

FAULT DIAGNOSIS OF MARINE DIESEL ENGINE BASED ON MIXED SIMILARITY ALGORITHM

Cuijia^{1*}, Chenchao, Jipeng²

^{*1,2}(School of Electronics and Information, Jiangsu University of Science and Technology Zhenjiang 212000, China)

***Corresponding Author:**

Abstract:-

In view of the problems of inlet and exhaust faults and clogging of the marine diesel engine, the appropriate thermal parameters are selected as the basis for fault diagnosis and positioning. In this paper, the improved Pearson correlation coefficient and grey relational diagnosis analysis are combined, and a hybrid similarity collaborative filtering algorithm is proposed. At the same time, the simulation model of the diesel engine is built by AVL-BOOST software, and the fault samples are simulated. The mixed similarity collaborative filtering algorithm is used to calculate the correlation degree of the fault data, and the final diagnosis result is given accordingly. The results show that the hybrid similarity diagnosis algorithm has excellent diagnosis speed and accuracy, which can ensure the fault diagnosis and location of diesel engine is more accurate and reliable.

Keywords:- Diesel engine; Pearson correlation coefficient; Grey correlation diagnosis; Collaborative filtering; Mixed similarity

CLC Number: TP399

INTRODUCTION

The marine diesel engine is the heart of the ship's power plant, and its health status determines the safety of the entire ship. Therefore, the diagnosis of diesel engines is a crucial research in ship systems. It is a common method in diesel engine fault diagnosis to evaluate its health status through various state parameters when the diesel engine is running. The vibration analysis method [1] refers to the method of condition monitoring and fault diagnosis of the diesel engine by collecting diesel engine noise and vibration signals, but the vibration signal at a certain point is affected by too many factors, and it is difficult to completely filter the noise signal. Oil analysis technology [2] refers to the use of ferrography and spectroscopy to obtain data, using multivariate statistical analysis dynamic cluster analysis method to analyze the diesel engine wear condition and lubricant quality, and obtain the diagnosis results. However, the oil analysis method cannot determine the fault location, and it is difficult to achieve real-time monitoring, and the cost is also high. The diesel engine's thermal parameters [3, 4] can characterize the working state of the diesel engine and contain a large amount of fault information, which can be used in various working parameters of the engine (such as power, speed, cylinder pressure and water temperature) and normal working conditions. Parameter comparison to analyze and judge the working state of the engine.

Domestic and foreign scholars have made great progress in the research of diesel engine fault diagnosis. Li Huabing [5] and others applied the gray prediction theory to the field of ship machinery failure and achieved good results. Han Min, Li Jinbing [6] proposed an enhanced intermittent unknown input Kalman filter, which can effectively reduce the complexity of modeling, respond to parameter predictions with different working states, and better faults on marine diesel engine systems. Make predictions. Cao Yu [7] combined the concept of grey relational degree with the principle of grey relational decision making, and proposed to apply the grey relational model to fault diagnosis decision-making, and establish case library by case-based reasoning technology to further improve the knowledge base system of equipment. Fu Yunwei, Jia Limin [8] and so on using the product function and Pearson correlation coefficient method, the vibration samples are mixed and crossed, making the fault diagnosis more intuitive and convenient. In recent years, the method based on feature orientation and statistical distance based method has been gradually applied and diagnosed.

In this paper, for the problems of intake and exhaust faults and clogging of the marine diesel engine, the appropriate thermal parameters are selected as the basis for fault diagnosis and location. A hybrid similarity collaborative filtering algorithm based on improved Pearson correlation coefficient and grey relational diagnosis analysis is proposed. The collaborative filtering theory is applied to the field of fault diagnosis, and the fault type is regarded as the user, and the fault sample is regarded as the evaluation of the thing. The user similarity function is introduced to improve the Pearson correlation coefficient similarity. By means of parameter adjustment, it is combined with the gray correlation similarity to form a hybrid similarity algorithm. Finally, using AVL-BOOST software, the diesel engine fault simulation is carried out to verify the effectiveness and accuracy of the algorithm.

1 Typical similarity index

1.1 Pearson similarity

The Pearson similarity interval range is [-1, 1], which is expressed in the correlation between its variables. When one variable increases and the other variable increases, it indicates that they are positively correlated, and the correlation coefficient is greater than 0. If one variable increases, the other variable decreases, indicating that they are negatively correlated. The coefficient is less than 0; if the correlation coefficient is equal to 0, there is no linear correlation between them.

$$sim_r(i, j) = \frac{\sum_{m \in I_{ij}} (R_{i,m} - \bar{R}_i)(R_{j,m} - \bar{R}_j)}{\sqrt{\sum_{n \in I_{ij}} (R_{i,n} - \bar{R}_i)^2} \sqrt{\sum_{n \in I_{ij}} (R_{j,n} - \bar{R}_j)^2}} \quad (1)$$

Where: I_{ij} represents the fault set jointly diagnosed by the fault criteria set i and j ; $R_{i,m}$ and $R_{j,n}$ respectively represent the scores of the fault criterion set i and j to be detected fault i , \bar{R}_i and \bar{R}_j indicates the average diagnosis result for the diagnosed fault, respectively.

1.2 Improve Pearson similarity

Generally speaking, the more times a certain type of fault is diagnosed by the diagnostic system, the higher the frequency of this type of fault is proved. Assuming that the number of fault types is I , the number matrix N of fault standards-fault pending results can be calculated:

$$N = \begin{bmatrix} N_{11} & N_{12} & \cdots & N_{1k} \\ N_{21} & N_{22} & \cdots & N_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ N_{s1} & N_{s2} & \cdots & N_{sk} \end{bmatrix} \quad (2)$$

Where, lines represents the number of parameter types; Column k represents the number of fault types; N_{sk} represents the number of k -type faults diagnosed by the parameter s .

The frequency of a certain type of fault can be expressed as:

$$I_{ia} = \frac{N_{ia}}{N_i} \quad (3)$$

Where N_{xa} represents the total number of a -type faults diagnosed by specific parameter i ; N_i represents the total number of diagnoses for a particular parameter i . Then the similarity between the fault pending set and the fault standard set is:

$$sim_n(i, j) = \frac{\sum_{a=1}^k I_{ia} I_{ja}}{\sqrt{\sum_{a=1}^k I_{ia}} \sqrt{\sum_{a=1}^k I_{ja}}} \quad (4)$$

1.3 Grey correlation

Definition 1 There are n parameters to form a parameter set U , $U = \{u_1, u_2, \dots, u_n\}$; m faults constitute fault set A, $A = \{a_1, a_2, \dots, a_m\}$; the diagnostic result matrix of each fault is

ψ :

$$\psi = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix} \quad (5)$$

Definition 2 For the fault pending set u_i and the fault criterion set u_j ,

$$\varepsilon_{ij} = \frac{1+|s_i|+|s_j|}{1+|s_i|+|s_j|+|s_i-s_j|}, i \neq j, i, j = 1, 2, \dots, n \quad (6)$$

The absolute degree of association of the fault set u_i to the fault criterion set u_j . Among them:

$$\begin{aligned} |s_i| &= \left| \sum_{k=2}^{m-1} x_i(k) + \frac{1}{2} x_i(m) \right|, \\ |s_j| &= \left| \sum_{k=2}^{m-1} x_j(k) + \frac{1}{2} x_j(m) \right|, \\ |s_i - s_j| &= \left| \sum_{k=2}^{m-1} (x_i(k) - x_j(k) + \frac{1}{2} (x_i(m) - x_j(m))) \right| \end{aligned} \quad (7)$$

If the faulty set i is more similar to the fault criterion set j , the larger ε_{ij} is, $\varepsilon_{ij} \in [0, 1]$.

Definition 3 From the definition 2, the gray absolute correlation degree of the fault to-test set u_i to the fault criterion set u_j is calculated, and the triangular matrix is obtained.

$$\phi = \begin{bmatrix} \varepsilon_{11} & \varepsilon_{12} & \dots & \varepsilon_{1n} \\ & \varepsilon_{22} & \dots & \varepsilon_{2n} \\ & & \ddots & \vdots \\ & & & \varepsilon_{nn} \end{bmatrix} \quad (8)$$

Where $\varepsilon_{ii} = 1$ ($i = 1, 2, \dots, n$), the matrix ϕ is called the fault characteristic variable correlation matrix.

The critical value r , $r \in (0.5, 1]$ is taken, and when $\varepsilon_{ij} \geq r$ ($i \neq j$), the fault pending set u_i and the fault criterion set u_j have the same characteristics.

Definition 4 The classification of the fault characteristic variable under the critical value r is called the r gray correlation cluster of the fault characteristic variable.

Where r can be determined according to the accuracy of the actual diagnostic requirements. When r is closer to 1, the finer the classification, the fewer the number of failures per cluster; conversely, the closer the r is to 0, the coarser the classification, the better the diagnostic accuracy is affected. The number of failures in each cluster is relatively large.

Definition 5 The gray similarity between the fault test set i and the fault standard set j is:

$$sim_m(i, j) = 1 - \varepsilon_{ij} = \frac{|s_i - s_j|}{1+|s_i|+|s_j|+|s_i-s_j|} \quad (9)$$

Calculate n fault similarity matrices according to formula (3)

$$\Gamma = \begin{bmatrix} sim(1,1) & sim(1,2) & \dots & sim(1,n) \\ & sim(2,2) & \dots & sim(2,n) \\ & & \ddots & \vdots \\ & & & sim(n,n) \end{bmatrix}$$

According to the grey correlation degree theory, the closer the geometry between the fault to-test set and the fault criterion set is, the more relevant they are. Therefore, in the collaborative filtering, the grayness of the fault is established by establishing the gray absolute correlation degree between the faults, and the fault is gray-associated clustering according to the given critical value and the number of clusters. Sort all the faults in the class, find the nearest neighbor of the fault, calculate the weighted average according to the existing diagnosis results of the nearest neighbor, and predict the diagnosis result of each parameter to the fault type, and the highest diagnostic value or the former TOP-N The fault is recommended to the system.

2 Fault Diagnosis of Marine Diesel Engine Based on Hybrid Similarity Collaborative Filtering Algorithm

In typical diesel engine fault diagnosis methods, there are some problems such as fault frequency drift and data sparsity. Therefore, a hybrid similarity calculation method is proposed by combining improved Pearson similarity and gray relational similarity by means of parameter adjustment, that is:

$$sim'(u, v) = \alpha sim_m(u, v) + \beta sim_n(u, v)$$

Among them, α 、 β are adjusted parameters $0 < \alpha < 1$, $0 < \beta < 1$, $\alpha + \beta = 1$.

By adjusting the two parameters and constantly optimizing the algorithm, a group of values with the best diagnostic effect is obtained. The best diagnostic results were obtained when $\alpha = 0.371$ 、 $\beta = 0.629$. The diagnostic process is shown in figure 1.

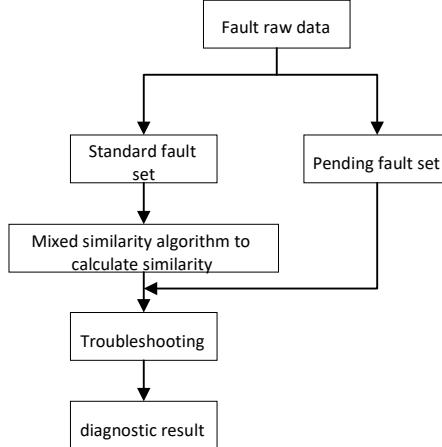


Fig.1 Diesel engine fault diagnosis flow chart

The fault original data is divided into fault standard set fault test set, and the similarity between the fault to be detected and the standard fault is calculated by the hybrid similarity algorithm. According to the similarity degree, the diagnosis result is given to achieve the purpose of fault location.

3 Marine diesel engine simulation model establishment

Due to the fault state data is difficult to get through the experiment of diesel engine, thus using AVL BOOST software for several common faults of diesel engine was simulated, based on the literature [13] of MAN B&W L16-24 high supercharged four stroke diesel engine AVL BOOST model, simulated compressor congestion, fuel injection Angle in advance, after the fuel injection Angle, horizontal bar broken diesel common failure forms such as oil, fuel injector jams. The proposed diagnostic algorithm is verified.

Tab.1 Main parameters of MAN B&W L16-24

Name	Value
Effective power/kW	9480
Speed /(r/min)	127
Bore/mm	500
Stroke/mm	2000
Compression ratio	13.64
Effective fuel consumption /(g/(Kw.h))	178.28
Ignition sequence	1-5-3-4-2-6

3.1 Establishment of simulation model

The MAN B&W L16-24 diesel engine simulation model under the AVL-BOOST platform is shown in figure 2. The feasibility of the model can be verified by comparing the simulation experimental data in literature [9] with the experimental data on the platform.

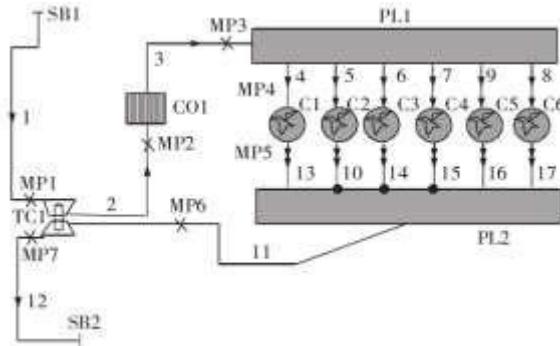


Fig.2 MAN B&W L16-24 diesel engine simulation model

Among them, Cylinder: C1~C6; Sensor measuring point: MP1~MP7; System boundary: SB1, SB2; Air cooler: CO1; Intake manifold: PL1, PL2; Turbocharger: TC.

In order to obtain the ideal simulation results, the parameters of the cylinder model need to be continuously adjusted. The following parameters are more reasonable for multiple tests:

Tab.2 Main parameters of MAN B&W L16-24 simulation model

Component	Parameter	Value
Piston	Surface area/mm ²	274750
	Inner wall temperature /°C	399.15
Cylinder head	Surface area /mm ²	196250
	Inner wall temperature /°C	362.15
Cylinder liner	Piston top dead center surface area /mm ²	2000
	Piston top dead center cylinder wall temperature /°C	216.15
	Cylinder bottom dead center cylinder wall temperature /°C	167.15
exhaust vent	Opening angle /°	137
	Closing angle /°	223
Supercharger	Equivalent flow coefficient	0.2815
	Supercharger efficiency	0.68
	Compressor pressure ratio	4.0
	Compressor efficiency	0.79
	Supercharger mechanical efficiency	0.98

3.2 Selection of thermal parameters

There are many types of thermal parameters that reflect the health status of diesel engines. Table 3 lists some of the thermal parameters and the meaning of the parameters.

Tab.3 Main parameters of MAN B&W L16-24

Numbering	Parameter Name	Parameter Meaning
1	Compressor inlet pressure /P _{ci}	Reflecting the circulation of the air inlet
2	Compressor inlet temperature /T _{ci}	Reflecting ambient temperature
3	Compressor outlet force /P _{co}	Reflecting the status of the supercharger system
4	Compressor outlet temperature /T _{co}	Reflecting the status of the supercharger system
5	Intercooler outlet pressure /P _{ao}	Reflect the status of the intercooler
6	Intercooler outlet temperature /T _{ao}	Reflect the status of the intercooler
7	Intake pipe pressure /P _{ii}	Reflecting the failure of the intake system
8	Intake pipe temperature /T _{ii}	Reflecting the failure of the intake system
9	Exhaust manifold pressure /P _{eo}	Reflecting the failure of the exhaust system
10	Exhaust manifold temperature /T _{eo}	Reflecting the failure of the exhaust system
11	Turbine outlet pressure /P _{to}	Reflecting the failure of the supercharger system
12	Turbine outlet temperature /T _{to}	Reflecting the failure of the supercharger system
13	Effective power /N _e	Reflecting the power performance of diesel engines
14	Average effective pressure /P _e	An important indicator reflecting the dynamics of diesel engines

According to the importance of the thermal parameters in the above table to evaluate the working state of the diesel engine and the limitations of the experimental conditions, five parameters were selected as the research objects: P_e , N_e , T_{co} , T_{to} , T_{eo} .

4 Experimental results and analysis

Because the simulation results fit well with the actual running rules of the diesel engine, the simulation model can well simulate the real working conditions. Five typical diesel engine faults, such as uneven oil supply, advanced injection Angle, single cylinder oil break, cooler blockage and low supercharging efficiency, are simulated. During the simulation, the setting parameters of the fault location are constantly changed to obtain corresponding fault samples. It is stipulated that the deviation of each parameter within the range of 3% is normal working condition, and any deviation beyond 3% is a fault. The observed values of each measuring point under the recorded fault state are shown in table 4:

Tab.4 fault diagnosis vector set to be tested

Fault code	P_e	N_e	T_{co}	T_{to}	T_{eo}
Fault 1	23.6	254.3	301.7	257.6	386.7
Fault 2	25.4	220.6	302.9	274.1	371.2
Fault 3	24.3	245.9	311.0	286.8	369.0
Fault 4	26.7	239.7	324.6	266.9	379.3
Fault 5	24.9	238.2	315.6	290.1	387.9

Table 5 shows the standard values of each parameter of the diesel engine in normal operation under rated load and rated power.

Tab.5 standard vector sets for fault diagnosis

Fault code	P_e	N_e	T_{co}	T_{to}	T_{eo}
Fault 1	28.6	260.1	310.5	276.4	394.3
Fault 2	29.3	232.9	316.8	288.5	389.0
Fault 3	25.4	256.7	320.2	295.0	382.1
Fault 4	27.3	245.9	327.4	279.7	392.2
Fault 5	26.9	247.8	322.6	301.2	390.1

Taking one of the pending mode X_0 as the sequence and the standard mode X_i as the behavior sequence of the system, the grey relational degree algorithm of Pearson correlation coefficient similarity algorithm and the mixed similarity algorithm proposed in this paper were used to calculate different degrees of similarity, and the diagnostic curves in five cases were obtained. Among them, faults 1~5 are five kinds of faults, namely, uneven oil supply, oil injection Angle, single cylinder break ahead of time, blockage of oil cooler, and low charging efficiency

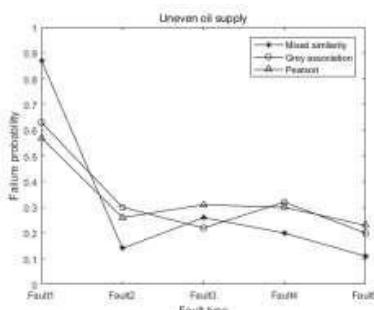


Fig. 3 fault diagnosis curve of uneven oil.

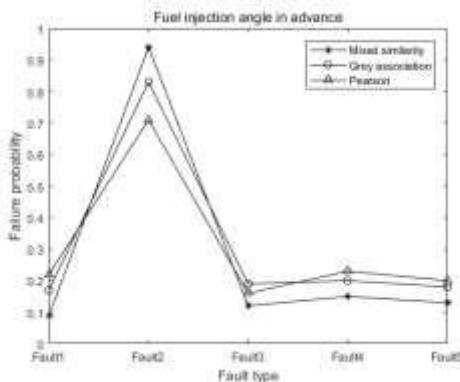


Fig.4 fault diagnosis curve of injection Angle in advance supply

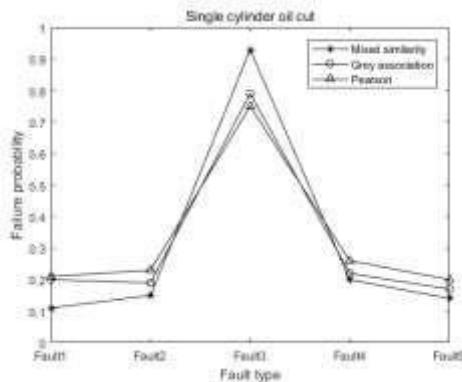


Fig. 5 diagnosis curve of single cylinder oil failure

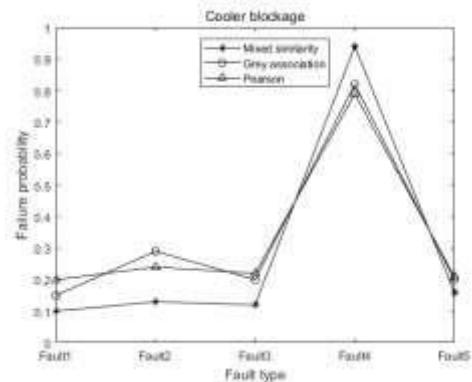


Fig. 6 fault diagnosis curve of cooler blockage

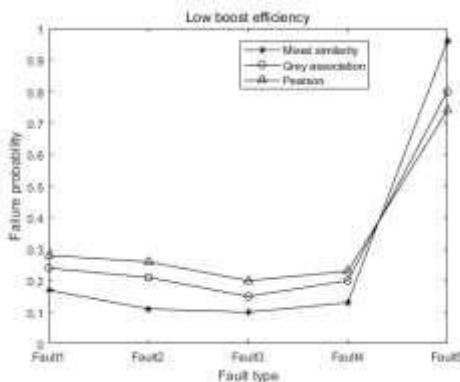


Fig. 7 low efficiency fault diagnosis curve of supercharger

The experiment shows that the traditional Pearson similarity algorithm, grey correlation analysis method and hybrid similarity algorithm have good accuracy in the diesel engine fault diagnosis, and the hybrid similarity algorithm has a diagnosis accuracy of up to 90% in each fault, which is obviously better than the traditional Pearson similarity algorithm and grey correlation similarity algorithm.

5 Conclusion

In this paper, a hybrid similarity collaborative filtering algorithm based on improved Pearson correlation coefficient and grey correlation diagnosis analysis is proposed. In view of the problems of Marine diesel engine, such as intake and exhaust failure and cooler blockage, the appropriate thermal parameters are selected as the basis for fault diagnosis and positioning. The collaborative filtering theory is applied to the field of fault diagnosis, and the fault types are regarded as users and fault samples as the evaluation of things. Finally, by using AVL-BOOST software, fault simulation of diesel engine is conducted to verify the effectiveness and accuracy of the algorithm.

Reference

- [1]. Jia Jide, Jia XiangYu. Misfire Fault Diagnosis of Diesel Engine Based on Wavelet and Deep Belief Network [J]. *Automotive Engineering*, 2018, 40(07):838-843.
- [2]. Zhang Shunle, Chen Minjie. Fault Characteristics Research and Countermeasures of Diesel Engine on Offshore Drilling Platform Based on Long-term Oil Monitoring [J]. *Lubrication Engineering*, 2016, 41(11):129-132+136.

- [3]. Yang Zilong. Thermal Performance Prediction of Diesel Engine Based on Three-Point Model [J]. *Ship Engineering*, 2018, 40(03):33-36+48.
- [4]. Ali Yousefzadeh, Omid Jahanian. Using detailed chemical kinetics 3D-CFD model to investigate combustion phase of a CNG-HCCI engine according to control strategy requirements [J]. *Energy Conversion and Management*, 2017, 133.
- [5]. Li Huabing, Huang Jinming, Rongli. Application of grey prediction theory in mechanical fault diagnosis of ships [J]. *Journal of Shanghai Maritime University | J Shanghai Mari Univ*, 2017, 38(03):85-89.
- [6]. Hanmin, Li Jinbing, Xu Meiling. Fault Prognosis of Marine Diesel Engine with Working State Transition Based on EIIKF [J]. *ACTA AUTOMATICA SINICA*, 2019, 1-7.
- [7]. Caocan. The Application of Grey Correlation Model in Fault Diagnosis Decision [A]. *Chinese Association of Automation*, 2015:5.
- [8]. Fu Yunxiao, Jia Limin. Roller Bearing Fault Diagnosis Method Based on LMD-CM-PCA [J]. *Journal of Vibration, Measurement & Diagnosis*, 017, 37(02): 249-255+400-401.
- [9]. Yuandui, Wang Yeqiu, Tang Xinfei. Research on simulation method for thermal failure of marine medium speed diesel engine [J]. *China Ship Repair*, 2018, 31(04):41-4