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A Study of Hybrid Predictions Based on the Synthesized Health Indicator for Marine Systems and Their Equipment Failure

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Abstract: Ship mechanical system health prognosis is one of the major tasks of ship intelligent operation and maintenance (O&M). However, current failure prediction methods are aimed at single pieces of equipment, and system-level monitoring remains an underexplored area. To address this issue, an integration method based on a synthesized health indicator (SHI) and dynamic hybrid prediction is proposed. To accurately reflect the changes in system health conditions, a multi-state parameter fusion method based on dynamic kernel principal component analysis (DKPCA) and the stacked autoencoder (SAE) is presented, along with construction of a system SHI. Taking into consideration that the system degradation process includes global degradation trends, local self-healing phenomena, and local interference, a dynamic hybrid prediction model is established after SHI decomposition. The performance of the proposed approach is applied to a ship fuel-oil system to show its effectiveness.



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Keywords: operation and maintenance; synthesized health indicator; degradation process; failure prognosis

1. Introduction

The newest generation of artificial intelligence technology has promoted the process of ship autonomy and unmanned operation. Ship mechanical systems should make full use of new technology to achieve scientific O&M based on improving safety, reliability, and efficiency [1,2]. The main research focus of ship O&M includes all-round state perception, real-time condition monitoring and evaluation, health condition prognostics, independent decision-making [3], and other technologies.

More and more academic researchers and O&M engineers have been involved in machinery failure prognostics. For single-component equipment, some research has shown that incorporating prognostic information helps make more reasonable O&M decisions [4,5]. Modern merchant vessels are complex systems constructed from numerous subsystems, with equipment and components provided by multiple different suppliers and integrated by a shipyard. There are often one or more types of economic, structural, and stochastic interactions between components. Intelligent O&M usually needs to consider the whole-system health condition in order to optimize system-level and even plant-level decision making [6–8]. The existence of these interdependencies makes the single-equipment prognostic model no longer applicable.

At present, system-level failure prediction mainly includes two main problems, one is to establish a suitable SHI that can accurately describe the health condition of the system, the other is to select an appropriate prediction method according to the HI to realize the failure prediction [8]. Ship systems are complex mechanical systems designed to complete specific

functions and lack the dominant physical characteristics which can directly represent their health condition. Therefore, it is necessary to use all kinds of sensor data to extract valuable data. Thus, the concept of a health indicator (HI) is introduced. A suitable HI is expected to simplify prognostic modeling and produce accurate prediction results. Zhang et al. [9] use the improved radar chart method for constructing a system HI to produce the system condition evaluation. Wen et al. [10] employ composite HI to realize complex systems RUL prediction based on condition-monitoring signals. Through these HI construction methods, the multi-dimensional data from the sensors is defined as a virtual SHI that may be able to describe the health condition of a system. For ship mechanical systems, the construction of physical HIs is relatively complex, so virtual SHIs are the best choice. Some researchers constructed virtual SHIs based on principal-component analysis (PCA) [11,12], self-organizing maps [13], Mahalanobis distance [14], and stacked autoencoders (SAE) [15]. SAE is an effective unsupervised, feature-extraction network, which is very suitable for adaptive and online extraction of HI in multi-parameter systems [15,16]. In addition, the degradation of ship mechanical systems includes at least three phenomena: global degradation, local self-healing, and other noise. Due to the coupling of multiple signals of SHI, it is unrealistic to directly select the prediction method to realize the prediction. Therefore, in order to improve the prediction accuracy, it is necessary to decompose the SHI to separate the degradation trend from fluctuations. Empirical mode decomposition (EMD) and variational mode decomposition (VMD) are often used in decomposition algorithms [17,18]. The VMD could specify the number of decompositions according to the understanding of the physical process to reduce the complexity of the prediction. After signal decomposition, different prediction methods could be chosen according to different signals with the goal of realizing hybrid prediction. The hybrid prediction model comprehensively considers the advantages of each model, realizes the complementarity between models in the construction process, and improves prediction accuracy and decision rationality [19,20].

The health condition of ship mechanical systems will directly affect safe and reliable navigation by an autonomous ship. Therefore, using the system running-state parameters to predict and track system health conditions is an important means for achieving system health management. To produce these assumptions, a system health condition prediction model based on SHI was proposed in this study. This model is an integrated method that can take into account the interactions between components, the impact of uncertainty, and the effects on function output on a system's degradation. The main contributions of this study are summarized as follows:

- (1) The system-level adaptive SHI construction method is proposed. The fixed HI construction was transformed into automatic SHI extraction with the DKPCA and SAE fusion method, which improved the expression ability of the HI for system degradation characteristics.

- (2) A method of decomposing SHI according to specified degradation characteristics is proposed. VMD was used to separate the SHIs into global degradation, local self-healing, and local interference.

- (3) A dynamic hybrid prediction model was proposed. Considering the different characteristics of the decomposed signal, a relevance vector machine (RVM) and long short-term memory (LSTM) were used to achieve hybrid prediction.

The remainder of this article is organized as follows. Section 2 describes the typical problem of ship mechanical systems and the framework. The proposed health state prediction model is described in Section 3. The parameters of a fuel-oil supply system were chosen as examples to verify the feasibility of the method, as described in Section 4. Conclusions are drawn in Section 5, along with discussions of future challenges as well as opportunities for machinery prognostics.

2. Problem Formulation and Framework

2.1. Problem Formulation

The main challenge in ship system-level health condition prognosis is the development of a modeling framework that allows the various factors influencing the evolution of system degradation to be taken into account, including the mutual interactions of the components, the impact of uncertainty, and O&M requirements. Before establishing the method for dynamic reliability assessment and health prognostics, some general specifications regarding the considered ship mechanical system are presented as follows:

(1) The ship mechanical system is an agent or intelligent unit composed of various components used to complete specific functions. From the perspective of intelligent O&M, the health prediction focuses on whether the system can meet the functional requirements.

(2) The system proposed in this study is a continuous-operation system. The system does not stop for maintenance, and the prediction end point is that the system function is lost or does not meet the actual demand.

(3) There are many state variables of the ship mechanical system that often lack dominant failure characteristics. The ship mechanical systems consist of m components, the state of each component at time t is denoted as $x_{i,t}$, and the states of all components are $x_{i,t} = (x_{1,t}, x_{2,t}, \dots, x_{m,t})$. When the system is in the process of degradation, a single $x_{i,t}$ cannot accurately describe the health condition of the system. Therefore, it is necessary to integrate multiple sensor information to form an SHI to represent the health condition.

(4) The system works alternately in a variety of working modes. When the modes are different, the optimal value (baseline value) and limit (threshold) value of the same variable will be significantly different. Therefore, the influence of different mode parameters must be considered when quantifying health status.

(5) The health conditions of the ship mechanical system are mainly affected by three factors. One factor is the global degradation caused by uncertainty. The second factor is the local self-healing influenced by the switching, self-clearing, and recoil of some devices and components. When the equipment in the system recovers some performance, the function of the whole system will also recover to a certain extent. This phenomenon has a great impact on system failure and should be considered in the prediction process. The third factor is local fluctuations caused by wind, waves, current, and other instantaneous disturbances.

2.2. Framework

The present work is based upon two main fields of research, the construction of SHI and failure prognostics. Consequently, the complete framework is depicted by Figure 1.

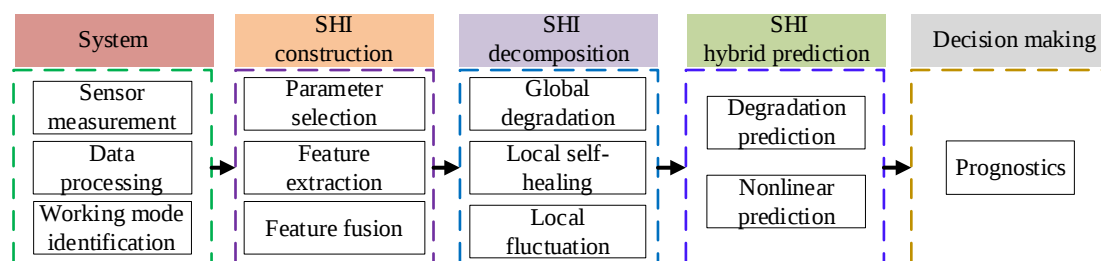


Figure 1. Schematic diagram of the proposed method for failure prognosis framework.

Step 1: The system operation parameters were measured by various sensors. These sensors usually included temperature, pressure, flow, liquid level, viscosity, etc. They were conventional sensors installed in ship systems. The measurement data needed to be processed before being used for failure prediction. The data processing technology included outlier filtering and data imputation, and those processes were completed by the alarm and monitoring system (AMS) at the ship's end. The dataset cited in this paper came from the AMS, meaning it was processed data. To meet the needs of green and economic navigation, the ship system usually includes a variety of working modes. Using the fuel supply system

as an example, it usually includes two working modes. Heavy oil mode is adopted for normal navigation in the ocean. When sailing in ports or special areas, the ship needs to switch to light oil mode in order to meet the demand for low emissions. The change of working modes leads to a great change of system state parameters and significantly affects the prediction results. This article studied failure prediction under one working mode, so the data obtained need to be classified and stored according to working modes.

Step 2: To further characterize degradation characteristics and improve prediction accuracy, for multivariate feature data, the DKPCA method was adapted to reduce the dimensions of the data, and the SAE method was used to fuse the processed data to obtain the SHI. The DKPCA implemented dynamic dimension analysis according to the change of the system state parameters, and the SAE could map multiple features to a single HI.

Step 3: The VMD method was used to decompose the SHI. According to the characteristics of the system degradation, the SHI sequence was decomposed into global degradation, local self-healing, and local interference signals.

Step 4: According to the characteristics of different decomposed signals, different prediction methods were selected to achieve hybrid prediction. According to the global degradation characteristics, considering the influence of the uncertainty, the RVM method was used to achieve the prediction. Compared with RVM, the LSTM prediction method has greater advantages in processing strong periodic and nonlinear signals. Therefore, LSTM is used to analyze local self-healing and interference signals.

Step 5: The health prediction was achieved by fusing the prediction results. The decision was made according to the change of the health condition.

3. Methodology

3.1. Data Acquisition

Through the ship–shore communication system, data from the alarm monitoring system (AMS) was transferred to the shore end. After imputation and outlier filtering, data was stored in an elastic cloud server. The data selected in this article was read directly from the server.

To adapt to different countries, ports, and navigation areas, a ship's mechanical system usually needs multiple modes to meet the requirements of navigation and environmental safety, such as low emission requirements of ports and different navigation modes for sea conditions. If the working modes of the system are different, the monitoring parameters change greatly. The effect of changing operational conditions has far greater significance than the influence of degradation uncertainty on system life. Therefore, when predicting the health condition of a system, the working mode of the system needs to be identified first.

If the state parameters are recorded with pattern information, pattern recognition is not needed. Otherwise, a pattern recognition algorithm is needed to identify the working mode o_t according to the measured data. The pattern recognition algorithms include k-means clustering [21], fuzzy c-means algorithm [22], and Bayes classifiers [23]. The measurement data for each time in this study were classified into the known M working modes $o = \{o_1, o_2, \dots, o_M\}$. The data that could not be classified into the known working mode could be discarded temporarily. When enough similar data are accumulated, a new working mode could be established.

3.2. SHI Construction

The change of system health condition is reflected by the characteristic parameters. To further reveal the degradation processes of ship mechanical systems, an adaptive SHI fusion method based on SAE is proposed in this paper. The method includes two parts. Firstly, DKPCA is used to complete the dynamic selection of parameters and preliminary feature extraction. Then, the mapping from multivariate features to SHI is realized by the SAE method.

3.2.1. Parameters Selection and Feature Extraction

In different degradation stages, the focus of the health condition was different, and different characteristics were needed to reflect the change. Therefore, it was of great significance to dynamically extract system features from many state features to represent the system state changes. Due to the large inertia and multi-parameter data of the ship mechanical system, DKPCA based on correlation dimension was proposed to select the number of characteristic principal components of the nonlinear dynamic data. First, the input-standardized data were preprocessed with the fractal theory and dynamic theory, and the optimal lag dynamic data matrix $\tilde{X}$ was constructed to reduce the autocorrelation and correlation between data, where $\tilde{X} \triangleq [X(t)X(t-\Delta)\dots X(t-l\Delta)] \in R^{(N-l)\times m(l+1)}$, which is the reconstruction matrix, and $X(t)$ is the m -dimensional observation data at time t , Δ is the interval time, l is the lag time factor, and N is the number of samples. The l was substituted into Equation (1) to calculate:

$$r_n = r - \sum_{i=0}^{l-1} (l-i+1) \times r_n(i), \quad (1)$$

where r_n was a cyclic function, and the initial $r_n(i)$ was calculated when $l = 0$. And $r = m(l+1) - C_D$, where C_D is the correlation dimension of the dynamic data matrix [24]. Its calculation method is shown in Equation (2):

$$C_D(\varepsilon) = \frac{2}{N_D(N_D-1)} \sum_{i=1}^{N_D} \sum_{j=i+1}^{N_D} H(\varepsilon - \delta_{ij}), \quad (2)$$

where ε is the distance of two points on the attractor and related to δ_{ij} , $\delta_{ij} = \|x_j - x_i\|^2$ is the Euclidian distances between ij rows to the input matrix $\tilde{X}$, and $N_D = N - l$. The H represents an indicator function defined as $H(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{else } z < 0 \end{cases}$. As the ε gets smaller, Equation (2) can be rewritten as:

$$C_D = \lim_{\varepsilon \rightarrow 0} \frac{\log(C_D(\varepsilon))}{\log(\varepsilon)}. \quad (3)$$

In Equation (3), assuming a sufficient number of points have been acquired lying closely in the underlying space, then the slope of the linear part of the log-log plot of C_D versus ε represents the C_D .

Calculate r_n using Equations (1)–(3) until $r_n \leq 0$, then the value of the correlation dimension corresponding to l in different cases can be obtained, and the most appropriate l_{opt} can be selected to construct $\tilde{X}_{opt} \in R^{N_D \times m(l_{opt}+1)}$.

The KPCA was used to analyze the matrix $\tilde{X}_{opt}$ to obtain the mapping data matrix as follows:

$$t^k = \frac{1}{\sqrt{\lambda^k}} \sum_{i=1}^N a_i^k K(x_i, x), \quad (4)$$

where $k = 1, 2, \dots, N$, $K(x_i, x)$ represents the core matrices after centering, and λ^k and a_i^k are the eigenvalues and eigenvectors, respectively, of matrix $K(x_i, x)$. The eigenvalue size was used to simply filter the data to reduce the amount of data calculation and obtain the corresponding data matrix $G_p = \{t_j^k\}_{k=1}^p \in R^{N_D \times p}$, where $j = 1, 2, \dots, N_D$.

The C_D was applied to obtain the number of principal components of G_p and G_t ($G_t = G_p A$, and the matrix A is the loading matrix obtained with an orthogonal transformation of the covariance matrix) and obtain the correlation dimension d_{G_p} and d_{G_t} . Then, the number of principal components of the matrix data was $\gamma = \max([d_{G_p}], [d_{G_t}])$, and the $[]$ is rounded up [25].

Using the correlation dimension to select the principal elements could improve the accuracy of the feature data extraction to a certain extent [26], and the output matrix $G_\gamma = \{t_j^k\}_{k=1}^\gamma \in R^{N_D \times \gamma}$ could finally be obtained. The output matrix was used for the analysis and calculation of the SHI. The specific process of feature extraction is shown in Figure 2.

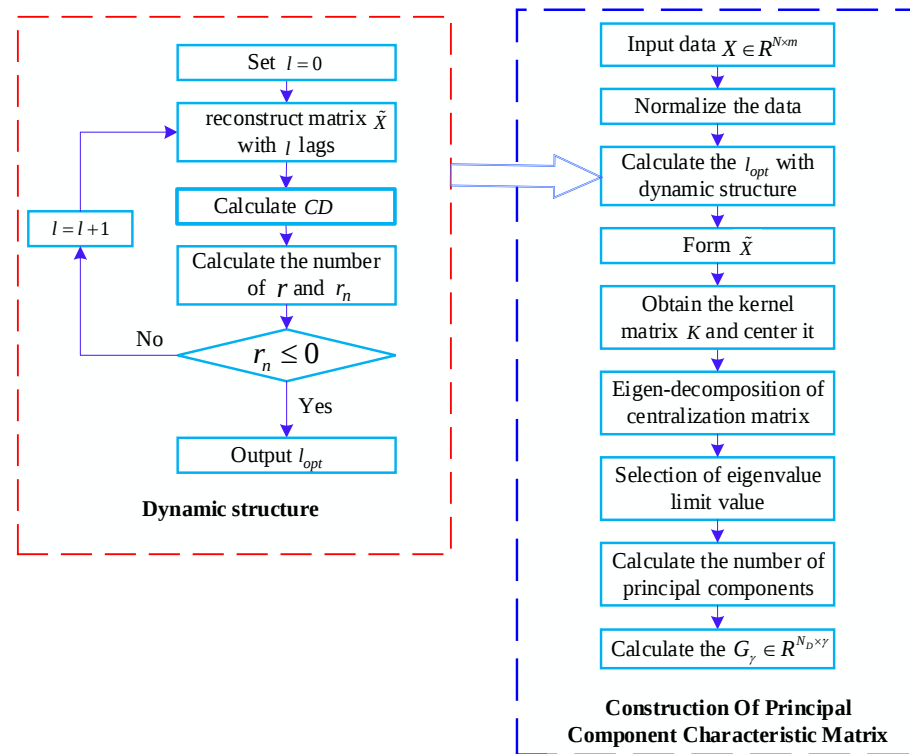


Figure 2. Schematic diagram of DKPCA.

3.2.2. Feature Fusion

The calculation process of the SHI was essentially a process of mapping the multi-dimensional physical characteristic information of the system collected by sensors to a one-dimensional virtual variable with a value range of (0, 1). The value of 1 indicated that the system was working normally, and the value of 0 indicated that the system had a total loss of function. Just like using physical characteristics to describe the health condition directly, the SHI was also based on the fusion of the available and real-state monitoring information to produce the health assessment of the system, and this method could describe the health condition of the system accurately and comprehensively.

The SAE deep neural network was used to fuse the features extracted dynamically to further reduce the dimensions and extract a fusion SHI that contained the degradation characteristics of the system. SAE's method of depth-feature fusion is to form a depth network by infinite stacking, take the output of the upper layer as the input of the next layer, and then minimize the reconstruction error of the input and output signals to complete the layer-by-layer compression of the input data. The basic structure is shown in Figure 3a.

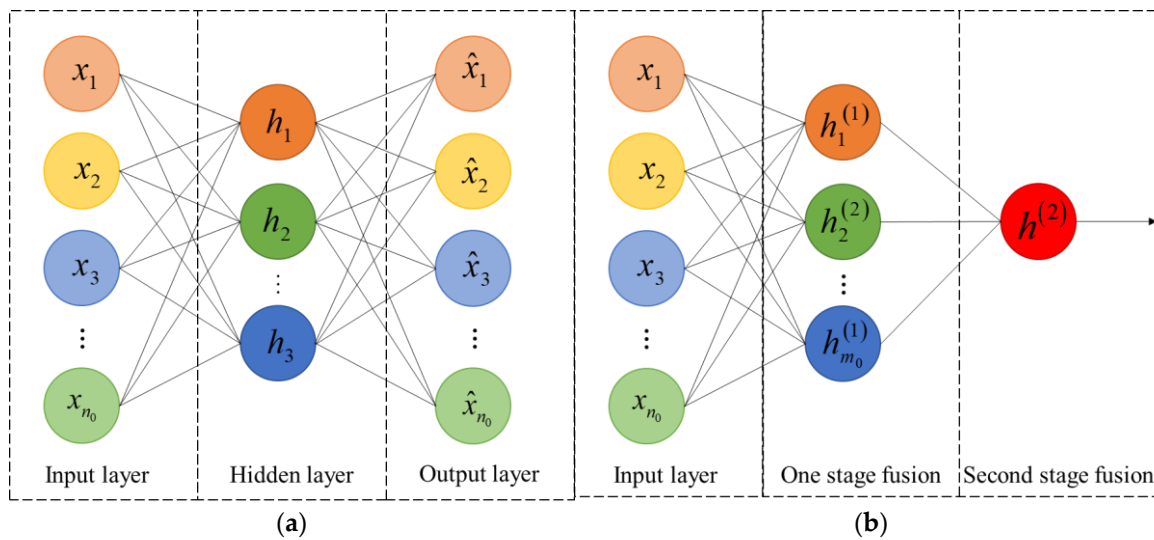


Figure 3. Schematic diagram of feature fusion by SAE: (a) SAE structure; (b) SAE fusion.

The input and output of the network are x and $\hat{x}$, hidden layer node output h_j and output layer node $\hat{x}_k$ can be defined by Equations (5) and (6):

$$h_j = f\left(\sum_{i=1}^{m_0} x_i w_{ij} + b_1\right), \quad (5)$$

$$\hat{x}_k = f\left(\sum_{j=1}^{n_0} h_j w_{jk} + b_2\right), \quad (6)$$

where $f(\cdot)$ is the active function, w_{ij} and w_{jk} are the weight matrices, b_1 , b_2 are the bias vectors, m_0 is the number of feature fusion, and n_0 is the number of input and output nodes and is equal to the γ calculated in Section 3.2.1 above.

The coding process of the network refers to mapping n -dimension as the input sample a into m -dimensional h_j , with the decoding function h_j remapping into n -dimensional $\hat{x}_k$ through decoding. The $\hat{\rho}_j$ represents the average activation amount of h_j , then:

$$\hat{\rho}_j = \frac{1}{T_n} \sum_{j=1}^{T_n} h_j, \quad (7)$$

where T_n is the number of training samples. In order to avoid useless learning, the sparsity system is added to the network, and only a few nodes are allowed to be active, that is, make $\hat{\rho}_j$ close to ρ , and ρ is a sparse parameter approaching 0. Kullback–Leibler divergence (KL) measures the deviation degree between $\hat{\rho}_j$ and ρ , as shown in Equation (8):

$$KL(\rho \parallel \hat{\rho}_j) = \rho \ln \frac{\rho}{\hat{\rho}_j} + (1 - \rho) \ln \frac{1 - \rho}{1 - \hat{\rho}_j}. \quad (8)$$

The overall cost function of the T_n samples can be defined as Equation (9):

$$J(w, b) = \frac{1}{T_n} \sum_{i=1}^{T_n} \|x_i - \hat{x}_i\|^2 + \lambda \|w\|^2 + \beta \sum_{j=1}^{m_0} KL(\rho \parallel \hat{\rho}_j), \quad (9)$$

where λ is the weight-decay parameter and β is the sparsity penalty term parameter used to control the relative importance between the first reconstruction term and the second penalty term.

According to the feature data extracted dynamically, two SAE stacks were used to form a trestle self-encoder for second-order parameter fusion.

One-level fusion: taking the initial parameters as the input and output of the network structure shown in Figure 3a, the number of hidden layer nodes was less than the network input. Network coding and decoding were conducted, and the network parameters from the input layer to the h_j layer were obtained. After the training, the decoding layer was removed, leaving only the input layer to the h_j layer, as shown in Figure 3b, and the output of the hidden layer was the first-order fusion result.

Two-level fusion: the result of the first-order fusion was taken as the input and output of the network structure shown in Figure 3b, and the number of hidden layer nodes was set to 1; that is, the final fusion was a sequence. The fusion process was similar to the first-order fusion, and the hidden layer output after removing the decoding layer was the two-level fusion HI. In addition, the number of hidden layers was determined with repeated experiments.

3.2.3. SHI Assessment

The evaluation of SHI performance is mainly considered from two aspects. Firstly, whether the change characteristics of SHI are consistent with the changing trend of the function indicator (while considering the overall trend and local characteristics); the second is to calculate the correlation coefficient of SHI and functional indicators.

Spearman's rank correlation coefficient has the widest application range and does not need the variables to conform to normal distribution [27]. Therefore, it is selected to measure the correlation between SHI and functional indicators.

For a data sample of size n , the SHI values A_i and function indicator B_i are converted to ranks $rg(A_i)$ and $rg(B_i)$, rg is an arrangement method from largest to smallest. The r_s is described as follows:

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}, \quad (10)$$

where $d_i = rg(A_i) - rg(B_i)$ is the significant difference between the two ranked variables. The value of r_s is from +1 to −1. If the absolute value of r_s is closer to 1, it indicates a strong correlation.

3.3. SHI Decomposition

It was considered that the degradation of the ship mechanical system was at least a complex degradation process composed of global degradation, local self-healing, and local interference. Therefore, the number of modal components of the VMD was set to three.

The data of fusion SHI were $H(t)$, and its VMD decomposition result could be expressed as:

$$H(t) = \sum_{k=1}^S u_k, \quad (11)$$

where S is the number of modal components, and u_k is a sub-signals (modes) of the real-valued input signal.

3.4. System-Level Health Condition Prediction

3.4.1. Hybrid Prediction Model

A single prediction method has its advantages and disadvantages, so it is more-or-less suitable for a given supervision problem. There is no universal prediction method that outperforms all other methods in all situations. Therefore, the hybrid model that takes into account the advantages of each model can predict the decomposed signals with different characteristics, realizes the complementarity between models, and then improves the prediction accuracy and decision rationality.

For the global attenuation trend decomposed signal, the RVM model with higher computational accuracy and lower computational complexity than the SVM algorithm was

selected for prediction, and it could output the uncertainty information of the prediction results. The adaptive RVM method was adapted for online prediction [28]. For the decomposed signal with obvious nonlinear characteristics, the LSTM [29] algorithm with a better nonlinear autonomous learning function was selected. The prediction results of the three models were accumulated:

$$\hat{u} = \hat{u}_1 + \hat{u}_2 + \dots + \hat{u}_k. \quad (12)$$

where $\hat{u}_k$ is the prediction results of u_k and $\hat{u}$ is the hybrid model predicting the final result. When the fusion features changed, the training sample of the hybrid prediction model was updated, and the health condition prediction was conducted again. To highlight the performance of the created SHI and limit the impact of the prediction methods on the final results, the default hyperparameters used in the methods were used without making adjustments.

3.4.2. Determination of Prediction Starting Time

A ship mechanical system has high reliability and a stable health value in the initial stage of operation. The existing SHI sequence will often not be enough to reflect the degradation trend of a system in the future. Using the existing data to complete the training and prediction would mean the prediction results were not necessarily accurate. With the increase of the system running time and the deepening of the degradation, the value of the SHI decreased continuously. More and more feature data that could be used to identify the degradation process were included in the SHI series, and the prediction results were close to the real state. Therefore, it was necessary to determine the prediction starting point according to the change trend of the SHI. The time-to-start (TTS) point was used to produce the online prediction of the health condition using real-time measurement data [30]. Based on this process, the baseline-threshold method was applied to determine the TTS.

(1) Baseline

The baseline was established with the system SHI. The baseline reflected the best state of the system operation. To simplify the calculation, the arithmetic mean μ could be selected to replace the baseline:

$$\mu = \frac{1}{N_0} \sum_{i=1}^{N_0} x_i, \quad (13)$$

where N_0 is the number of data. The baseline could also be calculated dynamically with the adaptive baseline method according to previous research results [31].

(2) Threshold setting

The threshold included the adaptive threshold and failure threshold. The adaptive threshold T_{AT} was calculated from the baseline, and the upper and lower limits of the adaptive threshold constituted the optimal distribution range of the health value:

$$\sigma = \sqrt{\frac{1}{N_0} \sum_{i=1}^{N_0} (x_i - \mu)^2}, \quad (14)$$

$$T_{AT} = \mu \pm 2\sigma, \quad (15)$$

where σ is the standard deviation and the mean value is μ .

The failure threshold is the health value corresponding to the system function not meeting the requirements, which were usually determined by the range of the function indicator parameters: $HI = 0$ indicates that the system had lost all functions. In practical application, it is generally believed that when a system cannot meet the functional requirements, the health condition prediction will stop, so health value at this time was set as the failure threshold.

Under normal conditions, the health value should fluctuate around the baseline and be within the range of the upper and lower limits of the threshold. If the health value ran out of the channel, the health condition changed. As shown in Figure 4, the trigger condition of

the state prediction was that when the SHI deviated from the baseline (deviated and did not recover, as shown at point (a) and quickly broke down the threshold (could not return to the threshold range, as shown at point (b)). Taking point b as the TTS, the data before this point were taken as the training sample to complete training and prediction. The training data included the data for stable operation and for the descent phase.

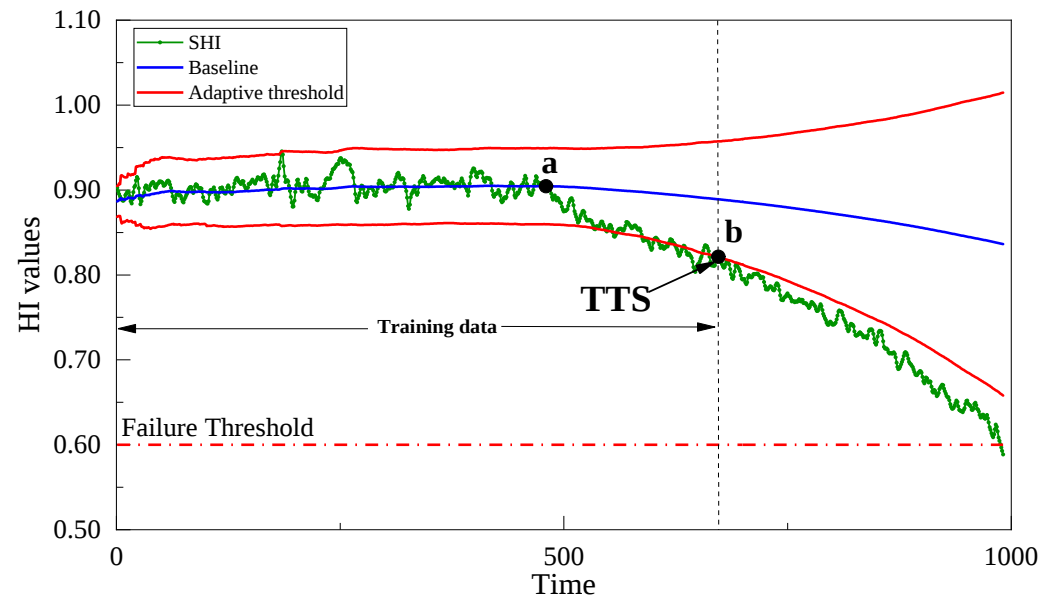


Figure 4. Determination of prediction starting point.

3.4.3. Metrics for RUL Prediction

Root mean square error (*RMSE*) measures the accuracy of the predictions and is the most commonly used regression metric [32]. *RMSE* is defined as the root mean square of the RUL prediction errors during the time interval from T_{END} to T_{TTS} and is expressed as:

$$RMSE = \sqrt{\frac{1}{T_{END} - T_{TTS}} \sum_{t=T_{TTS}}^{T_{END}} (L_t - L^*_t)^2}, \quad (16)$$

where T_{END} and T_{TTS} are the time indexes corresponding to the prediction start point and end point, and L_t and L^*_t are the predicted RUL and the ground truth RUL at time T . The larger the value of *RMSE*, the greater the average prediction error.

4. Case Study

A ship system is a mechanical system, such as an air system, lubrication-oil system, fuel-oil system, or cooling-water system. As described in this section, a main-engine fuel-oil supply system (FOSS), as shown in Figure 5a, was selected as the research object to verify the feasibility of the method. The function of the system is to provide suitable fuel for combustion. If the system failed unexpectedly, the ship propulsion system would shut down, and this would directly affect the safety of the ship.

The system consists of four types of components. One component type is the pumps, consisting of the supply pump (SP) and circulating pump (CP), which provide pressure for the system to maintain the system pressure stability. Another type is the filters, consisting of the duplex filter (DF) and the auto filter (AF), which ensure the quality of the fuel and protect the equipment downstream. The third type is the heat exchanger (HE), which is mainly the atomization heater in the system used to ensure the proper viscosity of the fuel. The fourth type is the accessory components, including the pipelines, valves, oil tanks, etc.

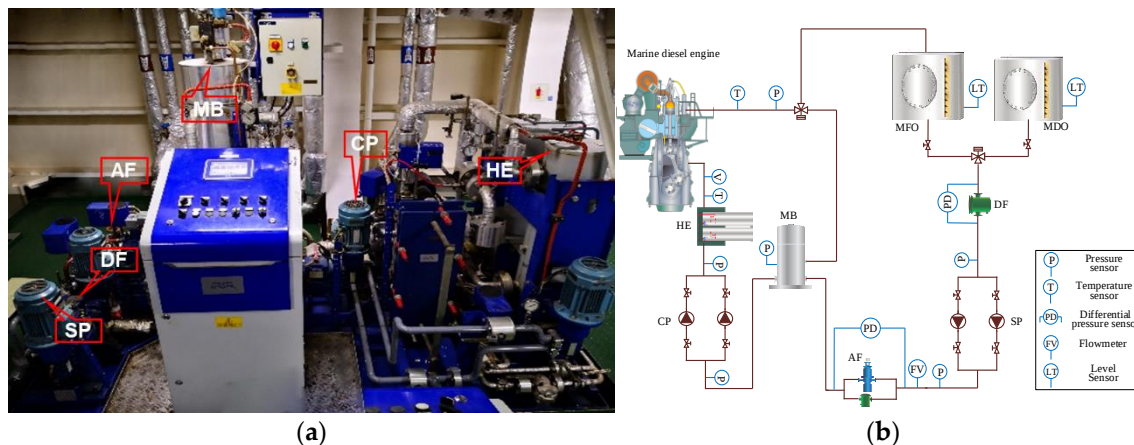


Figure 5. System structure diagram of FOSS: (a) structural diagram of real ship system; (b) system-schematic diagram.

Figure 5b illustrates the measurement parameters of the system, including: system working mode, pump inlet and outlet pressure, filter differential pressure, tank level, and fuel viscosity.

4.1. Working Mode Identification and Parameter Selection

4.1.1. Working Mode

Because different working modes have a great influence on system parameters, it was necessary to store the state parameters according to the working modes and to establish prediction models according to different modes. The working mode of FOSS usually has a judgment mark (by three-way valve), so an algorithm was not needed to achieve pattern recognition in this study. The system had two working modes: a diesel oil mode and a heavy oil mode. Because the system only worked in diesel oil mode for a short time, this mode had little impact on system performance. In the whole lifecycle of the system the heavy oil mode was dominant, and the diesel oil mode was equivalent to the local fluctuation of the system, so only the data from the heavy oil mode were used to produce the health-condition prediction.

4.1.2. System Parameters

To meet the condition monitoring, the acquisition parameters of FOSS were as shown in Table 1. The parameter ranges in the table were used to filter outliers.

All of the data described in the following sections were from the real ship operation parameters (from a training ship). The data set consisted of two parts:

(1) Dataset A:

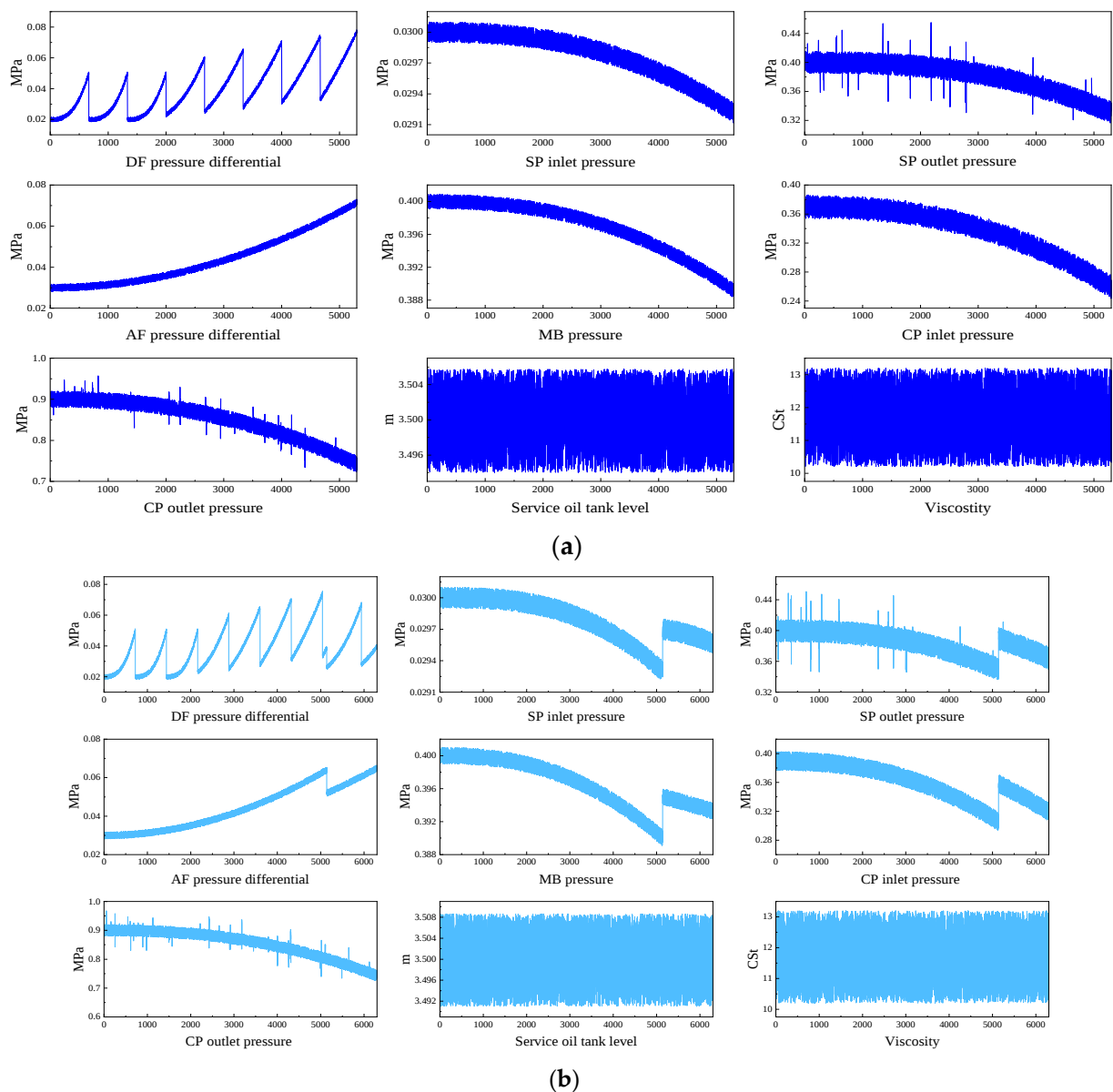
A system maintenance cycle from March 2019 to September 2019 was selected from the database of the AMS. During this period, the main factor that dominated the health of the system was the performance degradation of the system components. When the system ran for about 5300 h, the system was out of function. The change of each state parameter in the system is shown in Figure 6a.

(2) Dataset B:

Another system maintenance cycle between May 2020 and December 2020 was selected from the database of the AMS. During this period, in addition to the dominant degradation, the health condition of the system was affected by double pump switching; the degradation process changed and the system life increased. When the system ran for about 6195 h, the output pressure and flow of the whole system were insufficient due to the filter. This data sample was used to compare the prediction results of different prediction processes.

Table 1. Description of sensor data sets.

Variable	Parameter Descriptions	Unit	Benchmark Data		
			Lower Limit	Optimal Value	Upper Limit
1	SP outlet pressure	MPa	0.3	0.5	0.8
2	SP inlet pressure	m	0	3	3
3	CP outlet pressure	MPa	0.6	0.8	1.2
4	CP inlet pressure	m	0	3	3
5	Fuel oil viscosity	cSt	7.0	12.0~14.0	20.0
6	AF pressure differential	MPa	0.02	0.02	0.08
7	DF pressure differential	MPa	0.02	0.02	0.08
8	MB pressure	MPa	0.3	0.45	0.6
9	Service oil tank level	m	0.3	2.12	2.66
10	Three-way valve position			0/1	
11	Main engine fuel oil inlet pressure (Function)	MPa	7	8.5	16

**Figure 6.** Illustration of raw signals from two datasets: (a) Dataset A; (b) Dataset B.

4.2. System Failure Prognostics

4.2.1. System Health Prediction Based on Degradation

When the system was in normal production operation, the function of the system was mainly affected by the state of the filter. After cleaning, the system recovered some function, and the health state was characterized by local self-healing. According to the TTS setting method, when the health value reached the trigger condition, the training samples were constructed, and the prediction end point was set according to the threshold. Data set A was selected to verify the effectiveness of the method. The calculation steps of the health condition prediction were as follows:

(1) A dynamic feature extraction algorithm was used to achieve feature extraction.

The system presented different state features in the life cycle, so the dynamic feature extraction algorithm could capture the dynamic features of the system more accurately to represent the health state. DKPCA was used to extract the features of the data, and the calculation steps were as follows.

Step 1: The size of the data matrix was limited. According to the analysis requirements for the operation of the unmanned ship (>500 h), the matrix size had to be larger than the unmanned running time, so the number of samples was selected as $N = 520$, and the data matrix was $X \in R^{520 \times 9}$. To reduce the impact of the data amplitude differences, the matrix needed to be standardized.

Step 2: According to experimental experience, the selected value of the interval time is 1 ($\Delta = 1$). Then Equations (1)–(3) were applied to obtain the lag time $l_{opt} = 3$ of the reconstruction matrix, and the reconstruction matrix was $\tilde{X} \in R^{(N-3) \times 36}$. Using Equation (4) to obtain the mapping data matrix gives $G_{ND} = \{t_j^k\}_{k=1}^{N_D}$.

Step 3: After obtaining the mapping matrix, the $\lambda^p \geq 10^{-5}$ $p = 1, 2, 3, \dots, N_D$ condition was applied to filter G_{ND} , and the matrix G_p was obtained.

Step 4: The correlation dimension was used to solve the number of principal components of the matrix. The result is shown in Figure 7. It can be seen from the figure that the number of pivotal elements of the data in different time periods of the data was constantly changing, and this was not unique.

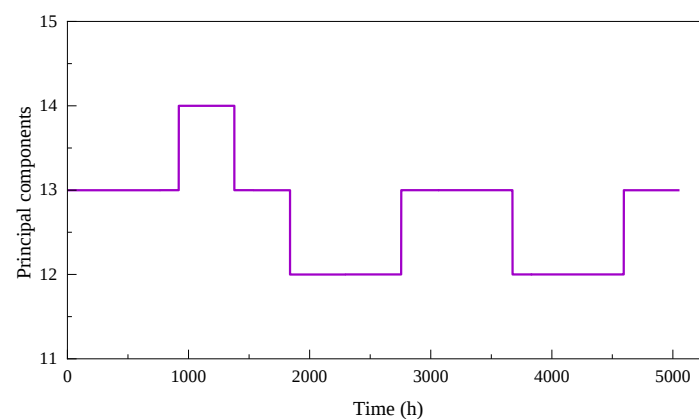


Figure 7. The number of features varying with time.

As depicted in Figure 7, the 13 features could describe the system state in the initial state. When the system fluctuated, the number of features increased to 14. With the system state in the transition processes, the number of features varied from 12 to 13. Finally, when the system was in the late degradation stage the number of features was stable at 13.

Different mapping matrices G_γ were constructed according to the principal components shown in Figure 7. These matrices contained the dynamic structure of the original data that could effectively reduce the influence of the cross-correlation between the data on the analysis results, which was beneficial to the construction of the SHI.

(2) SHI construction

Suitable fuel usually includes pressure, viscosity, and flow to meet the functional requirements of a main engine. During the working process, the viscosity was affected by the state of the HE, so this parameter was used as the characteristic parameter to describe the health condition of the system. The flow rate was mainly affected by the power of the main engine, which could be reflected by the pressure characteristics. Therefore, the main engine fuel oil inlet pressure could be used as the functional indicator of the system to judge whether the system SHI met the function requirements.

The SHIs of different feature fusion methods are shown in Figure 8. H1 was directly obtained with the PCA method [12], H2 was constructed by the proposed SAE fusion method. The number of network layers was 3, and the number of neurons in each network was 4, 4, and 1. In the training process, the reducing learning rate was set to 0.1, and the ratio of the training set to the test set was determined as 4:1.

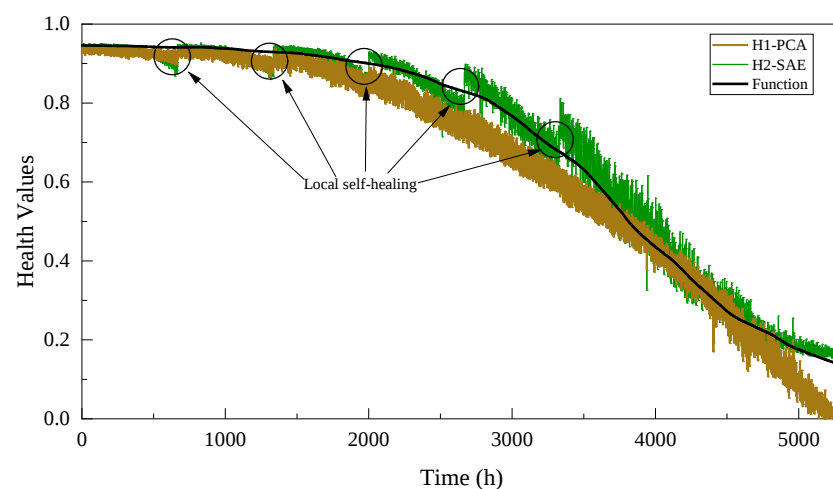


Figure 8. Fusion effect comparison.

H1 was basically consistent with the functional indicator at the initial stage, and the fusion result deviated greatly at the later stage. If H1 was used to produce the failure prediction, the deviation result was large. H2 could accurately fit the attenuation trend in the global attenuation, local self-healing, and interference stages, which was consistent with the target function and which could fully and accurately express the degradation characteristics of the system. The analysis results of Table 2 can be obtained by Equation (10); as shown in Table 2, the SHI constructed by the two methods are linearly correlated with the system function indicators. The SHI extracted by SAE has a stronger linear correlation with the functional indicator ($r_s = 0.998$).

Table 2. Correlation analysis of SHI and function indicator.

Spearman Correlation	SAE Fusion SHI	PCA Fusion SHI
Function indicator	0.998	0.994

Considering all the factors that influenced the SHI, the SHI fused by the SAE method could better express the health condition of the system. Therefore, using SHI to predict will obtain a more accurate system life.

(3) SHI decomposition

Using experience to choose the parameters of the VMD decomposition method, the initial value of the center frequency was set to 1, the update parameter was set to 0, and the termination condition was set to 10^{-6} . The penalty factor was determined by experiment. In the study of the ship system, only the separation of the global degradation, local self-healing, and other sources of noise were considered, so S was set to 3.

After signal decomposition, the SHI contained a mixture of three degradation phenomena. VMD was used to separate the local self-healing phenomenon u_2 from the global attenuation trend u_1 and other sources of noise u_3 in the SHI, and this could solve the problem of prediction bias caused by the local instability of the HI.

The three decomposed curves, u_1 , u_2 , and u_3 , shown in Figure 9 represent the dominant degradation, local self-healing, and local interference. Dominant degradation u_1 was affected by the internal uncertainty, and it showed a downward curve. The local self-healing u_2 and interference u_3 were influenced by the periodic function recovery characteristics of the equipment in the system and showed periodic curves. The characteristics of the decomposed signal could be predicted by different prediction algorithms. According to the characteristics of u_1 , the RVM model was selected for prediction. There were obvious nonlinear characteristics in u_2 and u_3 , so the LSTM algorithm was selected.

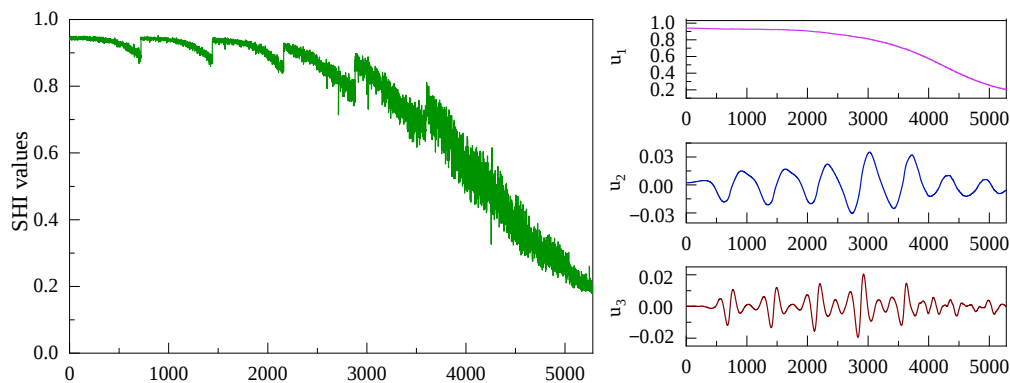


Figure 9. Decomposition of SHI.

(4) Hybrid prediction

After TTS calculation, when the system ran for 3334 h, the change of the health value met the requirement of the prediction conditions, so the prediction algorithm was started in order to predict the subsequent health condition. The health values before 3334 were used to train the RVM regression model and the LSTM model. The input data for the models were selected as the 1st–3334th samples of the health values. The step size of the multi-step prediction was set to 10, and the target data in the training process were the 11–3344th samples. The main engine fuel oil inlet pressure was taken as the evaluation standard of the system target function. When the pressure was lower than 0.7 MPa, it did not meet the demand of the main engine. At that time, the set health value was $HI = 0.2$, which was the failure threshold.

As shown in Figure 10, after TTS, the fusion features had undergone three obvious changes, so the training data of the hybrid model had been updated three times. The system failure time predicted by this method was about 5262 h, and the deviation from the real value was small.

4.2.2. RUL Prediction with Disturbance

There were many influencing factors in the actual system, and the health condition changed dynamically, so it was difficult to accurately evaluate the RUL of the system in one prediction. For example, there was redundant equipment in the system, and equipment switching would lead to a substantial recovery of function. Obviously, if the previous prediction method is used, the error could be very large. Therefore, it was necessary to achieve continuous tracking of the health condition of the system and the dynamic prediction. Dataset B was used to test the prediction of the health condition when some equipment of the system switched.

It can be seen from Figure 11 that if the equipment was not switched, according to the previous degradation law, the health condition of the system would reach the failure threshold at T2 h. In the vicinity of region B, when the pump was switched, system function

was restored and the degradation curve changed. At that time, using RUL prediction would not be able to accurately predict the remaining life. Therefore, to realize the adaptive prediction of health conditions, updating the training sample is necessary. With the new feature data added to the training set, the final life T1 was close to the real situation. The dynamic prediction method could track the change of system health condition and realize the dynamic prediction of failure time.

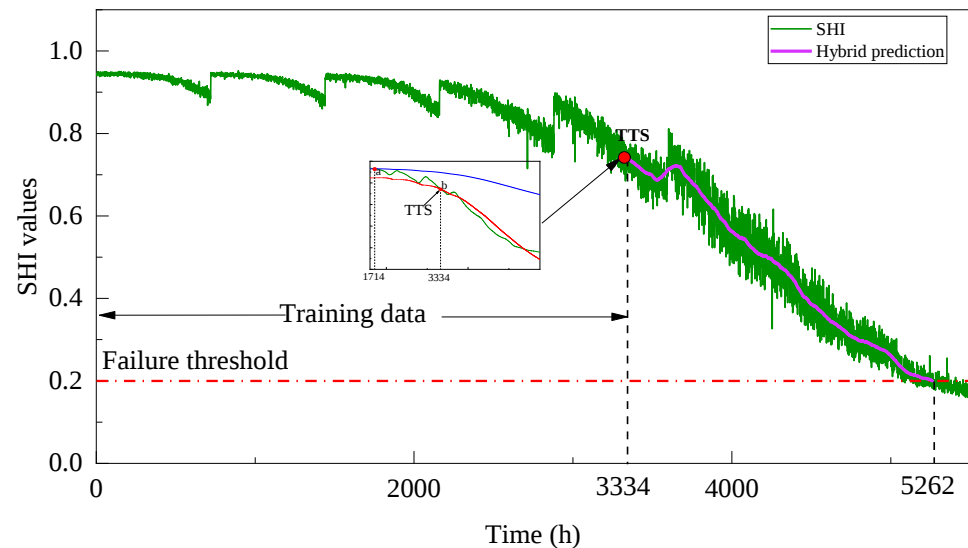


Figure 10. Hybrid prediction of system health condition.

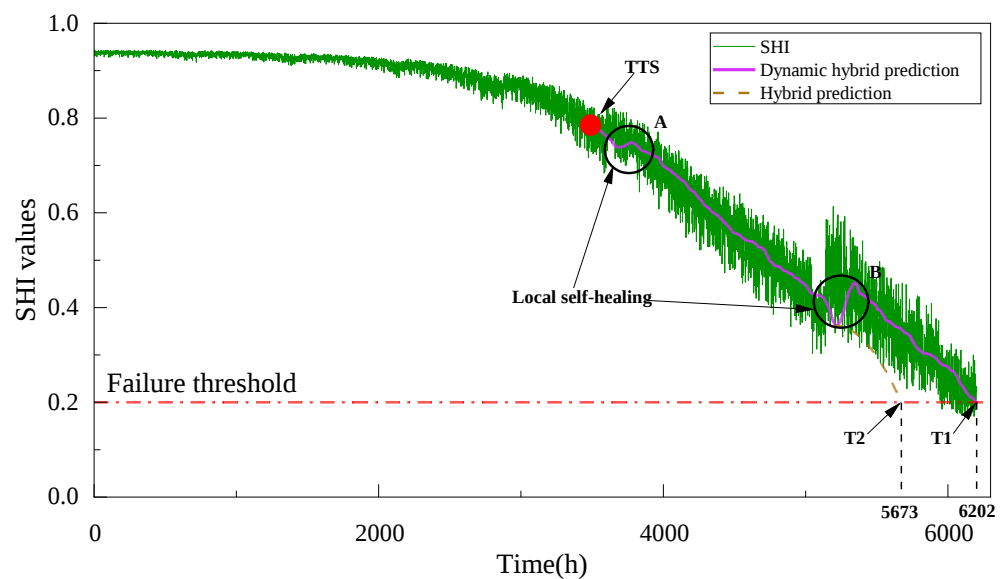


Figure 11. Change of system health condition for interference state.

4.3. Results and Discussion

In order to further demonstrate and validate the proposed method, RVM [23] and LSTM [29] were selected as comparison methods in this section. As shown in Figure 12, H1 is the prediction result obtained by the proposed method. H2 is realized by the LSTM prediction method. H3 uses the RVM method to build a reconstruction model to realize prediction.

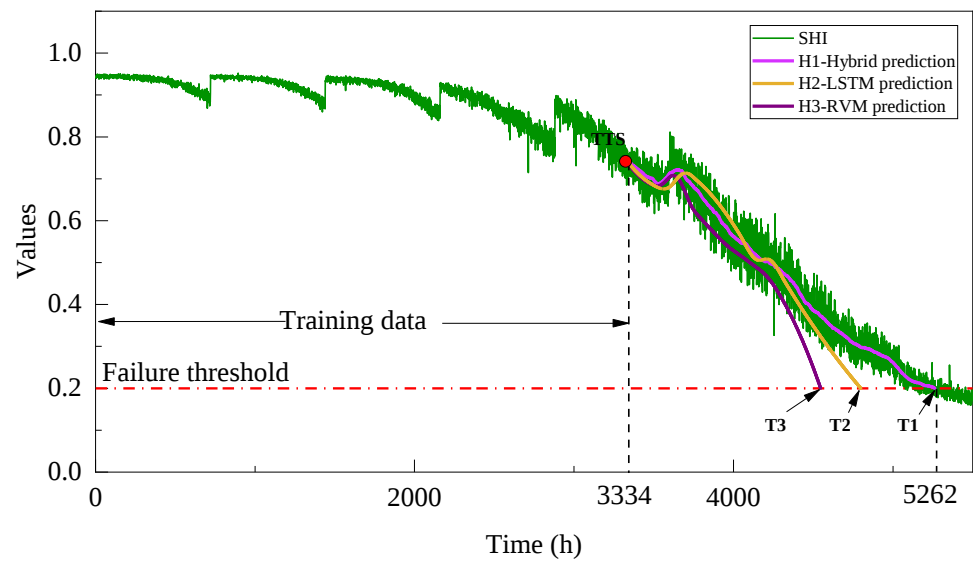


Figure 12. Prediction effect of different methods.

It can be seen from the prediction curve that the prediction time is within 500 h, and the three methods can achieve good prediction results. With the increase of prediction time, H2 and H3 deviate greatly from real life (after 1000 h). The method proposed in this paper can better extract the changes of characteristic data, and the prediction result T1 (5262 h) is closer to the real value (5300 h). According to Equation (16), the RMSE values used to measure the prediction effects of the different prediction methods can be obtained—the results were shown in Figure 13. From TTS to 500 h after the health condition prediction, the three methods could be used, and the error was relatively small. After 500 h, the prediction deviation was obviously large, and after 1000 h, the prediction result showed a large deviation. Through the evaluation index *RMSE*, it could be seen that the proposed method had high prediction accuracy throughout the whole process.

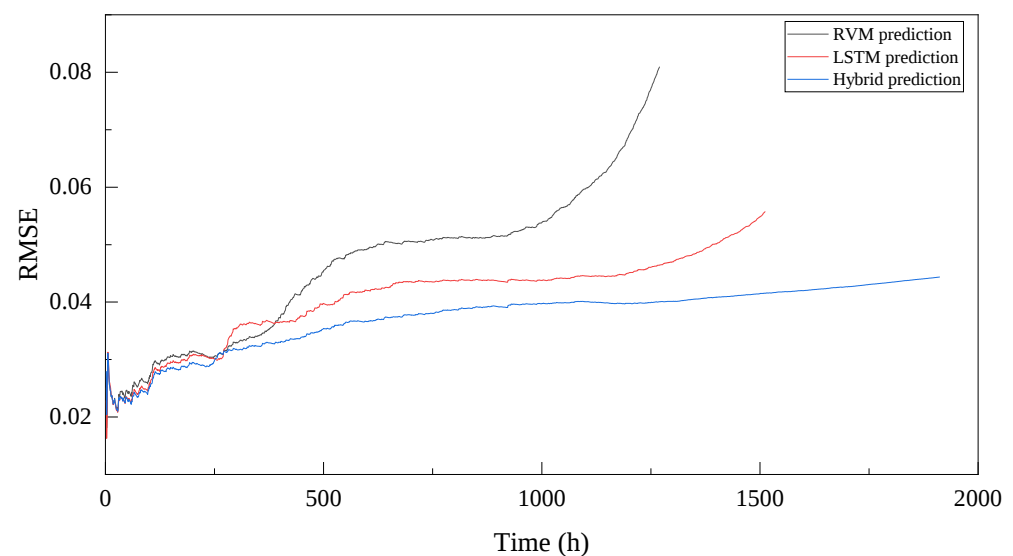


Figure 13. Comparison of prediction accuracy of different methods.

When predicting the health condition of a complex ship mechanical system, if the prediction time is too long, it will be affected by the internal and external uncertainties of the system, and the prediction result will be far from real life (as shown in T2 in Figure 11). The use of dynamically updating training data to track the health condition could achieve better prediction results. For the autonomous ship, the port mode was adopted for maintenance.

In other words, in most cases, the whole lifecycle of a ship's system or equipment does not need to be predicted. According to the voyage and port characteristics, the phased prediction was made. As long as there was enough margin in the current voyage, it could meet the needs of unmanned navigation. If the voyage operation time is T (at present, the requirement for unmanned ships is $T > 500$) hours, it is only necessary to predict the health of the system and make sure that its work could be guaranteed within these hours. In this way, advance maintenance or a specific port maintenance plan could be made according to the health allowance.

For a high-reliability ship mechanical system, equipment self-healing and switching would greatly affect the life of the system. The integration method proposed in this paper can dynamically extract SHI according to the changes of data features and describe the health condition of the system more accurately. At the same time, the prediction process realizes adaptive prediction by decomposing SHI and using a hybrid prediction method, and the prediction result is closer to the real system health condition.

5. Conclusions

This paper proposed a system-level health condition prediction model for ship mechanical systems. The model was mainly composed of two parts, one was the construction of a dynamic SHI, and the other was the realization of hybrid prediction. To accurately describe the health condition of the system, a more-general, indirect SHI adaptive extraction strategy was employed. Combined with the analysis of system degradation trends and functional correlation, the fused SHI could better retain local features and express the degradation trend more accurately. For a system degradation process including global degradation, local regeneration, and local interference, a single prediction method could not adapt to all conditions. Therefore, hybrid prediction was applied by decomposing the SHI according to the degradation characteristics. The effectiveness of the model was justified through case studies involving a FOSS. Through the analysis of the prediction results, the hybrid failure-prediction accuracy was higher, and the prediction results were closer to the actual failure time of the system. Therefore, the proposed method could be effectively used for system-level health condition prognosis. Meanwhile, when the system had an obvious self-healing function, the importance of dynamic continuous prediction was verified. The process was realized by updating new features to the training set. The continuous prediction could better track the change of health values, and this methodology was found effective in the real-world application.

Although the results presented in this work showed a promising prospect of the proposed methodology in real applications, it will require further studies optimizing the prognostics process to improve the RUL prediction accuracy. In addition, working modes and transition stages between modes affected system failure. To more accurately predict the health condition of the system, more research is needed.

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