Construction of Ship Main Engine Performance Evaluation System Based on Principal Component Analysis Method

Zhixin Jiang

Abstract—**By monitoring changes in thermal parameters, the relationship between the operating status of ship diesel engines and thermal parameters can be reflected, thereby determining the current state of ship diesel engines. Nevertheless, the high complexity of thermal parameters renders their evaluation a challenging endeavor. Therefore, to accurately evaluate the performance of ship engines and reduce the difficulty of data processing, this paper proposes to construct a ship engine performance evaluation system through Principal Component Analysis (PCA). The system uses PCA to check its thermal parameters, thereby elucidating the substantial intrinsic correlation between different thermal parameters of diesel engine performance. The results showed that compared with the fuzzy entropy weight method, PCA was more accurate in evaluating the performance of the propagation host, with a maximum relative error of only 4.2%. For the testing host, PCA accurately detected issues such as high cylinder cooling water temperature, high cylinder liner temperature, high exhaust temperature, and low steam compressor speed. The fuzzy entropy weight rule made it difficult to reflect these issues accurately. In addition, PCA could accurately reflect the severity of the above-mentioned faults through outliers and deviation rates. Meanwhile, compared with the information entropy method, PCA had smaller errors, with an average error of only 2.8%. The above results indicate that PCA can accurately evaluate the performance of ship engines, providing a strong reference for ensuring the performance of ship engines and stable operation of ships.**

Index Terms—**performance evaluation, principal component analysis, ship main engine, smart ship**

I. Introduction

WITH the rapid development of intelligent ships, intelligent ship systems play an increasingly important role in ship equipment maintenance, performance assessment, and monitoring. Ship equipment monitoring based on big data analysis methods and traditional equipment monitoring methods can help ship management personnel understand the operational status of ship equipment. Accordingly, the maintenance of ship equipment can be effectively planned and predicted in advance. As the key equipment for ship operation, the ship's main engine consists of many devices. Numerous devices can be divided into several subsystems. According to their functions and characteristics, they can be classified into exhaust gas and exhaust systems, cooling water systems, floating oil systems, etc. Accordingly, the monitoring of the host's performance can facilitate a comprehensive analysis of the operational status of the subsystems that are under the host. Checking the operating parameters of the host can timely determine the current operating status of the host and evaluate whether the performance of the host is decreasing or increasing [1].

To achieve real-time monitoring and effective evaluation of ship energy efficiency status, this study takes ship operation records and environmental data in good condition as samples. A ship navigation state recognition model is constructed using Principal Component Analysis (PCA) and the energy efficiency status of the ship's main engine is evaluated using this model. The constructed navigation state recognition model can be used to identify the current navigation state of the ship. The fuel consumption benchmark model can be utilized to ascertain whether the present energy consumption status of the ship's main engine is within the normal range. This allows for an intelligent and accurate evaluation of the main engine's energy efficiency, thereby providing a reference point for the research of intelligent ship energy efficiency evaluation.

II. The Realization of Principal Component Analysis

A. Overview of Principal Component Analysis

PCA is a widely used multivariate statistical analysis method. The method is founded upon a multidimensional orthogonal linear transformation, which lends itself to applications such as data downscaling and signal feature extraction. In 1901, PCA was initially proposed, and subsequent research was conducted by scholars in this field. This research was later summarized by researchers in the form of probability theory, which led to the development of the PCA algorithm [2]. Many industry scholars have carried out in-depth research on it, and PCA is widely used in various fields such as image processing, pattern recognition, etc. It has different names in different fields, such as the Karhunen-Loeve Transform (KL), Eigen-structure Approach, Hotelling Transform (Hotelling), etc.

As the most commonly used classical feature extraction method, the development of PCA is closely related to the development of the pattern recognition discipline. To conduct a comprehensive analysis of the system through pattern recognition, many potential influencing factors must be considered, which requires selecting a wide range of variables as parameter indicators. In this way, the recognition and analysis of the system will be relatively accurate. Research has shown that there is a certain degree of overlap in the

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information of selected variables and indicators. The utilization of these selected variables for direct analysis of the system will result in an elevated level of complexity in the problem-solving process. In addition, excessive data storage will occupy a large amount of memory space, consume more resources, and take longer to process information. Given this, how to extract features more effectively from the system to be analyzed has become a key link in the discipline of pattern recognition [3].

PCA converts the multivariate indicator problem from the original high-dimensional space to a low-dimensional space, forming a small number of new composite variable indicators. The recently developed composite indicators are employed to supplant the initial indicators in the subsequent data processing. This method facilitates the transformation of a high-dimensional problem into a low-dimensional one, thereby facilitating its resolution [4]. These new composite variable indicators are a special linear combination of the original indicators. This transformation also serves to reduce the difficulty of handling multivariate systems and simplify system variable indicators, thereby reducing the complexity of system analysis. When using the PCA to evaluate something, the thing itself is often composed of multidimensional data, and there is some internal connection between the multidimensional data. Processing data using PCA eliminates correlations between things and reduces workload.

B. Mathematical Model of Principal Component Analysis

According to the basic idea of PCA and its geometric significance that can be learned, PCA uses the idea of dimensionality reduction to concentrate the information contained in a set of variables on some composite variables (linear combinations of original variables). These composite variables obtained are uncorrelated with each other. From a geometric perspective, PCA rotates the original axes to obtain mutually orthogonal axes, thereby maximizing the spread of all data points. The new axes are then obtained by arranging them according to the numerical magnitude of the corresponding eigenvalues.

To analyze the PCA from an algebraic point of view: for a given set of data sample points $X=\left(x_1\ x_2\ ...\ x_n\right)$, there are n sample points in the data set, each of which contains p indicators, i.e. $p_{ix} \in R, i=1,2,...,n$. The expression is shown in equation (1).

$$X=\begin{vmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{vmatrix}=\left[x_1\ x_2\ ...\ x_p\right] \tag{1}$$

Then, the equation (2) is obtained.

$$x_i=\left(x_{1i},x_{2i},...,x_{ni}\right)^T, i=1,2,...,p \tag{2}$$

PCA is the linear combination of the original p indicators to obtain a new composite of p composite indicators, which is shown in equation (3).

$$\begin{cases} z_1=w_{11}x_1+w_{21}x_2+...+w_{p1}x_p \\ z_2=w_{12}x_1+w_{22}x_2+...+w_{p2}x_p \\ \vdots \\ z_p=w_{1p}x_1+w_{2p}x_2+...+w_{pp}x_p \end{cases} \tag{3}$$

Equation (3) is reduced to equation (4).

$$z_i=w_{1i}x_1+w_{2i}x_2+...+w_{pi}x_p, i=1,2,...,p \tag{4}$$

x_i and z_i represent n-dimensional. The coefficient w_{ij} needs to satisfy three conditions. First, z_i, z_j are uncorrelated, where $\left(i \neq j, i, j=1,2,...,p\right)$. Second, the variance of variable z_1 is greater than or equal to the variance of variable z_2, which is decreasing by degrees. Third, $w_{k1}^2+w_{k2}^2+...+w_{kp}^2, k=1,2,...,p$.

When the 3 conditions are met, the random variable indicators obtained after the transformation are uncorrelated between the two [5]. The variance is sequentially decreasing.

From the above, the transformation matrix of $p \times p$ can be obtained to equation (5):

$$W=\begin{vmatrix} w_{11} & w_{12} & \cdots & w_{1p} \\ w_{21} & w_{22} & \cdots & w_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ w_{p1} & w_{p2} & \cdots & w_{pp} \end{vmatrix} \tag{5}$$

Then there is equation (6):

$$Z=\left[z_1,z_2,...,z_p\right]=W^T X \tag{6}$$

The process of PCA is a process of de-correlation, and the variables obtained are uncorrelated with each others.

C. Contribution of Principal Components

The contribution ratio and cumulative contribution ratio of principal components reflect the extent to which the transformed metrics z_i portraying the information content of the original data X.

Contribution Ratio

The larger the proportion of the eigenvalues of the i-th largest covariance matrix to the sum of the eigenvalues of all covariance matrices, the stronger the ability of the i-th variable indicator to present more original data information and integrate the information of the original variable indicators. The formula for calculating the covariance matrix of the i-th largest eigenvalue λ_i is expressed as equation (7).

$$\omega_i = \frac{\lambda_i}{\sum_{i=1}^{p} \lambda_i} \quad (7)$$

Cumulative Contribution Rate

The larger the ratio of the sum of the first k eigenvalues of the covariance matrix to the sum of all eigenvalues of the covariance matrix, the more tender and sufficient the first k principal components represent the information of the original data. The formula is expressed as equation (8):

$$Z_k = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{p} \lambda_i} \quad (8)$$

In practical applications, the first k larger variable indicators are usually selected to achieve a certain threshold for their cumulative contribution rate (the cumulative contribution rate empirically selected in this article is not less than 90%). The first k larger composite indicators are used to replace the original p variable indicators for subsequent data analysis and processing, aiming to achieve the goal of data compression, dimensionality reduction, and extraction of the main features of the data [6].

D. Steps of Principal Component Analysis Algorithm

(1) The mean $\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$ of the samples in sample dataset $X = (x_1\ x_2\ ...\ x_n)$ is calculated, the samples are centered, and the centered sample is taken as $\overline{x}_i, \overline{x}_i = x_i - \mu$.

(2) The covariance matrix V of the original dataset X is calculated. The matrix is denoted as $V = \frac{1}{n}\overline{X}\overline{X}^T$.

(3) The eigen-decomposition is performed on covariance matrix V to obtain its eigenvalues and corresponding eigenvectors w_i, and the eigenvalues in descending order are arranged.

(4) According to the selected cumulative contribution rate, the first k eigenvalues is taken. $\lambda_1, \lambda_2, ..., \lambda_k$ is the k eigenvectors corresponding to the k eigenvalues extracted. The first k eigenvector combination matrix is noted as $W_k = [w_1, w_2, ..., w_k]$, then the k principal components extracted are $W_k^T \overline{X}$.

(5) After the principal components are determined, the corresponding comprehensive evaluation function can be constructed. The calculation formula is expressed as equation (9).

$$F = \omega_1 y_1 + \omega_2 y_2 + \cdots + \omega_n y_n \quad (9)$$

In equation (9), y_i represents the principal component.

III. Principal Component Data Analysis

A. Original Data Matrix

In Table I, rotational speed, shaft power, wind speed, current speed, wave level, water speed, and ground speed are the main data affecting the fuel consumption of the main engine. These seven important indicators can be used to establish a matrix for the purpose of analysis [7].

TABLE I
ENERGY EFFICIENCY DATA FOR SELECTED SEGMENT HOSTS

Segment	RPM (r/min)	Shaft power (kw)	Wind speed (kn)	Water velocity (kn)	Wave class (grade)	Speed over water (kn)	Speed to ground (kn)	Fuel consumption rate (g/kw·h)
1	80.0	7126	4	1.9	3	12.3	14.2	180.091
2	79.2	6940	5	0.9	4	12.0	12.9	180.115
3	79.4	7103	3	3.6	1	1.81	15.4	180.088
...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...
27	68.0	4951	4	2.9	3	9.5	12.4	180.098
28	68.0	5160	3	3.0	1	9.3	12.3	172.884

TABLE II
DATA AFTER STANDARDIZATION

Segment	RPM	Shaft power	Wind speed	Water velocity	Wave class	Speed over water	Speed to ground
1	1.5963	1.3987	0.0515	-0.9177	0.1472	1.8316	1.3878
2	1.4347	1.2016	1.4947	-2.0205	1.1776	1.6047	0.2526
3	1.4751	1.3743	-1.3916	0.9571	-1.9137	1.4534	2.4357
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
27	-0.8274	-0.9066	0.0515	0.1851	0.1472	0.1472	-0.1840
28	-0.8274	-0.6851	-1.3916	0.2954	-1.9137	-1.9137	-0.2713

B. Data Standardization and the Establishment of Covariance Matrix

The programming software is used to standardize the original data matrix, and the results are shown in Table II.

The covariance matrix of sample R is calculated using standardized data, as shown in equation (9).

$$R=\begin{bmatrix} 1.0000 & 0.9925 & 0.1403 & -0.2791 & 0.0839 & 0.9208 & 0.8420 \\ 0.9925 & 1.0000 & 0.1410 & -0.2590 & 0.0815 & 0.9017 & 0.8359 \\ 0.1403 & 0.1410 & 1.0000 & -0.2634 & 0.8734 & 0.1366 & -0.0508 \\ -0.2791 & -0.2590 & -0.2634 & 1.0000 & -0.1840 & -0.5249 & 0.1858 \\ 0.0839 & 0.0815 & 0.8734 & -0.1840 & 1.0000 & 0.0437 & -0.0952 \\ 0.9208 & 0.0917 & 0.1366 & -0.5249 & 0.0437 & 1.0000 & 0.7388 \\ 0.8420 & 0.8359 & -0.0508 & 0.1858 & -0.0952 & 0.7388 & 1.0000 \end{bmatrix} \tag{9}$$

C. Calculation of Eigenvalues and Contribution Ratio

The principal components and their corresponding eigenvalues and contribution rates are shown in Table III.

TABLE III
PRINCIPAL COMPONENTS AND THEIR CORRESPONDING EIGENVALUES AND CONTRIBUTION RATES

Principal component	Eigenvalue	Contribution	Cumulative contribution rate
1	3.749	46.860	46.860
2	2.047	25.592	72.452
3	1.775	22.185	94.637
4	0.229	2.859	97.296
5	0.116	1.455	98.591
6	0.070	0.985	99.936
7	0.005	0.064	100.000

D. Determining the Number of Principal Components

The total variance explanatory graph displays the differences and variations between the eigenvalues, variance contribution rates, and cumulative variance contribution rates of the seven principal components. The eigenvalues and variance contribution rates represent the amount of information on the seven ship parameters represented by the principal components. The larger the eigenvalue and variance contribution rate are, the more original information is retained by this principal component [8]. The values of the eigenvalues are arranged in descending order. The data of eigenvalues in PC1-PC6 are becoming increasingly insignificant. The cumulative contribution rate in Table III means the sum of the original information that the first n principal components can contain. In general, the principal components with a cumulative contribution rate ≥85% can be used as new parameters and represent most of the information of the original data [9].

Fig. 1 shows the gravel plot of the seven principal components, and the vertical coordinates in the figure are the eigenvalue values of each principal component. In PCA, the gravel plot is also an effective way to assist in selecting the number of components required. In general, the principal components with eigenvalues greater than 1 should be selected, and the information content of the principal components with eigenvalues less than 1 is incomplete [10]. At the same time, the slope of the curve in the gravel plot should also be considered. The number of selected principal components should be between the two principal component points where the slope of the curve changes significantly. Combined with the actual situation of the samples in this paper, the first three principal components (PC1 to PC3) are selected to construct the equation graphs.

Table IV shows that the correlation between the principal component 1 and the first, second, sixth, and seventh energy consumption indicators is relatively large. The principal component 1 can be regarded as the rotational speed (r/min), shaft power, speed to water, and speed to the ground, to affect the host energy efficiency of the integrated indicators [11]. The correlation between principal component 2 and the fifth indicator is relatively large. The principal component 2 can be regarded as a comprehensive indicator that the wave level affects the energy efficiency of the main engine. The correlation between principal component 3 and the fourth indicator is relatively large. The principal component 3 can be regarded as a comprehensive indicator of the influence of current speed on the energy efficiency of the main engine.

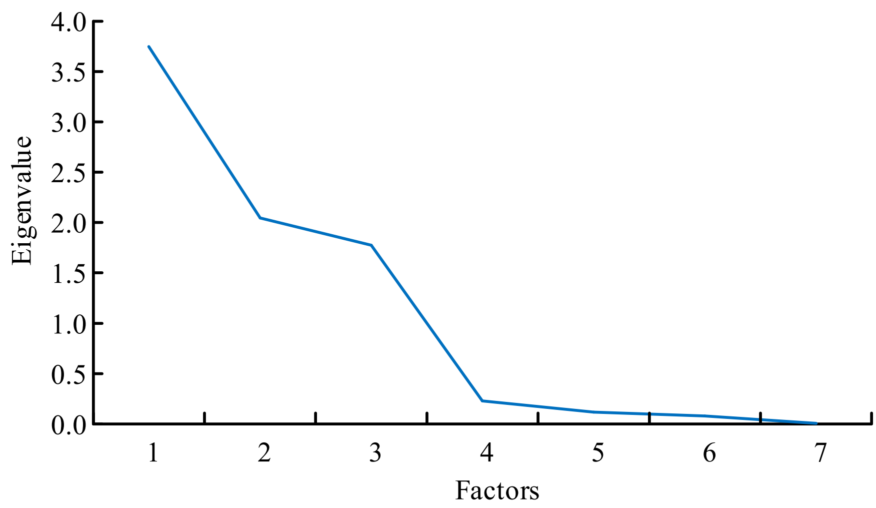


Fig. 1. Principal components of the crushed stone.

TABLE IV
COMPONENT MATRIX

Energy consumption indicators	PC1	PC2	PC3	PC4	PC5	PC6	PC7
RPM	0.264	-0.038	0.037	2.125	-0.759	-1.763	-11.509
Shaft power	0.262	-0.040	0.053	1.802	-0.840	-2.634	7.558
Wind speed	0.057	0.460	0.228	0.709	2.660	-1.201	0.027
Water velocity	-0.094	-0.216	0.786	-1.356	0.035	-4.464	0.202
Wave class	0.037	0.458	0.293	3.119	-2.449	1.595	-0.188
Speed over water	0.257	-0.009	-0.218	2.074	0.694	2.338	2.500
Speed to ground	0.223	-0.181	0.371	1.321	0.830	2.345	3.046

TABLE V
FACTOR WEIGHT ANALYSIS

Name	Explanatory rate of variance (%)	Cumulative variance explained (%)	Weight (%)
PC1	53.301	53.301	55.067
PC2	28.384	81.686	29.325
PC3	15.108	96.793	15.608

TABLE VI
COMPREHENSIVE EVALUATION VALUE

Ranking	Row Index	Composite Score	PC1	PC2	PC 3
1	6	1.316	1.682	0.867	0.867
2	2	1.093	1.482	1.500	-1.041
3	4	0.849	1.515	-0.497	1.024
4	1	0.823	1.664	-0.095	-0.417
5	7	0.756	1.432	-0.205	0.177
6	8	0.714	1.397	-0.067	-0.172
7	5	0.691	1.347	-0.067	-0.200
8	9	0.302	0.550	0.114	-0.220
9	14	0.244	-0.501	1.283	0.921
10	3	0.207	1.428	-2.228	0.590
11	16	0.207	-0.437	1.576	-0.091
12	26	0.193	-0.548	1.373	0.587
13	22	0.009	-0.795	1.749	-0.425
14	12	-0.196	-0.657	-0.197	1.430
15	19	-0.232	-0.633	-0.003	0.756

E. Comprehensive Evaluation of Principal Component Analysis

The cumulative contribution rate of the eigenvalues of the first three principal components is 96.793% (Table V), which is greater than 85%. Therefore, the principal components 1 to 3 are selected as the host energy efficiency data of the comprehensive evaluation index [12-13].

Table VI shows the comprehensive evaluation value and ranking of the energy efficiency data of the main engine under different fuel consumption.

Table VI shows that the comprehensive score of the first 15 data calculated by the F-value can be obtained from the comprehensive score and ranking of each sample. Table VI shows that the comprehensive evaluation function can represent the changes in the unit state reflected by seven indicators, such as rotational speed, shaft power, wind speed, current speed, wave level, water speed, ground speed, etc. The loss of information is small [14-16]. The analysis shows that the data can better reflect the operating status of the host. PCA is employed to reduce the dimensionality of raw energy efficiency data and integrate information to obtain a quantitative evaluation of host status indicators. This is advantageous for the monitoring of the operating status of the host.

F. Model Validation and Energy Efficiency Status Assessment

(1) Model Validation

Fig. 2 shows the plot of the residuals between the calculated host fuel consumption and the actual host fuel consumption. The graph reflects the error of the host fuel consumption benchmark model corresponding to each data point. After calculation, the accuracy of the model is 98.50% in the sample time period, which is highly accurate and can be used as the benchmark model of oil consumption for host energy efficiency state assessment.

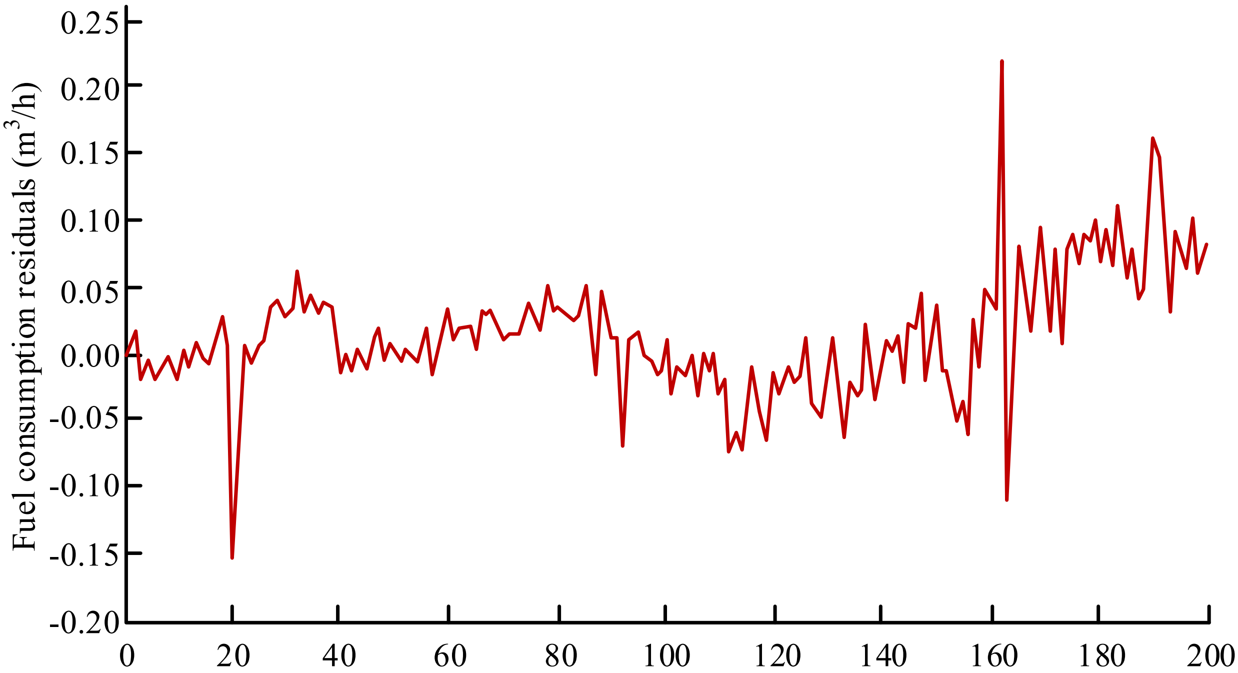


Fig. 2 Residual difference of fuel consumption amount

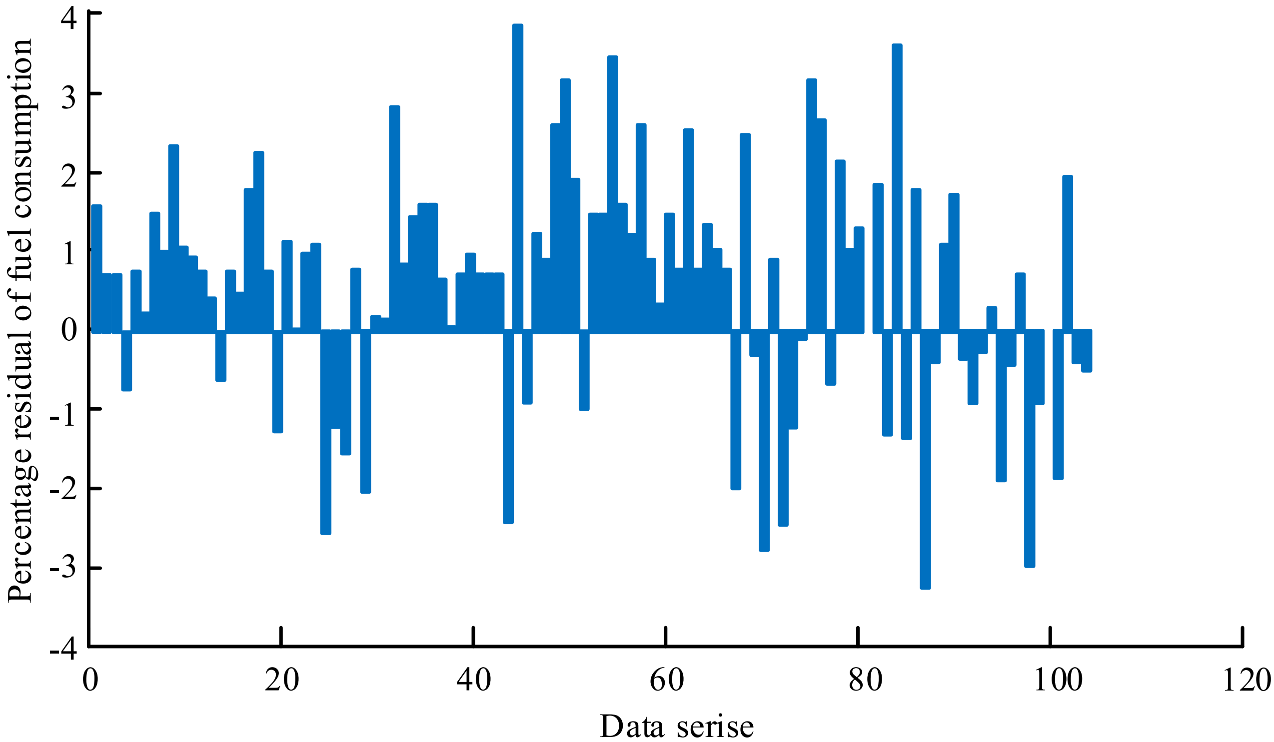


Fig. 3 Percentage residual of fuel consumption

(2) Energy efficiency state assessment

This paper selects ship operation data one year after training the fuel consumption benchmark model for energy efficiency status evaluation. After processing and PCA of some data, the oil consumption benchmark value is obtained by inputting it into the oil consumption benchmark model. The fuel consumption of the main engine of the ship operation is compared with the fuel consumption benchmark value of the model. Fig. 3 is a histogram of the remaining percentage between the actual fuel consumption and the benchmark fuel consumption of the model host. The actual fuel consumption value is at most 3.8% higher than the benchmark fuel consumption value. Overall, the actual fuel consumption is higher than the benchmark fuel consumption, with an average increase of 0.5%. The above data indicate that the mainframe is in a state of slightly higher energy efficiency level at this stage. Fig. 4 shows the comprehensive performance evaluation results of the ship's main engine. In Fig. 4, within the actual 120 data series, the comprehensive performance score of the ship's main engine is not lower than 70 points. The highest score is 98 points, the lowest is 90 points, and the average score is 83 points. This indicates that the main engine performance of the ship is excellent, which is consistent with its actual operating situation.

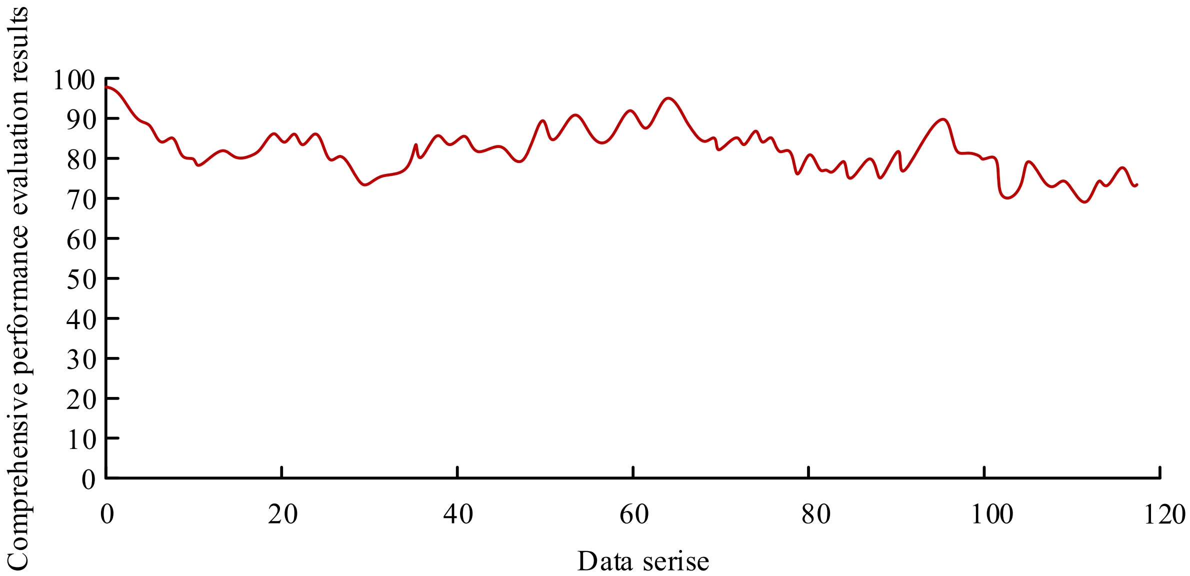


Fig. 4 Comprehensive performance evaluation results

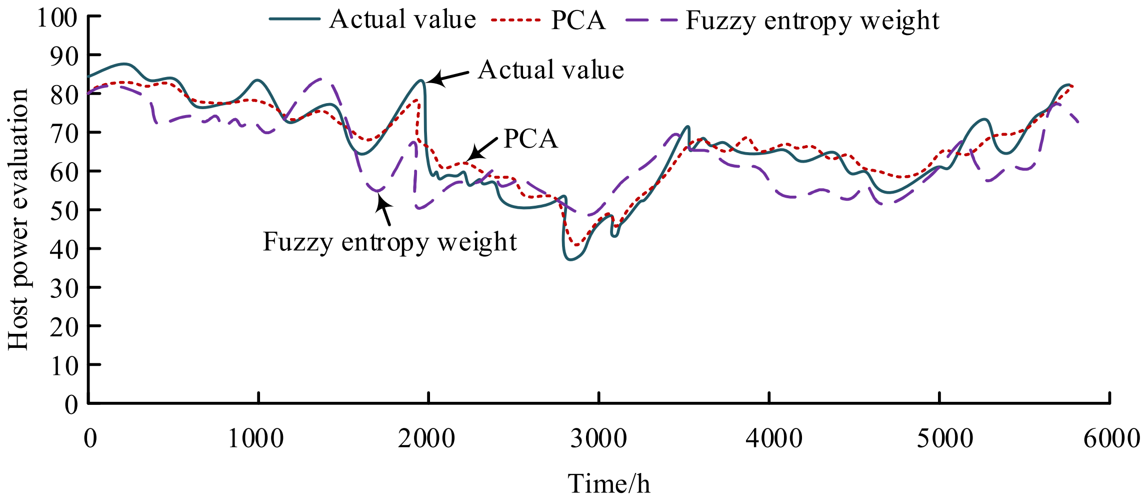


Fig. 5 Host power evaluation results

TABLE VII
FAULT DETECTION RESULTS

Parameter	Abnormal point position		Abnormal degree		Outlier		Drift rate/%	
	PCA	Fuzzy entropy weight	PCA	Fuzzy entropy weight	PCA	Fuzzy entropy weight	PCA	Fuzzy entropy weight
Cylinder sleeve	100	100	1	1	74	75	2.5	3.2
cooling water	130	320	2	2	80	77	10.8	8.4
temperature	160	160	3	2	86	78	19.1	10.2
Air cylinder	300	300	1	1	290	288	1.6	0.8
exhaust	330	340	2	1	300	291	5.1	2.1
temperature	360	350	3	2	310	295	8.6	3.9
Speed of the	500	500	1	1	3900	3982	-2.6	-1.2
turbine	530	530	2	1	3500	3856	-12.6	-5.8
compressor	560	550	3	2	3000	3793	-25.1	-9.6

To further explore the accuracy of PCA-based performance evaluation methods for ship engines, the power of ship engines is evaluated and compared with the fuzzy entropy weight evaluation method. The results are shown in Fig. 5. Compared to the fuzzy entropy weight method, PCA's evaluation value of host power is closer to the true value. The maximum relative errors between the evaluation results of the fuzzy entropy weight method and PCA and the true values are 20.2% and 4.2%, respectively. The above results indicate that PCA is more accurate in evaluating the performance of ship engines. To further explore the detection of the host performance evaluation method proposed in the study, a fault host is tested. The experimental results are shown in Table VII.

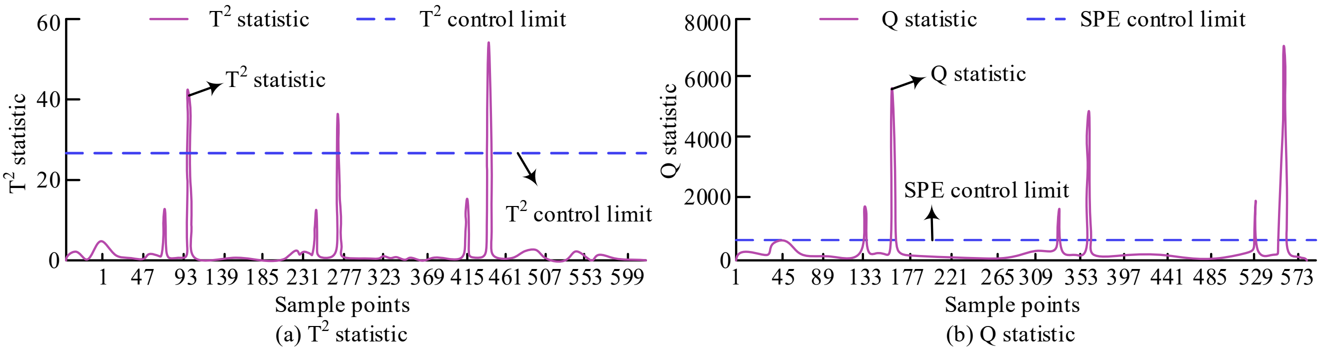


Fig. 6 T^2 and Q statistics of the test samples

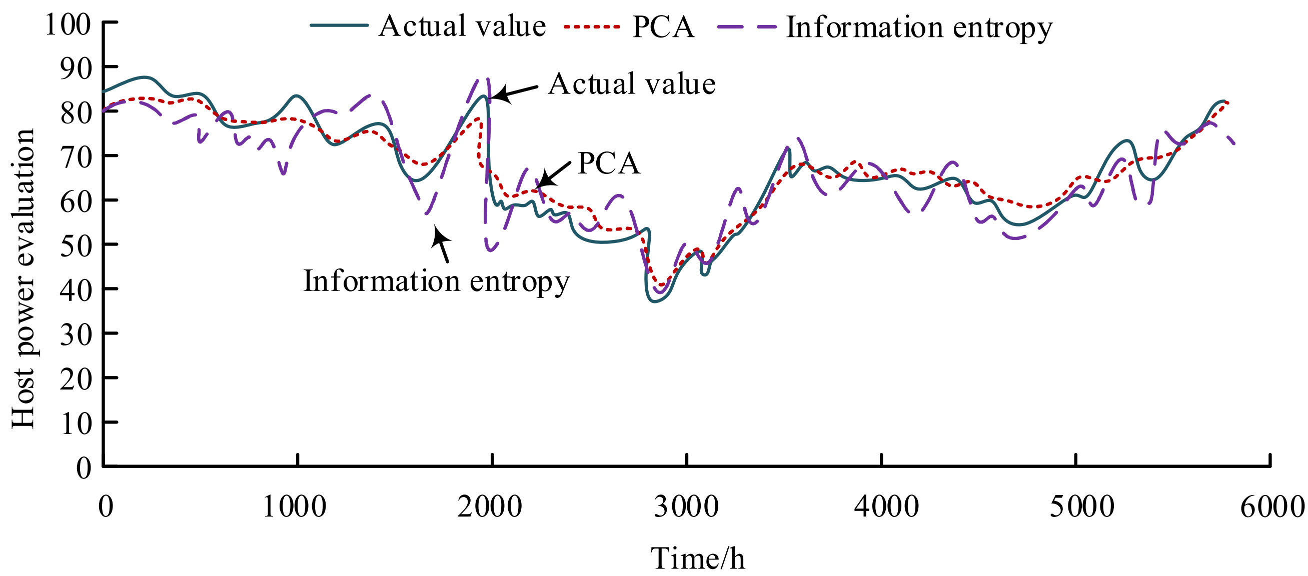


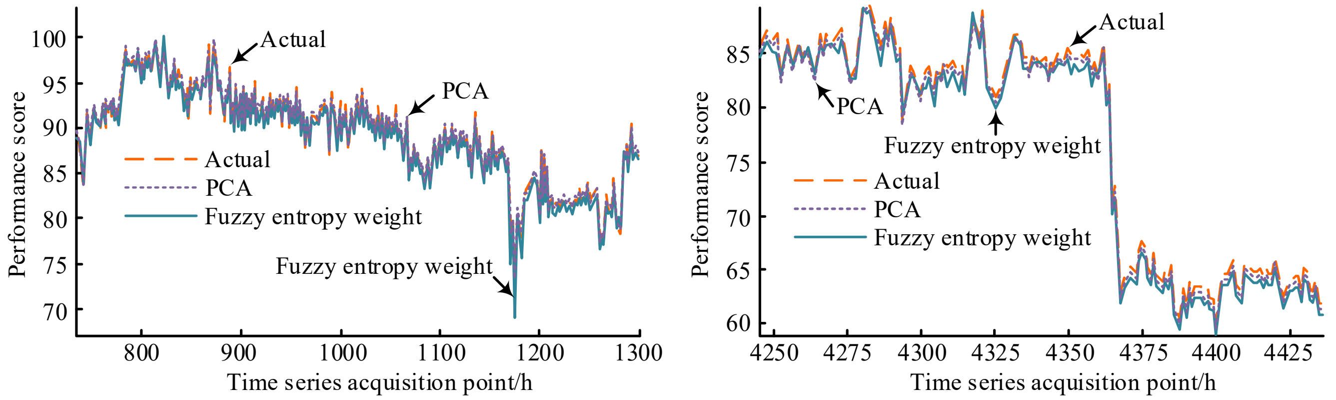
Fig. 7 PAC and information entropy evaluation results

According to Table VII, the PCA can effectively monitor the anomaly points of the host. The monitoring results show that the host has a high cylinder liner cooling water temperature, high cylinder exhaust temperature, and low steam compressor speed. Outliers and drift rates accurately reflect the severity of the above-mentioned faults, facilitating timely troubleshooting by the crew. Although the fuzzy entropy weight method can preliminarily distinguish the fault location and degree, there are some differences between the discrimination results and the actual result. PCA can more accurately evaluate and monitor the performance of ship hosts. The T^2 and Q statistics of the test samples are shown in Fig. 6.

Under the current operating conditions in Fig. 6, the T^2 statistic will only exceed the control limit when the parameter offset rate is large, while the Q statistic will exceed the control limit when the parameter offset rate is small. Therefore, during the normal operation of the host under a certain operating condition, the T^2 statistic can be used as the monitoring indicator for parameters with a large fluctuation range. The Q statistic can be used as the monitoring indicator for parameters with a small fluctuation range. This can reduce the probability of false positives and improve the accuracy of monitoring. To further validate the performance of the proposed method for averaging a ship's engine performance, it is compared with the information entropy-based engine performance evaluation method. The results are shown in Fig. 7.

As shown in Fig. 7, compared with the information entropy method, the host power evaluation value of PCA is closer to the true value. The maximum relative errors between the evaluation results of information entropy and PCA and the true values are 17.6% and 4.2%, respectively, and the average errors are 13.5% and 2.8%, respectively. The above results indicate that PCA is more accurate in evaluating the performance of ship engines. To further analyze the performance of the proposed ship host performance evaluation method, the overall performance trend in operation is evaluated by the fuzzy entropy weight method, which is shown in Fig. 8.

Fig. 8(a) shows that the overall trend of the ship's main engine is monotonically decreasing around 800-1300 hours. This indicates that the overall performance of the host is declining and there is a gradual trend of failures occurring. In Fig. 8(b), the ship's main engine undergoes a class transition at 4,365 hours, resulting in a sudden decline in engine performance. This indicates that the host may experience a sudden malfunction or that some unexpected factor has a significant impact on the host. Therefore, both PCA and fuzzy entropy weight methods can achieve an accurate evaluation of the performance of ship engines. However, compared to the actual situation, the evaluation results of PCA are more consistent. To further validate the performance evaluation method for ship engines proposed in the study, the cumulative failure rate of ship engines is analyzed using it, and the results are shown in Table VIII.



（a）750～1300h （b）4250～4425h

Fig 8 Overall change trend of ship host performance

TABLE VIII
CUMULATIVE FAILURE RATE OF SHIP'S MAIN ENGINE

Component	Fault	500h	1000h	1500h
Crankshaft bearing assembly	Bearing wear, burning, melting, and biting	0.015	0.029	0.048
	Fracture of crankshaft connecting rod	0.005	0.011	0.013
Piston, piston ring, cylinder liner components	Piston ring fracture or snap ring	0.019	0.043	0.065
	Piston crack or fracture	0.003	0.006	0.011
	Cylinder crack or fracture	0.003	0.007	0.010
Cylinder body	Crack or fracture	0.003	0.007	0.012
	Other faults	0.007	0.015	0.025
Fuel injection pump	/	0.010	0.022	0.032

According to Table VIII, when the ship's main engine operates normally for 500 hours, the incidence of “Bearing wear, burning, melting, and biting” and “Piston ring fracture or snap ring” is the highest, at 0.015 and 0.019, respectively. In summary, the proposed method for analyzing the performance of ship engines can reflect the reliability of safe operation of ship propulsion systems at a certain point in time. Due to the fact that the failure modes and failure rates of ship's main engine components are accumulated through a large amount of data, their reliability has reference value. From a lateral perspective, the collection of fault data for ship propulsion systems, the establishment of databases, and the sharing of data are extremely important for accurate analysis and ensuring the reliability of propulsion systems.

IV. CONCLUSION

This study used PCA to evaluate the performance of ship engines and constructed a clear and easily comparable comprehensive evaluation index system based on principal components by combining corresponding engine fuel consumption data. This provides a certain reference for evaluating the performance of the main engine and the stable operation of the ship.

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