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A Digital Twin Comprehensive Monitoring System for Ship Equipment

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ABSTRACT

In this study, a comprehensive digital twin monitoring system for ship equipment was designed and implemented, including the system architecture, key technologies, and applications. Through data-driven models and operational monitoring system analysis, our PSO-SVM-based time series prediction method demonstrated excellent predictive capabilities for catamaran equipment, achieving efficient fault warnings using a threshold method. The digital twin model and virtual scenarios constructed here provide a visualisation and simulation platform for equipment status monitoring, enhanced fault diagnosis and support for maintenance decisions. The system integrates real-time monitoring, fault warning, and data analysis, and testing results show good stability and accuracy. In addition, the system optimises the user experience through multi-round feedback testing, and ensures data security and privacy protection through multi-layer encryption, identity verification, and role-based access control. A case study indicates that the proposed system effectively monitors equipment status and provides fault warnings, and has broad application prospects and practical value. Future work will focus on optimising the functionality and improving the applicability and security of the system.

Keywords: various ship equipment; digital twin; comprehensive monitoring system; security privacy protection

INTRODUCTION

Digital twin technology is an emerging intelligent monitoring method in which virtual models of physical equipment are created to enable real-time data collection, analysis, and feedback. This technology seamlessly connects the physical and virtual worlds, allowing operators to comprehensively monitor and analyse the status of equipment on a unified platform. When applied to equipment management on a ship, digital twin technology [1, 2] helps operators better understand the status of equipment, operational trends, and potential issues, leading to more scientific maintenance planning [3, 4], reduced failure rates, and improved safety. For instance, in , a digital twin system was designed to collect data from the ship's sensor array, a comprehensive analysis was performed, fault parameters were designed, and the results were visualised in real time. Researchers have also proposed a digital twin architecture for optimising ship automation and a method for quickly obtaining structural strength evaluation stress for digital twin models of ships, thereby enabling rapid assessment of yield strength for both monitored and non-monitored points, and enhancing the efficiency and accuracy of ship structural safety monitoring .

With the rapid development of the global shipping industry, the safety and reliability of the ship's equipment [8, 9] are increasingly being emphasised. Ships operate in various complex environments with a diverse range of potential risks , and equipment failures can not only lead to economic losses but also significantly impact navigation safety and environmental protection. Hence, establishing an efficient and intelligent monitoring system for real-time monitoring and prediction of various types of ship equipment has become an urgent need in the industry. To address this issue, researchers proposed a fault diagnosis framework for maintaining the condition of ship oil filters , a critical auxiliary facility in the ship engine system. Another study introduced a hierarchical fault detection and diagnosis (HL-FDD) method that combined domain knowledge of ship engines with advanced data analysis techniques to enhance fault detection accuracy and improve diagnostic efficiency.

The demand for yachts as high-end leisure and entertainment vessels has been increasing over the years. Due to their superior stability and comfort, they have attracted widespread attention and application. However, as yacht equipment operates for extended periods in complex marine environments, it is affected by various factors, leading to frequent equipment failures that affect the safety and reliability of yachts. The issues of how to maintain various types of yacht equipment , conduct real-time monitoring and fault warning [16, 17], and ensure their safe and stable operation have become important, and urgently need to be addressed.

This study aims to design a comprehensive monitoring system for ship equipment, taking yacht equipment as an example, through data-driven models and digital twin technology for real-time monitoring and fault warning. First, a data-driven model is developed based on a PSO-SVM time series prediction monitoring method. Then, using Unity3D, MySQL, and the Visual Studio development environment, a system is implemented with functionality design, twin model construction, and scene building. The proposed system enhances human-computer interaction through a visual monitoring platform, making complex data analysis intuitive and understandable. Finally, a case study is conducted to validate the effectiveness and reliability of the system, and to provide scientific decision support for yacht equipment operation management.

the user experience through interaction with actual users. To ensure system security and user privacy, multiple security measures are designed , including data encryption and access control, to protect sensitive information from being compromised. These measures provide a comprehensive and reliable solution for the digital twin monitoring of ship equipment.

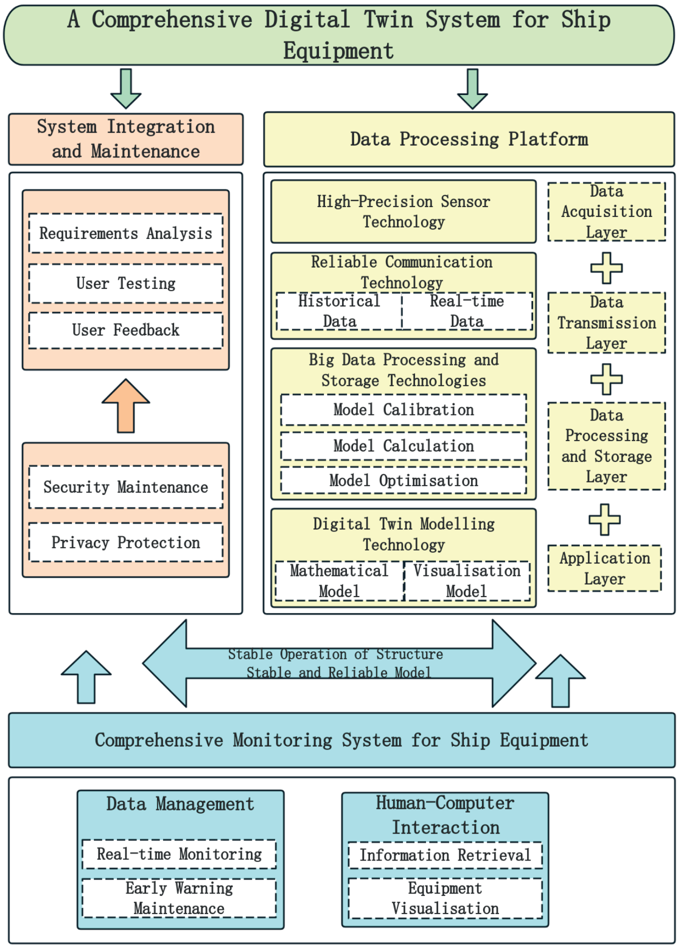

Fig. 1 Structure of the proposed digital twin-based comprehensive system for ship equipment

DESIGN OF A DIGITAL TWIN-BASED COMPREHENSIVE MONITORING SYSTEM FOR SHIP EQUIPMENT

In this section, we present the design of a digital twin-based comprehensive monitoring system for ship equipment, with a focus on the system architecture, key technologies, and implementation process, as shown in Fig. 1.

A multi-layered and modular system architecture is developed to facilitate the integration of different types of equipment and monitoring requirements. Regarding key technologies, the implementation methods for core functions such as data collection, real-time monitoring, and intelligent analysis are discussed. In this paper, we also focus on the incorporation of user testing and feedback [18, 19], to optimise

DESIGN OF A COMPREHENSIVE TWIN MODEL SYSTEM

In the process of constructing a model of the digital twin-based comprehensive monitoring system for ship equipment, various software tools such as Rhino, Matlab, and Unity3D were utilised for comprehensive design and implementation, with a focus on building a visual monitoring model, as shown in Fig. 2.

The design of the system first involved detailed modelling of the physical devices, in which high-precision three-dimensional modelling techniques were used to accurately represent the geometric shapes and functional characteristics of the ship equipment in a virtual environment. By integrating data from sensors, real-time monitoring and analysis of equipment status were achieved. We used digital twin technology to combine actual devices with their virtual models , and operational data were updated in real time. In addition, to enhance the user experience, a user-friendly visual interface was designed to allow users to intuitively monitor equipment performance and historical trends through interactive charts and dynamic displays. The system also incorporated data analysis tools to support intelligent decision-making and fault warning, thus ensuring the safety and efficiency of the ship's equipment.

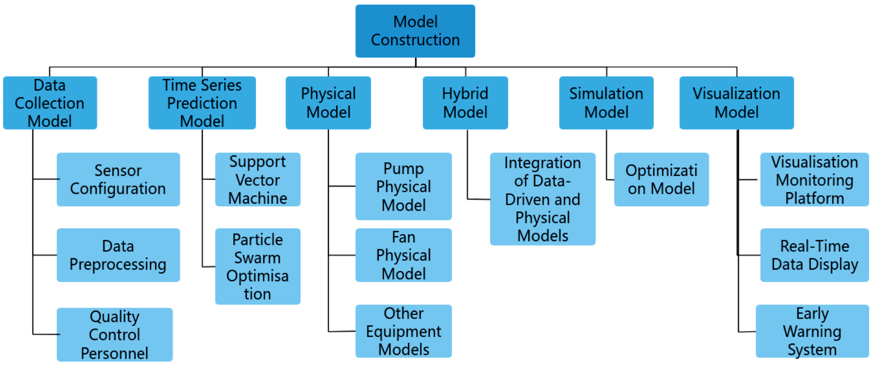

Fig. 2 Construction of the digital twin model

Time series prediction monitoring method based on particle swarm optimisation and support vector machine

We compared two time series prediction methods based on support vector machine (SVM) and particle swarm optimisation/SVM (PSO-SVM). Although SVM has strong classification and regression capabilities, its predictive performance relies heavily on the selection of hyperparameters (such as the penalty factor and kernel function parameters). Manual adjustment of these parameters is often time-consuming and ineffective, especially in situations with high data complexity. PSO-SVM takes advantage of the global search ability of the particle swarm optimisation (PSO) algorithm, which can automatically find the optimal hyperparameters, thereby significantly enhancing the model's adaptability and predictive capability and making it particularly suitable for complex time series data.

Although SVM performs well on medium to small datasets, it may not be as precise as other methods when dealing with highly nonlinear and dynamically changing time series data. PSO-SVM improves the performance of SVM under complex data patterns by optimising the hyperparameters, thus allowing it to capture the nonlinear characteristics of the data more accurately and enhancing the prediction accuracy. SVM has a relatively fast training speed, but the time cost for hyperparameter tuning is high. PSO-SVM increases the convergence speed by applying the PSO algorithm, which can often find optimal parameter settings in fewer iterations, thereby accelerating the efficiency of model training.

SVM is sensitive to noisy data, especially when parameters are poorly chosen, which can lead to subpar model performance. PSO-SVM enhances the model's robustness to noise and outliers through hyperparameter optimisation, allowing it to handle noisy time series data more effectively and improving the model's stability. Although SVM can handle nonlinear problems through kernel functions, it has limitations in terms of feature extraction in high-dimensional feature spaces. PSO-SVM increases the utilisation and adaptability of input features by optimising the parameters, making it a more effective method of extracting useful information, especially from complex datasets.

Due to the factors described above, the PSO-SVM time series prediction method outperforms traditional SVM in terms of parameter optimisation, prediction accuracy, convergence speed, and robustness, making it a more suitable choice for handling complex and dynamically changing time series data. We therefore employ the PSO-SVM time series prediction monitoring method in this paper to achieve precise monitoring and prediction of the operational status of yacht equipment based on data from vibration sensors.

At the data processing stage, normalisation is used to map data to a specified range (e.g. zero to one).

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where x are the original data and x' are the normalised data.

The time series data construction process uses the delay embedding method, which converts the time series data into feature vectors and target variables. For time series data *{x(t)}*, a delay step of d, and an embedding dimension of m, the feature vector is:

$$X_t = \left[x(t), x(t-d), x(t-2d), \ldots, x(t-(m-1)d \right]$$

The target variable is:

$$y_t = x(t+1)$$

The optimisation objective of SVM for regression problems is to find a function such that the deviation from the true value remains within the range ε, while ensuring that the model has good generalisation ability.

$$\min_{w,b} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{N} (\xi_i + \xi_i^*)$$

The constraint conditions are:

$$y_i - (w \cdot x_i + b) \le \varepsilon + \xi_i$$

$$(w \cdot x_i + b) - y_i \le \varepsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \ge 0$$

where w and b are model parameters, ξ_i and ξ_i^* are slack variables, and C is the penalty parameter.

PSO is used to optimise the SVM parameters C and the kernel parameter Υ. Each particle represents a possible parameter combination, and the formulae used to update its position and velocity are as follows:

$$v_{i,j}(t+1) = w \cdot v_{i,j}(t) + c_1 \cdot r_1 \cdot (p_{i,j} - x_{i,j}(t)) + \\ + c_2 \cdot r_2 \cdot (g_j - x_{i,j}(t))$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1)$$

where $v_{i,j}(t)$ is the velocity of particle i in dimension j, $x_{i,j}(t)$ is the position of particle i in dimension j, $p_{i,j}$ is the historical best position of particle i, g_j is the global best position, w is the inertia weight, c_1 and c_2 are acceleration constants, r_1 and r_2 andare random numbers between zero and one.

The SVM model optimised using PSO is then used for time series data prediction.

$$\hat{y} = \sum_{i=1}^{N} \alpha_i K(x_i, x) + b$$

where α_i are the Lagrange multipliers, $K(x_i, x)$ is the kernel function, and b is the bias term.

The data were divided into training and testing sets in a 4:1 ratio, and normalisation was applied to enhance the model's performance. Vibration data were trained and tested primarily using SVM as the mathematical model. The mapminmax function was used for data normalisation. The parameter settings included the parameters for the PSO algorithm, such as the local search capability and global search capability. The psoSVMcgForRegress function was used to extract the optimal SVM parameters (penalty parameter and kernel parameters), and the svmtrain function was then called to build the model. The svmpredict function was used to simulate predictions for both the training and testing sets, yielding the predicted values from the model. Finally, data denormalisation was performed, and the root mean square error (RMSE), coefficient of determination (R^2), mean absolute error (MAE), and mean bias error (MBE) were calculated. The predicted results were compared with the actual values through graphical representation to evaluate the model's prediction performance.

The model was trained using the vibration data collected from the equipment, and the SVM and PSO-SVM algorithms were compared, as shown in Table 1. It is evident that the PSO-SVM algorithm performed better. Figs. 3 to 5 present a comparison of the error in the results obtained from the PSO-SVM-trained model.

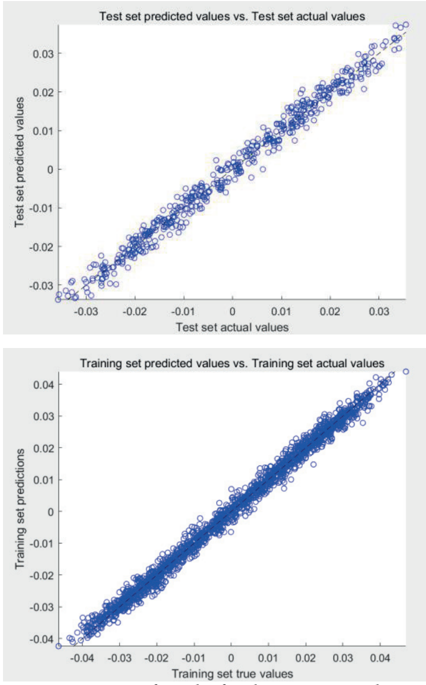

Fig. 3 Comparison of results for the training and test sets

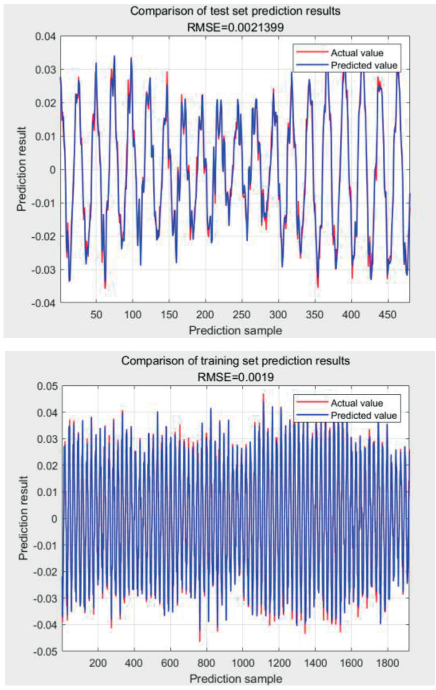

Fig. 4 Comparison of prediction results

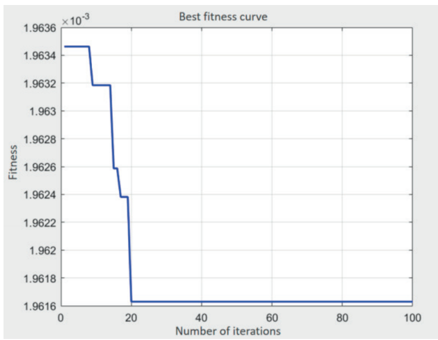

Fig. 5 Best fitness

Table 1. Comparison of errors between SVM and PSO-SVM

Algorithm	Training set	Test set
SVM	0.92894	0.88344
PSO-SVM	0.99248	0.98514

DESIGN OF AN OPERATIONAL MONITORING VISUALISATION SYSTEM

In this study, we designed and implemented a visual operational monitoring system for ship equipment. Our system can collect and display operational data in real time through an intuitive graphical interface, thus helping operators to promptly understand the status of the equipment and to prevent failures.

The monitoring system consists of three components: the data acquisition module, the data storage module, and the data visualisation module. The data acquisition module is responsible for obtaining operational data from sensors and sending it to the database. The data storage module uses a MySQL database to store the operational data of the equipment. The data visualisation module presents the operational status and historical data of the equipment through a graphical interface built using Unity3D.

The visual operational monitoring system for ship equipment was designed using Unity3D, MySQL Workbench, and Visual Studio, as shown in Fig. 6.

The main functions of the system include system login, interface transitions, equipment information input, monitoring of operational status, fault warning, and historical data viewing. The system integrates the visualisation capabilities of Unity3D, the data management features of MySQL Workbench, and the development functionalities of Visual Studio to achieve real-time monitoring of equipment operational status and fault warnings, thus providing an efficient and intuitive solution for the operation and maintenance of ship equipment.

Through this design, real-time monitoring and visualisation of the operational status of ship equipment can be realised. The system features an intuitive interface and efficient data processing capabilities, enabling operators to promptly identify and resolve equipment issues, thereby enhancing the safety and efficiency of ship operations.

INCORPORATION OF USER TESTING AND FEEDBACK

In the development process of the digital twin-based ship equipment visualisation monitoring system, the incorporation of user testing and feedback was crucial. As shown in Fig. 7, we first collected information on the needs and expectations of target users (such as operators and maintenance personnel) through user interviews and surveys to gain a deeper understanding of their pain points and key concerns in terms of equipment monitoring. Subsequently, we designed low-fidelity and high-fidelity prototypes and invited users to participate in task-driven tests, in order to observe their performance and gather feedback while they were completing specific operations. By analysing the user behaviour data from the system, we identified usage barriers and optimisation opportunities.

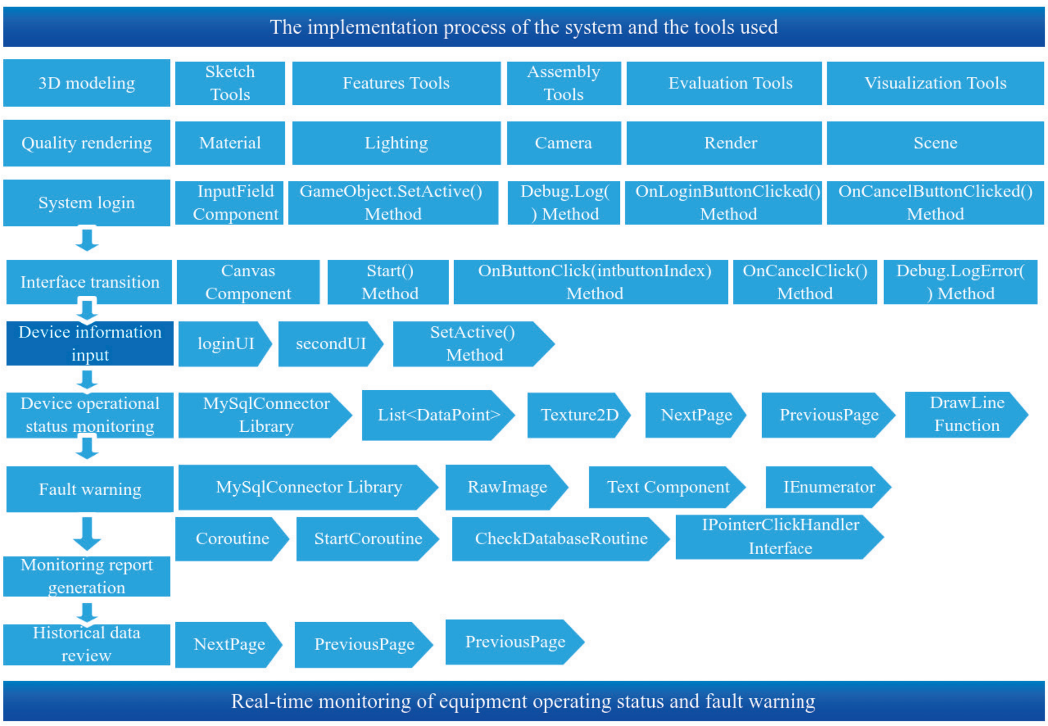

Fig. 6 System implementation process and tools used

In addition, we integrated a feedback mechanism within the platform, allowing users to submit comments and suggestions at any time, thereby creating a continuous feedback loop. Regular usability testing and A/B testing will further validate the effectiveness of system improvements, ensuring the platform undergoes continuous iteration to better meet the user's needs. Ultimately, through these systematic methods, we aimed to build an efficient and user-friendly visualisation monitoring system that enhances the current capabilities in terms of monitoring and prediction of the ship's equipment.

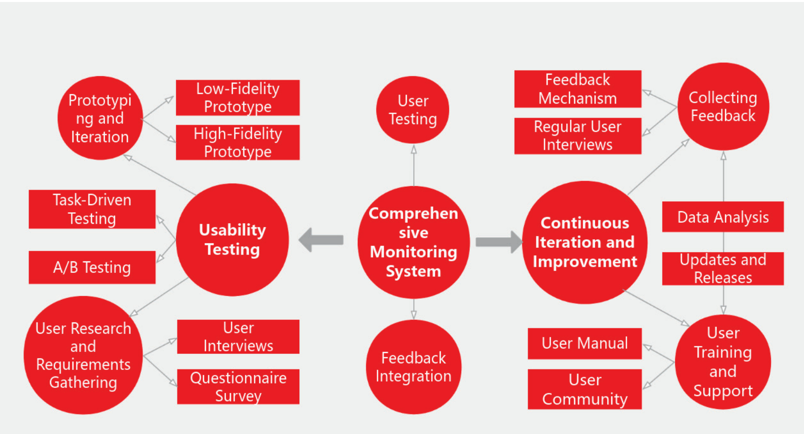

Fig. 7 Methods of incorporating user testing and feedback

Through the specific methods shown above, user testing and feedback could be effectively incorporated into the development process of the visualisation operation monitoring platform. By continuously focusing on user experience and conducting regular user research and iterative updates, the platform can become better aligned with the user's needs, thus enhancing the overall user satisfaction.

SECURITY AND PRIVACY PROTECTION

When designing the digital twin-based visualisation monitoring system for ship equipment, security and privacy protection were core considerations. As shown in Fig. 8, we adopt a multi-layered security architecture to ensure the safety of data transmission. By implementing encryption technology, we ensure that all data transmission from sensors to the monitoring platform will be done securely, to prevent unauthorised access. In addition, role-based access control (RBAC) is implemented to ensure that only authorised users can access sensitive data and functionalities. This mechanism can effectively reduce potential security risks.

To ensure privacy protection, data anonymisation and de-identification processes are implemented in the system to ensure that the identity information of users and devices is protected during analysis and storage. Regular security audits and risk assessments are also conducted to identify and address potential security vulnerabilities. Furthermore, users can be granted transparent rights to access and manage their data, allowing them to view and control how their personal data are used at any time. Through these comprehensive measures, we can create a secure and reliable monitoring system to ensure that the process of monitoring the ship's equipment is both efficient and compliant with best practices for security and privacy.

In a digital twin technology application, ensuring data security and privacy protection is fundamental to maintaining user trust and system reliability. A series of solutions, including encryption, access control, data anonymisation, and compliance with laws and regulations, can effectively enhance the security of digital twin systems and improve the level of user privacy protection. This not only helps safeguard user data but also promotes the sustainable development and widespread application of digital twin technology.

CASE STUDY: YACHT EQUIPMENT

We conducted a case analysis of specific equipment on yachts, taking the digital twin monitoring and management of yacht fans and pumps as examples. As shown in Fig. 9,

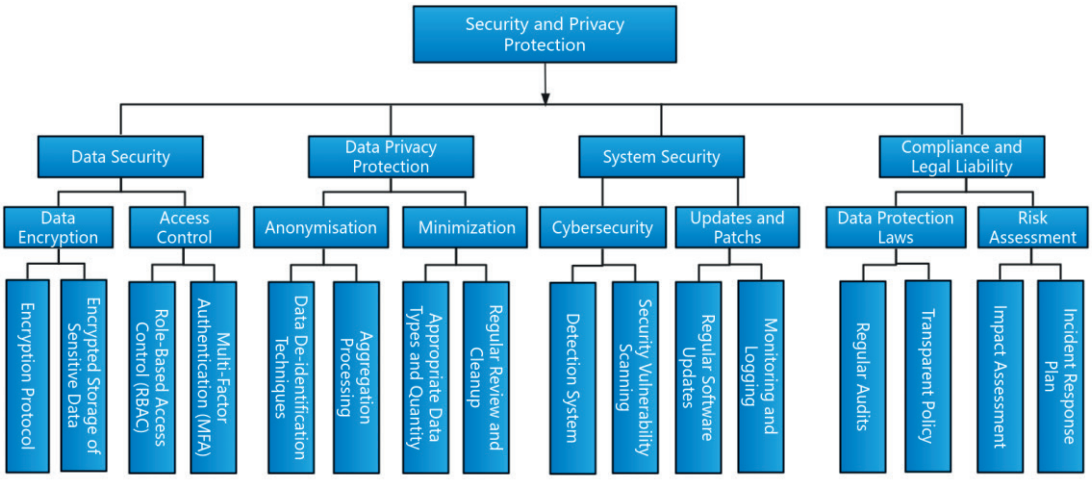

Fig. 8 Security and privacy protection

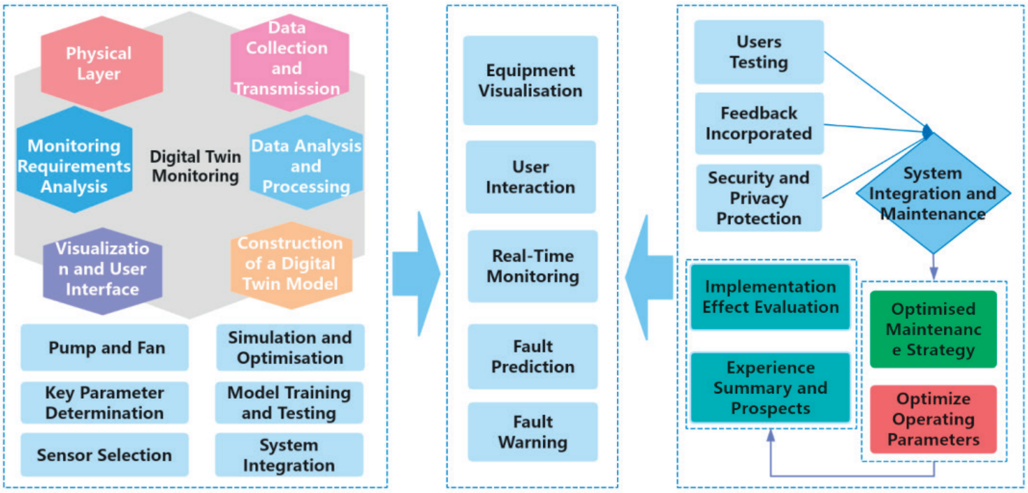

Fig. 9 Architecture of the proposed comprehensive monitoring system

the architecture of our comprehensive monitoring system involves the installation of smart sensors at the physical layer, allowing us to collect real-time operational data from the fans and to construct a digital twin model for them. This model accurately reflects the operational status of the equipment and predicts potential faults through data analysis, enabling preventive maintenance. Monitoring of the water pumps is equally critical, and vibration sensor monitoring is used to ensure efficient operation and reduce failure rates.

By integrating real-time data on these two types of equipment into the comprehensive monitoring system, we not only enhanced the safety and reliability of equipment operation but also provided important evidence for subsequent maintenance decisions. This case analysis demonstrates the value of practical applications of digital twin technology in yacht equipment management, and lays the foundation for improving the overall operational efficiency.

CONSTRUCTION OF THE DIGITAL TWIN MODEL

A sensor system was installed on the yacht's fan and water pump to collect vibration data in real time. The data were transmitted to the data storage layer via wireless communication technology, for storage and processing.

Using the data collected from the fan and water pump, a digital twin model was constructed, as shown in the fan equipment model in Fig. 10. The model includes information on the fan's geometric structure, operating status, and environmental parameters. Through simulation and analysis, the PSO-SVM-based time series prediction monitoring method was used to achieve a comprehensive understanding of the fan's operating status.

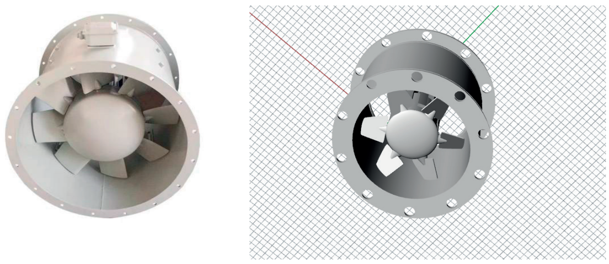

Fig. 10 Physical model and digital twin model of the wind turbine equipment

HUMAN-COMPUTER INTERACTION TESTING OF THE PROPOSED MONITORING SYSTEM FOR WIND TURBINE EQUIPMENT

Fig. 11 shows the application that was created. By double-clicking on the icon, the user can display the login interface for the ship's fan operating monitoring system. During the human-computer interaction process, users input the corresponding username and password to gain access, as illustrated in Fig. 12.

Fig. 11 Comprehensive monitoring system program

Fig. 12 Program access screen

Upon entering the fan operating monitoring system, the user sees that there are a total of four measurement points set for the ship's fan, as shown in Figs. 13 and 14. Sensors at these four measurement points monitor the vibration data, which are saved to the database in real time.

At the bottom, Measurement Points 1, 2, 3, and 4 are connected to the database, and vibration data curves for the four measurement points are displayed at a rotational speed of 1000 r/min. Each vibration curve graph has a corresponding time label that appears every five minutes, and 30 minutes of vibration data are displayed at a time. The blank area following Measurement Points 1, 2, 3, and 4 allows users to move the curve to review historical data, with the corresponding time label changing accordingly.

The four horizontal bars in the middle are scrolling indicators for the four measurement points, which update with the latest monitoring data. Above the scrolling bars, the current monitoring data for the four measurement points are displayed. At the bottom in the centre, there are four buttons that control the ship's fan model, which allow the user to rotate it through different angles. In the upper right corner, there is a button marked "Monitoring Report"; clicking this button displays the current status of the ship's fan and allows the user to download the report.

Fig. 13 Operation monitoring of the fan at 1000 r/min

The vibration range for the four measurement points is shown as follows: if the vibration data fall within the specified range, the curve is light blue; if the vibration data exceed the limit, the curve is displayed in red. If a continuous sequence of 10 data points outside the vibration range is recorded at all four measurement points, a fault warning button will pop up, as shown in Fig. 15.

Before the fault is resolved, clicking the fault warning button will cause it to disappear, but it will reappear after 10 s (this interval can be modified through the backend code). Once the system is accessed, any detection of a fault will trigger a fault warning to pop up on any visual interface. Fig. 16 shows a maintenance report.

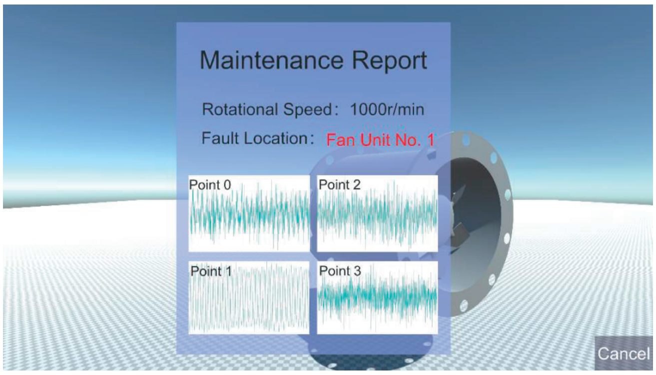

Fig. 16 Maintenance report

HUMAN-MACHINE INTERACTION TESTING OF THE SECOND-GENERATION INTEGRATED MONITORING SYSTEM FOR PUMPS BASED ON A DIGITAL TWIN

In the proposed system, the human-machine interaction mode for the pump system is similar, as shown in Fig. 17. Interactive buttons are used to represent the various operational functions, with a primary focus on intuitive viewing of the twin model and monitoring of data. Fault data are classified and displayed as illustrated in Fig. 18: normal data are shown in green, while abnormal data are represented in red, and trigger a warning.

The monitoring time for the data will change in real time below the corresponding data curves, and relevant fault reports are generated as depicted in Fig. 19.

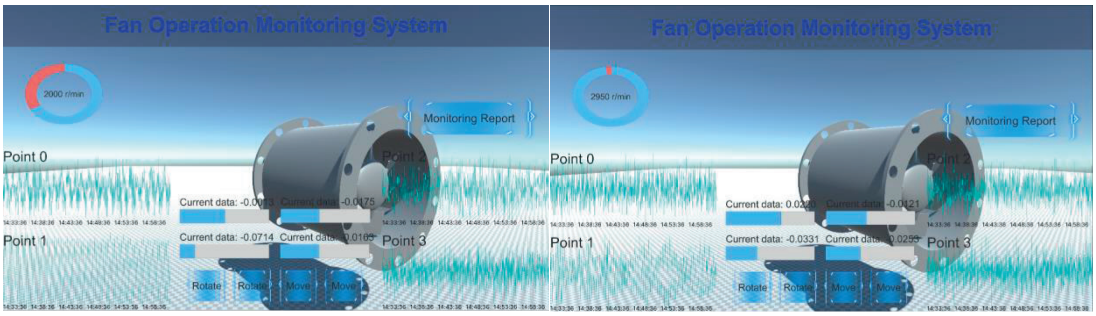

Fig. 14 Operation monitoring of the fan at 2000 and 2950 r/min

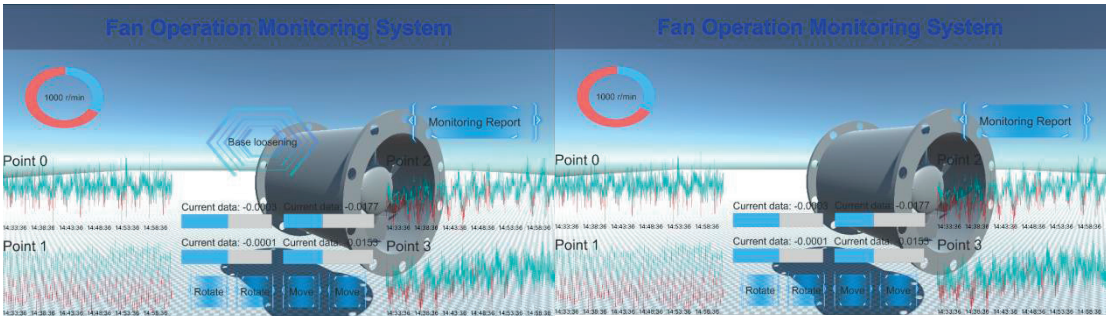

Fig. 15 Fault warning

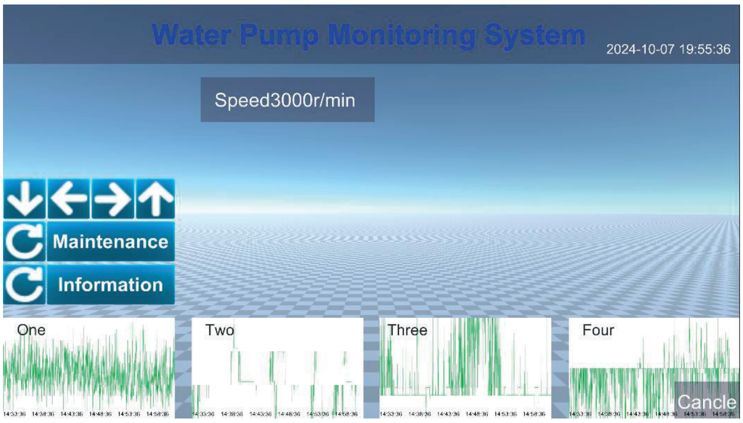

Fig. 17 Human-machine interaction interface of the pump visualisation system

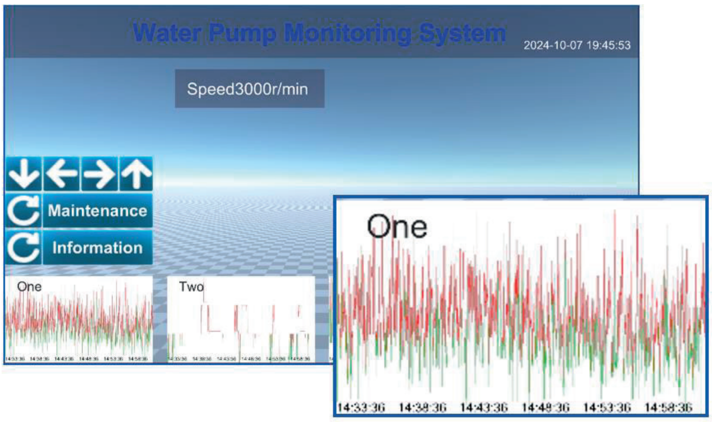

Fig. 18 Classification display of pump fault data

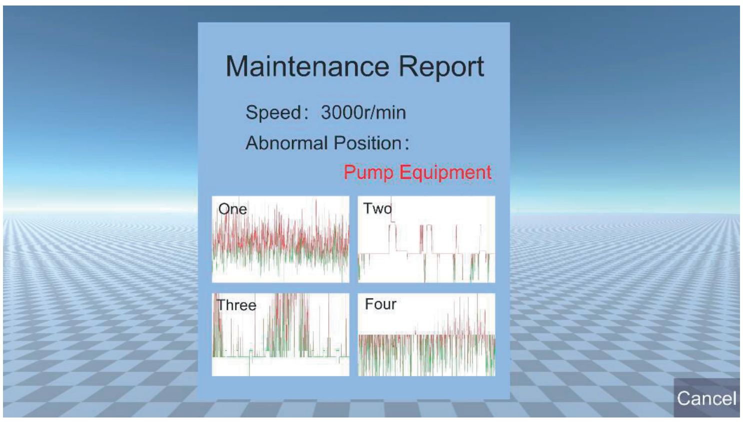

Fig. 19 Fault report

CONCLUSION

This study has focused on a comprehensive monitoring system for ship equipment, and has explored various aspects of system design, implementation, and application. Through an in-depth analysis of data-driven models and operational monitoring systems, we can draw the following main conclusions:

1. The time series forecasting method based on PSO-SVM demonstrated good predictive capabilities in terms of monitoring the operation of yacht equipment. The use of threshold methods for fault warning significantly improved the accuracy of fault detection.
2. By establishing detailed twin models and virtual scenarios, a visualisation and simulation platform for equipment monitoring was developed. The twin models not only facilitated real-time monitoring of equipment status but also effectively supported fault warning and maintenance decision-making. The construction of virtual scenarios ensured the accuracy and reliability of the models, effectively enhancing the overall functionality of the system.
3. The design of the comprehensive monitoring system took into consideration the need for real-time monitoring of the equipment operating status, fault warning, and data analysis functions, and advanced modelling, data processing, and visualisation technologies were employed. The results of online operational testing indicated that the design met the practical requirements for yacht equipment monitoring, as it demonstrated high stability and accuracy.
4. The effective integration of user testing and feedback mechanisms further enhanced the system's functionality and user experience. At the different stages of development of the system, we collected user operation feedback through multiple rounds of testing and optimised the system based on actual usage, thereby improving the usability and interaction experience. In addition, user feedback helped us to identify potential areas for system improvement, providing strong support for future iterations.
5. Security and privacy protection were crucial considerations in the system design. When processing real-time data from ship equipment, the system

applies a multi-layered encryption and authentication mechanism to ensure the security of data transmission and the privacy of sensitive information. The RBAC mechanism further restricts different users' access to system functionalities, thus ensuring the system's security during actual operation.

6. Through specific case studies of yacht water pumps and fans, the effectiveness of the comprehensive monitoring system in practical applications was validated. Twin models were constructed for water pumps and fans, and system operation testing was conducted to demonstrated that the system could accurately capture changes in equipment operating status and issue fault warnings in a timely manner, thereby enhancing the reliability and maintenance efficiency of the equipment.

In summary, the comprehensive monitoring system for ship equipment proposed in this study exhibits strong practicality and advanced capabilities, providing effective support for fault diagnosis, performance optimisation, and maintenance decision-making for ship equipment. Future work could focus on further optimising the system's functionality, expanding its range of application, and validating it across more types of marine equipment to enhance its universality and adaptability. In addition, continuous improvements to the user testing feedback mechanisms and data security measures will be essential to ensure the stable operation and safety of the system in various environments.

REFERENCES

1. Lv Z, Lv H, Fridenfalk M. Digital twins in the marine industry. Electronics 2023, 12(9), 2025. https://doi.org/10.3390/electronics12092025

2. Madusanka NS, Fan Y, Yang S, Xiang X. Digital twin in the maritime domain: A review and emerging trends. Journal of Marine Science and Engineering 2023, 11(5), 1021. https://doi.org/10.3390/jmse11051021

3. Zhong D, Xia Z, Zhu Y, Duan J. Overview of predictive maintenance based on digital twin technology. Heliyon 2023, 9(4). https://doi.org/10.1016/j.heliyon.2023.e14534

4. Karatuğ Ç, Arslanoğlu Y, Soares CG. Review of maintenance strategies for ship machinery systems. Journal of Marine Engineering & Technology 2023, 22(5), 233-47. https://doi.org/10.1080/20464177.2023.2180831

5. Hasan A, Asfihani T, Osen O, Bye RT. Leveraging digital twins for fault diagnosis in autonomous ships. Ocean Engineering 2024, 292, 116546. https://doi.org/10.1016/j.oceaneng.2023.116546

6. Kinaci OK. Ship digital twin architecture for optimizing sailing automation. Ocean Engineering 2023, 275, 114128. https://doi.org/10.1016/j.oceaneng.2023.114128

7. Liu Y, Ren H. Rapid acquisition method for structural strength evaluation stresses of the ship digital twin model. Ocean Engineering 2023, 285, 115323. https://doi.org/10.1016/j.oceaneng.2023.115323

8. Li Y, Zhang W, Cui L, Gao H. System reliability modeling and analysis for a marine power equipment operating in a discrete-time dynamic environment. Quality and Reliability Engineering International 2024, 40(6), 3422-38. https://doi.org/10.1002/qre.3577

9. Zhou Q, Li H, Zeng X, Li L, Cui S, Du Z. A quantitative safety assessment for offshore equipment evaluation using fuzzy FMECA: A case study of the hydraulic submersible pump system. Ocean Engineering 2024, 293, 116611. https://doi.org/10.1016/j.oceaneng.2023.116611

10. Deng J, Liu S, Shu Y, Hu Y, Xie C, Zeng X. Risk evolution and prevention and control strategies of maritime accidents in China's coastal areas based on complex network models. Ocean & Coastal Management 2023, 237, 106527. https://doi.org/10.1016/j.ocecoaman.2023.106527

11. Zhang D. Fault diagnosis of ship power equipment based on adaptive neural network. International Journal of Emerging Electric Power Systems 2022, 23(6), 779-91. https://doi.org/10.1515/ijeeps-2022-0103

12. Nejad AR, Purcell E, Valavi M, Hudak R, Lehmann B, Gutiérrez Guzmán F, et al. Condition monitoring of ship propulsion systems: State-of-the-art, development trend and role of digital twin.International Conference on Offshore Mechanics and Arctic Engineering: American Society of Mechanical Engineers, 2021. V007T07A05. https://doi.org/10.1115/OMAE2021-61847

13. Lee S, Lee T, Kim J, Lee J, Ryu K, Kim Y, et al. A study on the application of discrete wavelet decomposition for fault diagnosis on a ship oil purifier. Processes 2022, 10(8), 1468. https://doi.org/10.3390/pr10081468

14. Kang Y-J, Noh Y, Jang M-S, Park S, Kim J-T. Hierarchical level fault detection and diagnosis of ship engine systems. Expert Systems with Applications 2023, 213, 118814. https://doi.org/10.1016/j.eswa.2022.118814

15. Karatuğ Ç, Arslanoğlu Y, Soares CG. Design of a decision support system to achieve condition-based maintenance in ship machinery systems. Ocean Engineering 2023, 281, 114611. https://doi.org/10.1016/j.oceaneng.2023.114611

16. Ji Z, Gan H, Liu B. A deep learning-based fault warning model for exhaust temperature prediction and fault warning of marine diesel engine. Journal of Marine Science and Engineering 2023, 11(8), 1509. https://doi.org/10.3390/jmse11081509

17. Duan X, Gao Z, Qiao Z, Du T, Zou Y, Zhang P, et al. A study of adaptive threshold based on the reconstruction model for marine systems and their equipment failure warning. Journal of Marine Science and Engineering 2024, 12(5), 742. https://doi.org/10.3390/jmse12050742

18. Whaiduzzaman M, Sakib A, Khan NJ, Chaki S, Shahrier L, Ghosh S, et al. Concept to reality: An integrated approach to testing software user interfaces. Applied Sciences 2023, 13(21), 11997. https://doi.org/10.3390/app132111997

19. Pushpakumar R, Sanjaya K, Rathika S, Alawadi AH, Makhzuna K, Venkatesh S, et al. Human-computer interaction: Enhancing user experience in interactive systems. E3S Web of Conferences: EDP Sciences, 2023, 04037. https://doi.org/10.1051/e3sconf/202339904037

20. Sharma R, Arya R. Security threats and measures in the Internet of Things for smart city infrastructure: A state of art. Transactions on Emerging Telecommunications Technologies 2023, 34(11), e4571. https://doi.org/10.1002/ett.4571

21. Sheng B, Yin X, Zhang C, Zhao F, Fang Z, Xiao Z. A rapid virtual assembly approach for 3D models of production line equipment based on the smart recognition of assembly features. Journal of Ambient Intelligence and Humanized Computing 2019, 10, 1257-70. https://doi.org/10.1007/s12652-018-0753-z

22. Liu X, Jiang D, Tao B, Xiang F, Jiang G, Sun Y, et al. A systematic review of digital twin about physical entities, virtual models, twin data, and applications. Advanced Engineering Informatics 2023, 55, 101876. https://doi.org/10.1016/j.aei.2023.101876

23. Chu C-H, Liu Y-L. Augmented reality user interface design and experimental evaluation for human-robot collaborative assembly. Journal of Manufacturing Systems 2023, 68, 313-24. https://doi.org/10.1016/j.jmsy.2023.04.007

24. Katipoğlu OM, Yeşilyurt SN, Dalkılıç HY, Akar F. Application of empirical mode decomposition, particle swarm optimization, and support vector machine methods to predict stream flows. Environmental Monitoring and Assessment 2023, 195(9), 1108. https://doi.org/10.1007/s10661-023-11700-0