Research Article

Research on Multiobjective Optimal Operation Strategy for Wind-Photovoltaic-Hydro Complementary Power System

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To address the problems of wind and solar generation volatility and lose of wind and photovoltaic resources, on the basis of the complementary property of wind-solar-water, the topology structure of the wind-solar-water synergy power generation system is constructed. Taking the minimum grid fluctuation index, the minimum wind-photovoltaic-hydro discard rate and the greatest economic effectiveness of the power station as the goal functions and considering various constraints of the wind, photovoltaic, and hydrostation units, a triobjective optimization running model of the wind-photovoltaic-water synergy system is established. Meanwhile, this essay suggests an IMOSSA on the basis of tent chaotic sequence and random wandering strategy to settle the described triobjective optimization issue. Taking Hubei Pankou as an example for simulation analysis, after choosing the best scheme, IMOSSA compared with MOSSA, MOGWO, and NSGA-II, the volatility of sunny days is reduced by 12.39%, 19.5%, and 36.71%, respectively; the wind-photovoltaic abandonment rate is reduced by 11.17%, 22.5%, and 38.03%, respectively, while in the rainy days the volatility is reduced by 8.09%, 18.34%, and 47.03%, respectively; the wind-photovoltaic abandonment rate is reduced by 14.84%, 16.86%, and 40%, respectively. Therefore, it is possible to demonstrate the validity of the proposed three-objective model and the efficiency of the IMOSSA in solving the issue. The efficiency of the optimization operation approach suggested in this research is confirmed by the case study, providing a new idea for the large-scale consumption of new energy in high-proportion hydropower grids.

1. Introduction

With the current rapid development of society, the national energy strategy has gradually shifted to a “dual carbon” strategic objective, vigorously developing renewable energy sources and striving to balance economic development and green transformation simultaneously [1]. However, wind and photovoltaic generation are influenced by environmental conditions, and their grid connection will produce large fluctuations, which will place considerable strain on the electrical system’s ability to operate safely and reliably [2]. To alleviate the pressure of grid connection, measures such as abandoning wind and photovoltaic are required, which will also inevitably result in a waste of resources. How to combine wind, photovoltaic, and hydropower to minimize grid volatility and maximize resource utilization and economic efficiency is an issue that requires urgent research.

For the optimal operation of complementary power generation, a lot of research has been done at home and abroad. Literature [3–5] established an operation model of a combined power generation system containing wind-, photovoltaic-, and fire-distributed power sources and verified its good coordination. However, the model still cannot avoid the emission of pollutants and the quantitative calculation of environmental value in the power system is difficult. Literature [6, 7] established a single objective model of economic operation, but the traditional economic optimization did not meet the actual requirements. Literature [8] simulated the uncertainty of wind and solar output in the hybrid system and proposed the strategies
of risk avoidance and opportunity seeking, but it only considered the security of the power grid system and did not consider the economy. In literature [9, 10], the model of the wind-solar-hydro complementary power system was addressed by PSO. However, the performance of PSO was poor and the solution accuracy was low. In [11], a wind-photovoltaic-hydro-scheduling model was constructed from two different perspectives, namely, “source-source complementarity” and “source-load matching,” but the resource utilization was not considered, and the problem of wind and photovoltaic abandonment could not be avoided. In the paper [12], a hydro-photovoltaic-dispatching model was built to minimize water consumption in the hydrogradient, and it was verified that the hydropower regulation performance is good. But due to the limited system capacity, a large-scale grid connection cannot be made. All of the above literature has achieved certain results for the optimal operation of complementary power generation systems, but all of them have certain limitations.

To that purpose, this essay suggests a three-objective optimal operation strategy model for wind-photovoltaic-water complementary energy system, with the minimum grid-connected fluctuation index, the minimum wind-photovoltaic discard rate, and the greatest financial returns of the power station as the goal function, taking into account the constraints of the system, the characteristics of various distributed power sources, and the operation of reservoirs. In the meantime, MOSSA is improved in terms of tent chaotic sequence and random walk strategy to address the problem of low exploration ability of SSA. Using the wind, photovoltaic, and hydropower stations in Pankou as the research object, the NSGA-II, MOGWO, MOSSA, and IMOSSA were used to analog and evaluate the ideal operation model, and the results under different algorithms were compared to verify the best performance of the IMOSSA and the feasibility of the optimal operation strategy. The main contributions of this paper are as follows:

1. A microgrid system containing wind, photovoltaic, hydro, and load was established
2. A three-objective optimization model incorporating grid-connected volatility, wind-photovoltaic discard rate, and economic benefits is established
3. An operation strategy based on improved multiobjective sparrow algorithm is proposed

The rest of the paper is organized as follows: Section 3 gives the power output model of the distributed power source. Section 4 presents the optimization objectives and constraints of this paper. Section 5 describes the mathematical formulas of SSA and IMOSSA and their operation steps. The optimized operation strategy is given in Section 6. Finally, the conclusion in Section 7 is presented.


Figure 1 illustrates the natural and technical complementing features that wind, solar, and hydro have in the short run.

The natural complementary characteristic is manifested in the different energy production characteristics of wind and photovoltaic energy generation in day and night and under different weather conditions, while the technical complementary characteristic is manifested in the good complementarity between hydro, wind, and photovoltaic power generation by using the hydro’s characteristics of low regulation loss and rapid response.

Capacity complementarity refers to hydropower stations with the above-day regulation capacity to compensate in real time for wind and photovoltaic power output, while power complementarity means that hydropower stations can reduce output during the hours when photovoltaic power stations are carrying grid load, allowing more water energy to be stored in reservoirs for peaking power generation during peak grid load hours, thus improving the peaking efficiency of hydropower.

Based on the analysis of wind-photovoltaic-hydro complementary characteristics, the main topology of the wind-photovoltaic-hydro complementary power system is constructed, mainly including the hydrogenerators, wind generators, photovoltaic batteries, lithium batteries, rectifiers, inverters, and transformers. The topology is shown in Figure 2.

3. Distributed Power Models

3.1. Hydropower Output Model. The power generated by a hydropower unit is mainly determined by the net head, the efficiency of the turbine generator, and the water consumption. The net head does not vary much during the day, so the net head and efficiency are constants in this paper and the actual power output of a hydropower unit in period $t$ is

$$P_{H,t} = 9.8H_{H,t}Q_{H,t}\eta(H),$$

where $P_{H,t}$ is the output of a single hydropower unit in time $t$; $H_{H,t}$ is the net head in time $t$; $\eta(H)$ indicates the efficiency of the unit; $Q_{H,t}$ indicates the flow of water through the hydropower unit in period $t$.

3.2. Solar Energy Production Model. The main factors affecting the output power of solar energy production include both the intensity of solar radiation and the operating temperature of the photovoltaic panels. Therefore, its actual output power is

$$P_V = \left(P_T\frac{R_T}{R_{T\text{STC}}}\left[1+\eta(T_C+T_{T\text{STC}})\right]\right) \times (1-\gamma),$$

where $P_V$ is the output energy of an individual solar panel; $P_T$ is the solar panel’s rated output energy; $R_T$ is the real solar radiation’s strength; $R_{T\text{STC}}$ is the photovoltaic output under typical test circumstances; $\eta$ indicates the photovoltaic module temperature coefficient; $T_C$ is the photovoltaic module’s real temperature; $T_{T\text{STC}}$ is the temperature in the typical test environment; $\gamma$ is the shading factor of the photovoltaic array.
3.3. Wind Energy Production Model. A wind turbine’s energy production and current wind speed are closely connected; the regular operation of the wind turbine will be impacted by excessive or insufficient wind speed, and the relationship between the two is as follows:

\[
P_W = \begin{cases} 
0, & v < v_{\text{in}}, v \geq v_{\text{out}}' \\
\frac{v - v_{\text{in}}}{v_r - v_{\text{in}}}, & v_{\text{in}} \leq v \leq v_r \\
P_r, & v_r \leq v \leq v_{\text{out}} 
\end{cases}
\]  

(3)

where \( P_W \) is equivalent to a single wind turbine’s energy production; \( P_r \) is the wind turbine’s specified energy production; \( v_{\text{in}} \) is the cut-in wind velocity; \( v_{\text{out}} \) is the cut-out wind velocity; \( v_r \) is the specified wind velocity.

4. Optimal Operating Model

4.1. Goal Function. This essay uses a combined wind, photovoltaic, and hydrogeneration operation strategy for the residual power generated by the complementary generation system integrated into the larger grid. It is aimed at regulating the peaks and valleys generated by unstable wind and photovoltaic generation through hydropower based on meeting the constraints of the energy system, the characteristics of the various distributed
energy sources, and the operation of the reservoir, thus maximizing the volatility of the remaining power generation to the grid and reducing the incidence of wind and solar abandonment. This guarantees the grid’s and power plants’ efficient, secure, and safe functioning. Thus, a three-goal function is established to minimize the grid-connected fluctuation index, minimize the wind-photovoltaic discard rate, and maximize the economic return of the station.

1. Grid-connected fluctuation index: this paper measures the size of grid-connected fluctuation by calculating the standard deviation of the residual generation power integrated into the larger grid. The smaller the standard deviation means the smaller the grid-connected fluctuation of the system. The minimum grid-connected fluctuation index is established as the optimization objective, that is,

$$\min V = \sqrt{\frac{\sum_{t=1}^{T} [P_{W,t} + P_{H,t} + P_{V,t} - P_{av} - P_{fl}]^2}{T}}$$

2. Wind and photovoltaic discard rate: the connection of all power generated by wind and photovoltaic stations to the grid will increase the fluctuation of the grid, so the stations need to discard a certain proportion of wind and photovoltaic power. To ensure the use of wind and photovoltaic resources, it is necessary to establish the minimization of wind and photovoltaic discard rate as the optimization objective, that is,

$$\min P = \frac{\sum_{t=1}^{T} (P_{W,t} + P_{H,t} + P_{V,t} - P_{fl})}{P_{W} + P_{V}} \times 100\%.$$  

3. Economic benefit: in this paper, the residential load price and the grid-connection price are regarded as the same, and both are sold at the price of electricity. Establishing maximum benefits of the wind-photovoltaic-hydro complementary system as optimization objective, that is,

$$\max E = \sum_{t=1}^{T} (P_{av} \times C_{W} + P_{av} \times C_{H} + P_{av} \times C_{V}) \times \Delta t,$$

where $T$ is the dispatching period, here 24 hours; $P_{av}$ is the average of the grid-connected power of the system per unit period; $P_{W,t}, P_{H,t},$ and $P_{V,t}$ express the actual production of wind power, hydropower, and solar power in period $t$, respectively; $P_{fl}$ is the residential burden during time $t$; $P_{W,t}$ and $P_{V,t}$ are the power generated by wind and photovoltaic stations in period $t$, respectively; $C_{W}, C_{H},$ and $C_{V}$ represent the grid-connection price of wind, hydro, and solar energy, respectively; $\Delta t$ is the evaluation period duration.

4.2. Constraint Condition

4.2.1. Constraint on System Energy Balance. To fulfill load demand, guarantee system stability, and maintain the microgrid’s balance of input and output power, then, the following needs to be satisfied:

$$P_{pc,t} = P_{W,t} + P_{H,t} + P_{S,t} - P_{fl} \geq 0,$$  

where $P_{pc,t}$ is the residual power generated by the system for connection to the larger grid in time period $t$.

4.2.2. Constraint on Wind Energy Export. The wind power station’s real export must be lower than its rated energy export and less than the actual output in time period $t$, that is,

$$0 \leq P_{W,t} \leq P_{W,t} \leq P_{W,max},$$  

where $P_{W,max}$ is the rated output of the wind energy station, determined by the turbine production specification.

4.2.3. Constraint on Photovoltaic Energy Export. The real output of the photovoltaic power station should be less than the rated power output and less than the actual output in time period $t$, that is,

$$0 \leq P_{V,t} \leq P_{V,t} \leq P_{V,max},$$  

where $P_{V,max}$ is the maximum energy export of the photovoltaic energy plant, which is determined by the structure of the photovoltaic power station itself.

4.2.4. Hydropower Constraints

1. Water Balance Constraint. The water balance is the difference between inflow and consumption in this basin in time $t$ equal to the storage variable at that range, that is,

$$V_{H,t+1} = V_{H,t} + (I_{H,t} - Q_{H,t}) \Delta t,$$  

where $V_{H,t+1}$ and $V_{H,t}$ are the storage volume at the finish of periods $t+1$ and $t$, respectively, and $I_{H,t}$ represents the reservoir’s inlet flow during the time period $t$.

2. Reservoir Constraints. (i) Water storage constraint: the size of the water stored in the reservoir should be controlled within the top and bottom limitations of the reservoir.
where \( V_{H,\text{min}} \) and \( V_{H,\text{max}} \) are the maximum and minimum water capacity allowed in the reservoir, respectively.

(ii) Downstream flow constraint: to guarantee the safety of downstream flood prevention objects and ecological safety, the downstream flow constraint needs to be satisfied, that is,

\[
V_{H,\text{min}} \leq V_H(t) \leq V_{H,\text{max}},
\]

where \( V_{H,\text{min}} \) and \( V_{H,\text{max}} \) denote the lower and upper limits of the allowable downstream flow in time period \( t \). \( V_{H,\text{min}}(H, t) \) is determined by the combined water use and navigation requirements downstream, while \( V_{H,\text{max}}(H, t) \) is determined by the flood control requirements downstream.

(3) Hydropower Unit Constraints. (i) Hydropower unit flow constraint: the flow size of the hydropower unit at time \( t \) should be strictly controlled within the top and bottom limitations of the flow according to the turbine model, that is,

\[
Q_{H,\text{min}} \leq Q_{H,t} \leq Q_{H,\text{max}},
\]

where \( Q_{H,\text{min}} \) and \( Q_{H,\text{max}} \) are the smallest and largest flow rate of the hydropower unit, respectively.

(ii) Hydropower unit output constraint: the export power of the hydropower set at moment \( t \) should be strictly controlled within the top and bottom limitations of the energy production according to the turbine model, that is,

\[
P_{H,\text{min}} \leq P_{H,t} \leq P_{H,\text{max}},
\]

where \( P_{H,\text{min}} \) and \( P_{H,\text{max}} \) are the minimum and maximum output power of the hydropower unit, respectively.

4.2.5. Unit Climbing Constraint. Different units receive a climbing capacity constraint during regulation due to different regulation characteristics, that is,

\[
-P_W^D \leq P_{W,t} - P_{W,t-1} \leq P_W^U,
\]

\[
P_V^D \leq P_{V,t} - P_{V,t-1} \leq P_V^U,
\]

\[
P_H^D \leq P_{H,t} - P_{H,t-1} \leq P_H^U,
\]

where \( P_W^D \) and \( P_W^U \) are the greatest upward and downward effective power of a single wind turbine in two consecutive time periods, respectively. \( P_V^D \) and \( P_V^U \) are the greatest upward and downward effective power of a single photovoltaic panel in two consecutive time periods, respectively. \( P_H^D \) and \( P_H^U \) are the greatest upward and downward effective power of a single hydropower set in two consecutive time periods, respectively.

5. The Model Solving Algorithm

5.1. Sparrow Search Algorithm. SSA mainly simulates the process of the sparrow feeding, which resembles the finder-follower strategy with a reconnaissance early alert mechanism overlaid. It achieves optimal search through the process of predation by different identities. Due to the algorithm’s basic search theory, quick convergence, and effective search performance, it has been explored and used in a variety of disciplines [13].

The updated description of the discoverers’ positions reads

\[
X_{ij}^{t+1} = \begin{cases} 
X_{ij} \times \exp \left( -\frac{j}{\alpha} \times G \right), & R_2 < ST, \\
X_{ij} + Q \times L, & R_2 \geq ST,
\end{cases}
\]

where \( t \) is the current iteration count; \( G \) is the greatest amount of iterations; \( X_{ij} \) is the location data of the j-th sparrow in the i-th dimension; \( \alpha \) is a stochastic number between \( [0, 1] \); \( R_2 \) is the warning number, a random number between \( [0, 1] \); \( ST \) is the safety value, taking values in the range \( [0.5, 1] \); \( Q \) is a random variable that follows the normal distribution; \( L \) is an array having \( 1 \times m \) dimensions with a single element being 1.

The updated description of the followers’ positions reads

\[
X_{ij}^{t+1} = \begin{cases} 
Q \times \exp \left( \frac{X_{bj} - X_{ij}}{j^2} \right), & j \leq \frac{n}{2}, \\
X_{ij}^{t+1} \times A^\top \times L, & \text{others},
\end{cases}
\]

where \( X_{bj} \) is the best location searched by the current discoverers; \( X_{bj} \) is the global worst location; \( A \) is a \( 1 \times m \) matrix, where every element is given a value of either 1 or -1 and \( A^\top = A^\top (AA^\top)^{-1} \).

The updated description of the vigilancers’ positions reads

\[
X_{ij}^{t+1} = \begin{cases} 
X_{ij}^{t+1} + \beta \times \left( X_{ij}^{t+1} - X_{ij}^{t+1} \right), & f_j > f_g, \\
X_{ij}^{t+1} + K \times \left( \frac{X_{ij}^{t+1} - X_{ij}^{t+1}}{f_j - f_b} + \varepsilon \right), & f_j = f_g,
\end{cases}
\]

where \( X_{best} \) is the global optimum position; \( \beta \) and \( K \) are the step control parameters; \( \beta \) obeys a Gaussian distribution with mean 0 and variation 1, and \( K \) represents the direction of movement of the sparrow and takes the value of a stochastic number of \( [-1, 1] \); \( f_j \) is the adaptation degree of the current individual sparrow; \( f_g \) and \( f_b \) are the global optimum and worst fitness values, respectively; \( \varepsilon \) is a fixed value to avoid zero score error.

5.2. Multiobjective Sparrow Search Algorithm. In order to apply the sparrow search algorithm to multiobjective optimization problems and to give the algorithm a better
performance, this paper introduces a nondominated sorting of sparrow population in the SSA, as well as an external sparrow population policy for storing nondominated optimal solutions.

5.2.1. Individual Sparrow Nondominated Sorting. In order to use the sparrow search algorithm to solve issues involving many objectives in optimization to determine the adaptation degree, the individuals of the sparrow population are ranked, which in turn distinguishes between discoverers and followers [14].

In the nondominated sorting process, individuals in a population of sparrows of population size $P$ contain two parameters $N(p)$ and $S(p)$. $N(p)$ is the number of individuals $p$ that are dominated, and $S(p)$ is the group of individuals of the solution that are dominated by that entity. According to the Pareto dominance relation, the fewer individuals are dominated, the better the individual is. The steps are as follows:

1. Calculate $N(p)$ and $S(p)$ for each individual in the group

2. Add the entities in the group in the set $F_1$ with $N(p) = 0$
(3) For each individual \( m \) in set \( F_1 \), fix that the set of individuals it dominates is \( S(m) \) and execute \( N(l) = N(l) - 1 \) for each entity \( l \) in set \( S(m) \).

(4) If \( N(l) = 0 \), deposit individual \( l \) in a separate set \( F_2 \).

(5) Use \( F_1 \) as the first stage of the set of nondominated entities and assign the identical nondominated rate to the individuals in this set. Then, continue the above hierarchical function on \( F_2 \) and allot the matching nondominated rank till all the entities are hierarchically ranked.

5.2.2. External Sparrow Population Strategy. The multiobjective sparrow search algorithm sets up an external population of sparrows outside the population. It uses the new individuals produced by each iteration of the algorithm to compare with the individuals in the external population of sparrows, continuously updating the external archive, and three scenarios will occur [15].
(1) The new entity will not join the exterior population if it is completely controlled by members of the external population.

(2) The new entity will enter the external group and the entities it dominates will be removed from the external group if the new entity dominates one or more entities in the external group.

(3) If the new individual does not dominate any one individual in the external population, the individual will be added to the external population.

To prevent keeping too many analogous entities, the external group will remove similar entities based on the congestion, thus increasing the diversity close to the optimal frontier. The steps are as follows:

(i) Calculate the objective function \( f_1(x), f_2(x), f_i(x), \) and \( f_N(x) \) for all individuals and determine the extremum of each goal function \( f_i(x) \) separately, indicated as \( f_{\text{imax}} \) and \( f_{\text{imin}} \).

(ii) Calculate the congestion \( C(j) \) for each individual sparrow

\[
C(j) = \frac{\sum_{i=1}^{N} f_i(j+1) - f_i(j-1)}{f_{\text{imax}} - f_{\text{imin}}}, \tag{19}
\]

where \( f_i(j+1) \) and \( f_i(j-1) \) are the adaptation degree of the two individuals adjacent to sparrow individual \( j \) at the \( i \)-th objective function.

**Table 1:** Algorithm parameter settings.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Parameter settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSGA-II</td>
<td>( p_c = 0.9, p_m = 1.0/n, \eta_c = 20, \eta_m = 20 )</td>
</tr>
<tr>
<td>MOGWO</td>
<td>( a_{\text{max}} = 2, a_{\text{min}} = 0 )</td>
</tr>
<tr>
<td>MOSSA</td>
<td>( PR = 0.2, SD = 0.1, ST = 0.8 )</td>
</tr>
<tr>
<td>IMOSSA</td>
<td>( PR = 0.2, SD = 0.1, ST = 0.8 )</td>
</tr>
</tbody>
</table>

**Figure 5:** Process chart of IMOSSA.
Figure 6: Continued.
If the exterior group runs out of space in the iterative procedure, the algorithm will remove individuals with low $C(j)$ from the external population, increasing the diversity close to the optimal frontier.

5.3. Improved Multiobjective Sparrow Search Algorithm

5.3.1. Improved Tent Chaos Mapping. The advantage of the sparrow search algorithm is the high local search performance and quick convergence, but the disadvantage is also very obvious, mainly the global exploration ability is not enough and readily prone to local optimum, thus showing that the efficiency of individual sparrow search is not stable. It is very effective to address the issues of this algorithm by introducing tent chaotic mapping.

Due to the stochastic nature of chaotic variables, they can be used in search optimization problems to improve the population multiplicity of the algorithm and to refine the total search capability of the algorithm. The expression for the tent mapping is

\[
\begin{align*}
x_{n+1} &= \begin{cases} 
2x_n, & 0 \leq x_n \leq 0.5, \\
2(1 - x_n), & 0.5 \leq x_n \leq 1.
\end{cases}
\end{align*}
\]  

After using the Bernoulli shift transformation, the mathematical equation is

\[
x_{n+1} = (2x_n) \mod 1.
\]  

In the tent iteration, there is a certain possibility of entering small or unstable periodic points, so this paper adds a random variable $\text{rand}(0, 1) \times 1/N$ to the initial tent chaos mapping function, at which time the optimized tent chaos mapping function is shown in

\[
x_{n+1} = \begin{cases} 
2x_n + \text{rand}(0, 1) \times \frac{1}{N}, & 0 \leq x_n \leq 0.5, \\
2(1 - x_n) + \text{rand}(0, 1) \times \frac{1}{N}, & 0.5 \leq x_n \leq 1.
\end{cases}
\]  

The mathematical expression after the Bernoulli shift transformation is

\[
x_{n+1} = \frac{(2x_n) \mod 1 + \text{rand}(0, 1) \times 1}{N},
\]  

where $N$ is the number of particles within the chaotic sequence; $\text{rand}(0, 1)$ is the random number between $[0, 1]$.

The basic steps for generating a chaotic sequence of tent maps in a feasible domain are as follows:

1. Create the starting value $x_0$ at random between $[0, 1]$, denoted $i = 0$

2. Iterate according to Equation (23), with $i$ incrementing itself by 1 each time, which will produce a sequence named $Z$

3. When the maximum iteration times have been reached, the run ends and $Z$ generated by the iteration is saved

The distributions of tent chaotic sequences before and after the improvement are shown in Figures 3 and 4. It is evident that the tent mapping before the improvement has a higher probability of taking values in the 2 ranges of $[0, 0.05]$ and $[0.95, 1]$, so the efficiency of the search will be reduced; on the contrary, the improved tent mapping has more uniform values, so the algorithm can improve the
Figure 7: Continued.
quality of the initial guess and strengthen the global exploration ability of the algorithm.

5.3.2. Random Walk Strategy. In the later iterations of the algorithm, the sparrows gradually approach the optimal individual, causing the population diversity to decline and fall into a local optimum. In contrast, the random walk strategy can use the best adaptation degree sparrow entity in the group to adjust the location of the whole total sparrow population, helping sparrow individuals to leave the local optimum area, thus improving the global search performance of the algorithm as well as the local search performance of the optimum position. To ensure that the sparrow population walks randomly within the feasible range, it needs to be normalized according to

\[ X^n_m = \frac{(X^n_m - s_m) \times (c^n_m - r^n_m)}{(l^n_m - s^n_m)} + r^n_m n, \]  

where \( X^n_m \) is the new individual generated after perturbation of the \( m \)th dimensional variable at the \( n \)th iteration. \( s_m \) and \( l_m \) are the minimum and maximum values of the random tour of the \( m \)th dimensional variable, respectively. \( r^n_m \) and \( c^n_m \) are the maximum and minimum values of the \( m \)th dimensional variable at the \( n \)th iteration, respectively.

5.3.3. IMOSSA Algorithm Steps. The following are the steps of the IMOSSA:

1. Set up the variables of the sparrow search algorithm, including variables such as the size of sparrow population \( N \), the maximum size of the external population \( M \), the proportion of discoverers and followers

<table>
<thead>
<tr>
<th>Test functions</th>
<th>Indicators</th>
<th>NSGA-II</th>
<th>MOGWO</th>
<th>MOSSA</th>
<th>IMOSSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTLZ1</td>
<td>Mean</td>
<td>7.25E-02</td>
<td>1.49E-02</td>
<td>2.62E-02</td>
<td>5.33E-03</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>2.44E-02</td>
<td>5.77E-03</td>
<td>6.96E-03</td>
<td>3.59E-03</td>
</tr>
<tr>
<td>DTLZ2</td>
<td>Mean</td>
<td>2.19E-01</td>
<td>7.73E-02</td>
<td>4.59E-02</td>
<td>3.19E-02</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>2.31E-02</td>
<td>9.83E-03</td>
<td>3.76E-03</td>
<td>2.43E-03</td>
</tr>
</tbody>
</table>

Figure 7: Pareto frontier obtained by solving DTLZ2 with four algorithms.
in the population PR, the proportion of vigilancers SD, and the safety value ST

(2) Following the steps in Section 5.3.1, use the improved tent chaos mapping function to generate a chaotic sequence uniformly distributed throughout the solution space, which is the initial position of the sparrow population members in the solution space

(3) Conduct the nondominated sorting on the population, and select the locations of individual sparrows with the best and worst suitability values in the solution space

(4) Determine the number of discoverers in the sparrow population and calculate the location of discoverers, followers, and vigilancers, respectively, after the update according to Equations (16)–(18)

(5) Conduct the random walk strategy to allow the sparrow individual with the best adaptation degree to walk randomly, generate a new sparrow individual position according to Equation (24), and then compare the adaptation degree to update the global optimal solution

(6) Obtain the nondominated solutions of the updated sparrows, calculate the congestion according to Equation (19), and add these nondominated solutions to external population and removing partial solutions from external population, following the rules in Section 5.2.2

(7) In the event that the algorithm’s maximum number of iterations has been achieved, output the nondominated solution from the external population; otherwise, go to Step 4 and continue

Figure 5 depicts the flow diagram of the enhanced multi-objective sparrow search algorithm.

5.4. Algorithm Performance Testing. Use the standard multi-objective test functions DTLZ1 and DTLZ2 to evaluate IMOSSA’s performance and evaluate it against NSGA-II, MOGWO, and MOSSA. The lower the IGD level, the better the convergence and distribution of the algorithm, and the closer it is to the true Pareto front. The expressions are as follows:

$$\text{IGD}(P, Q) = \frac{\sum_{v \in P} d(v, Q)}{|P|},$$

where $P$ is the true Pareto front, $Q$ is the set of true Pareto optimal solutions gained from the algorithm, $d(v, Q)$ is the minimum Euclidean distance from individual $v$ in $P$ to
Figure 10: Continued.
population $Q$, and $|P|$ is the number of solution sets distributed over the true Pareto front.

The algorithm parameters are set as follows: population size $N = 300$, and maximum number of iterations $T = 500$. Each algorithm’s primary parameters are specified as given in Table 1.

The resulting nondominated solution Pareto frontier is shown in Figures 6 and 7.

Figures 5 and 6 show that all four algorithms are capable of locating the nondominated solutions and obtaining Pareto fronts. The optimal solution obtained by IMOSSA is more evenly distributed over the Pareto front, avoiding local convergence of the algorithm, compared to the other three algorithms.

On the two test problems, Table 2 displays the mean and standard deviation of the IGD for the four algorithms. Each result is obtained from 10 independent runs of the same algorithm on the same test problem.

Table 2 shows that IMOSSA performs better than MOSSA, MOGWO, and NSGA-II in every IGD measure, thus proving that the IMOSSA is superior in terms of its ability to solve the triple objective optimization issue.

In the initial iterations, IMOSSA is able to widen the search area, increasing the variety of the sparrow group,

Table 6: Simulation results of IMOSSA.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Grid-connected fluctuation index</th>
<th>Wind-photovoltaic discard rate</th>
<th>Economic benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.89</td>
<td>0.2343</td>
<td>478.3</td>
</tr>
<tr>
<td>2</td>
<td>55.81</td>
<td>0.0217</td>
<td>601.7</td>
</tr>
<tr>
<td>3</td>
<td>43.70</td>
<td>0.0295</td>
<td>629.5</td>
</tr>
<tr>
<td>4</td>
<td>15.69</td>
<td>0.1479</td>
<td>541.6</td>
</tr>
</tbody>
</table>

Table 7: Simulation results of MOSSA.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Grid-connected fluctuation index</th>
<th>Wind-photovoltaic discard rate</th>
<th>Economic benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.91</td>
<td>0.3011</td>
<td>446.3</td>
</tr>
<tr>
<td>2</td>
<td>60.31</td>
<td>0.0192</td>
<td>589.8</td>
</tr>
<tr>
<td>3</td>
<td>49.20</td>
<td>0.0234</td>
<td>624.7</td>
</tr>
<tr>
<td>4</td>
<td>17.91</td>
<td>0.1665</td>
<td>537.7</td>
</tr>
</tbody>
</table>

Table 8: Simulation results of MOGWO.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Grid-connected fluctuation index</th>
<th>Wind-photovoltaic discard rate</th>
<th>Economic benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7.41</td>
<td>0.2311</td>
<td>452.3</td>
</tr>
<tr>
<td>2</td>
<td>59.81</td>
<td>0.0275</td>
<td>572.3</td>
</tr>
<tr>
<td>3</td>
<td>51.43</td>
<td>0.0963</td>
<td>652.4</td>
</tr>
<tr>
<td>4</td>
<td>19.50</td>
<td>0.1909</td>
<td>549.1</td>
</tr>
</tbody>
</table>

Table 9: Simulation results of NSGA-II.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Grid-connected fluctuation index</th>
<th>Wind-photovoltaic discard rate</th>
<th>Economic benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15.14</td>
<td>0.2788</td>
<td>421.4</td>
</tr>
<tr>
<td>2</td>
<td>71.72</td>
<td>0.0460</td>
<td>549.3</td>
</tr>
<tr>
<td>3</td>
<td>62.17</td>
<td>0.0994</td>
<td>583.6</td>
</tr>
<tr>
<td>4</td>
<td>24.79</td>
<td>0.2387</td>
<td>471.0</td>
</tr>
</tbody>
</table>

Figure 10: Pareto optimal frontier from four algorithm optimization simulations.
while in the late iterations it is able to step out of the local optimum point, thus enhancing the global exploration ability of the algorithm, and the IMOSSA also has a better improvement in terms of convergence speed.

6. Example Analysis

6.1. Basic Information. This essay chooses wind, solar, and water power stations in Pankou of Hubei Province as the research object to research the intraday complementary operation strategy of wind, solar, and water. The area contains two hydropower stations: station F which has a 300 MW installed capacity and station G which has a 350 MW installed capacity. Station F contains three turbines with a capacity of 100 MW, and station G contains one turbine with a capacity of 200 MW and one turbine with a capacity of 150 MW, and both stations F and G have daily regulation capacity. It also contains a photovoltaic power station V with an installed capacity of 320 MW and two wind power stations W and E with an installed capacity of 200 MW and 180 MW, respectively. Basic information about the wind-photovoltaic-hydropower stations in Pankou is shown in Tables 3–5. Meanwhile, the grid-connection price for Hubei in 2022 is chosen in this paper, i.e., \( C_{W} = 0.48 \text{ RMB/kWh}, C_{H} = 0.7 \text{ RMB/kWh}, \) and \( C_{S} = 0.24 \text{ RMB/kWh}. \)

6.2. Case Analysis in the Sunny Day. The energy production from the wind and solar power stations and the resident load in a typical sunny 24-hour day in Pankou is shown in Figures 8 and 9, which are based on simulations of wind speed and photovoltaic radiation intensity provided by the European Centre for Medium-Range Weather Forecasts [16, 17].

According to the known conditions in Section 6.1, establish a three-objective optimal model that minimizes the grid fluctuation index, minimizes the wind-photovoltaic discard rate, and maximizes the economic benefits of the station. Use NSGA-II, MOGWO, MOSSA, and IMOSSA to simulate the model, respectively, and the obtained simulation results
are plotted in Figure 10. The four algorithms’ parameters are specified as given in Table 1; the population size is $N = 200$, the external population size is $M = 150$, and the maximum number of iterations is $T = 500$.

As can be seen in Figure 10, all four algorithms are capable of obtaining Pareto fronts and the nondominated solutions. However, NSGA-II has the worst distributivity and convergence and is ineffective for addressing the three-objective optimization issue posed in this study, while compared to MOSSA and MOGWO IMOSSA has a noticeable increase in the uniformity of the Pareto frontier distribution derived.

Among the nondominated solutions satisfying each objective, select the solution with the lowest grid-connected fluctuation index, the solution with the lowest wind-photovoltaic discard rate, the solution with the highest economic benefits, and a representative solution from the optimal solution set, respectively. The simulation results of IMOSSA, MOSSA, MOGWO, and NSGA-II are shown in Tables 6–9.

The analysis of Tables 6–9 show that, in general, when the grid-connected fluctuation decreases, the rate of wind-photovoltaic discard also increases, and the economic benefits decrease. The main reason for this is that the less grid-connected fluctuation is, the more hydropower is needed to regulate it, and more peak and valley energy from wind and photovoltaic is surrendered to reduce the peak-to-valley difference, resulting in a higher quotient of wind-solar discard. The price of wind and solar energy in the system is more expensive than the cost of hydropower, so the economic benefits are subsequently reduced. Therefore, when scheduling microgrid operations, the relationship between the three objectives needs to be properly evaluated.
Figure 16: Continued.
and balanced corresponding to the planning target’s real needs so that choose higher economic returns while ensuring low fluctuation and wind-photovoltaic discard rate.

Comparing the data derived from the four algorithms simultaneously, the results obtained by IMOSSA, MOSSA, and MOGWO algorithms are more superior compared with the NSGA-II algorithm. Taking scheme 4 as an example, compared with MOSSA and MOGWO, although the economic gain of MOSSA is smaller than that of MOGWO, the volatility and wind-photovoltaic abandonment rate of MOSSA are slightly less than those of MOGWO, decreasing by 8.15% and 14.65%, respectively. The economic gain of the results obtained by IMOSSA is similar to that obtained by MOSSA and MOGWO, but the grid-connected volatility index of IMOSSA is significantly smaller than that of MOSSA and MOGWO, with a reduction of 12.3% and 19.5%, respectively. Therefore, the results obtained by IMOSSA are better than the other three results.

The optimized operation results of the wind-solar-water cogeneration system corresponding to each scheme in IMOSSA are shown in Figure 11. Scheme 4 was chosen for further analysis. And the output shares of the different power stations under this scheme are shown in Figure 12. As shown in Figure 11(d), after complementation, hydropower generation output and wind-photovoltaic power output curves show a “peak to valley” characteristic. During the 10:00-17:00 hours, the photovoltaic power output is larger and smoothly changing, which can be used as a load base load, while wind power output fluctuates, so hydropower stations will store more water in reservoirs and smooth out the fluctuation of wind power output with the flexible regulation ability. During the 19:00-22:00 hours, when the wind and photovoltaic power output is significantly reduced and the residential load is at its peak, hydropower stations can use the water stored during the day to take on the task of peak generation at this time.

Further analysis of the fluctuation of the system grid connection, the output of combined wind, photovoltaic, and hydro, residential load, and grid-connected power is seen in Figure 13. As is evident, the fluctuation trend of combined wind, photovoltaic, and hydro output and the fluctuation trend of residential load almost remain the same, and the fluctuation curve of the system grid connection tends to be smooth. Therefore, the optimal operation strategy outlined in this study may fully use the adjustable capacity of hydropower stations, effectively helping wind and photovoltaic power units to realize peak-cutting and valley-filling and greatly reducing the fluctuation of the system integrated into the large grid [18].

6.3. Case Analysis in the Rainy Day. Now let us analyze the complementary wind-photovoltaic-hydropower generation in

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Grid-connected fluctuation index</th>
<th>Wind-photovoltaic discard rate</th>
<th>Economic benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7.21</td>
<td>0.2416</td>
<td>442.5</td>
</tr>
<tr>
<td>2</td>
<td>58.02</td>
<td>0.0195</td>
<td>528.1</td>
</tr>
<tr>
<td>3</td>
<td>47.28</td>
<td>0.0382</td>
<td>579.3</td>
</tr>
<tr>
<td>4</td>
<td>15.45</td>
<td>0.1302</td>
<td>486.9</td>
</tr>
</tbody>
</table>

Figure 16: Pareto optimal frontier from four algorithm optimization simulations.
Pankou in a rainy day and further verify the complementary optimization effect by comparing it with the complementary power generation in a sunny day. The 24-hour energy production from wind and solar energy plants and the local residential load in the typical rainy day are shown in Figures 14 and 15. The Pareto fronts obtained by solving them using the four algorithms are shown in Figure 16. The uniformity of the Pareto front distribution obtained by IMOSSA is significantly better than that of NSGA-II, MOSSA, and MOGWO. Among the nondominated solutions satisfying each objective, select the solution with the lowest grid-connected fluctuation index, the solution with the lowest wind-photovoltaic discard rate, the solution with the highest economic benefits, and a representative solution from the optimal solution set, respectively. The simulation results of IMOSSA, MOSSA, MOGWO, and NSGA-II are shown in Tables 10–13.

Comparing the data derived from the four algorithms simultaneously, obviously, the results obtained by the IMOSSA algorithm are better than those of the other three algorithms. Taking scheme 4 as an example, with close economic benefits, IMOSSA reduces the volatility by 8.09%, 18.34%, and 47.03% compared to MOSSA, MOGWO, and NSGA-II, respectively and reduces the wind-photovoltaic discard rate by 14.84%, 16.86%, and 40%, respectively.

Compared to the sunny day, the rainy day has lower light intensity and lower photovoltaic output, and the peak-to-valley difference in wind energy production is increased. On the rainy day, water energy carries the grid’s workload and has to regulate the production of wind and photovoltaic in time. When choosing the rainy day scheme 4 of IMOSSA, compared to the sunny day scheme 4 of IMOSSA, the rainy day grid-connection fluctuation index increases by 5.17%, the wind-photovoltaic discard rate decreases by 11.97%, and the economic benefit decreases by 9.77%. The optimized operation results of the wind-solar-water cogeneration system corresponding to each scheme in IMOSSA are shown in Figure 17. And the output shares of different power stations under scheme 4 are shown in Figure 18.

The output of combined wind, photovoltaic, and hydro, residential load, and grid-connected power is shown in Figure 19. As is evident, the fluctuation tendency of combined wind, photovoltaic, and hydro output and the fluctuation trend of residential load almost remain the same, and the fluctuation curve of the system grid connection tends to be smooth. Compared to the sunny day, the regulation ability of hydropower is weaker on the rainy day, which will lead to higher fluctuation of grid connection, while the economic efficiency of the power station will become lower accordingly. When it rains heavily, the hydropower output is higher, but from the perspective of grid security, while increasing the hydropower output, hydropower stations must also assume the role of flood control [19]. Therefore, the peak regulation capacity of the wind-solar-hydro complementary energy system during the flood season is not increased by more water resources.

In summary, the complementary system output is significantly optimized in both typical weather conditions, and the
Figure 17: Optimized output of wind, photovoltaic, and water in the rainy day.

Figure 18: Proportion of power output from different power stations.

Figure 19: Output of combined wind, photovoltaic, and hydro, residential load, and grid-connected power.
fluctuation of the grid-connected system is low. Therefore, using a flexible distributed power source like hydropower to smooth out the uncertainty and volatility of wind and solar output solves the problem of strong negative peak features of wind energy due to no photovoltaic output at night, reduces the possibility of wind and solar discard, and smoothly outputs the residual generated energy to the larger grid, thus maximizing the economic benefits of the power station [20].

7. Conclusion

In this essay, the topological structure of the wind-solar-water complementary system is established by analyzing the features of wind-solar-water synergy power production for microgrid containing wind-photovoltaic-hydropower stations. A three-objective optimum operation model and approach to finding a solution are given, taking into account the minimum grid fluctuation index, the minimum wind-photovoltaic discard rate, and the maximum economic benefit of the station. Through the modeling and simulation solution analysis of the actual calculation case in Pankou of Hubei Province, the rationality of the suggested model and the optimized operation approach is validated. Meanwhile, this essay suggests an improved multiobjective sparrow search algorithm on the basis of the tent chaotic sequence and random wandering strategy to solve the described three-objective optimization problem and verifies the feasibility of IMOSSA to solve the multienergy complementary energy generation system’s optimum operational strategy through simulation analysis and achieves a better Pareto front in comparison with NSGA-II, MOGWO, and MOSSA. The simulation results show that the IMOSSA can obtain a more satisfying solution set. Compared with MOSSA before improvement, the grid volatility and wind-photovoltaic discard rate are reduced 12.39% and 11.17% on sunny days and 8.09% and 14.84% on rainy days, respectively, with similar economic benefits. And compared with MOGWO, which is more frequently used in research, the grid volatility and wind-photovoltaic discard rate are reduced by 19.5% and 22.5% on sunny days and 18.34% and 16.86% on rainy days, respectively, while compared with NSGA-II, the grid volatility and wind-photovoltaic discard rate are reduced even 36.71% and 38.03% on sunny days and 47.03% and 40% on rainy days.

In the actual large-scale wind-photovoltaic-hydro complementary system, unilateral consideration of safety, resource utilization, or economic benefits can largely improve the performance of this aspect, but often leads to a certain degree of performance reduction in the other two aspects (as shown in Tables 6–9 and schemes 1–3), which will lead to the power plant problems not completely solved. So using the optimization model developed in this paper, the consideration of using the optimization model developed in this paper, not only the unilateral safety issues or economic issues but also the safety, resource utilization, and economic issues into an overall three-objective optimization model, can effectively reduce the volatility of the system to the grid, while ensuring high utilization of landscape resources and not low economic returns. Meanwhile, the IMOSSA proposed in this paper largely improves the problems such as weak global search ability and easy to fall into local optimum of MOSSA, and the results sought are more excellent compared with the other two algorithms with higher utilization rate, which verifies the superiority of IMOSSA. Therefore, the optimal operation model and solution method proposed in this paper can effectively solve the problem of safety and stability of power grid operation and at the same time can increase the economic benefits of local power plants, providing theoretical basis and technical support for the construction of multienergy complementary power generation systems. In addition, from a long-term perspective, as the global society develops, the future form of power generation will be more inclined to completely clean energy participation, so this strategy will ensure the economic issues of energy security while also improving the sustainability of the future energy landscape. In future research, this work will be more inclined to the long-term optimal operation strategy of wind-photovoltaic-hydro complementary system, taking more factors such as dry periods and flood periods into account in the model. This will lead to a better system for optimal operation of wind-photovoltaic-hydro complementary system (able to solve both short-term operation and long-term operation problems).

Data Availability

The meteorological data in this paper are from the European medium term weather center.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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References


