Presenting A New Algorithm To Diagnose Faults In Gas Turbine Compressors Using Vibration Analysis, T-test, And Support Vector Machine

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This research presents a new method for identifying faults in gas turbine compressors, using vibration analysis and statistical tests inside the support vector machine (SVM) algorithm. In the proposed technique, the dynamic signals are first received in the frequency domain, and the investigated frequency domain is divided into smaller ranges. Then, the RMS of each range is extracted as a frequency feature and given as input to the SVM algorithm. Because a large selection of features causes the classification accuracy to decrease, and also to select better features, the extracted feature vector is first passed through T-test filters with different significance levels and then given as input to the SVM algorithm. This method, while increasing the classification accuracy from 80.9% to 99.4%, helps the recognition of frequency ranges, which have noticeable variations under the influence of the fault. Based on the obtained results, compressor faults mostly increase the intensity of vibrations in frequency bands above 1500 Hz.

Keywords: Fault diagnosis, gas turbine compressors, vibration analysis, support vector machine.

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1. Introduction

Real-time monitoring of machine component operations increases security while reducing maintenance and repair costs. Controlling vibrations to detect abnormal oscillations resulting from faults is one of the methods of rotating machinery condition monitoring [1–3]. Vibration in machinery includes vibration in the gears, rotating axis, and bearings, which have a lower output frequency than the engine. Experimental vibration analysis of gearboxes, industrial equipment, compressors, turbines, etc., has many difficulties. In addition to repair costs, the breakdown of gas turbine compressors causes damage to related industries, which increases the importance of optimal maintenance of gas turbine compressors [4–6].

Saravanan and Ramachandran [7] were among the people who conducted initial research in intelligent troubleshooting. Li et al. [8] used the frequency features of rolling bearings as the neural network input. Kang et al. [9] used the extracted frequency features of the vibration signals using fuzzy neural networks in the motor-bearing system. Lou and Loparo [10] investigated bearings fault diagnosis by extracting standard deviation values wavelet coefficients and using the fuzzy classifier. By extracting the best statistical features of vibration signals and with the help of fuzzy inference, Saravanan et al. [11] designed an intelligent system to determine and diagnose the fault of the bevel gear gearbox. Lei and Zuo [12] classified the gear fault in a gearbox sample with the help of extracting statistical parameters and the nearest neighbor pattern classification method. Fault analysis of machine tools based on grey relational analysis and main factor analysis investigated by Shen et al. [13].

Various methods have been provided to diagnose the fault and monitor the condition, and condition monitoring based on vibration analysis is one of the safest and most accurate methods in this field [14–17]. Considering that the vibration signals taken from the machine contain useful information, by examining the physical characteristics of the vibration signals and extracting their features, it is possible to find out the existence of faults in different parts of the machinery [18–20]. Rajeswari et al. [21] used the time-frequency domain to extract the statistical features of the vibration signals related to faulty gears. They gave the obtained features as input to the error backpropagation neural network classification methods and the C4.5 decision tree algorithm. They investigated the effective parameters of the statistical features of signals and fault diagnosis in these systems. Bordoloi and Tiwari [22] used wavelet transform to process and extract features from faulty shaft signals. Lu et al. [23] tried to introduce a powerful feature that can lead to the correct classification of signals. Mohammed et al. [24] investigated vibration signal analysis to detect gear faults with different crack growth scenarios. Effect of noise on output-only modal identification of beams investigated by Jahangiri et al. [25] and Hernandez-Vargas et al. [26] presented a combination of singular value decomposition methods, statistical analysis, and artificial neural networks to process vibration signals. In their research, the steady-state signal has been used in the fault diagnosis process. The data is first converted from analog to digital data by a data acquisition system with a certain sampling frequency. Then, the singular values are extracted by the SVD method. Three statistical features are extracted for these single values, including the mean, variance, and information entropy (Shannon entropy). After the features are extracted from the single or combined fault classes, the classification step is implemented with the help of the error backpropagation neural network. Tang et al. [27] utilized a small sample transfer feature method to diagnose the faults in compressors. The results of their study indicated that the accuracy of the applied method is very high by decreasing the domain and source data distribution by up to 92%. The obtained accuracy suggests the superiority of transfer learning and deep learning diagnostic methods in issue detection. He et al. [28] proposed the application of an approximate entropy nonlinear method integrated with empirical mode decomposition for fault diagnosis in the rotating machinery. The outcomes demonstrated that the approximate entropy method is an effective method when associated with empirical mode decomposition, and the proposed method can be employed widely in rotating machinery. A review of feature selection and feature learning in machine learning applications for gas turbines has been published by Xie et al. [29]. As part of this review paper, 46 studies using feature selection and feature learning for gas turbine modelling with machine learning are reviewed. The work of Hidalgo-Mompeán et al. [30] relates specifically to the problem of feature selection when dealing with the detection of compressor failure modes using machine learning. In order to achieve this objective, several methods of feature selection ranking are examined. Mousavi et al. [31] proposed a fault detection approach for monitoring turbines. A neuro-fuzzy inference system is used in conjunction with an orthonormal basis function to construct nonlinear dynamical models using experimental data.

Nowadays, the use of neural networks and learning algorithms has increased in the field of mechanical equipment troubleshooting and general classification [32–35]. So far, different neural networks, such as ANFIS, RBF, MLP, etc., have been presented, which generally operate based on minimizing modeling or classification errors [36–39]. In this research, the support vector machine (SVM) algorithm is used to classify faults. SVM is a learning machine that was introduced in 1995 by Essam et al. [40]. SVMs are designed in such a way that they minimize the operational risk instead of minimizing the modeling error and thus perform better in classification problems. For this purpose, the vibration signals will be recorded experimentally using the accelerometer sensors installed on the turbocompressor body with the help of the data acquisition system. Using the frequency spectrum and according to the ISO standard 10816, faults in the turbocompressors have been studied by investigating received signals. Moreover, the main contributions of the presented study are as follows:

- A vibration analysis-based support vector machine is engaged to enhance the classification of the SVT in the fault diagnosis.
- The relation between the vibrations and faults is investigated.
- The accuracy of the proposed model is evaluated experimentally by the employment of a test section.

2. Methodology

According to the repair instructions for gas turbine turbocompressors, unloading and testing are done in an eight-month overhaul. In this research, after determining the optimal points for vibration data acquisition, data acquisition operations were obtained from the turbocompressors for two years before the eight-month overhaul. After checking the performance of turbocompressors, the data was divided into two parts: intact and faulty. It is necessary to explain that turbocompressors that continue to operate after data collection are considered intact, and if they stop after a short period of time or are defective, according to experts, they are considered faulty.

After classifying the data by processing the vibration signals obtained in the frequency domain, features are extracted for training the SVM network. In the algorithm presented in the present research, the vibration signals are first received in the frequency domain, and the investigated frequency range is divided into several smaller ranges. Then, the RMS of each range is extracted as a frequency feature to be given as input to the SVM network. To achieve accurate results, small frequency ranges should be selected. This increases the number of features, and a large number of features may decrease the accuracy of the SVM network. First, the features extracted in the T statistical test are examined to solve this problem, and features from the two classes, which have a significant difference in terms of the T-test, are selected as input to the SVM network. The T-test is a statistical examination that equates the variance and mean of features obtained from two separate classes. The T-test is employed when the samples show normality, independence, and equal variance conditions. The T-tests also can be used when two independent groups are compared with each other. The mentioned specification is one of the main advantages of the T-test [41]. It selects the features in different classes with a greater mean difference. The T value is obtained based on Eq. (1) and compared with the critical value of the T distribution to compare the mean of two characteristics from two different groups in the T-test. In general, if the value of the statistic T is smaller than the critical value of the T distribution, with the degree of freedom mentioned in Eq. (2) and at the alpha error level, the assumption of equality in the mean of the two populations is confirmed. That feature is removed from the feature vector. As a result, the T-test removes the features that behave almost the same in different classes. Their entry into the SVM network does not help the diagnosis process and reduces the classification accuracy.

$$T = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (1)$$

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{1}{n_1-1}\left(\frac{s_1^2}{n_1}\right)^2 + \frac{1}{n_2-1}\left(\frac{s_2^2}{n_2}\right)^2} \quad (2)$$

where $\bar{X}_i, s_i, n_i$ and df are the mean, variance, number of samples in the i^{th} group, and the degree of freedom of the T statistic, respectively.

The goal is to form the best feature vector of frequencies to achieve the highest classification accuracy according to their values. The algorithm presented in this research can be very useful for preliminary checks and diagnosing the faults of complex and unknown systems.

2.1. Support Vector Machine

SVM is a supervised classification method that predicts a sample's class. SVM separates two classes directly through an optimization process using all the bands. It determines the separating planes and the optimal decision boundary (hyperplane), so the hyperplane has the greatest distance from both sides to both classes. The closest training samples to these planes are called "support vectors" (Fig. 1) [42].

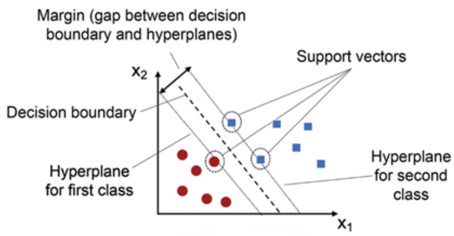

Fig. 1. Classification of the two classes using SVM [43]

In general, SVM is a two-class linear classifier, which can also be used as a multi-class and nonlinear classifier by developing it and using kernel functions. Assuming n training samples in a real space with dimensions N and two classes for each sample [44]:

$$S = \left\{(x_i, y_i) \mid x_i \in R^N, y_i \in \{-1, 1\}, i = 1, 2, \ldots, l\right\} \quad (3)$$

Where y_i is the output of each class of the i^{th} training sample. The goal is to find a plane that separates $y_i = 1$ class points from $y_i = -1$ class.

To calculate w and b for multi-class classification in nonlinear mode using kernel functions, the optimization problem must be solved. Basically, the SVM classifier is a binary classifier. The general approach is to reduce the multi-class problem to several binary problems for solving the multi-class problem. Each problem is solved with a binary separator. Then, the output of the binary separators of the SVM is combined, and thus the multi-class problem is solved.

2.2. Measurement of vibrations and experimental tests

Different vibration sensors with different installation locations are used to monitor the conditions and protect turbocompressors against high vibrations in gas pressure booster stations. In Fig. 2, a view of the turbocompressor under investigation used in the pressure boosting station is shown, along with the type and installation location of the sensors. Table 1 demonstrates the type and installation location of the sensors used to measure this equipment's vibrations.

The sensors used in the present research, as shown in Fig. 3, are proximity and acceleration probes. A data collector, also known as a data logger, is a small, portable device for temporary recording and data transfer to a computer. The portable equipment used to record vibration data is VibroTest60, made by Brüel & Kjær and STD3300. These two types of data collectors are shown in Fig. 3.

Experimental tests have been carried out on SIEMENS GT10B gas turbine. This turbine is used in distributed energy station project run by Guangzhou Development Group Co. Ltd. in Taiping Industrial Park, Guangzhou has been. The specification of this turbocompressor are listed in Table 2. Different vibration sensors installed on the turbocompressor are shown in Fig. 4. The accelerometer sensor is installed on the turbine, which measures horizontal vibrations. The proximity sensor, located at the end of the turbine, is used to record the vibrations of the main shaft. Also, the proximity sensor installed on the upper position of the compressor (this position is determined based on the ISO standard 10816) is used to record vibrations in the vertical direction of the turbocompressor.

In this work, compressors are classified into two categories: healthy and faulty. In order to determine the condition of the compressor, the ISO 10816 standard is used. This part of ISO 10816 establishes procedures and guidelines for the measurement and classification of mechanical vibration of reciprocating compressor systems. The vibration values are defined primarily to classify the vibration of the compressor system and to avoid fatigue problems with parts in the reciprocating compressor system, i.e. foundation, compressor, dampers, piping, and auxiliary equipment mounted on the compressor system. According to the ISO 10816 standard, the boundaries of overall vibration velocity limiting for gas turbines are shown in Table 3. The warning value should be 25% lower than the border of zone C. The stop value is also between C and D areas. In zone A and zone B the compressor systems with vibration within these zones are normally considered acceptable for long-term operation. Using the ISO 10816 standard, vibration signals can be analyzed to detect different types of gas turbine faults, including shaft misalignment, shaft bending, bearing failure, mechanical faults, and rotor faults. As the primary objective of the present study was to apply the algorithm to detect faults in gas turbine compressors, the data were classified into healthy and faulty compressors.

3. Results and discussion

3.1. Vibrations frequency spectrum

The vibration frequency spectrum of different points of the turbocompressor is presented in Fig. 5. These results are recorded and presented at 178Hz. By examining the frequency spectrum extracted at different points of the turbocompressor, it can be seen that the data collection location has a significant effect on the number of frequencies in the frequency response function (FRF). The results show that in the frequency spectrum obtained from BRG1 and DEB points, the odd frequencies appear in the FRF, while the even frequencies do not appear in it. Meanwhile, the FRF obtained from point DE contains all the system's natural frequencies. According to Fig. 5b, it can be observed that the first three frequencies of this type of turbocompressor are equal to 92Hz, 185Hz, and 278Hz, respectively. In addition, based on the recorded data, it can be seen that the maximum speed of recorded turbocharger oscillations is 4.58mm/s. Therefore, this compressor is located in the B/C area. Based on this, according to the ISO 10816 standard, it can be said that because the vibrations of the compressor are in the C region, this turbine is not suitable for long-term operation, and the performance of this turbine should be reviewed, and the repairs should be considered. Considering that the frequencies created in the frequency spectrum are 1x, 2x, and 3x, it is predicted that the shaft may be crooked or uneven. In addition, in this condition of compressor operation, there is a possibility of the influence of flow turbulence or gas flow variations on the system vibrations.

The time response of the turbocompressor recorded at the NDE and ND points is demonstrated together in Fig. 6. Time response registration is done within 200 seconds. As can be seen, at the NDE point, the system's frequency is almost constant over time, which indicates the linear behavior of the system. Despite this, the wavelet transformation of the signal recorded at the ND point shows that the frequencies appearing in the response are time-varying, indicating the system's nonlinear behavior. It can be the result of the fault's effect on the behavior of the turbocompressor.

3.2. Results of applying the fault diagnosis algorithm

To classify faults using SVM, first, through signal processing, useful features should be extracted from the vibration signal and given as input to the SVM network so that the network is trained and tested. One of the goals of this

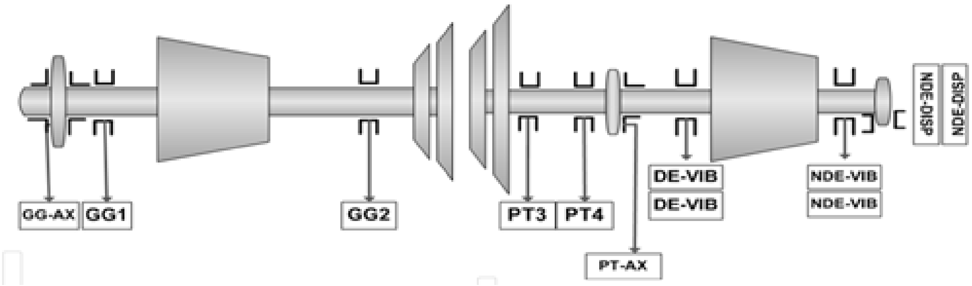

Fig. 2. Schematic of SIEMENS GT10B turbine and 10MV2A compressor.

Table 1. The type and installation locations of the sensors used in measuring the vibrations of the SIEMENS GT10B turbine.

Number of sensors	Installation location	Sensor type	
3	NDE-VIB, DE-VIB, NDE-DISP	Proximity probe	Compressor
4	PT-AX, GG-AX	Proximity probe	Turbine
2	GG1, GG2, PT3, PT4	Acceleration probe	

(a) (b)

Fig. 3. (a) VibroTest60 and (b) STD3300 model data loggers.

research is to provide a method for quick finding of important frequencies to diagnose the fault of an unknown system. Also, because of the high impact of crankshaft vibrations and other vibration sources unrelated to the turbocompressor fault on the value of the time features, only the frequency features are investigated.

First, the investigated frequency range, 10 to 6000 Hz in this research, is divided into smaller ranges, and the RMS of each range is extracted as a feature. In this research, the frequency range is divided into 100 equal parts, and the RMS of these parts forms the feature vector. Then, this feature vector is given as input to the designed SVM algorithm, which has the specifications shown in Table 4. In this case, without using a filter, the SVM network has been able to

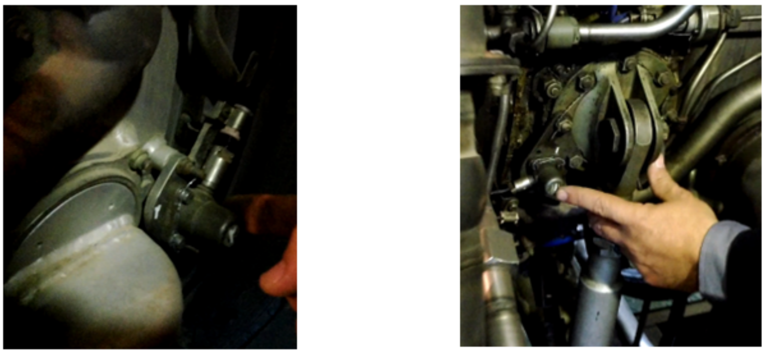

Fig. 4. Different vibration sensors installed on the SIEMENS GT10B gas turbocompressor.

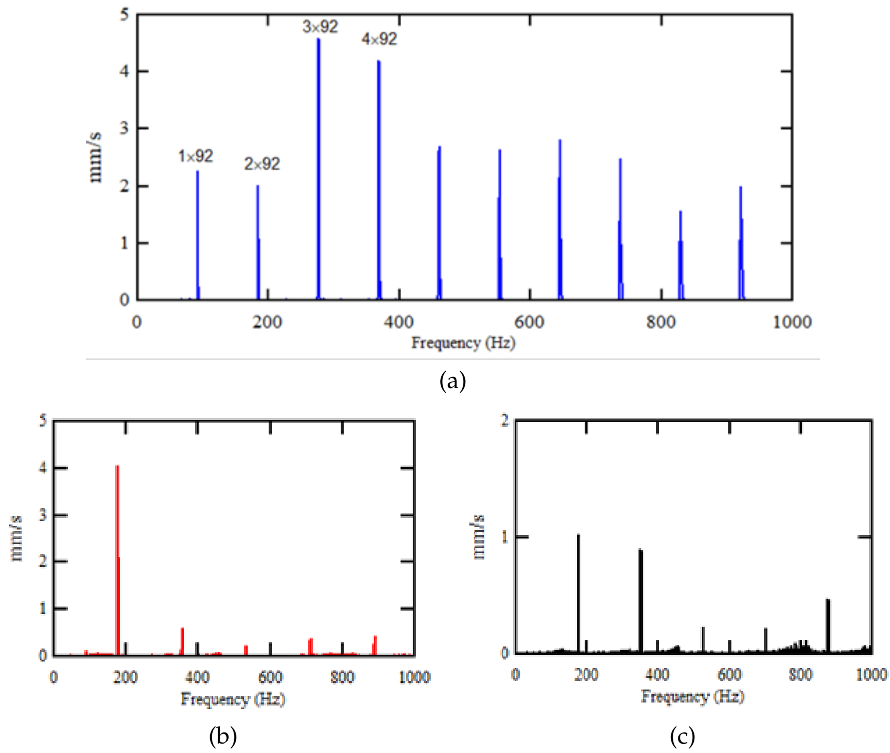

Fig. 5. Vibration frequency spectrum of different points of the turbocompressor: (a) point DE, (b) point BRG1 and (c) point DEB.

correctly diagnose faulty and intact turbocompressors with an accuracy of 80.9%, and the corresponding confusion matrix can be seen in Fig. 7. Here, class zero corresponds to faulty turbocompressors, and class one corresponds to intact turbocompressors. As can be observed, this algorithm has diagnosed 32.4% of intact turbocompressors as faulty and 6.8% of faulty turbocompressors as intact, which shows the rather improper accuracy of this model. This error percentage is unacceptable considering the costs and time of replacing a turbocompressor.

In intelligent fault diagnosis systems, the feature extraction and selection process is very important quantitatively and qualitatively. Suppose too many features are selected without preliminary checks. In that case, the neural network may be confused, and a large error will accompany the fault diagnosis process. In this study, with preliminary investigations, it was found that turbocompressor faults did not increase the intensity of vibrations at all frequen-

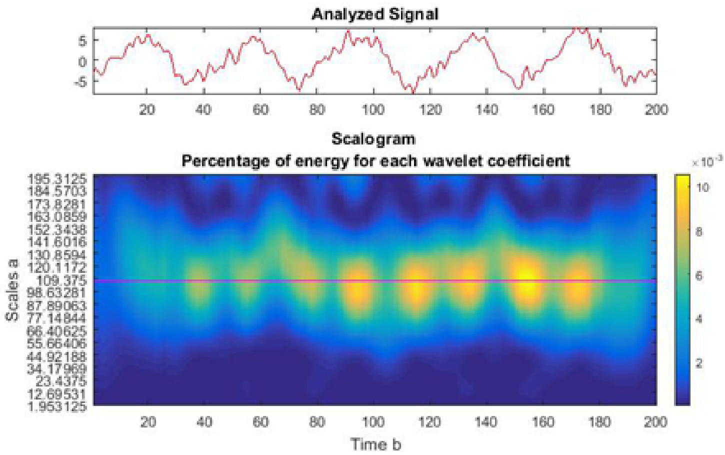

Fig. 6. The time response of the turbocompressor recorded at the NDE point.

Table 2. The specification of SIEMENS GT10B gas turbocompressor.

Manufacturer	Siemens Alstom
Model	GT 10B
Year	2002
Condition	Taiping Industrial
Power output	25.2MW
Hours	50000x Approx
Fuel type	Natural Gas
Frequency	50 Hz
Turbine speed	4800rpm
Exhaust temperature	508°C

cies; at some frequencies, systems with faulty and intact turbocompressors behave similarly (Fig. 8). For this reason, a T-test filter was used inside the SVM network to remove inappropriate features. The T-test is an inferential test for parametric data analysis that examines the difference between the mean of a sample and the statistical population or between the mean of two groups from two independent populations. After applying the T-test filter, the feature vector changes concerning the alpha coefficient and, as a result, the accuracy of the network. In the best case, with the alpha coefficient of 0.17 and the selection of 22 frequency features, the accuracy of the network is equal to 99.4%. Fig. 9 shows the confusion matrix related to the SVM network with the same specifications as Table 1 and with the T-test filter. This shows the T-test filter's positive effect on the network's accuracy.

4. Conclusion

As stated, the algorithm presented for diagnosing the gas turbine compressor faults can be used to evaluate the systems on which preliminary investigation is being done. According to the results of the present research, it can be said that the presence of faults in this type of compressor causes a noticeable increase in the intensity of vibrations. As seen, without using the signal filter, the proposed algorithm has diagnosed 32.4% of intact turbocompressors as faulty and 6.8% of faulty turbocompressors as intact, which shows the rather improper accuracy of this model. This

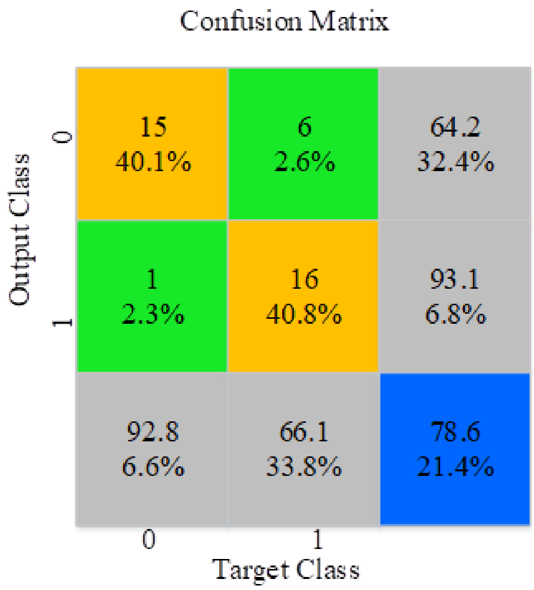

Fig. 7. The SVM network confusion matrix without the T-test filter.

Table 3. overall vibration velocity limiting for gas turbines.

	vibration speed (mm/s)	Evaluation zone boundary	Criterion
1	4.5	A/B	Acceptable
2	9.3	B/C	Marginal
3	14.7	C/D	Unacceptable

Table 4. The SVM algorithm specifications.

Kernel function	RBF
Kernel function parameter (sigma)	5
Penalty parameter	30
Size of the feature vector	100
Percentage of training data	70
Percentage of test data	30

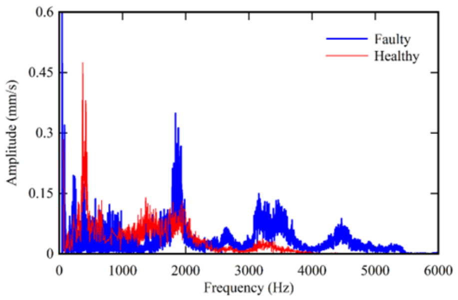

Fig. 8. Frequency diagram of the amplitude of the vibrations in a faulty turbocompressor compared to an intact caase.

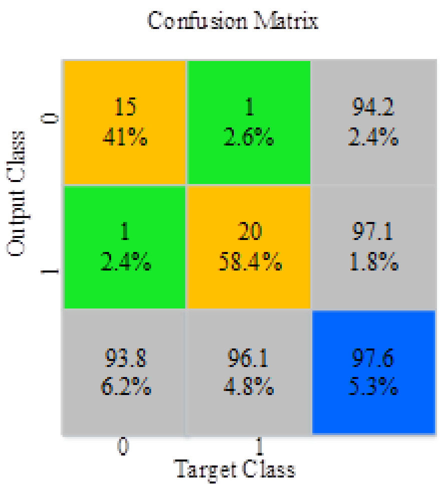

Fig. 9. The SVM network confusion matrix using the T-test filter.

error percentage is unacceptable, considering the cost and time of replacing a turbocompressor. If the T filter is used, the accuracy of the network becomes 99.4%. The confusion matrix related to the SVM network and the T-test filter shows this filter's positive effect on the network's accuracy. However, the proposed fault diagnosis model can be integrated more to achieve the ability to detect other types of faults, such as spalling, inner race, etc. More integrated models for lower correlation ranges can be considered for future evaluations.

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