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Article

Shipbuilding enterprise innovation management: Product R&D and market expansion strategies driven by machine learning, molecular science, and biomechanics

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Abstract: Background: With the increasing competition in the shipbuilding industry, enterprises are facing more stringent environmental protection requirements and challenges posed by the marine environment, particularly the corrosion of ship materials caused by microorganisms in seawater. This creates an urgent need for innovation management to introduce new technologies that can enhance the corrosion resistance of ships, extend their service life, and reduce maintenance costs. **Objective:** This paper aims to explore how molecular science and biomechanics can drive product research and development in the shipbuilding industry, especially in addressing the issue of seawater microbial corrosion, thereby promoting technological progress and market expansion for enterprises. **Method:** This study adopts a combination of case analysis and technological application research, focusing on how molecular technology can be used to develop antibacterial and anti-corrosive ship materials. It also investigates how biomechanics, through biomimetic principles, can enhance the adaptability and durability of ship designs. Additionally, the paper explores the application of molecular science and biomechanics in hull design, examining how nature's biological defense mechanisms can be mimicked to design more corrosion-resistant, low-maintenance ship structures. **Innovation:** This paper systematically applies molecular technology and biomechanics to the shipbuilding sector, proposing new technical approaches for the prevention and control of seawater microbial corrosion. This not only effectively enhances the durability and environmental performance of ships but also reduces operational costs. **Results:** By developing novel anti-corrosion materials, molecular and biomechanical technologies significantly improved the adaptability of ships in marine environments and reduced microbial corrosion on hulls. The introduction of biomimetic design principles not only improved the structural stability of ships but also enhanced their performance in harsh marine conditions.

Keywords: shipbuilding; machine learning; molecular technology; biomechanics

1. Introduction

Shipbuilding is one of the key pillars of the global economy, playing a critical role in international trade and maritime transportation. With the acceleration of globalization and the continuous increase in shipping demand, the shipbuilding industry is facing increasingly fierce market competition. However, ships must endure the challenges of complex marine environments during their use, especially the issues of salt and microbial corrosion in seawater [1]. This not only affects the structural safety and durability of ships but also directly relates to energy efficiency and environmental performance. Metal materials are currently the most widely used corrosion-resistant materials in shipbuilding, but due to prolonged exposure to seawater, metal surfaces are prone to corrosion points [2–4]. As corrosion spreads, the service life and safety of ships are significantly reduced. Therefore, shipbuilding companies urgently need to address the challenge of seawater corrosion through innovative technological solutions to enhance product performance and strengthen their competitiveness in the global market.

In recent years, molecular technology and biomechanics, as interdisciplinary frontier technologies, have gradually infiltrated the shipbuilding field. Material genetics refers to a theoretical system formed through the systematic analysis and study of factors such as the material’s microstructure, properties, and processing methods, which can guide the design and development of new materials. Biomimetic micro-nano structures refer to artificial structures designed to mimic the characteristics of biological structures in nature at the micro or nano scale, using advanced manufacturing technologies such as nanotechnology and microfabrication techniques to achieve similar functions or properties. Molecular technology, by finely controlling the molecular structure of materials, not only enhances the corrosion resistance and antimicrobial attachment properties of ship materials but also enables the development of more environmentally friendly and sustainable shipbuilding materials. Biomechanics, through mimicking the protective mechanisms of biological organisms in nature, has introduced new ship design concepts and technologies, such as the development and optimization of biomimetic materials [5]. Particularly in the control of microbial corrosion, biomimetic design in biomechanics provides ships with highly effective protective solutions, reducing the corrosion threat they face in marine environments. At the same time, machine learning, as an important artificial intelligence technology, has been widely applied in multiple industries. For the shipbuilding industry, machine learning can effectively identify surface defects of ship materials through big data analysis and image recognition, predict the development trend of corrosion points, and optimize decision-making based on actual conditions [6]. This technology not only improves the efficiency of ship design and production and reduces labor input but also provides crucial technical support for ship maintenance, extending the service life of ships and reducing maintenance costs [7].

Therefore, integrating molecular technology, biomechanics, and machine learning to promote innovation management in shipbuilding enterprises is a crucial approach to improving ship performance, ensuring navigation safety, and enhancing market competitiveness [8]. By applying cutting-edge technologies, shipbuilding companies can break the limitations of traditional production methods, improve product quality while reducing environmental impact, and adapt to the ever-changing market demands. This not only provides new technological pathways for shipbuilding companies but also offers theoretical support and practical guidance for the sustainable development of the industry [9].

2. Ship corrosion situation

This chapter provides a systematic analysis of ship corrosion issues, covering three major aspects: the implicit components of seawater, corrosion symptoms of the internal structure of the hull, and microbial corrosion of other metallic materials in the hull. Ships are exposed to the dual effects of seawater corrosion and microbial corrosion over long periods in the marine environment, and the corrosion process is continuous and complex.

2.1. Corrosion from seawater's implicit components

The implicit components in seawater have a significant corrosive effect on ships and offshore structures. Seawater contains oxygen, salts, microorganisms, and other components, which, over long periods, can cause serious corrosion to materials. Oxygen reacts with the metal surface to form an oxide layer, while salts exacerbate this corrosion, particularly sodium chloride, which has a high concentration in seawater spray and is highly corrosive. Sodium chloride can widely penetrate the ship's structure, especially in coastal areas, where the corrosion can extend up to hundreds of miles [10]. If the harmful effects of seawater's implicit components are not identified in time and appropriate protective measures are not taken, the corrosion problem will worsen and may even lead to "hotbed corrosion", accelerating the aging and damage of ships or offshore engineering structures [11].

2.2. Corrosion symptoms of internal ship structures

The symptoms of seawater corrosion on ships mainly manifest as varying degrees of damage to the hull structure, equipment, and pipelines. First, corrosion on the ship's surface is often seen as rust, especially in areas that come into contact with seawater, such as the hull bottom and the waterline. After prolonged immersion in seawater, these areas gradually develop pitting or peeling, which, if severe, can weaken the local structure and cause cracks [12]. Additionally, different types of corrosion, such as pitting and cracking corrosion, may occur on the metal surface. These corrosion forms affect the ship's overall strength and stability. Furthermore, if the ship's coating system fails, it accelerates the corrosion process by causing the separation of the primer layer from the metal, creating larger corrosion areas. The ship's piping system, especially in the cooling system, often experiences leaks, blockages, or thinning of the pipe walls due to seawater corrosion [13]. Corrosion not only impacts the structural safety of ships but may also reduce system efficiency, potentially affecting the normal operation of the vessel. This paper reports on the corrosion symptoms in the ship's fuel, lubrication oil, bilge water, and ballast water systems.

Table 1. Corrosion symptoms in fuel, lubrication oil, bilge water, and ballast water systems.

Medium	Fuel system	Lubrication oil system	Bilge water and ballast water system
Visual	1. When microorganisms reach a certain biomass, they cause fuel discoloration, cloudiness, and contamination. 2. suspended in the oil phase. 3. Purifiers and coalescers related to clean fuel and water may malfunction. 4. Pitting corrosion of the storage tank.	1. The oil becomes slippery, and a slime layer and rust layer appear on the crankcase door. 2. A honey-colored film forms on the journal, which is later associated with pitting corrosion. 3. Black bacterial strains appear on the surface of white alloy bearings, pins, and journals. 4. Brown or gray deposits can be seen on metal parts.	1. A black slime layer and sludge layer form or become black after peeling off. 2. Pitting corrosion on the steel structure, pipelines, and the bottom. 3. Rapid corrosion of the electroplated layer.
Operation	1. Bacterial polymers will block the filters and throttle orifice plates within a few hours. 2. Contaminated filters, pumps, and injectors lead to failure. 3. Uneven fuel flow and fluctuations during combustion will accelerate the wear rate of the piston rings.	1. Additional wear. 2. Foul or sulfurous odor. 3. Increased oil acidity or sudden loss of alkalinity. 4. The purifier fails to reduce the water content in the oil. 5. Filter blockage under harsh weather conditions. 6. Ongoing demulsification issues. 7. Reduced heat exchange efficiency of the condenser.	1. Unusual fouling and sulfurous odor. 2. Structural damage. 3. Loss of suction in the pipeline.

2.3. Microbial corrosion of other metal materials in the hull

Microbial corrosion of other metal materials in the hull is a common corrosion phenomenon in marine environments, especially on metals such as stainless steel, aluminum, zinc, copper, and their alloys. Sulfate-reducing bacteria (SRB) are the primary microorganisms responsible for corrosion. They not only corrode steel materials but also cause varying degrees of damage to other metal alloys. Studies show that copper-nickel alloys (Cu-Ni alloys) are particularly sensitive to microbial corrosion, especially in seawater systems. The presence of SRB significantly accelerates the corrosion rate in these alloys [14]. Research conducted by the U.S. Naval Research Laboratory has found that when copper-nickel alloys corrode in seawater, the corrosion morphology and the composition of the corrosion products exhibit unique characteristics. Under the corrosion product film, ammonia-producing bacteria can even be isolated, further confirming the microbial corrosion effect on the alloy. Similarly, domestic studies have confirmed a significant increase in the corrosion rate of B10 alloys in SRB-containing media, with selective dissolution of iron and nickel elements in the alloy, forming sponge-like corrosion patterns [15].

Table 2. Examples of microbial corrosion at typical ship locations.

Location	Evidence				Corrosion rate (mm/a)
	Corrosive microorganisms	Microbial corrosion products	High corrosion rate	Related corrosion morphology	
Bilge plating		√	√		4
Fuel tank and associated equipment	√	√	√		
Fuel tank	√				
Bilge and engine room	√				
Bilge plating, sludge tank, drinking water tank	√		√	√	> 10
Bilge	√	√	√	√	
Engine cooling system		√	√		
Seawater cooling piping	√	√	√	√	2
Hull steel, ballast tank	√	√	√	√	8
Ballast tank	√	√	√		6
Cargo oil tank	√	√	√		2
Hull steel and bilge	√	√	√		22

Additionally, microbial corrosion of stainless steel often occurs at weld seams and heat-affected zones. Studies show that the microstructure and surface structure of stainless steel play a significant role in resistance to microbial corrosion, especially the properties of the passivation layer. Microorganisms such as algae, SRB, iron-oxidizing bacteria, and manganese-oxidizing bacteria on the surface of stainless steel can lead to the formation of local oxygen concentration cells, further exacerbating the corrosion process. Under the combined action of these microorganisms, pitting and crevice corrosion phenomena are particularly prominent. The formation of local precipitates and nodules can create small gaps, resulting in more severe corrosion areas. Examples of microbial corrosion at typical ship locations are shown in **Table 2**.

3. Research methods

Chapter 2 focuses on the performance requirements of ship materials and the importance of defect detection, particularly the application of corrosion-resistant materials in ships and their impact on ship safety. In this context, Chapter 3 shifts to specific detection methods and technologies, especially the design and application of ultrasonic infrared imaging detection devices. It introduces how to combine ultrasonic and infrared technologies to improve the accuracy and efficiency of defect detection. Additionally, Chapter 3 delves into how data-driven algorithms, particularly machine learning and the ELM model, can be used to predict and optimize the performance and corrosion rate of ship materials.

3.1. Infrared imaging acquisition method for ship materials

3.1.1. Introduction to the ultrasound infrared imaging detection device

In shipbuilding, detecting surface defects of corrosion-resistant materials is crucial for ensuring the safety and reliability of vessels. To effectively capture infrared images of corrosion-resistant ship materials, this study designs a collection method based on an ultrasonic infrared imaging detection device. This method combines ultrasonic technology with infrared thermography, improving defect identification accuracy and efficiency. The core of the ultrasonic infrared imaging detection device consists of three parts: an ultrasonic probe, an infrared thermal imager, and a pre-tensioning unit. The ultrasonic probe is used to emit high-frequency DC pulse signals, which are converted into high-frequency vibration pulses that act on the surface of the ship materials [16]. The vibration pulses cause small thermal response changes on the material surface, which will appear in the infrared images. The infrared thermal imager is responsible for scanning the material's surface, capturing real-time temperature distribution images, and detecting temperature differences caused by the ultrasonic excitation, allowing for subsequent analysis and defect identification. A schematic diagram of the ultrasonic infrared imaging detection device is presented in **Figure 1**.

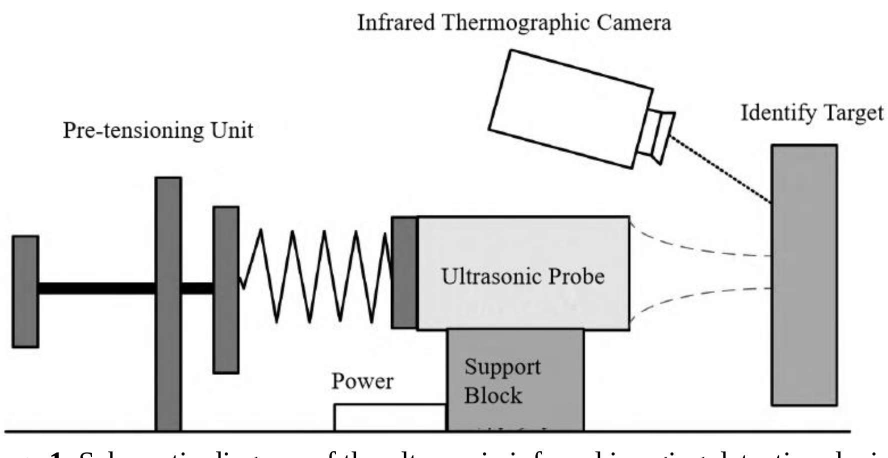


Figure 1. Schematic diagram of the ultrasonic infrared imaging detection device.

3.1.2. Calibration process of the ultrasound infrared imaging detection device

In order to ensure measurement accuracy, the ultrasound infrared imaging detection device must undergo strict calibration.

First, the infrared thermal imager and ultrasound gun need to be initialized. The temperature response range of the infrared thermal imager typically spans from −20 °C to +100 °C, with an accuracy requirement of 0.05 °C. By comparing it with a standard blackbody radiation source, the infrared thermal imager's temperature measurement accuracy is ensured. The transmission frequency and power of the ultrasound gun must be adjusted based on the thickness and properties of the material. Common frequencies range from 20 kHz to 50 kHz, and the power is set between 10 and 100 W to ensure effective signal propagation.

During the temperature response calibration, a standard sample with known defects is used for testing to ensure the infrared thermal imager can detect temperature differences of at least 0.2 °C. To avoid environmental temperature interference, the laboratory temperature should be controlled between 20 °C ± 2 °C. The ultrasound signal propagation calibration is carried out by adjusting the emission angle and contact pressure of the ultrasound gun, ensuring uniform signal transmission and inducing an effective thermal response. The contact pressure is generally controlled between 0.5 and 2 N/cm^2.

Once calibration is complete, the accuracy of the device is verified using standard defect samples. By comparing the location, size, and temperature difference of the defects, it ensures that the ultrasound infrared imaging detection device's measurements align with the actual defects. Finally, the reliability and accuracy of the device are verified by comparing the results with other detection methods, such as ultrasound or X-ray.

3.1.3. Data processing of the ultrasound infrared imaging detection device

First, the collected infrared images are pre-processed using median filtering or Gaussian filtering to remove noise and eliminate environmental interference. Background correction is then performed to remove the influence of background temperature fluctuations, highlighting the temperature differences caused by defects.

Next, a threshold segmentation method is used to identify regions that may contain defects, and Canny edge detection or Sobel operators are employed to extract the shape features of the defects. For irregularly shaped defects, morphological operations are used for correction to ensure clear edges in the image.

During the temperature difference analysis phase, the temperature difference between the defect area and the normal area is calculated to assess the strength of the thermal response of the defect. The depth and severity of the defect are further analyzed through temperature gradient analysis.

Subsequently, combining ultrasound excitation signals, correlation analysis, or Principal Component Analysis (PCA) is used to pair the ultrasound signals with the infrared thermal responses, predicting the depth and location of the defect.

Finally, cross-validation with traditional detection methods (such as ultrasound or X-ray CT) is performed, and statistical tests are used to evaluate the accuracy of the results, ensuring the precision and reliability of the detection. Common evaluation metrics include accuracy, sensitivity, specificity, and false positive rate.

3.2. Bilateral filter and adaptive edge compensation infrared image enhancement method

In order to improve the resolution and contrast of infrared images of corrosion-resistant ship materials, an image enhancement method combining bilateral filtering and adaptive edge compensation is adopted. First, the bilateral filter is used to denoise the infrared image, eliminating the interference noise generated during the collection process. Specifically, the filtering expression uses a weighted average of the spatial proximity factor and the grayscale similarity factor to denoise, effectively removing the noise in the image. The denoised image can be represented as $Q_{\text{out}}(x, y)$.

$$Q_{\text{out}}(x, y) = \frac{\sum_{(i,j)\in M_{x,y}} w_s(i,j)w_r(i,j)Q(x,y)}{\sum_{(i,j)\in M_{x,y}} w_s(i,j)w_r(i,j)},$$

where $Q_{\text{out}}(x, y)$ represents the filtered and denoised infrared image of the corrosion-resistant ship material, with *x* and *y* indicating the pixel coordinates; *i* and *j*.

Next, to enhance the image edges, an adaptive edge compensation method is applied. By calculating the deviation $\Delta Q(x, y)$ between the filtered image and the original image, the edge differences of the image are obtained, and the edge compensation factor is determined based on the sum of spatial grayscale similarity factors. The edge compensation factor $C(x, y)$ is dynamically adjusted according to the edge characteristics of the image, allowing for adaptive enhancement.

$$C(x, y) = \frac{h_i \times h_j - w_{\text{sum}}(x, y)}{\varepsilon \times h_i \times h_j}.$$

Finally, the filtered image is corrected using the edge compensation factor to obtain the infrared image $Q_{\text{cm}}(x, y)$ with adaptive compensation. This process not only removes the noise but also enhances the defect details in the image, making the defects in the corrosion-resistant ship materials clearer and providing higher-quality image data for subsequent defect recognition.

$$Q_{\text{cm}}(x, y) = Q_{\text{out}}(x, y) + R(x, y).$$

In the formula, $Q_{\text{cm}}(x, y)$ is the corrected infrared image of the corrosion-resistant ship material is represented.

This paper also provides performance evaluation, including signal-to-noise ratio (SNR), edge detection accuracy, and structural similarity index (SSIM).

The signal-to-noise ratio is used to measure the ratio of noise to the true signal in the image, and the formula is as follows:

$$\text{SNR} = 10\log_{10}\left(\frac{\sum_{x,y} Q_{\text{orig}}(x, y)^2}{\sum_{x,y}(Q_{\text{orig}}(x, y) - Q_{\text{denoised}}(x, y))^2}\right).$$

Edge detection accuracy can be quantified by comparing the edge overlap between the enhanced image and the original image, and the formula is as follows:

$$\text{Edge precision} = \frac{\text{True positive edges}}{\text{The positive edges+False positive edges}}.$$

The SSIM index measures the similarity in brightness, contrast, and structure between two images. A value closer to 1 indicates higher similarity between the two images. The formula is:

$$\mathrm{SSIM}\left(Q_{\mathrm{orig}}, Q_{\mathrm{enhanced}}\right) = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}.$$

3.3. Data-driven shipbuilding modeling algorithm

Data-driven shipbuilding modeling algorithms have increasingly become a key technology in the modern shipbuilding industry, particularly in improving the performance of ship materials, optimizing production processes, and enhancing manufacturing precision. The development and production environment of ship materials is complex, involving various requirements such as corrosion resistance, anti-pollution, weight reduction, and high strength. Traditional material research methods often rely on a ‘trial-and-error’ process, which is time-consuming, costly, and difficult to control accurately. Data-driven modeling algorithms, through the collection, processing, and analysis of massive amounts of material and production data, can effectively predict material performance in the early stages of ship design, optimize the process flow, and greatly improve production efficiency [17].

First, data-driven modeling algorithms rely on the construction of a comprehensive material database that includes the composition, processing techniques, and corresponding physical, chemical, and mechanical properties of the materials. The database not only contains data on existing materials but also includes real-time data obtained from experiments and production processes. Through data cleaning, standardization, and other preprocessing steps, the accuracy and usability of the data are ensured. Based on this high-quality data, researchers can build a set of descriptors that quantify the various characteristics of the materials and provide a foundation for subsequent predictive models.

In the process of establishing predictive models, selecting appropriate machine learning algorithms is crucial. Common algorithms, such as regression analysis, support vector machines (SVM), and random forests, can precisely predict both macroscopic and microscopic material properties. In some more complex material designs, intelligent optimization algorithms such as genetic algorithms and particle swarm optimization are used to further improve the accuracy and reliability of the models. Through these data-driven algorithms, the performance of ship materials can be predicted during the design phase, reducing the trial-and-error process common in traditional methods. The data-driven modeling algorithm is shown in **Figure 2**.

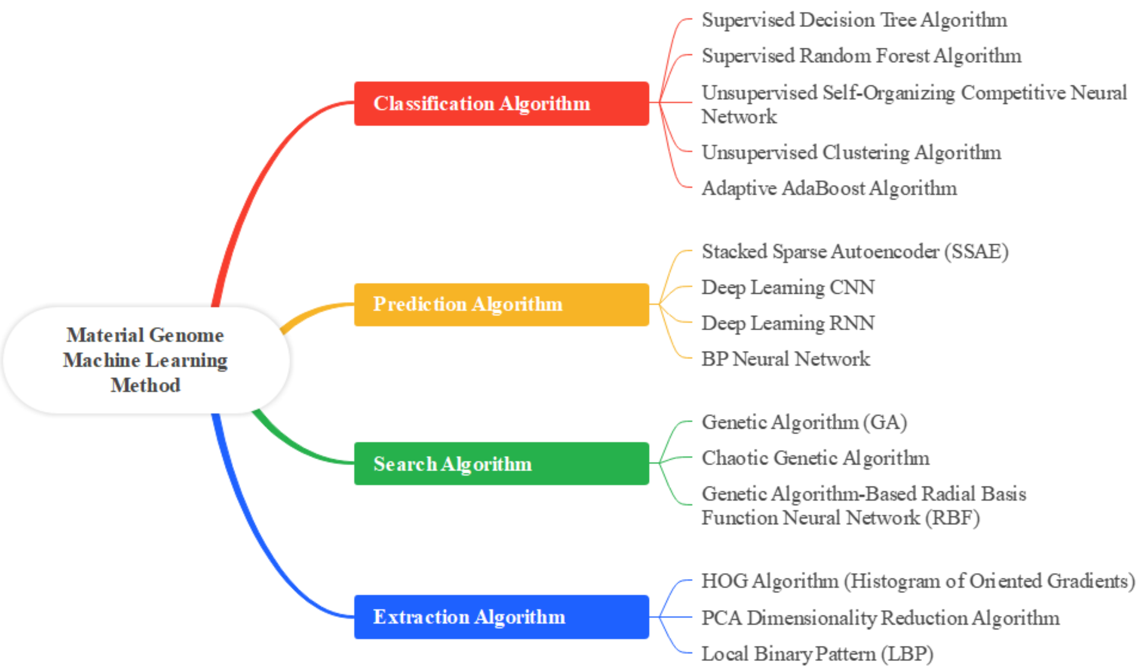


Figure 2. The data-driven modeling algorithm.

3.4. ELM prediction model for corrosion rate

ELM (Extreme Learning Machine) is a learning algorithm used for Single-Layer Feedforward Neural Networks (SLFN). The steps of the ELM algorithm are as follows:

First, initialization. The weights W and biases b of the hidden layer nodes are randomly generated. These values are typically randomly initialized and are not updated during training. The number of hidden layer nodes, N, is also set.

Second, input and hidden layer mapping. Given an input sample set $X = [x_1, x_2, ..., x_m]$, where each input x_i is an n-dimensional vector (i.e., $x_i \in R_n$). The activation function g (usually choosing Sigmoid, ReLU, or other activation functions) is applied to map the input to the hidden layer, resulting in the hidden layer output matrix $H = [h_1, h_2, ..., h_m]$, where each column h_i is the hidden layer output corresponding to input x_i, expressed as:

$$h_i = g(W * x_i + b).$$

where W is the weight matrix of the hidden layer, b is the bias, and h_i is the hidden layer output after applying the activation function.

Third, compute the output weights. Suppose the target of the output layer is $T = [t_1, t_2, ..., t_m]$, where each *ti* is the desired output.

To solve for the output layer weights β, we typically use the least squares method to solve the following linear equation:

$$H \times \beta = T.$$

where β is the weight vector of the output layer, which can be obtained by solving this equation, often using the pseudo-inverse of the matrix.

$$\beta = (H^T H)^{-1} H^T H.$$

Fourth, prediction. For a new input sample x_{new}, the hidden layer output is first calculated:

$$h_{\text{new}} = g(W \times x_{\text{new}} + b).$$

Then, the network's output is computed:

$$\hat{y}_{\text{new}} = h_{\text{new}} \times \beta.$$

3.5. Corrosion rate prediction framework

The corrosion rate prediction framework is based on a generalized gray relational analysis and an optimized model using an Extreme Learning Machine (ELM) network, aimed at predicting the corrosion rate of subsea pipelines. This framework demonstrates the overall process of data preprocessing, model construction, optimization algorithms, and prediction outputs, enabling precise prediction of the corrosion rate in subsea pipelines and providing strong support for early warning and maintenance decision-making for pipeline corrosion, as shown in **Figure 3**.

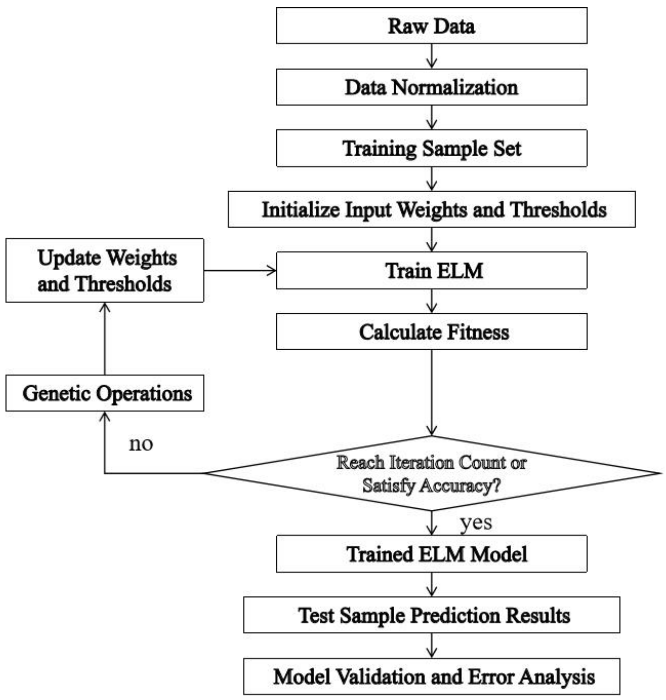


Figure 3. Corrosion rate prediction framework diagram.

4. Research results

Chapter 3 primarily explores the corrosion mechanisms of ship materials and their influencing factors, with a focus on analyzing the corrosion process of materials in the marine environment and traditional corrosion protection techniques. Chapter 4 shifts the focus to specific research outcomes and technological applications. It first presents the application pathway of material genomics in ship material development and further discusses how to improve corrosion prediction and defect detection accuracy under conditions of data scarcity and image noise by introducing the Extreme Learning Machine (ELM) model and infrared image processing technology, thus achieving more precise and efficient ship maintenance and management.

4.1. Application route of material gene in ship and equipment

The application route of material genes in ships and equipment mainly includes the following steps: First, analyze the material requirements of the ship and clarify performance indicators such as corrosion resistance, anti-fouling, weight reduction, etc. Based on the material needs, optimize the material formula and processing technology using material databases and high-throughput computational methods, establishing a quantitative relationship between material performance and formulation. Next, use virtual testing technology for preliminary performance verification, simulating actual service conditions on a virtual platform to reduce testing costs. Finally, perform physical testing to ensure that the material's performance meets the requirements in practical applications [18]. By combining data, computation, and experimentation, the research accelerates the development of ship materials, improving material performance and reducing costs.

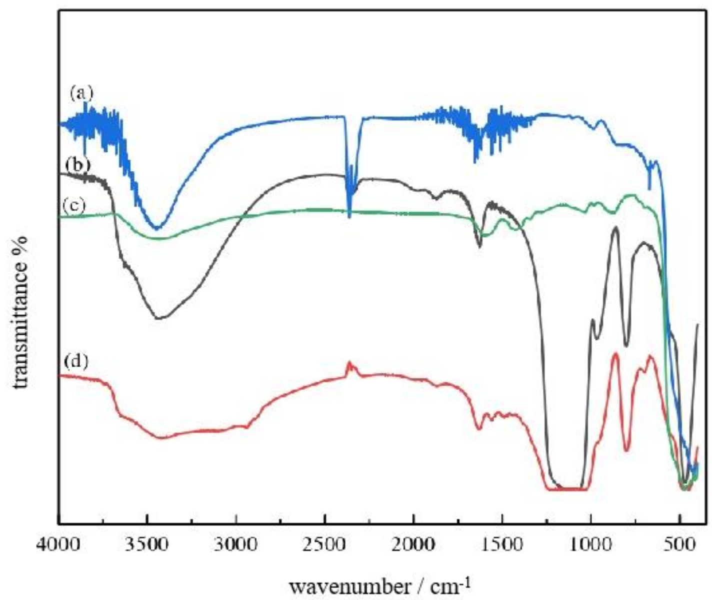
4.2. Anti-fouling performance of biomimetic micro-nano structured super-duplex hydrophobic coating

4.2.1. Biomimetic micro-nano structured super-duplex hydrophobic coating

The biomimetic micro-nano structured super-duplex hydrophobic coating is a type of anti-fouling coating based on a composite material of polydimethylsiloxane (PDMS) and epoxy resin (EP). By mimicking the microstructures on the surfaces of plants and animals in nature, nanoparticles and various mass fractions of additives are used to create a coating with super-duplex hydrophobic properties. The low surface energy of PDMS endows the coating with excellent water-repellent properties, while epoxy resin improves the adhesion strength of the coating to the substrate, solving the problem of poor mechanical properties and insufficient adhesion of low-surface-energy coatings. The coating's mechanical performance is enhanced by incorporating nano-fillers, which increase surface roughness and improve its anti-fouling effect. Research shows that the micro-nano structure of the coating exhibits significant self-cleaning properties and effectively resists biofouling. Experimental tests, including static and dynamic immersion tests, have proven the superior anti-fouling performance of the coating, demonstrating its potential as an environmentally friendly anti-fouling coating.

4.2.2. FTIR analysis of biomimetic micro-nano structured super-duplex hydrophobic coating

The design of the biomimetic micro-nano structured super-duplex hydrophobic coating primarily achieves efficient anti-fouling effects through the surface modification of nanoparticles. The coating uses nano-SiO_2 and nano-ZnO as the base materials, and they are hydrophobically modified by PFDTMS and APTES to enhance the coating's anti-fouling performance. Through infrared spectroscopy analysis, it was found that before modification, the surfaces of nano-ZnO and nano-SiO_2 contained many hydroxyl (O–H) groups, which may cause water molecule adsorption in the anti-fouling coating, thereby reducing hydrophobicity. After modification, PFDTMS and APTES effectively reduce the number of hydroxyl groups on the surfaces, forming C=C bonds and Si–C bonds on ZnO and SiO_2, respectively. These changes were confirmed by characteristic absorption peaks in the infrared spectrum. For example, the O–H absorption peak at 3447 cm^{-1} on the ZnO surface after modification was significantly reduced, proving the reduction of surface hydroxyl groups and further improving its hydrophobicity. Similarly, the O-H and H–O–H bending vibration peaks at 3426 cm^{-1} and 1631 cm^{-1} on the modified SiO_2 were also reduced, indicating a decrease in surface hydroxyl groups and confirming the success of the modification. The infrared comparison spectra before and after nanoparticle modification are shown in **Figure 4**.



(a) Unmodified ZnO; (b) Unmodified SiO_2; (c) Modified ZnO; (d) Modified SiO_2

Figure 4. Infrared comparison spectra before and after nanoparticle modification.

Through the surface modification method of the biomimetic micro-nano structure superhydrophobic coating, the ship not only improved the hydrophobic properties of nano ZnO and nano SiO_2 but also optimized their application effectiveness in anti-fouling coatings.

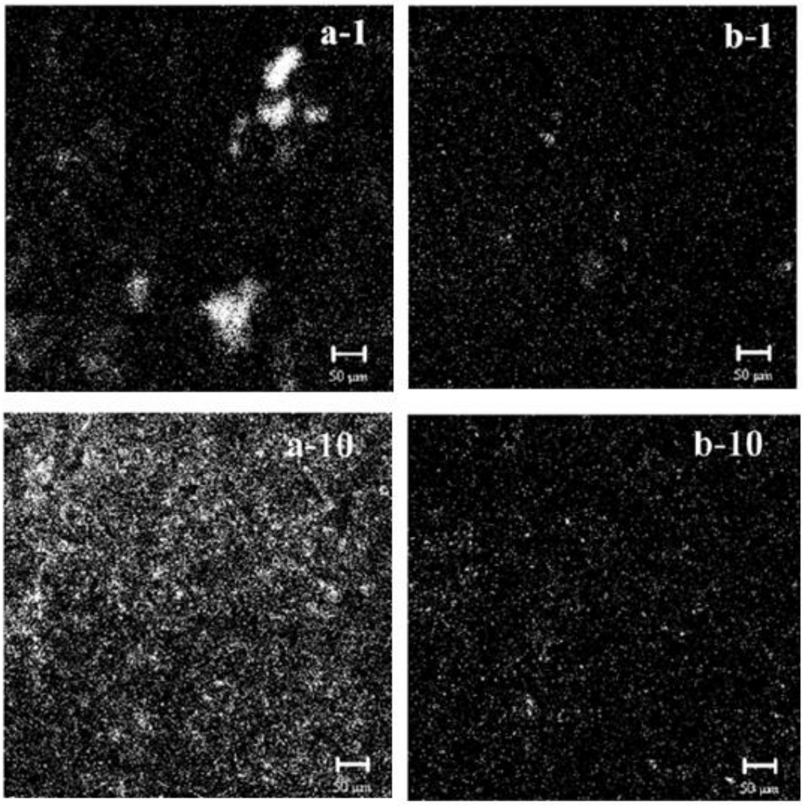


Figure 5. (a) Raw material; **(b)** biomimetic micro-nano structured superhydrophobic coating material.

In the anti-microalgae adhesion experiment, a 10-day anti-adhesion test on Chlorella liquid showed that the modified biomimetic micro-nano structured superhydrophobic coating exhibited good anti-microalgae adhesion performance compared to the unmodified samples. Statistical analysis using ImageJ software revealed that the adhesion rate of algae cells on the surface of the raw material was 22%, while the adhesion rate on the surface of the biomimetic micro-nano-structured superhydrophobic coating was 4%. The CLSM images of samples immersed in algae liquid for 1 day and 10 days are shown in **Figure 5**.

4.3. Corrosion depth prediction case analysis

4.3.1. Data selection

In general, traditional regression prediction methods usually require a large amount of data for training to ensure the accuracy of the model. However, in practical engineering applications, due to the particularity of the marine environment—such as high detection costs, harsh environmental conditions, and the difficulty of obtaining complete and valid detection data on platforms—it is often challenging to obtain a sufficiently large dataset. In contrast, Extreme Learning Machine (ELM) has significant advantages, particularly when handling small sample regression prediction problems. ELM can effectively learn and predict with less training data, making it especially suitable for applications like marine environmental monitoring, where data is difficult to obtain. Therefore, the ELM-based corrosion rate prediction model can still provide reliable prediction results even when faced with challenges such as data scarcity and complex environments.

4.3.2. Prediction results analysis

To evaluate the prediction performance of the model, this paper compares the prediction results of the BP model and the ELM model. The specific method is to input the test set into the trained model and compare the prediction accuracy of the two models on the same dataset. After experimental verification, the prediction results are obtained, as shown in **Table 3**.

Table 3. Model prediction performance.

No.	Actual corrosion rate	BP model		ELM model	
		Predicted value	Relative error of predicted value/%	Predicted value	Relative error of predicted value/%
1	3.2724	3.82689	17.1094	3.64206	11.41805
2	2.1311	1.92102	9.95557	2.42602	13.96527
3	6.7064	6.2014	7.61035	6.94577	3.60873
4	2.4341	2.05636	15.66611	2.64418	8.72741
5	8.6254	7.74064	10.36361	9.04253	4.88436

4.4. Corrosion effect of hull based on infrared image acquisition

4.4.1. Infrared image denoising effect

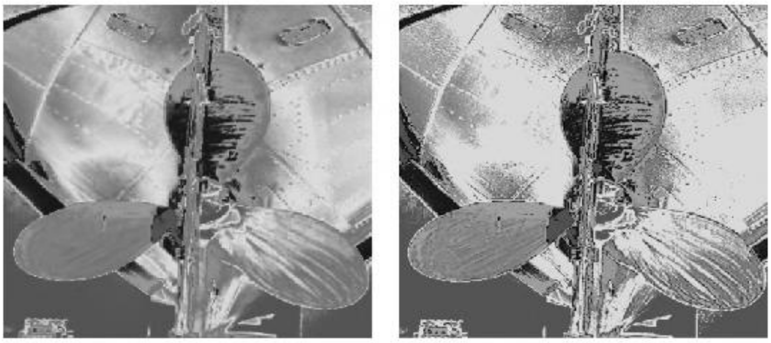
The analysis of the infrared image denoising effect shows that after applying the method in this paper to denoise the infrared images of surface defects on corrosion-resistant ship materials, the noise points in the images were effectively removed. The results indicate that the interference caused by noise in the original image is no longer prominent, and the quality of the image has significantly improved. The denoised infrared image is clearer, with the defect edges more distinct, providing more accurate data support for subsequent defect identification and analysis. This indicates that the method in this paper can effectively improve the accuracy and reliability of surface defect detection for corrosion-resistant ship materials in practical applications. The infrared image denoising effect is shown in **Figure 6**.

(a) Original infrared image (b) Denoised infrared image

Figure 6. Infrared image denoising effect.

4.4.2. Infrared image edge enhancement effect

After enhancing the infrared images of surface defects on corrosion-resistant ship materials, the clarity of the image edges significantly improved, as shown in **Figure 7**.



(a) Original infrared image (b) Enhanced infrared image

Figure 7. Infrared image edge enhancement effect.

Specifically, the edge of the propeller in the original image is somewhat blurry, but in the enhanced image, the edge of the propeller becomes clearer, with more prominent details. Meanwhile, the previously inconspicuous welding point at the top right becomes more noticeable after enhancement, further improving the image's readability and defect recognition accuracy. This shows that the method in this paper can effectively enhance the edge performance of surface defects in infrared images, which is helpful for subsequent detection and analysis.

4.4.3. Different defect recognition results

In this paper, the proposed method was tested for its ability to recognize surface defects of corrosion-resistant ship materials of various sizes. Two infrared images with different defect sizes were selected for testing, one containing a larger defect and the other containing a smaller defect. The experimental results showed that the method in this paper can effectively recognize defects of different types and sizes.

Specifically, for the infrared image of a corrosion-resistant ship material with small defects, the method accurately identified two small defects, as shown in **Figure 8**.

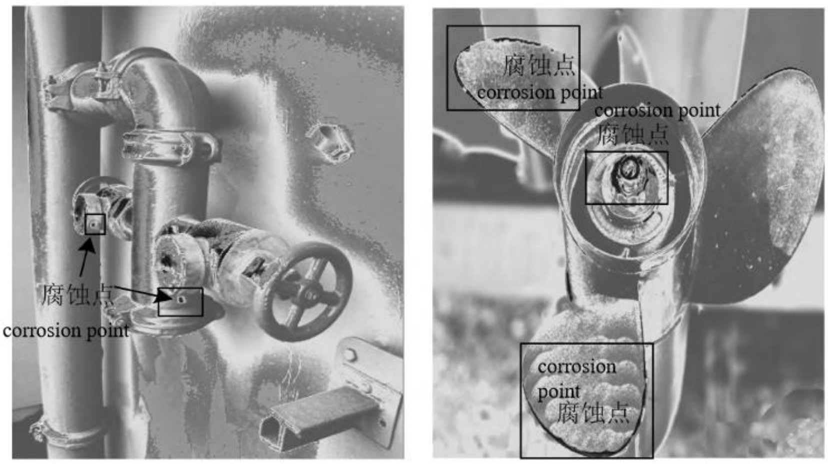


Figure 8. Different defect recognition results.

5. Discussion

This paper discusses innovation management in the shipbuilding industry and proposes strategies for driving product development and market expansion, incorporating modern technologies such as machine learning, molecular technology, and biomechanics. It introduces cutting-edge technologies in the traditional shipbuilding industry, offering new insights for innovation management, especially with the introduction of machine learning, which provides more efficient production and decision-making support. By combining molecular technology and biomechanics, this paper offers more precise performance prediction and optimization methods for ship design, driving product performance improvements and a more accurate grasp of market demand.

In the shipbuilding industry, the integration of machine learning, molecular science, and biomechanics offers significant potential for improving design, manufacturing, and maintenance levels. Firstly, material optimization is an important application direction of this technological integration. By using machine learning algorithms to model the performance of different materials, combined with molecular science's analysis of material molecular structures, the performance of new ship materials, such as corrosion resistance, strength, and elasticity, can be predicted. Based on this, the molecular arrangement can be simulated and optimized, selecting the most suitable material combination, thereby enhancing the overall durability and safety of the ship. Secondly, applications in intelligent manufacturing and maintenance are gradually becoming a key focus of industry innovation. By applying machine learning to intelligent ship manufacturing, the quality of materials during production can be monitored in real-time, optimizing the production process. At the same time, by integrating biomechanics and molecular science, an intelligent ship maintenance system can be developed, which collects operational data from the ship in real-time, analyzes these data using machine learning, predicts potential equipment failures, and plans maintenance work in advance. Lastly, the optimization of ship adaptability to the environment can also be achieved through this technological integration. In the harsh marine environment, ships face multiple challenges, such as complex seawater conditions, climate changes, and biofouling. By combining fluid mechanics from biomechanics with machine learning algorithms, the ship's design can be optimized to better adapt to different environmental conditions, improving speed and fuel efficiency. Additionally, the application of molecular science can improve ship coating materials, reduce biofouling, and decrease hull wear and fuel consumption.

However, this paper also has certain shortcomings. The application of machine learning, molecular science, and biomechanics in the shipbuilding industry faces several technical obstacles. Firstly, data collection and quality issues are a major challenge. The application of machine learning and other technologies heavily relies on large amounts of high-quality data, but data in the shipbuilding industry is often fragmented and difficult to obtain, especially real-time data on ship operational status, material properties, and environmental factors. The data differences under various ships and navigation conditions lead to insufficient generalization of the algorithms, and data quality issues such as noise and missing values can also impact the accuracy and reliability of the models. Secondly, the complexity of integrating multidisciplinary technologies is another challenge. Machine learning, molecular science, and biomechanics belong to different technical fields, and their differences in theory and methods increase the difficulty of integrating these technologies. Especially in interdisciplinary integration, how to effectively combine the results from different fields and design a unified framework for cross-disciplinary research and application remains a huge challenge. How molecular-level simulations and biomechanical modeling can be integrated with the macroscopic structural analysis and design of ships requires collaboration among cross-disciplinary experts and long-term technological accumulation. Finally, the gap between simulation and reality is also a significant barrier in technical implementation. Although machine learning and molecular simulations can provide theoretical support in laboratory or simulated environments, the application of these technologies in actual ship operations may face many complex situations.

6. Conclusion

The shipbuilding industry is facing increasingly intense market competition and technological development pressure, and the traditional innovation management model is no longer sufficient to meet the demands of the new era. Therefore, applying modern technologies, especially cutting-edge technologies like machine learning, molecular technology, and biomechanics, to product development and market expansion has become a key approach to enhancing the competitiveness of shipbuilding enterprises.

The research shows that machine learning can optimize production processes and decision support systems through data analysis, improving the efficiency and accuracy of ship design and manufacturing. Molecular technology and biomechanics have shown great potential in enhancing ship design performance, reducing weight, and increasing durability, driving product innovation and upgrades. At the same time, the effective implementation of innovation management requires consideration of the actual conditions of enterprises, focusing on the integration of technologies and a precise understanding of market demands. Therefore, future research could further explore how to optimize innovation management strategies in different types of shipbuilding enterprises, promoting the deep integration of technology and business.

Conflict of interest: The authors declare no conflict of interest.

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