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Abstract

Multiobjective evolutionary algorithm based on decomposition (MOEA/D) is an efficient mathematical strategy for solving multiobjective optimization problems. However, the MOEA/D algorithm has not yet been widely used on the multiobjective optimal power flow (MOPF) problems, which consider several conflicting objectives with varying tradeoff levels. This article proposes a novel differential evolution (DE) strategy based on the MOEA/D framework to quickly determine a set of optimal solutions of MOPFs, in the objective space formed from the different objectives, such as the most optimal economic dispatch, the least environmental emission objectives, and the minimum transmission losses, while considering the power system constraints. A judicious decision can be made by the user from the set of optimal solutions of the MOPF associated with the weight vectors representing the tradeoff levels of the different objectives. For improved performance, two aggregate objective functions, a load flow operator and a self-adaptive DE strategy work cooperatively: 1) to improve the weak convergence of the MOEA/D and to achieve a better decision speed; 2) to obtain more accurate optimal solutions even under non-convex conditions; 3) to ensure that the power system constraints are taken into account; 4) to integrate the above features into a fast and efficient algorithm. The proposed algorithm has been validated using the IEEE 30-bus system and a revised 33-bus radial system added to one node of the 30-bus system. The simulation results show that the proposed algorithm can provide a good accuracy and can converge to a set of optimal solutions of the MOPFs.

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A Judicious Decision-Making Approach for Power Dispatch in Smart Grid Using a Multi-objective Evolutionary Algorithm Based on Decomposition

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Abstract—Multi-objective evolutionary algorithm based on decomposition (MOEA/D) is an efficient mathematical strategy for solving multi-objective optimization problems. However, the MOEA/D algorithm has not yet been widely used on the multi-objective optimal power flow (MOPF) problems, which considers several conflicting objectives with varying trade-off levels. This paper proposes a novel differential evolution (DE) strategy based on the MOEA/D framework to quickly determine a set of optimal solutions of MOPFs, in the objective space formed from the different objectives, such as the most optimal economic dispatch, the least environmental emission objectives, and the minimum transmission losses, while considering the power system constraints. A judicious decision can be made by the user from the set of optimal solutions of the MOPF associated with the weight vectors representing the trade-off levels of the different objectives. For improved performance, two aggregate objective functions, a load flow operator and a self-adaptive DE strategy work cooperatively: 1) to improve the weak convergence of the MOEA/D and to achieve a better decision speed; 2) to obtain more accurate optimal solutions even under non-convex conditions; 3) to ensure that the power system constraints are taken into account; 4) to integrate the above features into a fast and efficient algorithm. The proposed algorithm has been validated using the IEEE 30-bus system and a revised 33-bus radial system added to one node of the 30-bus system. The simulation results show that the proposed algorithm can provide a good accuracy and can converge to a set of optimal solutions of the MOPFs.

Index Terms—multi-objective optimization, economic dispatch, decomposition, optimal power flow, decision making.

I. INTRODUCTION

In recent decades, there are increasing needs to obtain fast solutions [1] of the MOPF problems [2]–[3] for a more effective operation and planning in modern power systems [4]. The MOPF can be understood as an extension of the constrained single-objective optimal power flow (OPF) [5] that aims to minimize the total generation cost of the power system while meeting the need of a power balance between the supply and the demand, subject to the constraints [6] of the operating limits of the generator active and reactive powers, and the security of the overall system.

The MOPF is often solved by using a multi-objective optimization (MOO) [7] algorithm, which considers several conflicting objectives with varying trade-off levels [8]. Thus, the MOPF provides a set of optimal solutions, rather than a single optimum value in the traditional OPF. The set of optimal solutions of MOPF corresponds to different trade-off levels, which are often referred to as the Pareto optimal solutions [8]

(PoSs), in which each PoS corresponds to a point in the objective space formed from the different objectives, and the shape of all these points is called the Pareto Front (PF). The user can make a judicious decision on which trade off level and the associated optimum point on the PF that can best fit the power system objective.

According to [9]–[12], the optimization techniques to solve MOPF can be categorized into two groups: (i) mathematical programming methods and (ii) heuristic algorithms.

The mathematical programming methods [13] are often computationally fast even when dealing with a large scale MOPF and generally the optimal solution can be obtained stably each time. However, such methods are based on the use of derivatives, and can be easily trapped into local optima. Furthermore, they may not converge to the global optima for nonconvex problems.

Reference [14] uses an aggregate function and the Lagrangian optimization model to solve a 2-objective MOPF that simultaneously minimizes the fuel cost and the emission of pollutants (EED) [15]–[16] from the power system. The method has a good performance on both the computing time and the convergence rate [17], but it becomes less effective when applied to non-convex problems [18][19].

The heuristic algorithms for MOPFs include methods such as the evolutionary algorithms (EA) [20] and the genetic algorithm [7]. They do not make use of the derivatives but uses random probing to obtain the optimal solutions. They have many attractive features, such as the ability to quickly identify promising regions in the global decision domain, even for non-convex problems. However, such methods are often computationally time-consuming and are seldom used in practical applications.

Ref [21] use the non-dominated sorting genetic algorithm (NSGA-II) [22] to obtain the entire PF on which the fuzzy theory [3] is applied for the final ‘best compromise solution’. Such design is not efficient because it is not necessary to obtain the entire PF of the MOPFs for a compromise solution. Thus, it is more practical to obtain a set of good representative points on the PF (e.g., the points evenly distributed along the PF), which can accelerate the decision process significantly. The MOEA/D [23] provides such a good programming framework based on the use of decomposition, which can result in lower computational complexity than the NSGA-II algorithm [23]. However, the MOEA/D is weak in its convergence [24] because of its focus on the stochastic searching to ensure the PF diversity. This can make it inefficient to obtain the PoS set (i.e.,

the active power outputs of the generating units). Besides, the MOEA/D framework is quite different from the most frameworks of the existing evolutionary algorithms. Thus, many existing state-of-art evolutionary technologies are not compatible with the MOEA/D. Moreover, Ref. [25] includes the slack bus into the random decision variables for the stochastic searching. Due to the random probing, only reasonable optimal solutions (or nearly global optimal) are provided in the final output and the transmission losses in these methods are usually ignored (or assessed by an approximate substitute). Such random allocation of active power of the slack bus in the decision variables may violate the power system constraints, as the total load plus transmission losses are not balanced by the total generation.

In a real-world MOO application, the MOPF of a modern power system may be affected by many uncertainty factors (such as the intermittency in renewable power sources). Accordingly, the MOPF needs more frequent dynamic decisions to catch up with the dynamic environment [2]. Therefore, unlike normal MOOs, the algorithms designed for MOPFs should be more concerned with quickly obtaining the PoS and PF. However, such complexity has not been addressed well among the currently available MOPFs methods. Most researchers assume that the currently available methods for the MOO, such as the state-of-art approaches using NSGA-II and MOEA/D, can be automatically used and can work well to solve the MOPF problem [2]. The preliminary simulation results of a MOPF problem of a realistic power system show that this is not the case, when uncertainty is introduced in the algorithm. This motivates us to develop this paper to narrow the gap on this research topic.

This paper presents a self-adaptive DE algorithm that is compatible with the MOEA/D [23] framework to solve the MOPF, and discusses how the speed can be improved by using the proposed searching strategy of the new algorithm. A 2-objective MOPF (i.e. EED), and a 3-objective (the extended EED) MOPFs (based on three candidate objectives such as the optimal economic dispatch, the least environmental emission, the minimum transmission loss), both are investigated in this paper.

The novelty and the contributions of the paper are:

- This paper proposes a new DE operator that is compatible with MOEA/D framework to obtain the computational expenditure reduction. In the existing papers, the DE technique are often incompatible with the MOEA/D framework. Further, the MOEA/D has weak convergence which is not efficient to solve practical MOPF problems.
- This paper develops a self-adaptive strategy to evolve the control parameters of the proposed algorithm for the solution and a dynamic elite-solution set at each generation, and hence, the proportion of reasonable probing has been increased. The original MOEA/D fixes its control parameters as constants, which makes it ineffective to solve various problems but also weak on the rational probing. The existing papers and books often utilize the MOEA/D algorithm directly rather than update its strategy to solve the problem to achieve a better performance.
- This paper makes use of the evenly distributed weights to obtain the PF and PoS of the MOPFs, which is more

intuitive and can lead to more accurate results than the traditional fuzzy theory. The existing papers, on the decision-making strategy based on multi-objective optimization usually solve the problem in two steps: (i) to develop the whole Pareto Front (PF), and then (ii) to normalize the PF for a compromised solution based on the fuzzy theory. Such kind of strategy leads to more computational cost.

- This paper integrates a Newton-Raphson power flow operator into the MOEA/D frame at each solution process, which will ensure that the constraints in the power system are met and will provide accurate total system losses. The slack active power is not randomly chosen but is calculated by the power flow operator to ensure that there is a balance between the generation and the loads plus losses. The existing papers on the population-based algorithms, often utilize some approximated strategies to take into account the transmission losses, which is not suitable for practical applications.
- This paper also uses the standard IEEE 30-bus system incorporating the 33-bus radial system to validate the performance of the proposed algorithm.

The paper is organized as follows: Section II discusses the problem formulation; in Section III, the proposed approach is explained in detail; in Section IV, the simulation studies and results are discussed; and the conclusion is given in Section V.

II. PROBLEM FORMULATION

A. Mathematical Definition of MOO

$$\text{Minimize } \vec{F}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \dots, f_m(\vec{x})]$$

$$\text{Subject to: } \vec{x} = [x_1, x_2, \dots, x_n] \in \Omega \quad (1)$$

where $\Omega = \{\vec{x} \in [x_i^{\min}, x_i^{\max}]^n | i = 1, \dots, n, h_j(\vec{x}) \leq 0, j = 1, \dots, k\}$ is called the feasible region, in which, $h_j(\vec{x}) \leq 0$ is the k equality or inequality constraints, and $x_i^{\min}, x_i^{\max}$ are the bounds of the i -th independent variables. $\vec{x} \in \Omega$ is called a feasible solution.

As shown in (1), MOO [7] is concerned with an area of multiple criteria decision making, e.g., on the minimization of a vector of m objective functions (or a dependent vector), $\vec{F}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \dots, f_m(\vec{x})]$, while satisfying a group of bounds and constraints associated with the system. In this paper, the n dimensional space formed by the n independent variables (or decision variables), $\vec{x} = [x_1, x_2, \dots, x_n]$, (such as the generator active power outputs), is called the decision space. The m dimensional space formed by the m objectives, $\vec{F}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \dots, f_m(\vec{x})]$ (i.e., the dependent vector) is called the objective space. It is to be noted that the terms of the objective vector and the dependent vector, the terms of the decision vector (or the independent vector) and the solutions, and the terms of the point and the vector, are used interchangeably throughout this paper.

- 1) In a MOO, suppose any two feasible solutions $\vec{x}$ and $\vec{x}^q$, $\vec{x}$ is said to dominate (or better than) another $\vec{x}^q$, denoted as $\vec{x} < \vec{x}^q$, if $\vec{F}(\vec{x})$ dominates $\vec{F}(\vec{x}^q)$, i.e., $\vec{F}(\vec{x}) < \vec{F}(\vec{x}^q)$, which means there is no component of $\vec{F}(\vec{x})$ that is greater than the corresponding component of $\vec{F}(\vec{x}^q)$ and at least one component is smaller.
- 2) Pareto optimal solutions (POSs) are points in the decision space where any improvement in one component of the

objective vectors, will result in the worsening of at least one of the other components of the objective vector [8]. Given that, for all the Pareto optimal solutions in the decision space, their dependent vectors in the objective space can form a pattern consisting of points, the pattern is called the Pareto frontier or Pareto Front (PF) [8].

- 3) The PF quality is measured by two criteria: diversity and convergence. The diversity focuses on all points on the PF that can be distributed evenly, rather than collected on several specialized objective functions; and the convergence is concerned with the need for the calculated PF to approach the ideal PF as close as possible.

B. Objective Functions of MOPF and Constraints

The decision variables of the MOPF are the real power output of all generators excluding the output on the slack node. All objectives are dependent on the decision variables.

EED [13][17] is a typical two-objective MOPF with several constraints, in which a lower generation cost often relates to a higher emission magnitude, and similarly a lower emission usually relates to a higher generation cost. In this paper, transmission loss is adopted as the third objective function to demonstrate a comprehensive decision making using a trade-off strategy over more than two objectives.

The objectives are explained below:

- 1) *To minimize the generation cost:* The generation cost of each conventional generator can often be represented by a quadratic function, and the total fuel cost $C(\vec{P}_G)$ is described as,

$$\text{Min } f_1(\vec{P}_G) = C(\vec{P}_G) = \sum_{i=1}^N (a_i + b_i \cdot P_{G_i} + c_i \cdot P_{G_i}^2) \quad (2)$$

where N is the number of generators, a_i, b_i, c_i are the cost coefficients of the i -th generator.

- 2) *To minimize the emission cost:* The harmful pollutants, e.g., sulphur oxides, SOx, and nitrogen oxides, NOx, caused by fossil-fueled thermal units, can also be associated to its real power output. So, the total emission, $E(\vec{P}_G)$, which is often measured by ton/h, is expressed as,

$$\text{Min } f_2(\vec{P}_G) = E(\vec{P}_G) = \sum_{i=1}^N (\alpha_i + \beta_i \cdot P_{G_i} + \gamma_i \cdot P_{G_i}^2) \quad (3)$$

- 3) *To minimize the system real power losses:*

$$\text{Min } f_3(\vec{P}_G) = P_{\text{loss}} = G_{ij} \sum_{j=1}^{N_{\text{bus}}} V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij} \quad (4)$$

$$Y_{ij} = G_{ij} + jB_{ij} \quad (4.1)$$

where V_i is the voltage magnitude at the i -th bus ($i=1, \dots, N_{\text{bus}}$); θ_{ij} is the voltage angle difference between bus i and bus j ; Y_{ij} is the ij -th element of the admittance matrix.

The constraints are discussed below:

- 1) *Nodal Power Balance Constraints:* These constraints are typical load flow equations, and they include the active and reactive power balance as expressed below:

$$\Delta P_i = P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{N_{\text{bus}}} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0 \quad (5)$$

$$\Delta Q_i = Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{N_{\text{bus}}} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0 \quad (5.1)$$

where $i=1, \dots, N_{\text{bus}}$, $\theta_{ij} = \theta_i - \theta_j$ is the voltage phase angle difference between bus i and bus j . The balance between the supply and demand is established in such a way that the total generator power outputs must equal the total load demand P_D plus losses as shown in (6), from which the P_{loss} can be obtained.

$$\sum_{i=1}^N P_{G_i} = P_D + P_{\text{loss}} \quad (6)$$

- 2) *Generating Unit Constraints:* the active power outputs of the generating units are constrained by their minimum and maximum capacities, which are represented as below:

$$P_{G_i}^{\text{min}} \leq P_{G_i} \leq P_{G_i}^{\text{max}} \quad (7)$$

The reactive power outputs of the generating units are constrained as expressed by (7.1),

$$Q_{G_i}^{\text{min}} \leq Q_{G_i} \leq Q_{G_i}^{\text{max}} \quad (7.1)$$

- 3) *Security constraints:* the power flow in the transmission lines and transformers are constrained by their maximum capacity as below:

$$|S_l| \leq S_l^{\text{max}}, l = 1, \dots, nl \quad (8)$$

where nl is the number of transmission lines.

The voltage limits in the load bus are represented by,

$$V_l^{\text{min}} \leq V_l \leq V_l^{\text{max}}, l = 1, \dots, nl \quad (8.1)$$

The transformers have minimum/maximum tap setting limits,

$$T_j^{\text{min}} \leq T_j \leq T_j^{\text{max}}, j = 1, \dots, N_T \quad (8.2)$$

C. Decomposition of Multi-Objective Optimization

The MOPF can be transferred into a set of scalar function by using the aggregate objective function (AOF) [8]. The two most popular AOFs are: 1) the weighted sum AOF (WS AOF), and 2) the Tchebyscheff AOF (Ts AOF).

- 1) *Weighted sum AOF*

In the weighted sum AOF (WS AOF) [8], the weight vector reflects the relative importance of each design objective and is given by a weight vector. An objective with a higher importance will be given a higher weighting during the optimization process. However, in practical environment, the decision makers are most probably ignorant of what accurate weight vector to use to express their preferences.

From the viewpoint of MOO, each fixed weight vector represents a special trade-off level between objectives (i.e., a point on the PF). To obtain all representative points on the PF, a simplest way is to approximate the PF based on all distributed weight vectors (which are the representative preferences). Assume there are $M+1$ points on the PF, the MOPF, e.g., EED can be expressed with minimization function and WS AOF as follows,

$$\text{Minimize: } Y^{\text{ws}}(\vec{P}_G^j | \vec{w}^j) = \sum_{i=1}^m w_i^j \cdot f_i(\vec{P}_G^j)$$

$$\text{s.t. } \vec{P}_G^j \in \Omega, j \in [1, M] \quad (9)$$

where $Y^{\text{ws}}(\cdot)$ represents the weighted sum aggregation function; m is the total number total objectives; $1 \leq i \leq m$; weighting vector $\vec{w}^j = [w_1^j, \dots, w_i^j, \dots, w_m^j]$, $w_i^j \in [0, 1]$ and $\sum_{i=1}^m w_i^j = 1$; $\vec{P}_G^j$ represents the independent vector of the j -th sub-problem.

However, the weighted sum has a serious drawback to cope with the non-convex PFs; for example, Fig. 1 provides a simple non-convex PF example, which is a MOO with 2-dimensional objective space and 1-dimensional decision space. In the objective space, one objective function is designed with exponential items for the non-convex purpose, that is, $f_1(x) = x$; $f_2(x) = 5e^{-x} + 2e^{-0.5(x-2.1)^2}$, and in the decision space, $x \in [0, 6]$. Fig. 1(a) shows that some points on the ideal PF cannot be obtained due to the fact that the curve is not convex.

- 2) *Tchebyscheff AOF*

In the Tchebyscheff AOF (Ts AOF) [23], each subproblem ($1 \leq j \leq M$) to be minimized is aggregated into the AOF as given in Eq.(10):

$$Y^{\text{te}}(\vec{P}_G^j | \vec{w}^j, \vec{z}^{\#}) = \max_{1 \leq i \leq m} \{w_i^j \cdot |f_i(\vec{P}_G^j) - z_i^{\#}|\}$$

$$\text{s.t. } \vec{P}_G^j \in \Omega \quad (10)$$

where $\gamma^{te}(\cdot)$ represents the Tchebyscheff AOF, and $\bar{z}^\# = [z_1^\#, \dots, z_i^\#, \dots, z_m^\#]$ is the ideal minimum obtained by $z_i^\# = \min_{1 \leq j \leq M} (f_i(\bar{P}_G^j))$ based on all historical solutions.

Fig. 1(b) shows that the Tchebyscheff AOF can produce all the points on the Pareto front even when the curve is not convex. It is a useful tool for a robust design in the context of smart grids.

Fig. 1 Comparison between using (a) Weight Sum and (b) Tchebyscheff aggregation to approximate the non-convex Pareto Front, where $f_1(x) = x$; $f_2(x) = 5e^{-x} + 2e^{-0.5(x-2.1)^2}$

In general, via the AOF, the original m -objective MOO can be transformed into $M+1$ subproblems to be optimized. According to the AOF, each subproblem is associated with a fixed weight vectors, and this pattern can be extended to the MOO with more objectives.

III. THE PROPOSED ALGORITHM

The original MOEA/D is not designed for the MOPF, which means it cannot be applied directly to a power system, particularly, for obtaining the exact and stable POSs, while considering all the constraints.

A. Power Flow Operator

In this part, a N-R power flow operator is proposed into the MOEA/D framework (called the N-R MOEA/D). In the evolutionary programming, the new solution candidates are reproduced from the parent population by using the conventional genetic operators such as crossover and mutation, however, in power systems the solutions are required to balance the supply and demand while meeting the constraints of the power systems.

Hence, unlike the known heuristic algorithms, the evolving individuals (i.e., the independent vectors in the decision space) in this paper are defined as the active powers of all generating units except slack bus, i.e., $\bar{X} = [P_{G_2}, \dots, P_{G_N}]$. According to the active power output (i.e. $P_{G_2}, \dots, P_{G_N}$) and other given power system parameters such as the active and reactive power at each load bus, the voltage magnitude of each generating unit, the Newton Raphson (N-R) Power Flow [5] can evaluate the line losses, voltage magnitude and angle at each bus, while making sure that the power system constraints mentioned above are met.

B. Individual Evolving and Comparing

Fig.2 shows the mapping details from the decision vector in the decision space to its dependent vector in the objective space of 2-objective MOPF (i.e., EED). Suppose two random individuals $\bar{X} = [P_{G_2}, \dots, P_{G_N}]$ and $\bar{X}' = [P'_{G_2}, \dots, P'_{G_N}]$ in the decision space are being measured, and they are associated with two tradeoff levels denoted by two weight vectors respectively, e.g.,

$\bar{w} = [w_1, w_2] | w_1 + w_2 = 1$ and $\bar{w}' = [w'_1, w'_2] | w'_1 + w'_2 = 1$. All these information can be denoted by two vector structures $(\bar{X}, \bar{w})$ and $(\bar{X}', \bar{w}')$.

With any given $\bar{X}$, not only the N-R power flow, can provide all the generator active powers including the slack bus and the total line losses, but it can also meet all the constraints of the power system. After processing by the N-R power flow operator, as shown in Fig. 2, two corresponding feasible solutions, $\bar{P}_G = [P_{G_1}^*, P_{G_2}, \dots, P_{G_N}]$ and $\bar{P}_G' = [P_{G_1}^{*'}, P_{G_2}', \dots, P_{G_N}']$, are obtained. Consequently, the dependent vectors, $\bar{F}(\bar{X}) = [C(\bar{P}_G), E(\bar{P}_G)]$ and $\bar{F}(\bar{X}') = [C(\bar{P}_G'), E(\bar{P}_G')]$ as defined in (1)-(3), can be obtained in the objective space.

Fig.2 The philosophy of the proposed algorithm

However, in this paper, these two dependent vectors are not compared by the dominance relationship directly, but by the AOF value (e.g. the weighted sum) as given in (9) or (10). For example, $\bar{X}$ can be compared with another candidate $\bar{X}'$ based on the WS AOF at two tradeoff level $\bar{w}$ and $\bar{w}'$ respectively, if $\gamma^{ws}(\bar{P}_G | \bar{w}) > \gamma^{ws}(\bar{P}_G' | \bar{w})$, then the corresponding $\bar{X}$ at the tradeoff level $\bar{w}$ should be updated, i.e., the vector structure is updated from $(\bar{X}, \bar{w})$ to $(\bar{X}', \bar{w})$, and vice versa.

C. Mutation based on the Elite Individuals

Instead of exploring the entire PF, the MOEA/D [20] algorithm obtains a set of good representative points on the PF (e.g., the points evenly distributed along the PF), which can accelerate the decision process significantly.

The j -th point of the PF corresponds to the j -th sub-problem at the tradeoff level of $\bar{w}^j$, and the j -th decision vector $\bar{X}^j$. That is, for an input vector structures, $(\bar{X}^j, \bar{w}^j)$, the component of the decision vector, $\bar{X}^j = [P_{G_2}^j, \dots, P_{G_N}^j]$, can be updated by better decision vectors during the evolutionary process, but the tradeoff level (i.e., the weight vector), $\bar{w}^j = [w_1^j, \dots, w_m^j]$, is fixed. The corresponding output information can also be denoted in the vector structure style as given in (11),

$$(\bar{P}_G^j, \bar{F}^j, \bar{w}^j) \quad (11)$$

where $\bar{P}_G^j = [P_{G_1}^{*j}, P_{G_2}^j, \dots, P_{G_N}^j]$, $\bar{F}^j = \bar{F}(\bar{P}_G^j) = [f_1(\bar{P}_G^j), \dots, f_m(\bar{P}_G^j)]$ and $\bar{w}^j$ are the current evolving PoS (i.e., all active power outputs), the point on the current evolving PF and the weight vector (tradeoff level) of the j -th sub-problem respectively.

The mutation formula of the MOEA/D in [23] cannot meet the need to obtain fast solutions of the MOPF problem, thus a new mutation formula is proposed as shown in (12),

$$\bar{X}^{j+1} = \begin{cases} \bar{X}^{j3} + CR_0 \cdot (\bar{X}^{j1} - \bar{X}^{j2}) & \text{if } Pr > 0.5 \\ \bar{X}^j + CR_1 \cdot (\bar{X}^{j1} - \bar{X}^{j2}) + CR_2 \cdot (\bar{X}^j - \bar{X}^{j3}) & \text{if } Pr \leq 0.5 \end{cases} \quad (12)$$

where $\bar{X}^{j1}$, $\bar{X}^{j2}$ and $\bar{X}^{j3}$ are the three decision vectors extracted from the three input vector structures $(\bar{X}^{j1}, \bar{w}^{j1})$, $(\bar{X}^{j2}, \bar{w}^{j2})$ and $(\bar{X}^{j3}, \bar{w}^{j3})$.

The three input vector structures are randomly picked out from the entire parent structure population; where CR_0, CR_1 and CR_2 are the control coefficients (i.e., differential weight) which can be picked out of the set $[0.3, 0.5, 0.7]$, and can be used to control the probing magnitude based on the product of the picked coefficient and the corresponding differential factors, such as $CR_0 \cdot (\vec{X}^{j1} - \vec{X}^{j2})$.

The control coefficients (0.3, 0.5 and 0.7) represent the three levels of differential weight (named in the original differential evolution and often ranged in $[0, 1]$), where the value closer to 1 means a larger increase in the steps on the differential vector, and the value closer to 0 means a smaller increase on the differential vector.

The first equation in (12) focuses on stochastic searching, while in the second equation, the mutation operation is based on the current optimal decision vector $\vec{X}^j$, and also the differential factor $(\vec{X}^j - \vec{X}^{j3})$, which has increased the proportion to search towards $\vec{X}^j$ compared with that obtained from ransom searching. Thus, such kind of operator has the potential to increase the convergence speed (i.e., to decrease the time cost to meet the MOPF demands).

To balance the population diversity and the converging speed and to avoid premature convergence, the two operators (i.e., equations) in (12) need to probe alternatively according to the historical probing performance during the evolving process.

The probability function, Pr , in (12), is calculated as a random number (between 0 and 1) each time based on the historical probing performance. It is utilized to alternate the two operators in (12). The details are given in the next sub-section.

D. Self-Adaptive Strategy for the Control Parameters

According to (12), a probing decision vector, $\vec{X}^j$, represents the trial decision vector for the j -th sub-problem. Based on the use of the performance of $\vec{X}^j$ and the proposed self-adaptive strategy, the four corresponding control parameters in (12) (i.e., CR_0, CR_1, CR_2 and Pr) can be worked out rationally during each generation. The so-called ‘self-adaptive’ means the parameters can evolve simultaneously with the corresponding decision vector. In general, if the probing (or trail) decision vector (i.e., offspring) is better than its parents, the corresponding control parameters are trusted as successful control parameters.

The self-adaptive strategy can be divided into two stages:

Firstly, in the initialization stage, for the j -th sub-problem corresponding to (12), the control parameters (i.e., CR_0, CR_1, CR_2 and Pr) are respectively associated to four uniform random numbers (i.e., $r_{1,k}^j, r_{2,k}^j, r_{3,k}^j$ and $r_{4,k}^j$) varying within $[0, 1]$ as shown in (13) and (13.1), where k represents the k -th generation and the j represents the j -th sub-problem (e.g., $r_{1,k}^j$ represents the random number to generate CR_0 for the j -th sub-problem in the k -th generation).

$$CR_{i-1} = \begin{cases} 0.3 & \text{if } 0 \leq r_{i,k}^j \leq 0.33 \\ 0.5 & \text{if } 0.33 < r_{i,k}^j < 0.66 \\ 0.7 & \text{if } 0.66 \leq r_{i,k}^j \leq 1 \end{cases} \quad i = 1, 2, 3 \quad (13)$$

$$Pr = r_{4,k}^j \quad (13.1)$$

Assume a probing process based on (12) has finished in the j -th sub-problem, the four corresponding numbers ($r_{1,k}^j, r_{2,k}^j, r_{3,k}^j$ and $r_{4,k}^j$) need to be archived with the other data (e.g., decision vector, objective values) of the j -th sub-problem, and so on, till all sub-problems are solved in the current (the k -th) generation.

Secondly, the successful number-groups, which are corresponding to the successful control parameters, are survived in the next generation, while elements in the unsuccessful ones have to be updated respectively by using (14),

$$r_{i,k+1}^j = \bar{r}_{i,k} + randn \cdot [\min(|\bar{r}_{i,k} - 0|, |\bar{r}_{i,k} - 1|)], \quad (14)$$

where $\bar{r}_{i,k}$ is the average value of the successful numbers ($i = 1, 2, 3, 4$) in the k -th generation. The factor, $[\min(|\bar{r}_{i,k} - 0|, |\bar{r}_{i,k} - 1|)]$, acts as the standard deviation.

Then, the new CR_0, CR_1, CR_2 and Pr for each sub-problem in the next $(k+1)$ -th generation are decided by using (13) and (13.1), and so on.

E. Decision based on the Preference

From the discussion above, each PoS and each PF point are mapped with an accurate tradeoff level denoted by the weight vector. The weight vector can also be used to help the power system planner to make judicious decision making out of the many PoSs in the weighted PF in the objective space formed from the different objectives. By looking at the weighted PF, one can make judicious decision from the tradeoff that can be selected associated with each PoS. Such a weighted PF can be very helpful to the designer of the power system to optimize the system with many objectives.

F. The Proposed Algorithm:

Input structure: $\{(\vec{X}^1, \vec{w}^1), (\vec{X}^2, \vec{w}^2), \dots, (\vec{X}^{M+1}, \vec{w}^{M+1})\}$

Where in each element, $\vec{X}^j = [P_{G_1}^j, \dots, P_{G_N}^j] | P_{G_1}^{min} \leq P_{G_1}^j \leq P_{G_1}^{max}, i = 2, \dots, N$, represents the starting point of the j -th sub-problem, and $\vec{w}^j = [w_1^j, \dots, w_i^j, \dots, w_m^j]$, $w_i^j \in [0, 1]$ and $\sum_{i=1}^m w_i^j = 1$, is the weight vector of the j -th sub-problem, $j \in [1, M+1]$;

Output structure:

$$\{(\bar{P}_G^{-1}, \bar{F}^1, \bar{w}^1), (\bar{P}_G^{-2}, \bar{F}^2, \bar{w}^2), \dots, (\bar{P}_G^{-M+1}, \bar{F}^{M+1}, \bar{w}^{M+1})\}$$

Step 1: Solution Set Initialization:

- Generate randomly each $\vec{X}^j$ in the input structure (Parent):
 $\vec{X}^j = P_{G_1}^{min} + rand(0,1) * (P_{G_1}^{max} - P_{G_1}^{min}) \quad (15)$

Obtain the uniform weight vector as follows:

$$w_1^j = [0:1/M:1]; w_2^j = [1 - w_1^j]; \text{ (for 2-obj MOPF)}$$

or

$$\vec{w}^j = []; \text{ (for 3-obj MOPF)}$$

$$\text{For } w_1^j = 0: 1/M: 1$$

$$\text{For } w_2^j = 0: 1/M: 1 - w_1^j$$

$$\vec{w}^j = [w_1^j, w_2^j, 1 - w_1^j - w_2^j];$$

end

end;

- Evaluate each element in the input structure (parent) by Newton-Raphson operator as shown in Fig. 2 to obtain the corresponding results: $\{(\bar{P}_G^{-1}, \bar{F}^1, \bar{w}^1), \dots, (\bar{P}_G^{-M+1}, \bar{F}^{M+1}, \bar{w}^{M+1})\}$

Step 2 : Solution Set Reproduction

- Reproduce a new input structure (offspring) as the candidate structure $\{(\vec{X}'^1, \vec{w}^1), \dots, (\vec{X}'^{M+1}, \vec{w}^{M+1})\}$, in which $\vec{X}'^j$ in each component is calculated by (12);
- Use (15) to repair $\vec{X}'^j$, if any element is out of boundaries.
- Evaluate the new input structure (offspring):
 $\{(\bar{P}_G'^{-1}, \bar{F}'^1, \bar{w}^1), \dots, (\bar{P}_G'^{-M+1}, \bar{F}'^{M+1}, \bar{w}^{M+1})\}$

Step 3: Solution Set Updating:

Update the input structure (parent), using a suitable AOF defined by (9) or (10), each element is compared between the

offspring and the parent input structure as mentioned in the section III-A. If the new $\vec{x}'^j$ in the offspring structure is better than the $\vec{x}^j$ in the parent one, the $\vec{x}^j$ is rewritten by the $\vec{x}'^j$. The corresponding weight vector is not changed. If the AOF is set as the Tchebyscheff AOF as given in (10), i.e., $Y^{te}(\vec{P}_G^j | \vec{w}^j, \vec{z}^\#)$, where $\vec{z}^\# = [z_1^\#, \dots, z_m^\#]$ is the ideal point, and $z_i^\# = \min_{1 \leq j \leq M} (f_i(\vec{P}_G^j))$. Meanwhile, the corresponding control parameters have been updated as shown in (13), (13.1) and (14).

Step 4: Stopping Criterion (e.g., the maximum generation):

If the maximum generation number (Maxgen) is met, the algorithm halts and outputs the current POSs, PF and their corresponding weight vectors. Otherwise, the process returns to Step 2.

IV. SIMULATIONS AND RESULTS

To validate the proposed algorithm, five case studies will be investigated, which are (i) Case study 1: Decomposition based on the weighted sum (WS) AOF and the traditional Newton method for a 2-objective MOPF (i.e., EED) in convex space; (ii) Case study 2: Decomposition based on the weighted sum (WS) AOF and N-R MOEA/D for EED in convex space; (iii) Case study 3: Decomposition based on the weighted sum (WS) AOF and N-R MOEA/D for a 3-objective MOPF in non-convex space; and (iv) Case study 4: Decomposition based on the Tchebyscheff AOF and N-R MOEA/D for the 3-objective MOPF in non-convex space. (v) Case study 5: Performance evaluation in a combined system consisting of transmission and radial distribution networks in which the variations in the distribution of loads including low power factor ones are observed.

A. Case Study 1

This case study investigates how to decompose the EED into several representative sub-problems by the AOF of the weighted sum, thus Eq. (2) and Eq. (3) are selected as the cost function and the emission function respectively. For comparison, the sub-problems are initially solved by the traditional Newton method [14] and the results are used as the standard benchmark to compare with those from the proposed method using evolutionary programming.

The system for the investigation is based on the IEEE 30-bus test system [26], which has 30 buses, 6 generators and the total load demand is 189.2MW. The fuel cost and the emission coefficients corresponding to each generation unit (i.e., $G_1, \dots, G_6$) are extracted from [13] and listed in Table I. The weight vectors are set up in 21 tradeoff levels, i.e., $w_1^j \in [0:1/20:1]$; $w_2^j \in 1 - w_1^j$. Each sub-problem is based on the

AOF of the weighted sum as given in (12), and the linear combination of the cost and the emission via the weighted sum AOF, as well as constraints can be combined into a Lagrange function which can be solved by optimal power flow of Newton method [14]. Consequently, not only the algorithm can provide the PF and the POSs, but it can also provide the corresponding weight vector for each POS and each point on the PF.

Table I Cost and Emission Coefficients of IEEE 30 Buses

	Cost			Emission		
	a_i	b_i	c_i	α_i	β_i	γ_i
G_1	756.7988	38.5397	0.1525	662.7859	15.6700	0.2004
G_2	451.3251	46.1592	0.1059	662.7860	15.6700	0.2004
G_3	1049.3251	40.3966	0.0280	1925.6597	-26.0876	0.3266
G_4	1243.5311	38.3055	0.0355	1925.6597	-26.0876	0.3266
G_5	1658.5696	36.3278	0.0211	2051.3671	-24.4449	0.2205
G_6	1356.6592	38.2704	0.0190	2051.3671	-24.4449	0.2205

The weight vectors representing to the 21 trade-off levels of the cost and the emission are shown in Fig. 3(a). The resulting PF (or the weighted PF) is also approximated by 21 representative points. The three dotted lines in Fig. 3(a) link the PF points and their corresponding weight vectors (tradeoff levels) such as $[0, 1]$, $[0.5, 0.5]$ and $[1, 0]$. The weight vectors $[0, 1]$ and $[1, 0]$ are associated to the two anchor points on the resulting PF or the weighted PF as shown in Fig 3(b). Thus, in this way, the users can select their preferred tradeoff level by weight vector for the cost and the emission, further to find out the optimum point on the PF and accordingly the POS.

Fig. 3 (a) 21 Representative weight vectors Points, (b) the PF obtained from the 21 weight vectors

To get a better PF, the size of the weight vectors are increased to 101 tradeoff levels, i.e., $w_1^j \in [0:1/100:1]$; $w_2^j \in 1 - w_1^j$. Table II shows eleven sets of data from the entire results. There are eleven given weight vectors, the optimum total costs and total emission (i.e. points on the PF), the optimal generating unit outputs (i.e. POSs) and the total transmission loss in the power system. Since the load flow analysis was carried out to obtain the transmission and the slack node generator power output, all the constraints of the power system given in Section II have been taken into account.

Table II A Part of POSs, PF with the Corresponding Weight Vectors of the Case Study 1

$[w_1^j, w_2^j]$	[0,1]	[0.1,0.9]	[0.2,0.8]	[0.3,0.7]	[0.4,0.6]	[0.5,0.5]	[0.6,0.4]	[0.7,0.3]	[0.8,0.2]	[0.9,0.1]	[1,0]
P_{G_1} (MW)	18.0770	18.8139	19.6065	20.4618	21.3879	22.4066	23.5192	24.7280	26.0655	27.5831	29.3040
P_{G_2} (MW)	18.2147	17.4786	16.6899	15.8435	14.9335	13.9582	12.9071	11.7686	10.5466	9.27065	7.9634
P_{G_3} (MW)	34.5192	34.5102	34.4966	34.4765	34.4471	34.4239	34.3792	34.2831	34.1328	33.8967	33.4370
P_{G_4} (MW)	55.0000	55.0000	54.9999	55.0000	54.9999	55.0000	54.9999	54.9999	55.0000	54.9999	55.0000
P_{G_5} (MW)	26.2448	26.2429	26.2409	26.2388	26.2369	26.1510	26.0750	26.0783	26.0865	26.0274	26.0204
P_{G_6} (MW)	40.0000	39.9999	39.9999	40.0000	39.9999	40.0000	39.9999	39.9999	40.0000	39.9999	40.0000
$C(\vec{P}_G)$ (\$/h)	14308.10	14303.43	14298.71	14293.99	14289.30	14283.16	14277.59	14273.60	14270.16	14267.29	14266.11
$E(\vec{P}_G)$ (g/h)	7907.42	7907.67	7908.51	7910.096	7912.63	7917.80	7924.49	7931.95	7942.37	7959.08	7982.64
P_{loss} (MW)	2.85576	2.84550	2.83387	2.8206	2.80534	2.73960	2.68047	2.65795	2.63134	2.57783	2.52469

Table III A Part of POSs, PF with the Corresponding Weight Vectors of the Case Study 2

$[w_1^j, w_2^j]$	[0,1]	[0.1,0.9]	[0.2,0.8]	[0.3,0.7]	[0.4,0.6]	[0.5,0.5]	[0.6,0.4]	[0.7,0.3]	[0.8,0.2]	[0.9,0.2]	[1,0]
$P_{G1}(MW)$	8.4294	10.8980	11.7749	12.4253	13.0001	13.5310	14.0590	14.6124	15.2264	15.9713	17.3437
$P_{G2}(MW)$	8.5637	6.1067	5.2344	4.5877	4.0162	3.4885	2.9638	2.4140	1.8039	1.0642	0.0000
$P_{G3}(MW)$	50.0000	50.0000	50.0000	50.0000	50.0000	50.0000	50.0000	50.0000	50.0000	50.0000	50.0000
$P_{G4}(MW)$	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	55.0000	54.6876
$P_{G5}(MW)$	30.0000	30.0000	30.0000	30.0000	30.0000	30.0000	30.0000	30.0000	30.0000	30.0000	30.0000
$P_{G6}(MW)$	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000	40.0000
$C(\vec{P}_G)$ (\$/h)	14227.37	14212.56	14208.08	14205.02	14202.50	14200.33	14198.32	14196.37	14194.40	14192.28	14189.72
$E(\vec{P}_G)$ (g/h)	7480.27	7482.78	7484.86	7486.80	7488.79	7490.87	7493.16	7495.81	7499.03	7503.34	7514.06
$P_{loss}(MW)$	2.7931	2.8047	2.8094	2.8130	2.8163	2.8195	2.8228	2.8263	2.8304	2.8355	2.8313

For example, for $[w_1^j, w_2^j] = [0, 1]$, the preference is to use the weight of 0 for the cost and to use the weight of 1 for the emission; therefore the preference is not to consider the cost but to minimize the emission only, from which the minimum emission and hence the maximum cost are obtained in $E(\vec{P}_G)$ and $C(\vec{P}_G)$. Similarly for $[w_1^j, w_2^j] = [1, 0]$, the preference is to use the weight of 1 for the cost and to use weight of 0 for the emission, therefore the preference is not to consider the emission but to minimize the cost only, from which the minimum cost and hence the maximum emission is obtained in $C(\vec{P}_G)$ and $E(\vec{P}_G)$.

In summary, in the convex space, the MOPF can be split into sub-problems by using the weighed sum AOF, and the sub-problems can be solved one by one using the traditional Newton gradient method. In such design, the transmission loss is taken into account while at the same time, the power balance, the line limits and the generating unit active and reactive power constraints are satisfied. As well, the solutions will be exact and stable in each time if the optimizing process starts at a fixed starting point.

B. Case study 2

This case study investigates the use of the proposed method, N-R MOEA/D, with weighted sum (WS) AOF to solve the same problem as in the Case study 1 with the aim to obtain improved PF and POSs for the same number of weight factors. The stopping criterion for the maximum number of iterations is set to be 40.

Fig. 4(a) shows the evolving process as all the dependent vectors converge from their initial state to the final state to finally form the PF.

Fig.4. (a) The evolving process in the Case study 2 (b) the PF labelled with associated weight vectors.

Fig. 4(b) shows that in the final resulting PF result, each point in the PF corresponds to the individual weight vector. Fig. 4(b) shows that the two anchor points on the PF where $[w_1^j, w_2^j] = [0, 1]$, the minimum emission is 7480.27 g (as shown in Table III), is less than the result obtained using the traditional Newton gradient method, where the minimum emission is 7907.42 g (as shown in Table II). Similarly, for $[w_1^j, w_2^j] = [1, 0]$, the minimum

cost found by the proposed algorithm is \$14,189.72 (as shown in Table III), while the minimum cost for the same weight factor found by the traditional Newton gradient method is \$14,266.11 (as shown in Table II).

Table III shows 11 sets of data from the entire results. They are corresponding to the same tradeoff levels respectively as the results in Table II. The results obtained by the proposed N-R MOEA/D are much better than those from the traditional Newton gradient method. Fig. 5 (a) shows the corresponding comparison between the two PFs obtained in Case study 1 and Case study 2.

Fig. 5 (a) The PF comparison between the WS-Newton in the Case 1 and the WS-NR-MOEA/D in the Case 2; (b) The PF comparison between two strategies (i.e., the N-R MOEA/D and N-R MOEA/D~1) at the 10-th generation in the Case 2; (c) The PF comparison between the two strategies at the 20-th generation in the Case 2; (d) The PF comparison between the two strategies when the N-R MOEA/D is at the 20-th generation and the N-R MOEA/D~1 is at the 60-th generation in the Case 2.

In summary, a similar problem can be solved by the traditional Newton gradient method or by the proposed N-R MOEA/D method. However, the results in Fig. 5 (a) shows that the N-R MOEA/D is superior to the traditional Newton gradient method. Further, given a good initial condition, the proposed N-R MOEA/D is found to be stable and robust in determining the PF.

The comparisons of the convergence performance between the original MOEA/D [23] (denoted MOEA/D~1) and the proposed MOEA/D (denoted as MOEA/D) are shown in Fig. 5(b) to Fig.(d): Fig. 5(b) is the comparison of the results of the PF convergence when the two methods are in their 10-th

iteration (i.e., generation), in which the proposed MOEA/D has almost converged to the final PF while the original MOEA/D are still far away from converging to the final PF; Fig. 5(c) shows the results of the PF convergence in their 20-th iteration, in which the proposed MOEA/D has converged to the final PF, while the original MOEA/D only has converged to several points of the final PF; Fig. 5(d) shows the results of the PF convergence in the 60-th iteration, when the original MOEA/D has converged to the final PF, but the optimum points are distributed less evenly than those obtained using the proposed MOEA/D. These show that the proposed method has performed much better than the MOEA/D~1.

Table IV shows the comparison of the computation times of the three methods (the proposed MOEA/D, the original MOEA/D from [23] and the WS-Newton method mentioned in Case study 1).

Table IV The Comparison of Time Complexity about Three Methods to Obtain the PF Consisting of 101 Points

Metric	Methods		
	Proposed MOEA/D	MOEA/D~1 (Original)[23]	WS-Newton
PF Convergence (Iterations)	19	60	10
The Elapsed Time (Sec)	18.35500	59.88000	10.534548

The computation times are based on the average values of 30 independent experiments. Table IV shows that the WS-Newton is the fastest method, which can converge to the final PF of 101 points in 10 iterations, and 10.534548 seconds. However, its PF quality is worse than the other two methods.

The proposed MOEA/D needs almost three times less iterations and computation time to converge to the final PF than the original MOEA/D in [23] and with more evenly distributed PF.

C. Case study 3

This case study investigates a 3-objective MOO using the proposed N-R MOEA/D with the weighted sum AOF. The problems in Case study 1 and Case study 2 have been extended from a 2-objective MOO to a 3-objective one. The third objective is the P_{loss} defined in Eq. (4). The objectives of the MOO are now the minimum transmission loss, fuel cost and emission. The weight vectors are now extended to $\bar{w}^j = [w_1^j, w_2^j, w_3^j]$ with $w_1^j + w_2^j + w_3^j = 1$. In the simulation, the size of the sub-problems is now set to 229, i.e., the weight vectors have 229 elements (where the weight vectors for each objective are from 0 to 1 with a step of 0.05). The weight vectors of the cost, the emission and the transmission loss are shown in a 3-D format in Fig. 6(a).

Fig. 6. (a) Uniform weight vectors in 3-D space (b) the 3-D PF labeled with associated weight vectors, (c) the shadows of the 3-D PF compared with the PF obtained in the Case 2.

It shows the weight vector $[0, 0, 1]$, $[0, 1, 0]$ and $[1, 0, 0]$ associated to the three anchor points. The weighted PF is approximated by 229 representative points. The resulting 3-D PF from each of those weight factors is shown in Fig. 6(b). The mapping between the PF points and their corresponding weight vectors can allow the users to select their preferred weights in the cost, the emission and the transmission loss to find the optimum point on the PF and accordingly the POS. Fig. 6(c) shows the projected 3-D PF to the Cost-Emission-plane. To confirm that the result is correct, w_3^j is chosen to be zero, the result in Fig. 6(c) should correspond to the same points as the result in 4(b). However, new points have been found, as shown in red and circled by the dashed oval, when the tradeoff with P_{loss} is considered as shown in the 3-D PF in Fig. 6(b). That is, the new-found points are not better at criteria emission and fuel cost respectively, but such kind of solutions can achieve less transmission loss.

D. Case study 4

This case study investigates the comparison of the AOF performance of a 3-objective MOO between the use of the N-R MOEA/D with the weighted sum (WS) AOF and the use of the N-R MOEA/D with the Tschebysheff (Ts) AOF. Fig. 7 shows that there are several points that cannot be found on the 3-D PF

Table V A Part of POSs, PF with the corresponding weight vectors in 3-objective MOPF between the Case Study 3 and 4

$[w_1^j, w_2^j, w_3^j]$	[0,0,1]		[0,1,0]		[1,0,0]		[0.3,0.15,0.55]		[0.3,0.35,0.35]	
AOF	WS	Ts	WS	Ts	WS	Ts	WS	Ts	WS	Ts
P_{G1} (MW)	25.5814	6.2682	8.3955	8.4144	17.3707	17.3463	15.5354	14.4230	12.9324	13.3283
P_{G2} (MW)	5.5469	40.3730	8.5975	8.5786	0	0	1.4971	2.6021	4.0835	3.6900
P_{G3} (MW)	50	47.9699	50	50	50	50	50	50	50	50
P_{G4} (MW)	42.2734	28.9852	55	55	54.6595	54.6849	55	55	55	55
P_{G5} (MW)	28.1828	27.7736	30	30	30	30	30	30	30	30
P_{G6} (MW)	40	39.9076	40	40	40	40	40	40	40	40
$C(\bar{P}_G)$ (\$/h)	14233.95	14523.49	14227.60	14227.47	14189.72	14189.72	14193.49	14197.02	14202.79	14201.13
$E(\bar{P}_G)$ (g/h)	7758.89	8230.12	7480.27	7480.27	7514.40	7514.09	7500.76	7494.88	7488.55	7490.05
P_{loss} (MW)	2.3846	2.0774	2.7929	2.7930	2.8303	2.8312	2.8325	2.8251	2.8159	2.8183

by the N-R MOEA/D with the weighted sum AOF, because the curve of 3-D PF is non-convex.

Fig. 7. The comparison of the AOF performance of a 3-objective MOO between the use of the N-R MOEA/D with WS AOF and the Ts AOF

However, the use of the Tschebysheff AOF can help to find more points on the PF. For example, according to the sampling data listed in the Table V, with the same weight vector $[0, 0, 1]$, the results from the N-R MOEA/D with weighted sum AOF for P_{loss} is 2.3846 MW, while that from the Tschebysheff AOF is 2.0774 MW, which shows that the Tschebysheff AOF is superior to the N-R MOEA/D method with the weighted sum AOF.

In order to testify the stable performance of the proposed algorithm to determine the optimal solutions, each N-R MOEA/D experiment mentioned above, including the 2-objective EED and the 3-objective extended EED, using the Weighted Sum (WS) AOF or the Tschebysheff (Ts) AOF, that was repeated 30 times independently. For each concrete trade-off level, each N-R MOEA/D converges into its stable global minimum every time. Among them, the N-R MOEA/D with Tschebysheff (Ts) AOF shows the best performance even when the Pareto Front becomes complex (non-convex). The evolutionary algorithm provides a preliminary search to determine the globally optimal region where the gradient-based operator continues to search for the accurate optimum. This type of design can guarantee that a stable performance of the proposed algorithm can be achieved.

E. Case study 5

This case study investigates the use of the N-R MOEA/D, with Tschebysheff (TS) AOF on a combined system consisting of a revised IEEE 33-bus radial system and the IEEE 30-bus system.

The standard IEEE 30 bus system [26] is revised by connecting the IEEE 33-bus radial system [26] in bus 2, as shown in Fig. 8. The radial system consists of 33 buses, 32 lines, rated at 12.66kV, with a total load of 3.715MW and 2.3MVar.

Fig. 8 The combination system for the Case study 5 consisting of an IEEE 30-bus system and a 33-bus radial system

The resistance and reactance between bus 2 and bus 31 are 0.2030 (p.u.) and 0.1034 (p.u.) respectively. To simulate the low power factor load variations, the active power of the loads on buses 53, 54 and 57 have been decreased from 0.09 (p.u.), 0.42 (p.u.) and 0.06 (p.u.) to 0.05 (p.u.), 0.2 (p.u.) and 0.025 (p.u.) respectively, while the reactive loads on these buses have been increased from 0.05 (p.u.), 0.2 (p.u.) and 0.025 (p.u.) to 0.09 (p.u.), 0.42 (p.u.) and 0.06 (p.u.) respectively. For convenience sake, the simulation on the combined system without the load variations is denoted as 'Case 5', and with the load variations denoted as 'Case 5-1'. The stopping criterion for the maximum number of iterations is set to be 40 and number of weight vectors is 101.

The comparison of two 3-D PFs between the Case 5 and the Case 5-1 are shown in Fig. 9 (a) and the two PFs is enlarged in Fig. 9 (b). As shown in Fig. 9(b), the points on the PF of the Case 5-1 are generally smaller than the points on the PF of the Case 5, in terms of the fuel cost, the emission and the transmission loss. Table VI show the comparison between the simulation results of Case 5 and Case 5-1 are shown for five sets of trade-off levels. The results show that the proposed method will still converge with similar accuracy even when a radial system and variations in the distribution of load are included including the case with low power factor.

Table VI A Part of POSS, PF with the corresponding weight vectors in 3-objective MOPF between the Case 5 and Case 5-1

$[w_1^j, w_2^j, w_3^j]$	[0,0,1]		[0,1,0]		[1,0,0]		[0.3,0.15,0.55]		[0.3,0.35,0.35]	
Test Cases	Case 5	Case 5-1	Case 5	Case 5-1	Case 5	Case 5-1	Case 5	Case 5-1	Case 5	Case 5-1
P_{G1} (MW)	14.9430	27.3492	10.4425	10.2926	21.2112	20.9043	17.3517	17.2189	14.8339	14.6927
P_{G2} (MW)	19.4065	13.3031	10.6941	10.5391	0	0	3.8280	3.6556	6.3281	6.1641
P_{G3} (MW)	50	48.0434	50	50	50	50	50	50	50	50
P_{G4} (MW)	44.5974	41.3777	55	55	55	55	55	55	55	55
P_{G5} (MW)	26.7026	25.2179	30	30	30	30	30	30	30	30
P_{G6} (MW)	40	40	40	40	40	40	40	40	40	40
$C(\vec{P}_G)$ (\$/h)	14475.27	14457.41	14413.43	14399.68	14374.69	14360.89	14381.50	14367.59	14390.20	14376.34
$E(\vec{P}_G)$ (g/h)	7815.87	7981.03	7561.03	7554.97	7607.58	7600.18	7580.20	7574.24	7568.78	7562.75
P_{loss} (MW)	2.7345	2.6714	3.2216	3.2116	3.2962	3.2843	3.2647	3.2545	3.2470	3.2369

Fig. 9 The comparison of the AOF performance of a 3-objective MOO between the Case 5 and the Case 5-1 (a) the whole 3-D PFs (b) the enlarged part circled by the dashed oval in (a).

V. CONCLUSION

The paper has proposed the use of the MOEA/D framework with the power flow operator to make judicious decision based on the MOPF problem. Using uniform weights and two kinds of AOFs, the MOPF problem can be broken down into a set of sub-problems, which can be solved by the proposed algorithm.

The weighted sum AOF is helpful to obtain lower computational complexity, and the Tschebysheff AOF is useful to cope with the non-convex objectives. During the optimization of each sub-problem, the N-R power flow operator guarantees that all power system constraints are met, and there is always a balance in the supply and demand in the power system. Therefore, the proposed N-R MOEA/D not only inherits the robust performance from the heuristic algorithms to obtain the global minimum, but also can provide better but stable POSSs set each time. Furthermore, the proposed method has provided a mapping between the potential preferences and the Pareto optimal solutions (POSSs), which is very useful for the power system planner to make the final selection. The simulation results for the IEEE 30-bus system and for a revised IEEE 33-bus radial system added to a node of the IEEE 30-bus system using the N-R MOEA/D method (with weighted sum or Tschebysheff AOF) have demonstrated that the proposed method can provide better accuracy when compared with the traditional optimization methods.

VI. REFERENCE

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