Hindawi
Scientific Programming
Volume 2022, Article ID 7486271, 7 pages
https://doi.org/10.1155/2022/7486271

Research Article

Early Fault Diagnosis Model Design of Reciprocating Compressor Valve Based on Multiclass Support Vector Machine and Decision Tree

Zhihong Yu,[1] Bosi Zhang ,[1] Guangxia Hu,[1] and Zhigang Chen[2]

[1]*Department of Security Engineering, China University of Labor Relations, Beijing, China*
[2]*Institute of Mechanical and Electrical Engineering, China Architecture University, Beijing, China*

Correspondence should be addressed to Bosi Zhang; yuzh06@culr.edu.cn

Received 23 April 2022; Revised 9 May 2022; Accepted 16 May 2022; Published 8 June 2022

Academic Editor: Jie Liu

According to the character of frequent fault occurrence, difficult diagnosis of large reciprocating compressor valves, an early fault diagnosis model of reciprocating compressor valve based on multiclass support vector machine and decision tree is designed. A series of simulation experiments of the suction valve and exhaust valve on a large-scale reciprocating compressor experimental bench are made and the valve fault principle is analyzed. Using the advantages of fast and efficient decision tree classification and the prominent characteristics of support vector machine in small sample binary classification, a multivariate classification and recognition model is constructed. The typical characteristic parameters of gearbox vibration signal are extracted as the fault feature vector training model under different fault conditions, and the samples are tested. The experimental results show that the recognition effect of this method is significantly better than that of the neural network method in the case of small samples, and the recognition efficiency is improved more than that of the conventional multivariate support vector machine method which can be effectively applied to reciprocating compressor valve fault diagnosis.

1. Introduction

There are a large amount of dynamic equipment of different categories in the oilfield west of China. All different kinds of equipment for powering, frequency converting, ventilating, and fluid transporting are connected into a chain with series connection or parallel connection, and a complex system comes into being [1]. It is a big challenge to build a model due to mutual coupling, multiple fault models, and complicated patterns and even with implication. Reciprocating compressor has become the critical equipment of oilfield west of China due to the advantage of wide range and high efficiency of pressure and exhaust coupled with stable pressure when adjusting the gas volume. But its structure is complex and most of its components are susceptible to failure. According to the statistics, valves, packing seal, and piston ring are the components with the top failure rate which may cause irregular shut down of reciprocating compressor, among which the shut down due to the failure of the valves accounts for more than 36% [2]. The valves and cylinders have to endure high pressure and temperature. In addition, valves must inhale and exhale the high velocity gas within a short period. The working condition is very serious. How to extract feature parameters from complex and changeable signals is critical for diagnosis. It presents even stricter requirements for the diagnosis model due to tremendous difficulties in extracting feature parameters and unobvious characterization resulting from weak energy change of the feature parameters during the early fault.

The traditional diagnosis method is based on the statistical analysis of a large amount of samples. As a matter of fact, the amount of samples, especially the fault samples, is quite limited and even in the absence [3] in a real test. With the development of information science [4–7], various new theories and ideas begin to enter the field of fault diagnosis [8–11]. Support Vector Machine (SVM) theory presents the

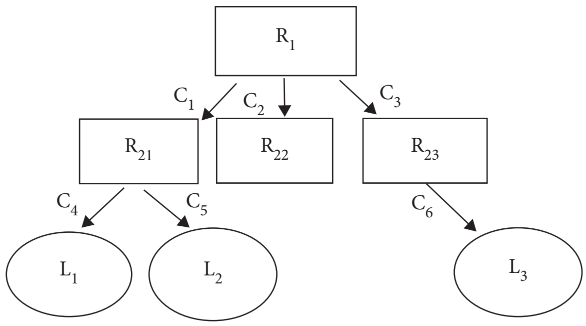

Figure 1: Structure of decision tree.

advantage of the small size of training samples, great generalization ability, and easiness of getting an optimal global solution. It has been widely applied to multiple areas such as electricity, economy, and medical science and diagnosis [12–14]. A decision tree is one kind of inductive learning algorithm based on data. It aims at finding the classification rules from a set of nonsequence and nonrule data. It can be applied to build a classifier and a prediction model which can be used to reduce the training amount of Support Vector Machine and improve the efficiency and accuracy of classification [15–18]. By adopting the method with the combination of a decision tree and Support Vector Machine to build a multiple classifier, the recognition effect and efficiency are much improved compared with the traditional neural network method and conventional multiclass Support Vector Machine.

2. Support Vector Machine Based on Decision Tree

2.1. Basic Principle of Decision Tree. The decision tree is a forecast model which represents the mapping relationship between the attribute of the object and the value of the object [19]. As is shown in Figure 1, a decision tree is comprised of nodes and branches, and the nodes include both internal nodes and leaf nodes. Each internal node, such as R1, R21, R22, and R23 in the figure, represents one attribute. Each leaf node, such as L1, L2, and L3 in the figure, represents one category. Each leaf node, such as cl, c2, c3, c4, and c5 in the figure, represents one test value of the attribute. Two steps are included in the whole process of the classification of the decision tree. The first step is to establish and refine a decision tree based on the clusters of the training sample and to set up the model of the decision tree. As a matter of fact, it is a process to obtain knowledge from data and undertake machine learning as a whole which normally can be divided into 2 stages: establishing and pruning. The second step is to analyze the new data by using the decision tree established [20, 21].

One classification subtask will be performed for each node in the tree. In the classification stage, the bottom-up aggregation algorithm is used to generate the logical structure of the decision tree [21]. Because there is no need to traverse all classifiers, the operation time and classification accuracy are relatively high.

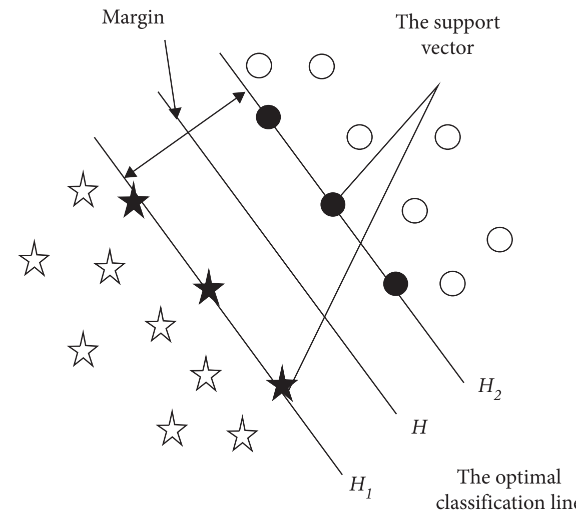

Figure 2: The diagram of optimal hyperplane.

2.2. Basic Theory of Support Vector Machine. The support vector machine method is used to propose the optimal hyperplane in the linearly separable case. As is shown in Figure 2, the star and the circle in the optimal hyperplane represent two types of samples separately, H represents the classification line, H1 and H2 represent the samples closet to and in parallel with the classification line in each category the distance between which is called classification margin [22].

Expanded to the linear nonseparable case, considering that some of the samples can not be correctly classified, the constraint condition of hyperplane can be expressed as follows: yi(xiω+b)-1≥0, in which b is the threshold value and ω is the normal vector of the hyperplane. The Lagrange multiplier method should be adopted to achieve the solution of the nonlinear optimal hyperplane.

$$L(\omega, b, a) = \frac{1}{2}\|\omega\| - \sum_{i=1}^{1} a_i \left[y_i \left(x_i \omega + b \right) - 1 \right], \tag{1}$$

where $a_i \geq 0$, $i = 1, 2, \ldots, 1$;

The extreme point of L is the saddle point. The minimum value of L for ω and b is set as $\omega = \omega*$, $b = b*$, and the maximum value for a set as $a = a*$.

Therefore, the original problem under linear separable condition is converted into a dual problem. The maximum value of the following dual formula is to be solved:

$$\max(a) = \sum_{i=1}^{l} a_i - \frac{1}{2} \sum_{j=1}^{l} \sum_{i=1}^{l} a_i a_j y_i y_j x_i x_j,$$

$$s.t \begin{cases} a_i \geq 0, \\ \sum_{i=1}^{l} a_i y_i = 0. \end{cases} \tag{2}$$

With regard to linear nonseparable problems, the sample x can be mapped to a high dimensional feature space H and the linear classifier is to be applied in H. Therefore, through adopting the appropriate inner product function K(xi,xj) in the optimal hyperplane, we can achieve a linear classification by nonlinear transforming without adding any computation complexity. So the objective function becomes as follows:

$$W(a)=\sum_{i=1}^{l}a_i-\frac{1}{2}\sum_{j=1}^{l}\sum_{i=1}^{l}a_ia_jy_iy_jk\left(x_ix_j\right),$$
$$s.t\begin{cases}0\le a_i\le C,\\ \sum_{i=1}^{l}a_iy_i=0,\end{cases}\tag{3}$$

where constant C is the penalty coefficient for the samples over the boundary controlling the degree of punishment for misclassification samples.

If a_i^* is the optimal solution, the decision function can be expressed as follows:

$$f(x)=\sum_{i=1}^{l}y_ia_i^*K\left(x_i,x_j\right)+b^*,\tag{4}$$

where $b^*=1/2\left\{\max_{\{i/y_i=-1\}}\left[\sum_{j\in(sv)}^{l}a_iy_ik(x_i,x_j)\right]+\max_{\{i/y_i=+1\}}\left[\sum_{j\in(sv)}^{l}a_iy_ik(x_i,x_j)\right]\right\}$.

The detailed derivation process can be seen in reference [23].

Different support vectors can be obtained by choosing different kinds of kernel functions. There are four kinds of frequently used kernel functions among which the radial basis kernel function is most commonly used [24].

2.3. Multivariate Classification Support Vector Machine

2.3.1. One-to-Many Support Vector Machine. The one-to-many algorithm [25] is first used for multivalue classification of Support Vector Machine. This method uses a two class support vector machine classifier to distinguish each category from all other categories in sequence. For a problem of *n* categories, *n* support vector machines will be trained by the one-to-many method, namely, to adopt *n* separating hyperplanes to classify.

However the disadvantages of this method are as follows: on one hand, there are requirements for the number of positive and negative samples which will greatly reduce the accuracy of classification by adopting the one-to-many method. On the other hand, because all the training samples shall be used in the training of each support vector machine, the computation efficiency is very low.

2.3.2. One-to-One Support Vector Machine. For a problem of *n* categories, one support vector machine is built for each of *n* categories of the samples by adopting a one-to-one method. So n(n-1)/2 support vector machines will be trained in total [26]. This method requires more samples, but the training speed is faster than that by using the one-to-many method. By comparison of above-mentioned classification methods of multi-value support vector machine with each other, the one-to-one method is believed to have the better classification effect with more expense. The one-to-many method has an ordinary classification effect with less expense.

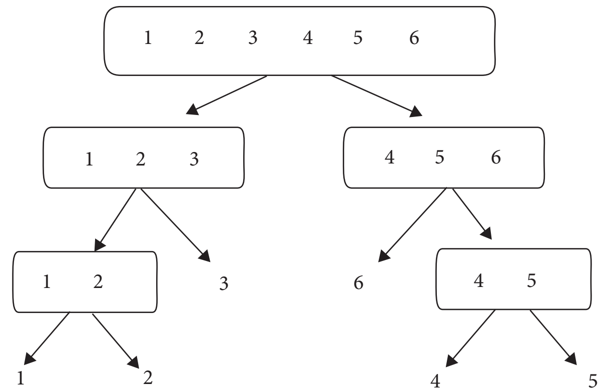

Figure 3: A sketch diagram of decision tree structure for multi-classification SVM.

2.3.3. Support Vector Machine Based on Decision Tree. Support vector machine has excellent generalization performance in the case of small training samples. But for multiclassification problems, it is often necessary to build multiple classifiers and the diagnosis efficiency is low. In this paper, a multiclass fault identification model of a reciprocating compressor valve is established by combining the decision tree and support vector machine.

Through this model, the multiclassification problem is decomposed into a series of two value classification problems, which are distributed in each node of the decision tree. In the classification, the decision tree root node and the branch node are divided into several subsets level by level according to the different attributes, until all the leaf nodes are obtained. One-to-many or one-to-one support vector machine model will be chosen according to the actual situation when dividing into subsets according to the attribute. As an example of dividing into 6 categories, Figure 3 is one kind of decision tree classification diagram, which shows the process of dividing 6 types of input samples into corresponding categories level by level. As can be seen from Figure 3, the advantages of the small number of vector machines of the one-to-many classification model, high classification identification accuracy of the one-to-many classification model, and high classification efficiency for decision tree classification are considered comprehensively in the support vector machine based on the decision tree.

The main failure parts of the valve include the valve seat, spring, and valve plate. The valve seat is the main part of the valve. The valve seat and lift limiter form the space of the valve set. The concentric convex surface of the valve seat and the valve plate form a sealing structure of the gas. The imperfect sealing of the valve sealing structure will result in the gas return, inefficiency of suction and exhaust, and abnormal thermal parameters such as gas temperature and pressure. It will also cause vibration signal and noise change. Therefore by adopting the vibration method, not only the air leakage of the valve can be monitored, but the size of the leakage gap can be determined. The main forms of the spring failure include broken and the elasticity change. If the elasticity becomes small, the closing of the valve plate will be delayed which will cause temperature and pressure changes of the circulating gas.

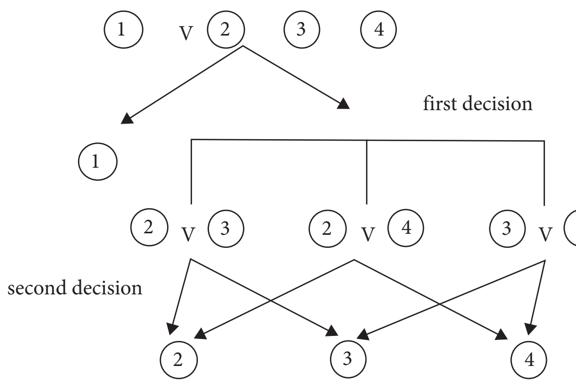

Figure 4: The classification diagram of DT-SVM.

The impact strength of the valve plate on the lift limiter will be increased which accordingly makes the impact vibration and noise increase. If the elasticity becomes large, air pressure can not make the valve plate stick to the lift limiter surface when opening the valve which will cause the vibration of the valve plate. A broken spring can cause complex vibration, blocked valve movement, nonuniform force on the valve plate, etc. Therefore, spring failure will be reflected in the thermodynamic and dynamic parameters. The vibration diagnosis method can diagnose the fault of spring break or elastic change. The valve plate is the key part of the valve the role of which is to close the air passage after the suctioning or exhausting. The main forms of valve plate include deformation and fracture. With the nonuniform force resulting from the valve plate deformation, the impact force is becoming stronger. However, complex vibration will be caused by fragmentation of the valve plate.

In this paper, the experimental object is a reciprocating compressor valve fault. Based on the analysis of the fault of the valve of the reciprocating compressor, the fault diagnosis model of multiclassification support vector machine is built by applying the principle of the decision tree support vector machine. As an example to identify the four kinds of faults such as normal valve, valve plate fracture, valve plate wear, and spring failure of the valve plate, the classification model is shown in Figure 4. As the device is in normal operation most of the time, it is quite easy to obtain the samples of the normal running status of the valve plate in the actual test. At the same time, distinguishing the normal operation from other faults of the compressor valve is relatively easy. Therefore, the main purpose of the decision for the first level is to exclude nonfault samples. Nonfault samples can be quickly identified by adopting a one-to-many classifier. At the second level, the three kinds of faults can be identified, respectively, by applying the one-to-one Algorithm. Three one-to-one classifiers will be required during this process. Only four support vector machines will be required in total for this model. Compared with $4 * (4 - 1)/2 = 6$ required in 2.3.2, two support vector machines will be reduced. In theory, it will take less time to train and test and diagnosis efficiency will be improved.

The location of the fault may be involved in the valve seat, spring, valve plate, and other key parts. Because each component has its own fault type, in order to improve the diagnostic efficiency, the fault component should be identified first and the specific type of failure of the component can be determined later. Therefore, in the case of an unknown valve fault of a reciprocating compressor, the first level of decision-making can be designed to identify the faulty components and the second level decision is to determine the fault type of the specific parts.

Table 1: Operating parameters of reciprocating compressor.

Rated operating pressure (Mpa)	Rated exhaust (m^3/min)	Rated speed (r/min)	Cooling mode
0.2	12	500	Water cooling

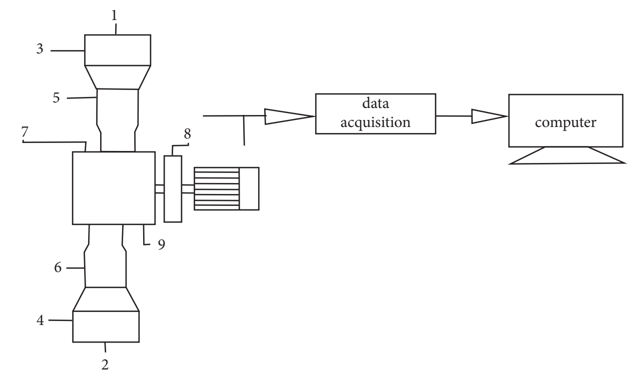

Figure 5: System of Valve of reciprocating compressor fault signal acquisition.

3. Experimental Investigations

3.1. Experiment Platform. The equipment used in the experiment is a reciprocating compressor of the double cylinder and double acting which is very close to the compressor used in the actual production of refining and petrochemical companies. A series of related destructive tests are designed for the suction valve and exhaust valve on the experimental platform of the real reciprocating compressor. Using the sensor to collect the vibration signal of the compressor set and temperature signal of the valve, the signal most similar to fault data of the real situation can be collected to the maximum extent. The specific operating parameters of the compressor are shown in Table 1.

The actual situation is shown in Figure 5, where 1 and 2 are cylinder head impact point and acceleration sensor; 3 and 4 are temperature measuring point and install platinum thermal resistance sensor; 5 and 6 are cross head impact point and acceleration sensor; 7 and 9 are crankcase outer surface, internal vibration measuring point, and acceleration sensor, respectively; and 8 is the key phase measuring point and eddy current sensor.

Four types of operating conditions such as normal valve, valve fracture, valve plate wear, and valve spring failure are simulated under the exhaust pressure (gauge) of 0 Mpa, 0.1 Mpa, and 0.2 Mpa, respectively. In this experimental

Table 2: Feature vector of signal sample.

Fault type	Sample number	Crest coefficient	Kurtosis index	Skewness index	Effective value	Standard deviation	Fault number
Normal valve	1	0.0303	0.0029	0.0458	0.7609	0.79257	①
	2	0.1023	0.2164	0.3279	0.5665	0.9026	①
	3	0.0402	0.0367	0.1469	0.6367	0.9881	①
	4	0.6129	0.0294	0.3205	0.6137	0.8351	①
	5	0.1425	0.0561	0.3361	0.4821	0.7093	①
Valve fracture	1	0.0478	0.0463	0.0917	0.84221	0.00135	②
	2	0.6190	0.0637	0.3275	0.6347	0.9027	②
	3	0.4543	0.3219	0.3575	0.5342	0.9434	②
	4	0.2011	0.0676	0.3821	0.5038	0.9221	②
	5	0.3579	0.1041	0.3528	0.5674	0.8657	②
Valve plate wear	1	0.9581	0.6287	0.4292	0.5821	0.5238	③
	2	0.9893	0.7953	0.3453	0.6281	0.8671	③
	3	0.7859	0.6513	0.4217	0.6915	0.9877	③
	4	0.9139	0.7385	0.5446	0.6609	0.8592	③
	5	0.8768	0.6054	0.4573	0.6581	0.9107	③
Valve spring failure	1	0.3082	0.2787	0.2168	0.7635	0.4891	④
	2	0.1027	0.1669	0.2461	0.7623	0.9135	④
	3	0.4103	0.3373	0.1931	0.8938	0.9437	④
	4	0.3841	0.2673	0.2037	0.7589	0.9276	④
	5	0.3724	0.1976	0.2524	0.7095	0.9471	④

platform, the valve is simulated with 4 scenarios, respectively: 1 as normal valve, 2 as valve fracture, 3 as valve plate wear, and 4 as valve spring failure. With experiments performed many times for each typical fault, multiple sets of feature vectors can be obtained and used as the sample of this kind of fault training which can reflect the fault rule. The vibration signal is measured in normal mode, and then the fault valve is tested. In the experiment, the piezoelectric IEPE acceleration sensor is used to collect the vibration data, and the sampling frequency is set at 10 KHz. 20 groups of original samples are extracted for each status with continuous sampling.

3.2. Feature Extraction of Reciprocating Compressor Valve. Different kinds of characteristic parameters of vibration signal will show different aspects of fault information. Sensitive parameters to the fault are chosen from the time and frequency domain such as amplitude maximum in the frequency domain, frequency domain mean, and dynamical indicators in the time domain (peak value, absolute value, effective value, and variance value). In reference [27], the following characteristic quantities are selected to describe the characteristic of the wave of the signal. Normalized treatment has to be done to make them into [0,1] data before building the model because of the different dimension between the parameters in the time and frequency domain. Feature vectors of the fault are shown in Table 2.

3.3. Learning and Training. Select 5 sets of samples of reciprocating compressors from each type of all the four types. A total of 20 sets of signal samples are used to learn and train according to the model in Figure 4 and the decision function of the corresponding support vector machine is built. Based on the fault diagnosis model of the reciprocating compressor valve established by using the multiclassification support vector machine, the radial basis kernel is chosen after the analysis. The training steps are as follows:

Table 3: Result of test samples.

No.	1 V 234	2 V 3	2 V 4	3 V 4
1	0.8609	—	—	—
2	0.9012	—	—	—
3	−1.0000	1.0000	1.0000	1.0000
4	−1.0000	−0.9843	0.0728	1.0000
5	−1.0000	0.2074	−0.5027	−1.0000
6	−0.1209	0.5352	1.0000	0.2051
7	−1.0000	-0.3492	1.0000	1.0000
8	−1.0000	1.0000	−0.3105	−1.0000

(1) Data format conversion to the recognizable format required by the libsvm software package

(2) Transform the scale of the training sample and map the sample set to [-1,1]

(3) Train model parameters (Penalty factor C and kernel function parameter σ)

(4) With parameters C and σ obtained in step 3, the training samples after scaling in step 2 can be used for training by using this model

(5) Input test samples into the trained model and check the classification result

Using the above-mentioned sample data to train the support vector machine classifier in sequence and obtaining the optimal classification function. Finally, the optimization of the parameters of the classifier is obtained with the penalty factor C equal to 2 and radial basis parameter σ of the kernel function equal to 2.

Table 4: Classification results based on the DT-SVM.

No.	Fault 1	Fault 2	Fault 3	Fault 4	Diagnosis result
1	1	0	0	0	Normal
2	1	0	0	0	Normal
3	0	2	1	0	Valve plate wear
4	0	1	2	0	Valve spring failure
5	0	1	0	2	Valve fracture
6	0	2	1	0	Valve plate wear
7	0	1	2	0	Valve spring failure
8	0	1	0	2	Valve fracture

Table 5: Comparison of identification result.

Model	Sample number	Correct diagnosis	Identification time (s)	Accuracy rate (%)
DT--SVM	30	28	1.69	93.3
SVM	30	28	2.55	93.3
BP($\delta = 0.01$)	30	25	11	83.3
BP($\delta = 0.05$)	30	23	15	76.7

3.4. Test. In order to test the effect of the classifier, 8 groups of samples which are known to be tested are used to verify the classifier. The generalization ability and accuracy of the classifier are to be tested. Table 3 gives the output of different decision functions of the support vector machine for samples to be diagnosed. As is shown in the first column, normal valve ① is distinguished from fault valves ②, ③, and ④ quickly. If the result is positive, it will be a positive sample which means a normal valve. The identification ends; If the result is negative, it will be classified into the other three types which mean fault valve. As is shown in columns 2, 3, and 4, a further one-to-one classification and identification will be needed.

According to the membership of the output of the independent support vector machine in the decision structure, the classification of the test sample is diagnosed. When one of the SVMi,j is determined to be classified as fault i for fault sample x, class i gets one vote. Vice versa, class j will get one vote. The fault type of each sample will be determined according to the respective score in each fault type of such sample. The final vote of each test sample is shown in Table 4.

As can be seen in Table 4, the diagnosis results are in complete agreement with the fault types preset for the samples, which are based on the decision rules for diagnosis set up in this paper.

3.5. Comparison with Conventional Methods. To further compare the classification results, 20 groups of samples are used to test different models. The classification effect is shown in Table 5.

As can be seen from Table 5, the recognition effect of the decision tree support vector machine established based on the actual fault is the same as that of the conventional multiple support vector machine. But it is obviously better than the recognition effect of the traditional neural network method. However, the classification and recognition time of the decision tree support vector machine is saved by about 35% compared with that of a conventional multiple support vector machine.

4. Conclusion

In this paper, with the advantages of the high efficiency of the decision tree combined with the advantages of the "one-to-one" and "one-to-many" multivalue classification method of SVM, the fault identification model of a reciprocating compressor valve based on decision tree and support vector machine is designed. Applying the model to the fault identification of a small sample number of reciprocating compressor valves, it can be seen from the test results and training classification results that the decision tree support vector machine diagnostic method has strong recognition ability and good classification result which is obviously better than the traditional neural network method when used in small sample cases and early fault diagnosis of the air valve.

Decision tree and support vector machine are used to construct a support vector machine model in the form of a decision tree the recognition effect of which is equivalent to a one-to-one multisupport vector machine, and the time for learning training and testing of which is much shorter than the conventional support vector machine. The effect is more obvious with the increase of the number of classification. Therefore, the DT-SVM is more efficient than the conventional support vector machine.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

This research was funded by the China University of Labor relations under Grant No. 22XYJS007.

References

[1] Y. Ai and C. Fei, "Rotor vibration fault diagnosis technology based on support vector machine," *Journal of Shenyang Technology University*, vol. 32, no. 5, pp. 527–531, 2010.

[2] D. Wu, "A gear box fault diagnosis method based on support vector machine," *Vibration, Testing and Diagnosis*, vol. 04, pp. 338–342, 2008.

[3] B. Schlkopf and A. J. Smola, *Learning with Kernels, Support Vector Machines, Regularization, Optimization and beyond*, The MIT Press, Cambridge, MA, USA, 2001.

[4] C. Wang, Z. Liu, and Y. Wang, "Intelligent fault diagnosis of photoelectric pod bearing based on multi-information fusion," *Journal of Physics: Conference Series*, vol. 2136, no. 1, 2021.

[5] L. Li, B. Lei, and C. Mao, "Digital twin in smart manufacturing," *Journal of Industrial Information Integration. January*, vol. 26, no. 9, Article ID 100289, 2022.

[6] L. Li, T. Qu, Y. Liu, S. Hongxia, and G. Yang, "Sustainability assessment of intelligent manufacturing supported by digital twin," *IEEE Access*, vol. 8, pp. 174988–175008, 2020.

[7] T. Tang, T. Hu, M. Chen, R. Lin, and G. Chen, "A deep convolutional neural network approach with information fusion for bearing fault diagnosis under different working conditions," *Proceedings of the Institution of Mechanical Engineers - Part C: Journal of Mechanical Engineering Science*, vol. 235, no. 8, pp. 1389–1400, 2021.

[8] L. Li and C. Mao, "Big data supported PSS evaluation decision in service-oriented manufacturing," *IEEE Access*, vol. 8, no. 99, p. 1, 2020.

[9] Y. Qian, "Research on fault diagnosis model of generative adss based on improved semisupervised diagnosis algorithm," *Mobile Information Systems*, vol. 2021, Article ID 3477667, 11 pages, 2021.

[10] L. Li, C. Mao, H. Sun, and L. Bingbing, "Digital twin driven green performance evaluation methodology of intelligent manufacturing: hybrid model based on fuzzy rough-sets AHP, multistage weight synthesis, and PROMETHEE II," *Complexity*, vol. 2020, no. 6, 24 pages, Article ID 3853925, 2020.

[11] H. Yin, Z. Li, J. Zuo, H. Liu, K. Yang, and F. Li, "Wasserstein generative adversarial network and convolutional neural network (WG-CNN) for bearing fault diagnosis," *Mathematical Problems in Engineering*, vol. 2020, Article ID 2604191, 11 pages, 2020.

[12] X. He and H. Zhao, "Support vector machine and its application in mechanical fault diagnosis," *Journal of Central South University*, vol. 36, no. 1, pp. 98–101, 2005.

[13] S. Sun, "Shield tunneling parameters matching based on support vector machine and improved particle swarm optimization," *Scientific Programming*, vol. 2022, Article ID 6782947, 11 pages, 2022.

[14] C. Tang, A. Tong, A. Zheng, H. Peng, and W. Li, "Using a selective ensemble support vector machine to fuse multimodal features for human action recognition," *Computational Intelligence and Neuroscience*, vol. 2022, Article ID 1877464, 18 pages, 2022.

[15] M. Rychetsky, S. Ortmann, and M. Glesner, "Support vector approaches for engine knock detection," in *Proceedings of the International Joint Conference on Neural Networks*, pp. 969–974, Washington DC, USA, July 1999.

[16] S. Liao and Z. Liu, "Enterprise financial influencing factors and early warning based on decision tree model," *Scientific Programming*, vol. 2022, Article ID 6260809, 8 pages, 2022.

[17] Y. Yang, "The evaluation of online education course performance using decision tree mining algorithm," *Complexity*, vol. 2021, Article ID 5519647, 13 pages, 2021.

[18] F. Wu, X. Liu, Y. Wang, X. Li, and M. Zhou, "Research on evaluation model of hospital informatization level based on decision tree algorithm," *Security and Communication Networks*, vol. 2022, Article ID 3777474, 9 pages, 2022.

[19] S. Feng, "Research and improvement of decision tree algorithm," *Journal of Xiamen University*, vol. 04, pp. 496–500, 2007.

[20] Y. Cheng, C. Huang, and Y. Zhang, "fault diagnosis of gear box based on particle swarm optimization decision tree," *Vibration, Testing and Diagnosis*, vol. 01, pp. 153–156, 2013.

[21] C. Sun and B. Liu, "A new SVM decision tree," *Journal of Fuzhou University (Natural Science Edition)*, vol. 03, pp. 361–364, 2007.

[22] V. N. Vapnik, *The Nature of Statistical Learning Theory*, Spring-Verlag, Berlin, Germany, 1999.

[23] H. Wang and Y. Ou, "Face recognition using PCA/ICA features and SVM classification," *Computer Aided Design and Graphics*, vol. 15, no. 4, pp. 417–420, 2003.

[24] Z. Yongtao and Y. Liu, "Research on support vector machine to solve multi classification problems," *Computer Engineering and Application*, vol. 41, no. 23, pp. 190–192, 2005.

[25] G. Wang, Y. Zhai, and D. Wang, "Application of fuzzy support vector machine in fault diagnosis of steam turbine," *Journal of North China Electric Power University*, vol. 30, no. 4, pp. 47–50, 2003.

[26] H. Wang, X. Zhang, and J. Yu, "Fault diagnosis method based on support vector machine," *Journal of East China University of Science and Technology*, vol. 30, no. 2, pp. 179–182, 2004.

[27] N. Saravanan, V. N. S. Kumar Siddabattuni, and K. I. Ramachandran, "Fault diagnosis of spur bevel gear box using artificial neural network (ANN), and proximal support vector machine (PSVM)," *Applied Soft Computing*, vol. 10, no. 1, pp. 344–360, 2010.