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RESEARCH ARTICLE

Optimal Scheduling of Wind-Photovoltaic-Pumped Storage Joint Complementary Power Generation System Based on Improved Firefly Algorithm

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ABSTRACT Complementary multi-energy power generation systems are a promising solution for multi-energy integration and an essential tool for diversifying renewable energy sources. Despite many studies on developing hybrid renewable energy systems, more research is still needed on applicable models or practical methods. Meta-heuristic algorithms such as the Firefly algorithm are becoming increasingly popular in optimizing hybrid renewable energy systems because they provide fast, accurate, and optimal solutions. Considering the natural complementarity and instability of wind and solar energy, the advantage of pumped storage power plants' ''peak adjustment and valley adjustment'', as well as the grid's need for a stable and reliable energy supply, the objective of this study is to economically optimize the design of wind-PV pumped storage complementary generation system scheduling with a two-generation Firefly algorithm based on spatial adaptive and Levy's flight improvement, in comparison with a variety of cutting-edge population intelligence optimization algorithms (GA, PAO, DE, WOA, FA) were compared and analyzed. The impact of pumped storage plants on economic and stabilization objectives is explored. The results show that several meta-heuristics are effective in finding the optimal design. However, the improved Firefly algorithm with an objective function value of 7.8331 is superior to several other algorithms by enhancing the wind and PV benefits while suppressing the output fluctuations of the system. After the construction of the additional pumped storage plant, the output fluctuation of the complementary operation system is only 9.7% of that of the wind power and PV in stand-alone operation after the multi-energy coordination and optimal scheduling. This demonstrates the effectiveness of the optimization method used in this paper. The results of this study can provide a reference for the complementary optimization of pumped storage power plants for intermittent renewable energy sources.

INDEX TERMS Multi-energy complementary power generation system, peak shaving and frequency modulation, economic dispatch, load fluctuation, improved firefly algorithm.

I. INTRODUCTION

In recent years, the escalating consumption of traditional fossil fuels has led to heightened environmental pollution and the exacerbation of climate change. Consequently, countries worldwide have shifted their focus towards renewable energy generation. However, wind and solar energy pose challenges to power system scheduling and operation due to their intermittency and variability [1]. The integration of these fluctuating energy sources into the grid presents difficulties

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for the swift adjustment of generation capacity, resulting in resource wastage and increased operational costs [2], [3]. Consequently, it is imperative to investigate methods for effectively integrating wind, solar, and hydropower to minimize grid fluctuations, optimize resource utilization, and enhance economic benefits. One widely applied approach in the power system is the incorporation of pumped storage in independent solar-wind hybrid systems, which serves to replace environmentally unfriendly batteries (containing lead and sulfuric acid) and compensate for renewable energy output [4].

To gain a scientific understanding of the complementary patterns of wind and solar energy generation and to promote a higher proportion of clean energy consumption [5], researchers commonly employ correlation coefficients such as the Pearson correlation coefficient [6], Spearman correlation coefficient [7], Kendall correlation coefficient [8], and standard deviation [9] to quantify the degree of complementarity among renewable energy sources. Juras et al. [10] employed spatial and temporal models in their study, which aimed to theoretically assess the complementarity of renewable energy and propose integration solutions. Empirical evidence confirms the effectiveness of multi-energy complementary utilization in terms of performance.

Pumped hydro storage is currently the most established energy storage technology, offering several advantages including flexible operation [11], large storage capacity [12], and high efficiency [13]. It plays a crucial role in compensating for the variability of wind and solar energy by providing ancillary services, thereby facilitating their integration into the grid system at a large scale. Current literature extensively focuses on optimizing the scheduling and operation of multi-energy systems incorporating pumped hydropower plants, with scholars both domestically and internationally proposing various models. For instance, Juras et al. [14] successfully implemented a ''wind-solar-pumped hydro storage'' system in Silesia, validating the effectiveness of pumped hydro storage in reducing the unpredictability of regional wind and solar power. Ebeed et al. [15] addressed the integration of wind and photovoltaic (PV) power generation into the STHS problem. They achieved this by implementing a novel Modified Artificial Hummingbird Algorithm (MAHA) for time-varying power generation scheduling, utilizing the available hydro and thermal units—the proposed approach aimed to reduce dependence on thermal units and minimize fuel costs. Ma et al. [16] proposed pumped hydro storage services for off-grid hybrid renewable energy systems, analyzing the complementary characteristics between wind and solar outputs in remote islands of Hong Kong. Gao et al. [17] developed a multi-objective optimization model aiming to maximize system economic benefits, minimize output fluctuations and load differences, and investigate the optimal capacity configuration of wind-solar-pumped hydro storage under limited transmission line capacity. The utilization of pumped hydro storage ensures the maximization of solar and wind energy outputs. Dauda et al. [18] proposed an Intelligent generation scheduling (IGS) mechanism that evaluation the economic, voltage secure, and emission minimization aspects of HPS configurations in terms of optimal fulfillment of operational objectives. Decision support is provided in areas that have a wealth of hydro and solar power. Ding et al. [19] developed an optimization scheduling model for a combined pumped hydro storage-wind-solar-thermal power generation system with an emphasis on source-load matching. This model utilized typical daily scenario outputs and load fluctuations from an energy base in Northwest China. To address uncertainties in the system, Wang et al. [20] have tackled the challenge of maximizing the complementarity of wind and solar power generation through addressing sizing and scheduling issues. They designed a multi-objective sizing and scheduling method for a hybrid renewable energy system powered by a long-distance transmission line. This innovative approach incorporates the decision maker's attitude parameters and utilizes the ε-constraint method. Their study provides a valuable management proposal for the system operator, the electric power industry, and management administrations. In another study, Li et al. [21] adopted chance-constrained p22rogramming to model uncertainties in a bi-objective optimization model of a hybrid system incorporating mini-hydropower generation, photovoltaic generation, and pumped hydro storage. Zhang et al. [22] employed a simulation-estimation method that incorporated probability forecasting to generate power generation plans in the form of probability density functions for the next day. This approach considered uncertainties in three distinct short-term optimization operation models, providing dispatchers with increased flexibility in decision-making.

Figure 1 depicts the general structure of the study. The aim is to achieve optimized operation of a wind-solar-pumped hydro storage complementary power generation system by considering correlations and improving overall energy utilization efficiency. The research is divided into two stages: 1) Multi-objective optimal scheduling: In this stage, a multi-objective optimization model is established for the wind-solar-pumped hydro storage power generation system. The objectives are to minimize the total operating cost of the system and minimize load fluctuations. This allows for more efficient scheduling optimization of the multi-energy power generation system. 2) Operational verification: In this stage, the operational performance of the system is verified based on the outcomes of the multi-objective optimal scheduling.

In the second stage of the study, a dual-generation firefly algorithm is developed, which incorporates spatially adaptive tracking and an improved Levy flight mechanism. The algorithm is then subjected to comparison with other commonly used optimization algorithms, namely GA, PSO, WOA, DE, and the traditional firefly algorithm (FA). The enhancement of the firefly algorithm improves its ability to explore the solution space and enables individuals to effectively evade local optima, thereby resulting

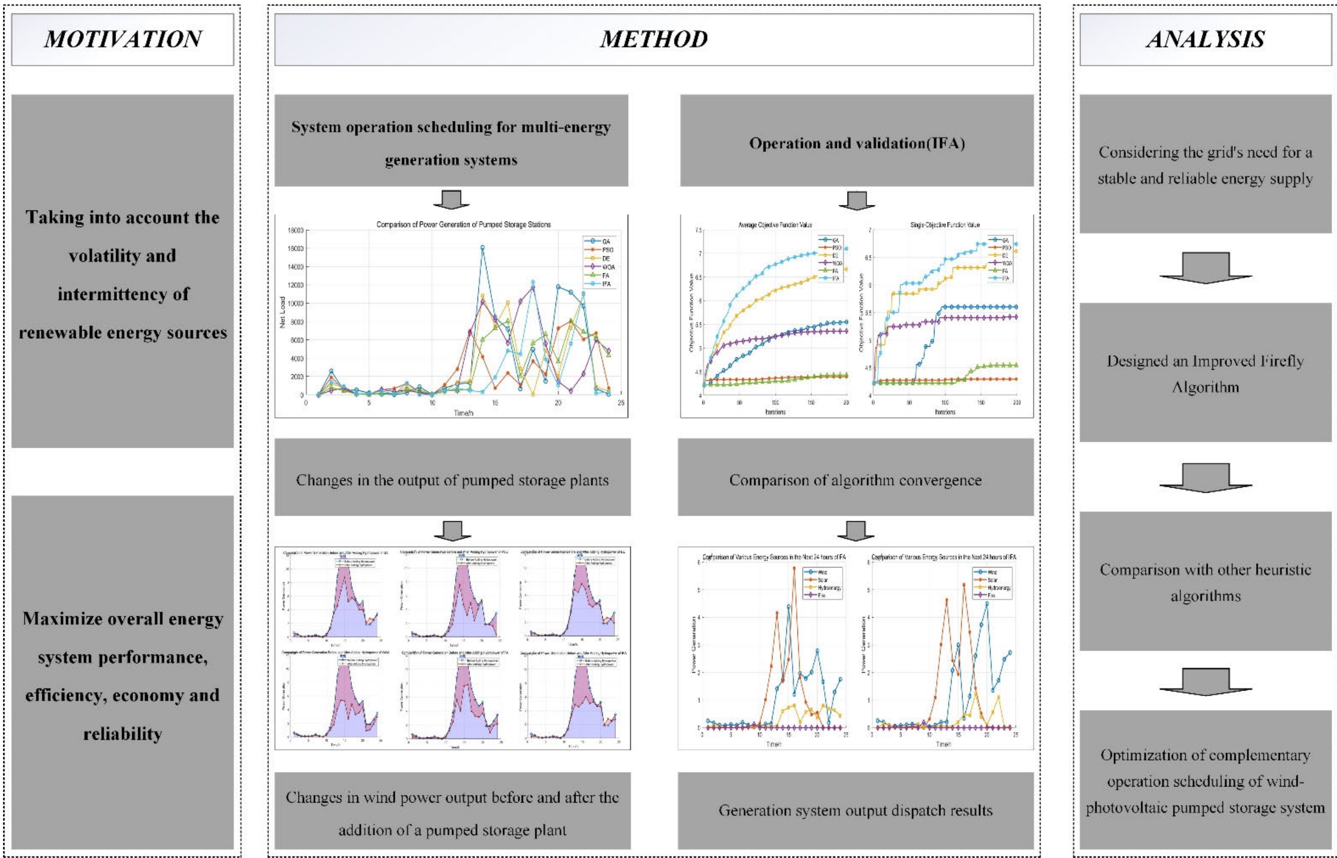

FIGURE 1. Model of a multi-energy complementary power generation operation system with pumped hydro storage power plant.

in an improvement in the optimization accuracy of the algorithm. The optimization problem of energy complementarity has been a prominent area of research. To maximize energy utilization efficiency, the problem can be effectively divided into two sub-problems: supply-demand matching and energy scheduling. This involves ensuring the alignment of supply and demand for various energy sources through load and energy supply prediction and formulating appropriate energy scheduling strategies to enhance system stability, efficiency, robustness, and reliability. When applying multi-objective optimization to clean energy and power systems, traditional methods often transform the problem into a single-objective optimization problem using weighting or linear programming, which makes it challenging to select appropriate weights and fails to effectively address problems with multiple conflicting objectives. With the advancement of heuristic algorithms and their successful application in multi-objective optimization problems, numerous multi-objective optimization algorithms have been employed in energy and power systems. In general, existing multi-objective meta-heuristic algorithms can be classified into three main categories: multi-objective evolutionary algorithms, multi-objective swarm intelligence, and multi-objective hybrid meta-heuristic algorithms. These algorithms include genetic algorithms [23], artificial bee colony algorithms [24], particle swarm algorithms [25], firefly algorithms [26], and dragonfly algorithms [27], among others. In literature [28], the MOPSO algorithm is proposed, which combines fuzzy adaptive techniques and self-learning strategies. Another study [29] integrates wind energy into the power system while considering strict constraints on charging and discharging behavior. The optimization objectives include economic and emissions considerations, and a combination of PSO and TLBO is employed to achieve optimal scheduling. Ebeed et al. [30] applied a lightning attachment process optimization algorithm (LAPO) to address the integration of hydroelectric, thermal, wind, and photovoltaic systems. They aimed to minimize the power losses and the total voltage deviations for optimal power generation planning. Luo et al. [31] used a novel mathematical model for the PV system to simulate solar irradiance. A modified Bat algorithm (MBA) was applied to optimize the day-ahead optimal scheduling. These methods are capable of finding optimal scheduling solutions under effective constraint conditions. Heuristic algorithms such as genetic algorithms, artificial bee colony algorithms, and particle swarm algorithms have advantages in terms of robustness, adaptability, and fast convergence. These algorithms are commonly used to address the planning and design of wind-hydro-pumped storage systems, aiming to achieve an optimal system layout and equipment configuration, thus improving overall energy utilization efficiency. To address the fundamental challenges in traditional energy supply and demand, a solution is proposed through in-depth analysis.

The structure of this paper is as follows: Section II presents a concise review of related work. Section III introduces the traditional operation mode of multi-energy generation systems and discusses the key challenges that need to be addressed. In addition, a comprehensive method for solving these challenges is proposed. Sections IV and V analyze simulation results using real data and validate the proposed model. Finally, Section 6 provides conclusions and outlines future research directions.

The main contributions and novelty of this research can be summarized as follows:

1) An economic optimization design for the dispatch of a wind-photovoltaic-pumped storage joint complementary power generation system is carried out. The impact of pumped storage power plants on economic and stabilization objectives is also explored.
2) A two-generation firefly algorithm based on spatial adaptation and Levy flight improvement is introduced, and the superiority of the firefly algorithm in improving system efficiency and reducing energy waste is demonstrated by comparing it with the traditional optimal scheduling methods.

The difficulties, limitations, and suggestions of this research can be summarized as follows:

1) The research is limited by aspects such as applications in specific environments may affect the generalizability of the results and the feasibility of practical applications.
2) The feasibility and operability of the research model and methodology in practical applications need further validation and improvement.
3) The research methods in this paper are applied to hybrid power generation systems of different sizes or types to verify their feasibility and effectiveness in practical applications.
4) Explore solutions to improve the overall efficiency and stability of the system through a more in-depth discussion of the coordination and scheduling issues between renewable energy and energy storage systems.

II. RELATED WORKS

When addressing the complementary operation of multi-renewable energy systems and pumped storage, a multitude of challenges arise, encompassing various dynamic factors. These factors include weather fluctuations, load requirements, and the condition of storage devices. In such a scenario, traditional heuristic algorithms are susceptible to local optima, which hinders their ability to generate feasible solutions. Consequently, there is an immediate requirement to enhance computational efficiency and solution accuracy to attain high-resolution and efficient modeling for this system.

Enhancing the performance, efficiency, economy, and reliability of the overall energy system and achieving optimized scheduling of the entire system by coordinating the complementary operations of different energy types have been significant research challenges. In the current research, scholars have predominantly focused on wind-solar-hydro multi-energy complementarity and multi-objective optimization scheduling as separate areas of study. However, in reality, these two aspects are interconnected and entail numerous interrelated issues that warrant in-depth exploration. For instance, it is important to investigate how power supply reliability can be improved, how energy storage systems can be optimized, and how the probability of power loss can be reduced. Therefore, future research on the optimization scheduling of multi-energy generation systems should emphasize exploring the impact of multi-energy complementarity on these key issues, to comprehensively and thoroughly uncover the optimization potential of multi-energy systems. This section presents a summary and discussion of the most recent research in this field. Numerous scholars have conducted valuable investigations in these domains, primarily focusing on optimizing multi-objective functions or improving multi-objective solving algorithms. However, given the increasing demand for integrating renewable energy and the associated constraints, this paper proposes a comprehensive approach that contributes to the field. By leveraging the benefits of pumped storage power stations in peak reduction and valley filling, a multi-objective optimization model for wind-solar-hydro energy storage and generation systems is developed. This comprehensive approach lays the foundation for decision-making regarding the stability and reliability of energy supply, effectively bridging the gap between the instability and unpredictability of renewable energy generation. Furthermore, it addresses key challenges in the field.

A. ENERGY GENERATION FORECASTING

Renewable energy generation forecasting is the process of estimating and predicting the future production of renewable energy sources, particularly solar and wind power. This forecasting involves the use of tools such as meteorological data, monitoring devices, and mathematical models to predict the output of renewable energy in the future. Since solar and wind energy are influenced by climate conditions and geographical locations, separate forecasts are necessary for different energy resources. Accurate renewable energy forecasting plays a crucial role in the operation and scheduling of the power system. It enables grid operators to effectively plan energy supply, reduce reliance on traditional fossil fuels, optimize the utilization of renewable energy, and minimize the environmental impact of energy production. Lu et al. [32] proposed a practical coordination mode of wind, photovoltaic, and hydropower. The total prediction error of the output power of wind and PV plants is simulated by using scenarios generated using Latin hypercubic sampling and k-means clustering. He et al. [33] integrated a wind-PV-battery-thermal hybrid power system to create a data-driven prediction model for addressing the uncertainties and losses associated with wind power generation. They leveraged the cost-effectiveness of thermal energy storage and the flexibility of batteries to enhance the system's economic viability and reliability. Introducing the preference information of decision-makers through a multi-objective evolutionary algorithm (MOEA-DM), guided the evolution towards the preferred region, resulting in improved economics and system reliability. In a similar vein, Lu et al. [34] proposed an enhanced interval optimization method to account for the uncertainties arising from in-flow runoff in cascade hydroelectric power stations and output from photovoltaic power generation. The study developed a long-term interval optimization scheduling model based on extreme scenarios, which aimed to balance the operational economy and robustness of the system. This was achieved through the use of mixed-integer linear programming (MILP) model. Furthermore, Qiu et al. [35] developed a novel methodology for assessing the potential of Pumped Hydro Storage (PHS) systems. Real data was utilized to calculate the potentials of wind and solar power, alongside evaluating the electrical energy quality of hybrid renewable energy systems. The objective of this research was to fill a research gap in the integrated evaluation of PHS potential, along with wind and solar potentials. The findings of this study contribute to the reduction of adverse effects of renewable energy on the power grid, as well as supporting the achievement of carbon neutrality goals in a timelier manner.

B. ENERGY STORAGE MATCHING

Energy storage matching is a critical aspect of renewable energy integration, as it involves converting excess wind and solar energy into electrical energy and storing it for later use. This is typically achieved through the use of energy storage devices such as batteries and pumped hydro storage. These devices can release stored energy during periods of low renewable energy supply or high demand, effectively balancing the needs of the grid. By optimizing the matching of energy storage systems, the overall economy and dispatchability of the system can be improved, enabling flexible scheduling and reliable power supply. This optimization process also has the potential to reduce operating costs and decrease carbon emissions. In a study conducted by Zhang and Tian [36] proposed a multi-source coordinated optimal scheduling method of wind-PV-hydro-thermal-nuclear-storage, taking the operation and dispatch data of a day of China's provincial power system as the object of study, and using the analytic hierarchy process to establish the mathematical model with the cost of purchasing power for the multi-source system and the consumption capacity of renewable energy as the objective function. It provides a reliable theoretical basis for solving the grid-connected renewable energy consumption problem and reducing the cost of electricity purchasing. In a study conducted by Zhu et al. [37] developed a new energy process based on a wind farm, Kalina cycle, and a LAES storage system. The LAES system can be integrated with different external energy sources to store electricity during peak hours. In another study by Tian et al. [38] proposed a capacity planning framework for HWPBS considering the characteristics of multi-energy integration into the grid. By constructing the capacity allocation model of HWPBS under CCP and DCP, the impacts of the configuration mode of wind power generation and battery storage, load demand, and planning capacity on the complementary system are investigated.

C. OPERATIONAL SCHEDULING OF MULTI-ENERGY POWER GENERATION SYSTEMS

The operational scheduling of multi-energy power generation systems involves the coordination and optimization of wind, solar, and hydro energy generation, as well as the operation of energy storage devices. The main objective is to meet grid load demand while ensuring the safe and stable operation of the power system. Key considerations in this process include generation scheduling, energy storage device scheduling, system stability, and reliability, as well as demand response and intelligent scheduling. These issues require the application of mathematical modeling, optimization algorithms, and real-time monitoring technologies for effective study and resolution. This research aims to provide technical support for the stable operation of wind-hydro complementary power generation systems. The ultimate goals are to increase the utilization of renewable energy, reduce operating costs for power systems, and promote the sustainable development of clean energy. In a study conducted by Ren et al. [39], the complementary operation of small-scale hydro, large-scale wind, and photovoltaic power generation systems was explored. Three multi-energy complementary operation schemes were proposed and compared using scenario partitioning and actual measurement data to identify the optimal scheme. The study demonstrated that leveraging the stable output and fast regulation capabilities of hydroelectric power can improve overall system stability and reduce curtailment of wind and solar power generation. In a study by Li et al. [40] constructed a wind power capacity scenario through a combined method based on a generative adversarial network and K-means clustering algorithm, and established a capacity optimization model for a wind-pumped storage hybrid system considering variable-speed pumping characteristics, including the three objectives of the levelized cost of energy, peak-shaving difference, and power output deviation. The complementary nature of wind and pumped storage and the advantages of variable-speed pumped storage and wind power over fixed-speed pumped storage units are described. Ma et al. [41] proposed the " monthly LCHES-WP operation strategy " and "short-term dispatch strategy for LCHES" using the example of a real terrace hydropower plant in Qinghai Province, China, and nested the monthly LCHES-WP operation simulation model into the yearly

TABLE 1. Taxonomy of related studies.

Author, year	Model		Obj. function	Constraints	Optimization problems solved	Meta-heuristic	Others
	Theoretical	Experimental					
L.Lu [32] (2021)	√	√	Maximize the expected generation profit of the system	Component requirements	MILP NLP		
Y.He [33] (2022)	√		Minimum net present cost Minimum loss of power supply probability	Component requirements	MOP	MOEA-DM	LPSP
N. Lu [34] (2024)	√		Minimization of the power output range Minimization of total abandoned hydroelectricity	Component requirements	MINLP		HPP
LH. Qiu [35] (2022)	√	√	Maximum pumped hydro storage potential	Component requirements			ESR
HN.Zhang [36] (2023)	√		Minimum multi-source system power purchase cost Minimum renewable energy consumption.	Component requirements	MOP	IGA	
LG. Zhu [37] (2023)	√		Minimum economic cost of energy systems	Component requirements	MOOP	GA	LAESS
YY. Tian [38] (2024)	√	√	Maximize expected generation of renewable energy Minimize expected power abandonment and load loss	Component requirements	MIP		CCP DCP
R. Yan[39] (2022)	√		Minimization of power output fluctuations	Component requirements	MOP		
Yang. L [40] (2023)	√		Minimizing the levelized cost of energy Minimizing peak-shaving difference Minimize power output deviation	Component requirements	MOP		

TABLE 1. ***(Continued.)*** **Taxonomy of related studies.**

C.Ma [41] (2024)	√	√	Minimum total curtailment energy Minimum total energy increment	Component requirements	MOP NLP		EED
Current Work	√	√	Maximization of system benefits Maximization of technical reliability	Component requirements	MOP	IFA	

dispatch optimization model to estimate the performance of the medium- and long-term operation.

To highlight the innovation of this study, a detailed comparison between existing research and the present work using statistical methods is conducted, as shown in Table 1. The coordination and integration of multi-energy systems involve a high level of complexity. This complexity arises from various factors, including the output characteristics of different energy sources, the volatility of tides, solar energy, and wind energy, as well as the complementarity between different energy sources. Furthermore, designing and optimizing wind-hydro energy storage systems and other energy storage technologies to maximize energy utilization efficiency, reduce system costs, and ensure reliable energy supply is a complex problem due to the unique output characteristics of different energy sources and their interactions. Therefore, this paper not only proposes new optimization models and algorithms, but also considers practical challenges in scheduling, such as the impact of energy cross-coupling on system dispatch, real-time operation and coordination control of the system, and flexibility requirements. This comprehensive approach aims to provide more effective solutions for the optimization scheduling of the system.

III. SYSTEM MODELING

A. PROBLEM BACKGROUND

In the development of modern energy systems, wind, solar, and hydropower systems play a crucial role as key components of renewable energy. They are essential in ensuring reliable energy supply and the stability of the power system. With the continuous growth of wind and solar capacity, the fluctuations and randomness of their power generation have increased the pressure on grid regulation and frequency control. The existing grid regulation capability is not sufficient to meet the requirements for integrating new energy sources and economically optimizing peak load. There is an urgent need to develop effective optimization models to coordinate and optimize various power generation systems, ensuring efficient energy utilization and stable operation of the power grid.

B. MODEL FRAMEWORK

The wind-solar energy storage system makes full use of the "peak shaving and valley filling" advantage of pumped storage power plants. It stores surplus electricity from wind and solar power generation and releases it during periods of high demand, thereby alleviating pressure on the power system. The system design aims to optimize power distribution, reduce the impact of distributed power generation on the system, effectively mitigate wind and solar curtailment due to power limitations, and conserve resources. This system enables smooth and controllable output of the integrated system, leading to significant economic benefits and environmental friendliness. The wind-solar energy storage system operates in two modes. Firstly, when there is excess capacity in the wind and solar power plants but low demand, surplus electricity is converted into potential energy of water and stored in the pumped storage power plant for later use during high-demand periods. Secondly, when demand increases but the capacity of wind and solar power plants is insufficient, the stored water in the pumped storage power plant can be quickly released. This converts the potential energy of water into electricity to meet the needs of the power grid. The system efficiently utilizes its capability for fast frequency and load regulation, ensuring stable operation of the power system and achieving effective energy utilization along with environmental friendliness.

C. MODEL ASSUMPTIONS

1) The electricity demand pattern is both known and relatively stable throughout the designated planning period.

2) The system parameters and energy storage losses are assumed to remain constant throughout the analysis period.

3) The electricity market price is fixed and not influenced by short-term fluctuations.

D. SYMBOL DESCRIPTION

See Table 2.

E. CALCULATION OF BASIC PARAMETERS

In our study model, it is essential to anticipate the power generation output of wind power, solar energy, and pumped storage power stations to determine their future power generation capacity. The prediction of these values is based on historical wind speed data, the characteristics of wind turbines, solar irradiance, and the characteristics of solar panels. These predicted values will be considered as the fundamental parameters within our model, which will subsequently be

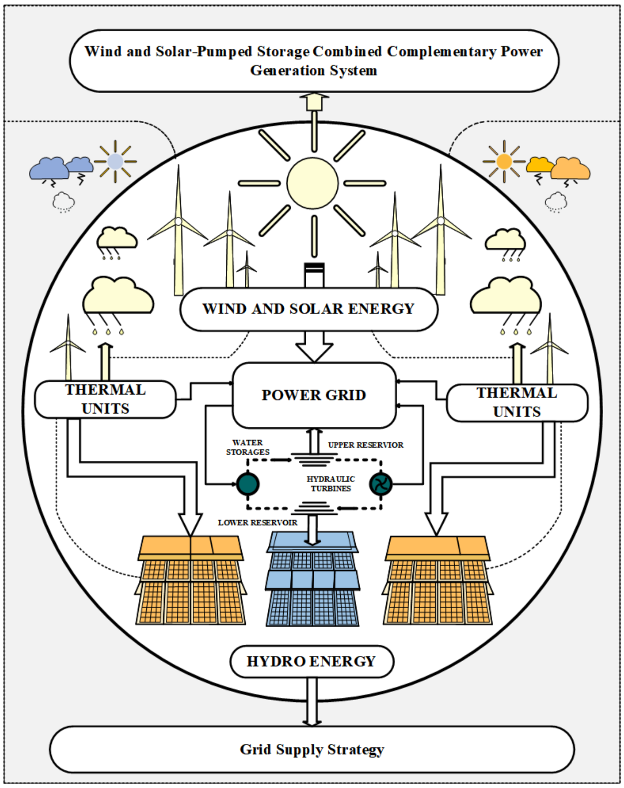

FIGURE 2. Operating principle of the wind-solar pumped storage energy storage complementary power generation system.

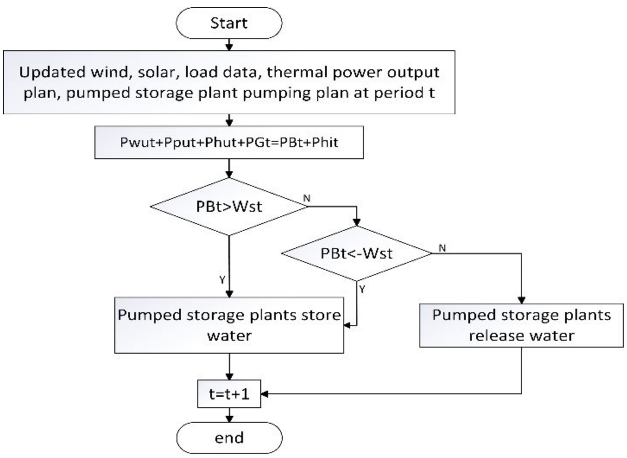

FIGURE 3. The flow chart of the operation principle of the wind-solar pumped storage energy storage complementary power generation system.

utilized to calculate future electricity demand.

$$P_{wt} = \frac{8}{\pi} c_p \rho d^3 v_{wt}^3 \tag{1}$$

$$P_{pt} = \eta_b AG \left[1 + \alpha \left(T - T_0\right)\right] \tag{2}$$

$$E_{hi} = \frac{H_1 V_t}{367.2 \eta_{in}} \tag{3}$$

$$E_{hu} = \frac{H_2 V_t \eta_{out}}{367.2} \tag{4}$$

TABLE 2. The model involves the description of variables.

Symbols	Description
p_{wt}	Wind power generation capacity at period t
p_{pt}	Photovoltaic power generation capacity at period t
E_{hi}	Electricity consumption for pumping
E_{hu}	Electricity consumption for power generation
W_{wpht}	The solar energy storage and power generation revenue at the period t
W_{Gt}	The revenue from thermal power generation during the period t
C_{Gt}	The fuel cost at the period t
c_{hit}	The price of pumped hydroelectricity at a period t
p_{hit}	The pumped hydropower at the period t
κ	The penalty electricity price for wind and solar curtailment
W_{st}	Pumped storage plant start-stop thresholds

$$V_t = \sum R_t \tag{5}$$

where, c_p, ρ, d, v_{wt} represents the coefficient of wind energy utilization, air density, wind turbine diameter, and wind speed; η_b, A, G, α, T represents the conversion efficiency of photovoltaic cells, effective area, radiation intensity, temperature coefficient, cell temperature, and reference temperature; $H_1, H_2, V_t, \eta_{in}, \eta_{out}$ represents the pumping head, power generation head, adjustable water volume, pumping efficiency, and power generation efficiency; R_t represents the runoff volume.

F. MODELING THE MULTI-ENERGY POWER GENERATION SYSTEM

The objective of this study is to address the load allocation issue between wind-solar power plants and pumped storage power plants. The objective function is set to maximize the revenue generated from electricity sales over the calculation period. This objective function helps determine the power flow from wind-solar power plants and the operating mode of the pumped storage power plants during system operation:

$$\begin{aligned} \max F_1 = \sum_{t=1}^{T} \big[& W_{wpht} + W_{Gt} - c_{hit} p_{hit} - C_{Gt} \\ & - \kappa \left(p_{wgt} + p_{pgt}\right) \big] \end{aligned} \tag{6}$$

$$W_{wpht} = c_t p_{wut} + c_t p_{put} + c_t p_{hut} \tag{7}$$

$$W_{Gt} = c_t p_{Gt} \tag{8}$$

$$C_{Gt} = a_k p_{Gt}^2 + b_k p_{Gt} + c_k \tag{9}$$

Equation (6) represents the overall revenue function of the power generation system. In this equation, p_{wgt} and p_{pgt} represent the amount of discarded wind and solar power, respectively. Equation (7) represents the revenue generated from wind-solar storage and generation. c_t represents the time-of-use electricity price; Equation (8) represents the revenue generated by thermal power generation. p_{Gt} denotes the power output of thermal power generation during the period "t"; Equation (9) represents the calculation of fuel cost, wherein 'a', 'b', and 'c' are coefficients that represent fuel characteristics.

$$p_{wut} + p_{put} + p_{hut} + p_{Gt} = p_{Bt} + p_{hit} \tag{10}$$

$$P_{m.\min} \leq p_{wut} + p_{put} + p_{hut} \leq P_{m.\max} \tag{11}$$

$$P_{w.\min} \leq p_{wut} \leq P_{w.\max} \tag{12}$$

$$P_{p.\min} \leq p_{put} \leq P_{p.\max} \tag{13}$$

$$p_{wg}, p_{pg} \geq 0 \tag{14}$$

$$p_{wgt} = p_{wt} - p_{wut} \tag{15}$$

$$p_{pgt} = p_{pt} - p_{put} \tag{16}$$

$$0 \leq p_{hit} \leq p_{hit.\max} \tag{17}$$

$$0 \leq p_{hut} \leq \min\left(p_{hut.\max}, E_{hu} \cdot \eta_{out}\right) \tag{18}$$

$$E_{t+1} = E_t + \left(\eta_{in} \cdot p_{hit} - \frac{p_{hut}}{\eta_{out}}\right) - E_{lose} \tag{19}$$

$$0 \leq E_t \leq E_{\max} \tag{20}$$

$$p_{Gt.\min} \leq p_{Gt} \leq p_{Gt.\max} \tag{21}$$

Among these, Equation (10) represents the power balance output, while Equation (11) represents the power limitation for the integration of new energy sources to ensure the stability of the power grid. $P_{m.\min}$ and $P_{m.\max}$ denote the upper and lower limits of grid-connected power, respectively. Equations (12)-(13) represent the power limitations for wind and solar power generation, while equations (14)-(16) represent the constraints on curtailed wind and solar power. p_{wgt} and p_{pgt} represent the curtailed wind and solar power, respectively. Equation (17) represents the power limitations for pumped storage, while equation (18) represents the limitations on power generation for pumped storage power plants. Equation (19) represents the energy balance constraint for reservoirs. E_t and E_{t+1} represent the energy stored in the energy storage system at time 't' and 't+1', respectively. η_{in} and E_{lose} represent the efficiency of the pumped storage system and the energy that is not stored. Equation (21) represents the power generation constraint for thermal power plants.

To minimize the frequent start-stop and adjustment of thermal power units, and prioritize the full consumption of renewable energy, the output of the wind-solar energy storage and generation system is adjusted in a way that minimizes the fluctuation of the net load curve. Additionally, minimizing the variance of the net load serves as another objective function:

$$\min F_2 = \sqrt{\sum_{t=1}^{T} \left(p_t - \bar{p}\right)^2 / T} \tag{22}$$

$$p_t = p_{Bt} - \left(p_{wut} + p_{put} + p_{hut}\right) \tag{23}$$

$$\bar{p} = \sum_{t=1}^{T} p_t / T \tag{24}$$

$$\max F = F_1 / F_2 \tag{25}$$

Equation (22) represents the minimum fluctuation of the residual load, which indicates the stability of the power grid operation. Equation (23) represents the net load power, while Equation (24) represents the average net load. Equation (25) represents the final single objective function.

IV. ALGORITHM DESCRIPTION

In the conventional Firefly Algorithm, an individual's position update primarily depends on the attractiveness between individuals within the population, guiding their search. Additionally, a random term is included in the search strategy to encourage the exploration of alternative feasible solutions in the solution space. However, when dealing with complex models, excessive reliance on the search strategy often traps individuals in local optima within the complex and high-dimensional solution space. Furthermore, compared to the search strategy, the random term introduced in the traditional Firefly Algorithm tends to have a limited step size, which often fails to effectively aid individuals in escaping local optima. Moreover, in the traditional Firefly Algorithm, the calculation of the updating step size is based on the distance between two individuals. Nonetheless, in scenarios where the problem dimension is high and proper normalization cannot be achieved, the search strategy may prove ineffective due to the significant distance between individuals.

This paper presents enhancements to the traditional Firefly Algorithm to address these concerns. The proposed improvements include the Space-Adaptive Search Strategy, Levy Flight Mechanism, and Differential Double Generational Crossover Optimization Mechanism. These enhancements have been introduced to improve the efficiency of exploration in the solution space and aid individuals in successfully traversing local optima, ultimately leading to enhanced optimization accuracy of the algorithm.

A. SPATIAL ADAPTIVE FOLLOWING SEARCH STRATEGY

In the traditional Firefly Algorithm, the following search term in the following search strategy for an individual is represented as follows:

$$L = \beta_0 e^{-\gamma r_{ij}^2} \left(X_j(t) - X_i(t)\right) \tag{26}$$

In the traditional Firefly Algorithm, the following search term in the following search strategy for an individual is represented as follows: where β_0 represents the maximum attractiveness, γ represents the absorption coefficient of light, and r_{ij}represents the Euclidean distance between individual 'i' and individual 'j'. However, when the traditional Firefly Algorithm is applied to optimize complex, high-dimensional solution spaces, the attraction term is likely to approach zero due to the large distance between individuals. Consequently, this can result in the failure of the attraction-based search. In such cases, the update of an individual's position is based on random exploration near its original position. This approach, however, diminishes the algorithm's ability to perform effective global searches and obtain high-quality optimization results. Another factor contributing to the algorithm's limitations is the presence of two hyperparameters, denoted as β_0 and γ, which can only be determined through empirical experience. Consequently, due to the nature of these hyperparameters, it is not guaranteed that the algorithm will be able to generalize effectively across various scenarios.

To address this issue, this paper proposes a spatial adaptive following search strategy. This strategy aims to overcome the limitations of the traditional firefly algorithm by eliminating the use of hyperparameters in the attraction term. Instead, regardless of the individual's position in the solution space, the adaptive strategy maps the step size of the attraction term of each individual to the range of [0, 0.5]. This adjustment ensures the algorithm's ability to generalize and adapt effectively across different scenarios. Furthermore, the strategy also eliminates the random term present in the original following search strategy, ensuring that the individual's search direction is not influenced by random factors. The improved following search strategy is outlined below:

$$X_i(t)=X_i(t)+\left(\frac{1}{1+exp(-10^{-log_{10}r_{ij}^2})}-0.5\right)\left(X_j(t)-X_i(t)\right) \tag{27}$$

To further reduce the complexity of the algorithm, the improved firefly algorithm eliminates the need for each individual to assess whether to move toward the direction of other individuals in every iteration. Instead, a roulette wheel selection method is employed to determine the target individual to be followed. This modification substantially reduces the computational time required for optimization in the algorithm.

B. LEVY FLIGHT MECHANISM

In the traditional firefly algorithm, a random search of individuals takes place after the following search and is confined to a fixed random search area near the original position. This restricts the ability to escape local optima and lacks global exploration capability. To overcome this limitation, we introduce the Levy flight mechanism into the improved firefly algorithm. In the improved algorithm, individuals will follow the equation for Levy random search outlined below:

$$s = \frac{u}{|v|^{\frac{1}{\beta}}} \tag{28}$$

$$u \sim N\left(0, \sigma^2\right), \ v \sim N\left(0, 1\right), \ \sigma = \left\{\frac{\Gamma(1+\beta)sin(\frac{\pi\beta}{2})}{\beta\Gamma(\frac{1+\beta}{2})2^{\frac{\beta-1}{2}}}\right\} \tag{29}$$

$$L(s, \lambda) = \frac{\lambda\Gamma(\lambda)sin(\frac{\pi\lambda}{2})}{\pi}\frac{1}{s^{\lambda+1}} \tag{30}$$

$$X_i(t) = X_i(t) + \alpha L(s, \lambda) \tag{31}$$

where β and λ are hyperparameters, α represents the step size of the search. The Levy distribution's heavy-tail characteristics enable the algorithm to make larger jumps in the search space, facilitating the escape from local optima and comprehensive exploration of the global search space. Moreover, due to its adaptiveness, the Levy flight mechanism can adjust itself based on the current search state, enhancing the algorithm's adaptability to complex problem characteristics. Furthermore, the long-distance jumps facilitated by the Levy flight mechanism accelerate the search process, particularly in large-scale optimization problems or high-dimensional search spaces.

C. DIFFERENTIAL DOUBLE TARGET CROSSOVER OPTIMIZATION STRATEGY

In the traditional firefly algorithm, in cases where only a single population is present, individuals within the population all follow the same search strategy. However, this can lead to premature convergence during the optimization process, which hinders effective exploration of the entire solution space and reduces optimization precision. To mitigate this issue, we propose a differential double-target crossover optimization strategy. In each iteration, the parent population first undergoes a differential strategy to generate the offspring population:

$$V_i(t) = X_{r1}(t) + F \bullet (X_{r2}(t) - X_{r3}(t)) \tag{32}$$

where 'r1', 'r2', and 'r3' are random integers, the offspring population will then undergo the spatial adaptive follow-search and Levy flight as described earlier. Finally, the offspring population will be combined with the parent population through a crossover operation to generate the final population:

$$eU_i^j(t) \begin{cases} V_i^j(t) & rand < CR \ or \ j = I \\ X_i^j(t) & else \end{cases} \tag{33}$$

In the differential double target crossover optimization strategy, the offspring population is initially generated from the parent population, while retaining some of the parent's characteristics and introducing slight variation. This process is governed by the crossover probability (CR), where 'I' represents a random integer ranging from 1 to NP, where NP stands for the total number of individuals in the population. Subsequently, the offspring population engages in spatial adaptive follow-search and Levy flight to explore the solution space. This involves continuously updating its position to maintain superiority. Finally, by crossing the offspring population with the parent population, premature convergence is prevented, and effective exploration of the solution space is ensured.

D. BASIC DATA AND PARAMETERS

To evaluate the effectiveness of the multi-objective optimization model for the wind-solar energy storage system proposed in this study, a case study is conducted in a southwestern region. The power generation system's key parameters are presented in Table 2 and Table 3. The case study simulation utilizes wind, solar, and water data for March to May, totaling two months. Figures 5 and 6 display the power output predictions of the wind and solar power stations, and the grid's net

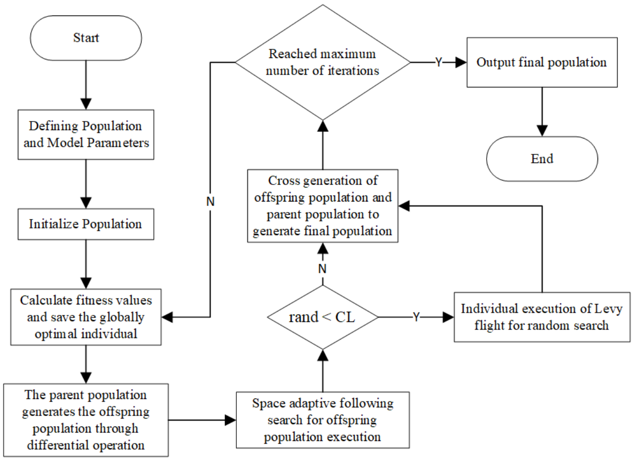

FIGURE 4. Algorithm flowchart.

load curve, respectively. MATLAB R2023a is employed as the simulation programming tool, operating on the Windows 11 platform, with 16 GB of memory and an Intel(R) Core (TM) i9-13900HX 13th Generation processor.

TABLE 3. Basic parameters of the power generation system.

Variables	numerical value
c_p	0.47
ρ	1.29
d	77
η_b	0.15
A	0.1
α	0.5
T	30
T_0	25
H_1	80
H_2	640
η_{in}	0.8
η_{out}	0.94
a,b,c	0.00211, 16.51, 502.7
κ	$5\,c_t$
c_{hit}	$0.5\,c_t$
η_{in}	0.80
η_{out}	0.94

E. ANALYSIS OF OPTIMIZATION DISPATCH RESULTS

To validate the efficacy of the aforementioned optimization dispatch model, we compare the proposed improved Firefly Algorithm in this paper with various cut-ting-edge swarm intelligence optimization algorithms, such as the Genetic

TABLE 4. Time-based Electricity Tariff (kWh).

0:00-7:00	7:00-9:00	9:00-12:00	12:00-17:00	17:00-22:00	22:00-23:00	23:00-24:00
0.139	0.278	0.417	0.278	0.417	0.278	0.139

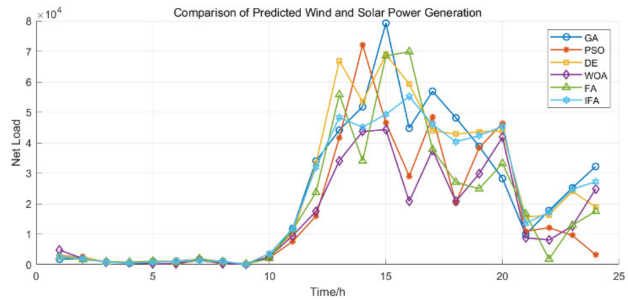

FIGURE 5. Predictive curves of wind power and solar power generation.

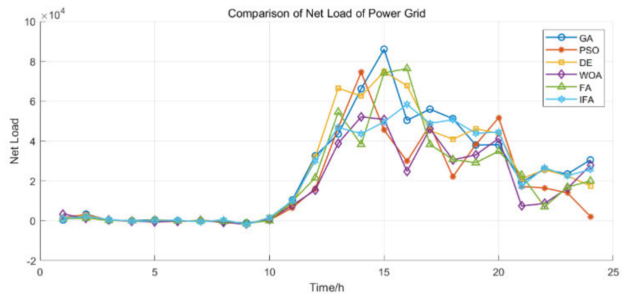

FIGURE 6. Predictive curve of grid net load.

Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Whale Optimization Algorithm (WOA), and Fireworks Algorithm (FA), to address the problem at hand. The output of the pumped storage power plant is illustrated in Figure 7.

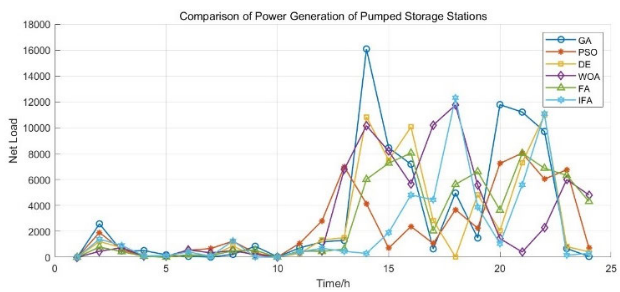

FIGURE 7. Power output graph of pumped storage power plant.

By examining Figure 8, it can be observed that the integration of pumped storage leads to a more stable power output fluctuation in the wind-solar complementary system when compared to the system without pumped storage.

In this study, the Improved Firefly Algorithm (IFA) was employed to solve a specific scheduling model.

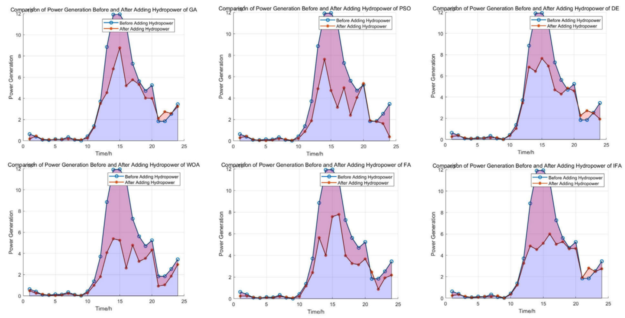

FIGURE 8. Comparison chart of wind-solar combined power output before and after the introduction of pumped storage.

TABLE 5. Dispatch generation results.

Wind power (kWh)	Solar power (kWh)	Hydroelectric power (kWh)
63141540	0	475872.7
40208170	0	461105.3
10774380	0	612337.8
7810295	0	743157.7
15105800	0	716123.3
12820110	0	726502.2
34163160	0	659781.2
10412820	0	644954.7
2328470	61122.23	644954.7
6616612	36092680	644954.7
17208150	119891300	646438.4
40817980	329907200	658299.3
293294500	591571500	587132.4
459189700	730808000	570822.2
524914500	668463300	395869.8
386516100	703975300	394386.1
256906000	469999400	409212.6
397981000	163257500	462589.1
417678200	52320630	459623.4
462370300	61641770	462589.1
183458500	702905.7	4611053.
184896600	0	464071
253124600	0	461105.3
344497400	0	464071

A comparative analysis was then conducted, comparing IFA with several other state-of-the-art swarm intelligence algorithms, including the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), Differential Evolution (DE), and the traditional Firefly Algorithm (FA). To comprehensively evaluate the performance of these algorithms, not only their performance in a single run was analyzed, but also the average results over 20 runs were considered, as depicted in Figure 9. The average results of 20 runs demonstrated that IFA exhibited excellent performance in terms of convergence speed and solution stability, thereby displaying its potential in solving complex scheduling problems. Notably, significant improvements were observed when comparing IFA to the traditional FA. Furthermore, IFA showed competitive performance in terms of convergence speed and global optimization when compared to GA, PSO, WOA, and DE.

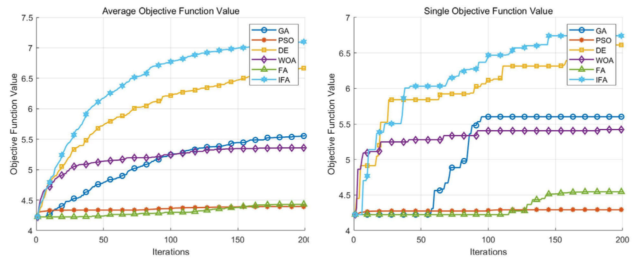

FIGURE 9. Convergence curve comparison of algorithms.

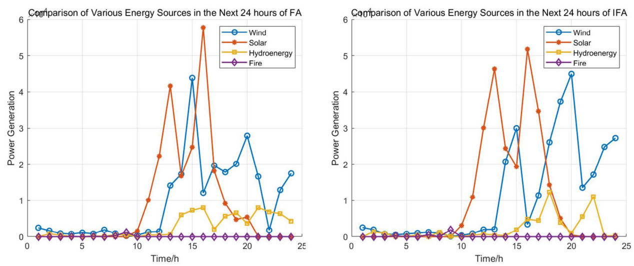

FIGURE 10. Optimization results.

TABLE 6. Comparison of objective function values.

Algorithms	Objective function value
GA	5.4384
PSO	3.4830
WOA	4.9756
DE	6.3759
FA	4.1751
IFA	7.8331

The power output of each power source in the joint system, obtained with the objective of maximizing the overall profit and minimizing the net load variance, is illustrated in Figure 10. Table 5 presents the specific operational results of the Improved Firefly Algorithm (IFA) for the renewable energy generation system. Additionally, Table 6 displays the comparison of objective function values among the six algorithms.

The results demonstrate that the Improved Firefly Algorithm (IFA) improves the power efficiency of the system while reducing load fluctuations and output variations. These findings validate the correlation between economic objectives and stability objectives and also reflect the changing characteristics of power demand in real-world power systems.

V. CONCLUSION

The economic benefits and absorption capacity of multi-energy complementary power generation systems are important factors that influence the sustainable development and large-scale utilization of renewable energy. These systems offer an effective solution for addressing the challenges associated with the transmission of large-scale intermittent energy. In this paper, our main focus is on the volatility of renewable energy, the scheduling of pumped storage power generation equipment, and the economic factors associated with joint power generation systems. The scheduling model for a wind-solar-hydro complementary power generation system with pumped storage is initially established, along with the corresponding constraints. Subsequently, an analysis and calculation of the weights assigned to various sub-factors in relation to the overall objective are conducted. This transformative process enables the conversion of the initial multi-objective problem into a single-objective problem. Lastly, the enhanced double-generation firefly algorithm is compared and analyzed alongside several state-of-the-art swarm intelligence optimization algorithms (GA, PSO, DE, WOA, FA) to validate the efficacy of the scheduling optimization model. Through the optimization scheduling process, the comparative results indicate that the improved firefly algorithm utilized in this study is more suitable for this specific case. These results not only affirm the effectiveness of the model but also establish the superiority of the designed algorithm. It also offers insights to tackle the challenges associated with large-scale intermittent energy transmission. In future research, the methodology will be expanded to include more hybrid energy systems, enabling further investigation of large-scale, real-time data examples and exploration of their applicability on a global scale. This will advance the broader application of renewable energy, maximize resource utilization, and enhance economic efficiency.

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