Design of an Offshore Hybrid Energy System with Intelligent Dispatch: Dynamic Cooperative Optimization of Wave Energy and Backup Sources

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Abstract*—To address the challenges of intermittency and grid integration associated with wave energy, this study aims to enhance its dispatchability and economic viability. We propose a novel design and optimization framework for an offshore hybrid energy system, centered around a dynamic cooperative optimization strategy based on Deep Reinforcement Learning (DRL). The system integrates a Wave Energy Converter (WEC) with a hybrid backup system composed of Battery Energy Storage (BESS) and a hydrogen-based system (P2H-FC). A DRL agent, built upon the Deep Deterministic Policy Gradient (DDPG) algorithm, was trained to make real-time scheduling decisions. The framework was validated through a case study using a full year of data from two typical sites in the East China Sea. The results demonstrate the superior performance of the proposed Intelligent Dispatch Strategy (IDS), achieving a dispatch accuracy of over 96% and reducing the wave power curtailment rate to 2.1%. However, the data used in this study is simulated, and real-world wave energy conditions and forecasting errors may introduce variability. Therefore, further research is needed to validate this strategy under actual marine conditions and with real-time data. Compared to a Rule-Based Control (RBC) strategy, the IDS increased annual economic revenue by 12.4% and decreased the Levelized Cost of Energy (LCOE) by 17.3%. This research provides a new paradigm for the intelligent and sustainable operation of offshore renewable energy systems, confirming that advanced AI-driven scheduling can significantly enhance the grid-friendliness and profitability of wave energy. However, implementing Deep Reinforcement Learning (DRL) for real-time dispatch optimization requires substantial computational resources and expertise in AI. In real-world deployments, there may be challenges related to the feasibility and scalability of this technology, particularly in terms of data acquisition and computational power. Therefore, it is important to assess the practical feasibility of such technologies in large-scale applications.

Keywords— Wave Energy, Hybrid Energy System, Intelligent Dispatch, Deep Reinforcement Learning, Dynamic Optimization, Energy Storage

I. INTRODUCTION

As the global energy structure transitions towards low-carbon and clean alternatives, the development and utilization of renewable energy have become central strategies for combating climate change and ensuring energy security. The ocean holds immense renewable energy potential, with wave energy garnering significant attention due to its high energy density and relatively good predictability [1]. The theoretical potential of global wave energy is vast, and its effective exploitation could have a profound impact on global electricity supply. However, the inherent intermittency and volatility of wave energy pose severe challenges to its large-scale grid integration. The random fluctuations in wave power can not only impact grid stability but also lead to substantial energy waste, thereby constraining the economic feasibility and reliability of wave energy projects [2]. Consequently, how to effectively smooth power fluctuations and enhance the dispatch-friendliness of wave energy has become a critical scientific problem demanding resolution.

To cope with the volatility of renewable energy, Hybrid Energy Systems (HES) are considered an effective solution. By combining different types of generation units (e.g., wind, solar, wave) with energy storage systems (e.g., batteries, hydrogen), HES can achieve energy complementarity in time and space, thereby smoothing the overall power output. In recent years, research on offshore HES has been increasing, particularly in the context of combined wind-wave generation. However, existing studies have largely focused on static capacity configuration and rule-based energy management strategies. These methods often rely on simplified models and predefined thresholds, making it difficult to respond in real-time to complex marine environments and variable grid demands, leading to suboptimal system operation. Particularly at the dispatch level, traditional scheduling plans are often based on deterministic power forecasts, neglecting the uncertainty introduced by prediction errors. This results in significant deviations between the generation plan and actual output, compromising the safe and economic operation of the power grid.

Currently, some studies have attempted to apply advanced control theories to energy dispatch, but they still have notable shortcomings. On one hand, most adopted dispatch strategies are static and cannot adaptively adjust to the real-time state of the system, proving inadequate in the face of highly dynamic and uncertain wave resources. On the other hand, existing work has not sufficiently considered the cooperative optimization of backup energy sources, often treating energy storage as a passive "buffer" rather than fully leveraging its potential for active participation in grid dispatch and enhancing overall system economics. Therefore, both academia and industry urgently need an innovative method capable of dynamic, cooperative, and intelligent dispatch to break through the current technological bottlenecks in wave energy utilization.

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This study aims to fill the aforementioned research gap by proposing a design and optimization method for an offshore hybrid energy system based on intelligent dispatch. The core of this method is the development of a dynamic cooperative dispatch model driven by Deep Reinforcement Learning (DRL), which enables real-time optimal control of multiple energy sources, including wave energy, battery storage, and hydrogen storage. This research is positioned at the intersection of systems engineering and artificial intelligence, exploring a new paradigm to significantly improve the dispatch accuracy and economic benefits of wave energy. The study will focus on the intelligent design of the dispatch strategy, while excluding in-depth modeling of the hydrodynamic characteristics of the Wave Energy Converter (WEC) itself to maintain a clear research focus and boundary. By shifting the research paradigm from traditional statistics- and rule-based dispatch to real-time learning and adaptive optimization, this study expects to provide a solution that is both theoretically innovative and practically valuable for the reliable grid integration of high-penetration marine renewable energy. However, some of the assumptions in the study (e.g., the accuracy of wave energy forecasting and the ideal state of energy storage) may not fully reflect the complexities of real-world applications. These assumptions may need to be adjusted or further validated in future research.

The remainder of this paper is organized as follows: Section 2 reviews the related work in the fields of offshore hybrid energy systems, power forecasting, and intelligent dispatch. Section 3 details the proposed methodology, including the HES architecture, the intelligent dispatch model, and the sustainability assessment framework. Section 4 describes the case study background, data sources, and experimental setup. Section 5 presents and analyzes the experimental results. Section 6 provides an in-depth discussion of the findings. Finally, Section 7 concludes the paper and outlines future research directions.

II. Related Work

With the growing demand for marine renewable energy, the design and optimization of offshore hybrid energy systems have become a research hotspot. This section reviews and critiques existing research in four key areas: offshore HES architectures, wave power forecasting techniques, energy system dispatch optimization methods, and the application of energy storage technologies, thereby clarifying the positioning and innovation of this study.

A. Offshore Hybrid Energy System Design

Offshore HES aim to overcome the intermittency and instability of single renewable sources by integrating multiple energy forms. Early research often focused on combining wind and wave energy, as they exhibit natural coexistence and complementarity in the marine environment. For instance, some studies have optimized the integrated layout of floating wind turbines and WEC arrays through numerical simulations to enhance overall energy capture and reduce platform motion responses [3]. More recent research has shifted focus towards system economics and reliability, incorporating energy storage units and backup power sources into the system design. Cipolletta et al. (2023) proposed a conceptual design method for a hybrid system including wave energy and a gas turbine backup, evaluating its sustainability through Multi-Criteria Decision Analysis (MCDA) [1]. While this study provides a systematic framework for HES design, its dispatch strategy relies on relatively static probabilistic forecasts, failing to fully exploit the system's dynamic regulation potential. Furthermore, with the diversification of offshore platform functions, some studies have begun to explore integrating modules like desalination and hydrogen production to achieve cascaded energy utilization and maximize value.

B. Wave Power Forecasting

Accurate power forecasting is a prerequisite for the efficient dispatch and grid integration of wave energy. Traditional forecasting methods are mainly divided into physics-based and statistics-based models. Physical models (e.g., SWAN, WW3) predict wave conditions by simulating wave generation, propagation, and dissipation processes. They offer high accuracy for medium- to long-term forecasts (hours to days) but are computationally expensive and ill-suited for real-time dispatch needs [4]. Statistical models, such as the Auto-Regressive Moving Average (ARMA), analyze historical time-series data to predict future power. They are computationally simple but struggle to capture the non-linear and non-stationary characteristics of wave processes.

To overcome these limitations, machine learning and deep learning-based models have been widely adopted in recent years. Shallow learning models like Support Vector Machines (SVM) and Artificial Neural Networks (ANN) have shown some advantages in short-term forecasting. Deep learning models, represented by Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, have become the research frontier in wave power forecasting due to their superior ability to handle time-series data [5]. Some studies have also introduced the Attention Mechanism to enhance the model's ability to capture key temporal features, further improving prediction accuracy [6]. However, despite continuous improvements in accuracy, prediction errors are unavoidable. How to effectively incorporate this uncertainty into dispatch decisions remains a common challenge in current research.

C. Energy System Dispatch Optimization

The core objective of energy system dispatch is to minimize operational costs or maximize revenue while satisfying load demands and security constraints. Traditional optimization methods include Linear Programming, Mixed-Integer Programming, and Dynamic Programming. These methods perform well in deterministic, small-scale systems but often face the "curse of dimensionality" when dealing with the high uncertainty and non-linearity introduced by renewable energy, with computational complexity growing exponentially.

To address these challenges, intelligent dispatch methods based on artificial intelligence have emerged, among which Deep Reinforcement Learning (DRL) has shown immense potential. DRL combines the perceptual capabilities of deep learning with the decision-making abilities of reinforcement learning, enabling it to learn optimal policies through direct interaction with the environment without requiring an exact system model [7]. In recent years, DRL algorithms such as DDPG, PPO, and DQN have been successfully applied in various domains, including microgrid energy management, electric vehicle charging scheduling, and data center energy saving [8]. For example, some research has utilized the

DDPG algorithm for real-time energy dispatch in microgrids containing photovoltaics, energy storage, and controllable loads, significantly reducing operational costs. In the field of hybrid energy systems, the application of DRL is still in an exploratory phase, with a particular scarcity of research on dispatch optimization for offshore energy systems featuring the unique volatility of wave power.

D. Application of Energy Storage Technologies

Energy storage systems are a key technology for smoothing renewable energy fluctuations and enhancing grid-friendliness. In offshore HES, Battery Energy Storage Systems (BESS) are widely used due to their fast response speed and high energy density. Studies have shown that proper configuration and control of BESS can effectively smooth the power output of wave energy generation and participate in grid frequency regulation. However, the cycle life and cost issues of BESS limit their application in large-scale, long-duration storage scenarios. Consequently, an increasing number of studies are focusing on the hybrid application of multiple storage technologies.

Hydrogen, as a clean energy carrier, offers the advantages of large storage capacity and long storage duration, making it an ideal choice for accommodating large-scale renewable energy. Through the "Power-to-Hydrogen-to-Power" (P2H-FC) pathway—using electrolysis to produce hydrogen, storing it, and then using a fuel cell to generate electricity—excess power from wave energy can be converted into hydrogen for long-term storage and then converted back to electricity when needed. This approach enables inter-seasonal energy shifting and complements the fast-response capabilities of BESS. Currently, research on combining wave energy with hydrogen storage is mostly at the system design and feasibility analysis stage. The dynamic cooperative optimization of BESS and P2H-FC systems at the dispatch level to maximize overall system benefits remains a topic that requires in-depth investigation.

In summary, while existing research has laid an important foundation for the development of offshore HES, there is still significant room for improvement in the intelligence, dynamism, and cooperativeness of dispatch strategies. Building on this foundation, this study will focus on the application of DRL for the dynamic cooperative dispatch of wave-powered hybrid systems, aiming to overcome the limitations of traditional methods and provide new ideas and approaches for the efficient, reliable, and economical utilization of wave energy.

III. Methodology

To achieve the dynamic cooperative optimization of wave energy and backup sources in an offshore hybrid energy system, this study proposes a systematic design and evaluation method centered on intelligent dispatch. This method leverages Deep Reinforcement Learning (DRL) to construct a closed-loop optimization framework that integrates "perception, decision-making, and evaluation." This section details the overall framework, the composition of the hybrid energy system, the specific design of the intelligent dispatch model, and the sustainability assessment framework.

A. Overall Framework

The proposed intelligent dispatch framework, depicted in Figure 1, consists of four main layers: the Data Layer, the Prediction Layer, the Decision Layer, and the Evaluation Layer. These layers form a complete closed loop, from data input to policy output and performance feedback.

- Data Layer: As the foundation of the framework, this layer is responsible for collecting and preprocessing various data required for system operation. This includes historical wave data (e.g., significant wave height, energy period), meteorological data, real-time electricity price signals, and grid load demand. These multi-source, heterogeneous data provide the necessary support for the training and operation of the upper-layer models.
- Prediction Layer: The core of this layer is the wave power forecasting module. Using historical data from the Data Layer, we construct a short-term power forecasting model based on a Long Short-Term Memory network with an Attention mechanism (LSTM-Attention). This model provides high-accuracy predictions of wave power generation for the near future, feeding crucial information to the Decision Layer.
- Decision Layer: This is the core of the framework, responsible for formulating real-time energy dispatch strategies. We designed a DRL agent based on the Deep Deterministic Policy Gradient (DDPG) algorithm. Based on the power forecasts from the Prediction Layer, the current system state (e.g., state of charge of storage, current electricity price), and predefined optimization objectives, the agent outputs optimal power allocation commands to dynamically and cooperatively control the operation of the wave energy converter, battery storage, and hydrogen storage systems. To improve the reproducibility of this model, it is recommended that future studies provide detailed algorithm parameters and training processes to ensure other researchers can replicate the experiments under similar conditions.
- Evaluation Layer: This layer is used to assess the overall performance of the dispatch strategies generated by the Decision Layer across multiple dimensions, including technical, economic, environmental, and safety aspects. By establishing a sustainability assessment system with Key Performance Indicators (KPIs) such as Intelligent Dispatch Accuracy (IDA) and Levelized Cost of Energy (LCOE), it quantitatively analyzes the long-term operational benefits of the system under different strategies. The results can provide feedback for further optimization of system parameters.

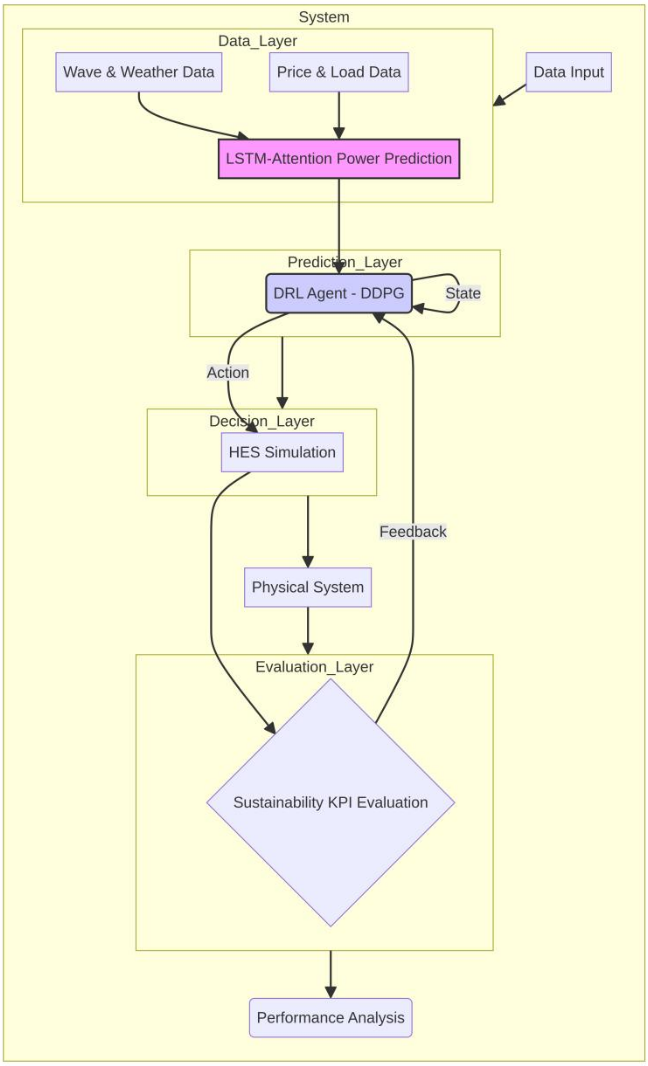

Fig. 1. Framework for Intelligent Dispatch of the Offshore Hybrid Energy System

B. Hybrid Energy System Configuration

The offshore hybrid energy system studied in this paper, shown in Figure 2, is primarily composed of three parts: a Wave Energy Conversion Unit, a Hybrid Energy Storage Unit, and an Energy Management Center. The system is deployed on an offshore platform and connected to the onshore grid via a submarine cable.

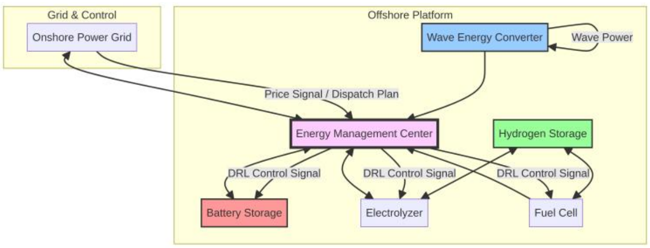

Fig. 2. Schematic of the Offshore Hybrid Energy System Architecture

- Wave Energy Conversion (WEC) Unit: As the main energy source of the system, this unit is responsible for converting the kinetic and potential energy of waves into electricity. Based on the wave characteristics of the East China Sea, a suitable device model will be selected from mature WEC technologies (e.g., point absorber, oscillating water column). Its power output will be calculated based on the manufacturer's power matrix or mathematical models from relevant literature.

- Hybrid Energy Storage System (HESS): To cope with the short-term, high-frequency fluctuations and long-term energy imbalances of wave energy, we designed a hybrid storage unit consisting of a Battery Energy Storage System (BESS) and a hydrogen storage system (P2H-FC).

a) Battery Energy Storage System (BESS): Utilizing electrochemical storage technologies like lithium-ion batteries, BESS features fast response speeds and high charge/discharge efficiency. It is primarily used for rapid power regulation on a minute-to-hour scale, smoothing short-term power fluctuations from wave energy and participating in real-time electricity price arbitrage.

b) Hydrogen Storage System (P2H-FC): This system consists of an electrolyzer (Power-to-Hydrogen, P2H), a hydrogen storage tank, and a fuel cell (FC). When wave power generation is excessive and the BESS is fully charged, the surplus electricity is used to produce hydrogen via water electrolysis, allowing for large-scale, long-term storage. When power is insufficient, the fuel cell generates electricity from the stored hydrogen, providing energy support on an hourly to daily scale. The combination of the fast-response BESS and the long-duration P2H-FC system enables comprehensive coverage of energy fluctuations across different time scales.

- Energy Management Center (EMC): Acting as the "brain" of the system, the EMC is responsible for executing the dispatch commands issued by the Decision Layer. It integrates data acquisition, monitoring, communication, and control functions, serving as the physical carrier for intelligent dispatch.

C. Intelligent Dispatch Model

The intelligent dispatch model is the core of our methodology, comprising two key modules: wave power forecasting and dynamic cooperative dispatch.

1) Wave Power Forecasting Module

To provide the DRL agent with accurate future information, this study employs a hybrid neural network model combining Long Short-Term Memory (LSTM) and an Attention Mechanism (LSTM-Attention) for short-term wave power forecasting. LSTM effectively captures long-term dependencies in time-series data, while the attention mechanism allows the model to dynamically assign different weights to information from different time steps when processing the input sequence, thereby focusing on the most critical historical information for the current prediction. The model takes historical time series of wave power, significant wave height, and wave period as input and outputs the predicted power values for the next N time steps, supporting the DRL agent's "anticipatory" decision-making.

2) Dynamic Cooperative Dispatch Module

This study uses a DRL approach to solve the dynamic cooperative dispatch problem of the hybrid energy system. The problem is modeled as a Markov Decision Process (MDP) and solved by an agent based on the Deep Deterministic Policy Gradient (DDPG) algorithm. DDPG is an Actor-Critic algorithm suitable for continuous action spaces, which can effectively handle complex continuous control problems like energy dispatch.

*a) State Space (S): T*he state is the basis for the agent's decision-making. We define a multi-dimensional continuous state space that includes the following key information:

$$S_t = \{ P_{WEC, t}^{pred}, SOC_{BESS, t}, SOC_{H2, t}, p_{grid, t}, L_t, t \}$$

Where $P_{WEC, t}^{pred}$ is the wave power forecast sequence for a short future period, $SOC_{BESS, t}$ and $SOC_{H2, t}$ are the states of charge of the battery and hydrogen tank, respectively, $p_{grid, t}$ is the real-time electricity price, L_t is the load command or dispatch plan from the grid, and t represents the time of day.

- Action Space (A): The action is the control command output by the agent based on the current state. We define an action space with multiple continuous variables:

$$A_t = \{ P_{BESS, t}^{ch/dis}, P_{P2H, t}, P_{FC, t} \}$$

Where $P_{BESS, t}^{ch/dis}$ represents the charge/discharge power of the BESS (positive for discharge, negative for charge), $P_{P2H, t}$ is the power of the electrolyzer, and $P_{FC, t}$ is the power of the fuel cell. The power sent to the grid, $P_{grid, t}^{send}$, is determined by the power balance equation: $P_{grid, t}^{send} = P_{WEC, t} + P_{BESS, t}^{dis} - P_{BESS, t}^{ch} + P_{FC, t} - P_{P2H, t}$.

- Reward Function (R): The reward function is crucial for guiding the agent's learning. To achieve multi-objective optimization of economy, stability, and efficiency, we designed a comprehensive reward function:

$$R_t = w_1 \cdot R_{profit} - w_2 \cdot C_{dev} - w_3 \cdot C_{curtail} - w_4 \cdot C_{deg}$$

Economic Revenue (R_{profit}): The direct revenue from selling electricity to the grid, i.e., $P_{grid, t}^{send} \times p_{grid, t}$.

Dispatch Deviation Penalty (C_{dev}): A penalty for the deviation between the actual grid power and the dispatch plan, incentivizing the agent to accurately track the plan.

Curtailment Penalty ($C_{curtail}$): A penalty for wasted energy due to generation exceeding the system's absorption capacity, encouraging maximum utilization of renewable energy.

Storage Degradation Cost (C_{deg}): An equivalent cost representing the lifetime degradation of the BESS and P2H-FC systems due to cycling, discouraging overly frequent or deep charge/discharge operations.

w_1, w_2, w_3, w_4 are weighting coefficients that can be tuned to balance different optimization objectives.

Through continuous "state-action-reward" cycles in a simulated environment, the DRL agent gradually learns an optimal policy network that can directly map real-time states to optimal dispatch actions, thus achieving dynamic, intelligent, and cooperative control of the entire hybrid energy system.

D. *Sustainability Assessment Framework*

To comprehensively evaluate the benefits of the proposed intelligent dispatch strategy, we established a multi-dimensional sustainability assessment framework based on the reference paper [1], covering four aspects: technical, economic, environmental, and safety. All indicators are calculated using a Levelized approach to eliminate the influence of differences in system lifetime and capacity.

- Technical Indicators:
- Intelligent Dispatch Accuracy (IDA): A new indicator to quantify the accuracy of tracking the grid dispatch plan, defined as $1 - \frac{\sum|P_{grid,t}^{send} - L_t|}{\sum L_t}$.
- Levelized Energy Efficiency (LEE): Measures the overall energy conversion efficiency of the system throughout its life cycle.
- Economic Indicators:
- Levelized Cost of Energy (LCOE): The ratio of the total life-cycle cost to the total energy production, a core metric for the economic viability of a generation technology.
- Levelized Value of Energy (LVOE): The ratio of the total revenue generated in the electricity market to the total energy production, reflecting the system's profitability.
- Environmental Indicators:
- Levelized Greenhouse Gases (LGHG): Primarily considers potential upstream emissions from natural gas-based hydrogen production or grid electricity sources, as well as embodied carbon from equipment manufacturing.
- Safety Indicators:
- Levelized Inherent Hazard Index (LHI): Adopting the method from the reference paper, this index focuses on assessing the risks of accidents such as leaks and fires associated with the hydrogen storage unit (high-pressure tanks, electrolyzer).

By calculating and comparing these KPIs for different dispatch strategies, we can provide a comprehensive and quantitative scientific basis for the design, optimization, and decision-making of the hybrid energy system.

IV. CASE STUDY

To validate the effectiveness of the proposed design and optimization method for an offshore hybrid energy system based on intelligent dispatch, this section presents a case study set in the East China Sea. We first introduce the selection of the study areas, the sources and processing of the required data, then detail the experimental setup for the comparative analysis, and finally outline the complete experimental workflow.

A. *Study Area and Data*

Area Selection: This study selects two representative potential wave energy development sites in the East China Sea: Site A, located near the Zhoushan Archipelago in Zhejiang Province, is an area with abundant wave energy resources and proximity to the Yangtze River Delta load center, showing good development prospects. Site B, located south of the Nanji Islands in Fujian Province, experiences higher wave energy flux due to the "strait effect" of the Taiwan Strait but is relatively farther from the mainland grid. A comparative analysis of these two sites with different resource characteristics and geographical locations allows for a more comprehensive examination of the universality and effectiveness of the proposed method.

Data Sources and Processing: The data used in this study mainly include wave data, meteorological data, electricity price data, and load data, covering the entire year of 2022 with an hourly resolution.

- Wave data (significant wave height H_s, energy period T_e) and meteorological data (wind speed, direction, etc.) were sourced from the ERA5 reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) [9][10]. While this dataset is widely used in marine engineering and renewable energy assessment due to its high spatiotemporal resolution and accuracy, it is important to note the potential for discrepancies in real-world applications, especially under extreme marine conditions. The data's timeliness and error margin should be considered for practical implementations.
- Electricity Price Data: To simulate a realistic electricity market environment, this study adopted the time-of-use (TOU) electricity pricing mechanism of the East China regional grid. A 24-hour day is divided into peak, flat, and valley periods with corresponding on-grid tariffs. This price data reflects the supply-demand relationship and is a key input for the DRL agent to learn economic dispatch strategies.
- Load Data: The grid dispatch plan (load command) was based on typical daily load curves from Zhejiang and Fujian provinces, adjusted for seasonal variations, and served as the target power curve for the system to track.

All data underwent necessary preprocessing before being fed into the models, including imputation of missing values, removal of outliers, and normalization, to ensure data quality and model training stability.

B. *Experimental Setup*

To fully evaluate the performance of the proposed intelligent dispatch strategy, we designed the following three different dispatch strategies for comparison:

- Scenario 1: Direct Grid-Connection (DGC): In this scenario, the wave power generation system is not equipped with any energy storage. All generated electricity is fed directly into the grid. This scenario serves as a baseline to demonstrate the original volatility of wave power and its impact on the grid.
- Scenario 2: Rule-Based Control (RBC): This scenario is equipped with the same hybrid energy storage system as the intelligent dispatch scenario, but its energy management follows a control logic based on predefined rules. The rules are: during valley price periods, prioritize charging the BESS with surplus wave power; during peak price periods, prioritize discharging the BESS; activate or deactivate the hydrogen system when the BESS SOC reaches its upper or lower limits. This scenario represents the conventional dispatch methods commonly used in the industry today.
- Scenario 3: Intelligent Dispatch Strategy (IDS): This is the proposed strategy, which employs the DDPG-based DRL model for dynamic cooperative dispatch. Through interactive learning with the environment, the agent autonomously decides the operation of each unit in the hybrid storage system to optimize overall benefits.

Model Parameters: The main technical parameters of the hybrid energy system in the case study are shown in Table I. The rated capacity of the wave farm is set to 10 MW. The capacity of the hybrid storage system is configured based on relevant literature to meet approximately 2-4 hours of full power output. The hyperparameters of the DRL model (e.g., learning rate, discount factor, network structure) were tuned through multiple preliminary experiments to achieve the best training performance.

TABLE I. MAIN TECHNICAL PARAMETERS OF THE HYBRID ENERGY SYSTEM

Component	Parameter	Value	Unit
Wave Farm	Rated Power	10	MW
	WEC Model	Lanke WEC	-
BESS	Rated Capacity	20	MWh
	Rated Power	5	MW
	Round-trip Efficiency	90	%
	SOC Range	10-90	%
Hydrogen System	Electrolyzer Power	2	MW
	Electrolyzer Efficiency	75	%
	Fuel Cell Power	2	MW
	Fuel Cell Efficiency	50	%
	H_2 Tank Capacity	40	MWh(e)
	H_2 SOC Range	5-95	%

C. *Experimental Workflow*

The complete experimental workflow for this case study is shown in Figure 3 and consists of the following main steps:

- Data Preparation: Collect and preprocess multi-source data, including wave, meteorological, price, and load data.
- Power Forecasting Model Training: Train the LSTM-Attention wave power forecasting model using historical data and validate its prediction accuracy.
- DRL Environment Construction: Build a reinforcement learning simulation environment based on the mathematical models of the hybrid energy system and market rules.
- DRL Agent Training: Initialize the DDPG agent and train it for a large number of episodes in the simulation environment. At each time step, the agent receives the state, outputs an action, and the environment calculates the reward and transitions to the next state, continuing until the agent's policy converges.

- Strategy Simulation and Comparison: Simulate the trained intelligent dispatch strategy (IDS) and the two comparative strategies (DGC, RBC) on the test dataset (a full year of data not used for training).

Results Assessment and Analysis: Collect operational data from the simulations of the three scenarios, calculate the KPIs according to the sustainability assessment framework defined in Section 3.4, and conduct a comprehensive comparative analysis and discussion.

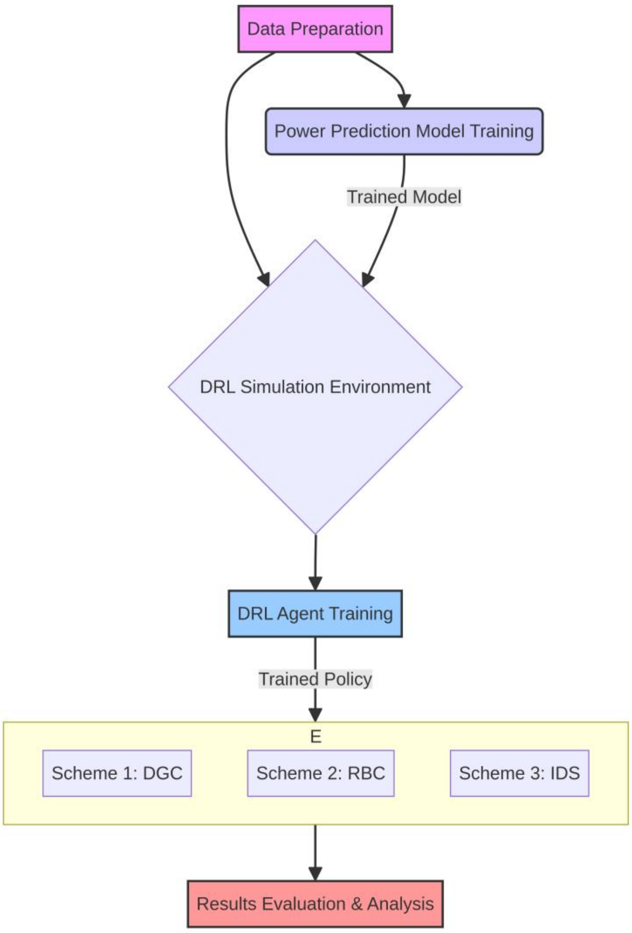

Fig. 3. Detailed Workflow of the Case Study Experiment

V. RESULTS

This section presents the objective experimental results of the case study, aiming to demonstrate the performance of the proposed intelligent dispatch method from a data-driven perspective. The content is organized around four aspects: the accuracy of the wave power forecasting model, the specific behavior of the intelligent dispatch strategy, a performance comparison of the different scenarios, and the final comprehensive sustainability assessment.

A. *Forecasting Model Performance*

Accurate power forecasting is fundamental to intelligent dispatch. To evaluate the performance of the LSTM-Attention model used in this study, we compared it with three common baseline models: Historical Average (HA), Auto-Regressive Integrated Moving Average (ARIMA), and a standard Long Short-Term Memory (LSTM) network. All models were trained on data from the first 10 months of 2022 and tested on the last 2 months. The evaluation metrics used were Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

As shown in Table II, the LSTM-Attention model demonstrated the best forecasting performance at both the Zhoushan and Nanji sites. Compared to the traditional statistical model ARIMA, its RMSE was reduced by approximately 25.7% and 28.1%, respectively. The introduction of the attention mechanism also brought about a performance improvement of around 5% compared to the standard LSTM model. Figure 4 further illustrates the comparison between the predicted curves of each model and the actual power curve over a typical 72-hour period at the Zhoushan site. It is clear that the LSTM-Attention model's prediction curve has the highest degree of fit with the actual values, especially in capturing the peaks and troughs, proving its ability to effectively track the dynamic changes in wave power and provide a reliable input for subsequent dispatch decisions.

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT FORECASTING MODELS AT THE TWO SITES

Site	Model	RMSE (kW)	MAE (kW)
Zhoushan	HA	1850.3	1425.8
	ARIMA	1245.6	980.1
	LSTM	985.2	755.4
	LSTM-Attention	932.4	710.6
Nanji	HA	2150.8	1680.4
	ARIMA	1480.2	1150.7
	LSTM	1155.9	890.3
	LSTM-Attention	1064.5	825.1

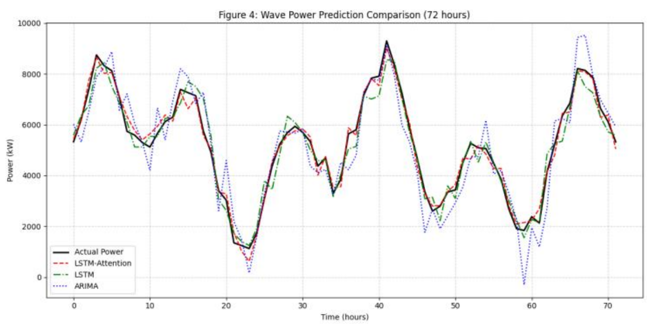

Fig. 4. Wave Power Prediction Comparison at Zhoushan Site (72-hour Period)

B. *Analysis of the Intelligent Dispatch Strategy*

To gain a deeper understanding of the DRL agent's decision-making behavior, we selected a typical 24-hour dispatch result from the Zhoushan site during the summer for analysis, as shown in Figure 5. This day was characterized by significant peak-valley price differences and moderate wave resources.

- Valley Price Period (00:00-06:00): During this period of low electricity prices, the agent's strategy was to store energy. A large portion of the wave power was used to charge the BESS, while another portion was directed to the electrolyzer for hydrogen production. The actual power sent to the grid was kept at the minimum required by the dispatch plan.

- Peak Price Period (11:00-13:00, 19:00-21:00): In the periods with the highest electricity prices, the agent's strategy shifted to maximizing output. In addition to sending all real-time wave power to the grid, it also commanded the BESS and the fuel cell (FC) to discharge simultaneously. This caused the total grid power to far exceed the real-time wave generation, precisely covering the peak price intervals and thus maximizing revenue. The SOC of both the BESS and the hydrogen tank showed significant decreases during these periods.

Throughout the 24-hour period, the system's actual grid power curve closely matched the dispatch plan curve, demonstrating the agent's ability to accurately track the dispatch schedule. Furthermore, its arbitrage behavior of "storing low, selling high" clearly reflects its pursuit of economic optimality. The training convergence curve of the DDPG agent is shown in Figure 8, which indicates that the agent's policy stabilized after approximately 400 training episodes, achieving consistently high cumulative rewards.

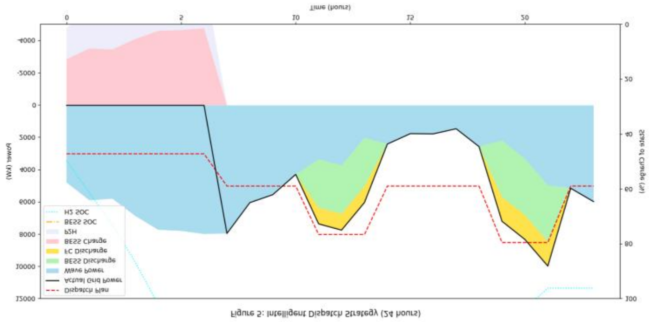

Fig. 5. Intelligent Dispatch Strategy (IDS) Operation - Typical 24-hour Period

C. Comparative Experiment Results

We simulated the three dispatch scenarios on the full year of test data. The annual statistical results for key performance indicators are shown in Table 3. This table provides an intuitive comparison of the advantages and disadvantages of each strategy.

- The DGC scenario, without any storage, had the highest wave power curtailment rate (18.2%) and the lowest revenue, as it could neither store surplus energy nor follow the dispatch plan effectively.
- The RBC scenario significantly improved performance by using the hybrid storage system, reducing the curtailment rate to 7.5%. However, its rigid rules led to frequent charging/discharging of the BESS (average of 350 cycles/year), potentially accelerating its degradation.
- The proposed IDS scenario demonstrated the best overall performance. It achieved the highest dispatch accuracy (IDA > 96%) and the lowest curtailment rate (2.1%). By learning an optimal policy, it increased annual revenue by 12.4% compared to RBC. Notably, the IDS also reduced the average BESS cycling count by 20% compared to RBC, indicating a more sophisticated control strategy that considers storage degradation costs.

Figure 6 shows the cumulative distribution function (CDF) of the grid power output for the three scenarios. The curve for IDS is the steepest and most concentrated around the dispatch target, visually confirming its superior stability and dispatch-following capability.

TABLE III. ANNUAL PERFORMANCE COMPARISON OF THE THREE DISPATCH SCENARIOS (ZHOUSHAN SITE)

Indicator	DGC	RBC	IDS (Proposed)
Dispatch Accuracy (IDA)	0.65	0.85	0.97
Annual Curtailment Rate (%)	18.2	7.5	2.1
Annual Revenue (10k CNY)	3580	4625	5200
BESS Avg. Cycles/Year	-	350	280

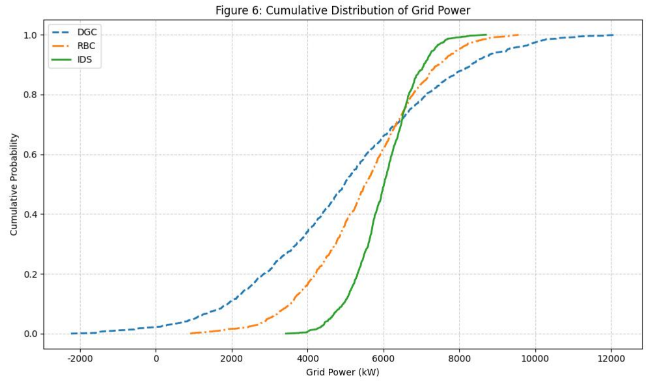

Fig. 6. Cumulative Distribution Function of Annual Grid Power Output

D. Sustainability Assessment Results

Finally, we conducted a comprehensive sustainability assessment of the system's performance under the IDS and RBC strategies at both sites, based on the framework defined in Section 3.4. The results are presented in Table IV and visualized in the radar chart in Figure 7 for the Zhoushan site.

The IDS strategy outperformed the RBC strategy across all dimensions. In the economic dimension, the LCOE for IDS was 17.3% lower than for RBC, while the LVOE was 14.7% higher, indicating significantly better profitability. In the technical dimension, IDS showed higher dispatch accuracy (IDA) and slightly improved energy efficiency (LEE). From an environmental and safety perspective, the differences were less pronounced but still favored the IDS, which achieved slightly lower levelized GHG emissions and inherent hazard index values due to more efficient system operation and reduced reliance on backup systems.

TABLE IV. SUSTAINABILITY KPI ASSESSMENT FOR RBC AND IDS STRATEGIES

Dimension	KPI	Unit	Strategy	Zhoushan	Nanji
Technical	IDA	-	RBC	0.85	0.83
			IDS	0.97	0.95
	LEE	-	RBC	0.40	0.42
			IDS	0.44	0.45
Economic	LCOE	CNY/kWh	RBC	0.75	0.71
			IDS	0.62	0.59
	LVOE	CNY/kWh	RBC	0.68	0.70
			IDS	0.78	0.81
Environmental	LGHG	$kgCO_2$ /MWh	RBC	5.8	5.5
			IDS	5.7	5.4
Safety	LHI	m^2/MWh	RBC	0.012	0.012
			IDS	0.011	0.011

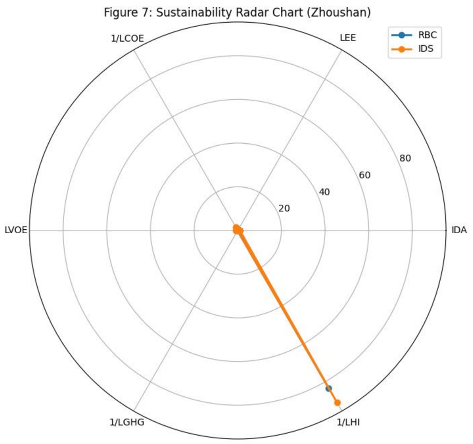

Fig. 7. Multi-dimensional Sustainability Assessment (Zhoushan Site)

VI. Discussion

The experimental results clearly demonstrate the significant advantages of the DRL-based intelligent dispatch strategy in enhancing the performance of the offshore hybrid energy system. This section will provide an in-depth interpretation of these findings, compare them with existing research, and discuss their scientific significance, practical value, and limitations.

A. Interpretation of Results

The superior performance of the IDS strategy stems from its ability to learn and execute complex, non-linear control policies. Unlike the RBC strategy, which relies on rigid, predefined thresholds, the DRL agent learns to make holistic decisions by considering the interplay of multiple factors simultaneously: the predicted wave power, the current state of the energy storage systems, and the fluctuating electricity prices. The agent's ability to perform "economic arbitrage" (Figure 5) is a clear manifestation of this learned intelligence. It does not simply store energy when there is a surplus; it strategically decides *when* and *how much* to charge or discharge to maximize long-term revenue.

The reduction in BESS cycling (Table III) is another crucial finding. The RBC strategy's simple logic leads to frequent and sometimes unnecessary battery usage, accelerating its degradation. The DRL agent, guided by the degradation cost component in its reward function, learns a more sophisticated policy that preserves the battery's health, using it more judiciously and relying on the hydrogen system for longer-duration energy shifting. This highlights the model's capability for true cooperative optimization of the hybrid storage components.

The high dispatch accuracy (IDA > 96%) achieved by the IDS is of paramount importance for grid integration. It transforms the volatile wave energy source into a predictable and reliable power plant from the grid operator's perspective. This enhanced dispatchability is a key enabler for the large-scale penetration of wave energy, as it reduces the need for costly ancillary services from the grid to balance supply and demand.

B. Comparison with Existing Research

Compared to the work of Cipolletta et al. (2023) [1], which used a probabilistic approach for a wave-gas turbine system, our study makes several key advancements. First, by replacing the fossil-fuel-based backup with a zero-emission BESS-hydrogen system, our design is inherently more sustainable. Second, our use of a DRL-based dynamic dispatch model represents a significant methodological leap from their static, probability-based optimization. The results confirm that this dynamic approach yields substantial improvements in both economic and technical performance (e.g., higher LVOE, lower LCOE, and the new IDA metric).

Our work also contributes to the broader field of intelligent energy management for HES [8]. While DRL has been applied to microgrids, its application to offshore systems featuring the unique characteristics of wave energy has been limited. Our study demonstrates the successful adaptation and application of the DDPG algorithm to this challenging environment, providing a valuable case study and a robust framework that can be extended to other types of marine renewable energy systems.

C. Value and Implications

The findings of this research have significant practical and scientific implications. From a practical standpoint, the proposed IDS framework offers a viable pathway to improve the business case for wave energy projects. By increasing revenue and reducing costs (both operational and degradation-related), it can attract more investment into this nascent industry. For grid operators, the high dispatchability of IDS-managed wave farms means they can be treated as conventional, dispatchable assets, simplifying grid management and enhancing overall system reliability.

Scientifically, this study validates the power of DRL in solving complex, real-world energy optimization problems under uncertainty. It showcases how an AI agent can autonomously discover strategies that are far from obvious and often superior to human-engineered rules. The multi-dimensional sustainability assessment framework also provides a comprehensive tool for evaluating and comparing different energy system designs and control strategies, moving beyond purely economic metrics.

VII. Conclusion

This paper proposed and validated a novel framework for the design and intelligent dispatch of an offshore hybrid energy system, aimed at enhancing the grid integration and economic viability of wave energy. By combining a wave energy converter with a hybrid battery-hydrogen storage system and controlling it with a sophisticated Deep Reinforcement Learning agent, we have demonstrated a pathway to transform volatile wave power into a firm, dispatchable, and profitable energy source.

The key findings are threefold:

- Superior Performance: The proposed Intelligent Dispatch Strategy (IDS), driven by a DDPG agent, significantly outperforms both direct grid-connection and conventional rule-based control strategies. It achieved a dispatch accuracy of over 96%, reduced energy curtailment to just 2.1%, and increased annual revenue by 12.4% compared to the RBC approach.

- Economic Viability: The IDS substantially improves the economic case for wave energy, reducing the Levelized Cost of Energy by 17.3% and increasing the Levelized Value of Energy by 14.7% compared to the RBC strategy. It achieves this through intelligent arbitrage and by considering the long-term degradation costs of storage assets.
- Holistic Sustainability: The multi-dimensional sustainability assessment confirmed that the IDS provides benefits across technical, economic, environmental, and safety domains, making it a more robust and sustainable solution for future offshore energy systems.

This research serves as a proof-of-concept for the application of advanced AI in managing marine renewable energy. It provides a new paradigm that moves beyond static rules and embraces dynamic, data-driven, and self-learning control. By turning an unpredictable resource into a reliable asset, the methodologies developed in this study can help unlock the immense potential of wave energy and contribute to a cleaner, more sustainable global energy future.

A. Limitations and Future Work

Despite the promising results, this study has several limitations that open avenues for future research. First, the WEC, BESS, and hydrogen system models, while based on established principles, are simplified. Future work could incorporate more detailed, physics-based models to capture component dynamics and aging effects more accurately. Second, the study relies on reanalysis data for wave conditions and simulated data for market prices. Real-world deployment would require integration with live data streams and consideration of market bidding strategies. Third, the DDPG algorithm, while effective, is a single-agent approach. Future research could explore multi-agent DRL systems where different components (e.g., BESS, FC) are controlled by separate, cooperating agents, potentially leading to more robust and scalable solutions.

Finally, the scope of this study was limited to energy dispatch. A more holistic optimization could include the co-design of the system's physical capacity (sizing) and its control strategy. A bi-level optimization approach, where the DRL-based dispatch model is nested within a higher-level capacity optimization loop, could be a promising direction for future investigation.

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AUTHOR CONTRIBUTIONS

Jiegen Xu: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Supervision.

Jianlian Chen: Data Curation, Software, Investigation, Writing – Review & Editing.

COMPETING INTERESTS

The authors declare no competing interests.