Journal of Computers Vol. 33 No. 3, June 2022, pp. 159-169
doi: 10.53106/199115992022063303013

Petrochemical Gearbox Fault Location and Diagnosis Method Based on Distributed Bayesian Model and Neural Network

Nai-Quan Su[1,2*], Qing-Hua Zhang[1], Shao-Lin Hu[1], Xiao-Xiao Chang[1], Mei-Chao Chen[1]

[1] Guangdong Provincial Key Lab. of Petrochemical Equipment and Fault Diagnosis,
Guangdong University of Petrochemical Technology, Maoming 525000, China
534306286@qq.com
[2] High-Tech Institute of Xi'an, Xi'an, 710025, China
534306286@qq.com

Received 21 August 2021; Revised 13 December 2021; Accepted 13 January 2022

Abstract. Increasing attention has been paid to the economic losses and personnel injuries caused by petrochemical gearbox faults. As a result, petrochemical enterprises started to pay huge attention on fault diagnosis technology to solve the fault diagnosis problem. Petrochemical gearboxes are characterized by many fault types, feature variables, and many-to-many relationships between the various fault parameters, which pose huge challenges in the fault diagnosis of petrochemical units. This paper proposes a petrochemical gearbox fault location and diagnosis method based on a distributed Bayesian model and neural network. The proposed approach is based on sample feature information and Bayesian network prior probability to construct a basic framework for petrochemical gearbox fault location. Neural network technology is used to to diagnose fault types. It is helpful to build a long-term fault diagnosis and monitoring system for rotating machinery of petrochemical units.

Keywords: petrochemical unit, gearbox, Bayesian model, neural networks, fault diagnosis

1 Introduction

In the 1970s, the United Kingdom Machine Health and Condition Association carried out a great deal of engine testing and diagnosis, mainly by extracting fault features from operating signals and using fault models to identify fault types. Reliable fault diagnosis models are essential to ensuring accurate fault recognition. With the development of sensor technology and artificial intelligence, research on condition monitoring and fault diagnosis has increasingly attracted scholars' attention.

Research on fault location, Bayesian models have several advantages in dealing with uncertain variables and fuzzy relations between variables. Bayesian networks can be used to update data in real-time. By continuously updating and accumulating data, new results are continuously inferred to improve decision-making processes [1]. The posterior probability of each characteristic is obtained from the prior probability and used to identify the correspondence between variables. Literature [2] proposed a Bayesian model-based positioning method for indoor positioning and navigation problems. Bicycles without onboard sensors have problems such as large parking range and nonstandard management. Therefore, a Naive Bayes model was previously proposed to determine fault locations [3]. Literature [4] solved process monitoring and fault diagnosis (PM-FD) of coal mills are essential to the security and reliability of the coal-fired power plant, a novel multi-mode Bayesian PM-FD method is proposed. Literature [5] solved monitoring a system is often not an easy task, a hybrid method for diagnosing single and multiple simultaneous faults is proposed. Literature [6] presented an innovative diagnosis model using the deep convolutional network with Bayesian optimization to diagnose the defect severity of bearings. Literature [7] proposed a novel fault diagnosis scheme for planetary gearbox using multi-criteria fault feature selection, and classifications are performed by the SVM and sparse Bayesian extreme learning machine.

Literature [8] proposed distributed dynamic process monitoring based on minimal redundancy maximal relevance variable selection and Bayesian inference. Literature [9] proposed a sparse Bayesian learning model method to solve the problem of inconsistency between the target position and initial grid points.

Advances in artificial intelligence technology and the application of neural networks to pattern recognition problems have provided a new direction for fault diagnosis [10-13]. Literature [14] improved the accuracy of complex compression valve fault diagnosis by combining a deep belief network and Teager-Kaiser energy operator. Fault signals often exhibit ambiguity and coupling; therefore, a fuzzy neural network for fault diagnosis

* Corresponding Author

was previously proposed to deal with this problem [15]. The rolling bearing is composed of four parts, including an inner ring, outer ring, rolling element, and cage. The rolling bearing is affected by the machining accuracy, loading conditions, and working environment in the operating state. Considering gearbox structure and operating condition, Literature [16] proposed based on multitask parallel convolutional neural network with reinforced input (RI-MPCNN). Literature [17] proposed data-driven wear monitoring for sliding bearings using acoustic emission signals and long short-term memory neural networks. Literature [18] solved a drawback of wind as an energy source lies in its high variability, propose a wind power forecasting-A data-driven method along with the gated recurrent neural network. Literature [19] combined the wavelet transform, principal component analysis, and an artificial neural network to solve the fault classification and prediction problem aimed at component damage, machine operation, and degradation prediction problems. Literature [20] used digital twin technology and DTs the logical structure, to process status monitoring and alarm.

Through the current situation analysis and existing problems of gearbox fault diagnosis, there is no clear quantitative boundary between petrochemical units features, which affects fault feature extraction. Collected signal data often does not fully reflect the fault state due to the nonlinearity and randomness in the vibration signals. This has led to an imperfect fault model and limitations in the fault identification process. Therefore， this paper proposes a petrochemical gearbox fault location and diagnosis method based on a distributed Bayesian and neural network.

This paper has four chapters: the first chapter is a brief introduction, the basic introduction to the research motive and the main contributions in this paper; the second chapter introduces the fault location and diagnosis based on distributed Bayesian model and neural network algorithm; the third chapter is experimental research on petrochemical gearbox diagnosis; the fourth chapter is conclusion and future prospect.

The main contributions and innovation of this work are as follows.

- This paper applies sample feature information and Bayesian network prior probability to construct a basic framework for fault location, and combines neural network technology to fault type diagnosis.
- Data resources with different health conditions are collected from a petrochemical unit monitoring equipment fault diagnosis platform.
- This method is used to test the petrochemical units gearboxes typical fault samples, including six fault samples. The each fault diagnosis accuracy is over 90% (with an average accuracy 93%).

2 Fault Location and diagnosis based on distributed Bayesian Model and Neural Network

This section mainly focuses on the basic framework construction of a distributed Bayesian network for fault location, the realization of a neural network for fault diagnosis, and the proposed petrochemical unit fault diagnosis process based on the distributed Bayesian model and neural network.

2.1 Distributed Bayesian Framework for Fault Location

2.1.1 Bayesian Network

The Bayesian network model is mainly composed of conditional probability and prior probability, which reflect the corresponding relationships between the normal state and high-value dimensionless features. Suppose the normal state is $A = \{ A_1, A_2, ..., A_n\}$ in different locations or during different time periods, each minor event has a probability, and fault state B and normal state A occur randomly [21].

(1) The conditional probability is the normal state probability of state A under fault state B. Expressed as,

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \tag{1}$$

where $P(A \cap B)$ is the joint probability, which refers to the probability of the two states occurring at the same time, i.e., the intersection of the normal state A and the fault state B.

(2) The prior probability is probability of the normal state or fault state, which is $P(A)$ or $P(B)$. Expressed as,

$$P(B_i|A) = \frac{P(B_i)P(A|B_i)}{\sum_{j=1}^{n} P(B_j)P(A|B_j)} = \frac{P(B_i)P(A|B_i)}{P(A)} \tag{2}$$

where $P(A|B_i)$ is the likelihood probability, $P(B_i)$ is the prior probability, and $\sum_{j=1}^{n} P(B_j)P(A|B_j)$ is the total probability.

(3) Bayesian network construction for petrochemical units

The Bayesian network is composed of nodes and directed edges connecting nodes. Nodes represent random variables and the directed edges between nodes represent the mutual relationship. The conditional probability expresses the strength of the relationship. Assume the normal state A is the main variable and the fault state B is the secondary variable.

States A and B are connected by a one-way arrow and there is a conditional variable probability $P(A|B)$ between the two variables. The correlation between the two variables is shown in Fig. 1.

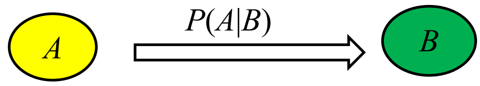

Fig. 1. Schematic diagram of the correlation between two variables A and B

(4) The probability of each random variable is multiplied by its local conditional probabilities. Suppose x set have N random variables and its probability,

$$P(x_1, x_2, \cdots, x_n) = P(x_n) \cdot P(x_{n-1}) \cdots P(x_1) \quad \textbf{(3)}$$

2.1.2 Distributed Bayesian Model Structure

The distributed structure is determined according to normal vibration signals collected by sensors in different positions or during different time periods. Normal high-value dimensionless features are used as training samples to construct the distributed Bayesian model. The high-value dimensionless feature training set is then used to calculate the category probability and posterior probability. The petrochemical unit status is defined according to the category probability and posterior probability.

Suppose the petrochemical unit normal state sample space is $Q = \{Q_1, Q_2, ..., Q_n\}$, the high-value dimensionless feature is X, the normal state is x_1 and the fault state is x_2, and the different locations or time periods of the normal state category are $Y = \{y_1, y_2, ..., y_m\}$. In addition, the category prior probability is $P(Y)$, the feature probability is $P(X)$, and the category conditional probability is $P(X|Y)$. Thus [22],

$$P(Y \mid X) = \frac{P(Y)P(X \mid Y)}{P(X)} \quad \textbf{(4)}$$

Given category y and its expressed as,

$$P(X \mid Y = y) = \prod_{i=1}^{z} P(x_i \mid Y = y) \quad \textbf{(5)}$$

Since $P(x)$ remains unchanged and it can be transformed into,

$$P(y_i \mid x_1, x_2) = \frac{P(y_i)(\prod_{i=1}^{z} P(x_i \mid y_i))}{\prod_{i=1}^{z} P(x_j)} \quad \textbf{(6)}$$

The distributed Bayesian model of the petrochemical unit can be constructed according to Formulas (1)-(5), as shown in Fig. 2.

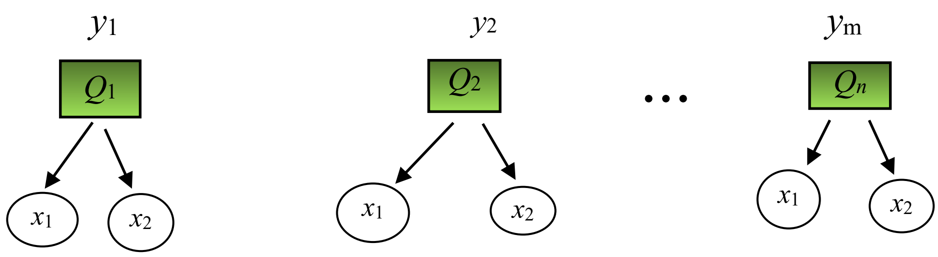

Fig. 2. Distributed Bayesian model

2.1.3 Distributed Bayesian Model Monitoring

This section presents the distributed Bayesian model monitoring process. Normal high-value dimensionless features are used as training samples. The distributed Bayesian model is established based on the sample feature independence and prior probability. The prior probability is used to obtain the posterior probability, which distinguishes the relationship between the training sample and the test sample, as shown in Fig. 3.

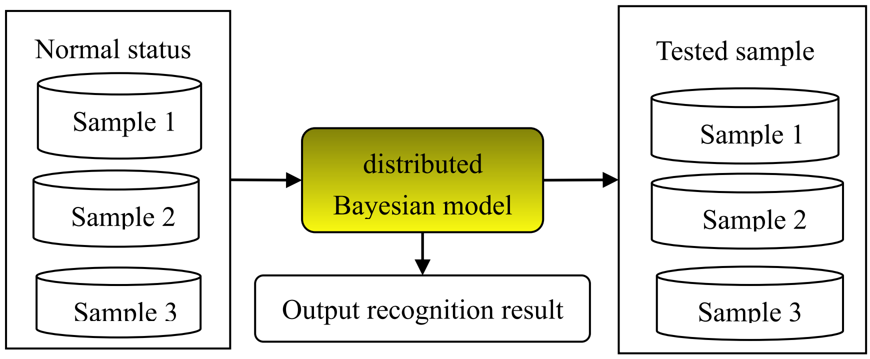

Fig. 3. Distributed Bayesian network Monitoring process

2.2 Neural Network Fault Diagnosis Technology

The distributed Bayesian model was used to realize state identification of petrochemical units. When a gearbox fault occurs, it is necessary to combine fault diagnosis technologies to identify the fault. The neural network is an imitation of the biological neuron structure and function model, which has good recognition effects in dealing with only a few labelled samples and imbalanced categories [23]. Here, high-value dimensionless features are used as the input layer, and each neuron receives input information that is transmitted to the middle layer. Through the forward-propagation learning process, the output layer information of the petrochemical unit sample is obtained.

Suppose the petrochemical unit high-value dimensionless feature P_i is the network input, t_i is the fault type target output, and the output of one layer is the input of the next layer. Thus [24],

$$a^{m+1} = f^{m+1}(w^{m+1}a^m + b^{m+1}), m = 0,1,\cdots,M-1 \tag{7}$$

where m is the network layer number, w^{m+1} is the weight matrix, and a^m is the external receiving input neuron.

The actual output is compared with the target output and the network parameters are adjusted to minimize the mean square error to achieve the best performance. The mean square error,

$$F(x) = E\left[e^2\right] = E\left[(t-a)^2\right] \tag{8}$$

The descent method is used to update weights and bias values as,

$$W^m(k+1) = W^m(k) - \alpha s^m (a^{m-1})T \tag{9}$$

$$b^m(k+1) = b^m(k) - \alpha s^m \tag{10}$$

where W^m (k) is the m layer weight matrix after k network trainings, $b^m(k)$ is the m layer bias value after the k network trainings, a^{m-1} is the m-1 layer output vector, and s^m is the sensitivity index of layer m.

By continuously inputting the high-value dimensionless features and comparing the mean square error of the actual output and the target output, the neural network is continuously trained and the result is output.

2.3 Petrochemical Gearbox Fault Diagnosis Process based on Distributed Bayesian Model and Neural Network

This section combines the distributed Bayesian model and neural network for petrochemical gearbox diagnosis. First, normal state signals of the petrochemical gearbox are collected, and high-value dimensionless features in different locations or during different time periods are extracted. Second, the distributed Bayesian model is established using the sample independence and prior probability, which can identify the relationship between training samples and test samples. Finally, the neural network fault diagnosis technology is used to identify the fault type. Fig. 4 presents a flowchart of the proposed petrochemical gearbox fault diagnosis method based on the distributed Bayesian model and neural network.

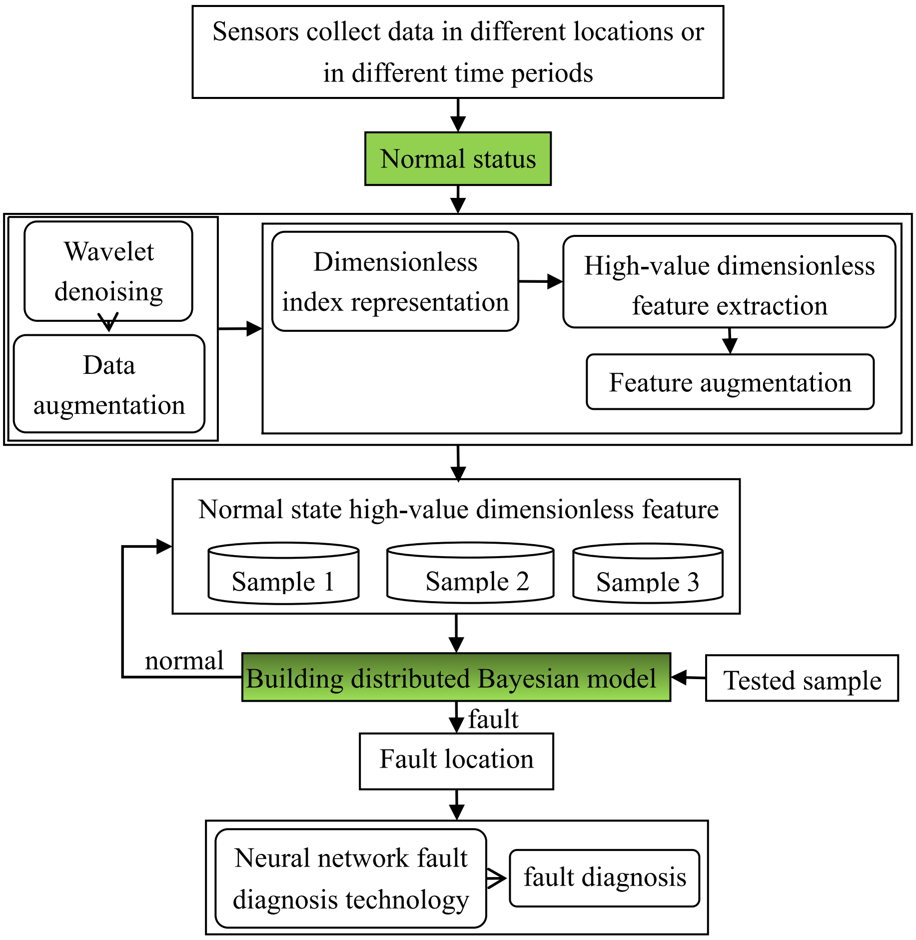

Fig. 4. Petrochemical gearbox fault diagnosis based on distributed Bayesian model and neural network

3 Experimental Research on Petrochemical Gearbox Diagnosis

Taking the petrochemical gearbox as the research object, the gear fault and the rolling bearing fault were selected to demonstrate the effectiveness of the petrochemical gearbox fault diagnosis method based on the distributed Bayesian model and neural network.

3.1 Experimental Setup

The experimental fault diagnosis platform, data sources, and monitoring equipment are shown in Fig. 5. The petrochemical monitoring and diagnosis platform can simulate various typical fault states, including a bearing outer ring fault, bearing inner ring fault, bearing ball fault, and gear fault. Composite fault design can be achieved through multiple fault components. The experimental platform is comprised of four main components, including an electric motor, load controller, gearbox, and air compressor.

Fig. 5. Petrochemical fault diagnosis platform

The fault type experiments included a bearing inner ring fault, bearing outer ring fault, bearing ball fault, and gear fault. The rolling bearing had an outer diameter of 110 mm, inner diameter of 50 mm, and thickness of 27 mm. The rolling element diameter was 14 mm and the number of elements was 13. The large gear was comprised of 29 teeth and the small gear had 23 teeth. The normal gears and faulty gears are shown in Fig. 6 and the normal bearings and faulty bearings are shown in Fig. 7.

Fig. 6. Normal gear and fault gear

Fig. 7. Normal and fault bearing

3.2 Experimental Results Analysis

The experimental parameters were set according to the dimensionless features (from [25-26], it is known that dimensionless features are less affected by working conditions) and laboratory requirements. An EMT390 fault analyzer was used to collect the data. Data were collected by sensors at a frequency of 1024 Hz, the sampling length was 1024, and one group was collected every 10s, and saved automatically. The experimental unit power supply was 1000 r/min.

3.2.1 Fault State Identification

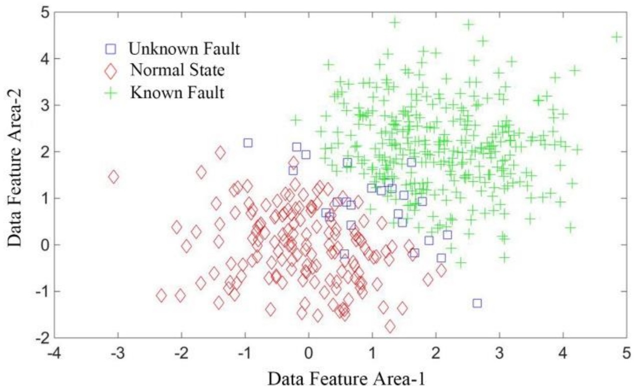

Fig. 8. Distributed Bayesian of normal and fault

Petrochemical unit fault experiments verified the proposed distributed Bayesian model for fault location. A fault probability analysis of the tested sample was performed using the distributed Bayesian model as the preliminary fault diagnosis. Fig. 8 shows distributed Bayesian model of the normal unit and faulty unit. It shows that the high-value dimensionless features of the training sample and test sample are consistent. The distributed Bayesian model can identify the test sample. In this work, recognition of the normal state was used as the basis for fault signal recognition.

3.2.2 Distributed Bayesian Model for Fault Location

The normal state and two fault states were designed to determine whether the training sample is the normal state and whether the test samples have bearing inner ring fault. Fig. 9 to Fig. 10 show high-value dimensionless features of the petrochemical gearbox in different states.

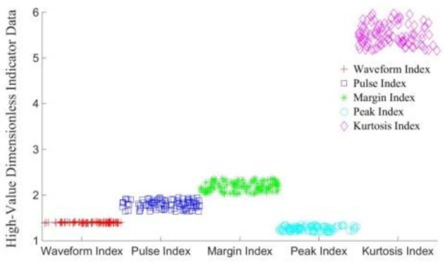

Fig. 9. Normal high-value dimensionless feature

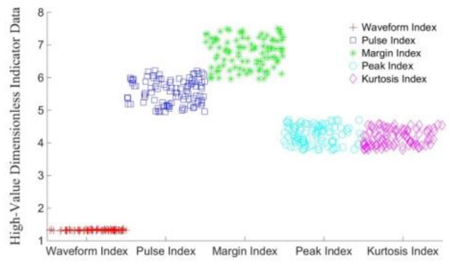

Fig. 10. Bearing inner ring fault high-value dimensionless feature

The normal state and bearing inner ring fault are clearly discriminated by the waveform index, pulse index, margin index, peak index, and kurtosis index. The high-value dimensionless features were clearly distinguished in this study, thereby realizing status recognition of the tested sample and determining the fault location.

3.2.3 Petrochemical Gearbox Fault Diagnosis

The fault location was obtained using the distributed Bayesian model method presented in section 3.2.2. Then, the neural network was used to verify the effectiveness of the fault diagnosis according to the identified fault location.

(1) Normal state and gear fault diagnosis

Table 1 presents the fault diagnosis results for a gear in the normal state and a large gear fault. The high-value dimensionless features of the normal gear and gear fault were used as training sample and test sample, respectively. From Table 1, the fault diagnosis results for the normal state are 91.67%, 90.67%, and the error rate is 1%; The large gear fault diagnosis results are 90.82% and 93.24%, and the error is 2.42%, with an average accuracy of 91.6%.

Table 1. Normal and large gear fault, diagnosis result of random training sample and random test sample

Fault type	Training samples	Test sample	Correct number	Errors number	Correct rate	Error rate
Normal status	596	204	187	17	91.67%	1%
	807	193	175	18	90.67%	
Large gear fault	604	196	178	18	90.82%	2.42%
	793	207	193	14	93.24%	

(2) Fault type identification of normal state and bearing fault state

The diagnosis of the normal bearing state and different bearing fault types were performed. Table 2 shows the diagnosis results for the normal state and bearing fault and the results for random training samples and random test samples.

The high-value dimensionless features of the normal bearing as well as bearing outer ring, inner ring, and rolling bearing faults were taken as training samples. From Table 2, the normal state diagnosis results are 93.64% and 93.52%, and the error is 0.12%; The bearing rolling ring fault diagnosis results are 92.31% and 91.83%, and the error is 0.48%; The bearing outer ring fault diagnosis results are 93.09% and 93.25%, and the error is 0.16%; The bearing inner ring fault diagnosis results are 95.65% and 95.12%, and the error is 0.53%; The average accuracy of the diagnosis results is 93.55%.

Table 2. Normal and bearing fault, diagnosis result of random training sample and random test sample

Fault type	Training samples	Tested sample	Correct number	Errors number	Correct rate	Error rate
Normal status	580	220	206	14	93.64%	0.12%
	599	401	375	26	93.52%	
Ball fault	592	208	192	16	92.31%	0.48%
	596	404	371	33	91.83%	
Outer ring fault	612	188	175	13	93.09%	0.16%
	615	385	359	26	93.25%	
Inner ring fault	616	184	176	8	95.65%	0.53%
	590	410	390	20	95.12%	

(3) Identification of normal state, bearing fault, and large gear fault

To study the diagnosis effect of normal and different fault types, a large gear fault, bearing outer ring fault, bearing inner ring fault, and bearing rolling ring fault were taken as research objects. Table 3 shows the diagnosis results of the same training sample and random test sample in the normal state and for a large gear fault and bearing fault.

The high-value dimensionless features of normal, gear fault and bearing fault were taken as training samples and test samples. From Table 3, the diagnosis results are 95.50% and 92.25% for the normal state, with an error rate of 3.25%; The bearing rolling fault diagnosis results are 92.96% and 93.84%, and the error rate is 0.88%; The bearing outer ring fault diagnosis results are 93.56% and 94.33%, and the error rate is 0.77%; The bearing inner ring fault diagnosis results are 94.50% and 93.35%, and the error rate is 0.17%; The large gear fault diagnosis results are 95.48% and 93.41%, and the error rate is 2.07%. The average accuracy of the diagnosis results is 93.91%.

Table 3. Normal, large gear and bearing fault, diagnosis result of same training sample and random test sample

Fault type	Training samples	Test sample	Correct number	Errors number	Correct rate	Error rate
Normal status	500	200	191	9	95.50%	3.25%
		387	357	30	92.25%	
Ball fault	500	199	185	14	92.96%	0.88%
		406	381	25	93.84%	
Outer ring fault	500	202	189	13	93.56%	0.77%
		406	383	23	94.33%	
Inner ring fault	500	200	189	11	94.50%	0.17%
		391	365	26	93.35%	
Large gear fault	500	199	190	9	95.48%	2.07%
		410	383	27	93.41%	

(4) This paper method is compared with different methods

In order to verify the diagnostic effect of this method and different methods in petrochemical gearbox. As shown in Fig. 11 and Fig. 12, the diagnosis effects of this paper method and different methods in petrochemical gearbox are shown.

As shown in Fig. 11 and Fig. 12, this paper method is compared with KNN (k nearest neighbor classification), EBB (Eigenvalue Based Beamforming), NBM (Naive Bayesian Model), LDA (Linear Discriminant Analysis) and SVM (Support Vector Machine). Through analysis the diagnosis effect of the normal state and gear fault, normal state and bearing fault, from Fig. 11 to Fig. 12 and Table 1 to Table 3. It show that the accuracy of petrochemical gearbox fault diagnosis based on distributed Bayesian and neural network is over 90% (average accuracy 93%), compared with five different algorithms are improved 10%.

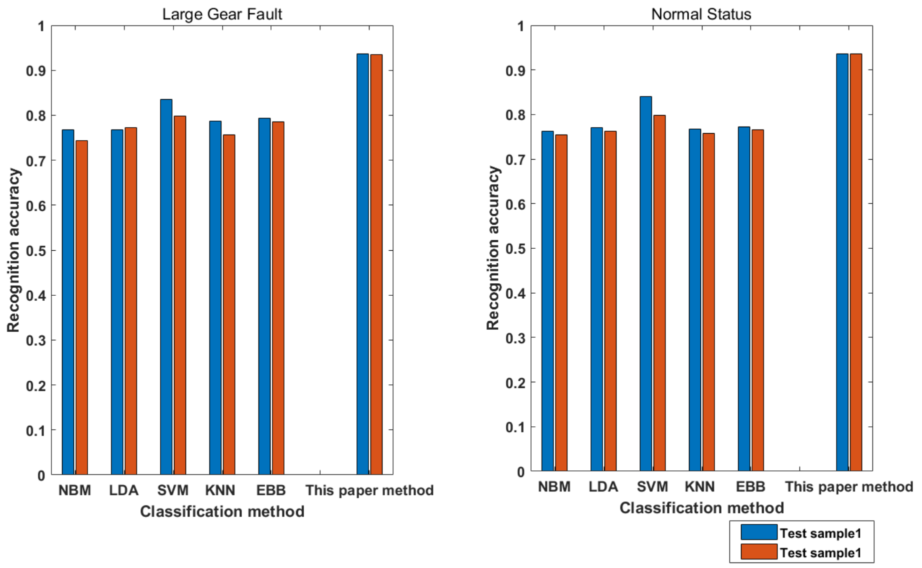

Fig. 11. Normal and large gear fault, different methods diagnosis result of random training sample and random test sample

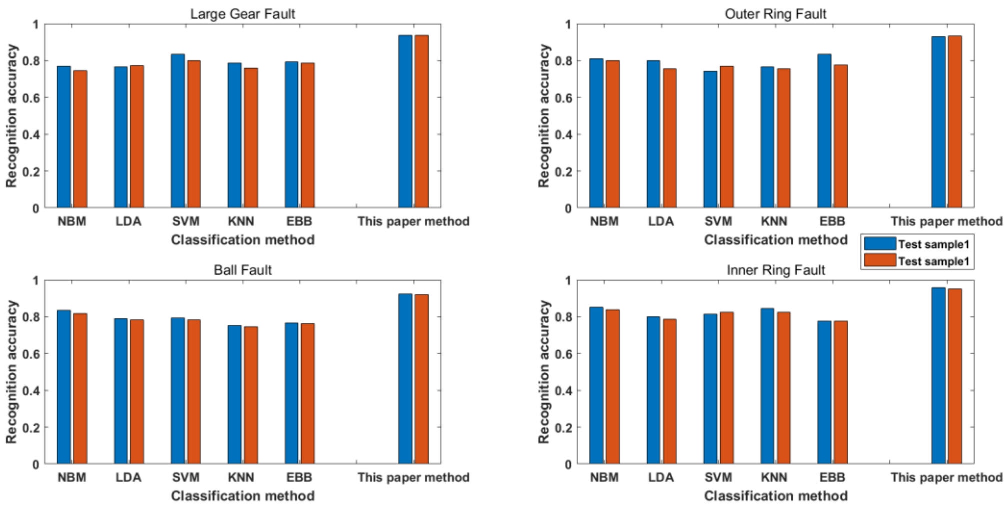

Fig. 12. Normal and bearing fault, different methods diagnosis result of random training sample and random test sample

4 Conclusions

This work built a basic framework for fault localization using sample feature information and Bayesian network prior probability, which can be integrated with neural network technology to achieve accurate fault type diagnosis. A petrochemical unit monitoring equipment diagnosis platform, data sources, and test settings were used to validate the proposed method. Typical petrochemical gearbox fault types were evaluated, and fault diagnosis accuracy was greater than 90%. (average 93%). The results show that high-value dimensionless characteristics combined with the distributed Bayesian model and neural network approach provide effective fault diagnosis. However, the reliability of the proposed solution in this field needs to be thoroughly investigated for the strong concealment of micro-fault signals of rotating machinery.

Acknowledgement

The research was supported by the Key Project of Natural Science Foundation of China (Grant No. 61933013) and the National Nature Science Foundation of China (Grant Nos. 61673127, 61973094). The work described in this paper was also partially supported by Natural Science Foundation of Guangdong (2022A1515010599) and Guangdong University key platform Youth Innovative Talents Project (2019KQNCX085). Maoming science and technology project (No. 201805, 2020522). The Ph.D. project of Guangdong University of Petrochemical Technology (No. 2020bs006).

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