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Robust Bi-Level Planning Method for Multi-Source Systems Integrated With Offshore Wind Farms Considering Prediction Errors

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Considering the economy, reliability, and output characteristics of multiple power sources (MPS) and energy storage (ES) comprehensively, a multi-source system integrated with offshore wind farms (OWFs) and its construction cost, and operating and maintenance cost model are established. The system is mainly composed of OWFs, thermal power plants, gas turbine power plants, and pumped hydro storage plants. Given the economy of the power system and offshore wind power accommodation, a bi-level optimal capacity configuration and operation scheduling method is proposed for the multi-source system integrated with OWF clusters with the objective function of optimal total cost. Then, a robust bi-level planning method for the multi-source system integrated with OWFs considering the dual uncertainty of load and offshore wind power prediction is proposed, in which the upper and lower models are solved by an improved particle swarm optimization (PSO) algorithm and CPLEX solver, respectively. Based on the method, the cost-optimal capacity configuration and operation scheduling scheme of an MPS and ES can be obtained. Finally, an OWF group in Shandong Province is taken as an example to check the validity and feasibility of the proposed method.

Keywords: offshore wind power integration, generation expansion planning, bi-level optimization, uncertainty, economic optimization, improved PSO

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1 INTRODUCTION

Onshore wind turbines have shown the trend of production saturation in recent years due to excessive competition. As a new direction of new energy development, offshore wind power has significant advantages (such as no occupation of onshore land, high wind speed, stable wind direction, and proximity to the load center), creating a new situation in the development of wind power all over the world (Nian et al., 2019; Wu et al., 2019). However, the anti-peak characteristics of offshore wind power are particularly noticeable. The degree and probability of strong anti-peak regulation of offshore wind power are greater than those of onshore wind power. Large-scale offshore wind power integration will increase the difficulty of peak regulation of an electric power system. The problem of poor controllability of a high proportion of new energy power generation can be solved effectively with a multi-source complementary strategy. Therefore, power system dispatching establishes the coordination mechanism of multi-source complementary advantages and realizes the optimal planning of multiple power sources (MPS) and energy storage (ES) on the premise of safety and stability, which is of great significance to reduce the power supply cost and to improve the operation economy of the power system and the level of renewable energy consumption.

In recent years, offshore wind power has developed rapidly and has broad market prospects. So far, extensive research has been conducted on offshore wind power (Kang et al., 2019; Costoya et al., 2020; Zhang et al., 2020; Riboldi et al., 2021). Li et al. (2020)compared and evaluated the characteristics and wind energy potential of onshore and offshore wind power based on the original wind records of onshore and offshore wind measured at wind towers in the southeast coastal area of China. Jiang (2021) proposed the review of the offshore wind turbine installation technology, and the future development of four technical fields was prospected to guide the development of offshore wind turbine installation. The opportunity for combining offshore wind turbines and wave energy converters was analyzed through a spatial planning method, and the possibility of combining different renewable technologies was considered based on existing pressures and vulnerabilities through quantitative indicators (Azzellino et al., 2019). Yang et al. (2020), considering potential maintenance opportunities brought by the dynamic speed of the winds, constructed a novel weather-centered operation and maintenance framework to combine the impact of wind on energy production and maintenance plans. Ji et al. (2020), considering the effects of an offshore station, DC cable, and onshore station, proposed an offshore AC side impedance model of an MMC-HVDC system for wind power integration. Most of the aforementioned studies focus on the technical problems of offshore wind turbines and the grid connection technology of offshore wind farms (OWFs), while research on the power system suitable for the integration of offshore wind power clusters with obvious anti-peak characteristics is rarely mentioned.

Power planning is a significant and essential preliminary work in the development of the power industry. As an important part of power system expansion planning, it has many positive effects, and there have already been a large number of relevant studies (Gan et al., 2020; Lv et al., 2020; Chen et al., 2021; Xie et al., 2021). Deng and Lv. (2020), to study the changes in optimization models caused by the large penetration of variable renewable energy, screened some studies on power system planning considering the addition of variable renewable energy, and these models were further deconstructed and compared. Li et al. (2021), given various uncertainties and multi-energy demand-side management, proposed a risk-averse method for heterogeneous energy storage deployment in a residential multi-energy microgrid. Hu et al. (2021)proposed a complementary power generation model of wind-hydropower-pumped storage systems, which used hydropower and pumped storage to adjust the fluctuation of wind power. Considering different vehicle-to-building schedules, a robust energy planning approach for hybrid photovoltaic and wind energy systems in a typical high-rise residential building was proposed (Liu et al., 2021). In the study by da Costa et al. (2021),a method of incorporating reliability constraints into the optimal expansion planning of power systems was proposed based on the loss of load probability and expected power of power systems, and the risk

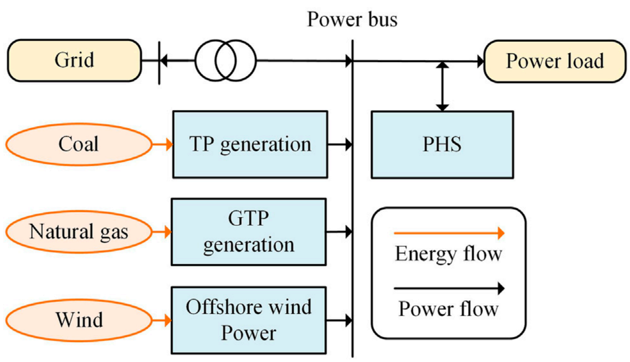

FIGURE 1 | Model of multi-source system integrated with OWFs.

measurement value-at-risk and conditional value-at-risk. However, for the multi-source system with offshore wind power having prediction errors that cannot be ignored, the methods of optimizing the power capacity configuration and operation scheduling are rarely mentioned.

Therefore, a robust bi-level planning method for a multi-source system integrated with OWFs is proposed to realize the optimal capacity configuration and operation optimization in the receiving-end grid. Aiming at the disadvantages of strong intermittency, large fluctuations, and the apparent anti-peak characteristics of offshore wind power, in this study, a multi-source system model suitable for the integration of offshore wind power clusters is established. Based on the coordination and optimization strategies of MPS and ES, a robust bi-level planning model of the system is proposed, completely considering the economy of the power system, the consumption level of offshore wind power, and the prediction error of offshore wind power and load. The improved particle swarm optimization (PSO) algorithm with adaptive inertia weight is used to solve its upper model, and through the case study, it is verified that under the same population size and iteration times, the convergence accuracy of the results is improved.

The remaining sections of this study are organized as follows: The multi-source system integrated with OWFs is constructed in **Section 2**. The robust bi-level planning model for the system considering prediction errors is proposed in **Section 3**. Then, the solution approach of the robust bi-level planning model is proposed in **Section 4**. Case studies, results' comparisons, and analyses are conducted in **Section 5**. Finally, the conclusions of this study are provided in **Section 6**.

2 MULTI-SOURCE SYSTEMS INTEGRATED WITH OFFSHORE WIND FARMS

Based on the research on the output characteristics of MPS and ES, selecting the appropriate equipment types is the basis for the rational planning and coordinated operation of the power system with offshore wind power. The model of the multi-source system integrated with OWFs is shown in **Figure 1**. It can be seen from **Figure 1** that the multi-source system is mainly composed of

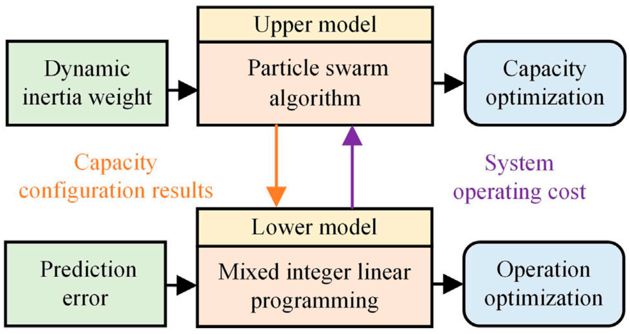

FIGURE 2 | Structure of the robust bi-level planning model.

offshore wind power, thermal power (TP) generation, gas turbine power (GTP) generation, and pumped hydro storage (PHS). TP units are hardly affected by the geographical environment and climate. Furthermore, TP plants have the characteristics of flexible site selection, stable and reliable operation, and fast and deep peak load regulation in the power system with offshore wind power. The capacity configuration and operation mode of a gas turbine (GT) are flexible, and the unit can quickly adjust the power. On the premise of safety and reliability, the GT unit can effectively improve the flexibility of the power system to reduce the impact of offshore wind power fluctuation on the system. PHS has high reliability and fast response speed, which can reduce the peak-valley differences of the system, and plays a certain role in reducing the effects of the anti-peak characteristics of offshore wind power. When the output of offshore wind power changes rapidly, the PHS system can make corresponding adjustments to its fluctuations in time.

3 ROBUST BI-LEVEL PLANNING MODEL OF MULTI-SOURCE SYSTEMS

On the basis of considering the prediction error of offshore wind power and load, a robust bi-level planning model of the multi-source system integrated with OWFs is constructed to optimize the capacity configuration and operation scheduling of MPS and ES. The model structure is shown in **Figure 2**. The improved PSO algorithm is used to optimize the capacity of MPS and ES in the upper model. Taking into account the prediction error, the operation scheduling scheme with the optimal cost is generated in the lower model based on the capacity configuration results. Through the optimization iteration of the upper and lower models, the planning scheme of the multi-source system with the best cost is obtained.

Upper Model

In this study, the coordinated planning of MPS and ES of a multi-source system integrated with OWFs is carried out from the perspective of realizing the optimal economy of the system. The upper model takes the minimum total cost of the system including construction, operating, and maintenance costs as the objective function, and its decision variables are the capacity of MPS and ES. To minimize the total cost of a typical day, the objective function of the upper model can be expressed by

$$\min C_{\mathrm{TOTAL}} = C_{\mathrm{IM}} + C_{\mathrm{OP}}, \tag{1}$$

where C_{TOTAL}, C_{IM}, and C_{OP} are the total cost, construction and maintenance cost, and operating cost of the multi-source system in a scheduling cycle, respectively.

The system construction and maintenance costs are allocated to each scheduling cycle in the life cycle through the discount rate, and its mathematical model is given by

$$C_{\mathrm{IM}} = \sum_{\varphi}\left(1+\beta_{\varphi}\right)P_{\varphi}W_{\varphi}\lambda(1+\lambda)^{L_{\varphi}}\Big/\left(365\left((1+\lambda)^{L_{\varphi}}-1\right)\right), \tag{2}$$

where β_{φ} is the ratio of the maintenance cost and construction cost of system φ, including TP, GTP, and PHS systems. P_{φ} is the unit cost of system φ. W_{φ} is the capacity of system φ. L_{φ} is the life cycle of the unit in system φ. λ is the discount rate.

The capacity constraints of MPS and ES are considered in the upper model, and its mathematical model is shown as

$$W_{\varphi\,\min} \le W_{\varphi} \le W_{\varphi\,\max}, \tag{3}$$

where $W_{\varphi\,\max}$ and $W_{\varphi\,\min}$ are the upper and lower limits of the planned capacity of system φ, respectively.

Lower Model

3.1.1 Objective Function

Considering the operating cost of TP, GTP, and PHS systems, the minimum operating cost of the multi-source system is taken as the objective in the lower model. The mathematical model of the objective function is formulated as

$$\min C_{\mathrm{OP}} = \sum_{t=1}^{T}\left(C_{\mathrm{FO}}(t) + C_{\mathrm{TO}}(t) + C_{\mathrm{PO}}(t)\right), \tag{4}$$

where $C_{\mathrm{FO}}(t)$, $C_{\mathrm{TO}}(t)$, and $C_{\mathrm{PO}}(t)$ are the operating costs of TP, GTP, and PHS systems at time t, respectively. T is the number of times in a scheduling cycle.

The operating cost of the TP system is the coal consumption cost of TP units, and its mathematical model can be described by

$$C_{\mathrm{FO}}(t) = \sum_{j=1}^{N_{\mathrm{F}}}\left(a_j P_{\mathrm{F},j}(t)^2 + b_j P_{\mathrm{F},j}(t) + c_j\right), \tag{5}$$

where a_j, b_j, and c_j are the operating cost correlation coefficients of TP unit j. $P_{\mathrm{F},j}(t)$ is the output power of TP unit j at time t. N_{F} is the total number of TP units.

The mathematical model of the operating cost of the GTP system can be expressed by

$$C_{\mathrm{TO}}(t) = p_{\mathrm{n}}\sum_{g=1}^{N_{\mathrm{T}}} P_{\mathrm{T},g}(t) \div \eta, \tag{6}$$

where p_{n} is the unit fuel consumption cost of natural gas. $P_{\mathrm{T},g}(t)$ is the output power of GT unit g at time t. η is the generation efficiency of GT unit g. N_{T} is the total number of GT units.

The mathematical model of the operating cost of the PHS system is given as

$$C_{\mathrm{PO}}(t)=\sum_{k=1}^{N_{\mathrm{H}}}\left(S_{\mathrm{gen},k}(t)+S_{\mathrm{pum},k}(t)\right),\tag{7}$$

$$\begin{cases}S_{\mathrm{gen},k}(t)=s_{\mathrm{gen},k}u_{\mathrm{gen},k}(t)\left(u_{\mathrm{gen},k}(t)-u_{\mathrm{gen},k}(t-1)\right)\\ S_{\mathrm{pum},k}(t)=s_{\mathrm{pum},k}u_{\mathrm{pum},k}(t)\left(u_{\mathrm{pum},k}(t)-u_{\mathrm{pum},k}(t-1)\right)\end{cases},\tag{8}$$

where $S_{\mathrm{gen},k}(t)$ and $S_{\mathrm{pum},k}(t)$ are the start-up costs of PHS unit k operating in generating and pumping modes at time t, respectively. N_{H} is the total number of PHS units. $s_{\mathrm{gen},k}$ and $s_{\mathrm{pum},k}$ are the start-up costs of PHS unit k operating in generating and pumping modes, respectively. $u_{\mathrm{gen},k}(t)$ and $u_{\mathrm{pum},k}(t)$ are used to verify whether PHS unit k is in generating and pumping modes at time t, respectively.

3.1.2 Constraints

1) Power balance constraint

$$\sum_{k=1}^{N_{\mathrm{H}}}P_{\mathrm{gen},k}(t)+\sum_{j=1}^{N_{\mathrm{F}}}P_{\mathrm{F},j}(t)+\sum_{g=1}^{N_{\mathrm{T}}}P_{\mathrm{T},g}(t)+\sum_{w=1}^{N_{\mathrm{W}}}P_{\mathrm{W},w}(t)-\sum_{w=1}^{N_{\mathrm{W}}}P_{\mathrm{E},w}(t)=\sum_{d=1}^{D}P_{d}(t)+\sum_{k=1}^{N_{\mathrm{H}}}P_{\mathrm{pum},k}(t),\tag{9}$$

where $P_{\mathrm{gen},k}(t)$ and $P_{\mathrm{pum},k}(t)$ are the generating and pumping power of PHS unit k at time t, respectively. $P_{\mathrm{W},w}(t)$ is the predicted value of the wind power of OWF w at time t. $P_{\mathrm{E},w}(t)$ is the wind power curtailment of OWF w at time t. $P_d(t)$ is the predicted value of active power of the load of node d at time t. N_{W} is the total number of OWFs. D is the number of load nodes.

2) Offshore wind power curtailment constraint

$$0\le\sum_{t=1}^{T}\sum_{w=1}^{N_{\mathrm{W}}}P_{\mathrm{E},w}(t)\le e\times\sum_{t=1}^{T}\sum_{w=1}^{N_{\mathrm{W}}}P_{\mathrm{W},w}(t),\tag{10}$$

where e is the upper limit of the curtailment rate of offshore wind power.

3) Equipment operating constraint

The operating constraints of TP units and GT units can be uniformly expressed as

$$\begin{cases}u_n(t)P_{\mathrm{min},n}\le P_n(t)\le u_n(t)P_{\mathrm{max},n}\\ r_{\mathrm{d},n}\Delta t\le P_n(t)-P_n(t-1)\le r_{\mathrm{u},n}\Delta t\end{cases},\tag{11}$$

where $u_n(t)$ and $P_n(t)$ are the on/off state and output power of unit n at time t, respectively. $P_{\mathrm{min},n}$ and $P_{\mathrm{max},n}$ are the minimum and maximum output power allowed by unit n, respectively. $r_{\mathrm{d},n}$ and $r_{\mathrm{u},n}$ are the speed limits of power reduction and power rise of unit n in unit time, respectively. Δt is the scheduling interval.

Power constraints of PHS units and storage capacity constraints of the PHS plant can be referred to the study by Lai et al. (2020).

Robust Bi-Level Planning Model Considering Prediction Errors

The robust optimization problem with uncertain parameters can be summarized as

$$\begin{cases}\min\limits_{x\in R^n}f(x,\varepsilon)\\ \text{s.t. } g_i(x,\varepsilon)\le 0\ \forall\varepsilon\in U, i=1,2,\ldots m.\end{cases},\tag{12}$$

where x is the decision variable. ε is an uncertain parameter and belongs to a bounded closed set U. f is the objective function. g is the constraint.

Because of uncertainty factors such as an abnormal offshore wind regime, errors often occur in prediction results of offshore wind power. According to experience, the actual value of offshore wind power and load can be equivalent to uncertain parameters with an unknown probability distribution in the given sets. Robust optimization is applicable to optimization problems with such uncertain parameters, and the uncertainty is completely considered in the modeling (Ratanakuakangwan and Morita, 2021). Therefore, a robust bi-level planning model is proposed for two uncertain parameters which are the predicted values of offshore wind power and load. The modified constraints (9) and (10) in the lower model can be expressed as

$$\begin{cases}\sum_{k=1}^{N_{\mathrm{H}}}P_{\mathrm{gen},k}(t)+\sum_{j=1}^{N_{\mathrm{F}}}P_{\mathrm{F},j}(t)+\sum_{g=1}^{N_{\mathrm{T}}}P_{\mathrm{T},g}(t)+\sum_{w=1}^{N_{\mathrm{W}}}P_{\mathrm{Wu},w}(t)-\sum_{d=1}^{D}P_{\mathrm{u},d}(t)-\sum_{k=1}^{N_{\mathrm{H}}}P_{\mathrm{pum},k}(t)\ge 0\\ \sum_{t=1}^{T}\left(\sum_{k=1}^{N_{\mathrm{H}}}P_{\mathrm{gen},k}(t)+\sum_{j=1}^{N_{\mathrm{F}}}P_{\mathrm{F},j}(t)-\sum_{d=1}^{D}P_{\mathrm{u},d}(t)-\sum_{k=1}^{N_{\mathrm{H}}}P_{\mathrm{pum},k}(t)\right)\le(e-1)\sum_{t=1}^{T}\sum_{w=1}^{N_{\mathrm{W}}}P_{\mathrm{Wu},w}(t)\end{cases},\tag{13}$$

where $P_{\mathrm{Wu},w}(t)$ and $P_{\mathrm{u},d}(t)$ are, respectively, the wind power value of OWF w and load value of node d considering prediction errors at time t, which are random variables.

4 SOLUTION APPROACH

The aforementioned model is a mixed-integer nonlinear bi-level planning model. The upper model is solved by the improved PSO algorithm to generate a capacity configuration scheme of MPS and ES. The inertia weight is fixed in PSO (Tsai et al., 2020), which is easy to make the algorithm fall into local optimization. The improved PSO algorithm changing the fixed weight into the dynamic weight adjusted based on the premature convergence and fitness value is adopted in this study.

The dynamic weight formula is shown as

$$\omega=\begin{cases}\omega_{\min}+\dfrac{\left[f_j-f_{\min}\right]\times(\omega_{\max}-\omega_{\min})}{f_{\mathrm{av}}-f_{\min}} & f_j\le f_{\mathrm{av}}\\ \omega_{\max} & f_j>f_{\mathrm{av}}\end{cases},\tag{14}$$

where f_j is the fitness value of the j^{th} particle. f_{av} and $f_{\min}$ are the average fitness and minimum fitness, respectively. $\omega_{\max}$ and $\omega_{\min}$ are the upper and lower limits of dynamic inertia weights, respectively. Corresponding to the bi-level planning model, f_j is the objective function of the upper model, that is, the total cost of the system including construction, operating, and maintenance costs. The location of the swarm corresponds to the capacity of MPS and ES planned by the upper model.

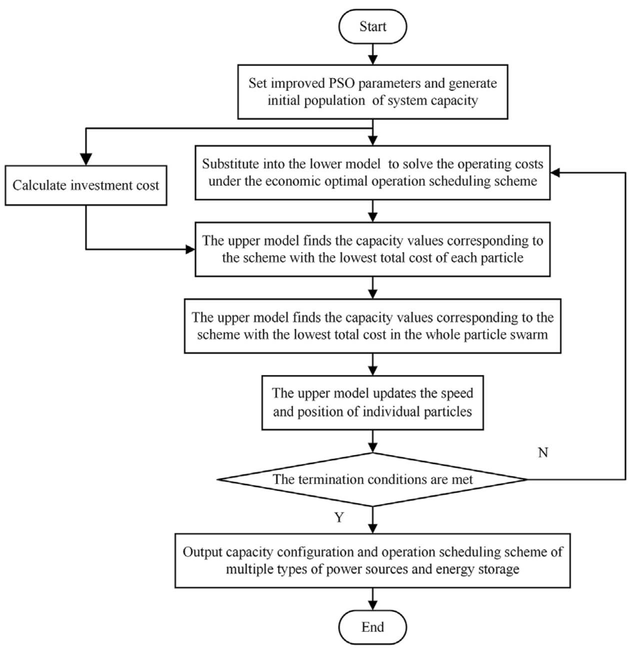

FIGURE 3 | Flowchart of the robust bi-level planning method for the multi-source system.

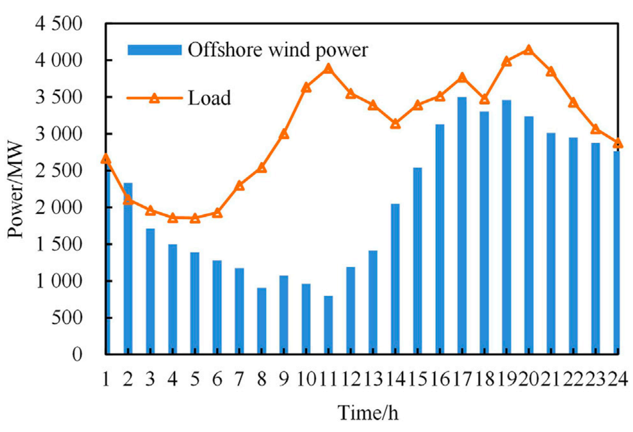

FIGURE 4 | Prediction curves of offshore wind power and load.

The lower layer of the robust bi-level planning model is a mixed-integer quadratic programming (MIQP) problem, and the parameter uncertainty is taken into account. The CPLEX solver is used to solve the lower model and generate an operation scheduling scheme of MPS and ES with minimum cost. The flow of the robust bi-level planning method for the multi-source system integrated with OWFs is shown in **Figure 3**.

5 CASE STUDY

The typical daily power prediction of an OWF group in Shandong Province, China, is used to verify the effectiveness of the proposed robust bi-level planning method. The prediction curves of offshore wind power and load in a scheduling cycle are shown in **Figure 4**.

TABLE 1 | Unit construction cost and life cycle.

Types	Construction cost ($\times10^3$¥/MW)	Life cycle of unit (year)
TP plant	182.00	30
GTP plant	125.00	20
PHS plant	528.57	80

The unit construction cost and life cycle of the TP, GTP, and PHS plants are shown in **Table 1**. The discount rate is 6.7%. The power generation efficiency of the GT unit is 33%. The fuel consumption cost of natural gas is ¥ 25 million/MW (¥ is the unit of CNY).

Considering the uncertain factors in the prediction process, three scenarios are designed for comparative analysis.

Scenario 1: Bi-level planning for the multi-source system integrated with OWFs without considering prediction errors.

Scenario 2: Robust bi-level planning that takes the prediction errors of offshore wind power into account, and the prediction error of offshore wind power is within 10%.

Scenario 3: Robust bi-level planning that considers the dual uncertainty of load and offshore wind power prediction. The prediction error of offshore wind power is within 10%, and the load prediction error is within 2.5%.

In the solution algorithm of the lower model, the population size of the particle swarm is set to 100, the number of iterations is set to 50, and the maximum and minimum inertia weights are 0.8 and 0.4, respectively. The capacity configuration scheme with the optimal total cost under each scenario is shown in **Table 2**. The construction cost corresponding to a scheduling cycle is shown in **Table 3**, and the operating and maintenance costs of each scenario in a scheduling cycle are shown in **Table 4**. As can be seen, the total cost of the corresponding planning scheme in scenario 1 is the lowest. With the increase of prediction uncertainty, the planning scheme of scenarios 2 and 3 increases part of the power capacity and operating and maintenance costs compared with scenario 1. Combined with **Table 3** and **Table 4**, it can be seen that the operating and maintenance costs account for the largest proportion of the total cost of the TP and GTP systems. The minimum total cost of the system is taken as the objective function in the robust bi-level planning model proposed in this study. Therefore, the planning results will give priority to the cost. It can be inferred that the total cost and output of the TP and GTP systems are largely determined by the operating cost.

The optimal scheduling results according to the capacity configuration scheme in each scenario are shown in **Figure 5**, **Figure 6**, and **Figure 7**, respectively. In scenario 1, according to the optimization results, the wind power curtailment is controlled within 0.2%. It can be seen that under the planning scheme, renewable energy is completely utilized on the basis of ensuring the safe and stable operation of the power system. The PHS system uses the excess electric energy at time 2 to pump water to the upper reservoir and converts it into high-value electric energy

TABLE 2 | Optimal capacity configuration results for each scenario.

Scenarios	TP system (MW)	GTP system (MW)	PHS system (MW)	Total cost (×10^5¥)
S1	1,246.00	1,856.44	187.44	952.45
S2	1,231.57	1,496.26	328.67	1,166.49
S3	1,616.44	1,538.11	623.45	1,278.99

TABLE 3 | Construction cost for each scenario.

Scenarios	TP system (×10^3¥)	GTP system (×10^3¥)	PHS system (×10^3¥)	Total construction cost (×10^3¥)
S1	485.68	586.20	182.88	1,254.76
S2	480.05	472.47	320.68	1,273.20
S3	630.07	485.68	608.30	1,724.05

TABLE 4 | Operating and maintenance costs for each scenario.

Scenarios	TP system (×10^5¥)	GTP system (×10^5¥)	PHS system (×10^3¥)	Total operating and maintenance costs (×10^5¥)
S1	479.70	459.60	60.24	939.90
S2	685.97	465.37	241.68	1,153.76
S3	729.70	529.02	302.70	1,261.75

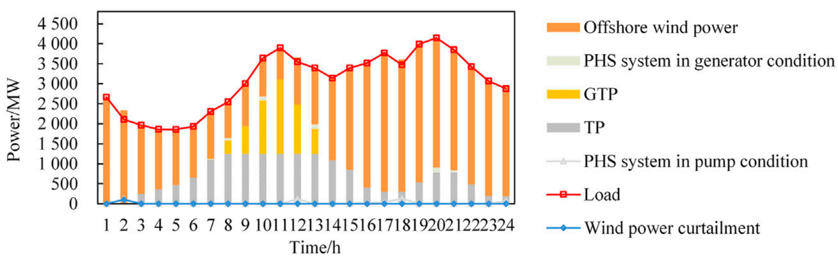

FIGURE 5 | Operation planning result for scenario 1.

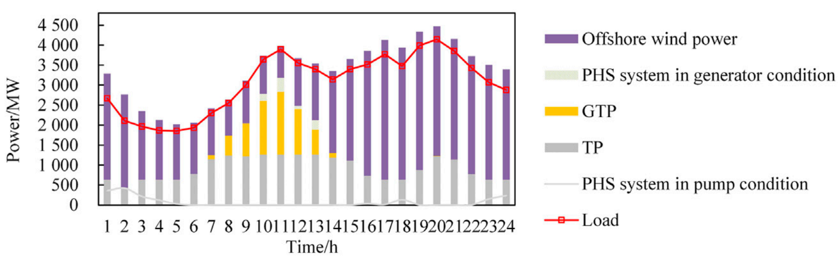

FIGURE 6 | Operation planning result for scenario 2.

when the load demand is large, which ensures the safe operation of the power system and solves the contradiction of supply and demand during the climax and ebb periods of the power grid effectively. It is known that in addition to time 2, when the wind power value of the OWF cluster is greater than the load, theoretically, there is no need for the PHS system to work in the pumping mode at other times. In the actual situation, considering the climbing constraints of the unit, the output power cannot drop to 0 quickly in a short time. Therefore, the excess power output from the OWF cluster and other power

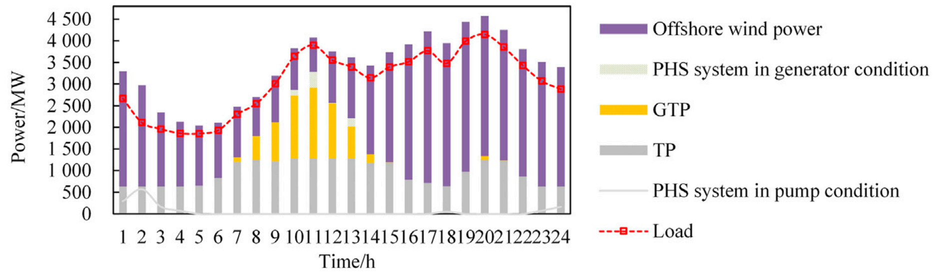

FIGURE 7 | Operation planning result for scenario 3.

TABLE 5 | Comparison of solution results.

Scenarios	Total cost (×10^5¥)	
	PSO	Improved PSO
S2	1169.28	1,166.49
S3	1,279.71	1,278.99

sources is absorbed by the PHS system as ES at 12, 18, and other times. The same is true for scenarios 2 and 3. Because the climbing constraint of the unit cannot fit the load curve, part of the output power is converted into ES through the PHS system and absorbed. According to **Figure 5**, **Figure 6**, **Figure 7**, and **Table 4**, the TP system can maintain the minimum demand in the power system, and its total cost is lower than that of GTP and PHS systems. The GT unit features outstanding dynamic characteristics and strong peak-load regulation capability, and can quickly adjust the power output. Therefore, it is used as the supplementary power source of the TP unit to meet the load demand. The PHS system is not the main output power source of the power system but mainly the power source for regulation because of the constraints of unit capacity and reservoir capacity.

In the interest of verifying the performance of the improved PSO algorithm with dynamic inertia weight in solving the robust bi-level planning model, the traditional PSO algorithm is applied to solve the upper model in scenarios 2 and 3 under the same population size and iteration times, and the solution results of the two methods are shown in **Table 5**. It can be seen that the optimal cost of the schemes solved by the improved PSO algorithm in scenarios 2 and 3 are 278.87 (×10^3¥) and 71.85 (×10^3¥) lower than that of the traditional PSO algorithm, respectively. This proves that the PSO algorithm with dynamic inertia weight has a stronger global optimization ability, and the power capacity configuration and operation scheduling scheme with a lower total cost can be obtained when using this algorithm to solve the robust bi-level planning model.

6 CONCLUSION

To adapt to the consumption of offshore wind power clusters, a multi-source system model was constructed, which included the offshore wind power, TP, GTP, and PHS systems. Moreover, considering the system economy and offshore wind power consumption level, and taking into account the dual uncertainty of load and offshore wind power prediction, a robust bi-level planning method for the multi-source system was proposed, in which the improved PSO algorithm with dynamic weight was used to solve the model. The economic optimal capacity configuration and operation scheduling scheme of MPS and ES were generated based on the method proposed in this study. The planning scheme realized the balance of supply and demand between power sources and load and the peak load shifting in the power grid. In addition, the method proposed in this study improved the inclusiveness of prediction errors and made the system have the advantages of good stability and high reliability.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

QJ: methodology, software, writing—original draft, and data curation. XL: investigation, software, writing—original draft, and data curation. XD: conceptualization of this study, software, and supervision. YZ: investigation, and review and editing. NW: data curation and review and editing. YS: writing—review and editing.

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The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.