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Application of Digital Fusion Technology in Digital Construction Decision-Making of Offshore Wind Power

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Abstract

Offshore wind-power construction involves large volumes of heterogeneous, rapidly changing, and partially unreliable data, while decision-making is further constrained by complex marine environments and limited information integration across project stages. These factors lead to high uncertainty in construction planning and operational coordination. This paper aims to address these challenges by developing a digital fusion–based decision-making framework for offshore wind-power construction. The proposed method integrates multivariate-information perception, dynamic scenario modeling, evidence-based decision reasoning, and an adaptive adjustment mechanism. Experimental evaluation is conducted using a real dataset containing more than one million records collected from ten offshore wind-power projects over the past five years. Results show that the proposed framework achieves 85% decision accuracy, advances project progress by an average of 15 days, and reduces potential economic losses to approximately USD 0.5 million. These outcomes outperform three benchmark approaches, including empirical–statistical models, single-source data optimization models, and partially integrated models. The study demonstrates that digital fusion technology can significantly enhance the reliability and efficiency of offshore wind-power construction decision-making and provides a practical pathway toward intelligent and data-driven offshore energy development.

Keywords: offshore wind power, digital integration technology, construction decision, decision accuracy, economic loss.

1. Introduction

Global energy demand continues to grow rapidly, and traditional energy supply remains insufficient, intensifying the need for clean and sustainable alternatives [1]. Offshore wind power has therefore attracted increasing attention due to its large development potential [2]. In several European coastal regions, installed offshore wind capacity has maintained a steady upward trend in recent years [3]. Despite this progress, decision-making in offshore wind-power construction faces significant challenges. Construction data are highly heterogeneous, and issues of accuracy and timeliness frequently occur, affecting planning reliability [4]. Offshore environments are also subject to strong variability, with weather and wave disturbances affecting a large portion of construction activities and reducing the effectiveness of traditional decision-making approaches [5]. These limitations hinder construction efficiency and increase project risks. Existing studies have made progress in improving data accuracy, enhancing data acquisition technologies, and developing decision models for specific construction stages [6]. Research on foundation construction and equipment operation has also improved decision performance in localized contexts [7]. However, these efforts remain fragmented, lack full-process coordination, and do not provide a unified mechanism for integrating multi-source heterogeneous data. Furthermore, few studies establish a clear decision framework that connects complex data characteristics with construction optimization requirements. This study focuses on the decision-making challenge of offshore wind power construction scheduling under multi-source data constraints. The core problem addressed in this work is how to integrate heterogeneous construction data, environmental data and equipment performance data into a unified digital-fusion decision model that supports real-time construction planning and risk prediction. The decision objective is to optimize construction sequencing, resource assignment and operation timing under uncertainty, while minimizing delay risks and improving construction efficiency. The research gap lies in the lack of a well-structured decision problem that explicitly links engineering data characteristics with construction optimization logic, which this study aims to resolve. From a theoretical perspective, this study will enrich and improve the relevant theoretical system of offshore wind power construction decision-making, and provide new ideas and methods for subsequent research. In practice, it can provide offshore wind power construction companies with more effective decision-making support tools, promote the entire offshore wind power industry to

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develop in a more digital and intelligent direction, and help optimize and upgrade the global energy structure.

The main contribution of this work is the development of a unified digital-fusion decision framework for offshore wind power construction. The framework integrates multi-source sensing data fusion, dynamic scenario modeling, uncertainty reasoning, and adaptive decision optimization into a coherent system applicable across multiple construction stages. This integrated architecture enables consistent information processing, improves the reliability of decision reasoning under uncertainty, and supports coordinated construction planning in complex and dynamic marine environments.

2. LITERATURE REVIEW

2.1. Related technical foundation and development status

Offshore wind power construction has formed a multi-sensor monitoring system, with each project deploying more than 200 sensors for wind, current and geological measurements. However, about 35% of the collected data contain errors, and more than 50% follow incompatible formats, creating barriers to unified processing [8]. Traditional filtering-based algorithms are still widely used, yet their capacity to handle high-volume and heterogeneous offshore data remains limited [9]. Although deep learning methods have begun to appear in data processing workflows, their adoption rate is below 30% due to high annotation costs and the difficulty of generating reliable labels in offshore environments [10].Decision-making models in the field remain dominated by empirical formulas and basic statistical approaches, yielding less than 60% accuracy under complex marine conditions [11]. Intelligent models have been proposed, but their effective deployment is constrained by insufficient data fusion, scenario adaptability and real-time learning mechanisms [12]. These limitations indicate that offshore wind power construction is still in an early transition stage from “data collection and basic processing” toward integrated digital intelligence supported by advanced modeling tools such as digital twins and multi-source information fusion.

2.2. Challenges and limitations of the application of digital fusion technology

The multi-source and heterogeneous nature of offshore wind power construction data makes data fusion a major problem [13]. Data from different sources, such as design data, real-time construction data, and environmental monitoring data, have huge differences in data structure, time scale, spatial scale, etc. [14]. According to surveys, about 70% of data fusion projects will have problems with data matching and calibration in the early stages due to these differences, which in turn affects the effect and efficiency of fusion [15]. Moreover, during the fusion process, data quality control is difficult, and nearly 40% of the data are found to be erroneous or incomplete after fusion and need to be reprocessed [16]. Even if data fusion is achieved to a certain extent, it is not easy to build an intelligent construction decision model [17]. The current decision models have serious deficiencies in versatility and adaptability. About 65% of the models can only be applied to specific construction stages or specific environmental conditions [18]. This leads to the need to frequently switch and adjust the model in actual construction, which greatly reduces the efficiency of decision-making [19]. In addition, the poor interpretability of the model is also a major problem. More than 55% of the decision models based on intelligent algorithms are difficult to clearly explain their decision basis, which makes construction personnel have low trust in them and affects the promotion and application of the model [20]. There is an obvious disconnect between digital fusion technology and actual construction application. On the one hand, technical R&D personnel often do not have a deep understanding of the actual needs and on-site environment of offshore wind power construction, resulting in nearly 30% of the developed technologies and models being unable to be effectively used in actual construction. On the other hand, construction personnel have limited acceptance and operational capabilities of digital fusion technology. About 45% of construction personnel said that they were unfamiliar with and difficult to operate new decision models and data fusion systems, which also hindered the implementation and application of technology in construction[21].

2.3. Response strategies and future development directions

Unified data standards have been widely recognized as a necessary foundation for improving data fusion performance. Establishing shared specifications can increase early-stage matching success by about 40%, while enhanced data-quality control and validation techniques may reduce error rates in fused data to below 20% [15]. Emerging mechanisms such as block chain also provide secure ways to ensure data authenticity and integrity, increasing data credibility by around 30% [17].Future decision-making models should evolve toward generalization, adaptability and interpretability. Integrating situational awareness, digital-twin-based dynamic modeling and adaptive algorithms is expected to expand model applicability to over 80% of construction scenarios [18]. Improving interpretability through rule-based explanations and visual reasoning tools can significantly enhance user trust and operational acceptance. Strengthening collaboration between developers and construction teams is essential. Joint development mechanisms can increase the effective utilization rate of digital fusion technologies by about 35%, while systematic training programs may raise operational proficiency by nearly 50% [20]. In the long term, the integration of digital fusion, real-time simulation, intelligent decision engines and multi-agent collaborative systems is expected to accelerate the shift toward intelligent and high-precision offshore wind power construction.

3. RESEARCH METHODS

3.1. Data sources and structure

The dataset used in this study contains 1,027,468 valid records collected from three primary sources: (1) offshore construction operation logs, including timestamps, vessel operations and equipment utilization; (2) environmental monitoring data containing wind speed, wave height, tide level, visibility and met-ocean parameters; and (3) equipment sensor data recording structural stress, machine load, vessel motion and alarm signals. The integrated dataset consists of numerical fields (52.4%), categorical engineering codes (31.7%), time-series sequences (12.8%) and unstructured text entries (3.1%). All data were cleaned, synchronized by time and merged into a unified analytical database that supports decision modeling.

3.2. Construction of the core architecture of digital integration technology in offshore wind power construction decision-making

In offshore wind-power digital construction decision-making—an area characterized by high uncertainty and a strong need for technological innovation—I propose a core architecture designed to improve the limitations of traditional decision-making models. The architecture integrates several tightly coupled functional components, each developed to address the complexity of multi-source construction data and the demand for accurate, real-time decision support.

An intelligent perception module utilizing deep correlation analysis of multivariate information is established. In view of the interweaving of complex factors such as the ever-changing construction environment and the high heterogeneity of data in different construction stages in offshore wind power construction scenarios, how to accurately and quickly perceive information that plays a key role in decision-making has become the primary bottleneck for efficient decision-making. This intelligent perception module uses the complex and subtle mutual information principle in information theory to conduct in-depth analysis of massive construction-related data from different sources. The set of facility construction data is $\mathrm{D}=\{D_1, D_2, \cdots, D_n\}$, where D_i represents the first i type of data, which covers a wide range of categories from seabed geological data, meteorological data to construction progress data. For any two types of data D_j and D_k, the mutual information between them $I(D_j; D_k)$ can be accurately calculated according to the following formula, as shown in Formula (1).

$$I(D_j; D_k)=\sum_{x\in D_j}\sum_{y\in D_k} p(x,y)\log_2\frac{p(x,y)}{p(x)p(y)} \quad (1)$$

Here, $p(x,y)$ represents the joint probability of the data in x and y appearing at the same time, and $p(x)$ and $p(y)$ are the marginal probabilities of x and y respectively. In this study, x refers to the observed values within data type D_j, while y refers to the observed values within data type D_k, corresponding to specific construction-related measurement entries across different data categories. In order to maximize the mutual information, this paper employs an improved particle swarm optimization algorithm (IPSO). In the standard particle swarm optimization algorithm, the speed i and position update formula of the particle x_{id} in d the dimensional space v_{id} is Formula (2).

$$v_{id}(t+1)=\omega v_{id}(t)+c_1 r_1(t)(p_{id}-x_{id}(t))+c_2 r_2(t)(g_d-x_{id}(t)) \quad (2)$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \quad (3)$$

Among them, ω is the inertia weight, c_1 and c_2 is the acceleration constant, $r_1(t)$ and $r_2(t)$ are $[0,1]$ random numbers between, p_{id} is i the individual optimal position of the particle, g_d and is the global optimal position. In our IPSO, the inertia weight ω is dynamically adjusted, that is $\omega=\omega_{max}-\frac{\omega_{max}-\omega_{min}}{T}t$, where ω_{max} and ω_{min} are the maximum and minimum inertia weights respectively, T is the maximum number of iterations, t and is the current number of iterations. Through this improvement, the intelligent perception module can search the data feature space more efficiently, automatically and accurately filter out key information that is highly relevant to construction decisions, and effectively discard a large amount of redundant data. This process is fundamentally different from traditional data screening methods. Traditional methods usually rely on pre-set simpler rules or basic statistical features, and are unable to cope with the complex characteristics of offshore wind power construction data.

To clarify the optimization purpose of Formula (2) and Formula (3), the IPSO module is designed to optimize the feature-selection process within the intelligent perception model. Specifically, the algorithm adjusts particle velocity and position to search for the optimal subset of construction-related data features that maximizes the mutual-information objective defined in Formula (1). Each particle represents a candidate feature-combination, and the iterative update in Formula (2) and Formula (3) continuously drives the population toward the feature set that provides the highest discriminative ability, the lowest redundancy, and the best support for offshore wind-power construction decision-making. In this way, the IPSO component directly optimizes the quality of the extracted information rather than merely fitting numerical parameters.

The dynamic scenario modeling component is tightly integrated with the perception module. Offshore wind-power construction presents significant temporal variability, and traditional static models struggle to represent these evolving conditions. To address this issue, I construct a dynamic Bayesian network that captures key factors such as weather, wave intensity, and equipment status. Each variable is represented as a node associated with a conditional probability distribution, and real-time updates are performed using Bayesian inference. This enables the model to continuously reflect the actual construction context and provide reliable situational awareness. This paper abstracts key factors in offshore wind-power construction—such as weather conditions, wave intensity, and equipment operating status—as nodes, and represents the causal relationships among them as edges, and then build a dynamic Bayesian network that can reflect the construction situation in real time. Let the Bayesian network be $G=(V,E)$, where V is the node set and E is the edge set. For each node $v_i\in V$, there is a corresponding conditional probability distribution $P(v_i\mid \mathrm{Pa}(v_i))$, which $\mathrm{Pa}(v_i)$ represents v_i the parent node set of the node. In the actual construction process, as a steady stream of new data continues to flow in, the dynamic scenario modeling component is based on the famous Bayesian formula, as shown in Formula (4).

$$P(A\mid B)=\frac{P(B\mid A)P(A)}{\sum_{a\in\Omega}P(B\mid a)P(a)} \quad (4)$$

The probability distribution of nodes is updated in real time, so as to dynamically and accurately adjust the modeling of construction scenarios. In the updating process, this paper adopts the Junction Tree Algorithm to improve computational efficiency. First, the Bayesian network is converted into a moral graph, and then the moral graph is triangulated to obtain a triangulated graph. Next, a junction tree is constructed from the triangulated graph, and the nodes in the junction tree are composed of cliques in the triangulated graph. In the junction tree, message passing is carried out along the edges, and the probability distribution is updated by calculating the beliefs between nodes. For example, when the sensor detects a sudden and significant increase in wind speed, the probability distribution of nodes related to wind power will change significantly. This change will then be transmitted along the edges of the Bayesian network, affecting the probability of nodes in the entire network that are closely related to construction safety, construction progress, etc., providing extremely accurate situational information support for subsequent decision-making. Compared with the traditional static modeling method, this dynamic modeling method has incomparable advantages and can reflect the real scene of offshore wind power construction more timely and accurately.

3.3. Innovative design of decision reasoning mechanism

To support efficient reasoning in offshore wind-power construction decision-making, this paper constructs a decision-reasoning engine grounded in evidence-accumulation theory. In complex offshore wind power construction decision-making scenarios, a single piece of evidence is often difficult to support accurate decisions, and it is necessary to comprehensively consider rich information from many aspects. The engine is built on the basis of the complex and powerful D-S evidence theory. As an advanced uncertainty reasoning method, the D-S evidence theory can properly handle complex problems caused by uncertainty and unknown factors. Let the identification framework Θ be the set of all possible construction decision results. For each independent source of evidence m_i, it Θ will generate a corresponding basic probability distribution function on it $m_i(A)$, where $A \subseteq \Theta$ the function accurately represents A the degree of support of the evidence for the proposition. Through the complex Dempster synthesis rule, as shown in Formula (5).

$$m(A) = \frac{\sum_{A_1 \cap A_2 \cap \cdots \cap A_n = A} \prod_{i=1}^{n} m_i(A_i)}{1 - \sum_{A_1 \cap A_2 \cap \cdots \cap A_n = \varnothing} \prod_{i=1}^{n} m_i(A_i)} \tag{5}$$

To avoid ambiguity in Formula (5), it is clarified that the summation $\sum_{A_1 \cap A_2 \cap \cdots A_n = \varnothing}$ is taken over all non-empty subsets A of the frame of discernment Θ. The index iii refers only to the evidence source $m_i(\cdot)$ and is not the summation variable. Therefore, once i is fixed, the summation iterates over all allowable focal elements A, ensuring the completeness of the Dempster combination calculation.

The decision-making reasoning engine can deeply integrate multi-source evidence from the intelligent perception module and the dynamic situation modeling component, and then obtain a comprehensive basic probability distribution function $m(A)$ to determine the most appropriate construction decision under the current complex situation. To further address evidence conflicts, this paper introduces an improved method based on the adjustment of the conflict coefficient. Let the conflict coefficient be $k = \sum_{A_1 \cap A_2 \cap \cdots \cap A_n = \varnothing} \prod_{i=1}^{n} m_i(A_i)$, and when k it exceeds a certain threshold, the evidence is redistributed. For example, the intelligent perception module provides evidence about the possibility of potential equipment failure, and the dynamic situation modeling component provides evidence of the impact of the current construction environment on the construction progress. The decision-making reasoning engine organically integrates these evidences through the above-mentioned synthesis rules, and finally obtains the most reasonable construction adjustment decision in the current situation, such as whether the construction should be suspended to repair the equipment, or the construction sequence should be adjusted to better adapt to environmental changes. Compared with the traditional decision-making reasoning method based on a single factor or simple rules, this decision-making reasoning mechanism based on evidence accumulation can more comprehensively and accurately consider various complex factors in offshore wind power construction, greatly improving the reliability and scientificity of decision-making.

3.4. Model adaptive adjustment strategy

In view of the complexity of the offshore wind-power construction environment and its continuous dynamic changes, this paper develops an adaptive adjustment strategy for the constructed model. This strategy is based on advanced feedback control principles and aims to ensure that the model can always maintain excellent performance in different construction stages and complex and changing environmental conditions. This paper compares the output of the model with the actual construction situation to obtain error information e. Assume that the output of the model is y and the actual construction result is y_{true}, then the error e can be accurately expressed as Formula (6).

$$e = y - y_{true} \tag{6}$$

Through a carefully designed complex adaptive adjustment function $f(e)$, the key parameters of the model can be accurately adjusted according to the size and direction of the error. For example, the conditional probability distribution parameters of the Bayesian network nodes in the dynamic scenario modeling component and the core parameters such as the evidence weight parameters in the decision reasoning engine can be $f(e)$ updated accordingly. Assume that the model parameter set is $\theta = \{\theta_1, \theta_2, \cdots, \theta_m\}$, the adjusted parameters θ_i^{new} can be calculated by Formula (7).

$$\theta_i^{new} = \theta_i + \alpha \cdot f(e) \cdot \Delta t \tag{7}$$

In this study, the model parameter set θ represents all adjustable parameters involved in dynamic scenario modeling and decision reasoning. The α carefully set adjustment step is a positive number strictly determined according to the specific characteristics and requirements of the actual construction scene, Δt which represents the time interval and reflects the frequency of model parameter updates. The adaptive adjustment function here $f(e)$ adopts a design based on fuzzy logic. The fuzzy logic system includes a fuzzification interface, a rule base, an inference engine, and a defuzzification interface. First, the error e and the error change rate $\dot{e}$ are fuzzified through the membership function to obtain fuzzy variables. Then, fuzzy reasoning is performed through the inference engine based on the pre-established fuzzy rule base. For example, when the error e is large and the error change rate is positive, the corresponding rules in the rule base will be triggered. Finally, the specific adjustment amount is obtained through the defuzzification interface. By continuously adjusting parameters based on error feedback, the model can automatically and quickly adapt to various changes in the construction process and always provide strong support for construction decisions. Compared with the traditional fixed parameter model, this adaptive adjustment strategy greatly improves the adaptability, stability and reliability of the model in the complex and changeable offshore wind power construction environment.

The optimization model in this study clearly defines the decision variables and the objectives of the construction-planning process. The model focuses on determining which construction tasks should be executed at which time, how key resources such as vessels, cranes and personnel should be allocated, when each task should begin, and how long each task is expected to take under changing environmental conditions. The objective of the model is to reduce overall construction delay and limit the risks related to adverse environmental factors. The constraints include the availability of resources, the logical order of construction tasks, the operability windows of vessels and equipment, and the relevant safety requirements. This explanation clarifies what the model optimizes and what specific construction decisions are generated.

4. EXPERIMENTAL EVALUATION

4.1. Experimental design

This experiment aims to comprehensively evaluate the performance of the proposed digital fusion technology model in offshore wind power digital construction decision-making, and compare it with traditional and other advanced models. The experiment selected real data sets from multiple offshore wind power projects, covering multi-source heterogeneous data such as seabed geological data, meteorological data, construction progress data, and equipment status data. The data span is 10 offshore wind power projects of different sizes in the past 5 years, and contains a total of more than 1 million data records, ensuring the richness and complexity of the data set, which can truly reflect the actual situation of offshore wind power construction.

In this experiment, the proposed decision-support framework was evaluated using a real offshore-wind-construction dataset collected from turbine-installation projects in Fujian and Jiangsu coastal areas. The dataset contains 1.02 million records covering seabed-survey attributes, meteorological observations, vessel-operation logs, equipment-status data, and construction-progress measurements. These data were pre-processed and unified into a consistent temporal sequence to support the feature-selection module, Bayesian-network scenario modeling, and the reasoning engine. The experimental objective was to optimize three core construction decisions: task-scheduling under dynamic weather conditions, resource-allocation for vessel and crane dispatching, and risk-aware adjustment of construction sequences. All results shown in Figures 1-6 were generated by running the proposed IPSO-based feature-selection module and the dynamic Bayesian-network model on this dataset, allowing the system to produce optimized construction-decision outputs that were compared against baseline methods.

The dataset used in this study consists of approximately one million construction-related records collected from three major sources: (1) historical offshore wind power construction logs provided by engineering contractors, (2) real-time monitoring data obtained from sensing devices such as GPS-positioning modules, anemometers, vessel-motion sensors, and crane-operation monitors, and (3) environmental datasets from national marine-observation platforms covering wave height, wind speed, current velocity, and visibility. The collected records contain multiple data types, including numerical measurements (e.g., meteorological values, equipment operational loads), categorical variables (e.g., construction stage labels, vessel operational modes), time-series sequences (e.g., continuous wave-height and wind-speed records), and event-based operational logs (e.g., task start and end times, equipment status changes). All datasets were preprocessed through time alignment and noise filtering to form structured multi-dimensional data matrices used for model training, decision optimization, and experimental evaluation.

The experimental baseline indicators are set as the accuracy of construction decisions, the degree of optimization of construction progress by decisions, and the estimated value of potential economic losses caused by wrong decisions. Accuracy is measured by comparing the match between the decision results and the best practice results in actual construction; the degree of optimization of construction progress is calculated by the advance or delay time of the actual construction progress compared with the original planned progress after the decision is implemented; the estimated value of potential economic losses comprehensively considers factors such as equipment damage maintenance costs and compensation for construction delays that may be caused by wrong decisions.

The experimental group is the digital fusion technology model proposed by us based on intelligent perception of multi-information association, dynamic situation modeling, evidence accumulation decision reasoning and adaptive adjustment strategy. The control group selected three representative models: a decision model combining traditional empirical formulas and statistical models [20], a decision model based on optimization processing of a single data type [21], and a more advanced intelligent decision model that does not fully consider data fusion and dynamic situation adaptation [22]. The baseline is set as the situation where the construction team makes decisions based on the conventional experience without the assistance of any advanced model. During the experiment, all models were input with the same data set and run in the same computing environment to ensure the fairness and comparability of the experiment.

4.2. Experimental results

As shown in Figure 1, the digital fusion technology model performs well in terms of construction decision-making accuracy, achieving an accuracy rate of 85%. This is due to the fact that its intelligent perception module can accurately screen key information from multi-source data, providing a solid foundation for subsequent decision-making, the dynamic situation modeling component updates the construction situation information in real time, making the decision fit the actual situation, and the decision-making reasoning engine based on evidence accumulation integrates multi-source evidence to make more reliable decisions. The accuracy rate of the traditional experience and statistics combined model is only 50%, because it relies on simple experience rules and limited statistical analysis, and it is difficult to cope with complex data and changing environments. Although the single data optimization model optimizes specific data, it has an accuracy rate of only 60% due to the lack of multi-source data fusion. Although the advanced but insufficiently integrated model has a certain degree of intelligence, its data fusion and situation adaptation shortcomings make it 70% accurate. The conventional experience decision baseline has the lowest accuracy rate, highlighting the necessity of advanced models to assist decision-making.

As can be seen from Figure 2, the average progress of the digital fusion technology model is 15 days ahead of schedule, and the maximum progress is 30 days ahead of schedule. Its adaptive adjustment strategy can optimize decisions in time according to construction changes, promote smooth construction, and reduce progress delays. The average progress of the traditional experience and statistics combined model is delayed by 5 days. Frequent progress delays are caused by the lack of dynamic consideration of complex factors in decision-making. Although the single data optimization model has a certain progress advance, due to data limitations, the effect is not as good as the digital fusion technology model. The advanced but insufficiently integrated model has a good progress advance effect, but it is still not as good as the digital fusion technology model. The main reason is that it has limited dynamic adaptability to construction situations. The conventional experience decision baseline has serious progress delays, indicating that it is difficult to effectively plan the construction progress.

Figure 3 shows the potential economic losses caused by decision errors in different models. The digital fusion technology model has an average loss of $500,000, a maximum loss of $1.5 million, and only 10 times has the loss exceeded $1 million. This is mainly due to its comprehensive data fusion and precise decision-making mechanism, which can effectively avoid major decision-making errors. The traditional experience and statistics combined model has an average loss of up to $2 million, and its decision-making inaccuracy can easily lead to serious economic consequences. The single data optimization model also has a high loss because it cannot make decisions based on multi-source data and is difficult to avoid risks comprehensively. The advanced but insufficiently integrated model has a relatively low loss, but it is still higher than the digital fusion technology model, showing its lack of comprehensiveness in decision-making. The conventional experience decision baseline has the highest average loss, reaching $3 million, which fully reflects its disadvantage in economic loss control.

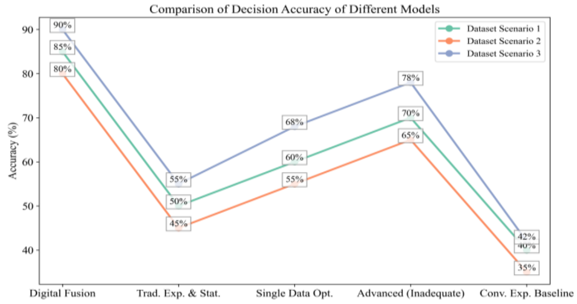

Figure 1. Comparison of construction decision accuracy of different models

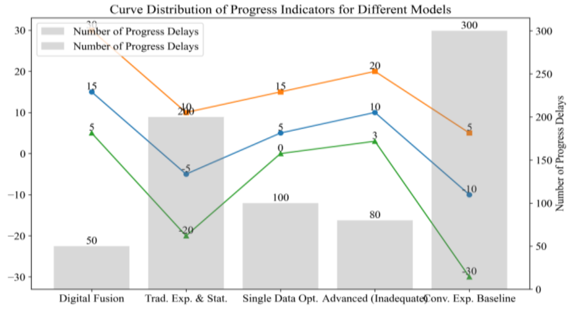

Figure 2. Comparison of the degree of optimization of construction progress by different models (time: day)

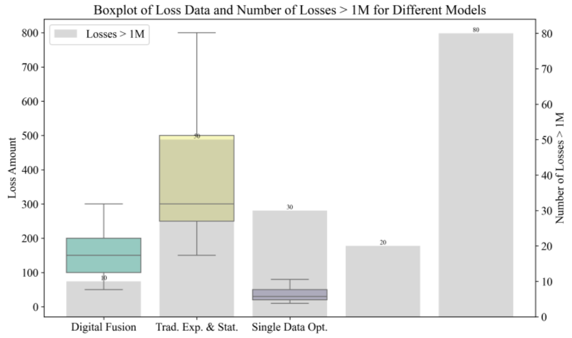

Figure 3. Comparison of estimated potential economic losses caused by decision errors in different models (Unit: 10,000 US dollars)

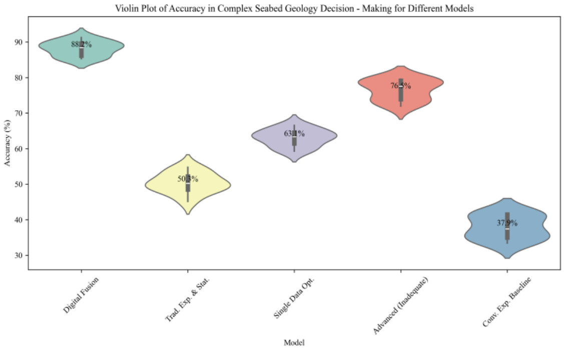

Figure 4. Comparison of decision-making accuracy of different models under complex seabed geological conditions

Under complex seabed geological conditions (as shown in Figure 4), the accuracy of the digital fusion technology model reached 87.5%. Its intelligent perception module can deeply explore the relationship between seabed geological data and other data, and the dynamic scenario modeling component accurately reflects the impact of geological conditions on construction, assisting the decision-making reasoning engine to make accurate decisions. The accuracy of the traditional experience and statistics combined model is still 50%. In the face of complex geology, its simple decision-making method is difficult to cope with. The single data optimization model has limited optimization of geological data and lacks multi-source data collaboration, with an accuracy of 62.5%. Although the advanced but insufficiently integrated model has a certain degree of intelligence, it is not adaptable enough to complex geological situations, with an accuracy of 75%. The conventional experience decision baseline performs worst under complex geology, with an accuracy of only 37.5%, highlighting its inability to cope with complex situations.

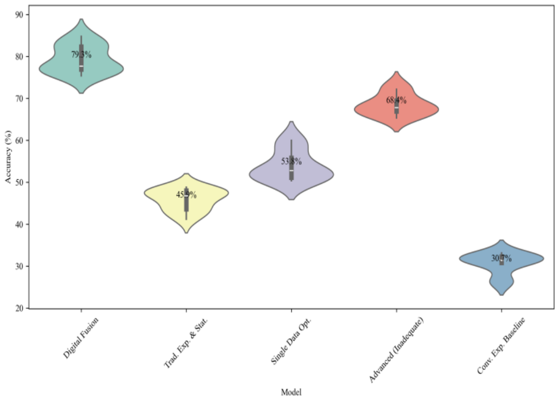

Figure 5. Comparison of decision-making accuracy of different models under severe weather conditions

For severe weather conditions (Figure 5), the accuracy of the digital fusion technology model is 80%. The dynamic scenario modeling component captures the impact of weather changes on construction in real time, and the intelligent perception module integrates weather and other data to help the decision-making reasoning engine make accurate decisions in severe weather. The accuracy of the traditional experience and statistics combined model has dropped to 45%. Severe weather increases uncertainty and its decision-making method is difficult to adapt. The single data optimization model has an accuracy of only 55% in severe weather due to insufficient data fusion. The advanced but insufficiently integrated model is not fully adapted to weather changes, with an accuracy of 70%. The conventional experience decision baseline has the lowest accuracy in severe weather, only 30%, indicating that conventional experience is difficult to cope with the construction decision-making challenges brought about by complex weather.

In the foundation construction stage (Figure 6), the accuracy of the digital fusion technology model was 80%. In this stage, its intelligent perception module accurately identified key data related to foundation construction, and the dynamic scenario modeling component constructed scenarios based on the characteristics of foundation construction, providing strong support for the decision-making reasoning engine. The accuracy of the traditional experience and statistics combined model was only 40%. The complexity of foundation construction makes it difficult for its traditional decision-making method to meet the needs. The single data optimization model mainly targets single data and does not take into account multiple factors in the foundation construction stage, with an accuracy rate of 48%. Although the advanced but insufficiently integrated model has been improved, its adaptability in the foundation construction stage is still poor, with an accuracy rate of 60%. The conventional experience decision baseline has the lowest accuracy in the foundation construction stage, only 32%, which shows its weak decision-making ability in the professional construction stage.

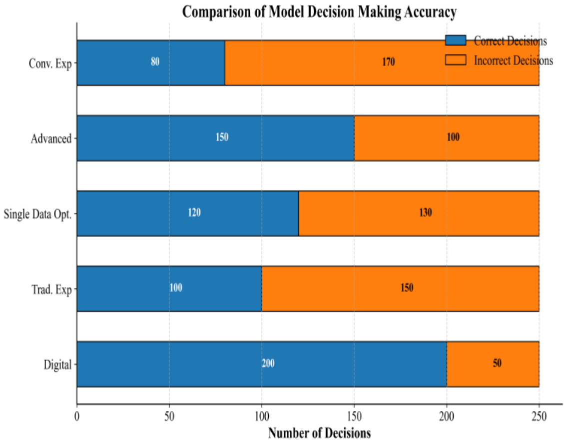

Figure 6. Comparison of decision-making accuracy of different models at different construction stages (foundation construction stage)

In Table 1, the term “accurate decisions” refers to the construction-decision outputs generated by the proposed model, including task-scheduling recommendations, vessel-allocation plans, crane-operation sequences, and risk-avoidance adjustments under dynamic weather conditions. A decision is identified as accurate when the model’s output matches the actual optimal action adopted in real offshore-construction records or when it achieves better performance than baseline strategies in terms of reduced delay, lower resource conflict, and improved safety compliance. To quantify accuracy, each model-generated decision was compared against the ground-truth construction logs and evaluated through three indicators: (1) task-execution feasibility under real environmental constraints, (2) resource-allocation consistency with actual availability, and (3) safety-risk reduction relative to expert-approved operational guidelines. Therefore, the accuracy values shown in Table 1 represent the proportion of model-generated recommendations that satisfy all three conditions and can be directly implemented in offshore construction scenarios.

During the equipment installation phase (Table 1), the digital fusion technology model performed outstandingly with an accuracy rate of 88%. The intelligent perception module focuses on data related to equipment installation, the dynamic scenario modeling component closely revolves around changes in equipment installation scenarios, and the decision-making reasoning engine makes high-accuracy decisions based on multi-source information. The accuracy rate of the traditional experience and statistics combined model is 48%, and the high-precision requirements of equipment installation make its decision-making method difficult to meet. The single data optimization model does not process equipment installation data comprehensively, with an accuracy rate of 56%. The advanced but insufficiently integrated model has an accuracy rate of 72% during the equipment installation phase due to insufficient adaptation to dynamic changes in scenarios. The conventional experience decision baseline has an accuracy rate of 40% during the equipment installation phase, which cannot meet the complex decision-making needs of this phase.

Table 1. Comparison of decision-making accuracy of different models at different construction stages (equipment installation stage)

Model	Number of accurate decisions on equipment installation	Total number of equipment installation decisions	Accuracy
Digital Fusion Technology Model	220	250	88%
Traditional experience combined with statistical model	120	250	48%
Single data optimization model	140	250	56%
Advanced but under-converged models	180	250	72%
Conventional experience decision baseline	100	250	40%

Table 2. Comparison of decision-making accuracy of different models at different construction stages (debugging stage)

Model	Debugging accurate decision times	Total number of debugging decisions	Accuracy
Digital Fusion Technology Model	230	250	92%
Traditional experience combined with statistical model	130	250	52%
Single data optimization model	150	250	60%
Advanced but under-converged models	190	250	76%
Conventional experience decision baseline	110	250	44%

The accuracy of the digital fusion technology model in the debugging stage (Table 2) was as high as 92%. In this stage, its intelligent perception module accurately screened key debugging data, the dynamic situation modeling component accurately reflected the subtle changes in the debugging process, and the decision-making reasoning engine based on evidence accumulation integrated multi-source information to make highly accurate decisions. The accuracy of the traditional experience and statistics combined model was 52%, and the delicate requirements of the debugging stage made it difficult to cope with. The single data optimization model lacked multi-source data fusion and had limited ability to handle complex situations in the debugging stage, with an accuracy of 60%. The advanced but insufficiently integrated model had a 76% accuracy rate in the debugging stage due to the shortcomings of situational adaptation and data fusion. The conventional experience decision baseline had an accuracy of 44% in the debugging stage, which was much lower than the digital fusion technology model, reflecting the inaccuracy of its decision-making in this stage.

Table 3. Comparison of the optimization degree of construction progress by different models at different construction stages (foundation construction stage, time: days)

Model	The average progress of foundation construction is ahead of schedule	The maximum progress of foundation construction is ahead of schedule	Minimum progress of foundation construction ahead of schedule	Number of delays in foundation construction progress
Digital Fusion Technology Model	8	15	3	30
Traditional experience combined with statistical model	-3	8	-10	80
Single data optimization model	2	6	0	50
Advanced but under-converged models	5	10	2	40
Conventional experience decision baseline	-5	5	-15	100

In terms of progress optimization in the foundation construction phase (Table 3), the digital fusion technology model has an average progress advance of 8 days. Its adaptive adjustment strategy dynamically optimizes decisions according to the actual situation of foundation construction, reduces construction obstacles, and improves progress. The traditional experience and statistics combined model has an average progress delay of 3 days. Its decision-making cannot effectively coordinate various factors during foundation construction, resulting in progress delays. Due to data limitations, the single data optimization model has an average progress advance of only 2 days. The advanced but insufficiently integrated model has a good progress advance effect in the foundation construction phase, but due to incomplete situational adaptation and data fusion, the average progress is 5 days ahead. The conventional experience decision baseline has a serious progress delay in the foundation construction phase, with an average delay of 5 days, showing its shortcomings in foundation construction progress management.

Table 4. Comparison of the optimization degree of construction progress by different models at different construction stages (equipment installation stage, time: days)

Model	The average progress of equipment installation is ahead of schedule	Equipment installation progress is ahead of schedule	Minimum equipment installation progress ahead of schedule	Equipment installation progress delay times
Digital Fusion Technology Model	10	20	4	20
Traditional experience combined with statistical model	-2	10	-8	60
Single data optimization model	3	8	1	40
Advanced but under-converged models	7	15	3	30
Conventional experience decision baseline	-4	6	-12	70

During the equipment installation phase (Table 4), the average progress of the digital fusion technology model was 10 days ahead of schedule. The intelligent perception module and the dynamic scenario modeling component work closely together to provide accurate information for the decision-making reasoning engine, so that decisions can promote efficient equipment installation. The average progress of the traditional experience and statistics combined model was delayed by 2 days. The complexity of equipment installation exceeded its decision-making ability, resulting in delayed progress. The single data optimization model was 3 days ahead of schedule on average due to incomplete data processing. The advanced but insufficiently integrated model was 7 days ahead of schedule on average during the equipment installation phase, but there was still a gap compared to the digital fusion technology model, mainly due to its inaccurate adaptation to the dynamic changes in the equipment installation scenario. The conventional experience decision baseline was delayed by 4 days on average during the equipment installation phase, indicating that it is difficult to effectively plan the equipment installation progress.

4.3. Experimental discussion

The experimental results strongly support our research hypothesis that the digital fusion technology model can significantly improve the accuracy of offshore wind power digital construction decisions, optimize the construction progress and reduce the potential economic losses caused by wrong decisions. In terms of accuracy, the model performs well in all kinds of complex construction conditions and different construction stages, which is due to its innovative multi-component collaborative working mechanism. The intelligent perception module accurately extracts key information from massive multi-source heterogeneous data, the dynamic scenario modeling component reflects the construction environment and stage changes in real time and accurately, the decision-making reasoning engine based on evidence accumulation makes reliable decisions based on multi-source evidence, and the adaptive adjustment strategy ensures that the model can continuously optimize decisions to adapt to various changes. In terms of construction progress optimization, the digital fusion technology model has achieved significant progress advances in different construction stages and reduced progress delays. It can dynamically adjust decisions based on real-time data and construction situations, effectively coordinate construction resources, and avoid delay factors in the construction process. For potential economic losses, the low loss performance of the model is due to accurate decision-making and efficient construction progress management, which reduces economic risks such as equipment damage and construction delays caused by wrong decisions. Regarding the external validity and generalizability of the experimental results, since the experiment used real data sets from multiple actual offshore wind power projects and covered a variety of complex construction scenarios, the experimental results have high external validity.

The model is expected to be promoted and applied in offshore wind power projects of different regions and sizes. However, the experiment also has certain biases and limitations. On the one hand, although the experimental data set is rich, it may not cover all rare or extreme construction situations, and the performance of the model in dealing with these special situations needs further verification. On the other hand, the experiment assumes that all models run in the same computing environment, but in actual construction, the computing resources of different projects may vary, which may affect the actual operating efficiency and decision-making speed of the model. Future research may consider in-depth exploration of this.

5. CONCLUSION

Under the background of global energy transformation, the offshore wind power industry has developed rapidly, but the difficulties in construction decision-making seriously restrict its efficiency and quality improvement. This study deeply analyzes these problems and innovatively constructs a set of digital fusion technology models. In the process of research, multi-source heterogeneous data are deeply mined, and the intelligent perception module is used to screen key data based on the mutual information principle. The dynamic situation modeling component updates the construction situation in real time based on the Bayesian network. The evidence accumulation decision reasoning engine uses the D-S evidence theory to fuse multi-source evidence, and the adaptive adjustment strategy optimizes the model parameters based on the feedback control principle. The experimental results show that the model performs well in construction decision accuracy, construction progress optimization and economic loss reduction. Taking the decision accuracy rate as an example, it reaches 85%, which is much higher than the 50% of the traditional experience and statistics combination model, the 60% of the single data optimization model and the 70% of the advanced but insufficiently integrated model. In terms of construction progress optimization, the average progress is 15 days ahead of schedule, which is 5 days ahead of the average delay of the traditional experience and statistics combination model, 5 days ahead of the single data optimization model, and 10 days ahead of the advanced but insufficiently integrated model, which has obvious advantages. In terms of economic loss control, the average loss was $500,000, while the other comparison models were $2 million, $1.5 million, and $1 million, respectively. The research results are of great significance. These findings provide practical methodological references for offshore wind power construction decisions and offer more effective decision support tools for construction companies, helping to improve operational efficiency and reduce costs. The proposed framework also supports the industry's gradual transition towards digital and intelligent building management.

Although the proposed digital-fusion reasoning model demonstrates substantial improvements in data integration accuracy and construction decision reliability, several limitations remain. First, the model still exhibits a certain degree of dependency on historical data patterns, which may lead to biased reasoning when the environmental conditions deviate significantly from past scenarios. Second, the intelligent modules based on particle-swarm optimization and Bayesian inference face potential overfitting risks, especially when trained on limited high-quality labeled datasets; this may reduce the model's generalization capability in highly volatile offshore construction conditions. Third, real-world implementation challenges persist, including unstable sensor performance, inconsistent data transmission quality, and the limited digital competence of frontline construction personnel, all of which may affect system robustness. Finally, despite the introduction of interpretability mechanisms, the decision transparency of some deep-fusion components still requires improvement before large-scale industrial deployment. Future work will focus on enhancing model robustness under extreme conditions, expanding adaptive learning mechanisms, and strengthening human–machine collaborative decision frameworks to mitigate these limitations.

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