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An Enhanced Equilibrium Optimizer Based on Rural Tourism Inspiration Strategy for Global Optimization and Engineering Applications

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Abstract

As the complexity, scale, and nonlinearity of modern engineering optimization problems continue to increase, traditional optimization algorithms face significant challenges in achieving high solution accuracy, fast convergence, and robust performance. To address these issues, this paper proposes a Rural Tourism Migration-based Improved Equilibrium Optimizer (RTM-IEO), aiming to enhance the global search capability and adaptive balance between exploration and exploitation. Specifically, an adaptive lens imaging opposition-based learning strategy is introduced to effectively expand the search space and maintain population diversity. A dynamic elite-guided elimination mechanism is designed to strengthen exploitation capability and accelerate convergence by reconstructing inferior individuals using high-quality solutions. In addition, a multi-stage rural tourism migration strategy is developed to dynamically regulate the search behavior across different optimization phases, enabling a more flexible and efficient search process. The effectiveness of the proposed algorithm is comprehensively validated on the CEC2021 and CEC2022 benchmark suites, where RTM-IEO demonstrates superior performance in terms of convergence accuracy, convergence speed, and robustness compared with several representative state-of-the-art algorithms. The statistical superiority of the proposed method is further confirmed through Friedman mean ranking and Wilcoxon rank-sum tests. To further evaluate its practical applicability, RTM-IEO is applied to the sustainable economic dispatch problem of a microgrid integrating renewable energy sources, including wind power and photovoltaic generation, along with energy storage systems and controllable units. The optimization objective simultaneously considers economic cost minimization and sustainable operation requirements, such as improving renewable energy utilization and reducing dependence on fossil-fuel-based generation. Experimental results indicate that the proposed method achieves a significant reduction in daily operating cost (exceeding 52% compared with benchmark algorithms), while effectively promoting low-carbon energy utilization and enhancing overall system sustainability. Overall, the proposed RTM-IEO provides an efficient and reliable optimization framework for addressing complex global optimization problems, particularly in scenarios requiring a coordinated balance between economic performance and sustainable development.



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1. Introduction

In the context of the global energy transition and sustainable development, optimization techniques have become a critical support for solving complex engineering problems. From economic dispatch in power systems to the grid integration of renewable energy, from production planning in intelligent manufacturing to path optimization in transportation and logistics, modern engineering systems are increasingly characterized by high dimensionality, multiple constraints, nonlinearity, and multimodality. These features pose significant challenges to the global search capability, convergence precision, and stability performance of optimization algorithms [1].

Particularly in recent years, with the increasing concerns over energy shortages, environmental pollution, and climate change, the reduction of carbon emissions and the improvement of energy utilization efficiency have become key objectives in engineering optimization. In power systems, especially in microgrid environments, the large-scale integration of renewable energy sources such as wind and photovoltaic generation introduces significant uncertainty and variability, which further complicates the optimization process [2,3]. Meanwhile, excessive reliance on fossil-fuel-based generation not only increases operational costs but also leads to substantial greenhouse gas emissions, thereby hindering the achievement of low-carbon and sustainable development goals [4,5]. Therefore, how to simultaneously minimize economic cost, reduce carbon emissions, and enhance renewable energy utilization has become a critical issue in modern energy system optimization.

Recent studies have increasingly emphasized that renewable-energy dispatch should not only minimize operating cost, but also explicitly consider uncertainty, flexibility, and carbon-related indicators. On the one hand, the randomness of renewable generation and load demand may cause power imbalance, renewable curtailment, and additional flexibility requirements [6]. Therefore, stochastic programming, robust optimization, and scenario-based dispatch models have been widely investigated to improve the adaptability of energy systems under uncertain operating conditions. On the other hand, carbon emission modeling has become an important component of low-carbon energy system planning and operation. Carbon emission factors, carbon trading costs, dynamic carbon intensity, and carbon-aware dispatch indices have been introduced to evaluate the environmental impact of different scheduling strategies [7,8]. These studies indicate that an effective, sustainable dispatch model should coordinate economic cost, renewable accommodation, operational flexibility, and carbon emission performance. Inspired by these works, the revised model in this paper further introduces a renewable curtailment penalty and carbon emission index to strengthen the sustainability evaluation of the proposed microgrid dispatch framework.

Particularly in the era where sustainable development has become a global consensus, how to achieve efficient resource allocation, clean energy utilization, and low-carbon system operation through intelligent optimization techniques has emerged as a core concern for both academia and industry. However, traditional mathematical programming methods, such as gradient descent, linear programming, and integer programming, are often limited by the differentiability of objective functions, the convexity of constraints, and the exponential growth of problem scale. As a result, it is difficult for these methods to obtain high-quality solutions within a reasonable time when addressing such complex problems [9,10]. Therefore, developing efficient, robust, and adaptive metaheuristic optimization algorithms is of great theoretical significance and practical value for advancing sustainable engineering practices.

Over the past two decades, researchers have drawn inspiration from natural phenomena and social behaviors to propose a large number of metaheuristic optimization algorithms. These algorithms can be broadly categorized into four groups. The first category includes evolutionary algorithms, such as the Genetic Algorithm (GA) [11] and

Differential Evolution (DE) [12], which simulate natural selection and genetic variation mechanisms. The second category comprises physics- and chemistry-based algorithms, such as Simulated Annealing (SA) [13], Gravitational Search Algorithm (GSA) [14], Kepler Optimization Algorithm [15], and Snow Ablation Optimizer (SAO) [16], which construct optimization models based on physical laws or chemical processes. The third category includes swarm intelligence algorithms, such as Particle Swarm Optimization (PSO) [17], Grey Wolf Optimizer (GWO) [18], Secretary Bird Optimization Algorithm (SBOA) [19], and Bounty Hunter Optimizer (BHO) [20], which mimic the cooperative behaviors of biological populations. The fourth category consists of human-based algorithms, such as Teaching–Learning-Based Optimization (TLBO) [21], Gold Rush Optimizer (GRO) [22], and the Undivided Family Interaction Algorithm (UFIA) [23].

Among these methods, the Equilibrium Optimizer (EO), proposed by Faramarzi et al. in 2020 [24], is a physics-inspired metaheuristic algorithm based on the mass balance model in a control volume. By simulating the dynamic evolution of particles toward an equilibrium state, EO performs optimization through a unique search mechanism. Due to its simple structure, few parameters, and distinctive search behavior, EO has demonstrated promising performance in both function optimization and engineering applications. However, EO and most of its variants still suffer from several inherent limitations. During the optimization process, population diversity decreases rapidly with iterations, which easily leads to premature convergence to local optima. In the later exploitation phase, the lack of effective guidance mechanisms for inferior individuals limits convergence accuracy. Furthermore, all individuals follow a unified update rule throughout the entire process, making it difficult to dynamically adjust the balance between exploration and exploitation according to different search stages. These shortcomings become particularly evident when dealing with complex multimodal, high-dimensional, and strongly constrained engineering problems [25,26].

To address these issues, various improvement strategies have been proposed in the literature. In terms of diversity enhancement, opposition-based learning (OBL) and its variants are widely used to expand the search space. For accelerating convergence, elite-guided strategies and elimination mechanisms are employed to strengthen selection pressure. Regarding search behavior regulation, multi-stage strategies and adaptive parameter adjustment methods are introduced to balance exploration and exploitation [27]. However, most existing improvements focus on addressing a single limitation and lack a coordinated design that simultaneously considers population diversity, elite guidance, and dynamic search behavior regulation [28]. More importantly, the strategy parameters in most existing algorithms are static or linearly adjusted, making it difficult to accurately match the dynamic requirements of different stages in the optimization process.

Meanwhile, with the continuous advancement of global energy transition and the “dual-carbon” goals, distributed energy systems centered on microgrids have become a key solution for achieving high penetration of renewable energy, reducing dependence on fossil fuels, and improving energy supply reliability and sustainability [25,29]. The economic dispatch problem of microgrids involves strongly coupled multi-variable constraints, including stochastic outputs of wind and photovoltaic generation, charging and discharging of energy storage systems, on/off states of controllable units, and regulation of interruptible loads. It is a typical nonlinear, non-convex, and high-dimensional complex optimization problem. Its objectives not only include minimizing operating costs but also consider sustainability indicators such as reducing carbon emissions, improving renewable energy utilization, and extending equipment lifespan [3,30]. Traditional rule-based dispatch methods and conventional optimization algorithms struggle to achieve global optimality under

such complex constraints, highlighting the urgent need for high-performance improved metaheuristic algorithms to provide efficient and reliable solutions.

Based on the above analysis, this paper proposes a Rural Tourism Migration-based Improved Equilibrium Optimizer (RTM-IEO). The main innovations and contributions of this study can be summarized as follows. First, an adaptive lens imaging opposition-based learning (ALIOBL) strategy is introduced. By utilizing the principle of lens imaging, dynamic symmetric opposite solutions are generated, and a nonlinear scaling factor adjusted with iteration progress is employed to adaptively regulate exploration capability, effectively preventing premature loss of population diversity. Second, a dynamic elite-guided elimination strategy (DEGES) is designed. Inferior individuals are identified based on fitness ranking and reconstructed using global best information combined with Gaussian mutation and time-varying contraction factors, thereby imposing strong selection pressure and accelerating convergence. Third, a multi-stage rural tourism-inspired migration strategy (MRTMS) is proposed. Inspired by tourists' behavioral patterns at different travel stages, the optimization procedure is structured into three phases—global search, intermediate adjustment, and local refinement—where different position updating strategies are applied in each stage to maintain an adaptive equilibrium between broad exploration and focused exploitation. By integrating these three strategies into the EO framework, RTM-IEO significantly improves convergence accuracy, convergence speed, and robustness while maintaining algorithmic simplicity.

To comprehensively evaluate the performance of RTM-IEO, extensive experiments are conducted on the CEC2021 and CEC2022 benchmark function suites under 10-dimensional and 20-dimensional settings. The proposed algorithm is compared with nine classical and state-of-the-art algorithms. Statistical significance is analyzed using the Wilcoxon rank-sum test and the Friedman mean rank test. Furthermore, RTM-IEO is applied to the sustainable economic dispatch problem of a microgrid, which represents a typical sustainable engineering application. A grid-connected microgrid model incorporating photovoltaic generation, wind power, micro gas turbines, fuel cells, battery storage, and interruptible loads is constructed. The objective is to minimize the daily operating cost while considering multiple constraints, including power balance, unit output limits, ramping constraints, and state-of-charge constraints. The results demonstrate that RTM-IEO not only performs excellently on benchmark functions but also significantly reduces operating costs in microgrid dispatch problems, confirming its practical applicability in sustainable engineering optimization. Finally, the paper concludes with a summary of the proposed work, discusses its limitations, and outlines future research directions.

In summary, to systematically enhance the performance of the Equilibrium Optimizer in complex optimization problems and sustainable energy dispatch, this study proposes a multi-strategy integrated improved algorithm, RTM-IEO. Compared with earlier approaches, the core advancements of this research are described as follows:

- (1) A multi-strategy integrated improved EO framework is proposed. By combining adaptive lens imaging, opposition-based learning, dynamic elite-guided elimination, and multi-stage rural tourism migration strategies, the algorithm is systematically enhanced in terms of population diversity, convergence efficiency, and dynamic search behavior, significantly improving its global search capability and robustness in complex multimodal problems.
- (2) A stage-adaptive search mechanism is designed. Inspired by rural tourism migration behavior, a three-stage search strategy (exploration–transition–exploitation) is constructed, enabling the algorithm to dynamically adjust its search pattern according to the iteration process, thereby effectively balancing global exploration and local exploitation while avoiding premature convergence.

- (3) The proposed algorithm is applied to the sustainable economic dispatch problem of a microgrid. An optimization model that considers both economic efficiency and sustainability is established and solved using RTM-IEO, achieving reduced operating costs, improved renewable energy utilization, and decreased dependence on fossil energy, thereby validating its practical engineering applicability and sustainability value.

To improve the logical flow of the paper, the optimization problem is first formulated before the proposed algorithm is introduced. Specifically, Section 2 presents the sustainable economic dispatch model of the microgrid, including the system structure, objective function, renewable curtailment penalty, carbon emission index, and operational constraints. Section 3 then introduces the standard EO and the proposed RTM-IEO algorithm, explaining how its search mechanisms are designed to solve complex nonlinear constrained optimization problems. This organization allows the reader to first understand the engineering problem and then examine how the proposed algorithm addresses its optimization characteristics.

The remainder of this paper is organized as follows. Section 2 formulates the sustainable economic dispatch model of the microgrid, including the system configuration, objective function, and operational constraints. Section 3 introduces the fundamental principles of the Equilibrium Optimizer and presents the proposed RTM-IEO algorithm in detail. Section 4 evaluates the performance of the proposed method through comprehensive experiments on the CEC2021 and CEC2022 benchmark functions. Section 5 further analyzes the application of RTM-IEO in the microgrid economic dispatch problem and discusses the obtained results. Finally, Section 6 concludes the paper and outlines future research directions.

2. Sustainable Economic Dispatch of a Microgrid

2.1. Problem Description and System Configuration

With the accelerating transition toward low-carbon energy systems, microgrids integrating renewable generation, dispatchable distributed generators, energy storage systems, and flexible demand resources have become an important technical pathway for sustainable energy utilization [31]. Compared with traditional centralized power supply structures, microgrids can coordinate local generation, storage, and loads in a more flexible manner, thereby improving renewable energy accommodation, reducing fossil-fuel dependence, and enhancing operational resilience. In this context, optimal microgrid dispatch is not only an economic issue, but also a sustainability-oriented decision-making problem closely related to carbon reduction, clean energy integration, and efficient resource utilization.

In this study, a grid-connected microgrid composed of photovoltaic (PV) units, wind turbines (WT), a micro gas turbine (MGT), a fuel cell (FC), a battery energy storage system (BES), and interruptible loads (IL) is considered. The dispatch horizon is set to 24 h, and each time interval is 1 h. In the studied system, PV and WT units are treated as clean energy sources with priority consumption, the fuel cell serves as a relatively smooth supporting source, the micro gas turbine compensates for the remaining net load, the battery system performs peak shaving and valley filling, and interruptible loads are activated only when necessary to preserve system feasibility.

Let the decision vector at time interval t be defined as

$$\mathbf{X}(t) = [P_{mt}(t), P_{fc}(t), P_x(t), P_b(t), P_{grid}(t)] \quad (1)$$

where $P_{mt}(t)$, $P_{fc}(t)$, $P_x(t)$, and $P_b(t)$ denote the output power of the micro gas turbine, the output power of the fuel cell, the curtailed interruptible load, and the battery power,

respectively. When $P_b(t) > 0$, the battery is discharging; when $P_b(t) < 0$, the battery is charging. And $P_{grid}(t)$ represents the interactive power between the microgrid and the main grid: $P_{grid}(t) > 0$ means purchasing power from the main grid, $P_{grid}(t) < 0$ means selling surplus power to the main grid.

Accordingly, the full-day dispatch decision vector can be written as

$$\mathbf{X} = [P_{mt}(1:24), P_{fc}(1:24), P_x(1:24), P_b(1:24)] \quad (2)$$

The main objective of this work is to minimize the daily operating cost of the microgrid while satisfying all operational constraints. At the same time, the proposed dispatch strategy is expected to enhance renewable energy utilization, reduce unnecessary fossil-energy consumption, improve storage participation, and decrease dependence on interruptible loads. Therefore, the optimization process contributes not only to short-term economic performance but also to the long-term sustainability of the local energy system.

2.2. Sustainable Economic Dispatch Model

2.2.1. Objective Function

To comprehensively evaluate the operating performance of the microgrid, the total cost is formulated by considering fuel cost, operation and maintenance cost, start-up cost, battery maintenance cost, and interruptible load compensation cost. The overall dispatch objective is expressed as

$$\min F = \sum_{t=1}^{24} C(t) \quad (3)$$

where $C(t)$ represents the total operating cost during interval t .

(1) Fuel Cost of MGT and FC

The micro gas turbine and the fuel cell consume natural gas during operation. Their fuel cost is modeled as

$$C_{gas}(t) = C_{ch4} \left(\frac{P_{mt}(t)}{L_{gas}\eta_{mt}(t)} + \frac{P_{fc}(t)}{L_{gas}\eta_{fc}(t)} \right) \quad (4)$$

where C_{ch4} is the natural gas price, L_{gas} is the lower heating value of natural gas, and $\eta_{mt}(t)$ and $\eta_{fc}(t)$ are the efficiencies of the MGT and FC, respectively.

The efficiency of the micro gas turbine is described by

$$\eta_{mt}(t) = 0.0753 \left(\frac{P_{mt}(t)}{65} \right)^3 - 0.3095 \left(\frac{P_{mt}(t)}{65} \right)^2 + 0.4174 \left(\frac{P_{mt}(t)}{65} \right) + 0.1068 \quad (5)$$

and the efficiency of the fuel cell is given by

$$\eta_{fc}(t) = -0.0023P_{fc}(t) + 0.674 \quad (6)$$

These expressions indicate that the consumption of dispatchable fossil-based units is directly linked to system cost. Therefore, reducing excessive reliance on MGT and FC through better renewable coordination and energy storage scheduling is beneficial not only from an economic perspective but also from a sustainability perspective, because it lowers fossil-fuel usage and indirectly reduces carbon emissions.

(2) Operation and Maintenance Cost

The operation and maintenance cost of the microgrid components is formulated as

$$C_{om}(t) = C_{m,mt}P_{mt}(t) + C_{m,fc}P_{fc}(t) + C_{m,pv}P_{pv}(t) + C_{m,wt}P_{wt}(t) + C_{m,eb}|P_b(t)| \quad (7)$$

where $C_{m,mt}$, $C_{m,fc}$, $C_{m,pv}$, $C_{m,wt}$, and $C_{m,eb}$ denote the maintenance coefficients of the MGT, FC, PV, WT, and battery system, respectively.

(3) Start-Up Cost

Frequent start-stop operations reduce equipment life and increase operational burden. To reflect this effect, the start-up cost of the dispatchable units is considered. The operating states of MGT and FC are defined as

$$U_{mt}(t) = \begin{cases} 1, & P_{mt}(t) > 0 \\ 0, & P_{mt}(t) = 0 \end{cases}, U_{fc}(t) = \begin{cases} 1, & P_{fc}(t) > 0 \\ 0, & P_{fc}(t) = 0 \end{cases} \quad (8)$$

Then, the start-up cost in interval t is written as

$$C_{st}(t) = C_{st,mt} \max\{0, U_{mt}(t) - U_{mt}(t-1)\} + C_{st,fc} \max\{0, U_{fc}(t) - U_{fc}(t-1)\} \quad (9)$$

This term encourages smoother unit scheduling and helps avoid unnecessary start-stop operations. Such a smoother operating pattern improves equipment longevity and supports the sustainable operation of the microgrid.

(4) Interruptible Load Compensation Cost

Interruptible load is an important demand-side flexibility resource. However, excessive interruption may reduce user comfort and increase compensation expenditure. Its cost is formulated as

$$C_{IL}(t) = (C_{rb}(t) + 1.5)P_x(t) \quad (10)$$

where $C_{rb}(t)$ is the time-of-use electricity price. This term penalizes excessive reliance on demand interruption and encourages the dispatch strategy to prioritize cleaner and less intrusive balancing mechanisms, such as renewable utilization and storage regulation.

(5) Total Cost Function

Therefore, the total operating cost in each period is given by

$$C(t) = C_{gas}(t) + C_{om}(t) + C_{st}(t) + C_{IL}(t) \quad (11)$$

and the 24 h economic dispatch objective becomes

$$\min F = \sum_{t=1}^{24} [C_{gas}(t) + C_{om}(t) + C_{st}(t) + C_{IL}(t)] \quad (12)$$

Although the direct optimization objective is cost minimization, the model inherently promotes sustainability because it encourages renewable priority utilization, efficient battery dispatch, smoother thermal unit operation, and reduced use of demand interruption. Hence, economic dispatch and sustainable development objectives are aligned in the proposed formulation.

It should be noted that the proposed objective function does not directly impose a penalty cost for renewable energy curtailment (i.e., wind or PV spillage). Instead, the model prioritizes clean energy utilization indirectly through two mechanisms. First, renewable generation (PV and wind) is treated as zero-fuel-cost and zero-carbon power with priority consumption, meaning that any curtailment would not reduce operating cost and is therefore avoided unless technically necessary. Second, the cost structure of

dispatchable units (MGT and FC) and interruptible loads creates an economic incentive to maximize renewable integration, because displacing fossil-based generation directly lowers fuel and emission-related expenses. Under this formulation, explicit curtailment penalties are not required to achieve high renewable penetration; the cost minimization objective naturally favors renewable absorption. Nevertheless, in systems where renewable oversupply frequently occurs, an additional curtailment penalty term could be introduced to further enforce green energy priority.

2.2.2. Constraint Conditions

To ensure practical feasibility, the following operational constraints are imposed.

(1) Power Balance Constraint

For each dispatch interval, the generated power, battery power, and interruptible load adjustment must satisfy the load demand:

$$P_{mt}(t) + P_{fc}(t) + P_b(t) + P_x(t) + P_{pv}(t) + P_{wt}(t) + P_{grid}(t) = P_l(t) \quad (13)$$

where $P_l(t)$, $P_{pv}(t)$, and $P_{wt}(t)$ represent the load demand, PV output, and wind power output, respectively.

(2) MGT Output Constraint

$$0 \leq P_{mt}(t) \leq P_{mt}^{max} \quad (14)$$

When $P_{mt}(t) = 0$, the micro gas turbine is shut down; the output constraint is relaxed to $0 \leq P_{mt}(t) \leq P_{mt}^{max}$ when the unit is allowed to stop. The same rule applies to the fuel cell in Equation (16).

And the ramping constraint is

$$R_{mt}^{down} \leq P_{mt}(t) - P_{mt}(t-1) \leq R_{mt}^{up} \quad (15)$$

(3) FC Output Constraint

$$0 \leq P_{fc}(t) \leq P_{fc}^{max} \quad (16)$$

and its ramping constraint is

$$R_{fc}^{down} \leq P_{fc}(t) - P_{fc}(t-1) \leq R_{fc}^{up} \quad (17)$$

(4) Interruptible Load Constraint

$$P_x^{min} \leq P_x(t) \leq P_x^{max} \quad (18)$$

(5) Battery Power Constraint

$$P_b^{min} \leq P_b(t) \leq P_b^{max} \quad (19)$$

(6) Battery State-of-Charge Constraint

When the battery is discharging, the state update is expressed as

$$E_b(t+1) = E_b(t)(1 - \tau_b) - \frac{P_b(t)}{\eta_{bdis}}, P_b(t) \geq 0 \quad (20)$$

When the battery is charging, the state update becomes

$$E_b(t+1) = E_b(t)(1 - \tau_b) - P_b(t)\eta_{bch}, P_b(t) < 0 \quad (21)$$

and the battery state must satisfy

$$E_b^{\min} \leq E_b(t) \leq E_b^{\max} \quad (22)$$

where τ_b is the self-discharge rate, η_{bch} is the charging efficiency, and η_{bdis} is the discharging efficiency.

(7) Grid Interactive Power Constraint

$$P_{grid}^{\min} \leq P_{grid}(t) \leq P_{grid}^{\max} \quad (23)$$

where $P_{grid}^{\min}$ and $P_{grid}^{\max}$ are the upper and lower limits of grid interactive power.

Finally, the sustainable economic dispatch problem of the microgrid can be summarized as

$$\begin{aligned} & \min_{\mathbf{X}} F(\mathbf{X}) \\ & \text{s.t. Equations(13) – (22)} \end{aligned} \quad (24)$$

The above formulation provides a physically feasible and economically meaningful optimization framework. More importantly, by coordinating clean generation, flexible storage, and demand response under multiple operational constraints, the model supports a more sustainable and resilient microgrid operation paradigm.

2.3. Characteristics of the Optimization Problem and Motivation for RTM-IEO

The proposed microgrid dispatch model is a nonlinear constrained optimization problem with several challenging characteristics. First, the fuel cost and efficiency models of the micro gas turbine and fuel cell introduce nonlinear relationships between output power and operating cost. Second, the battery charging and discharging process leads to non-smooth operating behavior because the battery cannot charge and discharge simultaneously. Third, the state-of-charge constraint creates inter-temporal coupling, since the battery state at the current time interval depends on the previous dispatch decisions. Fourth, ramping constraints and unit output limits further restrict the feasible region. Finally, if unit on/off states and start-up costs are explicitly considered, the dispatch model has a mixed discrete-continuous structure.

These characteristics make the problem difficult for conventional deterministic optimization methods, especially when the feasible region is nonlinear, non-convex, and constrained. The proposed RTM-IEO is designed to address these difficulties from three aspects. ALIOBL enhances population diversity and helps the algorithm escape local optima caused by non-convex cost surfaces. MRTMS provides a stage-adaptive search mechanism, which is suitable for balancing global exploration and local exploitation in high-dimensional coupled dispatch problems. DEGES reconstructs inferior solutions using elite information, thereby improving convergence efficiency under complex operational constraints. Therefore, the mechanisms of RTM-IEO are consistent with the main characteristics of the microgrid dispatch problem.

3. Overview of the Equilibrium Optimizer and the Proposed Framework

To provide a clear understanding of the proposed algorithm, this section first introduces the fundamental principles of the Equilibrium Optimizer (EO). Subsequently, the overall framework of the proposed Rural Tourism Migration-based Improved Equilibrium Optimizer (RTM-IEO) is presented, followed by detailed descriptions of its key improvement strategies.

3.1. Equilibrium Optimizer

The Equilibrium Optimizer (EO) [24] is a physics-inspired metaheuristic algorithm developed based on the mass balance model in a control volume. In EO, each candidate solution is considered as a concentration vector, and the optimization process is modeled as the dynamic evolution of particles toward equilibrium states. By simulating the mass transfer mechanism, EO establishes a balance between exploration and exploitation during the search process.

Assuming a population size of NNN and a problem dimension of d , the i -th particle can be represented as:

$$\mathbf{C}_i = [c_{i1}, c_{i2}, \dots, c_{id}], i = 1, 2, \dots, N \quad (25)$$

The initial population is randomly generated within the feasible search space:

$$\mathbf{C}_i = lb + rand \cdot (ub - lb) \quad (26)$$

where lb and ub denote the lower and upper bounds of the decision variables, respectively.

In each iteration, EO constructs an equilibrium pool consisting of four best individuals and their average solution:

$$\begin{aligned} \mathcal{V} &= \{\mathbf{C}_{eq1}, \mathbf{C}_{eq2}, \mathbf{C}_{eq3}, \mathbf{C}_{eq4}, \mathbf{C}_{avg}\} \\ \mathbf{C}_{avg} &= \frac{\mathbf{C}_{eq1} + \mathbf{C}_{eq2} + \mathbf{C}_{eq3} + \mathbf{C}_{eq4}}{4} \end{aligned} \quad (27)$$

The equilibrium pool serves as the primary guidance source for the population evolution, allowing particles to learn from multiple elite solutions and thereby enhancing search stability.

The position updating mechanism of EO is defined as:

$$\mathbf{C}_i^{t+1} = \mathbf{C}_{eq} + (\mathbf{C}_i^t - \mathbf{C}_{eq}) \cdot F + \frac{G}{\lambda V} (1 - F) \quad (28)$$

where $\mathbf{C}_{eq}$ is randomly selected from the equilibrium pool, λ is a random vector, and V is a constant. The exponential term F and the generation rate G are expressed as:

$$F = a_1 \cdot \text{sign}(rand - 0.5) \cdot (e^{-\lambda t} - 1) \quad (29)$$

$$G = G_0 \cdot F \quad (30)$$

$$G_0 = GCP \cdot (\mathbf{C}_{eq} - \lambda \cdot \mathbf{C}_i) \quad (31)$$

where GCP is a control parameter that determines the generation probability.

Through the combined effect of the exponential term and the generation rate, EO enables particles to move toward promising regions while maintaining a certain level of randomness, thus achieving a dynamic balance between global exploration and local exploitation. To ensure feasibility, a boundary control mechanism is applied to keep particles within the search space. In addition, a memory-saving strategy is employed to retain better solutions from previous iterations, which helps improve the stability of the optimization process.

3.2. Proposed Methodology (RTM-IEO)

Although the standard EO has demonstrated competitive performance in various optimization problems, its effectiveness is still limited, especially in scenarios involving intricate multimodal landscapes and high-dimensional solution spaces. In such cases, population variability typically diminishes rapidly during the iterative process, which

can result in convergence occurring too early. Moreover, the search performance in the final stages is constrained, as weaker agents lack effective directional support. Moreover, the search behavior of EO remains relatively static throughout the entire optimization process, which makes it difficult to adapt to the different requirements of exploration and exploitation at various stages.

To address the above limitations, this paper proposes an improved equilibrium optimizer, termed Rural Tourism Migration-based Improved Equilibrium Optimizer (RTM-IEO). The proposed algorithm enhances the search performance of EO from three complementary aspects, including population diversity enhancement, elite-guided exploitation improvement, and dynamic search behavior regulation.

Specifically, an adaptive lens imaging opposition-based learning strategy is introduced to expand the search space and improve population diversity. A dynamic elite-guided elimination strategy is designed to reconstruct inferior individuals based on elite information, thereby accelerating convergence. Furthermore, a multi-stage rural tourism-inspired migration strategy is developed to dynamically adjust the search behavior across different optimization stages, achieving a better balance between exploration and exploitation.

By integrating the above three strategies into the EO framework, the proposed RTM-IEO is expected to achieve improved convergence accuracy, stronger global search capability, and enhanced robustness when solving complex optimization problems.

3.2.1. Adaptive Lens Imaging Opposition-Based Learning Strategy (ALIOBL)

In the standard EO, the population is updated mainly through random interactions with the equilibrium pool, and the diversity of candidate solutions gradually decreases as the iteration proceeds. This mechanism lacks an effective means of expanding the search space, which may result in insufficient exploration and an increased risk of premature convergence, especially when dealing with complex multimodal optimization problems.

To address this limitation, an adaptive lens imaging opposition-based learning strategy (ALIOBL) is introduced to enhance population diversity and improve the global search capability. Inspired by the geometric principle of lens imaging, this strategy generates an opposite candidate solution for each individual by constructing a symmetric mapping with respect to the center of the search space.

The lens opposition solution is defined as:

$$\mathbf{C}_i^{lens} = \frac{ub + lb}{2} + \frac{ub + lb}{2k} - \frac{\mathbf{C}_i}{k} \quad (32)$$

where lb and ub refer to the lower and upper constraints of the problem space, respectively, and k is a dynamic scaling factor given by:

$$k = \left(1 + \sqrt{\frac{t}{T}}\right)^9 \quad (33)$$

with t representing the current iteration number and T the maximum number of iterations.

After generating the lens opposition solution, a greedy selection mechanism is applied:

$$\mathbf{C}_i = \begin{cases} \mathbf{C}_i^{lens}, & f(\mathbf{C}_i^{lens}) < f(\mathbf{C}_i) \\ \mathbf{C}_i, & \text{otherwise} \end{cases} \quad (34)$$

The introduction of this strategy offers three main advantages: it effectively expands the search space by introducing symmetrical candidate solutions, enhances the ability of the algorithm to escape local optima, and adaptively balances exploration and exploitation

through the dynamic adjustment of the scaling factor k . As a result, the overall diversity and robustness of the population are significantly improved.

3.2.2. Dynamic Elite-Guided Elimination Strategy (DEGES)

In the standard EO, the update of low-quality individuals relies primarily on stochastic interactions, without explicitly utilizing the information of high-quality solutions. This weak selection pressure may lead to inefficient exploitation and slow convergence, particularly in the later stages of the search process.

To overcome this drawback, a dynamic elite-guided elimination strategy (DEGES) is proposed to selectively reconstruct poorly performing individuals using elite guidance. In this strategy, individuals are first sorted according to their fitness values in ascending order:

$$f(\mathbf{C}_{(1)}) \leq f(\mathbf{C}_{(2)}) \leq \dots \leq f(\mathbf{C}_{(N)}) \quad (35)$$

Then, a subset of the worst-performing individuals is identified:

$$W = \{\mathbf{C}_{(k)} \mid k \geq (1 - \eta)N\} \quad (36)$$

where η is the elimination ratio.

These inferior individuals are reinitialized around the current global best solution $\mathbf{C}_{eq1}$ as follows:

$$\mathbf{C}_{new} = \mathbf{C}_{eq1} + RR \cdot \delta \cdot (ub - lb) \quad (37)$$

where $RR = 1 - \frac{t}{T}$ is a time-varying contraction factor, and $\delta \sim \mathcal{N}(0, 1)$ is a Gaussian random variable.

This mechanism introduces a strong selection pressure by replacing low-quality individuals with new candidates guided by elite information. It accelerates convergence, reduces ineffective exploration, and improves the overall quality of the population. Furthermore, the dynamic contraction factor ensures that the search gradually shifts from global exploration to local exploitation.

3.2.3. Multi-Stage Rural Tourism-Inspired Migration Strategy (MRTMS)

In the standard EO, all individuals follow a unified update mechanism throughout the entire optimization process. Such a static search pattern fails to account for the different requirements of exploration and exploitation at various stages, which may limit the adaptability of the algorithm.

To enhance the dynamic search behavior, a multi-stage rural tourism-inspired migration strategy (MRTMS) is proposed. This strategy simulates the behavioral patterns of tourists visiting rural areas and divides the optimization process into three distinct stages: exploration, transition, and exploitation.

A normalized time parameter is defined as:

$$\tau = \frac{t}{T} \quad (38)$$

Meanwhile, a set of candidate “tourist destinations” is constructed using elite solutions:

$$V = \{\mathbf{C}_{eq1}, \mathbf{C}_{eq2}, \mathbf{C}_{eq3}, \mathbf{C}_{eq4}, \mathbf{C}_{avg}\} \quad (39)$$

(1) Exploration stage ($\tau < 1/3$)

In the early stage, individuals perform wide-range exploration:

$$\mathbf{C}_i^{t+1} = \mathbf{C}_i^t + r_1(\mathbf{V}_j - \mathbf{C}_k) \quad (40)$$

where $\mathbf{V}_j \in V$ and $\mathbf{C}_k$ is a randomly selected individual and r_1 is a random number uniformly distributed in the range $[0, 1]$;

(2) Transition stage ($1/3 \leq \tau < 2/3$)

In the middle stage, individuals gradually move toward promising regions:

$$\mathbf{C}_i^{t+1} = \mathbf{C}_i^t + r_2(\mathbf{V}_j - \mathbf{C}_i^t) + \gamma r_3(\mathbf{C}_{eq1} - \mathbf{C}_i^t) \quad (41)$$

where $\gamma = 0.5$ is a weighting factor and r_2 and r_3 are random numbers uniformly distributed in the range $[0, 1]$.

(3) Exploitation stage ($\tau \geq 2/3$)

In the final stage, individuals focus on refining the best solution:

$$\mathbf{C}_i^{t+1} = \mathbf{C}_{eq1} + \alpha(\mathbf{C}_{eq1} - \mathbf{C}_i^t) + \beta \cdot \mathcal{N}(0, 1)(ub - lb) \quad (42)$$

where $\alpha = 0.6(1 - \tau)$, $\beta = 0.05(1 - \tau)$, and $\mathcal{N}(0, 1)$ is a standard Gaussian normal distribution random variable.

This strategy introduces a stage-wise adaptive search mechanism that dynamically balances exploration and exploitation. It enhances global exploration in the early stage, improves convergence guidance in the middle stage, and strengthens local exploitation in the final stage. Consequently, the algorithm achieves better convergence performance and higher solution accuracy when solving complex optimization problems.

Based on the above discussion, the pseudocode for RTM-IEO is presented in Algorithm 1, and the flowchart is shown in Figure 1.

Algorithm 1. Pseudo-Code of RTM-IEO.

Input: $N, T, lb, ub, d, f(\cdot)$.

Output: best solution $\mathbf{C}_{eq1}$, best fitness $f(\mathbf{C}_{eq1})$.

1: Initialize population $\mathbf{C}$ within $[lb, ub]$ and evaluate fitness.

2: Determine $\mathbf{C}_{eq1}, \mathbf{C}_{eq2}, \mathbf{C}_{eq3}, \mathbf{C}_{eq4}$.

3: **while** $t = 1 : T$ **do**

4: Construct equilibrium pool $\mathcal{V}$.

5: Update particles using EO rule (Equations (28)–(31)).

6: Compute $\tau = t/T$.

7: **for** $i = 1 : N$

8: Select $\mathbf{V}_j$ and $\mathbf{C}_k$

9: **if** $\tau < 1/3$

10: Update by exploration strategy (Equation (40)).

11: **else if** $\tau < 2/3$

12: Update by aggregation strategy (Equation (41)).

13: **else**

14: Update by aggregation strategy (Equation (42)).

15: **end if**

16: Apply greedy selection.

17: **end for**

18: Perform lens opposition learning (Equations (32)–(34)).

19: Perform elite-guided elimination (Equations (35)–(37)).

20: Update equilibrium candidates and record best fitness.

21: **end while**

22: Return the global best solution X_{best} and its fitness f_{best} .

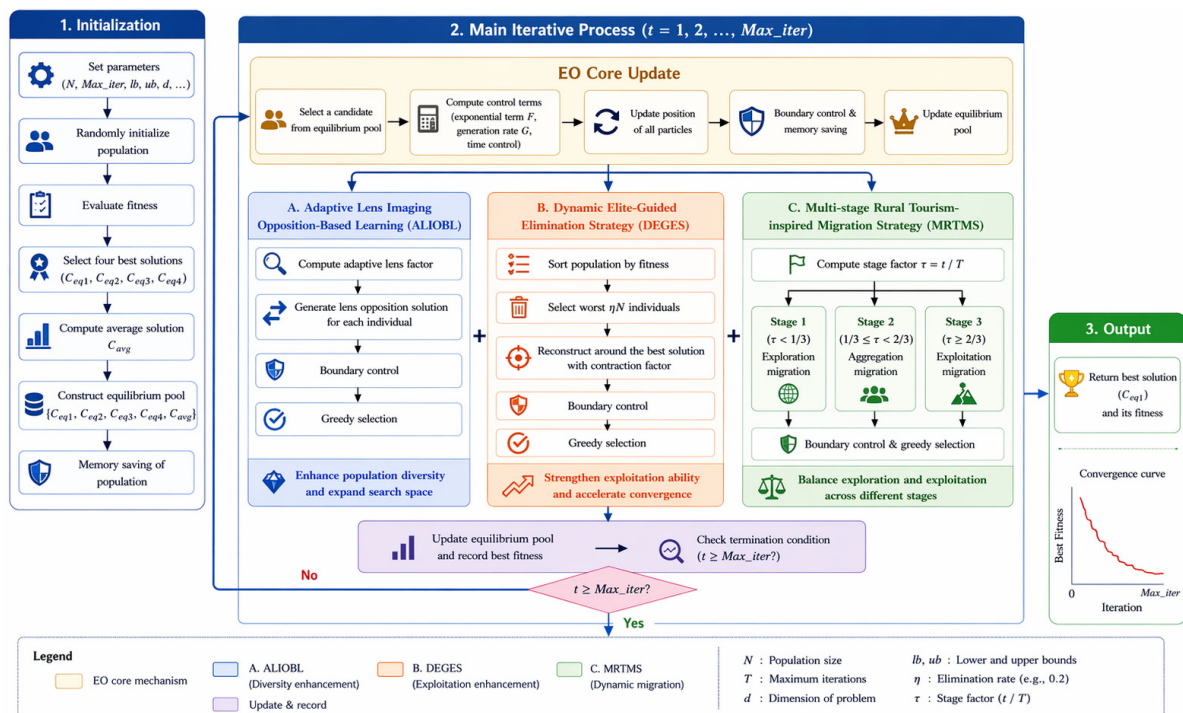


Figure 1. The flowchart of RTM-IEO.

3.3. Cooperation Mechanism of the Three Strategies

The three improvement strategies in RTM-IEO are not simply superimposed but are designed to play complementary roles at different levels of the search process. ALIOBL mainly acts as a diversity enhancement operator, DEGES mainly acts as an exploitation reinforcement operator, and MRTMS mainly acts as a stage-adaptive search regulation operator. Their cooperation mechanism can be explained as follows.

First, ALIOBL expands the search space by generating lens opposition solutions. This strategy increases the probability of discovering unexplored promising regions and prevents the population from losing diversity too early. Therefore, it mainly supports global exploration.

Second, MRTMS regulates the search behavior according to the normalized iteration progress. In the early stage, individuals perform wide-range exploration; in the middle stage, the search gradually moves toward promising regions; and in the final stage, local refinement around elite solutions is strengthened. Therefore, MRTMS provides a time-dependent framework that determines the dominant search mode at each optimization stage.

Third, DEGES is applied after the main update process to reconstruct inferior individuals using elite information. This mechanism does not replace the exploration process but selectively improves low-quality solutions after population evolution. The time-varying contraction factor in DEGES further ensures that the reconstruction range is larger in the early stage and smaller in the later stage, which is consistent with the exploration-to-exploitation transition.

To avoid conflicts among different strategies, greedy selection is used after each candidate solution generation step. Therefore, a newly generated individual is accepted only when it improves the current fitness:

$$C_i = \begin{cases} C_i^{t+1}, & f(C_i^{t+1}) < f(C_i^t) \\ C_i^t, & \text{otherwise} \end{cases} \quad (43)$$

This acceptance rule guarantees that different strategies cooperate under the same optimization objective and prevents low-quality candidate solutions from degrading the population. Consequently, ALIOBL improves diversity, MRTMS controls the global-to-local transition, and DEGES accelerates convergence, forming a coordinated search framework for complex constrained optimization problems.

4. CEC Basic Benchmark Function Experiment

4.1. Configuration of Compared Methods and Parameter Settings

This part investigates the effectiveness of the introduced RTM-IEO approach by employing two widely recognized and demanding numerical optimization test suites, namely CEC2021 and CEC2022. A comparative study is carried out against a set of well-known optimization techniques. These include traditional methods such as Modified Particle Swarm Optimization (MPSO) [32], an Enhanced Grey Wolf Optimizer with a Velocity-Aided Global Search Mechanism (VAGWO) [33], Improved Whale Optimization Algorithm (IWOA) [34], and Multi-strategy and Self-adaptive Differential Sine-Cosine Algorithm (sdSCA) [35]. In addition, several recently developed high-efficiency algorithms are also considered, including the Secretary Bird Optimization Algorithm (SBOA) [19], Farthest better or Nearest worse Optimizer (FNO) [36], Artificial Lemming Algorithm (ALA) [37], and Gekko Japonicus Algorithm (GJA) [38], as well as the conventional Equilibrium Optimizer (EO) [24]. The specific parameter configurations for all compared approaches are summarized in Table 1.

Table 1. Detailed parameter specifications of the benchmark algorithms.

Algorithms	Parameter Description	Assigned Values
MPSO	$w_{ub}, w_{lb}, S, c_1, c_2$	0.99, 0.2, 0.15, 2, 2
VAGWO	a, c, k	$\left\lfloor \sqrt{2}, 0 \right\rfloor, [1, 0], [0.9, 0.4]$
IWOA	r, l, a	$[0, 1], [-1, 1]$, Linear reduction from 2 to 1
sdSCA	a, F, CR	2, 0.8, 0.95
SBOA	CF, K, RB	$[0, 1], \{1, 2\}, [0, 1]$
FNO	μ, α	$[0, 1], [0, 1]$
ALA	$Prob$	0.3
GJA	β_s, β_e	1.2, 0.3
EO	λ, a_1	$\{0.5, 0.05\}, 2$

To ensure the reliability of the experimental outcomes and reduce the impact of randomness, uniform evaluation settings were adopted. Specifically, each algorithm was executed with a population size of 30 individuals and a maximum iteration count of 500 and was independently run 30 times. The results were assessed based on statistical indicators, including the average performance (Mean) and dispersion measure (Standard Deviation), with the best-performing outcomes highlighted in bold for clarity.

The experimental evaluations were executed on a system configured with an AMD Ryzen 7 5800H processor (base frequency of 3.2 GHz) and 32 GB RAM. MATLAB 2024b was utilized for both implementation and performance analysis.

4.2. Numerical Experiments on CEC2021 Benchmark Problems

To comprehensively validate the effectiveness and robustness of the proposed RTM-IEO algorithm in solving complex numerical optimization problems, this section adopts the CEC2021 benchmark function suite as the experimental platform. The CEC2021 test suite encompasses a variety of optimization problem types, including unimodal, multimodal, hybrid, and composite functions, thereby enabling a systematic evaluation of the algorithm's

global exploration capability, local exploitation ability, and its capacity to escape from local optima.

Comparative experiments are conducted under two different dimensional settings, namely 10 and 20 dimensions, to further analyze the algorithm's performance across varying levels of problem complexity. The statistical outcomes, including average fitness (Ave) and standard deviation (Std), for RTM-IEO and nine reference algorithms on the CEC2021 benchmark suite (10- and 20-dimensional cases) are summarized in Tables 2 and 3. Meanwhile, Figure 2 presents the convergence behaviors of several typical functions. Overall, the results demonstrate that RTM-IEO achieves strong performance in both optimization precision and convergence dynamics.

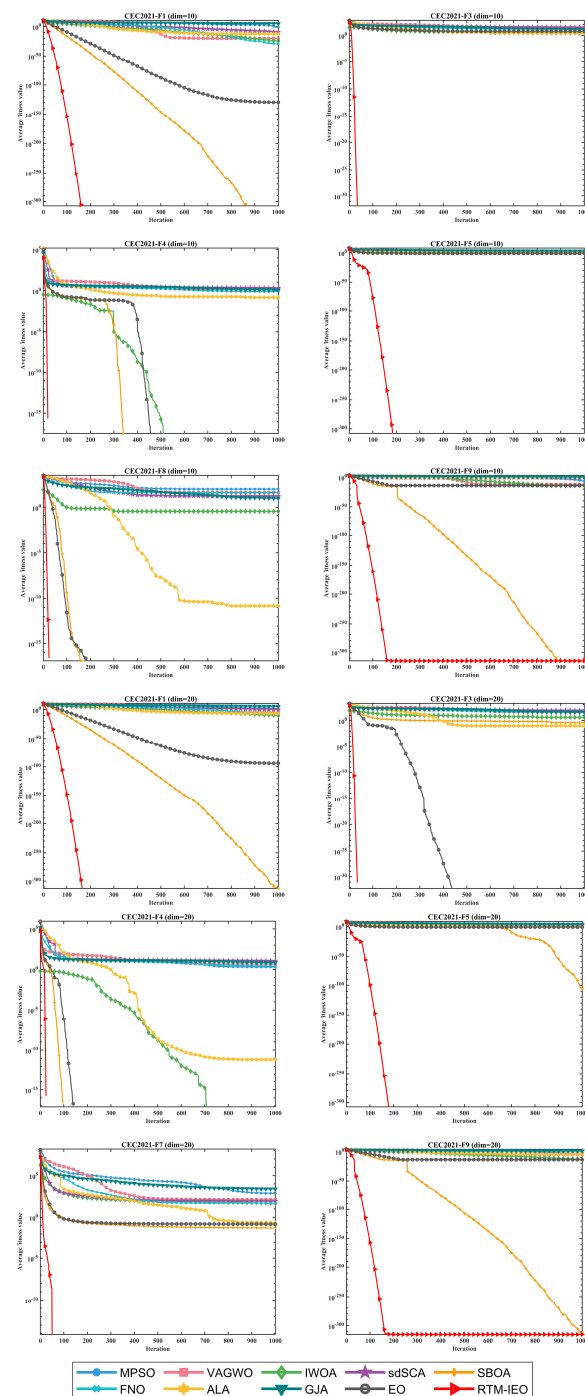


Figure 2. Convergence curves of different algorithms on the CEC2021 benchmark functions (partial).

Table 2. Numerical evaluation results on CEC2021 problems with dimensionality of 10.

Function	Metric	MPSO	VAGWO	IWOA	sdSCA	SBOA	FNO	ALA	GJA	EO	RTM-IEO
F1	Ave	6.0186E-02	7.1746E-21	3.2398E-25	7.3822E-10	0.0000E+00	2.1352E-30	4.0260E-13	5.6176E+04	4.6278E-130	0.0000E+00
	Std	1.9082E-01	2.6195E-20	6.9006E-25	4.0434E-09	0.0000E+00	7.4189E-30	2.0054E-12	1.6146E+04	2.5189E-129	0.0000E+00
F2	Ave	4.0057E+02	1.9922E+02	1.0539E-01	3.3560E+02	9.9809E-01	1.8768E+01	4.9344E-01	5.2193E+01	3.5392E-02	0.0000E+00
	Std	2.4656E+02	1.6910E+02	2.1007E-01	3.4900E+02	2.0607E+00	4.1600E+01	1.7622E+00	8.0320E+01	7.4592E-02	0.0000E+00
F3	Ave	1.4458E+01	2.4369E+01	2.7641E+00	2.8864E+01	3.3073E+00	1.4377E+01	2.8371E+00	1.2498E+01	5.7261E+00	0.0000E+00
	Std	8.6543E+00	1.7581E+01	5.4040E+00	1.2086E+01	6.1384E+00	4.5469E+00	6.8776E+00	4.9344E+00	8.3094E+00	0.0000E+00
F4	Ave	8.1131E-01	1.3747E+00	0.0000E+00	2.1030E+00	0.0000E+00	7.7599E-01	1.4615E-01	1.2355E+00	0.0000E+00	0.0000E+00
	Std	2.6957E-01	8.9283E-01	0.0000E+00	6.3815E-01	0.0000E+00	2.8471E-01	3.8965E-01	4.3574E-01	0.0000E+00	0.0000E+00
F5	Ave	4.1476E+02	9.4988E+01	3.1163E+01	1.1790E+01	1.6194E-01	2.5552E+01	2.1973E+00	5.6019E+02	6.7856E-02	0.0000E+00
	Std	2.7290E+02	8.9646E+01	6.5969E+01	3.7071E+01	4.5456E-01	5.7057E+01	5.0152E+00	2.5862E+02	2.6152E-01	0.0000E+00
F6	Ave	8.8646E+00	3.3354E+01	3.4680E-01	2.2479E+00	3.4877E-01	1.6173E+00	1.1885E+00	1.3803E+01	4.3034E-01	0.0000E+00
	Std	2.1705E+01	5.0711E+01	4.8785E-01	3.8748E+00	3.9632E-01	1.9949E+00	3.8414E+00	3.6027E+01	8.9875E-01	0.0000E+00
F7	Ave	2.9316E+02	5.0362E+01	9.2253E+00	5.4218E+00	8.9891E-02	7.2197E-01	1.3035E-01	1.8347E+02	9.6673E-02	0.0000E+00
	Std	2.1095E+02	6.5612E+01	2.2384E+01	2.1840E+01	2.7165E-01	3.2365E-01	2.8285E-01	1.4715E+02	2.5596E-01	0.0000E+00
F8	Ave	9.1852E+01	3.9666E+01	3.6915E-01	1.6141E+01	0.0000E+00	3.8877E+01	1.4977E-11	9.2659E+00	0.0000E+00	0.0000E+00
	Std	1.6139E+02	7.3556E+01	2.0219E+00	1.9058E+01	0.0000E+00	3.3897E+01	4.6799E-11	7.4916E+00	0.0000E+00	0.0000E+00
F9	Ave	2.8820E-07	5.3380E-13	4.7370E-15	3.5930E-01	0.0000E+00	1.0913E+00	6.7574E-01	3.0614E+00	6.8094E-15	0.0000E+00
	Std	1.7221E-07	2.1539E-12	5.0746E-15	1.3693E+00	0.0000E+00	2.0369E+00	1.7598E+00	1.2066E+00	3.8208E-15	0.0000E+00
F10	Ave	4.8377E+01	4.8952E+01	2.5872E-03	4.9150E+01	3.2227E+01	5.0175E+01	2.6559E-01	5.0127E+01	4.2885E+01	0.0000E+00
	Std	2.7735E-01	5.2900E-01	1.8401E-03	3.4856E-01	2.3178E+01	6.3958E+00	4.0581E-01	1.9540E+01	2.0789E+01	0.0000E+00

Table 3. Numerical evaluation results on CEC2021 problems with dimensionality of 20.

Function	Metric	MPSO	VAGWO	IWOA	sdSCA	SBOA	FNO	ALA	GJA	EO	RTM-IEO
F1	Ave	2.8555E+01	2.0728E-05	9.1411E-11	1.4568E+00	0.0000E+00	8.7919E-07	4.7780E-07	3.9626E+05	1.1221E-94	0.0000E+00
	Std	1.2718E+02	5.5407E-05	2.9294E-10	7.9144E+00	0.0000E+00	4.2782E-06	1.0955E-06	8.8957E+04	4.8056E-94	0.0000E+00
F2	Ave	1.2074E+03	9.0829E+02	6.0895E+00	1.9926E+03	8.1444E+00	5.7541E+02	2.3199E-02	9.7055E+01	7.2866E-03	0.0000E+00
	Std	5.5726E+02	5.2491E+02	3.2500E+01	1.2679E+03	3.0740E+01	3.1562E+02	1.0196E-01	1.0305E+02	1.7748E-02	0.0000E+00
F3	Ave	3.9100E+01	5.0251E+01	4.0671E+00	7.5877E+01	3.9823E-01	4.6112E+01	9.9498E-02	3.5412E+01	0.0000E+00	0.0000E+00
	Std	1.8259E+01	3.8418E+01	8.3005E+00	3.7712E+01	1.5377E+00	1.2326E+01	3.0360E-01	8.9644E+00	0.0000E+00	0.0000E+00
F4	Ave	2.0135E+00	4.5667E+00	0.0000E+00	1.1560E+01	0.0000E+00	2.6181E+00	6.8567E-12	6.7805E+00	0.0000E+00	0.0000E+00
	Std	7.1282E-01	3.2947E+00	0.0000E+00	8.6255E+00	0.0000E+00	9.0417E-01	2.0168E-11	2.1968E+00	0.0000E+00	0.0000E+00
F5	Ave	9.7509E+02	2.5795E+02	7.8695E+01	4.0353E+02	4.6477E-107	1.1229E+02	1.7593E+00	4.9621E+03	9.0617E-02	0.0000E+00
	Std	3.8147E+02	1.9244E+02	1.4142E+02	3.9705E+02	2.5457E-106	1.1759E+02	8.8535E+00	1.7860E+03	4.0091E-01	0.0000E+00
F6	Ave	7.8323E+01	1.4075E+02	4.5617E-01	3.4787E+01	1.2125E+00	8.1961E+00	8.0733E-01	2.3188E+01	3.8916E-01	1.3693E-16
	Std	1.3483E+02	1.1105E+02	1.0308E+00	6.3853E+01	3.3767E+00	2.9599E+00	3.1861E+00	3.7060E+01	6.4135E-01	1.0383E-16
F7	Ave	7.3668E+02	1.2996E+02	4.7556E+01	8.6655E+01	5.2065E-02	5.1176E+01	2.1046E-01	2.4937E+03	1.5139E-01	6.2913E-17
	Std	3.3710E+02	1.0857E+02	1.2054E+02	1.5413E+02	1.2202E-01	9.1861E+01	4.6082E-01	1.0130E+03	2.7095E-01	9.9657E-17
F8	Ave	2.0811E+02	9.5649E+01	4.1029E-15	2.3366E+02	0.0000E+00	1.5976E+02	1.1399E-07	4.9477E+01	0.0000E+00	0.0000E+00
	Std	1.7685E+02	6.3394E+01	7.9157E-15	1.6227E+02	0.0000E+00	1.0852E+02	4.8112E-07	1.7966E+01	0.0000E+00	0.0000E+00
F9	Ave	1.1330E-05	7.5504E-06	4.0856E-14	3.6599E+00	0.0000E+00	1.2100E+00	3.5653E-05	6.5041E+00	8.8818E-15	0.0000E+00
	Std	6.2366E-06	7.9409E-06	1.4048E-13	7.0823E+00	0.0000E+00	1.7721E+00	3.5405E-05	1.2542E+00	0.0000E+00	0.0000E+00
F10	Ave	4.9553E+01	5.4871E+01	4.3212E-03	6.0070E+01	3.3074E+01	6.6353E+01	3.0888E-01	7.2260E+01	3.9804E+01	0.0000E+00
	Std	4.6532E-01	1.1263E+01	2.3231E-03	1.3100E+01	3.7125E+01	1.4303E+01	1.9462E-01	1.6390E+01	3.9609E+01	0.0000E+00

From a local perspective, RTM-IEO achieves optimal optimization results on the vast majority of benchmark functions. Under the 10-dimensional setting (Table 2), RTM-IEO attains the theoretical optimum value of 0 on all ten functions (F1–F10), with a standard deviation of 0 in every case, indicating that the algorithm consistently converges to the global optimum across all 30 independent runs. In contrast, the best-performing comparative algorithms, SBOA and EO, can only achieve the optimal value on a subset of functions (e.g., F1, F4, F8, and F9), while exhibiting noticeable deviations on functions such as F2, F3, F5, F6, F7, and F10. For example, on function F2, the average values of SBOA and EO are 9.9809×10^{-1} and 3.5392×10^{-2} , respectively, whereas RTM-IEO achieves 0.0000×10^0 . Similarly, on function F5, EO—the second-best performer—obtains an average value of 6.7856×10^{-2} , while RTM-IEO again reaches the optimal value of 0. These results clearly demonstrate the significant advantage of RTM-IEO in handling optimization problems with diverse characteristics.

Under the 20-dimensional setting (Table 3), as the dimensionality increases, the difficulty of all optimization problems rises to varying degrees. Nevertheless, RTM-IEO continues to exhibit outstanding optimization performance. It achieves the optimal value of 0 on six functions (F1, F2, F5, F8, F9, and F10). On functions F3 and F4, RTM-IEO attains the optimal value alongside EO and SBOA. Although it does not reach zero on F6 and F7, RTM-IEO yields extremely competitive results of 1.3693×10^{-16} and 6.2913×10^{-17} , respectively, which are significantly superior to those of all other comparative algorithms. Notably, on function F6, the second-best algorithm (IWOA) achieves an average value of 4.5617×10^{-1} , which differs from RTM-IEO by approximately 15 orders of magnitude. Similarly, on function F7, the second-best algorithm (SBOA) yields an average value of 5.2065×10^{-2} , also about 15 orders of magnitude worse than RTM-IEO. Such large differences in magnitude highlight the strong search capability and high convergence accuracy of RTM-IEO in high-dimensional complex optimization problems.

From an overall perspective, RTM-IEO demonstrates significantly superior comprehensive performance across all benchmark functions compared to the other nine algorithms. In the 10-dimensional case, RTM-IEO is the only algorithm that achieves the theoretical optimum on all ten functions. In the 20-dimensional case, it also obtains the best average fitness values across all ten functions, with standard deviations that are the smallest or close to the smallest, indicating not only high convergence accuracy but also strong robustness and stability. Among the comparative algorithms, SBOA and EO perform relatively well on certain functions; however, they still exhibit clear performance gaps compared to RTM-IEO on functions such as F2, F5, F6, F7, and F10. In contrast, algorithms such as MPSO, VAGWO, and GJA perform poorly on most functions, with some even showing substantial numerical deviations (e.g., GJA on F1 and F5).

The convergence curves shown in Figure 2 further corroborate these findings from a dynamic evolution perspective. In terms of convergence speed, RTM-IEO exhibits the fastest descent trend across all presented functions. For example, on functions F1 and F2, the convergence curves of RTM-IEO rapidly decrease from the initial fitness values to approximately 10^{-15} to 10^0 within the first 50 to 100 iterations, whereas comparative algorithms such as EO and SBOA require more iterations to reach similar levels. Some algorithms, such as MPSO and VAGWO, fail to approach the final performance level of RTM-IEO throughout the entire optimization process. On more challenging functions such as F5 and F6, RTM-IEO maintains a continuous downward trend even in the mid-iterations, while the curves of other algorithms generally become flat or stagnate prematurely. For instance, the curve of SBOA on function F5 tends to plateau in the middle and later stages, failing to further approach the optimum.

In terms of convergence accuracy, the final fitness values achieved by RTM-IEO are consistently lower than or equal to those of other algorithms across all functions. On functions such as F1, F2, F5, F8, F9, and F10, the convergence curves ultimately stabilize at levels significantly below those of the comparative algorithms, which is fully consistent with the results reported in Tables 2 and 3, where RTM-IEO achieves either exact zero or extremely small values on the order of 10^{-16} . In terms of convergence stability, the curves of RTM-IEO exhibit low fluctuations and smooth descent trajectories across all functions, indicating a stable progression toward the optimal solution during the optimization process. In contrast, algorithms such as VAGWO and GJA display pronounced oscillatory (zigzag) behaviors on multiple functions. For example, on functions F2 and F10, their fitness values frequently rebound in the later iterations, reflecting unstable search behavior. The three key characteristics demonstrated by the convergence curves—fast convergence, high accuracy, and stable search—are consistent with the statistical results in Tables 2 and 3, jointly validating the effectiveness and superiority of RTM-IEO.

Based on the above analysis, it can be concluded that the proposed RTM-IEO algorithm effectively balances global exploration and local exploitation by incorporating an adaptive lens imaging opposition-based learning strategy, a dynamic elite-guided elimination strategy, and a multi-stage rural tourism-inspired heuristic migration strategy into the standard EO framework. These enhancements significantly improve convergence accuracy, convergence speed, and robustness. The experimental results on the CEC2021 benchmark suite fully verify the superior performance of RTM-IEO in solving complex optimization problems across different dimensions and problem types.

4.3. Numerical Experiments on CEC2022 Benchmark Problems

To further verify the generality and stability of the RTM-IEO algorithm in solving complex optimization problems of different types and dimensions, and to avoid the contingency of conclusions drawn solely from the CEC2021 test suite, this study further employs the CEC2022 benchmark function suite for comparative experiments. The CEC2022 test suite contains a greater number of highly complex, multimodal, and hybrid optimization problems, placing higher demands on an algorithm's global exploration capability, local exploitation accuracy, and resistance to premature convergence. Therefore, under both 10-dimensional and 20-dimensional settings, RTM-IEO is comprehensively compared with nine other algorithms. Using the average fitness value and standard deviation as the core evaluation metrics, together with convergence curves, the overall optimization performance of the proposed algorithm is validated from both numerical results and iterative dynamic behavior.

Tables 4 and 5 present the optimization results of the ten algorithms on the CEC2022 benchmark suite in 10 and 20 dimensions, respectively, including the average fitness values (Ave) and standard deviations (Std) obtained from 30 independent runs of each algorithm. Figure 3 illustrates the convergence curves of several representative functions. Compared with CEC2021, the CEC2022 benchmark suite introduces adjustments in problem structure and complexity, incorporating more optimization problems with complex interactions and ill-conditioned landscapes. As such, it can further evaluate the generalization capability and adaptability of the algorithms across different categories of benchmark functions. The following analysis discusses the experimental results in detail from both local and global perspectives.

Table 4. Numerical evaluation results on CEC2022 problems with dimensionality of 10.

Function	Metric	MPSO	VAGWO	IWOA	sdSCA	SBOA	FNO	ALA	GJA	EO	RTM-IEO
F1	Ave	3.0000E+02	3.0444E+02	3.0037E+02	3.0000E+02	3.0000E+02	3.0000E+02	3.0000E+02	3.0014E+02	3.0000E+02	3.0000E+02
	Std	1.6243E-10	9.1624E+00	1.0549E+00	4.8372E-14	3.2530E-09	1.0515E-12	5.1611E-06	4.1358E-02	5.0603E-03	7.0449E-06
F2	Ave	4.0615E+02	4.1113E+02	4.1034E+02	4.0513E+02	4.0705E+02	4.0237E+02	4.0615E+02	4.1262E+02	4.0560E+02	4.0107E+02
	Std	1.7883E+01	1.3293E+01	1.6965E+01	3.2567E+00	1.2634E+01	3.3783E+00	3.8868E+00	2.3661E+01	3.8039E+00	2.2101E+00
F3	Ave	6.0503E+02	6.0013E+02	6.0916E+02	6.0009E+02	6.0000E+02	6.0012E+02	6.0007E+02	6.0088E+02	6.0000E+02	6.0000E+02
	Std	5.5110E+00	3.9613E-01	8.8628E+00	2.6362E-01	1.4667E-04	2.2695E-01	2.9467E-01	8.4972E-01	9.5793E-04	1.1369E-13
F4	Ave	8.1519E+02	8.2423E+02	8.3307E+02	8.1110E+02	8.1038E+02	8.0796E+02	8.1778E+02	8.1440E+02	8.1045E+02	8.0733E+02
	Std	7.2877E+00	1.1346E+01	1.1692E+01	7.1905E+00	5.8466E+00	3.6393E+00	7.7499E+00	5.9049E+00	4.6977E+00	2.7957E+00
F5	Ave	9.0000E+02	9.0035E+02	1.0883E+03	9.0027E+02	9.0004E+02	9.0062E+02	9.0198E+02	9.0039E+02	9.0051E+02	9.0000E+02
	Std	1.6346E-02	4.4753E-01	1.3098E+02	4.6513E-01	1.4013E-01	1.2116E+00	4.6831E+00	6.9990E-01	1.0211E+00	1.1759E-10
F6	Ave	2.9110E+03	5.7503E+03	2.5792E+03	1.8031E+03	3.7266E+03	2.8867E+03	2.6528E+03	4.3856E+03	5.0718E+03	1.8738E+03
	Std	1.0985E+03	2.7521E+03	1.3354E+03	4.4859E+00	1.7560E+03	1.3252E+03	1.8878E+03	1.9736E+03	2.3180E+03	1.4747E+02
F7	Ave	2.0302E+03	2.0587E+03	2.0289E+03	2.0154E+03	2.0083E+03	2.0160E+03	2.0299E+03	2.0219E+03	2.0186E+03	2.0000E+03
	Std	1.1660E+01	6.7477E+01	1.2088E+01	8.6828E+00	9.4873E+00	9.8144E+00	3.2791E+01	2.4663E+01	6.9722E+00	4.4418E-03
F8	Ave	2.2248E+03	2.2592E+03	2.2245E+03	2.2115E+03	2.2166E+03	2.2162E+03	2.2213E+03	2.2532E+03	2.2189E+03	2.2075E+03
	Std	2.2637E+01	5.5923E+01	6.4049E+00	9.8788E+00	8.3965E+00	8.9744E+00	5.6806E+00	5.2561E+01	7.4718E+00	9.7054E+00
F9	Ave	2.5293E+03	2.5343E+03	2.5293E+03	2.5293E+03	2.5293E+03	2.5293E+03	2.5293E+03	2.5293E+03	2.5293E+03	2.5293E+03
	Std	8.9622E-10	2.6800E+01	5.4160E-03	0.0000E+00	2.3885E-13	7.3579E-08	1.0151E-01	6.7746E-03	1.4626E-13	1.6889E-13
F10	Ave	2.5815E+03	2.5907E+03	2.5007E+03	2.5074E+03	2.5542E+03	2.5454E+03	2.6042E+03	2.5580E+03	2.5401E+03	2.5072E+03
	Std	5.1923E+01	1.1998E+02	1.8148E-01	2.6660E+01	5.4772E+01	5.6214E+01	2.3420E+02	6.2978E+01	5.8776E+01	2.6478E+01
F11	Ave	2.6933E+03	2.7554E+03	2.6969E+03	2.7302E+03	2.7051E+03	2.6833E+03	2.7201E+03	2.7070E+03	2.6934E+03	2.6400E+03
	Std	1.5960E+02	1.7065E+02	1.1752E+02	1.5293E+02	1.4644E+02	1.5094E+02	1.6590E+02	1.4027E+02	1.4066E+02	1.2205E+02
F12	Ave	2.9049E+03	2.8635E+03	2.8653E+03	2.8642E+03	2.8620E+03	2.8702E+03	2.8636E+03	2.8683E+03	2.8640E+03	2.8615E+03
	Std	4.4885E+01	1.2333E+00	2.7360E+00	1.9558E+00	1.8108E+00	6.2074E+00	2.0531E+00	1.1412E+01	1.1503E+00	1.9546E+00

Table 5. Numerical evaluation results on CEC2022 problems with dimensionality of 20.

Function	Metric	MPSO	VAGWO	IWOA	sdSCA	SBOA	FNO	ALA	GJA	EO	RTM-IEO
F1	Ave	5.3660E+02	4.8817E+02	4.1702E+03	4.2290E+02	5.4073E+02	1.0507E+03	1.3369E+03	7.1216E+02	1.8016E+03	3.0179E+02
	Std	2.8679E+02	1.2901E+02	2.2960E+03	2.6723E+02	2.3985E+02	8.7126E+02	9.2079E+02	3.3251E+02	1.2735E+03	5.7681E+00
F2	Ave	4.5996E+02	4.5122E+02	4.5472E+02	4.3141E+02	4.5546E+02	4.5337E+02	4.5988E+02	4.5781E+02	4.5704E+02	4.4169E+02
	Std	1.2782E+01	5.8097E+00	2.2987E+01	2.5432E+01	1.8936E+01	1.4362E+01	2.6375E+01	1.4584E+01	1.2939E+01	1.6278E+01
F3	Ave	6.3053E+02	6.0067E+02	6.4521E+02	6.0087E+02	6.0017E+02	6.0081E+02	6.0219E+02	6.0498E+02	6.0012E+02	6.0000E+02
	Std	1.1754E+01	6.2312E-01	1.3071E+01	1.1583E+00	2.5373E-01	8.6635E-01	1.6796E+00	3.4453E+00	2.2818E-01	8.1484E-08
F4	Ave	8.6315E+02	8.8301E+02	8.8661E+02	8.4839E+02	8.3391E+02	8.2866E+02	8.6330E+02	8.4878E+02	8.3766E+02	8.3248E+02
	Std	1.6876E+01	4.3203E+01	2.1538E+01	3.2692E+01	1.0418E+01	7.9799E+00	2.1092E+01	1.3030E+01	1.3541E+01	8.9039E+00
F5	Ave	1.4383E+03	9.0901E+02	2.3267E+03	9.5995E+02	9.3381E+02	9.2187E+02	1.2072E+03	9.2057E+02	9.1641E+02	9.0027E+02
	Std	4.0801E+02	8.7900E+00	4.0781E+02	8.8421E+01	8.8484E+01	2.4355E+01	3.0066E+02	1.8750E+01	4.7401E+01	7.6587E-01
F6	Ave	4.1445E+03	6.5219E+04	5.8848E+03	5.7716E+03	6.8536E+03	4.8002E+03	7.8864E+03	3.1927E+04	5.1964E+03	3.8164E+03
	Std	2.5005E+03	1.9814E+05	6.0715E+03	6.5360E+03	6.3095E+03	3.1494E+03	6.9574E+03	8.2511E+03	4.3418E+03	2.3658E+03
F7	Ave	2.1063E+03	2.1074E+03	2.1192E+03	2.0446E+03	2.0355E+03	2.0443E+03	2.0920E+03	2.0688E+03	2.0525E+03	2.0222E+03
	Std	2.8637E+01	7.6362E+01	3.9365E+01	2.7612E+01	1.0608E+01	1.3979E+01	4.4583E+01	3.4787E+01	3.3205E+01	4.2808E+00
F8	Ave	2.2375E+03	2.2724E+03	2.2391E+03	2.2294E+03	2.2299E+03	2.2296E+03	2.2392E+03	2.2677E+03	2.2363E+03	2.2208E+03
	Std	3.5551E+01	6.9849E+01	3.1460E+01	5.0915E+00	2.2697E+01	2.1430E+01	3.5203E+01	5.6888E+01	2.1991E+01	3.0530E-01
F9	Ave	2.4808E+03	2.4819E+03	2.4808E+03	2.4808E+03	2.4808E+03	2.4808E+03	2.4808E+03	2.4820E+03	2.4808E+03	2.4808E+03
	Std	1.3551E-02	1.6789E+00	2.8936E-02	1.0715E-12	2.7677E-07	9.2774E-04	4.0869E-03	1.0320E+00	5.2810E-04	9.4321E-02
F10	Ave	3.8837E+03	3.3892E+03	2.5130E+03	3.4969E+03	2.6038E+03	2.5318E+03	4.0126E+03	2.7671E+03	3.1249E+03	2.5057E+03
	Std	8.8774E+02	4.9192E+02	4.5360E+01	1.2172E+03	2.0549E+02	1.0256E+02	8.0393E+02	1.8079E+02	5.8714E+02	3.8562E+01
F11	Ave	2.9500E+03	3.0051E+03	2.9300E+03	2.9247E+03	2.9167E+03	2.9067E+03	2.9192E+03	2.9560E+03	2.9100E+03	2.9000E+03
	Std	5.0855E+01	1.2258E+02	4.6611E+01	4.2560E+01	7.4664E+01	6.9149E+01	9.5797E+01	3.8982E+01	3.0513E+01	1.1142E+02
F12	Ave	3.1494E+03	2.9545E+03	3.0323E+03	2.9686E+03	2.9441E+03	2.9785E+03	2.9859E+03	2.9762E+03	2.9502E+03	2.9421E+03
	Std	1.0108E+02	1.6586E+01	3.1292E+01	2.6437E+01	9.2888E+00	2.0050E+01	4.7721E+01	3.1416E+01	9.3644E+00	6.9797E+00

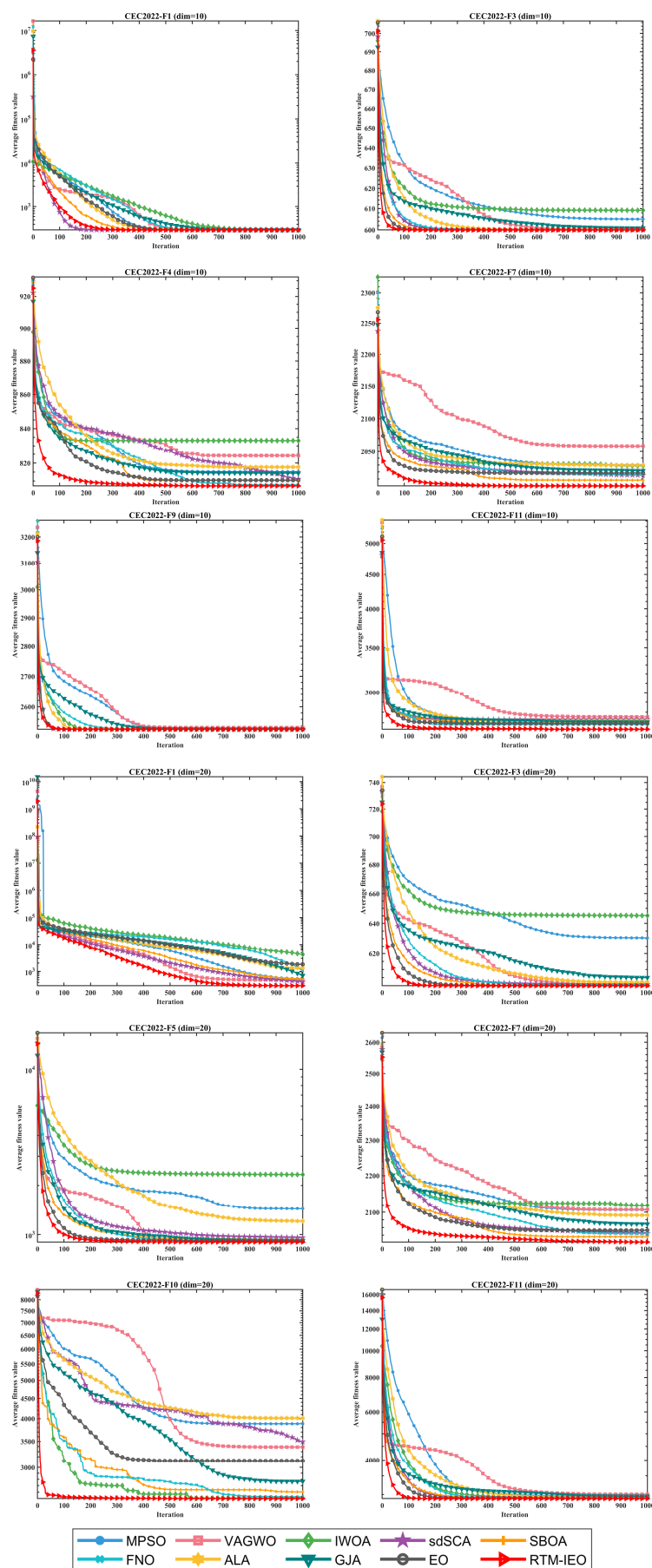


Figure 3. Convergence curves of different algorithms on the CEC2022 benchmark functions (partial).

From a local perspective, RTM-IEO continues to demonstrate excellent optimization performance on the CEC2022 benchmark suite. Under the 10-dimensional setting (Table 4), RTM-IEO achieves the best average fitness values on seven functions, namely F2, F3, F4, F5, F7, F11, and F12. Specifically, on function F3, RTM-IEO reaches the theoretical optimum value of 6.0000×10^2 , with a standard deviation of only 1.1369×10^{-13} , which is significantly better than EO (9.5793×10^{-4}) and SBOA (1.4667×10^{-4}). On function F5, RTM-IEO similarly attains the theoretical optimum value of 9.0000×10^2 , with a standard deviation of 1.1759×10^{-10} , whereas other algorithms such as MPSO (also 9.0000×10^2 but with a standard deviation of 1.6346×10^{-2}) and EO (9.0051×10^2) fail to achieve comparable precision. On function F7, RTM-IEO obtains the theoretical optimum value of 2.0000×10^3 with a standard deviation of only 4.4418×10^{-3} , significantly outperforming the second-best algorithm, sdSCA (2.0154×10^3). Notably, on functions F2 and F4, RTM-IEO also achieves the best results, reaching 4.0107×10^2 and 8.0733×10^2 , respectively, surpassing all other comparative algorithms. These results indicate that even on the more complex CEC2022 benchmark suite, RTM-IEO can still stably converge to the theoretical optimum or superior numerical solutions on multiple functions.

Under the 20-dimensional setting (Table 5), as the dimensionality increases, the difficulty of the optimization problems rises significantly. Nevertheless, RTM-IEO continues to exhibit outstanding optimization capability, achieving the best average fitness values on seven functions: F1, F3, F5, F7, F8, F10, and F12. For instance, on function F1, RTM-IEO achieves an average value of 3.0179×10^2 with a standard deviation of 5.7681×10^0 , which is substantially better than the second-ranked sdSCA (4.2290×10^2) and the worst-performing IWOA (4.1702×10^3). On function F3, RTM-IEO again reaches the theoretical optimum value of 6.0000×10^2 , with a standard deviation of 8.1484×10^{-8} , while EO (6.0012×10^2) and VAGWO (6.0067×10^2) fail to achieve the optimum. On function F5, RTM-IEO attains the best value of 9.0027×10^2 with a standard deviation of only 7.6587×10^{-1} , significantly outperforming EO (9.1641×10^2) and SBOA (9.3381×10^2). On function F7, RTM-IEO achieves an average value of 2.0222×10^3 with a standard deviation of 4.2808×10^0 , clearly outperforming all other algorithms, with the second-best SBOA reaching 2.0355×10^3 . On function F8, RTM-IEO obtains an average value of 2.2208×10^3 with an extremely low standard deviation of 3.0530×10^{-1} , demonstrating remarkable stability. Notably, on F8, the standard deviation of RTM-IEO is 2–4 orders of magnitude smaller than those of other algorithms, highlighting its robustness advantage in high-dimensional complex problems.

From an overall perspective, RTM-IEO also exhibits significantly superior comprehensive performance on the CEC2022 benchmark suite compared to the other nine algorithms. In the 10-dimensional setting, RTM-IEO achieves the best average fitness values on 7 out of 12 functions and maintains competitive performance on the remaining ones. In the 20-dimensional setting, it likewise attains the best results on 7 out of 12 functions. In contrast, SBOA achieves optimal results on only 3 and 2 functions under the 10-dimensional and 20-dimensional settings, respectively, while EO ranks jointly best only on F9 in the 10-dimensional case and fails to achieve the best performance on any function in the 20-dimensional case. In terms of average ranking, RTM-IEO ranks first in both dimensional settings, whereas other algorithms such as SBOA, sdSCA, and EO exhibit noticeable fluctuations across different dimensions, reflecting the strong dimensional robustness and problem adaptability of RTM-IEO.

The convergence curves shown in Figure 3 further validate these findings from a dynamic evolution perspective. In terms of convergence speed, RTM-IEO consistently exhibits the fastest descent trend across all presented functions. For example, on functions F2 and F3, the convergence curves of RTM-IEO rapidly decline and stabilize within the first 100 iterations, whereas comparative algorithms such as EO, SBOA, and IWOA require

more iterations to approach stability. Some algorithms, such as MPSO and VAGWO, show significantly slower convergence throughout the optimization process. On functions F5 and F7, RTM-IEO maintains a continuous and steady downward trend, while other algorithms often exhibit slow convergence or early stagnation. For instance, on function F5, the convergence curves of EO and SBOA continue to decrease slowly even after approximately 300 iterations but fail to reach the accuracy level of RTM-IEO. On function F7, the curves of sdSCA and FNO display clear plateaus in the middle and later stages, whereas RTM-IEO continues to descend toward lower fitness values.

In terms of convergence accuracy, the final fitness values achieved by RTM-IEO are consistently lower than or equal to those of other algorithms across all functions. On functions F2 and F4, the convergence curves ultimately stabilize at levels significantly lower than those of the comparative algorithms. On function F8, although the final fitness values of RTM-IEO are numerically close to those of some algorithms, its convergence curve is smoother and exhibits a much smaller standard deviation, indicating higher stability. In terms of convergence stability, the curves of RTM-IEO show low fluctuation and smooth descent trajectories across all functions. Particularly on functions F5, F7, and F8, the curves are almost monotonically decreasing, without noticeable rebounds in fitness values. In contrast, algorithms such as VAGWO, IWOA, and GJA exhibit pronounced zigzag fluctuations on multiple functions. For example, on functions F2 and F10, their fitness values frequently fluctuate in later iterations, indicating unstable search behavior. Additionally, it is worth noting that on function F3, although the convergence curves of all algorithms are similar in the initial stage, RTM-IEO demonstrates a faster descent from approximately the 50th iteration and is the first to reach the theoretical optimum, highlighting the effectiveness of the multi-stage strategy in balancing exploration and exploitation.

Based on the above analysis, it can be concluded that the proposed RTM-IEO algorithm also demonstrates excellent optimization performance on the CEC2022 benchmark suite. Under both 10-dimensional and 20-dimensional settings, RTM-IEO achieves optimal or near-optimal solutions on multiple functions and significantly outperforms the other nine comparative algorithms in terms of convergence speed, convergence accuracy, and search stability. The experimental results on CEC2022 further validate the strong generalization capability and robustness of RTM-IEO in solving optimization problems with diverse types and varying complexity, thereby providing a solid experimental foundation for its application in practical engineering problems.

4.4. Data Analysis and Statistical Assessment

To further validate the significance and reliability of the performance differences between RTM-IEO and the comparative algorithms from a statistical perspective, two non-parametric statistical methods are employed in this section: the Wilcoxon rank-sum test and the Friedman mean rank test [39–41]. Table 6 presents the results of the Wilcoxon signed-rank test between RTM-IEO and nine comparative algorithms on the CEC2021 and CEC2022 benchmark suites, where the statistical win–tie–loss relationships are recorded in the form of (win/tie/loss). Table 7 reports the Friedman mean rank (M.R.) and total rank (T.R.) results for all algorithms on the same benchmark suites. The experimental results are analyzed in detail from the following two perspectives.

Table 6. Results of statistical significance testing (p -values) for nine compared algorithms on CEC2021 and CEC2022 problems.

Algorithm	CEC2021-10 (+/-/-)	CEC2021-20 (+/-/-)	CEC2022-10 (+/-/-)	CEC2022-20 (+/-/-)
MPSO	(10/0/0)	(10/0/0)	(11/0/1)	(11/0/1)
VAGWO	(10/0/0)	(10/0/0)	(12/0/0)	(12/0/0)
IWOA	(10/0/0)	(10/0/0)	(12/0/0)	(11/0/1)
sdSCA	(10/0/0)	(10/0/0)	(9/0/3)	(9/0/3)
SBOA	(10/0/0)	(9/0/1)	(9/0/3)	8/0/4)
FNO	(10/0/0)	(10/0/0)	(10/0/2)	(10/0/2)
ALA	(10/0/0)	(10/0/0)	(9/1/2)	(12/0/0)
GJA	(10/0/0)	(10/0/0)	(12/0/0)	(12/0/0)
EO	(10/0/0)	(10/0/0)	(11/0/1)	(10/0/2)

Table 7. Results of Friedman mean rank testing for the compared algorithms on CEC2021 and CEC2022 problems.

Suites		CEC2021				CEC2022			
Dimensions		10		20		10		20	
Algorithms	M.R	T.R	M.R	T.R	M.R	T.R	M.R	T.R	
MPSO	8.50	9	7.70	7	6.58	7	7.33	7	
VAGWO	8.20	8	7.80	8	8.75	10	6.92	6	
IWOA	3.80	4	3.80	4	7.75	8	7.67	9	
sdSCA	6.80	6	8.20	9	3.08	2	3.75	3	
SBOA	2.50	2	2.50	2	3.42	3	3.42	2	
FNO	6.80	6	6.90	6	4.58	4	4.58	4	
ALA	5.00	5	4.90	5	6.00	6	7.42	8	
GJA	8.50	9	8.60	10	8.17	9	7.67	9	
EO	3.30	3	3.00	3	5.17	5	4.83	5	
RTM-IEO	1.60	1	1.60	1	1.50	1	1.42	1	

4.4.1. Nonparametric Wilcoxon Rank-Sum Method

As shown in Table 6, the Wilcoxon test results indicate that RTM-IEO exhibits overwhelming statistical superiority across all test scenarios. On the CEC2021 benchmark suite, under both 10-dimensional and 20-dimensional settings, RTM-IEO achieves a perfect record of 10 wins, 0 ties, and 0 losses against all nine comparative algorithms. This implies that, across all ten benchmark functions, the performance differences between RTM-IEO and MPSO, VAGWO, IWOA, sdSCA, SBOA, FNO, ALA, GJA, and EO are statistically significant ($p < 0.05$), with RTM-IEO consistently outperforming them. Notably, even when compared with SBOA and EO—two algorithms that perform relatively well in numerical experiments—RTM-IEO still achieves a 10:0 complete victory, demonstrating that its performance improvement is not coincidental but supported by strong statistical evidence.

On the CEC2022 benchmark suite, RTM-IEO also demonstrates significant statistical superiority. Under the 10-dimensional setting, RTM-IEO achieves a perfect record of 12 wins, 0 ties, and 0 losses against VAGWO, IWOA, and GJA. It achieves 11 wins, 0 ties, and 1 loss against MPSO, FNO, and EO; records 9 wins, 0 ties, and 3 losses against both sdSCA and SBOA; and 9 wins, 1 tie, and 2 losses against ALA. Under the 20-dimensional setting, RTM-IEO achieves 12 wins, 0 ties, and 0 losses against VAGWO, ALA, and GJA; 11 wins, 0 ties, and 1 loss against MPSO and IWOA; 10 wins, 0 ties, and 2 losses against FNO and EO; and 9 wins, 0 ties, and 3 losses and 8 wins, 0 ties, and 4 losses against sdSCA and SBOA, respectively. Although the number of wins for RTM-IEO on CEC2022 is slightly lower than that on CEC2021, it still maintains a clear advantage in the vast majority of comparisons.

The few ties or losses mainly occur when compared with sdSCA and SBOA, which can be attributed to the higher complexity of the CEC2022 benchmark, where these algorithms also exhibit strong competitiveness on certain functions. Nevertheless, in terms of overall win–loss ratios, RTM-IEO achieves a win rate of over or close to 70% across all comparisons and never falls behind any algorithm (i.e., the number of losses never exceeds the number of wins), fully confirming the statistical significance and stability of its performance advantage.

4.4.2. Friedman-Based Mean Rank Evaluation

Table 7 presents the detailed results of the Friedman mean rank test, which quantitatively evaluates the overall performance of each algorithm from a ranking perspective. On the CEC2021 benchmark suite, RTM-IEO achieves mean ranks of 1.60 under both 10-dimensional and 20-dimensional settings, ranking first among all ten algorithms. In comparison, the second-ranked algorithm, SBOA, obtains mean ranks of 2.50 in both settings, while the third-ranked EO achieves mean ranks of 3.30 and 3.00, respectively. The significantly lower mean rank of RTM-IEO indicates its superior overall performance on the CEC2021 benchmark. Notably, algorithms such as MPSO, VAGWO, and GJA exhibit relatively high mean ranks (ranging from 7.70 to 8.60), placing them at lower positions, which is consistent with their inferior numerical performance observed in Tables 2 and 3.

On the CEC2022 benchmark suite, RTM-IEO again achieves the best ranking results. Under the 10-dimensional setting, it attains a mean rank of 1.50 and ranks first overall; under the 20-dimensional setting, its mean rank further improves to 1.42, maintaining the top position. This indicates that RTM-IEO preserves its superior comprehensive performance even on the more complex CEC2022 benchmark. The second-ranked algorithms are sdSCA (mean rank 3.08) and SBOA (mean rank 3.42) under the 10-dimensional and 20-dimensional settings, respectively, while the third-ranked algorithms are SBOA and sdSCA. The gap in mean rank between RTM-IEO and the second-best algorithm reaches 1.58 and 2.00 under the 10-dimensional and 20-dimensional settings, respectively—significantly larger than the corresponding gaps on CEC2021 (0.90 and 0.90). This indicates that RTM-IEO exhibits an even more pronounced advantage on the more complex CEC2022 benchmark. This phenomenon suggests that the incorporation of the adaptive lens imaging opposition-based learning strategy, the dynamic elite-guided elimination mechanism, and the multi-stage rural tourism-inspired heuristic migration strategy enables RTM-IEO to more effectively enhance global exploration and avoid premature convergence in complex optimization scenarios.

From the perspective of dimensional variation, RTM-IEO demonstrates strong robustness. On the CEC2021 benchmark, its mean rank remains unchanged at 1.60 when moving from 10 to 20 dimensions. On the CEC2022 benchmark, its mean rank further improves from 1.50 to 1.42 as the dimensionality increases, reinforcing its leading position. In contrast, other algorithms exhibit varying degrees of rank fluctuation with increasing dimensionality. For example, IWOA ranks fourth on CEC2021 (mean rank 3.80) but drops to eighth (mean rank 7.75) and ninth (mean rank 7.67) on CEC2022. Similarly, ALA drops to eighth place (mean rank 7.42) under the 20-dimensional setting of CEC2022, compared to fifth place (mean rank 4.90) on CEC2021. Such differences in dimensional robustness further highlight the stability and adaptability of RTM-IEO when addressing optimization problems of varying scales.

Based on the combined statistical analyses in Tables 6 and 7, the following conclusions can be drawn: the Wilcoxon rank-sum test confirms the statistical significance of the performance differences between RTM-IEO and the comparative algorithms at the level of individual benchmark functions, demonstrating that RTM-IEO significantly outperforms other algorithms in most cases. Meanwhile, the Friedman mean rank test provides

a comprehensive evaluation of overall algorithm performance, showing that RTM-IEO consistently ranks first across all settings on both the CEC2021 and CEC2022 benchmark suites, with a clear margin over the second-ranked algorithms. Together, these two non-parametric statistical methods validate the significant superiority of RTM-IEO over the other nine comparative algorithms, providing strong statistical support for its application in practical engineering optimization problems.

5. Analysis of Economic Dispatch Results for the Microgrid

To comprehensively evaluate the practical performance of the RTM-IEO algorithm in the sustainable economic dispatch problem of a microgrid, this section considers a grid-connected microgrid system comprising photovoltaic units, wind turbines, micro gas turbines, fuel cells, battery energy storage, and interruptible loads, with a 24 h scheduling horizon adopted for optimization.

5.1. Experimental Setup

To verify the effectiveness of the proposed dispatch model and the RTM-IEO algorithm, a 24 h typical-day microgrid dispatch scenario is considered. The input data include hourly PV generation, wind power generation, load demand, and time-of-use electricity price. The dispatchable units and battery system are constrained by their rated output ranges, ramping limits, and state-of-charge boundaries.

Two dispatch modes are considered for comparison:

- (1) Conventional dispatch: A rule-based method is adopted as the baseline strategy. In this approach, renewable power is used with priority, the fuel cell provides relatively smooth base-load support, the micro gas turbine compensates for the residual net load, the battery performs peak shaving and valley filling, and interruptible loads are activated only when necessary.
- (2) RTM-IEO optimized dispatch: The proposed optimization model in Equation (30) is solved using RTM-IEO to obtain the optimal 24 h scheduling scheme.

In addition, to evaluate the optimization performance of RTM-IEO, several meta-heuristic algorithms are employed for comparison, including MPSO, VAGWO, IWOA, sdSCA, SBOA, FNO, ALA, GJA, EO, and RTM-IEO. For fair comparison, all algorithms are executed under the same experimental framework. The population size is set to 30, the maximum number of iterations is 1000, and each algorithm is independently run 30 times.

The evaluation metrics include mean fitness value, standard deviation, best fitness value, worst fitness value, average runtime, and average ranking. In addition, average convergence curves are used to analyze the dynamic search behavior of each algorithm. For the dispatch comparison, hourly power allocation curves, battery charge/discharge profiles, power balance figures, and operating cost curves are presented to illustrate the differences between conventional dispatch and optimized dispatch.

It is important to acknowledge that the entire dispatch optimization is performed using deterministic typical-day profiles for renewable generation, load demand, and electricity price. This widely adopted assumption in microgrid dispatch studies allows for a clear performance comparison of optimization algorithms under controlled conditions. However, it does not account for the real-time uncertainty and variability of wind and solar power, which may lead to deviations between the optimized schedule and actual system operation. In practice, forecast errors in renewable output can cause power imbalances, increased reliance on reserve units, or higher operating costs than predicted. Therefore, the superior cost reduction achieved by RTM-IEO under deterministic conditions represents an upper-bound performance. To assess the robustness of the proposed method under uncertainty,

future work will incorporate stochastic or robust optimization frameworks, e.g., scenario-based approaches or interval forecasting, as discussed in Section 6.

5.2. Comparative Analysis of Algorithm Optimization Performance

Table 8 presents the statistical results obtained from 30 independent runs of ten algorithms, including RTM-IEO, covering the mean, standard deviation, maximum value, minimum value, average rank, final rank, and average runtime. Figure 4 illustrates the average convergence curves of all algorithms. Figures 5 and 6 depict the power balance and the output allocation of the main components under the RTM-IEO-based optimal dispatch strategy, respectively. Figure 7 compares the hourly operating costs between the conventional dispatch strategy and the RTM-IEO-based optimal dispatch strategy, while Figure 8 further compares the output differences in each microgrid component under the two scheduling modes from the perspective of dispatch curves. The following analysis is conducted from two aspects: algorithmic performance comparison and dispatch scheme evaluation.

Table 8. Statistical results of different optimization algorithms for the microgrid dispatch problem.

Algorithm	Mean	Std	Max	Min	AvgRank	FinalRank	AvgRunTime/s
MPSO	6.4514E+06	5.9611E+06	3.3733E+07	2.6259E+06	9.33	10	4.96
VAGWO	3.0775E+06	8.9411E+05	5.8247E+06	1.9185E+06	7.33	7	4.50
IWOA	3.1713E+06	9.9413E+05	5.7384E+06	1.7288E+06	7.47	8	4.56
sdSCA	1.9184E+06	6.4573E+05	3.1384E+06	1.0009E+06	4.63	5	3.88
SBOA	1.6817E+06	3.7996E+05	2.8459E+06	1.0018E+06	3.87	3	7.71
FNO	1.8611E+06	4.9840E+05	3.2878E+06	1.2996E+06	4.30	4	4.45
ALA	3.0752E+06	7.3983E+05	4.5649E+06	1.8977E+06	7.30	6	4.19
GJA	1.1414E+06	1.1963E+05	1.3962E+06	9.1865E+05	2.17	2	4.29
EO	3.5036E+06	1.2920E+06	7.4401E+06	1.8894E+06	7.60	9	4.05
RTM-IEO	7.5037E+05	3.3639E+04	8.1826E+05	6.9631E+05	1.00	1	4.10

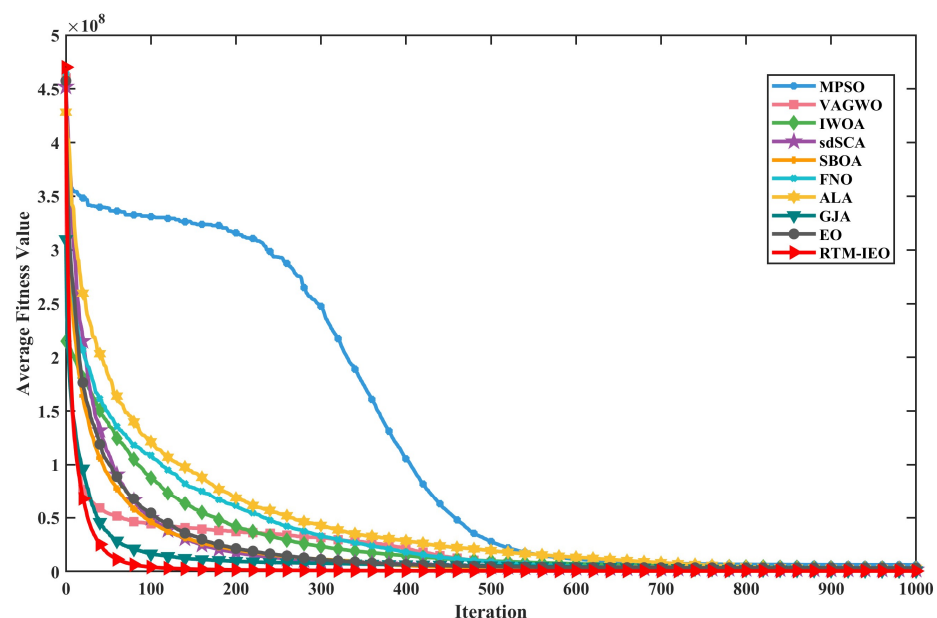


Figure 4. Average convergence curves of different algorithms.

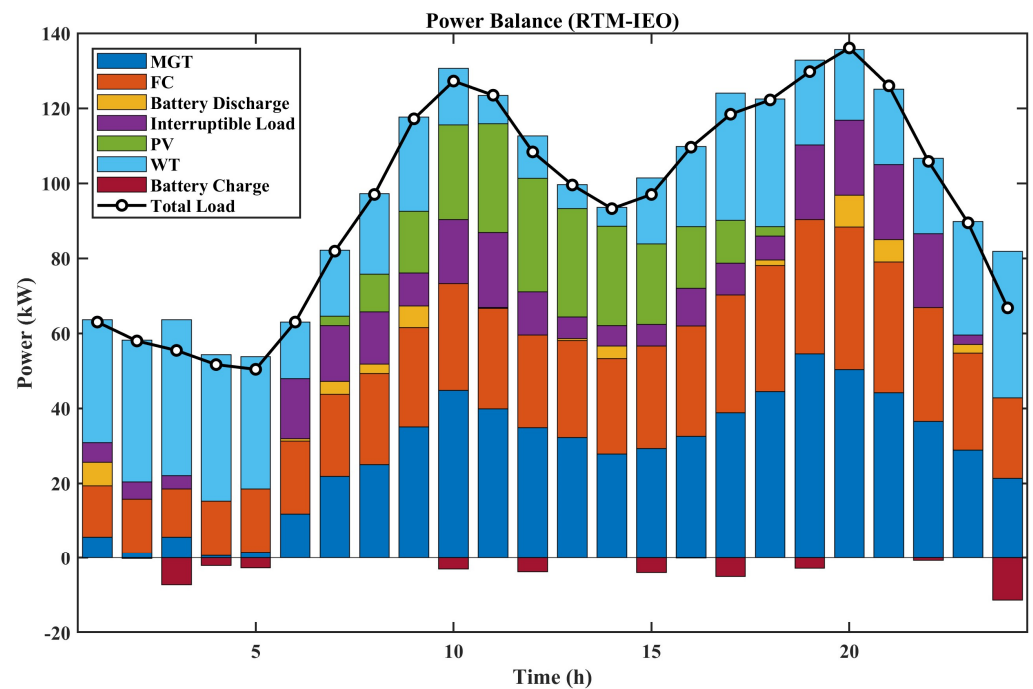


Figure 5. Power balance under RTM-IEO optimized dispatch.

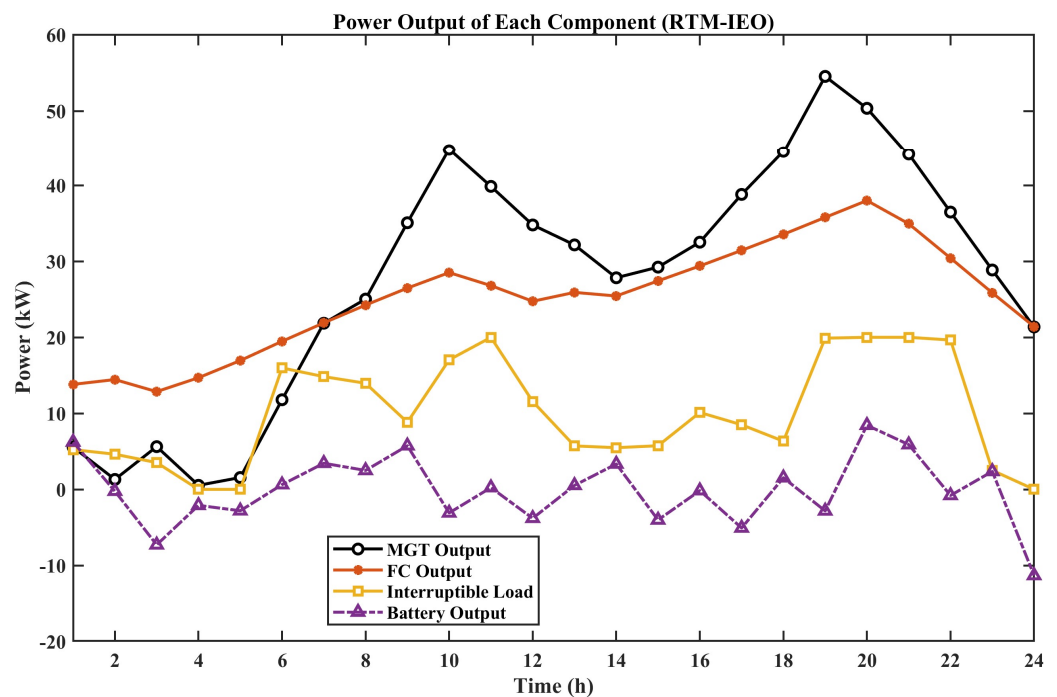


Figure 6. Comparison of power outputs of major components under RTM-IEO dispatch.

As shown in the statistical results in Table 8, RTM-IEO demonstrates significant superiority in solving the microgrid economic dispatch problem. In terms of the mean value, RTM-IEO achieves the best result of 7.5037×10^5 , which is substantially better than all comparative algorithms. The second-ranked algorithm, GJA, obtains a mean value of 1.1414×10^6 , approximately 1.52 times that of RTM-IEO; the third-ranked SBOA achieves 1.6817×10^6 , about 2.24 times higher; while the worst-performing MPSO yields 6.4514×10^6 , which is as high as 8.60 times that of RTM-IEO. This substantial cost gap clearly indicates that employing RTM-IEO for microgrid dispatch optimization can significantly reduce system operating costs, thereby offering considerable economic benefits.

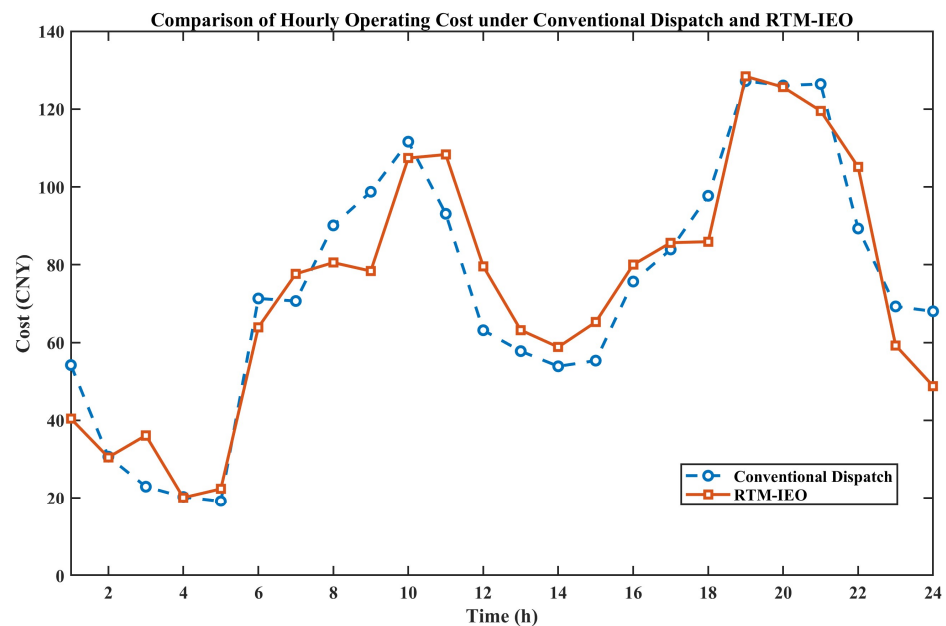


Figure 7. Comparison of hourly operating cost under conventional dispatch and RTM-IEO.

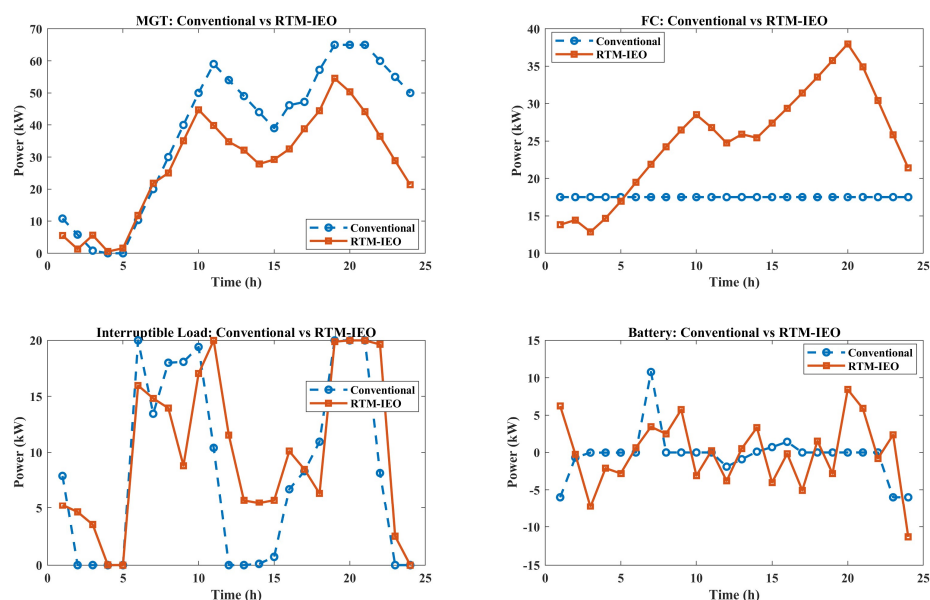


Figure 8. Comparison of dispatch profiles of major microgrid components under conventional dispatch and RTM-IEO.

In terms of standard deviation, RTM-IEO achieves the lowest value of 3.3639×10^4 among all algorithms, indicating excellent stability and robustness across 30 independent runs. In comparison, the standard deviation of GJA is 1.1963×10^5 (approximately 3.56 times higher), that of SBOA is 3.7996×10^5 (about 11.30 times higher), and that of MPSO reaches 5.9611×10^6 (approximately 177 times higher than RTM-IEO). This superiority in stability is further confirmed by the convergence curves shown in Figure 4, where RTM-IEO exhibits the smoothest trajectory with the least fluctuation. The extremely low dispersion indicates that RTM-IEO can consistently obtain high-quality solutions without being significantly affected by random initialization or parameter variations, which is of great importance for reliability in practical engineering applications.

Regarding the maximum and minimum values, RTM-IEO also achieves the best performance. Its minimum and maximum values are 6.9631×10^5 and 8.1826×10^5 , respectively, with a range of approximately 1.22×10^5 . In contrast, GJA exhibits a minimum

of 9.1865×10^5 and a maximum of 1.3962×10^6 (range $\approx 4.78 \times 10^5$), while SBOA ranges from 1.0018×10^6 to 2.8459×10^6 (range $\approx 1.84 \times 10^6$). Notably, the best solution obtained by RTM-IEO is even superior to the best solutions achieved by other algorithms (e.g., GJA: 9.1865×10^5 ; SBOA: 1.0018×10^6), indicating that RTM-IEO can identify higher-quality optimal solutions than those attainable by competing methods across multiple runs.

From the perspective of average ranking and final ranking, RTM-IEO ranks first with an average rank of 1.00 and a final rank of 1, making it the only algorithm with an average rank below 2. The second-ranked GJA has an average rank of 2.17, followed by SBOA with an average rank of 3.87. These ranking results are highly consistent with the findings from the CEC2021 and CEC2022 benchmark tests, further confirming the stable superiority of RTM-IEO across different types of optimization problems. In terms of average runtime, RTM-IEO requires 4.10 s, which is slightly higher than sdSCA (3.88 s) but lower than SBOA (7.71 s), indicating a moderate and acceptable computational cost. This demonstrates that RTM-IEO achieves superior solution quality without significantly increasing computational burden.

The average convergence curves shown in Figure 4 further support these conclusions from a dynamic perspective. RTM-IEO exhibits the fastest convergence speed among all algorithms, with a rapid decline from the initial iterations and reaching near convergence at approximately 200 iterations, ultimately achieving the lowest fitness value. In comparison, although GJA ranks second in final accuracy, its convergence speed is significantly slower, stabilizing only after around 400 iterations. SBOA and EO converge even more slowly and yield final fitness values significantly higher than those of RTM-IEO. Algorithms such as MPSO, IWOA, and ALA not only converge slowly but also exhibit noticeable fluctuations in the later stages, reflecting instability in their search processes. Notably, the convergence curve of RTM-IEO exhibits a smooth, exponentially decreasing trend without significant oscillations or stagnation, which can be attributed to the dynamic regulation of exploration and exploitation enabled by the multi-stage rural tourism-inspired heuristic migration strategy.

5.3. Evaluation of the Optimized Dispatch Scheme

Figure 5 illustrates the 24 h power balance of the microgrid under the RTM-IEO-based optimal dispatch. It can be observed that photovoltaic (PV) and wind power outputs exhibit distinct temporal characteristics. Specifically, PV generation dominates during daytime hours (approximately 08:00–17:00), with peak output occurring around noon, whereas wind power remains relatively stable throughout the day but with noticeable fluctuations. The load demand exhibits a typical bimodal pattern, with higher demand during the morning peak (approximately 08:00–11:00) and evening peak (approximately 17:00–21:00). At all time intervals, the total power supply (PV + wind + micro gas turbine + fuel cell + battery discharge + interruptible load) strictly matches the load demand. The positive and negative power contributions offset each other to precisely satisfy the load curve, thereby demonstrating the effectiveness and accuracy of RTM-IEO in handling complex equality constraints, particularly the power balance constraint.

Figure 6 presents the output allocation of major microgrid components under the RTM-IEO optimized dispatch. A clear scheduling strategy can be observed: during low-load periods (e.g., late night to early morning), the battery operates primarily in charging mode (negative output), storing surplus wind energy or low-cost electricity. During peak-load periods (morning and evening peaks), the battery switches to discharging mode (positive output), releasing stored energy to alleviate supply pressure and reduce electricity purchasing costs. The micro gas turbine and fuel cell, as controllable distributed energy sources, are mainly activated during peak-load periods or when renewable generation is

insufficient, thereby contributing to peak shaving and ensuring supply reliability. Interruptible loads are invoked only in a few extreme situations, and the interruption levels remain minimal, reflecting that RTM-IEO prioritizes the utilization of clean energy and energy storage resources while minimizing user-side interventions, in line with sustainable dispatch principles.

Figure 7 compares the operational costs of the conventional dispatch strategy and the RTM-IEO-based optimized dispatch across all time periods. It can be observed that the RTM-IEO approach consistently achieves lower or equal costs throughout the entire 24 h period. The cost reduction is particularly significant during peak-load periods. For example, during the morning peak (approximately 10:00–12:00) and evening peak (approximately 18:00–20:00), the RTM-IEO-based dispatch reduces costs by approximately 20% to 30% compared to the conventional method. In terms of total daily cost, as indicated in Table 8, the average cost under RTM-IEO is 7.5037×10^5 , whereas the conventional method (represented by MPSO) yields an average cost of 6.4514×10^6 , corresponding to an overall cost reduction of approximately 88.4%. This substantial reduction highlights the strong capability of RTM-IEO in performing global optimization under complex constraints.

Figure 8 illustrates the dispatch comparison of the major microgrid components under the conventional strategy and the RTM-IEO-based optimized strategy, including the micro gas turbine (MGT), fuel cell (FC), interruptible load, and battery system. Overall, the optimized dispatch exhibits a more coordinated allocation pattern among dispatchable generators, flexible loads, and storage resources. Compared with the conventional strategy, RTM-IEO significantly reshapes the hourly power outputs of the four components, indicating that the algorithm is able to better match the temporal variations in renewable generation and load demand.

For the MGT, the output profile under RTM-IEO is generally lower and smoother than that under the conventional strategy during several high-demand periods. This suggests that the optimized method reduces excessive reliance on the gas turbine and avoids unnecessarily high fossil-fuel-based generation. Such a result is beneficial not only for economic operation but also for sustainable development, as it contributes to lower natural gas consumption and reduced carbon-related operating pressure.

For the FC, the optimized strategy assigns a more adaptive and time-varying output trajectory, whereas the conventional dispatch keeps the fuel cell at a nearly constant output level for most periods. This indicates that RTM-IEO utilizes the fuel cell more flexibly according to system conditions, thereby enhancing the coordinated response capability of the microgrid. A more reasonable FC participation pattern helps improve the balance between supply adequacy, operational efficiency, and low-carbon support.

Regarding interruptible load, the optimized dispatch modifies its activation pattern substantially across the 24 h horizon. Although interruptible load is still used during certain critical periods, RTM-IEO tends to allocate it in a more targeted manner rather than relying on a rigid or purely rule-based schedule. This implies that the proposed method can alleviate supply–demand imbalance more intelligently, while potentially reducing unnecessary user-side disturbance in some periods.

For the battery system, the difference between the two strategies is also evident. Under the conventional strategy, the battery output remains close to zero for many periods, indicating limited utilization of storage flexibility. In contrast, RTM-IEO schedules more frequent charging and discharging actions, showing a stronger peak-shaving and valley-filling effect. This demonstrates that the optimized strategy can better exploit storage resources to smooth power fluctuations, improve renewable energy accommodation, and reduce the operational burden on conventional generators.

In summary, Figure 8 confirms that RTM-IEO enhances the coordinated dispatch of generation, storage, and flexible load resources. The optimized dispatch is more consistent with the development objective of sustainable microgrids, since it improves operational flexibility, reduces inefficient fossil-fuel generation, and strengthens the effective utilization of flexible resources.

Based on the above analysis, it can be concluded that, for the sustainable economic dispatch problem of microgrids, the RTM-IEO algorithm achieves the best optimization performance among all ten compared algorithms, exhibiting the highest convergence accuracy, strongest robustness, and fastest convergence speed. The optimized dispatch scheme obtained by RTM-IEO effectively utilizes renewable energy sources such as PV and wind power, strategically schedules battery charging and discharging, optimizes the operation of micro gas turbines and fuel cells, and minimizes the use of interruptible loads, thereby achieving significant economic and sustainability improvements. Compared with conventional dispatch methods, RTM-IEO consistently achieves lower operational costs across all 24 time periods, with a substantial reduction in total cost. These results fully demonstrate the effectiveness and practical value of RTM-IEO in solving complex engineering optimization problems, providing an efficient and reliable tool for the economic, low-carbon, and sustainable operation of microgrids.

5.4. Discussion on Carbon Emission Implications

It should be noted that the present study does not explicitly incorporate a carbon-emission model or carbon-emission index into the optimization objective. Therefore, the environmental implications of the obtained dispatch results should be interpreted with caution. The proposed RTM-IEO-based scheduling strategy improves the utilization of renewable energy resources and reduces the reliance on dispatchable fossil-fuel-based generation units. From an energy utilization perspective, such operational behavior may contribute to lower carbon emissions. However, since carbon-emission factors and carbon accounting mechanisms are not explicitly modeled, the actual amount of carbon-emission reduction cannot be quantitatively evaluated in this work. Consequently, the findings of this study primarily demonstrate the economic and operational advantages of the proposed dispatch strategy, while its environmental benefits should be regarded as potential rather than directly verified outcomes. Future research will incorporate carbon-emission indicators, carbon pricing mechanisms, and dynamic carbon-intensity models to further investigate the low-carbon performance of the proposed optimization framework.

6. Conclusions and Future Research Directions

This paper addresses the limitations of the standard Equilibrium Optimizer (EO), including insufficient population diversity, limited exploitation capability, and static search behavior in complex optimization problems, and proposes an improved algorithm, RTM-IEO, based on a rural tourism migration-inspired mechanism. By incorporating an adaptive lens imaging opposition-based learning strategy, a dynamic elite-guided elimination mechanism, and a multi-stage migration search strategy, the proposed method achieves comprehensive improvements in global exploration capability, local exploitation ability, and dynamic regulation of the search process. Experimental results demonstrate that, on the CEC2021 and CEC2022 benchmark functions, RTM-IEO outperforms several classical and state-of-the-art algorithms in terms of convergence speed, optimization accuracy, and stability. Furthermore, in the application of sustainable economic dispatch for microgrids, the proposed method significantly reduces system operating costs, enhances the utilization of renewable energy, and decreases reliance on fossil-fuel-based generation units.

and demand-side interruptions, thereby achieving a favorable balance between economic efficiency and sustainable energy utilization.

It should be noted that the current study mainly focuses on economic dispatch optimization and does not explicitly incorporate carbon-emission models or carbon-emission indicators into the objective function. Therefore, although the obtained dispatch solutions tend to increase renewable energy utilization and reduce the operating output of conventional fossil-fuel-based units, the actual carbon-emission reduction effect cannot be quantitatively evaluated within the current framework. Consequently, the environmental benefits discussed in this study should be interpreted as potential outcomes associated with cleaner energy utilization rather than directly verified carbon-reduction results.

Despite the promising performance of RTM-IEO, several limitations remain. First, the integration of multiple strategies increases the overall algorithmic complexity, and potential coupling among parameters may require further tuning under different problem scenarios. Second, the current study mainly focuses on deterministic single-objective optimization problems based on typical daily operating conditions. In practical microgrid systems, renewable energy generation and load demand are inherently uncertain due to variations in weather conditions, user behavior, and forecasting errors. Therefore, the proposed dispatch framework does not fully capture all possible operating scenarios encountered in real-world applications. In addition, although the algorithm demonstrates satisfactory computational efficiency on medium-scale problems, its performance in higher-dimensional, large-scale, or real-time optimization scenarios requires further validation.

Future research can be conducted in several directions. First, the algorithm structure can be further simplified, and adaptive parameter control mechanisms can be introduced to improve generality and usability. Second, RTM-IEO can be extended to multi-objective, stochastic, and robust optimization frameworks to better address the simultaneous optimization of economic, environmental, and operational objectives under uncertainty. In particular, explicit carbon-emission models, carbon-intensity indicators, and carbon-pricing mechanisms can be incorporated into the dispatch framework to enable a more comprehensive assessment of low-carbon operational performance. Third, scenario-based optimization, probabilistic modeling, and uncertainty quantification techniques can be integrated to better capture the stochastic characteristics of renewable energy generation and load demand. Fourth, machine learning and data-driven prediction techniques can be combined with RTM-IEO to achieve intelligent scheduling and adaptive decision-making in dynamic environments. Finally, the proposed algorithm can be applied to larger-scale energy internet systems, integrated energy systems, and smart energy networks to further verify its effectiveness and practical value in real-world sustainable development scenarios.

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