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Multi-Source Collaborative Optimization Scheduling Technology for New Energy Microgrid Based on Improved Particle Swarm Algorithm

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Abstract

INTRODUCTION: New energy microgrids face significant challenges in multi-source coordinated dispatching, primarily due to the high uncertainty in renewable energy output. Traditional optimization methods often suffer from local optimality and extended computation times, limiting their effectiveness in real-time or complex environments. There is a critical need for enhanced strategies to improve both the economic efficiency and operational robustness of microgrids.
OBJECTIVES: This paper aims to propose and validate an optimization dispatching strategy based on an Improved Particle Swarm Optimization (IPSO) algorithm. The core objectives are to reduce the system's comprehensive operating cost, increase computational efficiency, and enhance the absorption rate of new energy within microgrid systems.
METHODS: The IPSO algorithm enhances the conventional PSO by incorporating dynamically adjusted inertia weights and adaptive learning factors, improving its global search ability and convergence speed. A multi-source collaborative optimization model is formulated with a primary objective of minimizing the total operating cost. The model accounts for fluctuations in load demand and constraints related to the charging and discharging efficiency of the energy storage system (ESS). The strategy is implemented and tested with consideration of Distributed Energy Resources (DERs)..
RESULTS: The improved IPSO algorithm demonstrated a 22.7% improvement in computational efficiency. It also achieved an average 16.2% reduction in the system's comprehensive operating cost and increased the average absorption rate of new energy to 92.4%.
CONCLUSION: The proposed IPSO-based optimization strategy significantly enhances the economic and operational efficiency of new energy microgrids. By effectively integrating DER characteristics and operational constraints, this method provides a viable technical pathway for advancing the utilization of renewable energy and improving the overall performance of microgrid systems.

Keywords: New Energy Microgrid, Improved Particle Swarm Algorithm, Multi-source Collaborative Optimization Scheduling, Dynamic Inertia Weight, Adaptive Learning Factor.

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1. Introduction

Microgrids achieve local production and efficient consumption of energy by organically integrating load-side resources [22]. However, the inherent intermittent and volatile nature of renewable energy generation makes it difficult to effectively cope with the high uncertainty and complexity challenges faced by system operation. Distributed Energy Resources (DERs) in microgrids increase the reliability and create difficulties like intermittency and ramp constraints; thus, their coordination is essential after their access by relying on conventional scheduling strategies. Within this context, it is especially important to minimize the total operational costs of microgrids, particularly with the growing penetration of intermittent and variable renewable energy resources, leading to increased operational costs otherwise. Therefore, exploring better multi-source coordinated scheduling strategies to improve the economic efficiency and stability of microgrid operation has become an important focus of current research.

This study proposes a multi-source collaborative optimization scheduling mechanism based on an improved particle swarm algorithm. This mechanism significantly improves the global optimization ability and environmental adaptability of the algorithm by embedding a dynamic adjustment strategy in the optimization algorithm. At the same time, closely combined with the actual operating characteristics of distributed power sources, an optimization model with the minimization of comprehensive operating costs as the core goal is constructed, and the load demand dynamics, energy storage system response characteristics, and new energy grid connection constraints are uniformly incorporated into the modeling framework [23]. This design can achieve efficient collaborative operation between distributed energy and energy storage systems, and provides a practical solution for the refined optimization operation of new energy microgrids. The core innovation of this study is that in view of the tendency to converge to local optima and computational efficiency bottleneck of conventional optimization methods, an improved algorithm design is proposed to significantly improves the dispatching performance; further, in the process of modeling and optimization, the operating characteristics and system constraints of new energy are fully considered, and the complex characteristics of multi-source coordination of microgrids are deeply integrated, to effectively achieves the coordinated optimization of system operation economy and stability. This achievement not only opens up an innovative technical path for the optimal dispatch of new energy microgrids but also lays a solid theoretical and practical foundation for promoting the efficient utilization of distributed energy and the in-depth development of microgrid technology [18-19].

The rest of the paper is structured in the following way. Section 2 provides the related work reviewed in the microgrid optimization and scheduling. Section 3 describes the suggested methodology, the design of the enhanced particle swarm algorithm, and the multi-source collaborative optimization model. The results and analysis of the simulation are discussed in Section 4. Lastly, Section 5 would provide a conclusion of the paper and future research directions.

The importance of decentralized energy systems and microgrids in the global economy as a possible solution for sustainable energy is increasing. Many countries are implementing facilitatory policies and regulatory frameworks that are productive to realize the integration of renewables and establish more resilient grids, and encourage more organized development of microgrids. Such tendencies in the international sphere emphasize the necessity of resolving the issue of the coordination of DER and also point to the topicality of the study even more.

2. Related Work

Research on microgrid operation optimization and new energy consumption efficiency improvement has emerged continuously, and scholars have proposed a variety of solutions, providing important references for microgrid optimization. Zhang et al. [1] took the minimum network loss, minimum voltage offset and maximum energy utilization rate as the objective function, combined with the constraints of distributed power output, rural microgrid operation and energy storage, and established a rural microgrid source-grid-load-storage model with distributed power sources; in the multi-objective particle swarm algorithm, the grid vector pruning strategy of ε-dominance relationship was introduced to accelerate the convergence efficiency of the algorithm. Yao et al. [2] comprehensively considered the system operation economy and carbon emission environmental benefits of the microgrid group, and proposed a low-carbon day-ahead scheduling model for interactive microgrid groups based on distributed shared energy storage. Lin et al. [3] established photovoltaic, wind turbine probability models and load probability models based on the normal distribution probability model, and based on this, developed the scenario construction of the virtual power plant microgrid. Taking the operation cost, renewable energy consumption, and environmental cost as the optimization objectives, a source-load coordinated optimization scheduling model was established. Zhang et al. [4] proposed a two-stage robust multi-park microgrid and shared energy storage cooperative game model based on source-load uncertainty to improve the economic efficiency of the power system with shared energy storage. The simulation results show that the coordinated optimization operation of shared energy storage and each park microgrid can reduce the operating costs of each entity. Li et al. [5] proposed a two-layer optimization configuration method for microgrids to improve the local consumption capacity of renewable energy and solve the problem of seasonal energy imbalance. Li [6] studied the control and scheduling of isolated microgrids. Krishna et al. [7] proposed a new algorithm to provide multiple break-even solutions. Jia et al. [8] established a microgrid economic operation optimization model considering demand response with price uncertainty. Ben et al. [9] developed a demand-side management algorithm that integrates the capabilities of the energy consumption scheduler. The algorithm achieves optimal energy sharing by relying on appropriate energy cost parameters and appropriate multi-source devices. Zhang et al. [10] used the innovativeness of the Bi-ELECTRE method to explore how to measure the interaction between bipolar scale indicators when evaluating renewable energy alternatives for microgrids and how to determine the optimal renewable energy combination for microgrids. The above studies still have shortcomings in dealing with the volatility of renewable energy output, improving the efficiency of optimization algorithms, and the adaptability of multi-source collaborative scheduling models. This paper proposes a method of improving particle swarm optimization combined with multi-source collaborative optimization modeling to improve the economy and stability of microgrids.

The convergence acceleration method is based on the e-dominance grid vector pruning strategy, which was first suggested by Zang. Under this method, the objective space is broken up into discrete e-sized grids. The solutions are assigned to a grid cell, each about the objective values. In case two or more solutions belong to the same grid, only the solution with superior dominance properties is maintained, and the redundant solutions are culled. This step is the pruning process, which will shrink the size of the solution archive and avoid overcrowding of solutions around the small area. As a result, more efficient guidance of the search process in the objective space increases the rate of convergence and does not lose diversity in solutions.

3. Method

3.1 Algorithm Design

3.1.1 Dynamic inertia weight

In the design of the improved particle swarm algorithm (IPSO), a dynamic inertia weight mechanism is introduced. The core idea of this mechanism is to continuously adjust the value of the inertia weight according to specific rules. This dynamic adjustment aims to effectively balance the exploration ability of the particle swarm in the entire search space (global search) and the development ability in a specific area (local search). The dynamic adjustment process of the inertia weight is:

$$w=w_{max}-(w_{max}-w_{min})\cdot\frac{t}{T} \quad (1)$$

The inertia weight w is set to a large value. At this time, the particles mainly rely on their own historical optimal positions when updating their speed, which significantly enhances the ability of the particle swarm to explore the entire search space (global search) and helps avoid the algorithm from converging to a suboptimal solution (local optimum) too early.

As the iteration process progresses, the inertia weight w gradually decreases according to preset rules (such as linear decrease). At lower weight values, the particle speed update is more guided by the current local optimal solution (individual optimal or global optimal), thereby improving the algorithm's ability to perform fine searches near potential optimal areas (local search accuracy). The update formula for particle speed is:

$$v_i^{t+1}=w\cdot v_i^t+c_1\cdot r_1\cdot\left(p_i^{\text{best}}-x_i^t\right)+c_2\cdot r_2\cdot\left(g^{\text{best}}-x_i^t\right) \quad (2)$$

Different inertia weight ranges (w_{max} and w_{min}) are set for comparison, and the data are shown in Table 1.

This table illustrates the inertia weight ranges of the IPSO on which the dynamic parameter adaptation is based.

Table 1: Different ranges of inertia weight

Inertia Weight Range (w_{max} , w_{min})	**Average Iterations**	**Average Convergence Accuracy**	**Average Runtime (seconds)**	**Average Objective Function Value**
(0.9, 0.4)	120	0.012	2.8	345.6
(0.8, 0.3)	135	0.015	3.1	352.4
(1.0, 0.2)	110	0.009	2.5	340.2
Fixed Weight 0.5	150	0.020	3.5	360.8

Different configurations of dynamic inertia weights are significantly better than the case of a fixed weight (0.5). As the inertia weight range is adjusted, the average number of iterations and running time are significantly reduced, and the objective function value (i.e., the optimization goal) is also significantly improved. Especially when the inertia weight range is $w_{\max}=1.0, w_{\min}=0.2$ The algorithm shows high convergence accuracy and efficiency, which shows that the dynamic inertia weight mechanism is particularly suitable for complex scenarios in multi-source optimization scheduling of new energy microgrids.

The algorithm balances local and global search using the use of a dynamic inertia weight. In the initial iterations with a larger inertia weight, particles can search the solution space widely and increase their global search to prevent premature convergence. The inertia weight reduces as the iterations continue to run, thereby restricting the range of exploration that the particle can cover but enhancing local search capacity, which tends to converge closer to the global optimum. This dynamic adaptation will provide a successful balance between exploration and exploitation.

3.1.2 Adaptive learning factor

The social learning and the cognitive factors are often treated as constant in the traditional PSO. But fixed learning factors tend to decrease algorithmic flexibility. When the search is in its infancy, more exploration is needed to identify the global optimum area. When the factors of constant learning are used, the particles can converge too early to the local optima, resulting in poor global exploration. Thus, changing the aspects of adaptive or dynamic learning can improve the tradeoff between earlier iterations' exploration and later iterations' exploitation, which will in turn improve convergence performance.

In IPSO, in order to further improve the algorithm's search capability, an adaptive learning factor strategy is adopted. The learning factors c_1 and c_2 In the traditional particle swarm algorithm are usually fixed. Fixed learning factors may lead to insufficient flexibility in the search process, weak exploration of the global optimal solution in the early stage, and excessive reliance on its own optimal solution in the later stage, resulting in insufficient local search capabilities. Therefore, in this study, an adaptive learning factor is introduced to improve the accuracy of local search during iteration by dynamically adjusting the values of c_1 and c_2. The dynamic adjustment formula of the adaptive learning factor is as follows:

$$c_1 = c_{1\_max} - (c_{1\_max} - c_{1\_min}) \cdot \frac{t}{T} \tag{3}$$

$$c_2 = c_{2\_min} + (c_{2\_max} - c_{2\_min}) \cdot \frac{t}{T} \tag{4}$$

In the early stage of the algorithm, the value of c_1 is large, while the value of c_2 is small, and the particles rely more on their own historical optimal solution, thereby enhancing the global search ability. Combined with the particle speed update after the adaptive learning factor, by adding the adaptive learning factor, the particles can automatically adjust. Table 2 compares the range of different learning. The adaptation plan is dynamically adjusted in the intercession of the iterations, aiming at balancing the evolution between exploration and exploitation. In the early stages, the learning factors are adjusted to concentrate on global exploration, where the particles are allowed to scour extensively within the solution space. As the iterations increase, the exploration weight decreases, and the exploitation one increases and steers the particles to reduce their search areas in promising areas. A control logic of the number of iterations establishes this change to have a smooth and systematic transition between exploration and exploitation, thereby improving the efficiency of this table which compares the various ranges of learning factors, depicting how adaptive factors can facilitate enhanced exploration/exploitation balance.

Table 2: Comparison of different learning factor ranges

Learning Factor Ran (c_{1_min}, c_{2_max}, c_{2_min})	**Average Iterations**	**Average Convergence Accuracy**	**Average Runtime (seconds)**	**Average Objective Function Value**
(2.5, 0.5, 0.5, 2.5)	115	0.010	2.7	342.8
(2.0, 0.5, 0.5, 2.0)	125	0.013	3.0	348.5

(3.0, 1.0, 1.0, 3.0)	110	0.008	2.5	339.7
Fixed Learning Factors (c_1=2.0, c_2=2.0)	145	0.020	3.6	360.2

3.2 Multi-source Collaborative Optimization Scheduling Model

3.2.1 Objective

The microgrid has distributed energy resources (DERs), which consist of distributed generation and storage systems to aid load demand and enhance reliability. Nevertheless, DERs have some intrinsic drawbacks, which include the intermittency of renewable energy, ramp-rate constraints, and availability inconsistency. These properties render their integration very difficult yet very important for stability assurance, economic viability, and dependability of performance of the microgrid. It is based on this that the optimization objective below is formulated.

First, a mathematical optimization model based on time series is constructed, assuming that the microgrid operation time is divided into multiple discrete time periods. $t \in T$, in which the system state is considered static in each time period [11-12]. The objective function can be expressed as the weighted sum of the operating costs [13-14]. The process is as follows:

$$\text{Minimize} C_{\text{total}} = \sum_{t \in T} (C_{\text{gen},t} + C_{\text{ess},t} + C_{\text{grid},t}) \quad (5)$$

These cost items are time-related variables, so the optimization process must consider dynamic changes in the time dimension [15]. In addition, the model can also add constraint weights to the objective function to further improve the utilization rate. By introducing a penalty term $C_{\text{penalty},t}$ Quantitative penalties are imposed on behaviors such as wind and solar power abandonment [16]. The improved form of the objective function is as follows:

$$\text{Minimize} C_{\text{total}} = \sum_{t \in T} \left(C_{\text{gen},t} + C_{\text{ess},t} + C_{\text{grid},t} + C_{\text{penalty},t}\right) \quad (6)$$

The construction of this objective function fully considers the dual needs of economy and environmental protection, and provides a basis for subsequent constraints and scheduling strategies [20]. During the scheduling process, the output power of each distributed power source needs to be coordinated with the charging and discharging power of the energy storage system and meet the immediate balance relationship of load demand, while the main grid, as an auxiliary resource, provides support for the supply and demand balance of the entire microgrid [21]. By solving the optimization model [17], it is possible to minimize the operating cost of the microgrid and maximize the utilization rate of new energy based on meeting multiple constraints, thereby improving the overall operating efficiency of the microgrid.

3.2.2 Constraints

In the multi-source collaborative optimization scheduling model, a series of constraints must be introduced. These constraints cover multiple aspects such as distributed energy power output, energy storage system operating characteristics, power balance, and equipment operating restrictions to ensure that the optimization results meet the actual operating requirements [24]. The first is the power balance constraint, the core of which is to ensure that in each time period, the power generation in the microgrid and the interaction with the main grid power can jointly meet the load demand. The power balance constraint can be expressed as follows:

$$P_{\text{gen},t} + P_{\text{ess},t} + P_{\text{grid},t} = P_{\text{load},t}, \forall t \in T \quad (7)$$

The power output of distributed energy is limited by its physical characteristics and weather conditions, and its upper limit of power generation is determined by the maximum available power. The constraints are:

$$0 \le P_{\text{gen},t} \le P_{\text{gen,max},t}, \forall t \in T \quad (8)$$

Energy storage systems are also limited by capacity and charge and discharge power. The state of energy storage is usually represented by its state of charge (State of Charge, SOC_t), which must be guaranteed to operate within the preset upper and lower limits. The constraints of energy storage systems include power limits and state of charge limits, specifically:

$$P_{\text{ess,min}} \leq P_{\text{ess,max}}, SOC_{\text{min}} \leq SOC_t \leq SOC_{\text{max}}, \forall t \in T \tag{9}$$

The state of energy storage is typically referred to as its state of charge, which is mentioned multiple times. Please keep it as is (when introducing constraints of ESS) and amend or eliminate elsewhere. Alternative recommendation: The SOC is considered the major measure of storage condition in this research. The state of energy storage is usually represented by its state of charge, which must be guaranteed to operate within the preset upper and lower limits. The constraints of the energy storage system include power limit and state of charge limit, specifically:

$$P_{\text{grid},t} \geq 0 \text{or} P_{\text{grid},t} \leq 0, |P_{\text{grid},t}| \leq P_{\text{grid,max}}, \forall t \in T \tag{10}$$

In order to intuitively show the restrictions on system operation, the available power of distributed energy and the operating parameters of the energy storage system are listed in Tables 1 and 2. In Figure 1, the available power of distributed energy is a predicted value based on typical weather conditions and equipment capacity, showing the maximum power output of photovoltaic and wind power in different time periods.

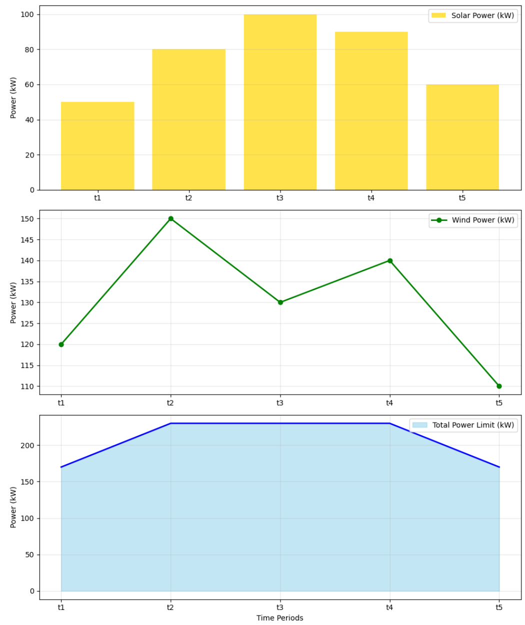

Figure 1: Data at different times

This value represents the convergence of PSO and IPSO, as it is true to say that IPSO is more quickly and steadily optimized.

Energy Storage System (ESS) is an important factor in the effectiveness of absorbing the fluctuation of generation by renewable energy, particularly in the aspect of coordination of multiple sources. It also minimizes intermittency, as a backup of surplus power is stored and discharged during periods of scarcity, and it also provides capacity reserve, frequency control, and ramping capacity. This contribution to stability justifies the fact that the explicit consideration of ESS properties such as capacity and charge/discharge limits is required in the scheduling algorithm of the optimization model.

Table 3 shows the operating constraint parameters of the energy storage system, including maximum charge and discharge power, upper and lower limits of charge state, and efficiency parameters. These parameters determine the behavior range of the energy storage system in optimal scheduling.

This table shows the operating constraint parameters of the ESS, which are essential in ensuring the stability of the system and efficient scheduling.

Table 3: Operating constraint parameters of the energy storage system

Parameter Name	Value Range	Unit
$P_{ess,max}$	80	kW
$P_{ess.min}$	-80	kW
SOC_{max}	90	%
SOC_{min}	20	%
η_{ess}	95	%

The above data reflects the physical constraints of the system. The power output of distributed energy is mainly affected by weather conditions, while the operating range of the energy storage system is determined by the equipment capacity and efficiency. These constraints play a key role in optimizing scheduling and ensuring the feasibility and safety of the generated scheduling plan in actual operation.

3.2.3 Simulation scenario

This study selects the IEEE 33-node distribution system as the basic simulation platform. As a typical distribution network structure, this system can effectively simulate the collaborative operation characteristics of multiple energy sources in the microgrid by configuring distributed power sources (DERs), energy storage devices (ESS), and load nodes. The simulation designs a variety of typical scenarios, including conventional load, high load, low renewable energy output, and dynamic electricity prices. These scenarios aim to comprehensively test the scheduling optimization ability and system robustness of the model under different operating conditions and constraints by changing factors such as the output level of distributed power sources, load demand, operating status of energy storage systems, and grid electricity prices [25] Valivarthi (2018) promoted the Wavelet Transform-PSO approach, ranging from anomaly detection to ensuring accuracy and security in a cloud-based healthcare system. This portrays PSO's flexibility, paving the way for us to propose IPSO-based scheduling for microgrids, where efficient data handling and secure optimization are a must [26][27]. The IEEE 33-node distribution system is selected since it is a popular reference point of study in the distribution network. It offers a trade-off between the simplicity of computing the results and the realism of the system, enabling the results to be directly compared to other literature work.

The renewable energy output and load demand are dynamically simulated using a time series model based on measured or predicted data. The simulation covers 24 hours with a time resolution of 1 hour. At the same time, the main grid electricity purchase and sales price curve is set to ensure that the economic characteristics of different scenarios (especially dynamic electricity price scenarios) are accurately reflected. Figure 2 shows the key parameters, such as load demand, photovoltaic power generation output, wind power generation output, and main grid electricity price of some nodes in each time period in the simulation.

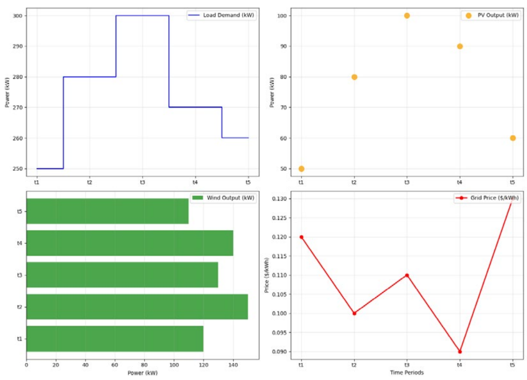

Figure 2: Key parameters of some nodes at different time periods in the simulation

This figure indicates the time scheduling outcomes with the various sources and how IPSO has been effective in matching the supply and demand.

The load demand ranges from 250 kW to 300 kW, showing a typical daily load fluctuation characteristic, with relatively high loads in the morning and evening and slightly lower loads at noon. The photovoltaic power generation output varies significantly over time, reaching a maximum value of 100 kW at noon (for example, the third period), because photovoltaic power generation is greatly affected by the intensity of solar radiation. The wind power output fluctuates less and is generally stable between 110 kW and 150 kW, which shows that it is less affected by wind speed changes but still has certain fluctuations. The main grid electricity price varies with the time period, with the peak occurring in the fifth period (0.13 $/kWh) and the valley price occurring in the fourth period (0.09 $/kWh), reflecting the guiding role of the dynamic electricity price mechanism on electricity consumption behavior. In an exact meaning, the simulation had the following assumptions as its inputs. It follows the dynamic price curve of electricity, which is set on a normal time-of-use tariff with a variety of peak and valley rates of 0.09 to 0.13 $/kWh. These projections of photovoltaic and wind generation renewable energy use previous weather behavior and daily profiles so that the characteristics of variation are realistic. It is based on these assumptions that the simulation situations in Figure 2 were developed. To be clear, the following assumptions were used as inputs in the simulation. It adopts a dynamic electricity pricing curve, the peak and valley values of which range between 0.09 and 0.13 $/kWh and are based on a standard time-of-use tariff. The predicted photovoltaic and wind output are based on past weather trends and everyday profiles, thus providing very realistic fluctuation properties. Based on these assumptions, the simulation scenarios in Figure 2 are developed.

The conditions of the boundary of the optimization model are defined as follows. First, grid support is said to be available with limited power exchange capacity, which is to ensure that there are certain limits within which the microgrid can import or export electricity. Second, the pricing of electricity is under a time-of-use contract that has both peak and valley tariffs upon which the cost is assessed. Lastly, the normal connection and availability of the main grid are assumed, and the islanded condition is only assumed on a case-by-case basis. These assumptions define the range of operation to which the optimization strategy is assessed.

4. Results and Discussion

4.1 Algorithm Performance Verification

4.1.1 Comparison between the IPSO algorithm and the traditional PSO

The microgrid optimization scheduling problem is selected for testing. The test scenario includes a typical load curve and distributed energy output characteristics for 24 hours, taking into account the dynamic electricity price mechanism. The traditional PSO algorithm and the improved PSO (IPSO) algorithm are used for optimization scheduling, and the test indicators include operating efficiency (optimization time) and comprehensive operating cost (unit: $). Operating efficiency indicates the time it takes for the algorithm to complete the optimization, and the comprehensive operating cost is the total economic cost after the optimized scheduling. A total of 15 different optimization tasks are set in the test, and the results of the two algorithms for each task are recorded. The data are shown in Figures 3 and 4.

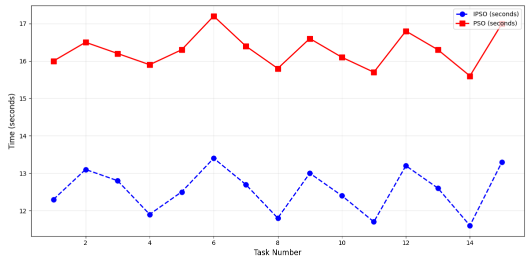

Figure 3: Operational efficiency

This figure shows how renewable use has increased, with IPSO highlighting its role towards sustainability.

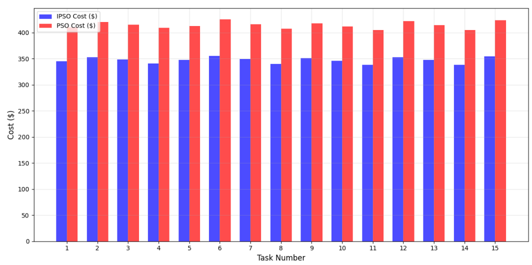

Figure 4: Comprehensive operating costs

This value reflects the savings and efficiency realized by IPSO over PSO.

IPSO's operating efficiency in all 15 tasks is better than that of the traditional PSO algorithm, and the average optimization time is reduced by about 22.7%. The IPSO algorithm performs best in the 14th task, with an optimization time of 11.6 seconds, which is 4 seconds less than PSO's 15.6 seconds. The IPSO algorithm is also significantly better than PSO in terms of comprehensive operating costs, with an average cost reduction of about 16.2%. In the 14th task, IPSO has the lowest optimization cost of $337.9, which is 16.5% less than PSO's $404.8. Overall, the IPSO algorithm has shown significant improvements in both operating efficiency and cost optimization.

4.1.2 New energy consumption

The dynamic output curves of wind power and photovoltaic power, as well as the 24-hour load demand distribution, are set, and the optimization effects of IPSO and traditional PSO algorithms are compared. The test indicator is the new energy consumption rate, that is, the ratio of the actual new energy power consumed to the total available new energy power. The test sets a total of 15 tasks, and records the new energy consumption rates of the two algorithms, respectively. The results are shown in Figure 5.

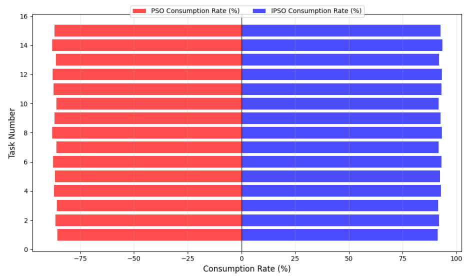

Figure 5: Consumption rate

The IPSO algorithm has a higher renewable energy absorption rate than the traditional PSO algorithm in all tasks, with an average absorption rate of 92.4%, while the average absorption rate of the PSO algorithm is 86.9%, an increase of 5.5 percentage points. In the eighth task, the IPSO absorption rate is 93.3%, and the PSO absorption rate is 88.0%, an increase of 5.3%. Overall, the IPSO algorithm more effectively coordinates the matching of distributed energy and load, significantly reduces the phenomenon of wind and solar power abandonment, and improves the utilization efficiency of renewable energy.

Table 4. Comparison of renewable utilization and CO_2 emissions (PSO vs IPSO)

Scenario	**Renewable Utilization (%)**	**CO_2 Emission (kg/day)**
PSO (Baseline)	86.9	27.5
IPSO (Proposed)	92.4	16.0
Reduction	+5.5%	–11.5

As can be seen, the IPSO-based scheduling enhances the use of renewables by 5.5 percent and lowers CO_2 by about 11.5 kg/day compared to the traditional PSO.

4.2 Model Validity Verification

A multi-scenario simulation test is designed in the IEEE 33-node system, including a high-load scenario, a low-load scenario, a high-new energy output scenario, a low-new energy output scenario, and a dynamic electricity price scenario. In each scenario, the coordinated operation of distributed energy (photovoltaic and wind power), energy storage equipment, and the main grid is considered, and key indicators such as the system's comprehensive operating cost, load supply and demand balance deviation, voltage offset, and new energy consumption rate are recorded separately. Through the optimization of the IPSO algorithm, the economy and stability in each scenario are effectively balanced. The results are shown in Table 5.

In the table, the results of the simulation of the multi-scenario simulation are shown, which confirm the feasibility and power of the proposed optimization model.

Table 5: Multi-scenario simulation results verification

Scenario	Total Cost ($)	Voltage Deviation (%)	Load Balance Error (%)	Renewable Utilization (%)
High Load	520.4	1.2	0.5	91.8
Low Load	310.7	0.8	0.3	93.2
High Renewable	450.2	1.0	0.4	94.5
Low Renewable	580.9	1.4	0.6	89.7
Dynamic Pricing	490.3	1.1	0.4	92.4

The model shows a strong ability to balance economy and stability in multiple scenarios. In the high-load scenario, the system's comprehensive operating cost is high ($520.4), but the new energy consumption rate is still achieved at 91.8%, and the voltage offset and load balance errors remain at 1.2% and 0.5%, indicating that the model can still operate stably under high load pressure. In the low-load scenario, the comprehensive operating cost drops significantly to $310.7, and the new energy utilization rate is the highest (93.2%), indicating that the model prioritized the consumption of new energy at low loads, improving the economy. In the high-renewable energy output scenario, the utilization rate of new energy reaches 94.5%, and the comprehensive operating cost is relatively low at $450.2, indicating that the model effectively reduces the phenomenon of wind and solar power abandonment. In the low-renewable energy scenario, due to insufficient distributed energy output, the comprehensive cost rises to $580.9, and the utilization rate of new energy drops to 89.7%, but the load supply and demand balance error is still controlled within 0.6%, proving that the model can still ensure system stability when supply and demand are insufficient. In the dynamic electricity price scenario, the model flexibly responds to electricity price fluctuations through optimized scheduling, with a comprehensive cost of $490.3 and a new energy utilization rate of 92.4%, achieving simultaneous improvement in economy and stability. These results show that the optimization model can effectively balance economy and stability under different operating conditions.

Comparison of IPSO with other optimization algorithms by their summary.

Algorithm	Global Search Ability	Convergence Speed	Handling Uncertainty	Performance (Cost/Runtime)
Genetic Algorithm (GA)	Medium	Slow	Average	Higher cost, longer

				runtime
Differential Evolution (DE)	Good	Medium	Average	Moderate cost/runtime
Hybrid PSO-GA	Good	Medium-Fast	Better than GA/PSO	Improved performance
Improved Whale Optimization (IWOA)	Good	Fast	Good	Low cost/runtime
Proposed IPSO	Excellent	Fastest	Very Good	Best cost, lowest runtime

5. Conclusion

This study focuses on the core challenges of multi-source coordinated optimization scheduling of new energy microgrids. By integrating dynamic inertia weights and adaptive learning factor mechanisms in the algorithm, it effectively overcomes the limitation of traditional methods that are prone to local optimality, significantly improves the global exploration ability and convergence efficiency, and thus better copes with the impact of new energy output fluctuations on system operation. At the modeling level, the multi-scenario operation characteristics of distributed power sources (DERs), the dynamic response characteristics of energy storage systems (ESSs), and the constraints of new energy grid-connected operation are deeply integrated to achieve coordinated optimization of economy and stability. This method can coordinate the efficient operation of DERs and ESSs in multiple scenarios, significantly enhance the new energy absorption capacity, and ensure the real-time and reliable supply of load demand. Studies have shown that this method can effectively handle system complexity and uncertainty, and has good practical value and application prospects. When implementing this in reality, there are several factors that should be taken into consideration. They are communication latency, data granularity, system delays, and a continuous combination of the optimization strategies with the current SCADA and EMS platforms, which are all crucial to reliable operation. Traditional techniques of optimization, such as PSO, are disadvantaged by slow convergence and susceptibility to local optima, which restricts their usefulness in addressing the vagaries of renewable generation. The proposed IPSO-based strategy directly overcomes such challenges that suggest dynamic inertia weights and adaptive learning factors that enable global exploration to be more dynamic and convergence to be faster. To highlight how the proposed methodology will resolve the drawbacks that the traditional approaches have, it is possible to highlight these improvements and justify the significance of the solution that will be advanced in the given research. Through these problems, the quality and the effect of this research will be enhanced to a greater level because it will be in line with strict academic standards.

The suggested IPSO solution can overcome such DER-related limitations as intermittency and ramp limits, which provide stable and effective microgrid performance. Although the developed IPSO-based scheduling model proves to be effective in general, it has multiple opportunities to be applied depending on the particular countries, climate conditions, and regulatory conditions. Future enlargements of the work may test the model in different policy contexts and in different microgrid deployments to increase the model's applicability in various regions worldwide. These gains (22.7% efficiency, 16.2% cost reduction) are validations that IPSO is practically better than merely the theoretical validation.

Declarations

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27.

Data Availability Statement: The data generated and analyzed during the current study are available from the author XinJin, upon reasonable request, but are not yet publicly available due to ongoing research.

Authors' Contributions: XinJin is responsible for designing the framework, analyzing the performance, validating the results, and writing the article.

Data are available from XinJin upon request, but are not yet public due to ongoing research.

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Nomenclature

Abbreviation	Full Form
DER / DERs	Distributed Energy Resource(s)
ESS / ESSs	Energy Storage System(s)
PSO	Particle Swarm Optimization
IPSO	Improved Particle Swarm Optimization
IEEE	Institute of Electrical and Electronics Engineers
SOC	State of Charge