**0.0962**	**0.0042**	**0.0024**	**0.0389**	**0.0548**	**0.0312**
MOHHO	0.0531	0.0838	0.0028	0.0022	0.0331	0.0491	0.0241
LMEA	0.0572	0.0946	0.0038	0.0023	0.0380	0.0536	0.0305
NSGA-III	0.0566	0.0954	0.0038	0.0023	0.0375	0.0543	0.0304
SPEA2	0.0571	0.0955	0.0038	0.0023	0.0374	0.0533	0.0311
TwoArch2	0.0543	0.0926	0.0039	0.0022	0.0384	0.0416	0.0278

From Table 3, it is observed that the proposed TwoArchHHO gave the best hypervolume values for all cases when compared to its traditional algorithms and also the other considered algorithms in this system. The best hypervolume values of the TwoArchHHO in this system were better than the compared algorithms around 0.32% to 33.96%.

The best-compromised solutions provided by the TwoArchHHO for cases 1-7 were compared with many other algorithms in the literature as presented in Tables 4 and 5.

It is seen that no algorithm achieved dominance across all the objective functions employed in the test cases; instead, dominance was only achieved on a single objective function. The proposed TwoArchHHO obtained the dominant solutions in the cost objective for cases 1, 2, 5 and 6 and in the emission objective for case 4.

B. IEEE 57-BUS SYSTEM

The efficacy of the TwoArchHHO approach in addressing the MOOPF and MaOOPF problems in larger systems, as in cases 8-14, was assessed using the IEEE 57-bus system. This system encompasses 7 generators, 15 transformers, and 80 transmission lines, with power demand of 1250.8 MW and 336.4 MVAR. Bus and branch data were sourced from [66]. Both the TwoArchHHO and the compared algorithms were configured with uniform settings, including a population size, maximum iterations, and archive size of 100.

1) MOOPF PROBLEMS

The proposed TwoArchHHO was applied to solve the MOOPF problems in the IEEE 57-bus system consisting of 2-objective problems as in cases 8-11 and 3-objective problems as in cases 12-13. The Pareto optimal fronts of the proposed algorithm and those of the compared algorithms are presented in Fig 4 for cases 8-11 and Fig 5 for cases 12-13.

It is noticeable from Fig 4 that the traditional algorithms of the proposed algorithm comprising MOHHO and TwoArch2 generated very low-quality Pareto fronts. However, the proposed TwoArchHHO algorithm could successfully provide high-quality Pareto fronts which were obviously better than those of the compared algorithms, especially for cases 9-11. It could also be observed from Fig 5 that the Pareto fronts provided by the TwoArchHHO of the 3-objective problems possessed high diversity.

2) MAOOPF PROBLEMS

For solving the MaOOPF problem, the best-compromised solutions obtained from the proposed algorithm were compared to those of the other considered algorithms as presented in Table 6.

From Table 6, it is noticeable that the best-compromised solutions of the proposed algorithm could not reach the best value in any objective value; however, the proposed algorithm provided good values in all objectives compared to the other algorithms. Although NSGA-III provided the best objective values in three aspects, the obtained cost value was also very high. So, the hypervolume will be computed in the next subsection to accurately investigate the performance of the proposed algorithm.

3) PERFORMANCE COMPARISON

The hypervolume values of the TwoArchHHO and the compared algorithms were calculated as presented in Table 7 to compare the quality of the Pareto optimal fronts generated by each algorithm.

It is evident in Table 7 that the proposed TwoArchHHO generated the best hypervolume values for all cases in the IEEE 57-bus system that are around 0.46% - 78.49% better than the compared algorithm. The hypervolume values obtained by TwoArchHHO are also much better than those of the compared algorithms especially cases 9-13. For case 14, although the proposed TwoArchHHO could not reach the best value in any objective aspect, it could give the best hypervolume value which means its compromised solutions are good in all aspects.

The obtained best compromised solutions by the TwoArchHHO of cases 8-14 were compared with those of various competitors in the literature as shown in Tables 8-9.

It is observed that the TwoArchHHO generated dominant solutions in the cost aspect for case 8, in the emission aspect for case 14, and in the VD aspect for case 13. It is also noticed that the TwoArchHHO obtained the dominant solutions in two aspects for cases 9, 11 and 12. However, the comparison results for case 10 could not be found in the literature.

C. IEEE 118-BUS SYSTEM

The TwoArchHHO was lastly tested in the IEEE 118-bus system to verify its performance in solving the MOOPF and MaOOPF problems in the large system as in cases 15-19. The total demands of this system were 4242 MW and 1439 MVAR, and detailed data was provided in [74]. The population number and the Pareto archive size were 100, and the maximum iteration number was 500 for all algorithms.

TABLE 4. Best-compromised solutions for case 14.

	Case 1		Case 2		Case 3		Case 4	
	Cost ($/h)	Emis (ton/h)	Cost ($/h)	Loss (MW)	Cost ($/h)	VD	Emis (ton/h)	Loss (MW)
TwoArchHHO	**817.1282**	0.2720	**819.6184**	6.3701	802.5637	0.1378	**0.2049**	3.3046
IMOMRFO [67]	817.9615	0.2736	-	-	**801.3908**	0.4435	-	-
MOEA/D-SF [68]	829.5150	0.2501	-	-	802.4060	0.1362	-	-
MOMICA [40]	865.0660	**0.2221**	848.0544	**4.5603**	804.9600	**0.0952**	-	-
MOICA [40]	865.3184	0.2246	850.9001	4.5625	805.0345	0.1004	-	-
ESDE [69]	833.4740	0.2540	828.8413	5.5901	-	-	-	-
ESDE-MC [69]	830.7180	0.2483	827.1592	5.2270	-	-	-	-
ISPEA [43]	865.9500	0.2234	-	-	-	-	-	-
GBICA [24]	830.8520	0.2488	-	-	-	-	-	-
MGBICA [24]	830.8510	0.2484	-	-	-	-	-	-
MODFA [70]	831.6650	0.2432	833.9365	4.9561	-	-	0.2054	**2.8841**
MSFLA [30]	823.2780	0.29078			-	-	-	-
MPIO-PFM [71]	833.1703	0.2397	832.2274	5.1270	-	-	-	-
MPIO-COSR [71]	832.4655	0.2351	831.5576	5.1085	-	-	-	-

TABLE 5. Comparison of best-compromised solutions for cases 1, 2, 3, and 4.

	Case 5			Case 6			Case 7			
	Cost ($/h)	Emis (ton/h)	Loss (MW)	Cost ($/h)	Emis (ton/h)	VD	Cost ($/h)	Emis (ton/h)	Loss (MW)	VD
TwoArchHHO	**852.5314**	0.2308	5.2278	**808.8942**	0.3263	0.1840	856.8454	0.2374	5.2350	0.1663
IMOMRFO [67]	855.0115	0.2318	5.2886	811.8350	0.2908	0.2206	**816.4599**	0.2785	7.2697	0.2738
MOEA/D-SF [68]	881.0120	0.2164	4.1441	842.4460	0.2406	**0.1092**	883.3220	**0.2187**	**4.4527**	**0.1322**
MOEA/D [47]	902.5400	0.2107	**3.4594**	850.2800	**0.2332**	0.1155	-	-	-	-
MOPSO [47]	891.4800	0.2144	3.9557	846.9300	0.2386	0.2188	-	-	-	-
NSGA-II [47]	903.7900	**0.2103**	3.7917	825.8600	0.2648	0.1421	-	-	-	-
MPIO-PFM [71]	866.0601	0.2160	4.4474	-	-	-	-	-	-	-
MPIO-COSR [71]	863.9503	0.2126	4.3177	-	-	-	-	-	-	-
MOMICA [40]	-	-	-	-	-	-	830.1880	0.2523	5.5850	0.2978

TABLE 6. Comparison of best-compromised solutions for cases 5,6, and 7.

	Cost ($/h)	Emission (ton/h)	Loss (MW)	VD
TwoArchHHO	42519.13	1.3431	12.3491	0.7686
MOHHO	42622.6	1.8063	14.6076	1.0530
LMEA	42645.81	1.3376	12.9395	0.7220
NSGA-III	42930.57	**1.3001**	**12.1708**	**0.6819**
SPEA2	**42371.45**	1.3247	15.5713	0.8126
TwoArch2	42571.95	1.3821	13.0646	0.7687

1) MOOPF PROBLEMS

By solving the MOOPF problems in this system, the generated Pareto fronts for 2-objective problems which are cases 15-16 and 3-objective problems which are cases 17-18 are plotted in Figs 6 and 7, respectively. It can be noticed that MOHHO provided very low-quality Pareto fronts for cases 15 and 17, and MOHHO could not even converge to the optimal solution within the given maximum iteration number for cases 16 and 18. In contrast, the proposed TwoArchHHO obtained very high-quality Pareto optimal fronts compared to the other algorithms, especially in case 16. TwoArchHHO also found 3-dimensional Pareto fronts with high diversity compared to the other algorithms especially for case 18 as in Fig 7(b).

For the 2-objective problems in this large system, it is observed from Fig 6 that the traditional MOHHO generated very low-quality Pareto fronts for case 15, and it could not converge to the solution within the given iteration for case 16 whereas the TwoArchHHO generated high-quality fronts which were better than those of the compared algorithms including the traditional TwoArch2, especially in case 16. In Fig 7, cases 17 and 18, it can be noticed that the TwoArchHHO obtained high-quality Pareto fronts with high diversity for the 3-objective problems compared to those of the other algorithms including its traditional algorithms.

2) MAOOPF PROBLEMS

For the MaOOPF problems in the IEEE 118-bus system, the proposed TwoArchHHO successfully provided the best-compromised solutions whereas its traditional algorithm which is MOHHO could not converge to the optimal solution by the given iterations. The best-compromised solutions generated by TwoArchHHO compared to those of the other algorithms are expressed in Table 10.

It is seen that TwoArchHHO achieved the best objective in only the VD aspect; however, hypervolume comparison needs to be investigated to compare the optimal solutions of the MaOOPF problems as presented in the next subsection.

3) PERFORMANCE COMPARISON

To compare the effectiveness of the generated Pareto optimal fronts, hypervolume values of all algorithms were calculated

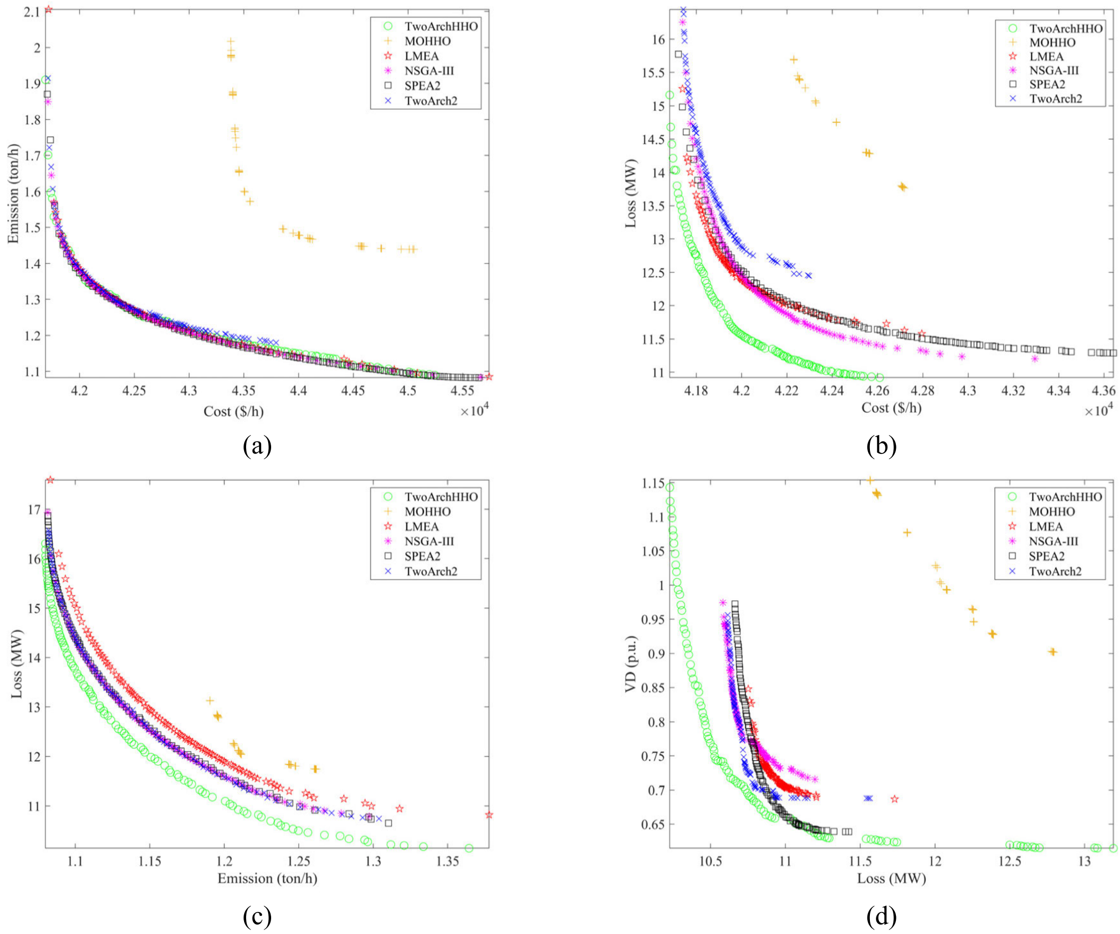

FIGURE 4. The comparison of Pareto optimal fronts for a) case 8, b) case 9, c) case 10, d) case 11.

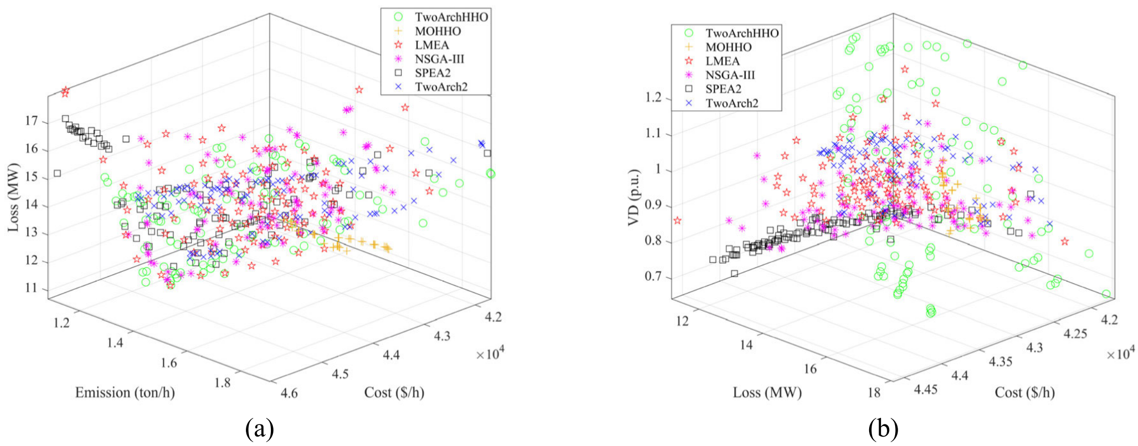

FIGURE 5. The comparison of Pareto optimal fronts for a) case 12, b) case 13.

for cases 15-19 in the IEEE 118-bus system as presented in Table 11.

It is observed that TwoArchHHO generated Pareto fronts with the best hypervolume for all cases except for case 17 where TwoArchHHO had slightly less hypervolume than that of LMEA. It can be seen that the traditional MOHHO found very low hypervolume values in cases 15 and 17, and it could not converge to the optimal solutions in cases 16, 18, and 19. It is also noticeable that TwoArchHHO provided a very high hypervolume value compared to those of the other algorithms for the MaOOPF problem as in case 19. The hypervolume values of the TwoArchHHO are around 0.17% to 99.59% better than those of the compared algorithms in this system.

To verify the superiority of the TwoArchHHO over other algorithms in this system, its best-compromised solutions of

TABLE 7. Hypervolume comparison in the IEEE 57-bus system.

	Case 8	Case 9	Case 10	Case 11	Case 12	Case 13	Case 14
TwoArchHHO	**0.0581**	**0.0243**	**0.2212**	**0.1837**	**0.0189**	**0.0179**	**0.0269**
MOHHO	0.0296	0.0126	0.1682	0.0862	0.0095	0.0039	0.0119
LMEA	0.0570	0.0218	0.2024	0.1542	0.0179	0.0148	0.0242
NSGA-III	0.0578	0.0216	0.2059	0.1547	0.0169	0.0152	0.0248
SPEA2	0.0574	0.0217	0.2076	0.1657	0.0181	0.0156	0.0182
TwoArch2	0.0563	0.0195	0.2071	0.1577	0.0146	0.0156	0.0247

TABLE 8. Comparison of best-compromised solutions for cases 8, 9, 10, and 11.

	Case 8		Case 9		Case 10		Case 11	
	Cost ($/h)	Emis (ton/h)	Cost ($/h)	Loss (MW)	Emis (ton/h)	Loss (MW)	Loss (MW)	VD
TwoArchHHO	**41711.45**	1.7010	**41948.51**	**11.7243**	1.1640	11.6724	**10.8690**	**0.6636**
IMOMRFO [67]	41742.94	1.7912	-	-	-	-	-	-
MOEA/D-SF [68]	42160.09	1.3183	-	-	-	-	-	-
ISPEA [43]	42444.55	1.2904	-	-	-	-	-	-
NSGA-II [43]	43567.77	1.2979	-	-	-	-	-	-
ESDE [69]	42863.32	1.2662	42020.74	12.2155	-	-	-	-
ESDE-MC [69]	42857.49	**1.2191**	41998.36	11.8415	-	-	-	-
GBICA [24]	42138.37	1.3941	-	-	-	-	25.3628	0.85359
MGBICA [24]	42369.07	1.2940	-	-	-	-	25.3664	0.83711
MOMICA [40]	41886.80	1.4784	-	-	-	-	-	-
MOICA [40]	41919.71	1.6010	-	-	-	-	-	-
MODFA [70]	43174.57	1.2679	-	-	-	-	-	-
MPIO-PFM [71]	43205.85	1.2386	-	-	-	-	-	-
MPIO-COSR [71]	43131.27	1.2314	-	-	-	-	-	-

TABLE 9. Comparison of best-compromised solutions for cases 12, 13, and 14.

	Case 12			Case 13			Case 14			
	Cost ($/h)	Emis (ton/h)	Loss (MW)	Cost ($/h)	Loss (MW)	VD	Cost ($/h)	Emis (ton/h)	Loss (MW)	VD
TwoArchHHO	42441.50	**1.3538**	**11.1364**	42118.30	13.3361	**0.6637**	42519.13	**1.3431**	12.3491	0.7686
NSGA-II [71]	42187.93	1.5765	13.4586	-	-	-	-	-	-	-
MPIO-PFM [71]	43133.99	1.5027	11.7899	-	-	-	-	-	-	-
MPIO-COSR [71]	**42133.33**	1.4360	11.7711	-	-	-	-	-	-	-
IMOMRFO [67]	-	-	-	**41668.14**	14.9096	1.6113	**41727.31**	1.9297	16.1631	0.9823
MDE [72]	-	-	-	42070.00	**12.4024**	0.6933	-	-	-	-
CMICA4 [73]	-	-	-	41781.73	13.9936	0.8127	-	-	-	-
NSGA-II [73]	-	-	-	41930.94	21.5325	2.6699	-	-	-	-
MOPSO [73]	-	-	-	41901.36	16.8022	2.0059	-	-	-	-
MOEA/D-SF [68]	-	-	-	-	-	-	42648.69	1.3437	**11.8860**	**0.6713**
MOMICA [40]	-	-	-	-	-	-	41983.06	1.4960	13.6970	0.7970
MOICA [40]	-	-	-	-	-	-	41998.57	1.7605	13.3350	0.8748

TABLE 10. Best-compromised solutions for case 19.

	Cost ($/h)	Emission (ton/h)	Loss (MW)	VD
TwoArchHHO	135854.5	3.2427	44.4916	**0.4805**
MOHHO	-	-	-	-
LMEA	141871.7	2.4321	**28.3225**	0.7654
NSGA-III	145314.8	**2.3036**	36.1714	0.8830
SPEA2	144386.9	2.4392	29.6267	0.8202
TwoArch2	**135298**	3.8876	57.0843	1.3332

TABLE 11. Hypervolume comparison in the IEEE 118-bus system.

	Case 15	Case 16	Case 17	Case 18	Case 19
TwoArchHHO	**0.1019**	**0.0127**	0.1315	**0.0649**	**0.0503**
MOHHO	4.1×10^{-4}	-	0.0216	-	-
LMEA	0.0755	0.0096	**0.1387**	0.0451	0.0404
NSGA-III	0.0986	0.0105	0.1307	0.0462	0.0302
SPEA2	0.1018	0.0105	0.1280	0.0440	0.0378
TwoArch2	0.0902	0.0099	0.0821	0.0291	0.0088

cases 15-17 were compared with those of several algorithms in the literature as expressed in Table 12.

From Table 12, it can be noticeable that the TwoArchHHO obtained dominant solutions in the cost objective for case 15. In addition, the TwoArchHHO provided the dominant solutions in all objective functions for cases 16-17. Unfortunately, the comparison of the best-compromised solutions for cases 18 and 19 cannot be found in the literature.

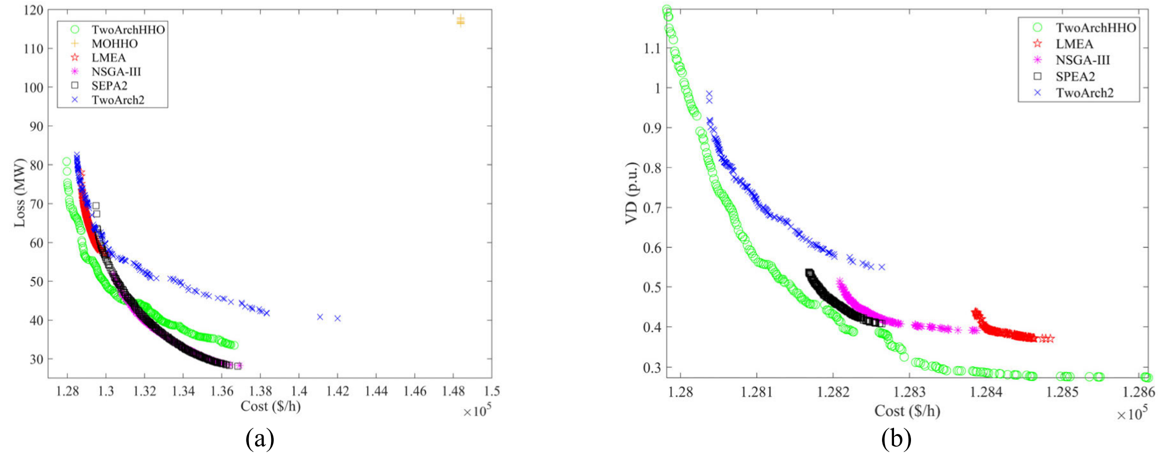

FIGURE 6. The comparison of Pareto optimal fronts for a) case 15, b) case 16.

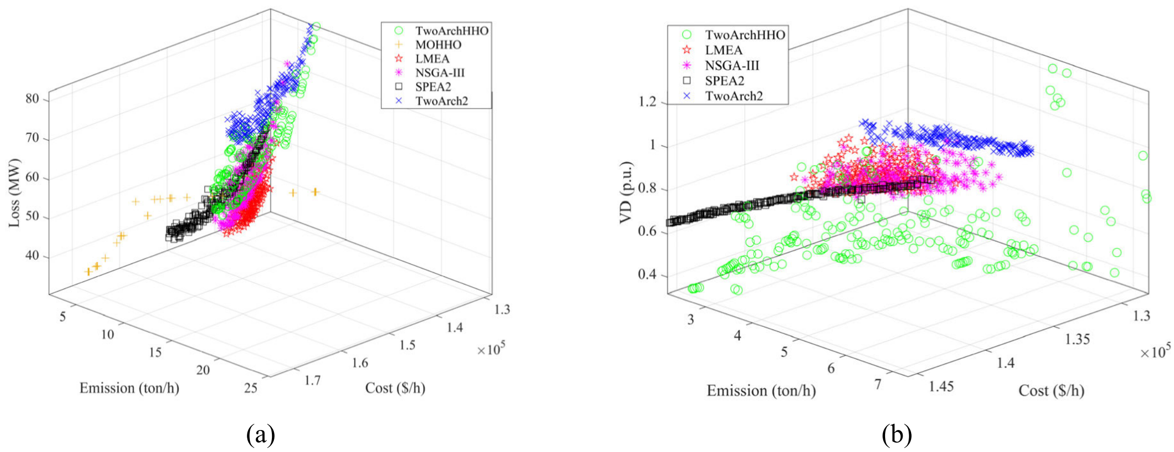

FIGURE 7. The comparison of Pareto optimal fronts for a) case 17, b) case 18.

TABLE 12. Comparison of best-compromised solutions for cases 15, 16, and 17.

	Case 15		Case 16		Case 17		
	Cost ($/h)	Loss (MW)	Cost ($/h)	VD	Cost ($/h)	Emis (ton/h)	Loss (MW)
TwoArchHHO	**128742.3**	60.4417	**128160.3**	**0.4682**	**135539.3**	**3.3123**	**41.1055**
BBO [75]	129895.0	65.3000	130105.0	0.9638	-	-	-
GSA [75]	129692.0	62.7200	130169.0	0.8629	-	-	-
MOBSA [76]	138669.2	**37.7904**	-	-	-	-	-
FAHSPSO-DE [77]	-	-	-	-	139324.6	258.7802	145.6000
HSC-GWO [78]	129,289.3	52.2310	129,141.4	0.6730	-	-	-

D. STATISTICAL ANALYSIS RESULTS

To further analyze the performance of the proposed TwoArchHHO, the Friedman test rankings obtained by the proposed algorithm and competitors according to one over hypervolume (1/hypervolume) metric values are presented in Table 13.

It can be observed that the proposed TwoArchHHO absolutely performed better than all of the compared algorithms followed by LMEA, NSGA-III, and SPEA2, respectively, while its traditional TwoArch2 and MOHHO algorithms were at the last two ranks.

To evaluate the quality of the solutions generated by the algorithms and their convergence quality, box-plot graphs were plotted to present the hypervolume metric values of the first three algorithms including TwoArchHHO, LMEA, and NSGA-III with competitive performance according to Friedman scores. Approximation graphs for 6 cases (2 cases per system) consisting of cases 1, 6, 9, 13, 16, and 17 are demonstrated in Fig 8.

It can be noticed from Fig 8 that the convergence qualities of each considered algorithm in the considered cases are

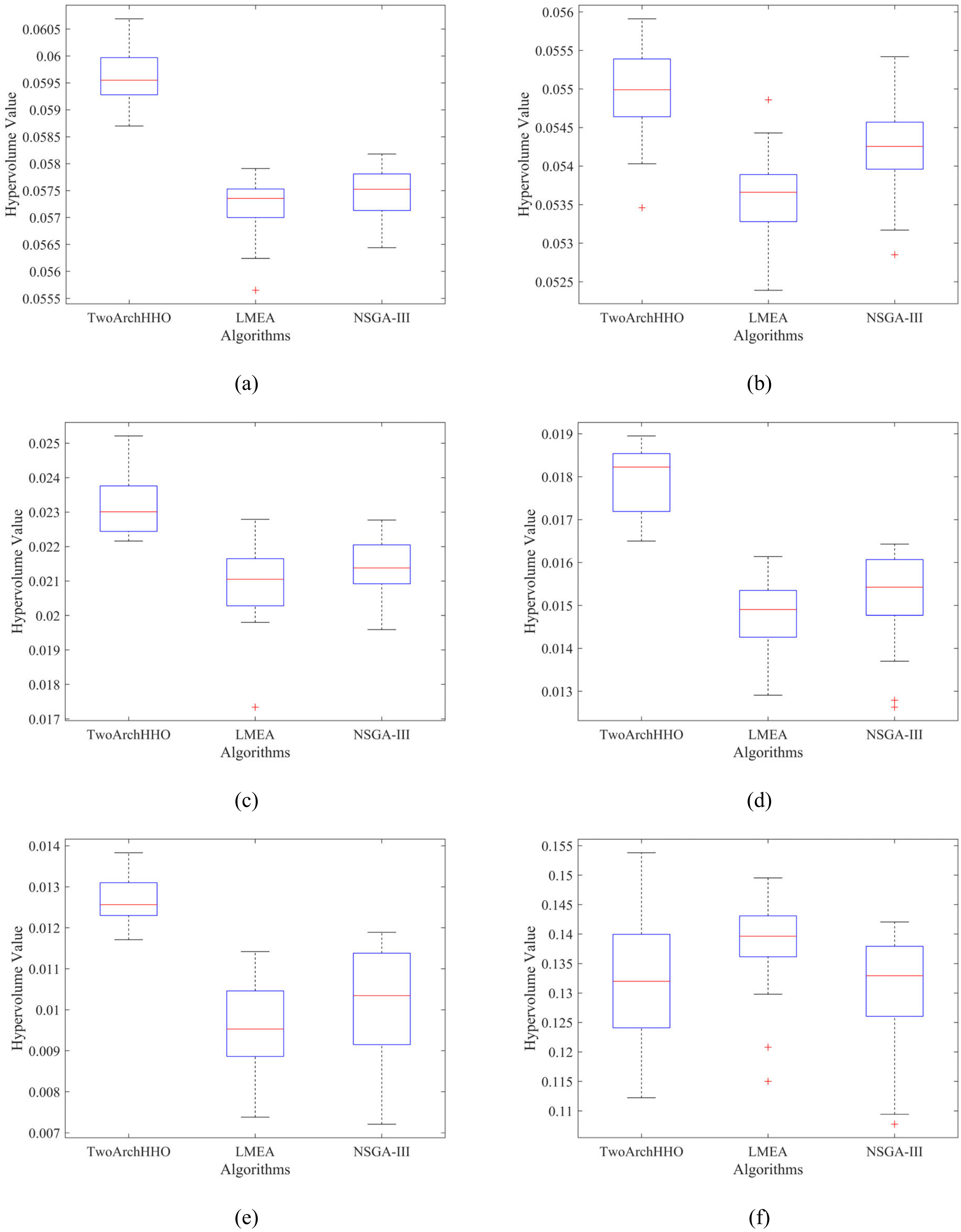

FIGURE 8. Performance of algorithms for hypervolume values for a) case 1, b) case 6, c) case 9, d) case 13, e) case 16, f) case 17.

very competitive. It can also be observed that the proposed TwoArchHHO provided significantly better hypervolume values than the considered compared algorithms for all considered cases except case 17 which LMEA obtained slightly better hypervolume value. However, LMEA could not converge to the solutions for 2 runs of the 30 runs for both

TABLE 13. Friedman test rankings obtained by algorithms according to 1/hypervolume metric values.

Algorithms	Average ranking
TwoArchHHO	**1.052632**
MOHHO	4.921053
LMEA	2.526316
NSGA-III	2.868421
SPEA2	3.131579
TwoArch2	3.947368

cases 16 and 17 of the IEEE 118-bus system, and NSGA-III could not converge to the solutions for 4 and 3 runs of the 30 runs for cases 16 and 17, respectively while the proposed TwoArchHHO converged to the solutions in all runs.

VII. CONCLUSION

The research conducted for this study yielded a significant contribution which is the introduction of a newly proposed TwoArchHHO for solving the MaOOPF problem in order to enhance power system operation and management. By combining the two-archive method from Two_Arch2 algorithm into HHO algorithm, the search process was significantly improved. The validation of this enhancement was evident in the analysis outcomes derived from experimental trials conducted on 19 different case studies. From the simulation results of all systems, it can be concluded that the proposed algorithm successfully provided Pareto fronts and best-compromised solutions for both MOOPF and MaOOPF problems with better solutions than those of several compared algorithms and its traditional algorithms which are MOHHO and TwoArch2 that are evident by hypervolume values. It was observed that the proposed TwoArchHHO obtained the dominant solutions in the different objective aspects for most cases. MOHHO found very low-quality Pareto fronts, especially in large systems and could not converge to the solutions in the IEEE 118-bus system whereas TwoArch2 could converge to the solutions with acceptable quality. In addition, the statistical analysis results were verified by the hypervolume metric through Friedman test ranking and boxplots. When investigated in this point of view, TwoArchHHO has high performance on solving MOOPF and MaOOPF problems for all system sizes, especially in large systems. With the proposed algorithm, the power system operation and management were improved in several terms including cost, emission, transmission loss and voltage deviation reductions surpassing the outcomes achieved by other algorithms. However, by solving MaOOPF problems, the optimal solutions could not meet all best objective values at the same time as it is called best-compromised solutions giving good average values in all aspects. So, system operators should select objective functions depending on situations. In the future, the proposed algorithm could be applied to address real-world MaOOPF challenges in practical systems to improve the operation and management in various aspects. Moreover, there's potential to introduce supplementary objective functions, such as the L-index, into the framework.

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