

Challenges and potential solutions for the global optimization of "Offshore Wind Energy – Multi-Marine Resources" integration system in the Beibu Gulf of Guangxi

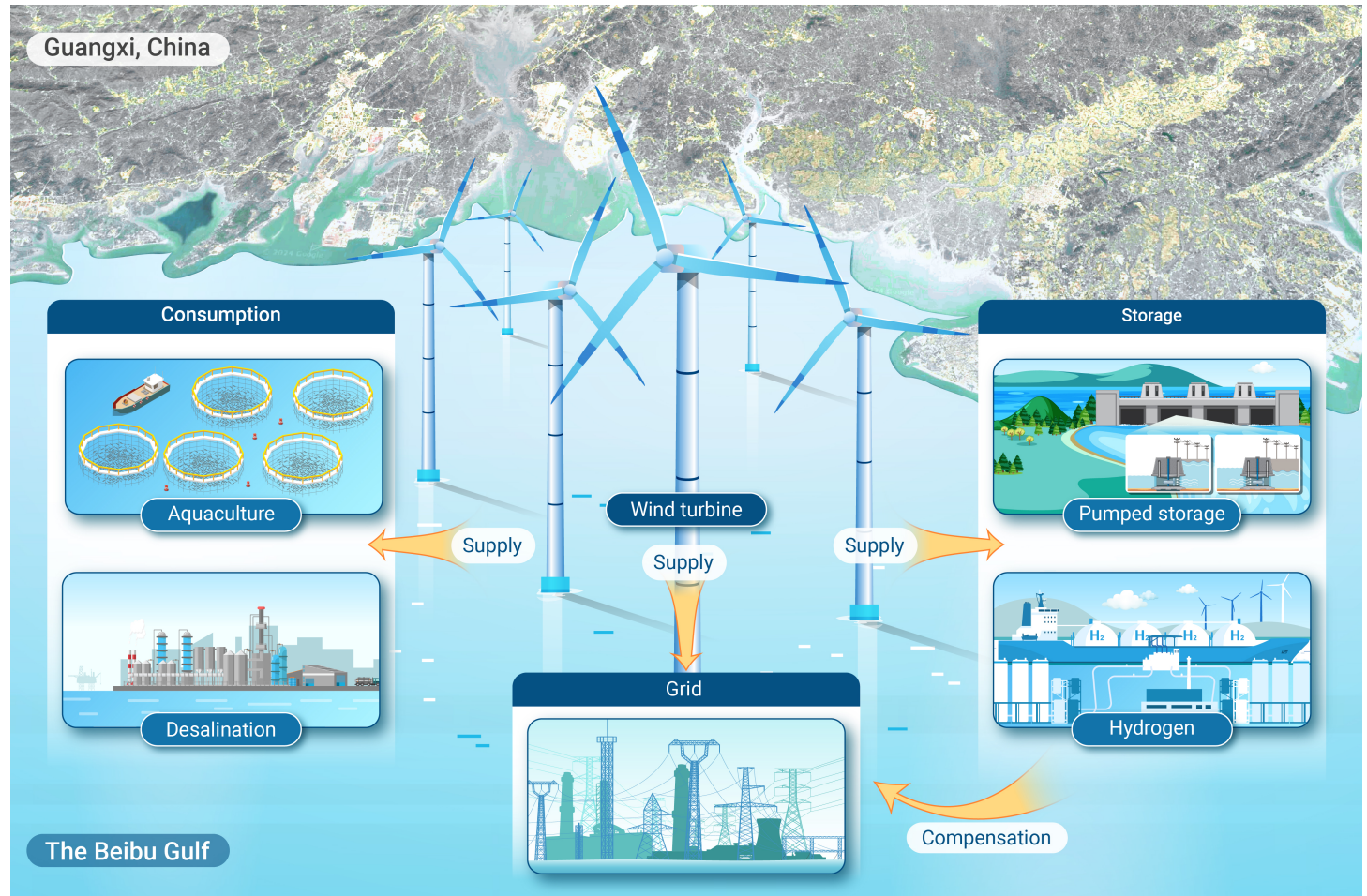
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Beibu Gulf aims to integrate offshore wind energy with multi-marine resource development.
- Accurate resource forecasting, global optimization, and resilience enhancement are essential for system success.
- Develop supply-storage-consumption integration to balance efficiency, cost, and stability of energy output.
- Assess typhoon resilience to safeguard the system against extreme weather impacts.

Challenges and potential solutions for the global optimization of "Offshore Wind Energy – Multi-Marine Resources" integration system in the Beibu Gulf of Guangxi

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The development of a national energy base and modern energy system in the Beibu Gulf of Guangxi requires an innovative energy system. General energy system only consists of a single marine energy resource, this work introduces an "Offshore Wind Energy – Multi-Marine Resources" integration system, which distinctively centers on offshore wind power while incorporating seawater hydrogen production, pumped storage, seawater desalination, marine aquaculture, and other marine resource utilization complexes. Its potential challenges during its future construction and potential solutions for the global optimization that need to be addressed are as follows: 1) creating a high-precision wind speed prediction model across multiple scales; 2) developing a global optimization model for the system under multiple uncertainties; and 3) proposing a resilience assessment method for systems subjected to unconventional external shocks. This integration system can contribute to the comprehensive development of marine resources and the establishment of a national comprehensive energy base in Guangxi Province and around the world.

INTRODUCTION

The Beibu Gulf in Guangxi Province, rich in marine resources, boasts geographical advantages and holds an important strategic position, offering unprecedented development opportunities and significant future potential. Located in the northern part of the South China Sea, serves as a bridgehead connecting 12 provinces, autonomous regions, and municipalities in western China facing the Pacific Economic Circle. It is also an important land and sea node of the southbound navigation route of the national "Belt and Road Initiative" of China (Figure 1). In 2022, the National Development and Reform Commission's "14th Five-Year Plan for the Construction of the Beibu Gulf Urban Agglomeration" proposed "jointly build a high-level blue ecological bay area". Similarly, "Guangxi's 14th Five-Year Plan for Energy Development" proposed "build a national comprehensive energy base and a modern energy system".

To achieve this significant goal, an "offshore wind energy—multi-marine-resources"(OW-MR) integration system would be an innovative approach and an essential component of the sustainable development of marine space. This system, centered on offshore wind power, also includes seawater hydrogen production, pumped storage, seawater desalination, marine aquaculture, and other marine resource utilization complexes (Figure 2). The Beibu Gulf has a coastline of 1,628 kilometers and is rich in offshore wind energy, offering significant potential and feasibility for this system. It is estimated that by 2030, Guangxi will have a total installed clean energy power capacity of more than 110 million kW. While compared to other coastal provinces in China, the offshore wind power industry in Guangxi Beibu Gulf is still in its early stages of development but could benefit from the advantage of being a latecomer in adopting a new OW-MR integration system, especially after its global optimization with more energy production.

Compared with traditional offshore wind farms, the OW-MR integration system may offer the advantage of realizing the global optimization of offshore wind power and other marine resources, enhancing the overall efficiency of marine resource utilization. For instance, (1) the unstable output of wind power could be converted into seawater hydrogen production/pumped

storage as an energy "power bank" and mitigate the problem of "wind curtailment"; (2) seawater desalination to produce freshwater can utilize excess offshore wind power on-site, reducing long-distance transmission losses and associated costs; (3) integrating offshore wind power and marine aquaculture can boost fishery production.

However, three main challenges regarding the OW-MR integration system in Beibu Gulf of Guangxi need to be promptly addressed: (1) How to assess the potential production of different types of marine resources accurately? (2) How to achieve global multi-objective optimization for the OW-MR integration system? (3) How to ensure the long-term stability of the OW-MR integration system?

To address these challenges, this paper aims to propose potential solutions for the global optimization of the OW-MR integration system in Beibu Gulf of Guangxi. This work could contribute to establishing a nationwide comprehensive energy base in Guangxi province and promoting the integrated development of marine resources.

PRESENT STATE

The Beibu Gulf of Guangxi boasts abundant marine resource reserves and significant potential for excavation (Table 1). The unique geographical location and favorable climate of the Beibu Gulf make it an ideal region for developing sea pastures. With an estimated total output value of 100 billion yuan for the marine fishery economy, the area aims to establish three national coastal fishing port economic zones and six national demonstration areas for ecological and sustainable aquaculture, building upon the foundation of its existing four national "marine pastures."

On the other hand, the OW-MR integration system in the Beibu Gulf is still in its initial stages, despite having significant development prospects. For example, the construction of 10 kW-level pumped storage power plants in Guangxi is progressing rapidly, with plans to build 8.4 million kW of pumped storage power plants. Several pumped storage projects are already under development. Furthermore, although on-site hydrogen production from offshore wind power can reduce power loss and transportation costs, no green hydrogen industrialization project has been completed so far. In terms of seawater desalination, there are few relevant enterprises operating in the Beibu Gulf area, and only preliminary work is being carried out to produce desalinated water for industrial and domestic use. To meet the practical needs of island construction, Guangxi Beibu Gulf has begun implementing seawater desalination projects, aiming to achieve an average annual growth rate of about 10% in the added value of the comprehensive utilization of the seawater industry in Guangxi¹.

Compared to a single marine resource system where capacity production and resilience analysis are required, this OW-MR system consists of several different marine energy resources, which has increased complexity with additional challenges addressed as follows.

LITERATURE REVIEW AND CHALLENGES ADDRESSED

Challenge 1: How to assess the potential production of different types of marine resources in Beibu Gulf of Guangxi accurately?

A fundamental challenge in the OW-MR integration system is achieving efficient and accurate predictions of offshore wind power generation across multiple time and spatial scales on the energy supply side, specifically wind

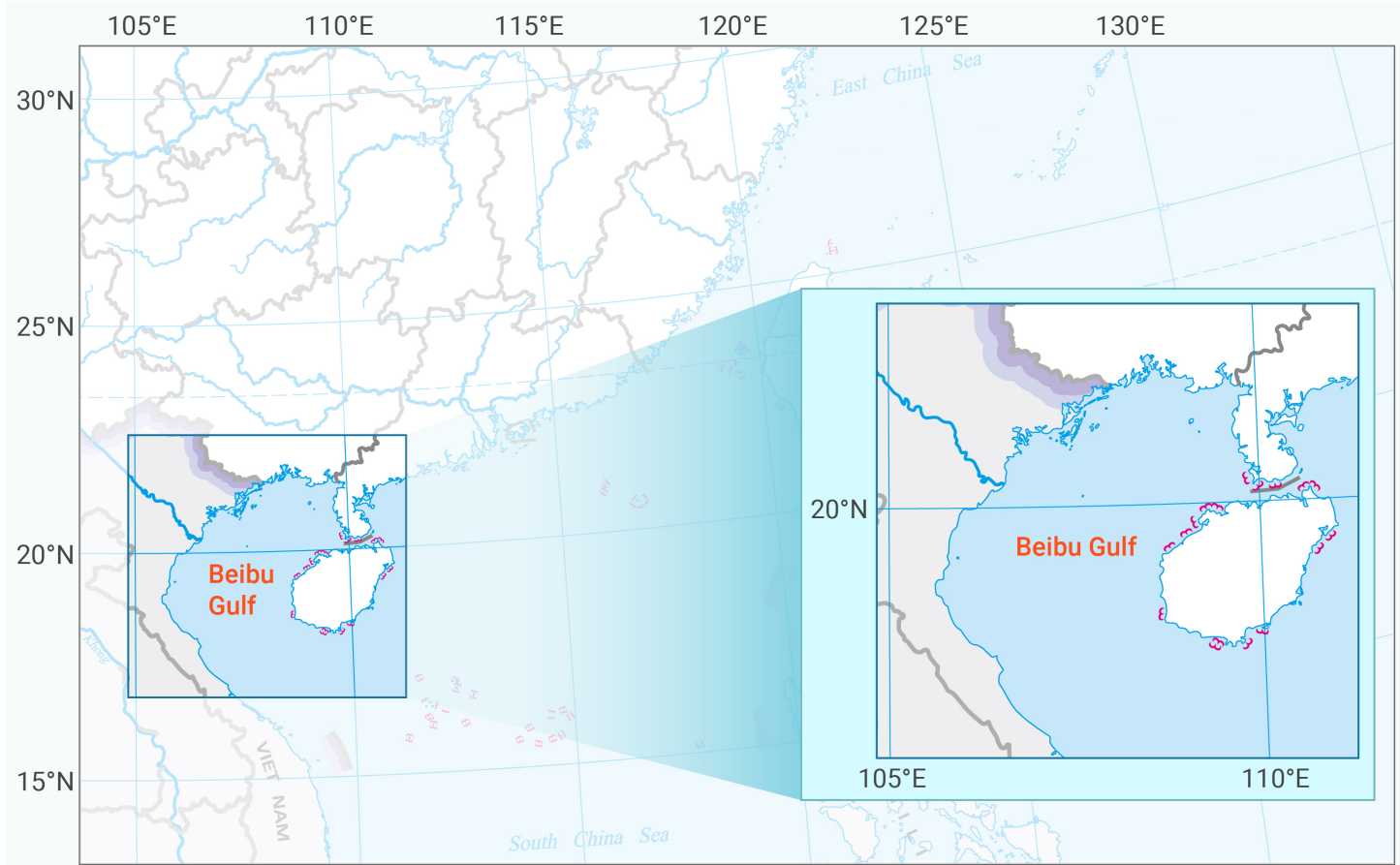


Figure 1. The Beibu Gulf in Guangxi Province.¹

speed forecasting (Figure 3). As wind speed is a direct factor affecting offshore wind power generation, its accurate prediction can help assess the power output of wind farms. Large-scale wind speed prediction^{2,3} is mainly used for the site selection, design, and long-term planning of wind farms, while small-scale wind speed prediction^{4,5} is mainly employed to achieve the scheduling and balance of power systems. Since the marine environment is essentially a complex physical field at multiple scales, the superposition mechanism of complex physical phenomena such as heat and water vapor exchange,^{6,7} wind-wave coupling,^{8,9} and turbulence¹⁰ all still lacks a clear explanation, which brings great challenges to the forecast of ocean wind speed. Traditional numerical weather prediction (NWP) methods aim to numerically solve a set of partial differential equations that describe atmospheric motion, and obtain environmental data such as temperature and wind speed at the grid scale from the calculations. However, the accuracy of numerical calculations is limited by the reliability of numerical models, the computationally expense reduced from high grid solutions, and chaos caused by nonlinear meteorological systems.^{11–13} This makes NWP suitable for wind speed forecasts at larger spatial resolutions, but difficult to directly apply wind speed forecasts at wind farm scales. Data-driven meteorological prediction models,^{14,15} such as time series models and machine learning, can avoid large-scale numerical calculations. The trained models can quickly realize short-term future wind speeds based on historical data. In recent years, these techniques have been widely used in the domains of wind speed prediction and meteorological forecasting in recent years.^{16–18} However, the applications of these techniques require the acquisition of a large amount of authentic and reliable wind speed data. Common offshore wind speed monitoring sensors include Doppler radar, lidar,^{19,20} ultrasonic anemometer,²¹ etc. However, due to the limited spatial coverage of data sensors and the stability of data transmission, these sensors cannot achieve the purpose of measuring the real-time wind speed in the sea area where the wind farm is located. Satellite remote sensing technology^{22,23} can provide large-scale, continuous wind speed data, but the resolution of both space and time is insufficient to

record changes in wind speed that are local or immediate.

The assessment of the capability of marine resources, apart from wind power, is another key challenge in the OW-MR integration system. The evolution of seawater desalination and seawater hydrogen production is mostly dependent on equipment technology, plant scale, and wind farm power generation when it comes to capacity forecast.^{24,25} Predicting the capacity of these two marine resources in the OW-MR system is challenging, primarily due to the need to develop a power-capacity-cost forecasting model under arbitrary wind power production to support the configuration optimization of various facilities within the integration system. Establishing an assessment and prediction model that gauges past fishing data and projected output based on local fishery data in the Beibu Gulf—such as biomass, species distribution, growth rate, survival rate, and water quality parameters—^{26–29} is essential for forecasting the potential of aquaculture. Additionally, as aquaculture is one of the energy-consuming linkages of the OW-MR system, the energy used by aquaculture must be documented. Finally, pumped storage plays an important role in the dispatching and regulating of electric energy in the OW-MR systems. The main difficulty in predicting its capacity also lies in the accurate prediction of power generation of offshore wind farms mentioned above.^{30,31} Its design capacity needs to be coordinated with the fluctuation characteristics of wind farm power generation.

As mentioned earlier, the development of the OW-MR integration system in the Beibu Gulf of Guangxi Province is still in its early stages. Industries such as pumped storage, seawater hydrogen production, seawater desalination, and aquaculture, which are integrated with offshore wind power, each have unique organizational structures and energy utilization approaches. Consequently, their industrial capacity assessments and prediction methodologies differ, yet related models remain underdeveloped, making it challenging to achieve a global optimization goal. The primary challenge of this topic lies in reasonably and accurately assessing the potential production of various types of marine resources within the OW-MR integration system.

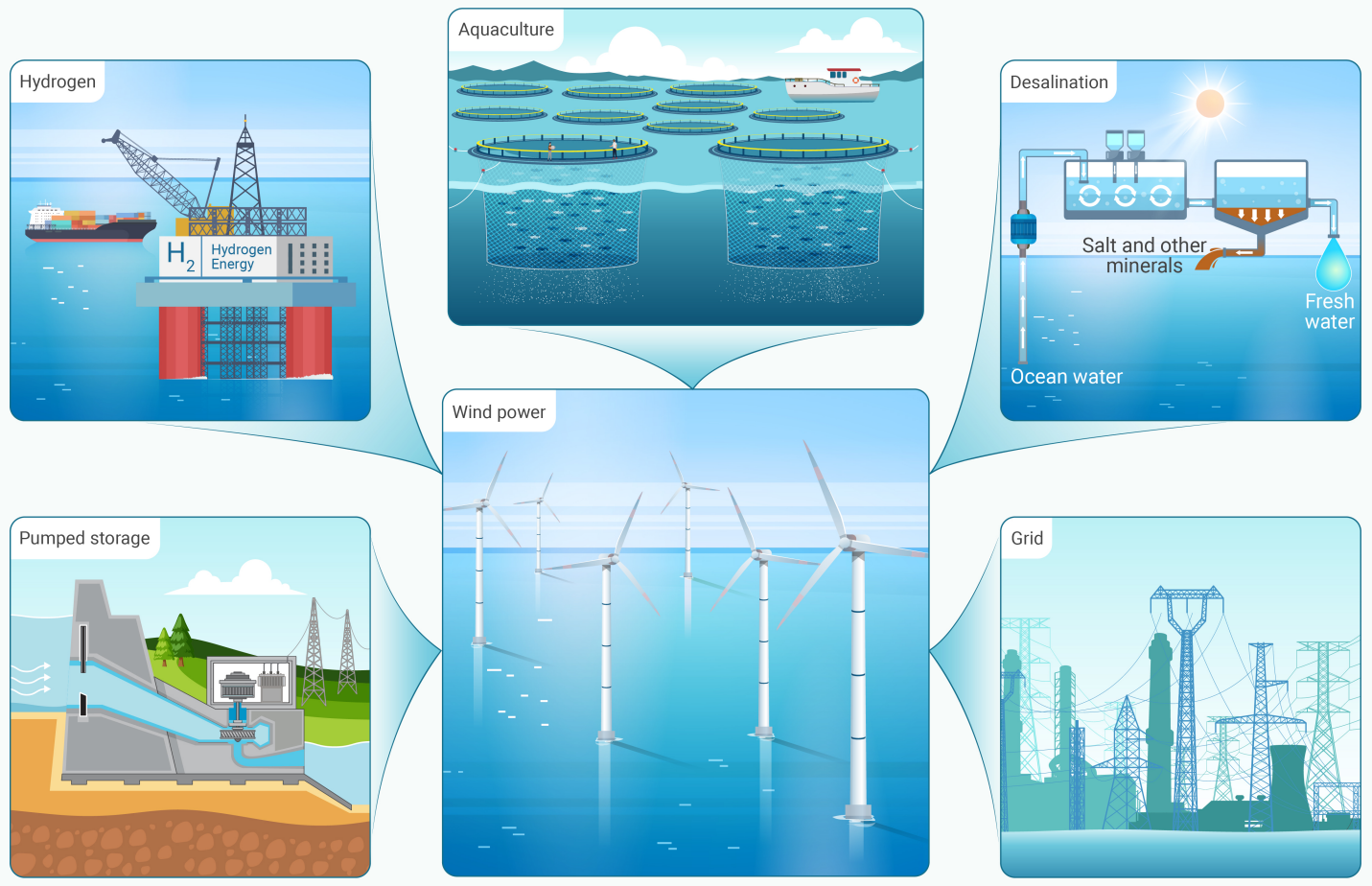


Figure 2. The Schematic of the OW-MR Integration System.

Challenge 2: How to achieve global multi-objective optimization for the OW-MR integration system in the Beibu Gulf of Guangxi?

Wind energy has strong variability and anti-peak regulation characteristics,³²⁻³⁷ and its large-scale grid connection presents a significant challenge to the safety and robustness of the power supply system. The problem of curtailment and absorption has become key factors restricting the high-quality development of offshore wind farms. This is caused by the constant fluctuation characteristics of wind, which also elevates high cost and low efficiency. In order to promote the coordinated development of the scale, efficiency, and safety of the offshore wind power industry, researchers and engineers have reached a consensus on integrating and leveraging the advantages of various energy sources and resources to build a new form of multi-energy complementary energy structure.^{35,38-40}

There have been some researches indicating that there is complementarity between different resources, which is conducive to improving the overall resource efficiency. Based on the ERA5 reanalysis database, Nascimento et al.⁴¹ estimated that the annual average complementarity of wind and solar resources in the studied sea area was between 20% and 30%. Similarly, Li et al.⁴² found that wind resources and solar energy resources in four major sea areas of China are highly complementary. Wu and Zhang⁴³ established a multi-objective risk assessment framework for a wave-wind-solar compressed air storage (WW-S-CAES) offshore multi-energy complementary system by fuzzy methods. Lucas et al.⁴⁴ analyzed the economic feasibility of hydrogen production by wind energy in WindFloat Atlantic offshore wind farm. Raoux et al.⁴⁵ investigated how fish aggregation and benthos were affected by offshore wind power development, and discovered that the establishment of wind farms increased system resource recycling.

Coordinating large-scale development and high-level consumption of offshore wind power based on the principle of multi-energy complementarity, while ensuring the safe and reliable supply of electricity, is crucial for improv-

Table 1. Marine energy resources in Beibu Gulf of Guangxi

Energy resources	Amount
Coastline	~1628 km
Average annual wind speed	5.8~7 m/s
Average annual wind power density	300 to 350 W/m ²
Planned 25 offshore wind farm number	25
Total installed capacity	22.5 million kW

ing the efficiency of the offshore wind power industry.^{34,35,40} Zhang et al.⁴⁰ proposed multi-objective capacity configuration optimization and operation strategies for wind and hydrogen energy storage complementary systems. Li et al.⁴⁶ studied the optimal allocation of photovoltaic energy storage capacity and established a two-layer optimization model for energy storage capacity and operation strategy. Zhang et al.⁴⁷ considered cascade reservoirs and wind-solar complementary systems, and proposed an optimal capacity decision-making method aiming at minimum cumulative fluctuations. Yang et al.⁴⁸, aiming at the randomness of renewable energy output and the volatility of load, established an optimization model considering multiple systems and multiple time scales, and proposed a day-rolling optimization scheduling method to improve the economy and stability of the system. Zhang et al.⁴⁹ comprehensively considered the spatial-temporal correlation and distribution uncertainty of wind power output, and the modeling difference and coupling relationship of electricity and gas systems at different running time scales, and suppressed the power fluctuation of wind turbines by complementarily adjusting the active power of wind turbines with different spatial distribution in wind farms. Zhang et al.⁵⁰ also proposed a double-stage distribution robust optimization (DRO) model that accounts for the volatility of wind power and

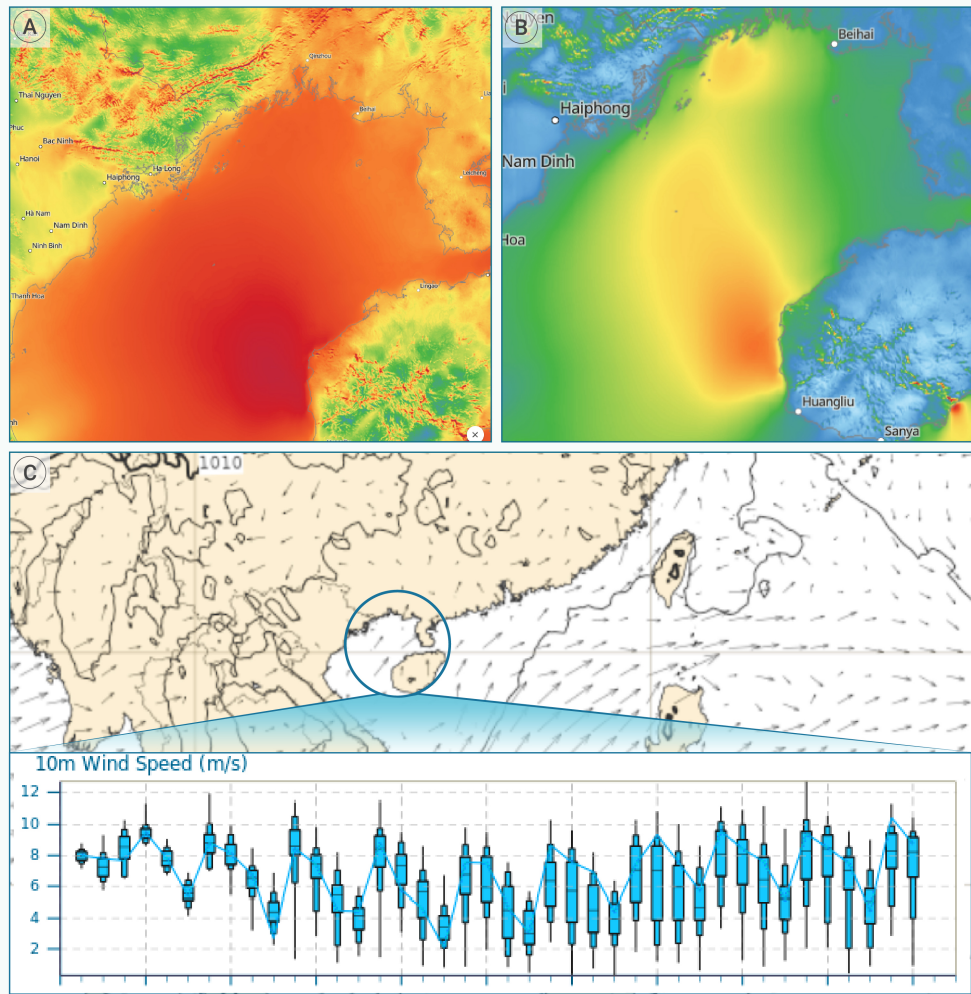


Figure 3. (A) Mean Wind Speed in Beibu Gulf; (B) Mean Power Density of Wind in Beibu Gulf; (C) High-Resolution Forecast of Wind Speed in the Beibu Gulf.

Furthermore, the structural integrity of wind farm facilities is seriously threatened by significant natural disasters like typhoons, which could jeopardize the stability of electricity transmission.⁵⁸ The complicated transmission systems and numerous marine engineering equipment are features of the OW-MR integration system. The power facilities and fundamental structures of each subsystem, except wind farms, are also vulnerable to failure due to the effects of the marine environment, particularly catastrophic natural disasters. Therefore, it is important to appropriately estimate the disaster resistance capacities of both the system and the subsystems as a whole. Numerous risk identification and resilience assessments have been conducted for equipment safety in desalination^{59,60} and hydrogen production systems;^{61–63} however, the stability of the energy system and infrastructure has not yet been the primary focus of these studies. In recent years, several studies have been published on the hydrodynamic properties of aquaculture.^{64–67} However, there remains a lack of research on resilience assessments for marine aquaculture facilities, and the resilience of wind power facilities integrated with aquaculture has not yet been fully addressed. The pumped energy storage system has been extensively utilized in the configuration opti-

produces the best outcome possible while considering operational efficiency and dependability.

Capacity allocation in an integrated energy system is a complex problem that involves multi-objectives, multi-constraints, non-linearity, and high-dimensionality.^{39,40,51} Prior research has focused on microsystem or micro-grid capacity allocation and operation optimization^{52,53} but still lacks comprehensive consideration of multiple uncertainties in large-scale integrated energy systems. Excess emphasis on economic cost optimization while neglecting energy efficiency, overly conservative robust optimization, and insufficient accuracy in the optimization results.³⁷

Therefore, establishing a global optimization model of OW-MR integration system, based on the temporal and spatial distribution characteristics of offshore wind power and multi-industry marine resources, is another challenge for achieving high-quality development of offshore marine energy in Beibu Gulf.

Challenge 3: How to ensure the long-term stability of the OW-MR integration system in the Beibu Gulf of Guangxi?

The resilience assessment of the integrated system is a key factor in ensuring its long-term stable operation and ability to manage extreme weather events. Resilience refers to the capacity of a system to resume regular operations following a disruption or calamity, or its ability to sustain essential operations under challenging circumstances,^{54,55} with main indicators of redundancy, recovery capacity, and robustness in general. The intricate marine environments that offshore wind farms encounter, including storms, waves, biological contamination, salt spray corrosion, and even geological activity, can cause slow damage or failure to wind turbine blades, transmission cables, pipelines, and other components,^{56,57} leading to additional maintenance costs and affecting the reliability of the entire system.

mization of the energy supply system, as it serves as the resilience provider for the OW-MR integration system.^{68–70} However, the contribution of pumped storage systems to the resilience of the integration system has not been adequately assessed or quantified.

The Beibu Gulf region experiences a significant monsoon climate, with frequent typhoons in summer and a strong northeast monsoon in winter, both of which pose considerable challenges to the stability of ocean engineering equipment. Conventional models for assessing the susceptibility and resilience of wind farms primarily rely on statistical and probability analysis techniques,^{71–73} as well as index system analysis methods,^{74,75} etc. However, due to the OW-MR integrated system consisting of multiple subsystems with distinct features, these techniques may not be suitable. Therefore, evaluating the resilience of the OW-MR integration system and ensuring its long-term stability, particularly under the influence of harsh maritime weather conditions such as strong typhoons, remains a crucial challenge. Additionally, it is necessary to strengthen its disaster prevention and post-disaster recovery capacities. Addressing these problems requires developing specialized approaches and methods that account for the unique characteristics of the system and the environmental stresses it faces.

RESEARCH OVERVIEW AND PROPOSED SOLUTIONS

In order to overcome the three challenges mentioned above, it is essential to conduct a study on the global optimization and resilience assessment of the OW-MR integration system. Therefore, a research overview is proposed as follows, which includes three research focus areas and three corresponding solutions related to the challenges of the OW-MR integrated system.

Research Overview

Three research overview points are listed as follows; production assess-



Figure 4. The Basic Structure of Multi-Format Marine Resources and Energy Flow Direction.

ment, global optimization, and resilience assessment of the OW-MR system are depicted. Understanding production assessment in point I could directly influence the interaction mechanism and global optimization discussed in point II. The resilience assessment in point III guarantees the long-term safety and stability of the total system after optimization in point II.

Production assessment and forecasting of offshore wind power and multi-marine resources in the Beibu Gulf of Guangxi.

The first stage involves compiling a database of the typical spatiotemporal distribution characteristics of the offshore wind resources by obtaining historical wind speed observation data for the Beibu Gulf region. This database could be used to develop and validate accurate wind speed predictions such as AI-generated wind model for the specified sea area. Next, high-resolution wind speed predictions at various spatiotemporal scales for the target sea area can be performed using numerical meteorological forecasting methods and short-term wind speed forecasting techniques. Based on the wind speed forecast data, a potential wind farm location is selected, and a prediction model for the anticipated power generation of the wind farm is developed using wind turbine designs and a wake model.⁷⁶⁻⁷⁸ Finally, prediction models for the production of electrolytic hydrogen, seawater desalination, aquaculture, and the capacity of pumped storage can be independently established based on the energy consumption characteristics and wind power-output conversion relationship of each subsystem.

The interaction mechanism of primary and secondary resources and the global optimization regulation of the OW-MR integration system in Beibu Gulf of Guangxi.

Based on the production capacity of offshore wind power and various types of resources in the Beibu Gulf of Guangxi, the second research focus at this stage is to analyze the spatiotemporal development characteristics of marine resources and reveal the interaction mechanism between primary and

secondary resources by examining the energy flow direction (Figure 4). The diversified marine resources primarily include offshore wind power, supplemented by seawater hydrogen production, pumped storage, seawater desalination, and aquaculture. This OW-MR system has high complexities associated with multi-objective optimization, such as potential trade-offs between efficiency, cost, and resilience. Considering the leveled cost of electricity (LCOE), cost predictions for integrating offshore wind power with various marine resource operations can be conducted. This approach allows for the extraction of spatial-temporal development characteristics of offshore wind resources and other marine resources, while also facilitating the analysis of their interaction mechanisms based on energy flow directions.

Based on understanding the spatial and temporal characteristics and interaction mechanisms of multi-marine resources, the topological structure modeling and system optimization of OW-MR integration system will be the key following research content with the following steps in this stage: (1) determine the multi-resource energy interaction mode, and establish the energy flow direction model of the OW-MR integration system; (2) establish its specific two-layer optimization logical framework, and explore local optimization methods between the upper layer and lower layer; (3) Based on the two-layer optimization calculation model, propose the upper design scheme and lower operation strategy of the OW-MR integration system, and evaluate the utilization rate of each energy resource and its effectiveness; (4) establish the multi-objective optimization model and develop the global optimization method of the multi-mode OW-MR integration system.

Resilience assessment of the OW-MR integration system under marine environmental conditions

There are two types of potential risks: structural risk, which includes damage or failure of structures such as towers, pipelines, cables, towers, and

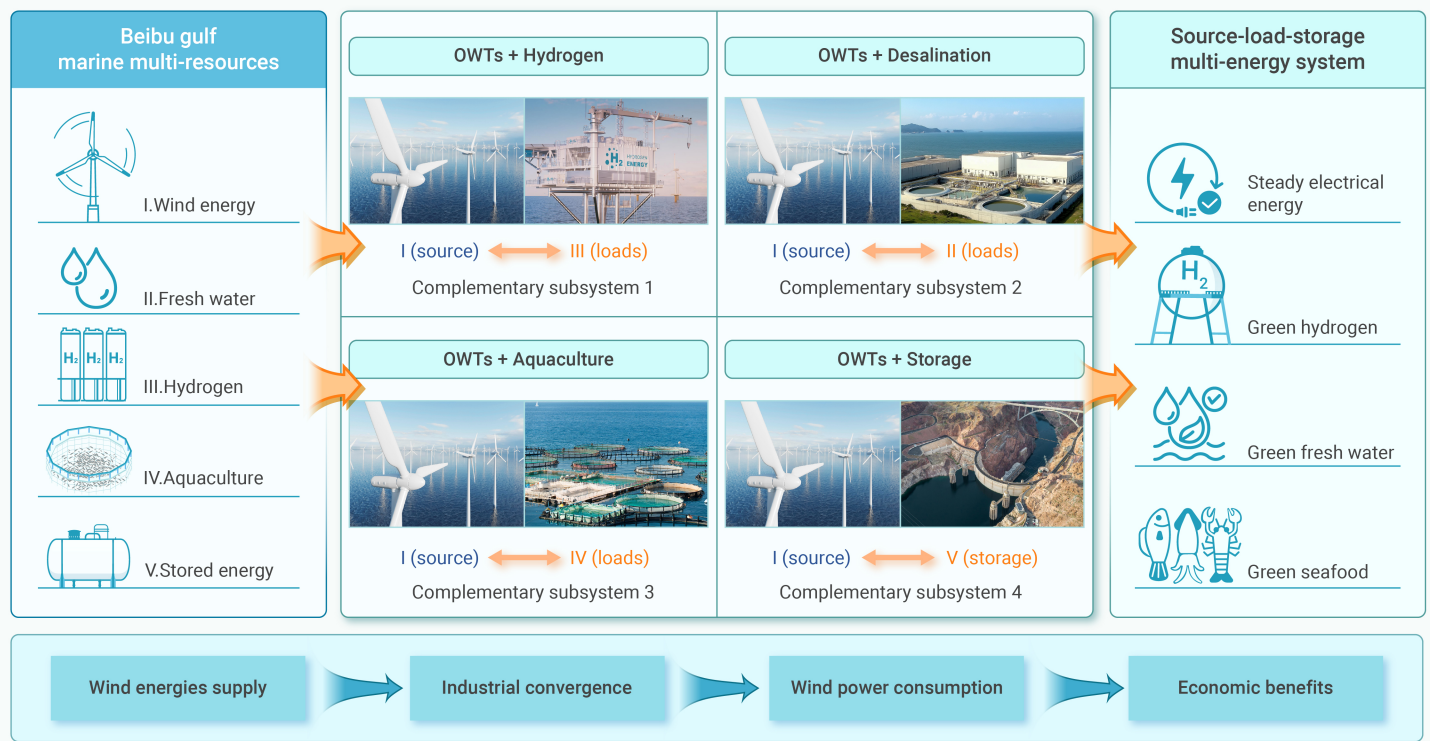


Figure 5. The Operational Mode of the Offshore Multi-Format Energy System in the Beibu Gulf.

foundations; and power risk, which includes power system failures such as overload, short circuits, and software errors. These two risk types can be used to analyze the damage mechanisms of each subsystem in the OW-MR integration system, establish the functional evaluation of the subsystem in the damaged states, and build a vulnerability analysis model for the OW-MR integration system. This model enables the calculation of the overall damage probability of the system under various disaster conditions and natural disaster scenarios.

Subsequently, two index systems could be developed. The first is a structural function evaluation index system, which is based on factors such as structural strength, durability, and maintainability of structural damage under natural disasters. The second is a power function evaluation index system, which considers factors such as power system stability, energy storage system efficiency, and system residual power supply rate under natural disasters. These two index systems can work in conjunction with the vulnerability analysis model to establish a system repair model. This repair model would allow for the evaluation of the resilience of the entire OW-MR integration system.

A high-resolution multi-spatiotemporal model for wind speed prediction in the OW-MR system

Establishing a high-resolution wind speed prediction model for the OW-MR system is crucial, as offshore wind speed plays a significant role in assessing offshore wind power generation.

As part of the preparatory work, a wind resources historical database of the Beibu must be created. This database will be developed using data from numerous meteorological observation stations and satellite remote sensing, with a focus on the spatial distribution characteristics of wind, including average wind speed, wind power density, effective wind frequency, and main wind direction frequency,⁷⁹⁻⁸¹ etc. On a very large spatiotemporal scale (covering the entire sea area over months or years), the geographic information system (GIS)^{82,83} will be combined with data analysis on terrain, water depth, seabed geological structure, marine ecological environment, and other variables to identify areas rich in wind resources. This process primarily uses historical wind speed data. Additionally, marine spatial planning will be considered when selecting potential high-quality offshore wind farm sites. For wind farm-scale assessments and medium-term wind speed predictions (spanning

hours or days), additional meteorological observation equipment, such as lidar and anemometers, must be installed at wind farm sites. These tools will gather real-time meteorological data, enriching the wind resource history database with critical information on wind speed and direction.

For the wind speed prediction problem on a very short time scale (in seconds or minutes) and at the wind turbine structure scale, models such as nonlinear time series,⁸⁴ Bayesian Networks^{85,86} or recurrent neural network (RNNs)^{87,88} can be constructed using the short-term wind speed historical data provided in the wind resource history database. A possible solution involves breaking down the wind speed series into a set of intrinsic mode functions (IMFs) by employing a new hybrid time series decomposition approach based on variational mode decomposition (VMD).⁸⁹ These IMFs are then used as input features for a Long Short-Term Memory (LSTM) network.⁹⁰ When dealing with extensive wind speed data, a significant number of IMFs may be generated by VMD. A genetic algorithm (GA)⁹¹ can be employed to automatically optimize the IMFs set to achieve a specific degree of data dimensionality reduction, which ultimately reduces the training cost of neural networks. The LSTM is then utilized to predict wind speeds at a later time.

Multi-objective global optimization model of a "supply-storage-consumption" system under multiple uncertainties

Numerous uncertainties surround offshore wind power and multi-marine resources. The second major issue is that the global optimization of the OW-MR system requires establishing a global optimization model of a supply-storage-consumption system under multiple uncertainties. This model considers multiple optimization goals, such as achieving high production capacity, low cost, and stable output for the integration system.

Therefore, based on an examination of the spatiotemporal development features and the interaction mechanisms of the multi-marine resources, the basic design of the "source-load-storage" integration is proposed, as shown in Figure 3. Offshore wind power is identified as the primary energy source, with pumped storage and hydrogen storage gas power generation serving as supplementary sources. Hydrogen production from seawater, pumped storage, seawater desalination, and aquaculture contribute to wind power consumption as a complementary charge. By utilizing hydrogen and reservoirs as energy storage carriers, an energy network is established, built on the

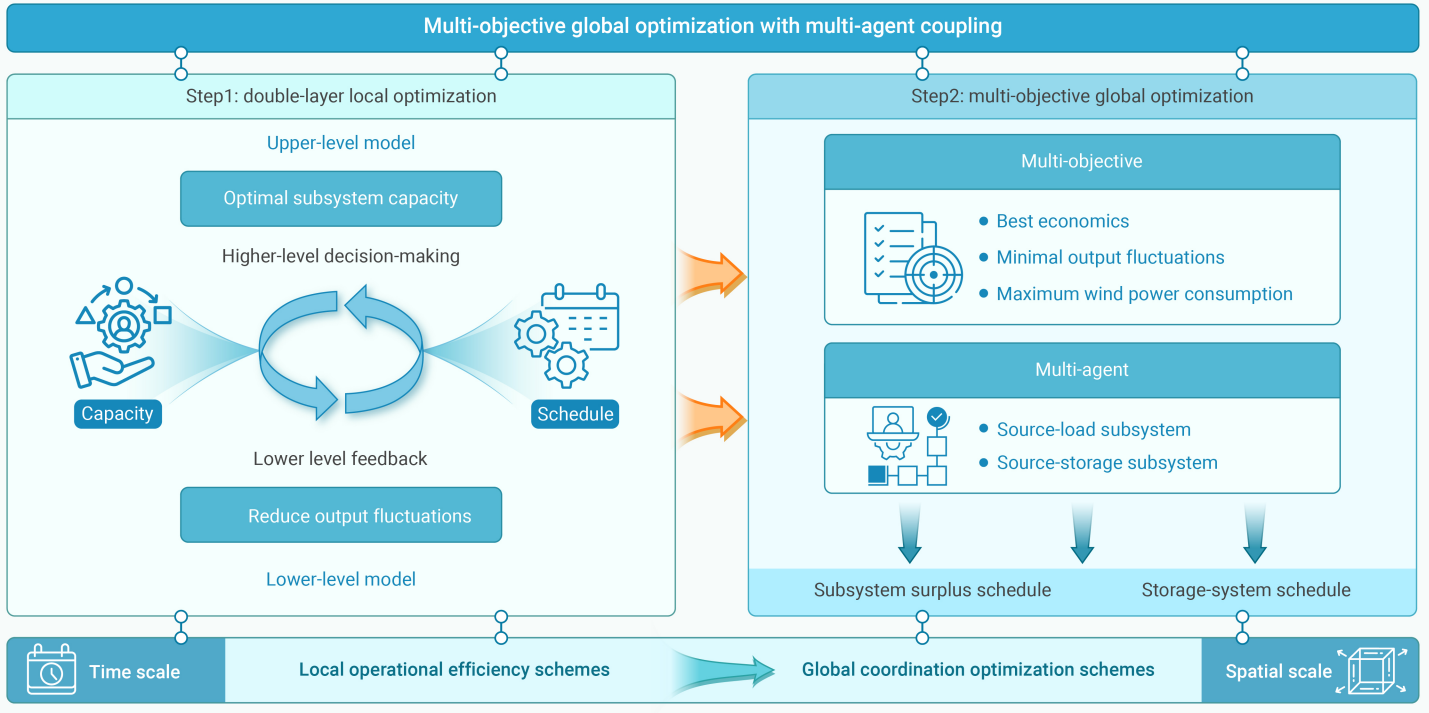


Figure 6. Multi-Objective Optimization Model of OW-MR Integration System in Beibu Gulf.

foundations of micro-grid and gas transmission.

After that, following the strategy of "local self-optimization and global re-optimization", the multi-objective optimization research of the OW-MR system is carried out, as illustrated in Figure 4. To address the problem of local area self-optimization within the integrated energy system, a two-layer programming approach is used to analyze the capacity configuration of the upper model and the efficient operation of the bottom system,^{36,92-95} as shown in (1).

$$\begin{aligned} &\text{upper:} \\ &\min_{\lambda} \{f_u(\lambda) + \min_{P,L} f_d(\lambda, P, L)\}, \lambda \in \Omega_u, \\ &\text{s.t. } \phi_u = 0, \psi_u \leq 0; \\ &\text{lower:} \\ &\min_{P,L} \{f_d(\lambda, P, L)\}, P, L \in \Omega_d, \\ &\text{s.t. } \phi_d = 0, \psi_d \leq 0. \end{aligned} \quad (1)$$

where f_u and f_d represent the objective functions of the upper and lower optimization of the system respectively. The vector λ represents the configured capacity of the subsystem; The vectors P and L represent the energy input and energy output of the subsystem respectively. ϕ_u , ϕ_d , ψ_u and ψ_d represent the constraints of two-layer optimization. " Ω_u " and " Ω_d " represent the variable space.

Upper-level planning considers the utilization rate of each energy source, the allocation capacity of each industry in the system as a decision variable, and the optimal allocation cost of the system as the objective to achieve comprehensive optimal energy development while ensuring energy supply and demand balance.^{36,92,93} The local energy-load operation scheduling of the system serves as the lower-level decision variable. Considering the multiple uncertainties of the system energy and load, the typical daily analysis and stochastic programming methods are used to investigate the efficient operation strategy of the lower-level planning through time-scale scheduling.^{36,94} In conjunction with the two-layer programming logic, the local self-optimization approach is achieved by employing an evolutionary algorithm³⁶ with the system economy index as the optimization target and the system energy-load balance as the constraint condition. This approach allows for general re-optimization of the system, providing a moderate balance between different optimization goals such as high production capacity and low cost. The optimization objectives include the lowest levelized cost of energy (LCOE) for offshore wind power (2), the maximum absorption ratio (3), and the least

amount of output variation (4). The decision variables are wind power production and energy storage schedules in each region. A multi-objective optimization model was developed to perform interval complementary and coordinated optimization on both geographical and spatial scale.^{37,95-98} Finally, The single-mode local optimization operation strategy of the integration system is merged to achieve global optimization regulation.

$$LCOE = \frac{\text{Life cycle costs}}{\text{Life cycle power generation}} = \frac{\sum_{t=1}^n \frac{C_t}{(1+r)^t}}{\sum_{t=1}^n \frac{E_t}{(1+r)^t}} \quad (2)$$

where t indicates the time of production, C_t is the total cost in year t , E_t is the total power generation in year c , r is the discount rate, n is the expected life cycle of the project.

$$f_2 = \frac{\text{Wind power surplus output}}{\text{Total output of offshore wind power}} = \frac{\sum_i x_{k,t}}{\sum_i W_{k,t}} \quad (3)$$

where vector x represents the self-optimized surplus output of wind turbines in the subsystem, vector W represents the total output of offshore wind power. k indicates the serial number of a subsystem.

$$f_3 = \text{Output fluctuations} = \sum_i \sum_{t=1}^{t-1} (|x_{k,t+1} - x_{k,t}| + |y_{k,t+1} - y_{k,t}|) \quad (4)$$

where vector y represents the energy supply output of the energy storage system to the subsystem.

A resilience assessment method for the "supply-storage-consumption system" under unconventional external shocks

An efficient resilience assessment approach under unconventional external shocks is desperately needed, as the regular operating system state of the OW-MR will be vulnerable to more serious security problems during catastrophic natural disasters such as typhoons.

The first phase involves assessing the vulnerability to typhoons for the integration system of OW-MR. This can be achieved by utilizing the WRF model^{99,100} to simulate standard metrics such as central pressure differential, wind speed, and direction angle, or by applying neural networks to forecast variations in these standard parameters of typhoons.¹⁰¹⁻¹⁰³ The risk of structural damage can then be evaluated using the water wave dynamic simula-

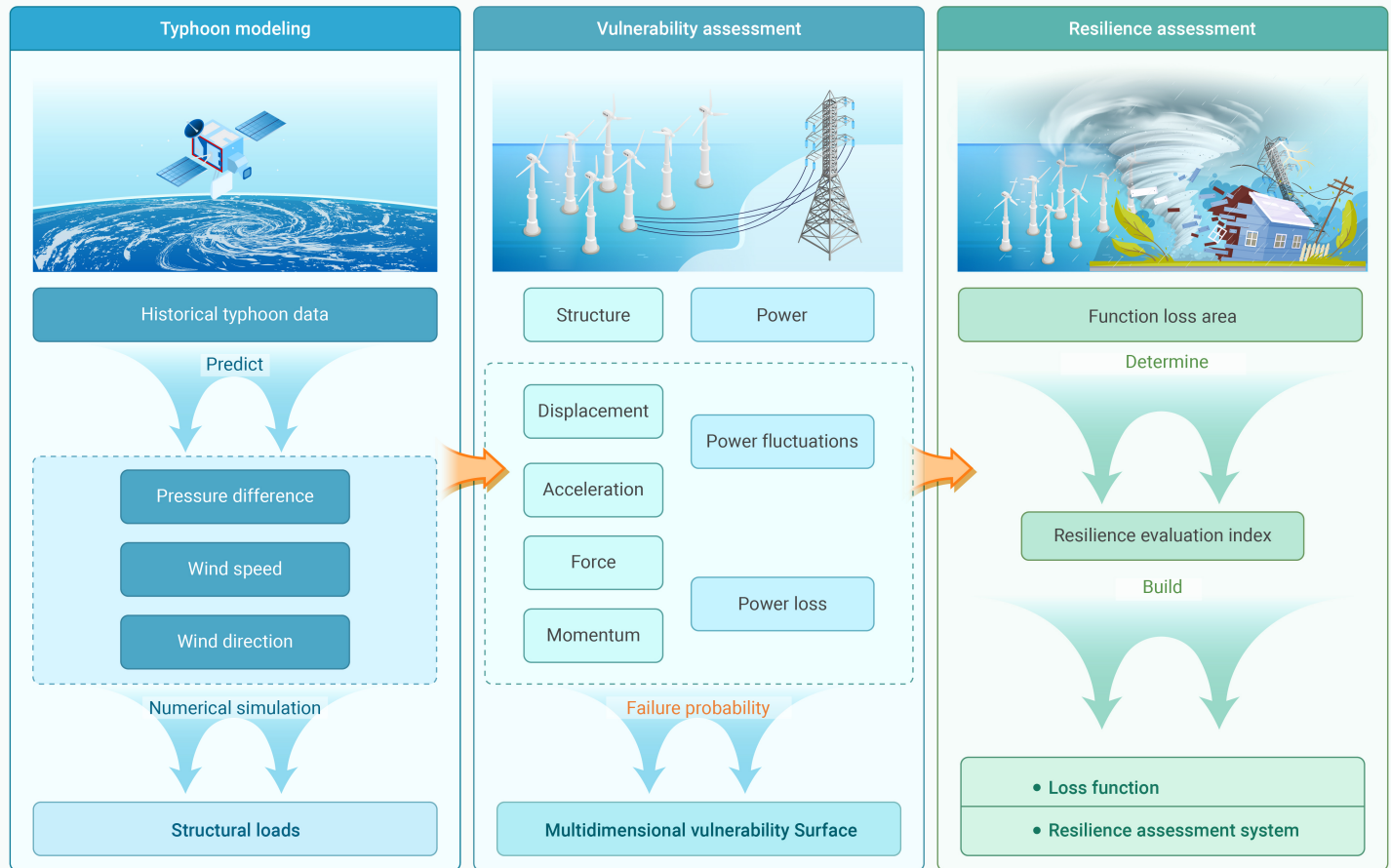


Figure 7. Schematic of Resilience Assessment Method in the Presence of Typhoons.

tion^{104,105} and structural dynamic analysis^{106,107} in conjunction with these typical typhoon metrics. The load on the main working structure and the residual power supply rate following a disaster are selected as the functional evaluation indices. The power generation capacity of wind farms can then be evaluated based on the nonlinear relationship between wind speed and power output.

The network topology model is created for each subsystem in the OW-MR integration system. The weights of functional importance for the various subsystems are applied, and the typhoon vulnerability of each subsystem is analyzed using different failure configurations, combinations of structures, and functional logic relationships, all based on the probabilistic analysis methods. The multi-dimensional vulnerability surface of the integration system is then plotted to complete the typhoon vulnerability assessment. The overall failure probability of the integration system under various typhoon metrics is calculated using the Monte-Carlo sampling method and typhoon simulation techniques.

The next step involves assessing the typhoon resilience of the OW-MR integration system. First, the resilience evaluation index of the system is established. Factors such as capital supply, function transfer, human resource supply, economic supervision, and decision-making capabilities are recognized when developing the repair stage model. Ultimately, the repair stage model is constructed using the ladder function, and key metrics such as system function, function loss area, and system resilience evaluation indices are obtained. These metrics are combined with the damaged state of each structure and the repairing capability of the system, including the number of repair teams and the repair path configuration.

The findings from the resilience assessment can help improve infrastructure planning or operational strategies. For instance, post resilience assessment, redundancy design of the system can be enhanced for key nodes that are prone to damage, ensuring that systems still maintain basic functions when equipment failure transpires. Various wind resistance levels of equip-

ment or structural optimization designs can be adopted according to different risk areas. The emergency plan after a disaster has occurred is improved to minimize system recovery time.

CONCLUSIONS

To realize the complementary advantages of resources and improve the overall benefit of the resource business in the Beibu Gulf of Guangxi, the construction of an OW-MR system is proposed. This system, centered on offshore wind power, also includes seawater hydrogen production, pumped storage, seawater desalination, marine aquaculture, and other marine resource utilization complexes.

Compared to a single marine resource system where capacity production and resilience analysis are required, as this OW-MR system consists of several different marine energy resources, it has increased complexity with additional challenges as well as potential solutions.

The first challenge is to reasonably and accurately assess the potential production of different types of marine resources, with the provided solution of a high-resolution multi-spatiotemporal model for wind speed prediction in the OW-MR system.

The second challenge is to achieve global multi-objective optimization for the OW-MR integration system, which can be solved by utilizing a multi-objective global optimization model of a "supply-storage-consumption" system.

The third challenge is ensuring the long-term stability of the OW-MR integration system, a solution can be provided by using the resilience assessment method under unconventional external shocks for the "supply-storage-consumption" system.

The establishment of a national comprehensive energy base can utilize this OW-MR integration system, which will contribute to the comprehensive development of marine resources in Guangxi Province of China and around the world.

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AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AND MATERIALS AVAILABILITY

Data are available from the corresponding author upon reasonable request.