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Optimal System Analysis for Hybrid Wind-Solar-Pumped Storage Systems under Renewable Output Uncertainty

Zhijie Cai[1], Shihao Zuo[2]

[1]School of Energy and Power Engineering, University of Shanghai for Science and Technology, Shanghai, 200093, China
[2]College of Energy and Power Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, 210016, China

Abstract: *In the domain of renewable energy, the pronounced variability inherent in wind and solar power generation poses substantial challenges to the stable functionality of electrical grids. This study acknowledges the significant variability inherent in wind and solar energy, which can affect the stability of power grids. This paper proposes a comprehensive model that integrates Copula sampling, K-means and hierarchical clustering, and Particle Swarm Optimization (PSO) algorithms to analyze and optimize the performance of hybrid wind-solar-pumped storage systems. This model accurately captures the dependency structures between wind and solar outputs, using clustering techniques to classify diverse energy production scenarios. Additionally, this paper employs the PSO algorithm to address a multi-objective optimization problem, balancing both operational and environmental costs in hybrid wind-solar-pumped storage systems. This paper findings reveal notable improvements in reducing energy waste due to uncertainties in renewable resource availability and achieving lower operational costs through the optimization of the hybrid wind-solar-pumped storage system. This research provides insights into the sustainable integration of renewable energies into power grids, with a particular focus on economic and environmental benefits.*

Keywords: *Wind-solar uncertainty, K-means clustering, Hierarchical clustering, Pumped storage systems, Energy management, Particle Swarm Optimization*

1. Introduction

The global energy consumption landscape is undergoing profound changes, prominently featuring wind and solar energy. Despite their environmental benefits, these sources exhibit significant variability and uncertainty, presenting challenges for grid stability and necessitating efficient energy management solutions. This variability is particularly evident under suboptimal conditions, often resulting in unstable power supplies and emphasizing the importance of energy storage systems [1-3]. This paper aims to address these challenges by analyzing and optimizing the performance of hybrid wind-solar-pumped storage systems [4].

In response to the challenges posed by the volatility of renewable resources, researchers and engineers are actively exploring various solutions aimed at enhancing the stability and economic viability of energy systems. Energy storage technologies, particularly electrochemical storage, mechanical storage, and chemical storage, are considered among the most effective strategies. These storage systems can store excess electricity during times of surplus and release it during peak demand periods, effectively balancing supply-demand discrepancies and strengthening the grid's regulatory capacity [5]. A comprehensive review identifies electrochemical energy storage, hydrogen storage, and optimal system configuration as research hotspots. It also examines future challenges, such as managing transient shocks affecting power grid stability [6]. Meanwhile, the Turgut M. Gür emphasizes that despite the prevalence of pumped-hydro storage, a diverse portfolio of electrical energy storage technologies is necessary to meet the varying needs of large-scale grid storage. Their review underscores the importance of mechanical, thermal, and advanced electrochemical storage in improving grid reliability and fully integrating renewable energy into the power grid [7]. Additionally, current research is investigating how to further optimize the operational efficiency and cost-effectiveness of storage facilities by integrating advanced control systems and intelligent algorithms. Cost-effectiveness analyses of wind and solar power systems indicate that, with technological advancements and scale economies, the costs associated with wind and solar power are expected to decrease further. Moreover, by integrating with storage technologies, not only is their market competitiveness enhanced, but the overall reliability and flexibility of the power system are also significantly improved [8].

In addressing the economic and technological maturity challenges faced by storage systems, this study adopts a comprehensive approach to optimize the design and operation of wind-solar-pumped hydro storage systems, effectively dealing with the uncertainties and fluctuations of renewable resources. Firstly, the Copula method is utilized to simulate the dependency relations between wind and solar outputs, enhancing understanding and predictive capability of these variable energy interactions. Then, through K-means clustering and hierarchical clustering techniques, electricity production scenarios are meticulously categorized to identify and manage various patterns and characteristics in the production process. Additionally, the Particle Swarm Optimization (PSO) algorithm is employed for multi-objective system design optimization, addressing complex decision-making problems that include operational costs and environmental protection costs. The integration of these methods not only increases the energy utilization efficiency of the system but also reduces operational costs. A review of the relevant literature indicates that this approach is closely aligned with current academic discussions and technological advancements. For instance, Miao X explored operational optimization control principles and strategies for wind-solar complementary generation systems, providing specific strategies for optimizing electricity production and storage utilization [9]. Sun Y offered insights into capacity optimization methods for hybrid storage systems in wind-solar complementary generation systems, demonstrating the potential to enhance system efficiency through simulation and optimization techniques [10]. Zhou Y discussed trends in the development of wind and solar power generation and storage technologies, emphasizing the importance of cost reduction and technological maturity in enhancing market competitiveness [11]. Liang J highlighted the application value of an improved particle swarm optimization algorithm in the multi-objective optimization scheduling of microgrids [12].

While numerous optimization methods for wind-solar complementary generation systems have been proposed, many remain limited in fully addressing the high uncertainties of energy outputs and the intricate environmental factors. Consequently, these methods are often ill-suited for managing energy fluctuations in extreme weather conditions. Furthermore, conventional optimization algorithms frequently lack efficiency and optimization capability when confronted with large-scale or complex problems, impeding the attainment of an optimal balance between cost, reliability, and environmental impact. In response, this paper introduces a novel approach integrating an enhanced PSO algorithm with a multi-objective optimization model. By incorporating dynamic adjustment strategies and adaptive parameter tuning mechanisms, the model significantly improves global search capabilities and convergence speed, allowing for effective mitigation of energy output uncertainties while dynamically adapting optimization objectives to shifting environmental and economic conditions. These advancements offer promising avenues for enhancing economic and stability metrics in renewable energy systems while contributing new perspectives and practical applications to the field.

2. Wind-solar-pumped storage hybrid power generation system

2.1 Power Generation System Structure

The wind-solar-pumped storage hybrid energy system comprises four main components: the wind power generation unit, the solar power generation unit, the Pumped Storage System (PSS), and the Battery Energy Storage System (BESS). These components collaborate to provide a comprehensive energy supply and regulation. The wind power generation unit captures wind energy via wind turbines and converts it into electrical energy; similarly, the solar power generation unit utilizes photovoltaic panels to convert sunlight directly into electricity. These sources can supply power directly or store excess electricity in the PSS and BESS when production exceeds demand.

The PSS, as a crucial hydraulic energy storage component within the system, uses surplus electricity during periods of low demand to pump water to a higher elevation reservoir and releases it through turbines to generate electricity during peak demand periods. Additionally, the BESS, as an electrochemical storage component, stores energy in efficient lithium-ion batteries, providing the system with more flexible energy management and emergency response capabilities.

To achieve effective balancing of wind and solar outputs and maximize the utilization of these renewable resources, this paper introduces an Electrical-to-Storage (E2S) technology. This technology converts excess electricity generated by wind and photovoltaic power into stored energy within the PSS and BESS. By employing this strategy, surplus wind and solar energy is preserved as stored energy during low-demand periods and converted back to electrical energy during peak demand, thus achieving peak shaving and valley filling functions within the system.

Through efficient energy management, the optimized wind-solar-pumped storage hybrid generation system significantly enhances the flexibility of energy utilization. This system not only ensures the continuity of energy supply but also enhances grid responsiveness through precise load management. Compared to traditional single-source systems, this integrated system effectively combines the advantages of wind and solar energy, achieving temporal optimization of energy resources. This integrative strategy aims to enhance the complementary benefits of wind and solar resources while potentially improving the overall operational efficiency and reliability of the power system. It offers promising approaches to address energy absorption challenges.

2.2 Wind-Solar-Pumped Storage System Optimization Model

2.2.1 Wind Turbine (WT) Unit Model

The power output of wind turbines is critically dependent on wind speed, which influences their operational efficiency through a series of thresholds [13]. Below the cut-in threshold, turbines do not generate electricity, resulting in zero output. Between the cut-in and rated wind speeds, output increases linearly with wind speed. At speeds above the rated but below the cut-out threshold, output stabilizes at the rated power. Above the cut-out speed, the turbines shut down, and power output drops to zero. The power output of a wind turbine can be mathematically represented by the following piecewise function:

$$P_{wt}=\begin{cases}0, & v<v_1\\ av^3+\mathrm{b}v^2+cv+\mathrm{d}, & v_1\leqslant v\leqslant v_2\\ P_\mathrm{r}, & v_2<v<v_3\\ 0, & v\geqslant v_3\end{cases}\tag{1}$$

Where: Pwt represents the output power of the wind turbine. Pr is the rated power, which the turbine maintains as long as the wind speed is between the rated wind speed ($v2$) and the cut-out wind speed ($v3$). The terms $v1$, $v2$, and $v3$ are the cut-in wind speed, rated wind speed, and cut-out wind speed, respectively. These thresholds define the operational limits within which the turbine can safely and effectively generate power. The coefficients a, b, c, and d are parameters that describe the polynomial relationship between the wind speed.

2.2.2 Photovoltaic (PV) Power Plant Model

In the wind-photovoltaic-water storage system model, the power of photovoltaic power generation needs to be predicted. The power of PV generation is [14]:

$$P_\mathrm{pv}=R_\mathrm{pv}q_\mathrm{pv}\frac{I_R}{I_\mathrm{STC}}[1+\alpha(T_\mathrm{c}-T_\mathrm{stc})]\tag{2}$$

Where: P_pv is the output power of photovoltaic; R_pv is the output power of photovoltaic under standard conditions; q_pv is the reduction coefficient of photovoltaic, which is generally 0.8; I_R is the actual solar radiation intensity; I_STC is the solar radiation intensity under standard conditions; α is the temperature coefficient of the photovoltaic panel; T_c is the photovoltaic panel temperature of the current time step; T_stc is the temperature under standard conditions.

2.2.3 Pumped Storage Model

Pumped hydro storage, as a form of energy storage, releases stored hydraulic energy when the combined generation from wind and solar sources is insufficient to meet demand. This release provides stable energy to users and ensures the continuous and stable operation of the system. The Pumped hydro storage generation is:

$$PSE(t)=\begin{cases}PSE(t-1)+\frac{1}{\eta^-}P_s(t), P_s(t)\leqslant 0\\ \\ PSE(t-1)+\eta^+P_s(t), P_s(t)>0\end{cases}\tag{3}$$

Where: $PSE(t)$ represents the remaining capacity of the hydroelectric station at time t. $Ps(t)$ denotes the charging or discharging power of the hydroelectric station at time t, where a positive value indicates charging and a negative value indicates discharging. $\eta+$ and $\eta-$ respectively represent the charging and discharging efficiencies.

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3. Uncertainty Management

3.1 Scenario Generation

To address the inherent uncertainties in wind and photovoltaic power outputs, this study introduces a scenario generation methodology that incorporates kernel density estimation and Copula functions. Initially, this approach utilizes non-parametric kernel density estimation to accurately model the distribution characteristics of extensive wind and solar power data samples. This initial fitting ensures the realistic representation of the dataset distributional properties.

Upon establishing the kernel density profile, a joint distribution model for wind and solar outputs is constructed using Copula functions. According to Song and Li, various common Copula functions such as Frank, Clayton, and Gumbel were assessed using Kendall's tau and Spearman's rho correlation coefficients to evaluate the models' fit and comparative effectiveness. From these, the Copula that best represented the goodness of fit and correlation coefficients was selected to model the joint probability distribution of wind and photovoltaic outputs. This optimal Copula function ensures that the generated scenarios not only reflect the independent nature of the energy sources but also effectively capture their interdependencies [15].

The selected optimal Copula function is then employed to generate a multitude of scenarios using the Monte Carlo simulation method. These scenarios represent potential combinations of output under varying wind speeds and solar irradiance conditions, thus providing essential data for the power system's reliability analysis and planning. Through inverse transformation techniques, Copula-based samples are converted back into actual wind and photovoltaic output values, yielding detailed scenarios suitable for further analytical pursuits.

This paper will address relevant case problems using this methodology, demonstrating high consistency with actual output data and affirming the model's advantage in generating scenarios with relevant correlations between wind and solar outputs. Furthermore, these scenarios exhibit a high level of accuracy in depicting the real-time outputs specific to geographical regions, thereby offering substantial insights for subsequent analyses on power system reliability and grid planning.

3.2 Scenario Reduction

Following the generation of wind and solar power output scenarios, the sheer number of scenarios can become computationally burdensome when directly applied to optimization and decision-making processes. To address this, this paper explores two different scenario reduction techniques: hierarchical clustering and K-means clustering, aiming to effectively reduce the number of scenarios while preserving essential information.

3.2.1 Hierarchical Clustering

Hierarchical clustering is a method that merges individual data points into clusters step by step. Its principal concept involves building a hierarchy of clusters either by progressively merging smaller clusters into larger ones until a single cluster remains, or by starting with one cluster containing all data points and successively splitting it until each cluster contains only one data point. Hierarchical clustering does not require a predetermined number of clusters. The general process is outlined as follows [16]:

1) Initialization: Treat each point as a cluster.

2) Merging: Find the two closest clusters and merge them.

3) Repetition: Repeat the merging step until all objects are grouped into a desired number of clusters or a single cluster is left.

The measure of distance or similarity typically used is the Euclidean distance. If the centers of clusters Ci and Cj are μi and μj respectively, the distance D (Ci, Cj) can be calculated as:

$$D(C_i, C_j) = \| \mu_i - \mu_j \| \tag{4}$$

3.2.2 K-means Clustering

K-means is a partitioning method that assigns data points to *K* clusters in such a way that the variance within each cluster is minimized. The steps of the K-means clustering algorithm are as follows [17]:

1) Select Initial Centers: Randomly pick *K* data points as the initial cluster centers.

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2) Assign Data Points: Assign each data point to the closest cluster center.

3) Update Centers: Recalculate the center of each cluster, typically using the mean of all points in the cluster.

4) Repeat: Repeat steps 2 and 3 until the cluster centers no longer change.

The calculation formula for the variance within a cluster is:

$$SSE = \sum_{i=1}^{k} \sum_{x \in C_i} \parallel x - \mu_i \parallel^2 \tag{5}$$

Where: x represents a data point, μi is the center of cluster Ci, and SSE denotes the sum of squared errors within the clusters. The objective of the K-means algorithm is to minimize SSE.

In the analysis of wind turbine and photovoltaic power output scenarios, hierarchical clustering was applied to reduce and organize the data. The hierarchical clustering technique systematically groups data points into clusters to identify typical scenarios in the power output. As shown in Figure 1. The wind turbine output scenarios illustrate variations in wind power generation over time, reflecting diverse conditions and operational patterns. Meanwhile, the photovoltaic power output scenarios capture variations in solar energy output throughout the day.

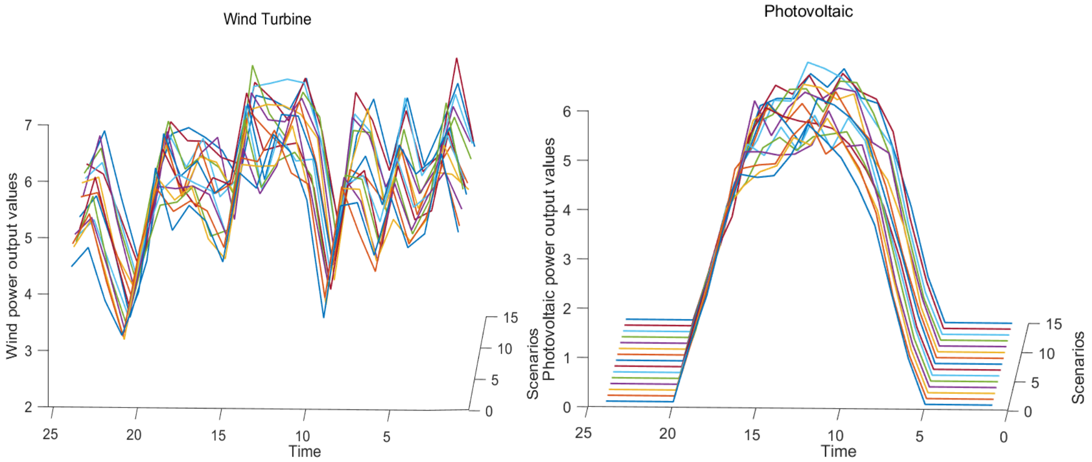

Figure 1: Reduction of Typical Scenarios Using Hierarchical Clustering

In addition to hierarchical clustering, the k-means clustering method was also employed to reduce the typical scenarios of wind and photovoltaic power outputs. This approach involves partitioning the data into a predefined number of clusters based on similarity, thereby reducing the total number of scenarios while retaining key characteristics. Figure 2 demonstrates the results of applying k-means clustering to reduce typical photovoltaic power scenarios and the wind turbine output scenarios, clearly highlighting patterns in solar power generation throughout the day. This method provides an effective way to categorize and manage scenarios for further analysis and optimization.

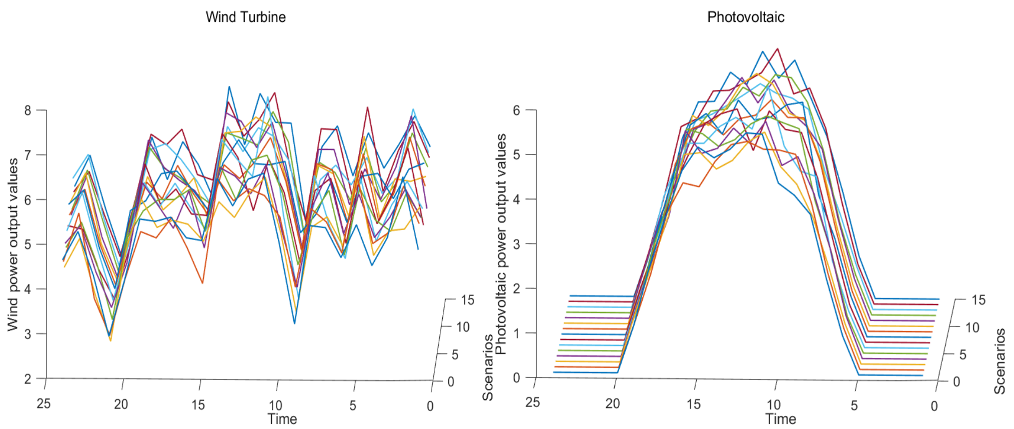

Figure 2. Reduction of Typical Scenarios Using K-means Clustering

3.2.3 Method Comparison and Selection

K-means clustering displayed superior computational efficiency, providing consistent clustering

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outcomes with reduced processing times, especially when handling large datasets. This efficiency is crucial in scenario reduction, where quick data processing is essential. The results, shown in Figure 3 for wind power output and Figure 4 for photovoltaic output, are illustrated by the blue lines and demonstrate less variability and tighter groupings than hierarchical clustering, indicating improved stability and reliability in scenario generation.

In contrast, hierarchical clustering—represented by the red lines in the graphs—exhibited higher sensitivity to noise and outliers, leading to greater inconsistency across different scenarios. Although hierarchical clustering offers a detailed hierarchical structure valuable for understanding complex data relationships, its high computational complexity hinders its practical application in large-scale energy scenario reduction.

Overall, the k-means clustering method is particularly advantageous for managing and simulating renewable energy outputs due to its ability to handle large volumes of data with consistent output quality.

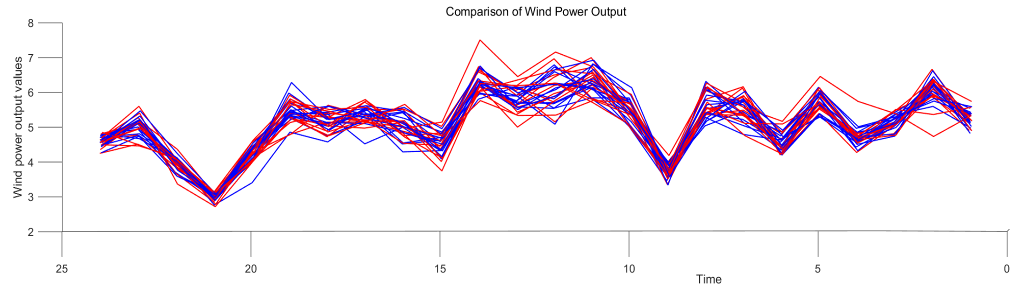

Figure 3: Comparison of Wind Power Output Using K-means and Hierarchical Clustering

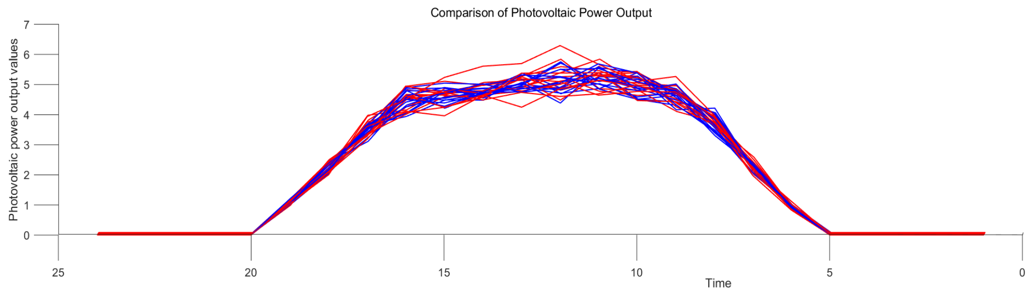

Figure 4: Comparison of Photovoltaic Output Using K-means and Hierarchical Clustering

4. Multi-objective Optimization Model

4.1 Objective Functions

In striving for an integrated system that maximizes the complementary characteristics of wind, solar, and hydro storage resources while also enhancing the consumption rate, the objective is to minimize both operational costs and environmental protection costs. The objective functions are outlined as follows:

1) System Operational Costs

The operational cost function is designed to quantify the total expenses involved in the regular operation of the integrated wind, solar, and pumped hydro storage system. This includes costs associated with generation, maintenance, and the necessary adjustments for balancing power supply and demand across the system. The formula for the operational cost is generally represented by:

$$f_1 = \sum_{t=1}^{T} C_{\mathrm{g}}(t) \tag{6}$$

$$\begin{cases} C_{\mathrm{g}}(t) = C_{\mathrm{b}}(t) + C_{\mathrm{s}}(t) \\ C_{\mathrm{b}}(t) = c(t)P_{\mathrm{b}}(t) \\ C_{\mathrm{s}}(t) = c_{\mathrm{s}}(t)P_{\mathrm{s}}(t) \end{cases} \tag{7}$$

Where: the terms $Cg\ (t)$ and $Cb(t)$ represent the total cost of interactions between the system and the main grid and the maintenance cost of the energy storage system at time t, respectively. The variable Pb (t) denotes the power output of the hydroelectric station at the corresponding time t. Furthermore, $Ps\ (t)$ and $Pb\ (t)$ indicate the power sold to and purchased from the main grid by the system at time t, respectively. The unit prices at which electricity is bought and sold are denoted by $Cb(t)$ and $Cs(t)$.

2) Environmental Protection Costs

The environmental cost function aims to account for the external costs incurred due to environmental impacts such as emissions, resource depletion, or other ecological impacts associated with the operation of the renewable energy system. These costs are typically modeled as a function of the energy generated, where the goal is to minimize the negative environmental impacts per unit of energy produced. The formula can be represented as:

$$f_2 = \sum_{t=1}^{T} C_{g.e}(t) \tag{8}$$

$$C_{g.e}(t) = \sum_{k=1}^{n} \left(C_k \gamma_{\text{grid},k}\right) P_{\text{b}}(t) \tag{9}$$

Where: $C_{g.e}(t)$ represents the pollution treatment cost of the large power grid; $\gamma_{\text{grid},k}$ is the emission of type k pollutants produced by the operation of the large power grid; Ck is the cost coefficient for treating type k pollutants.

4.2 Objective Function of the Scheduling Model

The objective function of the scheduling model is to minimize the total cost, which includes not only the operational costs but also the environmental protection costs. Therefore, the objective function is defined as follows:

$$Z = f_1 + f_2 \tag{10}$$

Where: Z represents the total cost of the microgrid, consisting of the sum of the microgrid's operational costs and environmental protection costs.

4.3 Constraints

Power balance constraint:

$$P_{pv}(t) + P_{wt}(t) + P_{\text{grid}}(t) + P_{\text{b}}(t) = P_{\text{L}}(t) \tag{11}$$

Power transmission constraints of the grid:

$$P_{\text{grid}}^{min}(t) \leqslant P_{\text{grid}}(t) \leqslant P_{\text{grid}}^{max}(t) \tag{12}$$

Pumped-storage hydroelectricity system constraints

$$\begin{cases} P_{\text{b}}^{min}(t) \leqslant P_{\text{b}}(t) \leqslant P_{\text{b}}^{max}(t) \\ PSE^{min}(t) \leqslant PSE(t) \leqslant PSE^{max}(t) \end{cases} \tag{13}$$

Where: $P_{grid}^{max}(t)$ and $P_{\text{grid}}^{min}(t)$ represent the upper and lower transmission power limits of the grid, respectively; $P_{\text{b}}^{max}(t)$ and $P_{\text{b}}^{min}(t)$ denote the upper and lower output limits of the energy storage system, where a positive value indicates power input and a negative value indicates power output; $PSE^{max}(t)$ and $PSE^{min}(t)$ are the upper and lower limits of the energy storage capacity at time t.

5. Model Solution

The wind-solar-pumped storage systems is characterized by high-dimensionality, non-linearity, and multiple constraints [18]. Compared to other algorithms, the PSO algorithm demonstrates a stronger optimization capability. Additionally, it is more readily applicable to solving optimization problems. Therefore, this paper proposes the use of the PSO algorithm to solve the wind-solar-hydro storage system.

The performance of the PSO algorithm is influenced by the selection of its parameters. In traditional PSO algorithms, the inertia weight and learning factors are fixed, making it prone to becoming trapped in local optima [19]. To address this drawback, the PSO algorithm has been improved from two aspects: the inertia weight and the learning factors. The improved strategy is as follows [20]:

$$w = w_{\text{e}} + \frac{(w_{\text{s}} - w_{\text{e}})(MI - IT)}{MI} \tag{14}$$

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$$\begin{cases} c_1 = c_{1s} + (c_{1e} - c_{1s})\frac{IT^2}{MI^2} \\ c_2 = c_{2s} + (c_{2e} - c_{2s})\frac{IT^2}{MI^2} \end{cases} \tag{15}$$

Where: IT represents the current iteration number; MI is the total number of iterations; w_s and w_e are the initial and final values of the inertia weight factor, respectively; c_{1s} and c_{1e} are the initial and final values of c_1; c_{2s} and c_{2e} are the initial and final values of c_2

6. Result Analysis

Based on the wind farms, photovoltaic power stations, and hydro storage plants in a specific region of Northwestern China, a combined power generation system is constructed to test the feasibility of the model and algorithm proposed in this paper. The operational parameters and costs of each component are presented in Table 1. The pollutant emission coefficients and associated costs for each component can be found in Table 2 [21]. The parameters for the pumped storage are detailed in Table 3.

Table 1: Unit parameters

Parameter Name	Wind Turbine	Photovoltaic	Grid
Maximum Power/MW	100	50	30
Minimum Power/MW	0	0	-30

Table 2: Coefficient and cost of pollutants

Pollutant Type	Treatment Cost (¥/kg)	Emission Coefficient (g/kWh)			
		Wind Turbine	Photovoltaic	Grid	Pumped Storage
CO_2	0.023	0	0	889	0
SO_2	6	0	0	1.8	0
NO_x	8	0	0	1.6	0

Table 3: Pumped Storage parameters

Type	Parameter	Value (kW)
Pumped Storage	Maximum Input Power/kW	150
	Maximum Output Power/kW	150

The data from the 15 typical scenarios of wind and solar power output, along with typical daily load data, were input into the optimization configuration model constructed in Section 4. The PSO algorithm was then used to solve the model, with settings including a population size of 100, an archive size of 100, a total of 100 iterations, an inflation rate of 0.1, and a mutation rate of 0.1. The solution yielded the Pareto frontier, as shown in Figure 5. Each point on the graph symbolizes a solution in the Pareto optimal set, meaning that improving one objective requires compromising the other. The pattern shows a clear inverse relationship between operational and environmental costs, providing decision-makers with valuable insights into balancing these two aspects when designing and managing the system.

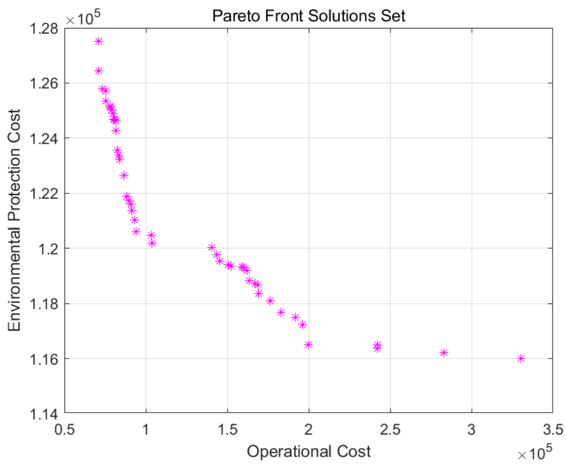

Figure 5: The solution yielded the Pareto frontier

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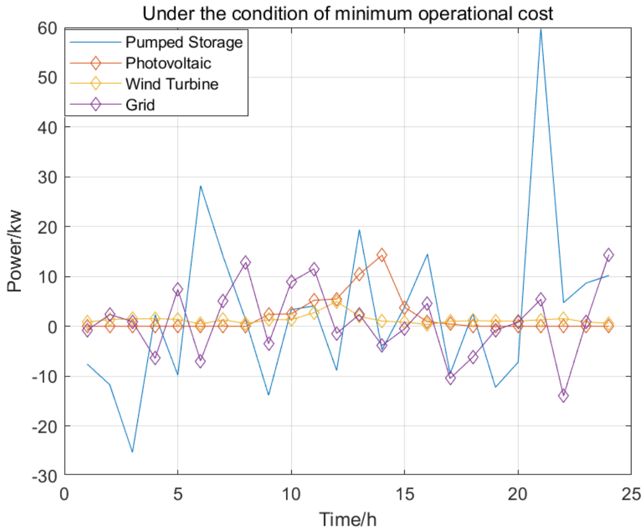
The objective function of the proposed model is to minimize the overall system cost, including both operational and environmental protection costs. To understand the impact of varying objective functions on system optimization, Figure 6 presents three distinct scenarios that show the dispatch results under different optimization goals:

1) Figure 6(a) depicts the dispatch results when minimizing operational costs. Here, the use of pumped storage (blue) fluctuates significantly, while the grid (purple), wind turbines (yellow), and photovoltaic (orange) outputs remain relatively stable. This demonstrates that maximizing the utilization of pumped storage effectively minimizes operational costs.

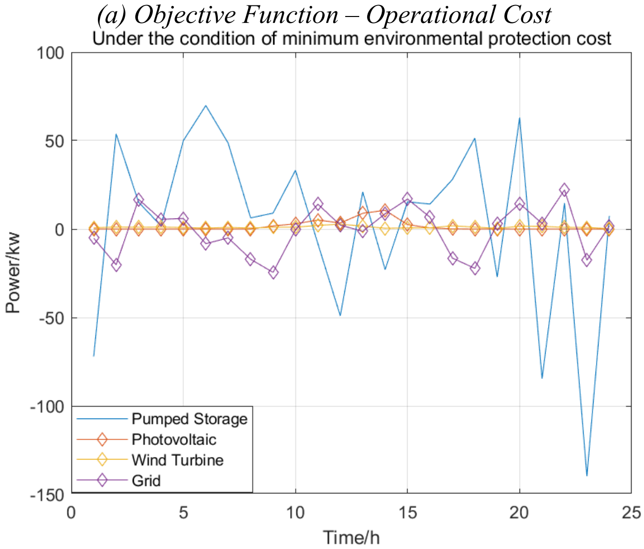
2) Figure 6(b) shows the dispatch scenario under minimized environmental protection costs. In this case, the grid (purple) and pumped storage (blue) show larger variations, indicating higher grid import/export activity. This approach leverages the grid and storage to minimize environmental impacts, despite higher costs.

3) Figure 6(c) represents the dispatch results when the objective is to minimize total costs. This combined approach balances the trade-offs between operational and environmental costs, leading to moderate variations in all energy sources.

These comparisons reveal that the choice of objective function has a significant impact on the power system's dispatch strategy. Each optimization goal leads to different usage patterns of pumped storage, photovoltaic, wind turbine, and grid systems, ultimately offering insight into how best to configure the power system to meet specific economic and environmental targets.



(a) Objective Function – Operational Cost



(b) Objective Function – Environmental Protection Cost

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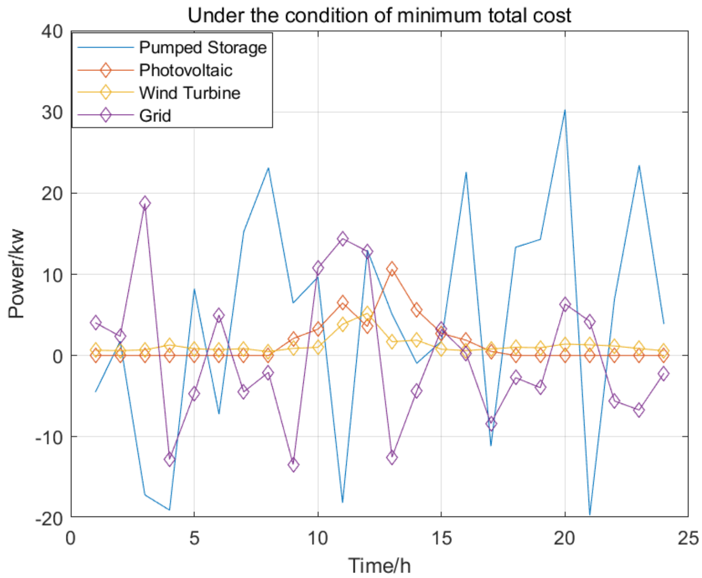

(c) Objective Function – Total Cost

Figure 6: Scheduling results under different objective functions

To assess the discrepancy between the prediction model and actual values, a comparison was made between actual absorbed power and predicted wind and photovoltaic power outputs. Figure 7 displays these results:

1) Photovoltaic Output: The graph on the left shows the comparison between actual (blue line) and predicted (red line) photovoltaic power. The predicted values are generally higher than the actual values, particularly during the peak hours around noon. This indicates the model overestimated the photovoltaic output under these specific conditions.

2) Wind Turbine Output: The graph on the right compares actual (blue line) and predicted (red line) wind turbine output. The predicted values again exceed the actual values, especially around midday, suggesting the model tends to overestimate wind power output as well.

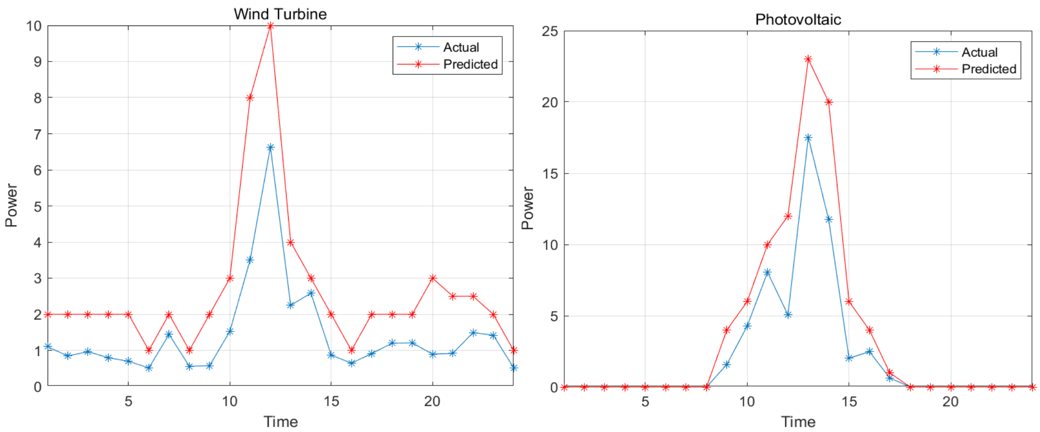

Figure 7: Comparison results for actual and predicted

Employing the fuzzy multi-attribute decision-making approach within the PSO algorithm enables the calculation of multi-attribute decision indices for various scenarios. This facilitates the selection of the best compromise solution, which is presented in Figure 8. In this solution, the pumped storage system exhibits substantial variability as it helps to balance the power supply by storing excess energy and providing additional power when required. The grid and wind turbine outputs are relatively stable, while the photovoltaic output follows the characteristic daily cycle.

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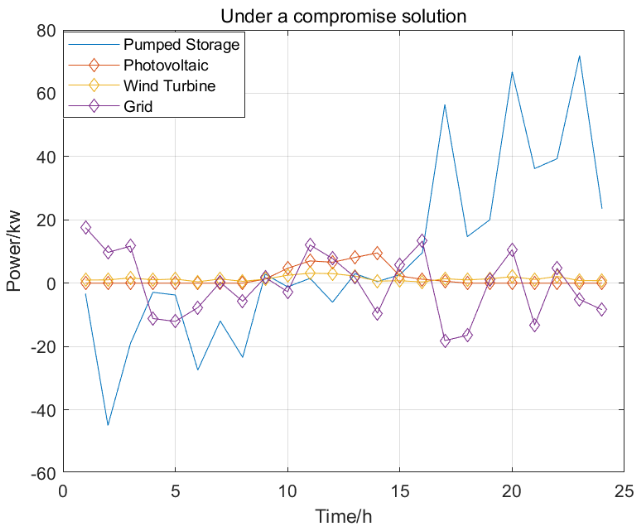

Figure 8: Compromise solution

7. Conclusion

This paper aims to harness the complementary effects between wind power and pumped-storage hydroelectricity, enhancing the intake of new energy sources in regions abundant with wind and solar resources. By integrating wind turbines, photovoltaics, and pumped-storage hydroelectricity, a Wind-Solar-Pumped Storage Power Generation System (WSPSPGS) was established. The system addresses the uncertainty in the prediction error of wind and solar output fluctuations through uncertainty modeling. Based on typical scenarios, an optimization configuration model for the WSPSPGS was constructed with the objectives of minimizing operational costs and environmental costs. Theoretical research and the results from numerical examples lead to the following conclusions:

1) The study demonstrates that employing the Copula function to model uncertainties in wind and solar outputs, followed by using the k-means clustering method for scenario reduction, significantly minimizes the impact of variability on optimization results.

2) Utilizing pumped-storage technology in combination with wind and solar power stations allows for efficient energy time-shifting, reducing both operational and environmental costs while capitalizing on the complementary advantages of these generation systems.

3) The WSPSPGS model provides a reliable framework for grid planning by offering accurate representations of real-time outputs across various geographical regions. This enables better management of energy fluctuations, leading to improved power system stability and promoting sustainable integration of renewable energy sources.

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