

Research paper

Stable matching-enhanced MOEA/D for solving multi-objective optimal power flow problems

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ABSTRACT

Optimal Power Flow (OPF) plays a fundamental role in the secure and efficient management of power systems, both in system design and real-time operation. Existing OPF approaches often struggle with the problem's non-linearity, non-convexity, and mixed-variable characteristics, which hinder convergence and compromise solution diversity. This paper addresses these challenges by applying a **multi-objective evolutionary algorithm based on decomposition (MOEA/D)** enhanced with **stable matching theory**. The proposed method ensures a balanced and effective trade-off between solution accuracy and diversity in multi-objective optimization. Comparative evaluations against well-established algorithms demonstrate the superior performance of the proposed approach in approximating the Pareto front, improving computational efficiency, and maintaining solution diversity. The results highlight the effectiveness of the method in addressing OPF problems with conflicting objectives such as cost minimization, loss reduction, and voltage stability enhancement. This research provides a new perspective on applying stable matching mechanisms into evolutionary algorithms for power system optimization.

1. Introduction

1.1. General context & motivation

As optimization problems in various disciplines become increasingly complex, the limitations of classical optimization methods—such as their propensity to converge to local optima, the necessity for differentiability and continuity, and significant computational burdens—necessitate the development of more robust tools for optimal problem-solving. In recent years, meta-heuristic methods have emerged as popular and successful alternatives. Researchers are drawn to these algorithms due to their derivative-free nature and their ability to escape local optima in pursuit of global solutions. However, a notable concern with meta-heuristics is that, given the diversity of optimization problems, each algorithm tends to provide satisfactory solutions for specific problem types but not for others, as highlighted by the No Free Lunch theorem [1]. Therefore, the development of new optimization

algorithms remains a central focus in scientific research.

1.2. Related work

The field of optimization has seen the development of numerous innovative algorithms aimed at addressing complex problems across a wide range of domains. A number of algorithms have shown strong performance and stability, including the Multi-objective Geometric Mean Optimizer (MOGMO) [2], which balances convergence speed and diversity by incorporating a geometric mean-based update strategy. The Multi-objective Snow Ablation Algorithm [3] mimics the melting behavior of snow under varying environmental conditions to enhance search performance. A novel metaphor-free optimization approach known as Holistic Swarm Optimization (HSO) was introduced in [4]. It leverages full population data to enhance convergence behavior. By combining a self-tuning mutation mechanism with a selection approach modeled on simulated annealing principles, HSO effectively handles the

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exploration–exploitation trade-off and has shown strong performance on both standard benchmark and engineering problems. The Multi-objective Exponential Distribution Optimizer (MOEDO) [5] introduces an adaptive probability-based approach to control exploration and exploitation. The Multi-objective RIME Algorithm [6] utilizes a region-based intensity measure to guide solutions toward diverse Pareto-optimal fronts, and the multi-objective liver cancer algorithm [7] applies medical-inspired diagnostic techniques to enhance global search capabilities. The MORIME algorithm [8] is introduced as a multi-objective optimization framework aimed at enhancing truss structure design by optimizing both weight reduction and structural compliance. Some other recent meta-heuristic algorithms are convex combination search algorithm [9], A greedy non-hierarchical grey wolf optimizer [10], mutational northern goshawk-based artificial rabbits optimizer (MNEARO) [11], hiking optimization algorithm [12], a particle swarm optimization (PSO) enhanced based on hummingbird flight strategy [13], multi-objective hippopotamus optimizer (MOHO) [14], phasor particle swarm optimization (PPSO) and Lévy-flight PPSO [15–17], an improved equilibrium optimizer [18], quick crisscross sine cosine algorithm (QSCSA) [19], a fully informed search algorithm devised by improving Rao algorithms [20], a hybrid evolutionary optimization framework [21], an enhanced dragonfly algorithm [22], Wild Geese Algorithm [23], a crossover-embedded discrete PSO [24], Pbest-guided differential whale optimization algorithm [25], wolf-bird optimizer [26], an improved flower pollination algorithm [27], multi-objective chimp optimization algorithm (MOChOA) [28], Coulomb's and Franklin's laws algorithm [29,30], Lévy chaotic artificial hummingbird algorithm (LCAHA) [31], gooseneck barnacle optimization algorithm [32], turbulent flow of water-based optimization (TFWO) [33], and self-competitive differential evolution algorithms [34].

Recently, OPF has drawn considerable interest and plays a vital role in the design and operation of modern power systems. This technique optimizes objective functions such as generation costs and losses, enhances the voltage profile, and improves power system voltage stability by optimally adjusting control variables subject to the system's equality and inequality requirements [35–37]. For example, equality constraints include maintaining power balance at each node, while inequality constraints involve keeping the magnitude of voltages at each bus and the power flows of all lines within acceptable ranges. The control variables typically include the active power generations and voltage magnitudes of generators (except for the active power of the reference generating unit), the ratios of tapped transformers, and the reactive power generation of parallel capacitors [36].

Classical methods for solving OPF include Newton's method, gradient-based methods, Lagrangian relaxation, and others. Nevertheless, these techniques are unsuitable for problems with nonconvex and/or nonlinear objective functions [38]. Consequently, meta-heuristic optimization algorithms, such as particle swarm optimization (PSO), genetic algorithm (GA), evolutionary algorithm (EA), and differential evolution (DE) have been employed to address these limitations. The study in [39] introduced the Red-Tailed Hawk Optimization (RTH) algorithm as a novel metaheuristic approach for solving the OPF problem in power systems. By mimicking the hawk's hunting behavior, the algorithm enhances exploration and exploitation capabilities. The study in [40] proposed a Teaching-Learning-Based Optimization (TLBO) variant to address non-convex optimal power flow challenges. The authors of [41] presented a methodology for solving Direct Current (DC) OPF using a hybrid Arithmetic Optimization Algorithm (AOA) and Successive Approximation (SA). Furthermore, [42] explored the application of Moth Swarm Algorithm (MSA) to OPF. Other recent meta-heuristic algorithms used for solving OPF problems include Rao algorithms [43], an improved pelican optimization algorithm [44], moth-flame optimization (MFO) [45,46], a modified Rao-2 algorithm [47], a modified butterfly optimizer [48], enhanced wombat optimization algorithm [49], salp swarm optimizer (SSO) [50], a hybridization of Differential Evolution (DE) and harmony search (HS) algorithms [51], tree-seed

algorithm (TSA) [52], a hybrid evolutionary algorithm [53], a hybrid of differential evolution and particle swarm optimization [54], a novel sine-cosine algorithm (SCA) [55], an enhanced social network search algorithm [56], a hybrid of arithmetic optimization algorithm and aquila optimizer [57], and vortex search algorithm (VSA) [58].

Due to the diverse and sometimes conflicting objectives involved in solving the OPF problem—including minimizing power loss, generation cost, emissions, and voltage variation, in addition to enhancing voltage stability—multi-objective methods that focus on finding a set of solutions are suitable alternatives for addressing OPF challenges. Recently, extensive research has been conducted on multi-objective OPF (MOPF) problems. For example, an enhanced NSGA-III with an adaptive elimination strategy was proposed in [59]. Different improved variants of the bat algorithm were utilized in [60,61] across various test systems. The MOPF problem involving uncertain energy sources was addressed in [62] using an improved multi-objective multi-verse optimization algorithm. Additionally, various versions of the Jaya optimization algorithm were introduced in [63–65]. Boucekara [66] presented an electromagnetic field algorithm enhanced with chaos for solving the MOPF. A DE-based methodology for MOPF was proposed in [67]. Other recent algorithms for solving MOPF problems include an improved moth-flame optimization [68], an improved Archimedes optimization algorithm [69], an adaptive parallel seeker optimization algorithm [70], an enhanced sine cosine algorithm with pattern search [71], multi-objective HS algorithm [72], a modified pigeon-inspired optimization algorithm [73], an enhanced democratic political algorithm [74], teaching-learning-studying-based optimizer [75], a new hybrid PSO and artificial physics optimization [76], a novel self-adaptive wild geese algorithm [77], and an improved krill herd algorithm [78].

These studies indicate that while existing approaches significantly improve OPF optimization, challenges remain in ensuring computational efficiency, Pareto front diversity, and convergence reliability.

1.3. Objective & approach

Evolutionary algorithms designed for multiple objectives (MOEAs) are among the most effective approaches for addressing multi-objective optimization problems (MOPs) [79]. In 2007, a novel approach decomposition-based MOEA (MOEA/D) was proposed, as detailed in [80]. This approach involves decomposing a MOP into multiple sub-problems, each concentrating on a single objective, which will be then solved concurrently.

In [81], a new method called Stable Matching (STM) was used in MOEA/D for selecting suitable solutions at each iteration of the MOEA/D algorithm, resulting in STM-MOEA/D. The method demonstrates high capability in solving MOPs due to its innovative use of stable matching theory. This approach effectively balances convergence and variety of the solutions throughout the evolutionary process, significantly enhancing the performance over traditional methods.

The study in [81] provides empirical evidence that STM-MOEA/D consistently outperforms other leading Multi-Objective Evolutionary Algorithms (MOEAs) on various test instances. STM-MOEA/D demonstrated effectiveness in preserving a diverse and convergent set of solutions. Additionally, the stable matching mechanism of STM-MOEA/D ensures that population diversity is preserved, preventing premature convergence and enabling continued improvement in the search space, even toward the end of the algorithm.

Several selection strategies have been proposed in the literature for multi-objective optimization, including crowding-distance-based selection, angle-based selection, and distance-based selection [82–84]. These methods aim to balance diversity and convergence in multi-objective problems but exhibit limitations in addressing complex distributions of the Pareto front. Crowding-distance-based selection [82] maintains solution diversity by preserving sparsely populated regions of the front but struggles in dynamic problem spaces and high-dimensional objectives. Angle-based selection [83] improves convergence by prioritizing

solutions based on directional spread but may lead to excessive clustering around dominant points. Distance-based selection [84] provides improved diversity control but incurs high computational overhead in large-scale problems.

To address these limitations, Stable Matching-Based Selection method was proposed by [81] and integrated into MOEA/D. This approach ensures a more equitable distribution of solutions across the Pareto front by leveraging stable matching principles, reducing selection bias, and improving diversity maintenance, particularly in dynamic environments.

A comparative summary of selection methods is provided in Table 1.

The comparative analysis confirms that the STM-based selection method balances diversity preservation, convergence speed, and computational efficiency, while also improving selection stability. Unlike traditional selection methods, the STM-based selection approach dynamically adjusts selection preferences to ensure a well-distributed Pareto front while maintaining moderate computational complexity.

Given these benefits, STM-MOEA/D presents a promising approach for addressing OPF, a critical challenge in power system optimization. The algorithm's robust performance in maintaining both diversity and convergence can significantly enhance solution quality of OPF problems. Therefore, this paper applies STM-MOEA/D for the first time to solve OPF, leveraging its strengths to achieve more efficient and robust optimization outcomes.

1.4. Organization of the paper

The paper is organized as follows: Section 2 outlines the OPF problem, including the variables, objectives, and constraints considered. The next section describes the proposed approach. Section 4 introduces the system under study, and Section 5 covers the simulation outcomes along with the discussion.

2. OPF problem

The Optimal Power Flow problem is addressed in a multi-objective framework, with the decision variables (optimization variables), objective functions, and constraints outlined in the following subsections.

2.1. Decision variables

The decision variables consist of the voltage magnitudes at all generator buses (PV buses), including the reference and PV buses, the active power output of generators at PV buses, the tap settings of transformers, and the reactive power generated by installed capacitors. The reactive power of capacitors and the transformer tap settings are

Table 1
Comparison of selection methods in multi-objective optimization.

Selection Method	Diversity Preservation	Convergence Speed	Computational Cost	Stability
Crowding-Distance-Based [82]	High	Moderate	Moderate	Low
Angle-Based Selection [83]	Moderate	High	Moderate	Low
Distance-Based Selection [84]	High	High	High	Moderate
Stable Matching-Based Selection [81]	High	High	Moderate	High

discrete variables, while the other variables are continuous. Consequently, the OPF formulation results in a mixed-integer non-linear programming problem.

2.2. Generation cost

The objective function (OF) for generation cost is expressed as per following equation [85]:

$$F_1(X) = \sum_{i=1}^{N_{gen}} (a_i P_{gi}^2 + b_i P_{gi} + c_i) \text{ \$ / h} \quad (1)$$

where $F_1(X)$ indicates the total fuel cost (\$/h); N_{gen} is the number of generators; a_i , b_i and c_i are the fuel cost parameters for the i_{th} unit; and P_{gi} denotes the active power generated by the i_{th} unit.

2.3. Emissions

The emission OF is [85]:

$$F_2(X) = \sum_{i=1}^{N_{gen}} (\gamma_i P_{gi}^2 + \beta_i P_{gi} + \alpha_i + \xi_i \exp(\lambda_i P_{gi})) \text{ ton / h} \quad (2)$$

In which γ_i , β_i , α_i , ξ_i and λ_i denote the emission parameters for the i_{th} generator.

2.4. Power loss

The transmission power loss OF is determined by solving the load flow equations, as shown below [85]:

$$F_3(X) = \sum_{i=1}^{N_{line}} g_k [V_i^2 - V_j^2 - 2 V_i V_j \cos(\theta_i - \theta_j)] \text{ MW} \quad (3)$$

In this equation, V_i and V_j represent the voltage levels of i_{th} and j_{th} buses, respectively, while θ_i and θ_j denote the voltage angles at buses i and j , respectively; also, g_k denotes the conductance of the k_{th} line, and N_{line} represents the total number of lines.

2.5. Voltage stability index

The L- index values for load buses are determined as follows [85]:

$$L_j = \left| 1 - \sum_{i=1}^{N_{gen}} F_{ji} \frac{V_i}{V_j} \right| \quad j = N_{gen} + 1, \dots, n \quad (4)$$

In Eqn. (4) F is a matrix to be determined as follows:

$$[F] = -[Y_{LL}]^{-1}[Y_{LG}] \quad (5)$$

where Y_{LL} and Y_{LG} represent the subcomponents of the overall admittance matrix. To derive Y_{LL} and Y_{LG} the network equations based on the admittance matrix are arranged as given in Eqn. (6).

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \quad (6)$$

In above equation, I_L and I_G are current injections to load and PV buses, respectively. Also, V_L and V_G represent the voltages at load and PV buses, respectively. The highest L- index values signifies the system's closeness to voltage collapse; hence, the VSI objective function is considered as $F_4 = \max\{L\}$.

2.6. Equality constraints

The sum of net power injections into the system buses must correspond to the power losses in the transmission lines. The following equations represent this relationship [85]:

$$P_i = P_{gi} - P_{di} = \sum_{i=1}^{n_{bus}} V_i V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad (7)$$

$$Q_i = Q_{gi} - Q_{di} = \sum_{i=1}^{n_{bus}} V_i V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \quad (8)$$

2.7. Inequality constraints

Inequality constraints are as follows [85]:

$$P_{gi \min} \leq P_{gi} \leq P_{gi \max} \quad i = 1, 2, \dots, N_{gen} \quad (9)$$

$$P_{gi \min} \leq P_{gi} \leq P_{gi \max} \quad i = 1, 2, \dots, N_{gen} \quad (10)$$

$$P_{ij} \leq P_{ij \max} \quad (11)$$

$$V_{i \min} \leq V_i \leq V_{i \max} \quad i = 1, 2, \dots, N_L \quad (12)$$

A penalty-based approach is used to reformulate the OPF problem, removing constraints to create an unconstrained optimization model. This approach penalizes each control vector that violates the constraints, ensuring that these vectors are excluded in subsequent iterations. The objective function considered for unconstrained optimization problem is:

$$J(X) = \begin{bmatrix} J_1(X) \\ J_2(X) \\ J_3(X) \\ J_4(X) \end{bmatrix} = \begin{bmatrix} F_1(X) + Z_1 \left(\sum_{j=1}^{N_{eq}} (h_j(X))^2 \right) + Z_2 \left(\sum_{j=1}^{N_{ineq}} (\text{Max}[0, -s_j(X)])^2 \right) \\ F_2(X) + Z_1 \left(\sum_{j=1}^{N_{eq}} (h_j(X))^2 \right) + Z_2 \left(\sum_{j=1}^{N_{ineq}} (\text{Max}[0, -s_j(X)])^2 \right) \\ F_3(X) + Z_1 \left(\sum_{j=1}^{N_{eq}} (h_j(X))^2 \right) + Z_2 \left(\sum_{j=1}^{N_{ineq}} (\text{Max}[0, -s_j(X)])^2 \right) \\ F_4(X) + Z_1 \left(\sum_{j=1}^{N_{eq}} (h_j(X))^2 \right) + Z_2 \left(\sum_{j=1}^{N_{ineq}} (\text{Max}[0, -s_j(X)])^2 \right) \end{bmatrix} \quad (13)$$

In this equation, $F_i(X)$ represents the i_{th} objective of the constrained optimization problem, $J_i(X)$ denotes the corresponding objective of the unconstrained optimization problem, $h_j(X)$ represents the j_{th} equality constraint, $s_j(X)$ is the j_{th} inequality constraint, and Z_1 and Z_2 denote the penalization factor vectors for handling equality and inequality constraints, respectively.

3. Optimization method

3.1. Multi-objective evolutionary algorithm

A MOP is expressed mathematically as the minimization of the following objective functions [81]:

$$\text{Min. } F(x) = (f_1(x), f_2(x), \dots, f_m(x))^T \text{ s.t. } x \in \Omega \quad (14)$$

in which $\Omega = \prod_{i=1}^n [a_i, b_i] \subseteq R^n$ is the space of optimization variables, $x = (x_1, \dots, x_n)^T \in \Omega$ is the potential solution, and $F: \Omega \rightarrow R^m$ represents m objectives.

Researchers have widely investigated MOEAs as efficient methods for tackling MOPs. They aim to discover a diverse set of Pareto optimal outcomes in one execution. The foundation of these algorithms lies in the concept of Pareto dominance, defined below:

Definition 1: A solution x^1 dominates x^2 in the Pareto sense, written as $x^1 \preceq x^2$, if it is not worse in any objective and strictly superior in at least one objective.

Definition 2: x^* is said to be Pareto optimal if no x^* dominates it.

Definition 3: The Pareto optimal set includes all optimal solutions; their image under the objective functions defines the Pareto front.

A Pareto optimal solution for MOPs can be achieved by converting the problem into a single-objective one, combining all objectives via weighted sums or nonlinear functions. Thus, obtaining Pareto optimal solutions involves dividing the problem into several single-objective sub-problems. MOEA/D is a recent variant of multi-objective evolutionary algorithms designed to address MOPs using this decomposition approach. Multiple techniques exist to decompose the Pareto front approximation into scalar sub-problems, as detailed in [81].

3.2. Overview of the applied MOEA framework

MOEAs have been widely adopted for solving optimization problems with conflicting objectives. Several benchmark approaches, including NSGA-II, MOEA/D, and SPEA2, use distinct selection, reproduction, and updating mechanisms to improve solution quality and robustness. While these classical approaches rely on crowding distance and Pareto dominance, recent advances incorporate decomposition-based techniques to enhance solution stability.

The proposed Stable Matching-Based MOEA/D (STM-MOEA/D) differs from existing methods in its selection mechanism, which leverages stable matching theory to ensure a balanced allocation of solutions across the Pareto front. Unlike conventional MOEAs that rely on the Euclidean distance metrics or angle-based dominance criteria, our method integrates a dynamic preference-based pairing strategy that enhances selection stability and maintains diversity.

Comparative Discussion with Benchmark MOEAs:

- **NSGA-II:** Uses crowding-distance-based selection, which maintains diversity but struggles with high-dimensional objectives.
- **MOEA/D:** Decomposition-based framework that enhances convergence but is sensitive to weight vector distribution.
- **SPEA2:** Utilizes an archive-based mechanism but lacks adaptability in dynamic problem spaces.
- **STM-MOEA/D:** Integrates stable matching principles to balance convergence and diversity while maintaining computational efficiency.

The pseudocode of the proposed method is presented below, detailing key algorithmic steps from initialization to the final solution.

Pseudocode for STM-MOEA/D

1. Initialize:
2. Generate an initial population P consisting of N individuals
3. Define the weight values $\{\lambda_1, \lambda_2, \dots, \lambda_n\}$ for decomposition
4. Set a neighborhood structure based on weight vector distances
5. Initialize reference point z with the best objective values found so far
6. Define survival strategy parameters for STM
7. while termination criteria not met do
8. for each individual i in P do
9. Select a set of mating parents from the neighborhood of i
10. Generate offspring using crossover and mutation operators
11. Evaluate the objective functions of the offspring
12. Update reference point z with the best objective values found
13. Update neighboring solutions:
14. for each neighbor in the weight vector neighborhood do
15. Apply replacement criteria based on decomposition approach
16. Use STM-based selection to maintain diversity and convergence
17. end for
18. end for
19. end while
20. return The final set of solutions P as the Pareto-optimal front

By aligning the proposed algorithm structure with existing methodologies while introducing an innovative selection mechanism, STM-MOEA/D ensures improved diversity maintenance, selection stability, and computational efficiency.

3.3. Selection method

In MOEA/D, solutions are selected based on their aggregated objective function values, and population diversity is ensured through the distribution of sub-problems. If we treat sub-problems and candidate solutions as two groups of agents, the selection step in MOEA/D becomes a two-sided matching framework. Accordingly, the design of selection operators can be systematically guided by principles and techniques from matching theory.

Matching, originally introduced and explored in a Nobel Prize-winning paper [86], has found numerous applications across various fields, such as capacitated non-transferable utility (NTU) games, workforce allocation, cloud resource allocation, and weighted capacitated house allocation problems [87–91]. The stable marriage problem, originally introduced in [86], addresses the task of pairing individuals from two distinct groups, such as males and females. In this context, every individual from one group creates a preference list over the members of the opposite group. A pairing is deemed unstable if there exists at least one duo—currently assigned to others—who mutually favor each other over their assigned partners. Such a scenario indicates that the individuals would prefer to be matched with one another rather than stay with their current partners. To ensure the matching remains stable, these types of pairs must be avoided. Let's examine a simple marriage market scenario depicted in Fig. 1. It involves three men and three women, each of whom has ranked the members of the opposite gender according to their preferences. As an example, the vector $[m_3, m_1, m_2]$ for w_1 means that w_1 prefers m_3 over m_1 and m_1 over m_2 . Two different matching sets are shown in Fig. 1. The matching shown by solid

lines is stable, while the dashed-line matching is unstable, because m_2 ranks w_3 higher than his current wife, and w_3 prefers m_2 over her husband.

Reference [81] presents a straightforward, efficient STM model designed to implement the selection operator within MOEA/D, where each sub-problem agent ranks all solutions based on their cumulative function values, favoring those with higher values, thereby aiding algorithm convergence. Conversely, all sub-problems are ranked by each solution agent based on their distance from the corresponding direction vector, supporting diversity. Therefore, a matching algorithm may be applied to allocate solutions to sub-problems. By using stable matching, the preferences of sub-problems and solutions are balanced, balancing convergence and diversity within the evolutionary algorithm.

In the MOEA/D method [81], a MOP is divided into N sub-problems, each associated with a solution in the existing population. For every sub-problem, the selection step identifies the selection identifies the best match within the solution set $S = \{x^1, \dots, x^M\}$, ($M > N$). Considering the set of sub-problems $P = \{p^1, \dots, p^N\}$ and the solution set S as two independent groups of agents, the selection operator is implemented using the STM model. This matching model is based on the stable marriage problem described previously.

In an STM problem, each agent in one set has complete preferences over agents in the opposite set. By leveraging the preferences of sub-problems and solutions for each other, a stable matching can be established between the agents of these two sets. According to [81,86], the "deferred acceptance" method is employed to find a stable matching between sub-problems and solutions, allowing a subset of solutions $\bar{S}$ from the solution set S to be selected. It is proved in [81] that the matching produced by this method is stable. Additionally, if is the most suitable solution currently available for a specific sub-problem, it will be included among the selected solutions.

A simple example is presented in [81] to compare the selection process of the STM model with the original MOEA/D. As illustrated in

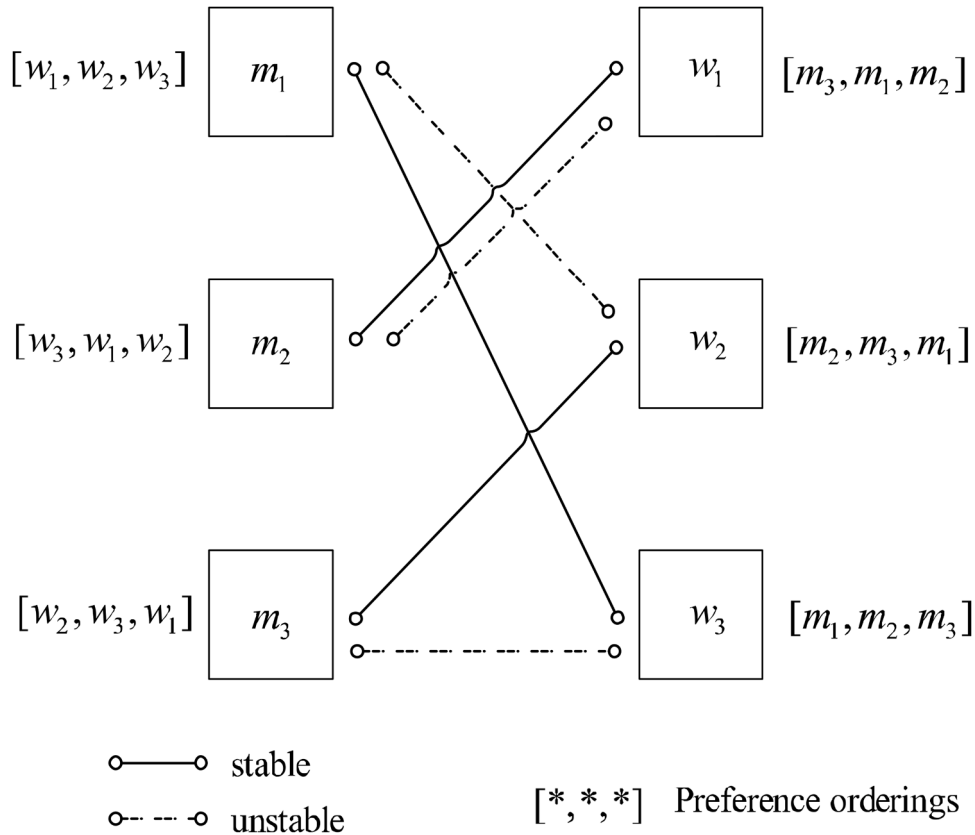


Fig. 1. A simplified schematic of stable marriage problem.

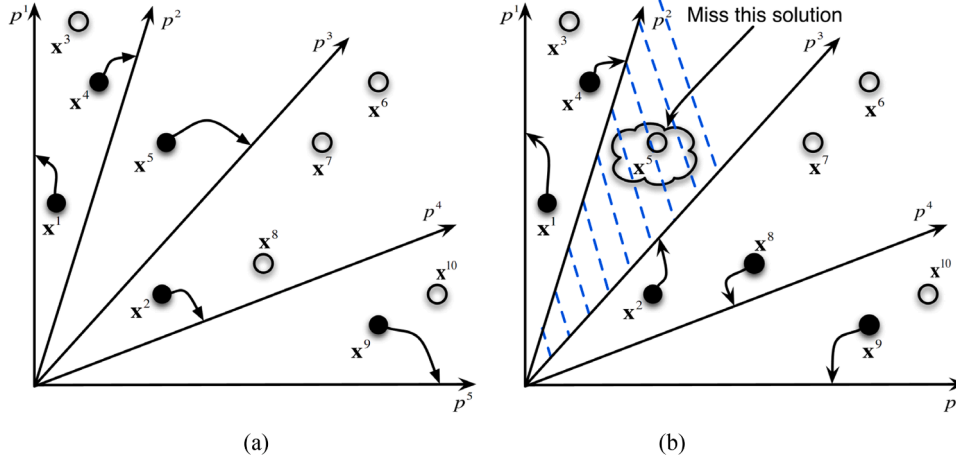


Fig. 2. Examples illustrating various matching relationships; (a) matching outcomes: (a) those derived from the STM model, and (b) those produced by the original MOEA/D method [81].

Fig. 2, there are ten solutions (x) and five sub-problems (p , represented by direction vectors). These solutions represent the set of parents and offspring, and five of them, equal to the population size, must be selected for the next generation. The selection process in the standard MOEA/D can establish a matching as follows $\{(p^1, x^1), (p^2, x^4), (p^3, x^2), (p^4, x^8), (p^5, x^9)\}$. However, p^4 prefers x^2 to x^8 and also x^2 prefers p^4 to p^3 . Due to the fact that x^2 and p^4 prioritize one another above their current matches, this results in an unstable matching. On the other hand, if solutions are chosen through the stable matching method, the resulting selection will be stable. Additionally, x^5 , which lies amid the direction vectors of p^2 and p^3 (indicated by dashed lines), plays a key role in maintaining population diversity and should not be excluded, as it contributes to maintaining diversity along critical regions of the Pareto front. Consequently, solutions selected via the STM method demonstrate improved diversity and distribution across the objective space.

3.4. Reproduction process

Any genetic or mathematical programming method can be used as a reproduction operator whose objective is to generate an offspring solution from N members of parent solutions. This study utilizes the DE operator along with polynomial mutation for reproduction, based on the approach in [81].

3.5. Fuzzy decision maker

In each iteration, N solutions are chosen by STM from the population, which includes both parents and offspring, to advance to the next iteration. Note that N corresponds to the predefined population size. After a full execution, one solution is selected as the best trade-off based on the relative priorities assigned to the objective functions. To achieve this, a fuzzy decision maker (DM) is employed [85]. Initially, the objective function values of each solution are transformed into membership functions:

$$\mu_i(X) = \begin{cases} 1 & \text{if } F_i(X) \leq F_i^{\min} \\ \frac{F_i^{\max} - F_i(X)}{F_i^{\max} - F_i^{\min}} & \text{if } F_i^{\min} \leq F_i(X) \leq F_i^{\max} \\ 0 & \text{if } F_i(X) \geq F_i^{\max} \end{cases} \quad (15)$$

where X is the solution, $\mu_i(X)$ represents the membership function of i_{th} objective function of X . Also, for the i_{th} objective in relation to X , the bounds $F_i^{\min}$ and $F_i^{\max}$ are derived from independently optimizing that specific objective function. The value of the DM function for the j_{th}

solution is then calculated as follows:

$$N_{ij} = \frac{\sum_{k=1}^{N_{obj}} \beta_k \times \mu_k(j)}{\sum_{j=1}^m \sum_{k=1}^{N_{obj}} \beta_k \times \mu_k(j)} \quad (16)$$

where $\mu_k(j)$ represents the value of membership function of the k_{th} objective function for the j_{th} solution, and β_k is the weight factor for the k_{th} objective function. The solution with the highest value of the DM function is considered the best compromise solution.

4. System under study

To evaluate the performance and robustness of STM-MOEA/D in solving the multi-objective OPF problem, simulations are conducted on the 30-bus IEEE test system. Detailed data for this system can be found in [92]. The system consists of 41 transmission lines, 6 generators, 4 regulating transformers, and 10 parallel capacitors. During the OPF solution process, bus voltage magnitudes and transformer tap ratios are constrained between 0.9 pu. and 1.1 pu., respectively. The step size for transformer taps is 0.0125 pu. Parallel capacitor values range between 0 pu and 0.05 pu, with each step being 0.01 pu.

5. Simulation results

The results obtained by the STM-MOEA/D algorithm are illustrated in Figs. 3–8, alongside the outcomes of other methods such as MOPSO [93], NSGA-II [82], ev-MOGA [94], MCSA [95], RM-MEDA [96], and RTEA [97]. In these figures, the solid black circle indicates the best compromise solution derived from the proposed method, selected from the final solutions obtained using Eqn. (16) and assuming equal relative importance for all objective functions ($\beta_k = 0.5$, $k = 1, 2$).

Notably, STM-MOEA/D does not use Pareto dominance in the selection phase of each iteration, but it ensures solution quality through stable matching between sub-problems and solutions. As a result, all final solutions obtained by STM-MOEA/D are approximately non-dominated. These solutions effectively form the Pareto optimal set. Moreover, the proposed method consistently provides a close approximation to the Pareto front, giving decision-makers more options to select an appropriate solution based on the relative importance of each objective function.

Furthermore, as demonstrated in Figs. 3–8, the STM-MOEA/D algorithm delivers the best approximation of the Pareto front, and the solutions obtained dominate those produced by other methods. The proposed method offers selection opportunities to solutions with significant characteristics without relying on Pareto dominance. In

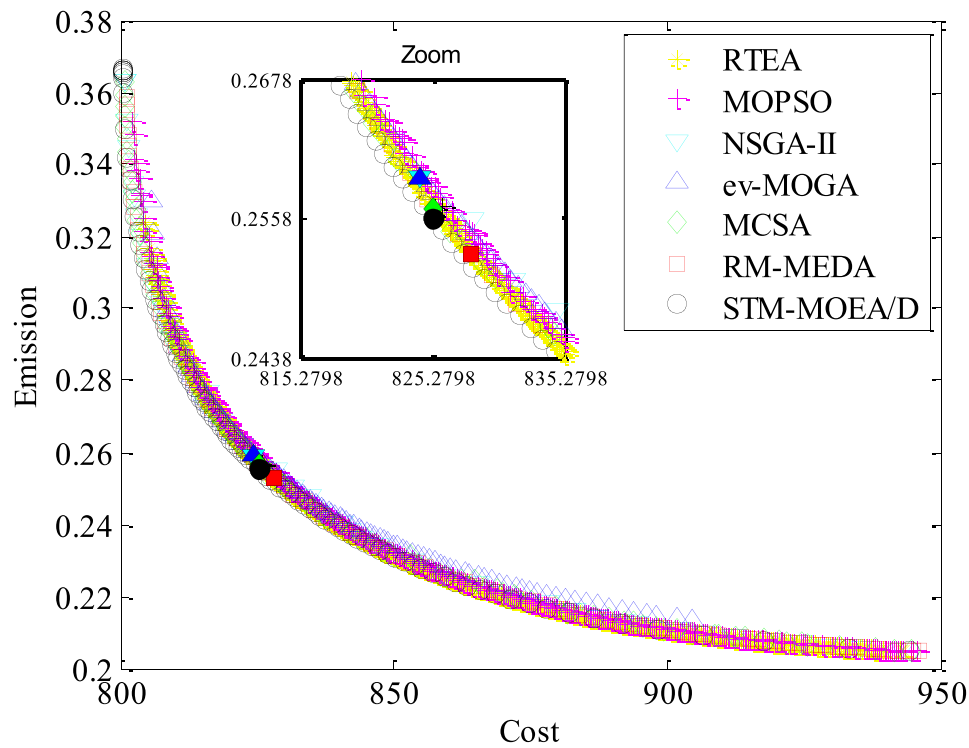


Fig. 3. Optimal results of OPF with cost and emission objectives.

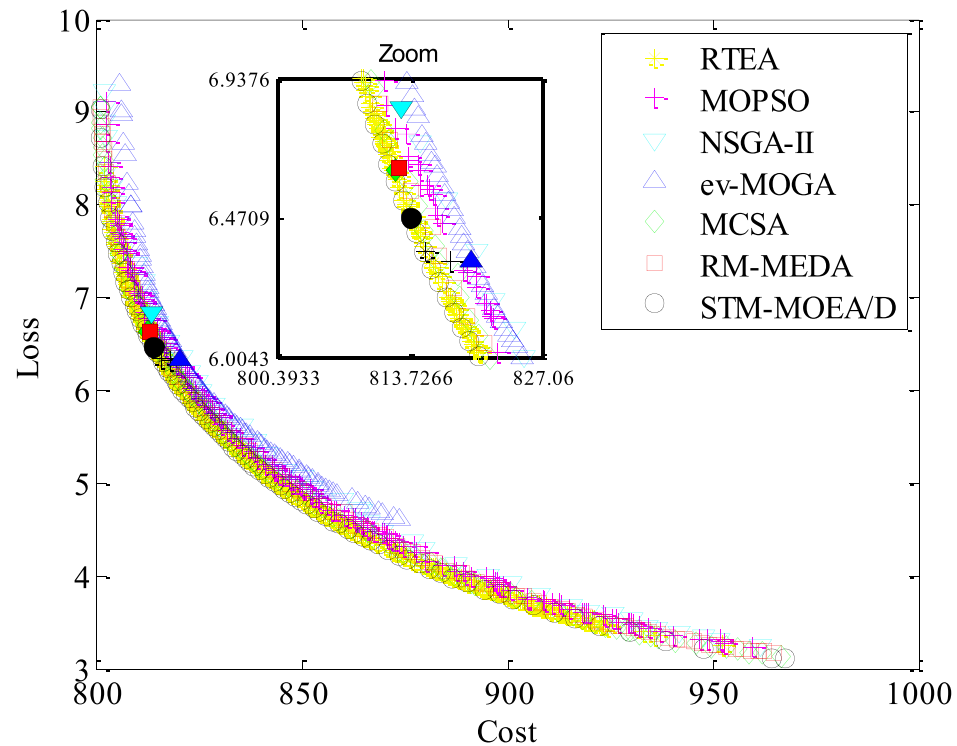


Fig. 4. Optimal results of OPF with cost and loss objectives.

contrast, Pareto dominance-based methods tend to limit the survival chances of Pareto-dominated solutions, reducing the diversity of solutions and leading to insufficient exploration in some critical areas of the solution space.

By evaluating the decision variables and objective functions of the

solutions in the resulting Pareto front, the following observations are made.

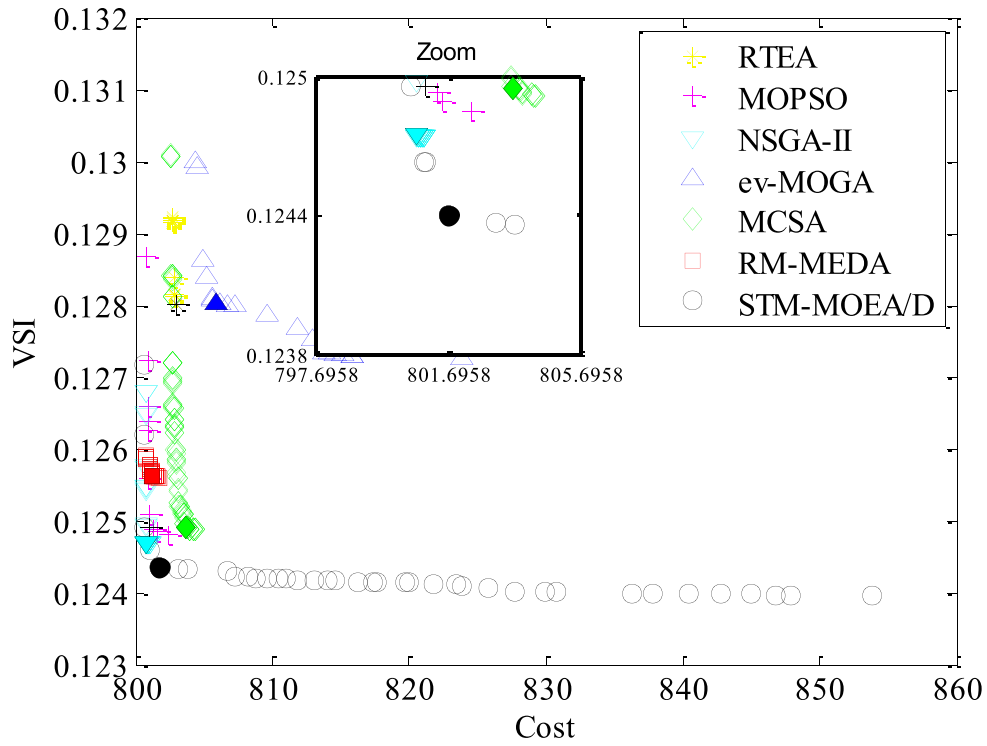


Fig. 5. Optimal results of OPF with cost and VSI objectives.

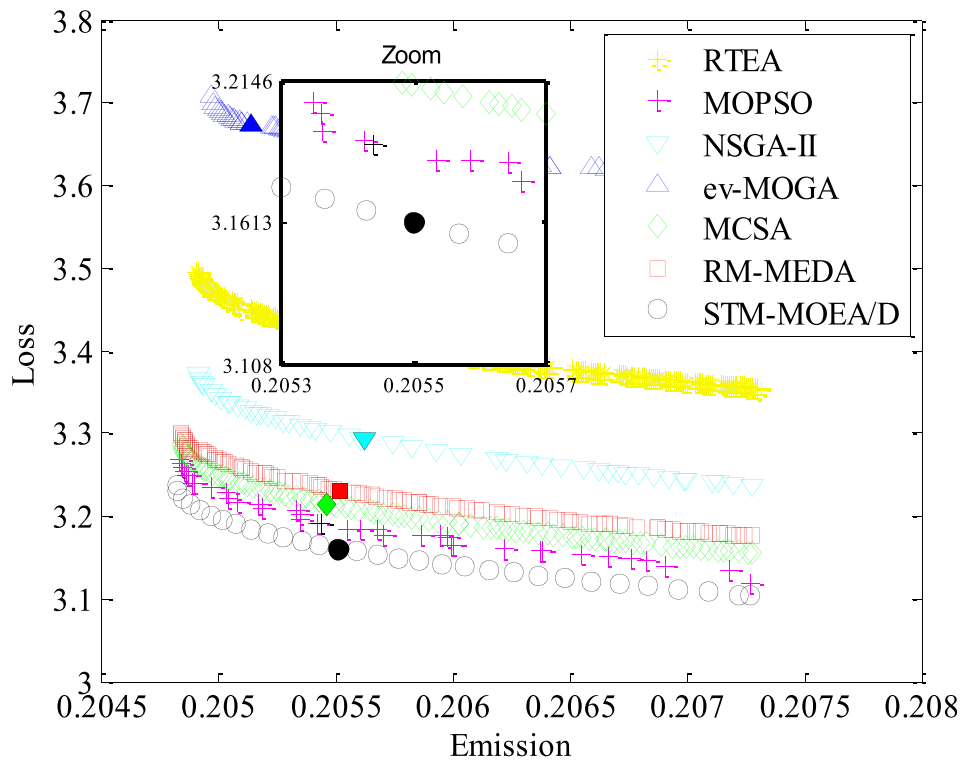


Fig. 6. Optimal results of OPF with emission and loss objectives.

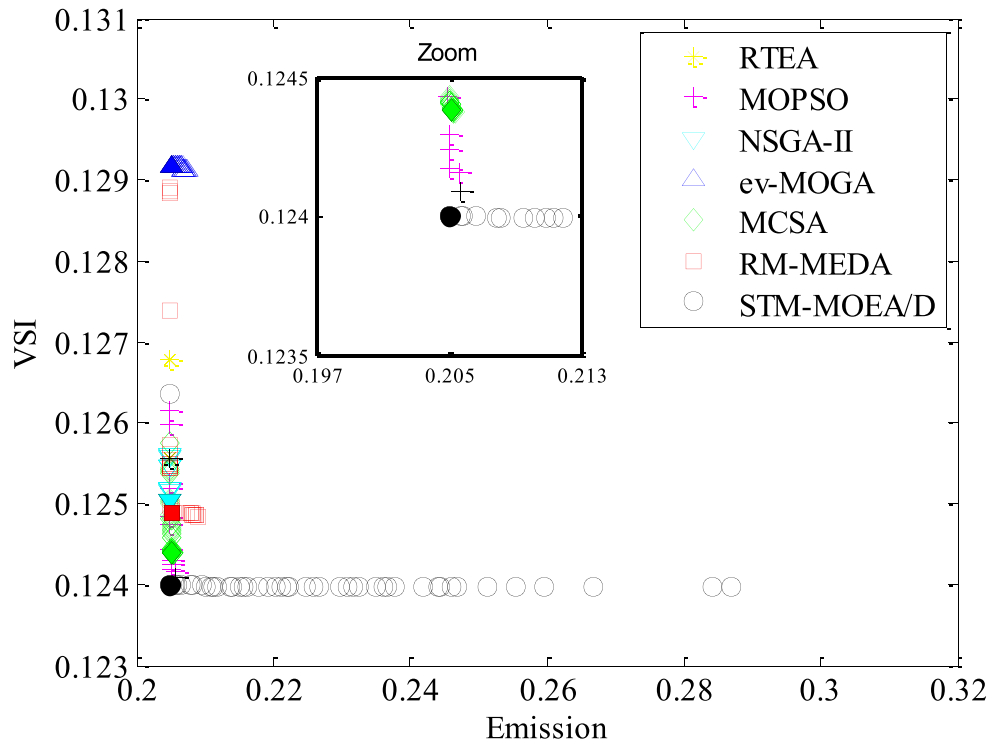


Fig. 7. Optimal results of OPF with emission and VSI objectives.

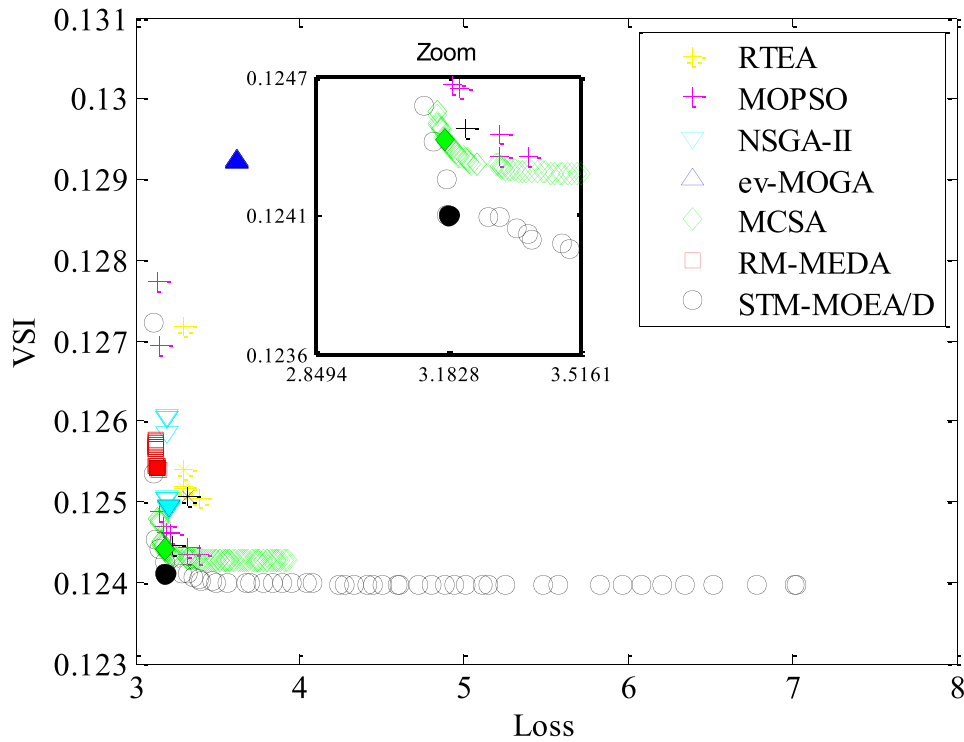


Fig. 8. Optimal results of OPF with loss and VSI objectives.

- In different cases, the minimum amount of VSI is achieved by setting the reactive power generation of all parallel capacitors on their maximum capacity.

- In different results in Pareto front, by varying the decision variables, the emissions and the losses almost behave the same, but the variation of the costs is contrary to them.

- Minimum emissions and losses occur when the active power generations of all generators are set to their maximum values, except for the reference generator which is not one of the decision variables. However, this gives the highest costs with a high value of VSI.

By assigning equal weighting coefficients to all objective functions, the best compromise solution values for each combination of objective functions are selected using Eqn. (16) and summarized in Table 2. As shown in Table 2, the optimal outcome for each objective in the best compromise solutions occurs when that objective is optimized in

isolation. As an example, the minimum cost objective function value is 801.6958 \$/h in case 3, where both cost and VSI are optimized. The best values for cost, loss, and VSI are 0.2049 ton/h, 3.1613 MW, and 0.1239, respectively, observed in cases 5, 4, and 5.

Furthermore, incorporating each new objective function improves its value, but at least one other objective function's value diminishes. Thus, within the set of all best compromise solutions, none of the solutions is dominated by any other. For instance, in case 1, where only cost and emission are optimized, the best compromise solution has a cost of 825.2798 \$/h and an emission of 0.2557 ton/h. When loss is also

Table 2
Optimal compromise solutions for OPF with various objective combinations.

Variables	Objectives					
	Case 1: Cost+Emission	Case 2: Cost+Loss	Case 3: Cost+VSI	Case 4: Emission+Loss	Case 5: Emission+VSI	Case 6: Loss+VSI
P_{G2} (MW)	57.9857	51.55	48.548	74.196	66.8262	79.8166
P_{G5} (MW)	26.1194	26.8545	22.3561	49.9999	50	49.9999
P_{G8} (MW)	34.953	35	19.8211	35	35	34.9839
P_{G11} (MW)	23.938	21.0169	14.028	30	30	29.9441
P_{G13} (MW)	23.3829	17.0211	12	40	39.9968	39.9839
V_1 (p.u.)	1.0711	1.0756	1.0688	1.062	1.0466	1.0593
V_2 (p.u.)	1.0591	1.06	1.055	1.057	1.0445	1.0569
V_5 (p.u.)	1.0293	1.0328	1.0352	1.0375	1.0573	1.0377
V_8 (p.u.)	1.0423	1.0414	1.0563	1.0439	1.0511	1.0532
V_{11} (p.u.)	1.1	1.0936	1.0573	1.0736	1.0972	1.0999
V_{13} (p.u.)	1.0581	1.0572	1.0477	1.055	1.0623	1.0311
$T_{6,9}$ (p.u.)	1.0625	1.0625	1.0375	1.0875	1.05	1.0875
$T_{6,10}$ (p.u.)	0.925	0.9	0.925	0.9	0.95	0.9125
$T_{4,12}$ (p.u.)	0.9875	0.9875	0.9875	1	1.025	0.975
$T_{28,27}$ (p.u.)	0.975	0.975	0.9875	0.975	0.9875	0.9875
C_{10} (p.u.)	0.01	0	0.05	0.05	0.05	0.05
C_{12} (p.u.)	0	0	0.05	0.05	0.05	0.05
C_{15} (p.u.)	0.03	0.04	0.05	0.05	0.05	0.05
C_{17} (p.u.)	0.05	0.05	0.05	0.05	0.05	0.05
C_{20} (p.u.)	0.03	0.03	0.05	0.04	0.05	0.05
C_{21} (p.u.)	0.05	0.05	0.05	0.05	0.05	0.05
C_{23} (p.u.)	0.03	0.03	0.05	0.03	0.05	0.05
C_{24} (p.u.)	0.05	0.05	0.05	0.05	0.05	0.05
C_{29} (p.u.)	0.02	0.03	0.05	0.02	0.05	0.05
Cost (\$/h)	825.2798	813.7266	<u>801.6958</u>	955.9689	944.1045	967.2811
Emission (ton/h)	0.2557	0.2793	0.3619	0.2055	<u>0.2049</u>	0.2072
Loss (MW)	5.8857	6.4709	9.1841	<u>3.1613</u>	3.6094	3.1827
VSI	0.129	0.1275	0.1243	0.1272	<u>0.1239</u>	0.1241
Objectives	Case 7:	Case 8:	Case 9:	Case 10:	Case 11:	
Variables	Cost+Emission+ Loss	Cost+Emission+ VSI	Cost+Loss+ VSI	Emission+Loss+ VSI	Cost+Emission+ Loss+VSI	
P_{G2} (MW)	58.7404	58.5954	50.269	74.5784	58.5378	
P_{G5} (MW)	28.7062	23.9311	28.1312	49.9999	33.945	
P_{G8} (MW)	34.8779	31.0096	34.9766	34.9839	35	
P_{G11} (MW)	30	30	21.2502	29.9441	29.9999	
P_{G13} (MW)	26.1802	21.9973	17.5558	39.9833	26.5386	
V_1 (p.u.)	1.0688	1.0582	1.0759	1.0593	1.0516	
V_2 (p.u.)	1.0567	1.0304	1.0602	1.0569	1.0398	
V_5 (p.u.)	1.0317	1.0328	1.0322	1.0377	1.0367	
V_8 (p.u.)	1.0434	1.0524	1.0412	1.0532	1.0525	
V_{11} (p.u.)	1.0999	1.0982	1.082	1.1	1.0983	
V_{13} (p.u.)	1.0559	1.0585	1.053	1.0311	1.0622	
$T_{6,9}$ (p.u.)	1.075	1.05	1.05	1.0875	1.1	
$T_{6,10}$ (p.u.)	0.925	0.95	0.925	0.9125	0.9	
$T_{4,12}$ (p.u.)	0.9875	1.025	0.9875	0.975	1.025	
$T_{28,27}$ (p.u.)	0.975	0.9875	0.975	0.9875	0.975	
C_{10} (p.u.)	0.05	0.05	0.01	0.05	0.05	
C_{12} (p.u.)	0.01	0.05	0.04	0.05	0.05	
C_{15} (p.u.)	0.04	0.05	0.05	0.05	0.05	
C_{17} (p.u.)	0.04	0.05	0.04	0.05	0.05	
C_{20} (p.u.)	0.04	0.05	0.03	0.05	0.05	
C_{21} (p.u.)	0.05	0.05	0.05	0.05	0.05	
C_{23} (p.u.)	0.02	0.05	0.03	0.05	0.04	
C_{24} (p.u.)	0.05	0.05	0.05	0.05	0.05	
C_{29} (p.u.)	0.02	0.05	0.04	0.05	0.02	
Cost (\$/h)	842.8533	827.9571	815.2172	956.7079	852.0229	
Emission (ton/h)	0.2425	0.2571	0.2773	0.2056	0.2318	
Loss (MW)	5.3497	6.323	6.3636	3.237	5.1259	
VSI	0.1295	0.1242	0.1262	0.1241	0.1256	

included (case 7), the cost increases for the best compromise solution, whereas emission and loss values are reduced compared to those in case 1. Additionally, the VSI value in case 7 is higher than in case 1. When VSI is added to the objectives of case 7 (case 11), the cost rises again, but other objective function values decrease. Notably, the VSI value in case 11 is lower than those in cases 1 and 7, indicating improved voltage stability.

In the best compromise solutions for all cases shown in Table 2, the worst values for cost, emission, loss, and VSI are 967.2811 \$/h, 0.3619 ton/h, 9.1841 MW and 0.1295, respectively. These values are associated with cases in which the corresponding objective function is not explicitly optimized.

A strong correlation is observed between the active power outputs at buses 2 and 13 and the total generation cost of meeting demand. Hence, in scenarios where the cost objective function is not prioritized, the active power values of these generators are higher than in scenarios where cost minimization is included as an objective. For cases where VSI is an objective function, all shunt capacitors tend to be set at their upper limit of 0.05 pu. to improve voltage stability.

Overall, based on the presented simulation results, the STM-MOEA/D method surpasses other optimization algorithms in addressing multi-objective OPF problems, consistently finding the best Pareto optimal solutions for all scenarios. Additionally, the STM-MOEA/D method provides the most accurate approximation of the Pareto front. Consequently, the STM-MOEA/D method demonstrates itself to be an effective and efficient technique for solving MOPF problems.

5.1. Scalability consideration

Although the STM-MOEA/D was applied to the IEEE 30-bus system with three objectives, its structure is inherently scalable due to the modular design of MOEA/D and the polynomial-time complexity of the stable matching mechanism. However, as power system size and the number of objectives increase, the dimensionality of the decision space and Pareto front complexity may pose additional computational and convergence challenges. Future work will include testing the algorithm on larger systems such as the IEEE 57-bus and 118-bus networks, as well as extending the objective space to include additional criteria such as emission control or renewable curtailment, to rigorously evaluate the scalability and robustness of the proposed method under high-dimensional and large-scale OPF scenarios.

6. Conclusion

This study proposes the application of Stable Matching-Based MOEA/D (STM-MOEA/D) to address the multi-objective OPF problem. By integrating stable matching theory into the selection mechanism, the proposed method enhances solution diversity, convergence, and robustness compared to existing algorithms.

The STM-MOEA/D method for solving multi-objective OPF focuses on establishing stable matching between sub-problems and solutions to select suitable solutions in each iteration, instead of relying on the Pareto dominance criterion. By considering the preferences of both solutions and sub-problems, this approach improves solution diversity. As a result, it identifies superior Pareto optimal solutions compared to other methods, as solutions with significant characteristics, even if dominated by Pareto, are more likely to be retained in subsequent populations. This method also provides a superior approximation of the Pareto front compared to other approaches. Experimental results demonstrate that STM-MOEA/D outperforms well-established methods, including NSGA-II, MOEA/D, and SPEA2. Furthermore, the results highlight the importance of addressing OPF within a multi-objective framework, as all objective functions must be considered simultaneously due to their conflicting nature.

Despite these promising results, future work could explore hybridizing STM-MOEA/D with advanced local search strategies to further

improve solution quality. Additionally, extending the algorithm to handle large-scale OPF systems and incorporating machine learning-based prediction models could enhance its applicability.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT-4o, developed by OpenAI, to enhance the cohesion and coherence of the text. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Compliance with Ethical Standards

Conflict of Interest: The authors declare that they have no conflict of interest.

CRediT authorship contribution statement

Ebrahim Akbari: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Amin Khodabakhshian:** Writing – review & editing, Validation, Supervision, Software, Resources, Methodology, Investigation. **Abolfazl Rahimejad:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis. **Stephen Andrew Gadsden:** Supervision, Resources, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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