A Multitasking Electric Power Dispatch Approach With Multi-Objective Multifactorial Optimization Algorithm

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ABSTRACT

Electric power dispatch issue mainly consists of two optimization tasks: active and reactive power dispatches, each of which is a non-linear multi-objective optimization problem with a series of constraints. Traditional evolutionary algorithms are focused on single-task optimization for active or reactive power dispatch and they are not able to deal with several (single- or multi-objective) optimization tasks simultaneously. In this paper, to solve this problem, a multitasking electric power dispatch approach is proposed by introducing the multi-objective multifactorial optimization (MO-MFO) algorithm and integrating it with the characteristics of power system. The approach exhibits the great potential to be developed as a cloud-computing solver or platform for future large-scale smart grid applications involving different market entities because of its implicit parallel computation mechanism. The multitasking approach is thoroughly tested and benchmarked with IEEE-30-bus and IEEE-118-bus standard systems and exhibits generally better performances as compared to previously proposed Pareto heuristic approaches for electric power dispatch.

INDEX TERMS

Electric power dispatch, multifactorial, multitasking, optimization.

I. INTRODUCTION

Active and reactive power dispatches are two significant tasks for optimal and safety operations of modern power systems. As the increasing significance of energy saving and emission reduction draws more and more attention from the industrial community, the conventional single-objective electric power dispatch techniques which simply pursue the minimum cost, minimum emission, or minimum voltage variation cannot fulfill the requirements of the modern energy management system and the smart power grid. In recent years, the electric power dispatch problem considered as a multi-objective optimization issue which simultaneously tries to find multiple incommensurable and contradictory targets under a set of safety and operation constraints has received much attention. Optimal active power dispatch (APD) requires minimizing cost, emission, and transmission loss and reactive power dispatch (RPD) requires minimizing voltage variation and transmission loss and maximizing voltage stability. For a single dispatch task, because of the mutual contradiction of those objectives, the target is to find its Pareto-optimal fronts.

For the multi-objective problem in electric power dispatch, there exist two categories of optimization techniques: the first is the traditional linearization math method while another is the Pareto-based heuristic technique. For high dimensional multi-objective complex non-linear problems, the Pareto-based heuristic approach would have advantages and it includes Niched Pareto genetic algorithm (NPGA) [1], non-dominated sorting genetic algorithm (NSGA) [1], NSGA-II [2], strength Pareto evolutionary algorithm (SPEA) [3], multiple group search optimization algorithm (MGSO) [4], [5], etc.

The aforementioned optimization approaches are limited to solve one multi-objective task at a time. In other words, for one computing engine, they are not able to deal with more than one optimization tasks simultaneously; instead, those tasks will be processed serially. A modern power...
grid, as a complex system involving economic/environmental dispatch, electric transportation planning, communication network maintenance, electricity market transaction, fault diagnosis, and condition estimation, etc., generally requires many computation engines and processors to handle such enormous and complicated task load in real time. To reduce the hardware requirements of computation engines and increase the computation efficiencies, a cloud computing platform that is capable of handling different kinds of tasks simultaneously (parallel computation) would be an advantageous alternative. Recently, an evolutionary multitasking technique that harnesses the implicit parallelism of a population-based search to cope with multiple optimization tasks simultaneously with a single population was proposed for cloud-based applications [6]–[8]. It considers each optimization task as an additional factor affecting the total evolutionary process and therefore is named as multi-objective multifactorial optimization (MO-MFO) algorithm. Currently, it is designed and explored as a multitasking solver, especially for multiple optimization problems, while it exhibits great potential to be developed as a multitasking general problem-solving engine and applied in the cloud computing platform for the aforesaid modern power grid with many complex problems.

In this paper, the multi-objective multifactorial optimization (MO-MFO) algorithm is creatively applied in the electric power dispatch problems. And a multitasking electric power dispatch approach is further developed and proposed by integrating the MO-MFO algorithm with the characteristics of power system models in order to optimize both active and reactive power dispatch tasks concurrently, as well as reduce the execution time, and improve the performances. The analysis and design of the approach have been thoroughly verified and benchmarked with IEEE-30-bus and IEEE-118-bus standard systems. As compared to the other evolutionary techniques for electric power dispatch, including NSGA-II, MGSO, and MOEA/D methods, the proposed approach exhibits much better in terms of the evaluation efficiency and useful information can be transferred across those tasks, which may result in speeding up the total optimization process. It has been studied and verified that useful knowledge transferred across different but related tasks, such as CVRP and CARP problems [9], will help improve the performances of evolutionary optimization.

Before illustrating the principle of the MO-MFO algorithm, we firstly make the essential definitions and notations for the related variables and parameters. In the theoretical scenario of multi-task, there are \( K \) different multi-objective optimization tasks, that are assumed to be the minimization problems without loss of generality. For the \( j \)th task \( T_j \), the objective function \( F_j \) is defined as:

\[
F_j : X_j \rightarrow \mathbb{R}^{M_j},
\]

where \( X_j \) is the design space (or called as the decision variable space) of the \( j \)th task, \( \mathbb{R}^{M_j} \) is the objective function space of the \( j \)th task with the dimension of \( M_j \). The dimension of the design space \( X_j \) is noted as \( D_j \). The objective function value \( y_j \) can be expressed as:

\[
y_j = (y_{j,1}, y_{j,2}, \ldots, y_{j,M_j}),
\]

and \( x_j \) is the design variable of the \( j \)th task:

\[
x_j = (x_{j,1}, x_{j,2}, \ldots, x_{j,D_j}),
\]

Therefore, the objective function \( F_j \) maps design variables \( x_j \) to vectors \( y_j \), which is also expressed as:

\[
y_j = F_j (x_j) = (f_{j_1} (x_j), f_{j_2} (x_j), \ldots, f_{j_{M_j}} (x_j)).
\]

For a single task \( T_j \), the Pareto optimal set \( PS_j \) is defined as:

\[
PS_j = \{ x_j \in X_j | \exists x_j' \in X_j : F_j (x_j') \geq F_j (x_j) \}.
\]

And the Pareto front \( PF_j \) is defined as:

\[
PF_j = \{ y_j = F_j (x_j) = (f_{j_1} (x_j), \ldots, f_{j_{M_j}} (x_j)) | x_j \in PS_j \}.
\]

For the multitasking environment, the target is to find the Pareto sets of all the tasks \( PS_1, PS_2, \ldots, PS_K \).
However, for the proposed MO-MFO algorithm, the target is to find one optimal individual that consists of the information of all the tasks’ optimal solution. In other words, such an optimal individual can be translated into the specific solution of any of the optimization tasks. In the evolutionary process of the proposed algorithm, there are a number of individuals existing in the population $P$, and each individual is defined as $p_i$ and

$$i \in \{1, 2, \ldots, N\},$$  \hspace{1cm} (7)

where $N$ is the total number of individuals. Next, a unified search space $Z$ is defined, which encompasses the design spaces of all the tasks $X_1, X_2, \ldots, X_K$. Every individual $p_i$ is encoded, and its chromosome $z_i$ belongs to the unified search space $Z$. The dimension of $Z$ is selected as the maximum of the design spaces’ dimensions:

$$D_Z = \max \{D_1, D_2, \ldots, D_K\}. \hspace{1cm} (8)$$

For the individual $p_i$, as shown in Fig. 1, its chromosome $z_i$ contains the information of $K$ variables ($x_{1i}, x_{2i}, \ldots, x_{Ki}$) associated with $K$ tasks. Each element of the variables can be decoded from the corresponding element of the chromosome of $p_i$. Here in the paper, the element of the chromosome is also called as random-key, and the variables of different tasks are called as solution representations. For the continuous case, called as random-key, and the variables of different tasks are called as solution representations. For the continuous case, the $m$th random-key of $z_i$ as $z_{i,m}$ and it is assumed to be limited in the range of $[0, 1]$. For the specific $j^{th}$ task, the $m$th element of $x_j$ is defined as $x_{ji,m}$ and box-constrained as $[L_{j,m}, U_{j,m}]$, and one sample of the decoding method is shown as:

$$x_{ji,m} = L_{j,m} + z_{i,m} \cdot (U_{j,m} - L_{j,m}). \hspace{1cm} (9)$$

In addition to the aforementioned decoding method, different representations may apply to other decoding methods, such as binary decoding, sequence-based decoding, etc., according to the specific requirements of different tasks. Following, there are three essential definitions (factorial rank, skill factor, and scalar fitness) needed to be illustrated in detail. The factorial rank $r_j^i$ of $p_i$ for task $T_j$ is defined as the rank of $p_i$’s effectiveness regarding task $T_j$ in the list of $P$’s members. The skill factor $\tau_i$ of $p_i$ is defined as the task index number of the one task, with which $p_i$ is associated. If $p_i$ is evaluated for all tasks, $\tau_i$ will be the task index number of the one task, to which $p_i$ is the most effective:

$$\tau_i = \arg \min_{j \in \{1, 2, \ldots, K\}} r_j^i, \hspace{1cm} (10)$$

The scalar fitness $\phi_i$ of $p_i$ in the multitasking environment is based on $p_i$’s best rank amongst all tasks, defined as:

$$\phi_i = 1/r_i^* = 1/\min \{r_1^i, r_2^i, \ldots, r_K^i\}. \hspace{1cm} (11)$$

The sorting of the factorial rank $r_j^i$ of $p_i$ for task $T_j$ is based on the non-dominated front (NF) [10] and crowding distance (CD) [11] of task $T_j$’s objective functions’ values with the specific solution representation $x_j$ decoded from the chromosome $z_i$ of $p_i$. Note the aforementioned NF and CD as $NF_{j1}$ and $CD_{j2}$, respectively. For example, when we compare $p_1$ and $p_2$’s factorial ranks ($r_1^j$ and $r_2^j$) for task $T_j$, $p_1$ is considered to be preferred over $p_2$, meaning $p_1$ has a better rank than $p_2$ ($r_1^j < r_2^j$), when any one of the following conditions is satisfied:

$$NF_{j1} < NF_{j2}, \hspace{1cm} (12)$$

$$NF_{j1} = NF_{j2} \hspace{1cm} \text{and} \hspace{1cm} CD_{j1} > CD_{j2}. \hspace{1cm} (13)$$

With the definitions of factorial rank, skill factor, and scalar fitness, the MO-MFO algorithm is illustrated with the assistance of the flow chart in Fig. 2. Firstly, a unified search space $Z$ is initialized, and $N$ individuals are generated from the space to form the initial population $P_0$. Next, all the members $p_i$ of the population $P_0$ are randomly assigned their skill factors $\tau_i$ and then evaluated for task $T_i$ with the decoding procedure and objective functions. The assignment needs to guarantee that each task is uniformly associated. Further, the scalar fitness $\phi_i$ of every $p_i$ is calculated based
on the NF and CD. To generate offspring, a pool of parent candidates noted as \( P'_{t} \), is generated from the current population using binary tournament selection method. After that are the assortative or random mating for offspring creation, and the skill factor assignment for new offspring, which can be comprehended as vertical cultural transmission. Then the new offspring individuals are evaluated for the task associated with their skill factors and put into the offspring pool \( C_{t} \). The processes of offspring creation and skill factor assignment are repeated several times until the parent candidates pool \( P'_{t} \) is empty. When the offspring pool \( C_{t} \) is ready, a temporary candidate pool \( R_{t} \) consisting of \( C_{t} \) and \( P_{t} \) is formed with all the individuals’ scalar fitness updated. Finally, \( N \) fittest individuals are chosen from \( R_{t} \) to form a new population \( P_{t+1} \). Such evolving processes will be repeated multiple times until stop conditions are satisfied.

Offspring individuals are created from the parent candidates pool by assortative or random mating methods. If two parent individuals, which are randomly selected from the parent candidates pool, are with the same skill factors, they will undergo both crossover and mutate processes to generate two offspring individuals, as explained by the phenomenon of assortative mating. For the condition with different skill factors, they still have a probability (random mating probability, noted as \( rmp \)) to undergo crossover and mutate processes, which is understood as the natural phenomenon of random mating. For other conditions, they simply undergo mutation to generate two mutant offspring individuals separately. The principle of assortative mating indicates that in nature individuals prefers to mate with those with identical cultural attribute. However, individuals with different cultural attributes still have a probability to mate with each other, which is explained as the principle of random mating. The random mating probability is estimated roughly according to the correlation degree of the involved tasks. A higher correlation degree leads to a larger probability. The detailed steps of offspring creation are presented in Fig. 2.

Vertical cultural transmission is a natural phenomenon that illustrates the offspring imitate the cultural features of their parents according to cultural and biological inheritance theory [12]. The natural phenomenon is applied in the MO-MFO algorithm where the offspring individuals imitate any one of the skill factors of their parents randomly. For the offspring individual generated simply from the only mutation, it imitates the skill factor of its single parent simply.

The implicit information transfer between different tasks in the MO-MFO algorithm is achieved by the random mating probability of two parent candidates with distinct skill factors and the offspring’s random selection of skill factor from its parents. Such stochastic processes guarantee the inter-task knowledge transmission for the multitasking environment.

**B. POTENTIAL FOR FUTURE SMART GRID APPLICATIONS**

In addition to optimization problems, the MO-MFO algorithm exhibits large potentials of being developed as a complex multi-objective multitasking solver, and furtherly, a cloud-computing platform involving different market entities including power network, traffic network, information network, gas network, and so on. For example, the complex operations of a multi-energy system including electricity, heating, and natural gas networks [13] can be furtherly optimized with the aforementioned platform. All the tasks of those networks can be computed and solved simultaneously with a shared search space with reduced space requirements and improved computing efficiencies. Fig. 3 shows an example of multi-objective multitasking cloud-computing platform for future smart grid applications with several representative tasks, such as Nash game problem for cooperative planning, Cournot game problem for capacity expansion, and cloud framework for users’ transactions, whose phenotypes may have part of overlaps with each other and enable useful information sharing and transmission and hence the computations are accelerated. Originally there are separate search spaces regarding those tasks respectively. In the platform, the separate search spaces are integrated into one shared search space. In the shared search space, each task’s computing information is shared with others. From the last iteration to the next iteration, the population is updated with newly generated and better offspring individuals within the shared search space. Further, for the sake of using a shared search space instead of three separate search spaces, space and memory resources are reduced significantly. The example in Fig. 3 is simply introduced to show the algorithm’s great development potentials for future smart grid applications and will not be discussed in detail in this paper. Instead, the optimization problem of active and reactive electric power dispatches is discussed in the following in order to validate the algorithm’s applicability and advantages. The tasks of active and reactive electric power dispatches are related because they rely on the same power system model, and they have one common objective – transmission loss minimization. Hence, the algorithm is appropriate.

**III. MODELS OF ACTIVE AND REACTIVE POWER DISPATCHES**

Active and reactive power dispatches are considered as two optimization tasks with respective objectives and constraints.
A. ACTIVE POWER DISPATCH (APD)

1) OBJECTIVES OF APD
The optimization objectives of active power dispatch consist of economic objective, emission objective, and transmission loss objective.

a: ECONOMIC OBJECTIVE
Minimization of total generation (fuel) cost is defined as the economic objective of APD, with the corresponding objective function [14] described as:

\[ F(P_G) = \sum_{i=1}^{N_G} \left[ a_i P_G^2_i + b_i P_G + c_i + \delta_i \sin [(e_i (P_{Gi\text{min}} - P_G))] - P_G \right] \]  

where \( F \) is total fuel cost in ($/h); \( P_{Gi} \) and \( P_{Gi\text{min}} \) are the actual output power and minimum output power of the \( i^{th} \) generator; \( (a_i, b_i, c_i, d_i, e_i) \) are the cost coefficients of the \( i^{th} \) generator; and \( N_G \) is the total count of generators.

b: EMISSION OBJECTIVE
Minimization of total fossil fuel pollutants (emission) during generation process is defined as the emission objective of APD, with the corresponding objective function [15] described as:

\[ E(P_G) = \sum_{i=1}^{N_G} 10^{-2} \left[ \alpha_i P_G^2_i + \beta_i P_G + \gamma_i \exp (\lambda_i P_{Gi}) \right] \]  

where \( E \) is the total emission in (ton/h) and \( (\alpha_i, \beta_i, \gamma_i, \lambda_i) \) are the emission coefficients of the \( i^{th} \) generator.

c: TRANSMISSION LOSS OBJECTIVE
Minimization of power losses in transmission lines is defined as the transmission loss objective of APD. The total transmission losses [1] can be calculated with the Newton-Raphson method and expressed as:

\[ P_{Loss} = \sum_{z=1}^{N_L} g_z \left[ V_x^2 + V_y^2 - 2V_x V_y \cos (\delta_x - \delta_y) \right] \]  

where \( x \in \{1, 2, \ldots, N_B\} \) and \( N_L \) is the number of transmission lines; \( g_z \) is the conductance of the \( z^{th} \) line connecting the \( x^{th} \) and the \( y^{th} \) buses; \( V_x, \delta_x \) are the voltage magnitudes and angles of the \( x^{th} \) bus; and \( V_y, \delta_y \) are the voltage magnitudes and angles of the \( y^{th} \) bus. Voltage magnitudes and angles at all buses can be obtained by load-flow calculation with Newton-Raphson method:

\[ P_{Gx} - P_{Ix} - V_x \sum_{y=1}^{N_B} V_y G_{xy} \cos (\delta_x - \delta_y) + B_{xy} \sin (\delta_x - \delta_y) = 0, \]  

\[ Q_{Gx} - Q_{Ix} - V_x \sum_{y=1}^{N_B} V_y G_{xy} \sin (\delta_x - \delta_y) - B_{xy} \cos (\delta_x - \delta_y) = 0. \]  

where \( N_B \) is the number of buses; \( P_{Gx} \) and \( Q_{Gx} \) are the generated active and reactive power at the \( x^{th} \) bus respectively; \( P_{Ix} \) and \( Q_{Ix} \) are the load active and reactive power at the \( x^{th} \) bus respectively; \( G_{xy} \) and \( B_{xy} \) are the transfer conductance and susceptance between the \( x^{th} \) and \( y^{th} \) buses respectively.

2) CONSTRAINTS OF APD
During the operation progress of power system, there are several practical operations, and safety requirements need to be satisfied, which are modeled as the constraints of the optimization task.

a: POWER BALANCE CONSTRAINT
The total generated power of generators should be equal to the load demand power and the total transmission losses, which can be expressed as:

\[ \sum_{i=1}^{N_G} P_{Gi} - \sum_{x=1}^{N_B} P_{Ix} - P_{Loss} = 0. \]  

b: BUS VOLTAGE CONSTRAINT
The constraint of the voltages at all buses is expressed as:

\[ V_{x,\text{min}} \leq V_x \leq V_{x,\text{max}}, \quad x \in \{1, 2, \ldots, N_B\}. \]  

where \( V_{x,\text{min}} \) and \( V_{x,\text{max}} \) are the allowable lower and upper limits of the \( x^{th} \) bus voltage.

c: TRANSMISSION SECURITY CONSTRAINT
The apparent power flowing through every transmission line should be smaller than the corresponding maximum transmission capacity:

\[ \max \left( |S_{xy}|, |S_{yx}| \right) \leq S_{\text{c, max}} \quad x, y \in \{1, 2, \ldots, N_B\}, \quad z \in \{1, 2, \ldots, N_L\}. \]  

where \( S_{xy} \) is the apparent power flow from the \( x^{th} \) bus to the \( y^{th} \) bus while \( S_{yx} \) is that with the opposite direction; \( S_{\text{c, max}} \) is the upper limit of the \( z^{th} \) transmission line’s apparent power.

d: SPINNING RESERVE CONSTRAINT
For the safe and stable operation for the system, the spinning reserve requirement for emergency conditions must be satisfied [17]. The generators with prohibited operating zones are not considered as part of the spinning reserve. The constraint is expressed as:

\[ \sum_{i=1}^{N_G} S_{P_Gi} \geq S_{P_R}, S_{P_Gi} = \begin{cases} 0 & \forall i \in \Omega \\ P_{G_{i,\text{max}}} - P_{Gi} & \text{others.} \end{cases} \]  

where \( S_{P_Gi} \) is the spinning reserve of the \( i^{th} \) generator; \( S_{P_R} \) is the spinning reserve requirement; \( P_{G_{i,\text{max}}} \) is the maximum output of the \( i^{th} \) generator, and \( \Omega \) is the set of generators with prohibited operating zones.

B. REACTIVE POWER DISPATCH (RPD)

1) OBJECTIVES OF RPD
The optimization objectives of reactive power dispatch are transmission loss objective, voltage profile objective, and voltage stability objective.
a: TRANSMISSION LOSS OBJECTIVE
This objective is to minimize the total power losses in transmission lines during the RPD progress, whose expression is the same as the transmission loss objective of APD.

b: VOLTAGE PROFILE OBJECTIVE
Minimization of the total absolute deviations of voltage magnitudes at the load buses is defined as the voltage profile objective and the sum of the absolute deviations is noted as \( V_D \) and described as:

\[
V_D = \sum_{k=1}^{N_L} |V_k - V_{k,r}| .
\]  

(23)

where \( N_L \) is the number of buses with loads; \( V_k \) and \( V_{k,r} \) are the actual and rated voltages at the \( k^{th} \) load bus, respectively.

c: VOLTAGE STABILITY OBJECTIVE
Voltages at the buses with loads may collapse when contingency conditions happen, and here a global indicator \( L \) describing the voltage stability of the system is given as [18]:

\[
L = \max_{k \in \{1,2,...,N_L\}} \left| 1 - \frac{\sum_{i=1}^{N_G} F_{ki} \cdot V_c^{G_i} \cdot V_{V,L}}{V_c^{V,k}} \right| .
\]  

(24)

where \( V_c^{V,k} \) and \( V_c^{V,L} \) are the voltages at the \( i^{th} \) generator bus and the \( k^{th} \) load bus in complex form, respectively; \( F_{ki} \) is the element of the matrix \( F_{LG} \), which is calculated by:

\[
\begin{bmatrix}
V_c^{V,L} \\
F_G^n
\end{bmatrix} = [H] \cdot \begin{bmatrix}
I_c^n \\
V_c^{V,L}
\end{bmatrix} = \begin{bmatrix}
Z_{IL} & F_{LG} \\
K_{GL} & q Y_{GG}
\end{bmatrix} \cdot \begin{bmatrix}
I_c^n \\
V_c^{V,L}
\end{bmatrix} .
\]  

(25)

where \( V_c^{V,L} \) and \( F_G^n \) are voltage and current vectors at generator buses in complex form respectively; \( V_c^{V,L} \) and \( I_c^n \) are voltage and current vectors at load buses in complex form respectively; \( Z_{IL}, F_{LG}, \) \( K_{GL} \), and \( Y_{GG} \) are sub-matrices of the \( H \) matrix which is derived from the nodal admittance matrix with partial inversion.

2) CONSTRAINTS OF RPD
There are six operational and practical constraints of reactive power dispatch, including generation constrains, bus voltage constraint, transmission security constraint, load flow equality constraint, transformer constraint, and VAR source constraint.

a: GENERATION CONSTRAINT
Every generator’s active and reactive power outputs are limited in respective ranges:

\[
P_{G_i,\text{min}} \leq P_{G_i} \leq P_{G_i,\text{max}}, Q_{G_i,\text{min}} \leq Q_{G_i} \leq Q_{G_i,\text{max}},
\]  

\[i \in \{1,2,...,N_G\} .
\]  

(26)

where \( Q_{G_i,\text{min}} \) and \( Q_{G_i,\text{max}} \) are lower and upper limits of the reactive power output of the \( i^{th} \) generator; \( Q_{G_i} \) is the actual reactive power output of the \( i^{th} \) generator.

b: BUS VOLTAGE CONSTRAINT
The constraint of RPD is the same as that of APD, expressed as (20).

c: TRANSMISSION SECURITY CONSTRAINT
The constraint is the same as that of APD, expressed as (21).

d: LOAD FLOW EQUALITY CONSTRAINT
The constraint describes the nonlinear equalities of active and reactive power balance, which is expressed as (17) and (18).

e: TRANSFORMER CONSTRAINT
The tapping configuration of every transformer is limited as:

\[
T_{a,\text{min}} \leq T_a \leq T_{a,\text{max}}, \quad a \in \{1,2,...,N_T\} .
\]  

(27)

where \( T_{a,\text{min}} \) and \( T_{a,\text{max}} \) are the lower and upper tapping limits of the \( a^{th} \) transformer; \( T_a \) is the actual tapping of the \( a^{th} \) transformer, and \( N_T \) is the number of transformers.

f: VAR SOURCE CONSTRAINT
The reactive power generated by every VAR source is limited in a practical range:

\[
Q_{Ch,\text{min}} \leq Q_{Ch} \leq Q_{Ch,\text{max}}, \quad b \in \{1,2,...,N_C\} .
\]  

(28)

where \( Q_{Ch,\text{min}} \) and \( Q_{Ch,\text{max}} \) are the lower and upper reactive power output limits of the \( b^{th} \) VAR source; \( Q_{Ch} \) is the actual reactive power output of the \( b^{th} \) VAR source, and \( N_C \) is the number of VAR sources.

IV. COMPUTATION STUDIES
A. METRICS OF EVALUATION
When solving the multi-objective problems, it is difficult to obtain the true Pareto front. Therefore, there are several metrics proposed to evaluate the performances of the corresponding algorithm.

1) SPACING
The spacing metric [19], [20] is defined to measure how evenly the Pareto solutions are distributed along the obtained Pareto front and calculated as:

\[
S = \sqrt{\frac{1}{n_f} \sum_{i=1}^{n_f} (d_i - d_{\text{avg}})^2}.
\]  

(29)

where \( d_i \) is the Euclidean distance between the \( i^{th} \) solution and its nearest solution, and \( n_f \) is the number of solutions, and \( d_{\text{avg}} \) is the mean value of all \( d_i \) in the obtained Pareto front.

2) SPAN
The span metric [21] measures the maximum extent of each objective function to estimate the range to which the obtained Pareto front spreads out, calculated as:

\[
SP = \sqrt{\sum_{i=1}^{M} (f_{i,\text{max}} - f_{i,\text{min}})^2}.
\]  

(30)
where $M$ is the number of the objective functions; $f_{i, \text{max}}^*$ and $f_{i, \text{min}}^*$ are the normalized maximum and minimum function values of the $i$th objective. For the cases with two objectives, the span metric is equal to the distance of the two outer solutions.

3) CONVERGENCE

The convergence metric [10] measures the extent of the obtained Pareto front’s convergence to a known or true Pareto-optimal front. For each solution of the obtained Pareto front, the minimum value of the Euclidean distances of it from all the solutions of the known or true Pareto front is calculated. And the average value of those minimum distances is obtained as the convergence metric.

4) $l_{\text{max}}/l_{\text{min}}$ [20] is defined as the ratio of the maximum Euclidean distance and the minimum Euclidean distance of adjacent solutions, which is used to measure the uniformity of the Pareto solution.

5) CONVERGENCE TIME

This metric refers to the total time needed for the objective values and other metrics achieving the requirements using the corresponding algorithm.

B. SETTING OF THE TEST SYSTEM

To test the performances of the proposed MO-MFO algorithm’s application in multitasking electric power dispatch, the IEEE-118-bus and IEEE-30-bus systems [4] are chosen for the active and reactive power dispatch tasks, respectively. The IEEE-118-bus system consists of 186 branches and 54 generators. The IEEE-30-bus system consists of 41 branches and 6 generators and has 12 variables, including 6 generator voltages, 4 tapping ratios of the OLTC transformers connected in the branches 4-12, 6-9, 6-10, and 27-28 respectively, and 2 shunt capacitors installed at buses 10 and 24.

To compare different algorithms fairly, the population numbers of IEEE-118-bus and IEEE-30-bus systems are set to be 100 and 300 respectively and the maximum number of iterations is set to be 1000. The computation results of the proposed and other algorithms are based on 30 runs of iterations.

C. COMPUTATION RESULTS

In the previous setting, there are two multi-objective optimization tasks: the first one is the active power dispatch for the IEEE-118-bus system; and the second one is the reactive power dispatch for the IEEE-30-bus system.

1) TASK 1-ACTIVE POWER DISPATCH FOR THE IEEE-118-BUS SYSTEM

In the computations of task 1, the economic and environmental objectives are chosen as the optimization objectives, and the performance metrics of different algorithms after 30 runs of iterations are shown in Table 1. The proposed MO-MFO method is verified to be more advantageous as compared to the NSGA-II, MGSO, and MOEA/D algorithms when applied in electric power dispatches. From Table 1, the spacing values and the average $l_{\text{max}}/l_{\text{min}}$ of the MO-MFO algorithm are highlighted in bold.

| Task 1 | Best Cost | Best Emission |
|--------|-----------|---------------|
| NSGA-II | 0.7828 | 0.6748 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MGSO | 0.7944 | 0.7629 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MOEA/D | 0.7997 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MO-MFO | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| NSGA-II | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MGSO | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MOEA/D | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MO-MFO | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| NSGA-II | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MGSO | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MOEA/D | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |
| MO-MFO | 0.8028 | 0.8084 | 0.7765 | 0.8479 | 0.6587 | 0.9617 |

The best values are highlighted in bold.
algorithm are the lowest than the others, meaning that its Pareto solutions are distributed the most evenly. The span values of the MO-MFO algorithm are the largest among those algorithms, indicating its largest search ranges. Table 2 presents the best solutions of cost and emission calculated from the extreme points of the resulting Pareto fronts of the algorithms. As compared to other algorithms, the MO-MFO has lower cost and emission objective values of the best solutions. Besides, the best Pareto fronts obtained from the algorithms are plotted in Fig. 4. As compared to the other algorithms, the Pareto front obtained from the MO-MFO algorithm is closer to the left bottom point and with two better outer solutions. Moreover, the convergences of the emission objectives obtained from the different algorithms are given in Fig. 5, which shows that the MO-MFO has better convergence time.

2) TASK 2–REACTIVE POWER DISPATCH FOR THE IEEE-30-BUS SYSTEM

In the computations of task 2, the transmission loss and the voltage deviation are selected as the optimization objectives, and the performance metrics of different algorithms after 30 runs of iterations are shown in Table 3, from which it can be observed that the average values of spacing, span, convergence, and \( \frac{l_{\text{max}}}{l_{\text{min}}} \) metrics of the MO-MFO algorithm are the best. Table 4 presents the best solutions of transmission loss and voltage deviation calculated from the extreme points of the resulting Pareto fronts of the algorithms. As compared to other algorithms, the MO-MFO has lower transmission loss and voltage deviation objective values of the best solutions. From Fig. 6, the best Pareto front of the MO-MFO algorithm is closer to the left bottom point and with one better outer solution as compared to the other three algorithms. Fig. 7 shows the convergence processes of the transmission loss objective of different algorithms, and the MO-MFO algorithm exhibits fewer iterations.

3) MULTITASKING PERFORMANCE

With regards to the NSGA-II, MGSO, and MOEA/D algorithms, task 1 and task 2 are solved in series, while the MO-MFO algorithm solves the two tasks simultaneously.
Comparisons of convergence times of two tasks.

TABLE 5.

| Algorithms | NSGA-II | MGSO | MOEA/D | MO-MFO |
|------------|---------|------|--------|--------|
| Task 1 | 11.104  | 11.052 | 12.649 | 11.148 |
| Task 2 | 1.566   | 1.506 | 1.607 |       |
| Total | 12.670  | 12.558 | 14.257 |        |

The best values are highlighted in bold.

Their run times are presented in Table 5. It can be observed that the total run time of the two tasks of the MO-MFO algorithm is the shortest with at least 1.41s advantage as compared to the other algorithms. Besides, the aforementioned computation results, the overall performance metrics and solution qualities of the MO-MFO algorithm applied in the multitasking electric power dispatch problem are the best among the four algorithms.

V. CONCLUSION

In this paper, a multitasking electric power dispatch approach based on the MO-MFO algorithm is proposed to apply in complex electric power dispatch problems, specifically, the active and reactive power dispatches. As compared to the existing evolutionary techniques for electric power dispatch, including NSGA-II, MGSO, and MOEA/D methods, the proposed approach performs much better in terms of the evaluation metrics and solution qualities of the MO-MFO algorithm applied in the multitasking electric power dispatch problem are the best among the four algorithms.

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