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Lifelong Condition Monitoring Based on NB-IoT for Anomaly Detection of Machinery Equipment

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Abstract

The condition monitoring for machinery equipment is vital for safe and economical production in the industry. In modern manufacturing, data-driven methods for machine prognosis and health management (PHM) have been paid greater importance due to the development of machine learning. For another, the emerging Internet of Things (IoT) technique makes it possible for large scale data collection using distributed IoT terminal devices. In this paper, a condition monitoring system for machinery equipment is designed based on Narrow Band Internet of Things (NB-IoT) technique. Combined with the wavelet packet decomposition (WPD) and one-class support vector machine (OCSVM) algorithm, the abnormal data can be effectively identified. The system is verified by a small fan working at two conditions: normal and blade imbalance. The experiment results prove that the system can achieve reliable and stable online monitoring. What's more, the low power design of the IoT terminal ensures the system's longtime operation.

Keywords: lifelong condition monitoring; PHM; NB-IoT; WPD; OCSVM

1. Introduction

Large machinery equipment such as wind turbines widely used in metallurgy, electric power, petroleum, and chemical engineering plays an important role in industrial production. Generally, the various components of the equipment are prone to get damaged due to complex working condition and long working hours, which causes the production shutdown and huge economic losses. The stability operation and the degradation prediction of the equipment not only determine the production capacity, product quality and production cost, but also the production safety.

Lots of efforts have been made to promote the progress in PHM of the machinery equipment. The majority of the studies focus on the modeling and reasoning system and the conventional wired monitoring system has been employed in many applications 0. However, some critical equipment is still unable to been monitored easily for the inconvenience of wire transmission and power supply. With the rapid development of IoT, it has injected new vitality to Industry 4.0 and intelligent manufacturing, which further improves the automation level of modern industrial production by more efficient monitoring and control [2]. Some studies have taken a beneficial quest for wireless condition monitoring [3][5]. Through IoT and wireless sensor networks (WSNs) installed in the crucial components of the equipment, the vibration, temperature, current, and other signals can be measured by the sensor nodes and transmitted to the server. Then, the server deployed with the physical or data-driven model performs the anomaly detection, i.e., identifying the abnormal operation states in terms of sampled data sensor data. Combing with the causes of the failures, it will help to locate and eliminate the faults in time and prejudge the underlying damage, which can further decrease the safety risks, extend equipment life and

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reduce enterprise cost. Bluetooth [6] and ZigBee [7][8] commonly used techniques for wireless monitoring suffer from short transmission distance and high power consumption. NB technique can realize long distance transmission and is less energy demand, thereby overcoming the deficiencies of current art.

In this paper, a lifelong condition monitoring system for machinery equipment is proposed. An IoT terminal device is designed to measure and transmit the vibration data based on the NB-IoT module. The NB-IoT module and the terminal controller are selected and work in a low power consumption way. The node energy of the last layer is extracted by WPD and normalized as the input of OCSVM model. And the diagnosis model is trained only using the normal data, which can overcome the imbalance of anomaly data. Besides, the effectiveness of the presented system is evaluated by a small fan in both normal and blade imbalance conditions.

2. Systematic design

As demonstrated in Fig. 1, the developed monitoring system is composed of three parts: data collection terminal, server, and local client. The vibration signal is measured by a tri-axial acceleration sensor, and the acceleration data is sent to the low-power microprogrammed control unit (MCU) by I2C communication. Then, NB-IoT module uploads the vibration data stored in the MCU to the server using the UDP protocol. The server mainly receives the compressed data from the IoT terminal and transmits the decompressed data to the client. The client performs the fault detection procedure and displays the diagnosis results as well as the waveform in the time domain (TD) and frequency domain (FD) at the user interface.

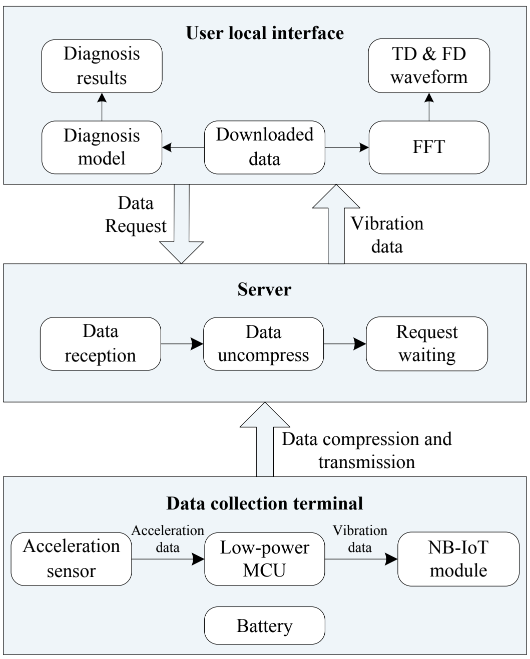


Fig. 1. Monitoring system architecture.

2.1. IoT terminal

2.1.1. Terminal controller

For a variety of IoT applications, power consumption has always been a sensitive issue. Since most IoT devices are powered by batteries, some equipment may need to be shut down when replacing the battery, resulting in economic losses. For the sake of minimizing the number of battery replacement and prolonged running time, it is especially important to select a suitable MCU and its operating mode. In this system, STM32L0 MCU produced by STMicroelectronics is selected as the controller of the terminal and intermittent working mode is adopted for longer working hours. The STM32L0 is specifically designed to meet the IoT application requirement of low power consumption. In consideration of the large transmission power of NB-IoT module when uploading data, the terminal developed in this study works in intermittent mode. Collecting the acceleration data and sending it at intervals can avoid the NB-IoT module continually running for a long time and save terminal energy effectively.

2.1.2. Acceleration sensor

The subsequent experiments are conducted using a small fan with low rotate speed. MPU-6050 is suitable for low-frequency vibration measurement and easy to implement by connecting with the MCU through an I2C bus. The MPU6050 is the world's first Motion Tracking device which combines a 3-axis gyroscope and a 3-axis accelerometer on the same silicon die together with an onboard Digital Motion Processor. Compared to the multi-component solution, MPU6050 eliminates the time difference between the integrated gyroscope and the accelerator and reduces the packaging size. However, MEMS sensors, such as ADXL 1001/1002, can deliver high-resolution measurements in the real plant where the vibration frequencies are comparatively higher.

2.1.3. NB-IoT module

The issues of data communication such as transmission bandwidth, stability and construction cost, etc. need to be concerned in IoT applications. In consideration of the complicated working environment, the wireless communication technique is employed in the presented monitoring system. At present, the short-range wireless communication technologies, including Wi-Fi, Bluetooth and ZigBee, widely used in smart home applications. To connect to the public network, it is necessary to build the based station, which will lead to higher construction cost.

Focusing on the Low Power Wide Area IoT fields, NB-IoT is an emerging communication technology built on the cellular network with the support for cellular data connection of low-power devices in the Wide Area Network. NB-IoT has four characteristics: Firstly, wide coverage can provide extended indoor coverage. In the same frequency band, NB-IoT gains 20dB more than the existing networks, which is equivalent to increase the coverage ability of by 100 times; Secondly, NB-IoT has a stronger ability to support the device connections; The third is NB-IoT has lower power consumption with a standby time up to 10 years; Finally, it is cost-efficient to deploy the NB-IoT system [9]. It can be introduced to diverse applications, such as the remote meter reading, asset tracking, intelligent parking, intelligent agriculture, and so on.

Compared to the existing GPRS network and LTE network, the power consumption of NB-IoT is much better [10]. Except for traditional Discontinuous Reception (DRX) mode, Power Saving Mode (PSM) and Extended DRX (eDRX) mode are introduced to reduce the terminal power consumption and extend the battery lifetime. When working in DRX mode, the terminal is always online detecting the downlink data, thus it has high power consumption. eDRX mode is the extension of the LTE network, which allows lower the frequency for listening to the network. For some IoT applications, it is acceptable for the device to be unavailable for a few seconds or longer. Combining with PSM mode, eDRX can provide a good balance between device performance and power consumption.

For NB-IoT module in our system, PSM mode is set to monitor the mechanical component. PSM is designed to save battery power and potentially achieve 10 years of battery life. As shown in Fig. 2, the downlink data can only be received when the terminal actively sends the uplink data. In the PSM state, the terminal goes to sleep to conserve battery power with several W, and the received downlink data is not accessible at this time, which is suitable for the services with no delay requirement for downlink data. However, the device needs to reconnect to the network when it turns back on. Therefore, the cumulative energy consumption of the reattachment process may become significant during the device lifetime [10]. By setting appropriate active time, the network can retain the status information and the device is able to remain registered in the network. In this way, there is no need to reconnect to the network if the device wakes up and sends data before the expiration of active time interval. In the proposed application, the PSM mode is enabled and configured the sustain time of 24 hours, i.e., the device reports the status to the monitoring server daily. And if the device detects the abnormal condition before the agreed sleep interval, it will immediately wake up and send the important information to the monitoring server, without performing the reconnection process.

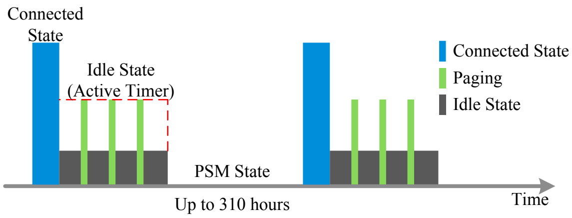


Fig. 2. PSM mode.

The NB-IoT module used in this system is the BC95-B5 module produced by Quectel. The BC95-B5 module is a compact NB-IoT wireless communication module with ultra-low power consumption and ultra-high sensitivity. It can directly communicate with the MCU through the serial port using Quectel Enhanced AT command set. The picture of NB-IoT module is shown in Fig. 3.

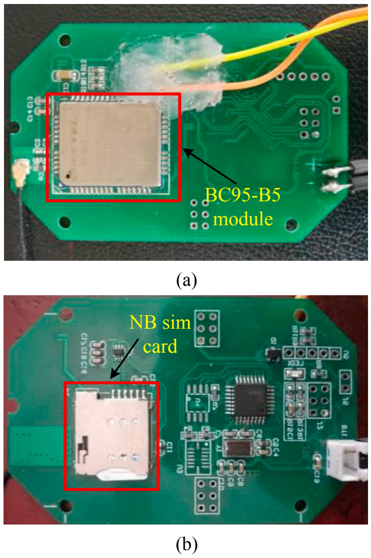


Fig. 3. NB-IoT module (a) front side; (b) back side.

2.2. Anomaly detection algorithm

The WPD and OCSVM are combined to detect the abnormal conditions as demonstrated in Fig. 4. Before the feature extraction, the raw vibration signal is preprocessed by the high pass filter to remove the low-frequency noise components. The filtered vibration data is decomposed by wavelet packet, and then the energy of each node in the last layer is normalized to form the feature vector. The data set in normal condition is fed to the OCSVM model to learn the optimum separating hyperplane. After that, the trained model can be applied to diagnose the newly acquired data.

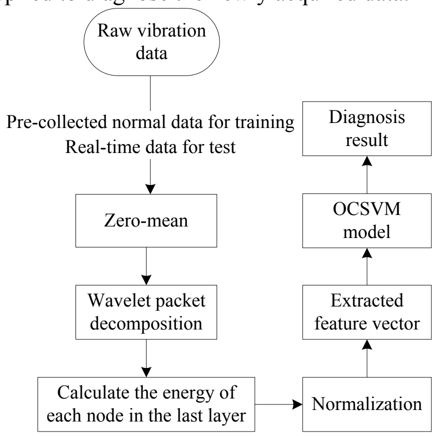


Fig. 4. Flowchart of the anomaly detection algorithm.

2.2.1. Wavelet packet decomposition

Wavelet analysis has attracted great attention and acts a significant role in the signal processing filed. Due to its adaptive, multi-resolution capability, wavelet transform has been extensively studied and enormous researches and application have been exploited in the areas of fault diagnosis [11]. The WPD is employed to extract the feature of the vibration signal, which is the more refined processing of wavelet decomposition (WD). Unlike WD, WPD not only decomposes the low-frequency signal but also decomposes the high frequency. WPD has neither redundancy nor omissions so that it can perform better time-frequency localization analysis on signal and more helpful information of medium and high frequency.

Commonly used wavelet packet bases are Haar wavelet, Daubechies (DB) n wavelet, Morlet wavelet, etc. Different wavelet packet bases can affect the performance of the fault diagnosis [12]. However, a consensus has not been reached yet which is wavelet is superior for the diagnosis task. Generally, the wavelet can be determined by the characteristics of the signal and the choices of the existing research. The DB 2 is selected as the wavelet packet base for five layers decomposition to get the coefficients in term of the maximization of the energy to Shannon entropy ratio [13]. As the energy of each node is correlated to the fault characteristic, it is an effective condition monitoring indicator [14]. The node energy can be calculated based on the corresponding wavelet coefficients, as defined in:

$$E(j,n)=\sum_{k=0}^{N_j-1}\left|\mathbf{W}(j,n,k)\right|^2 , \tag{1}$$

where $E\,(j,\,n)$ denotes the energy of the n-th node at depth of j, $\mathbf{W}(j,\,n,\,k)$ is the wavelet coefficient vector, N_j is the length of coefficients vector $\mathbf{W}(j,\,n)$ at level j. Furthermore, the energy of the terminal nodes is normalized as the percentage of total energy to constitute a $32(2^5)$-dimensional feature vector. The normalization procedure can be expressed as follows:

$$p(j,n)=E(j,n)/\sum_{n}E(j,n) . \tag{2}$$

2.2.2. One-class SVM

The OCSVM is a kind of domain-based methods for anomaly detection as depicted in Fig. 5. To identify the outlier data, a separating hyperplane is constructed by the nominal data. Thus, any data points falling outside the trained boundary will be flagged to the anomaly class [15]. The fact that the fault samples are scarce and hard to collect causes heavily imbalanced class distribution in the real applications. Since only data in normal condition is needed to train OCSVM model, it is conducive to deal with the imbalanced data issue, reduce the data collection cost and improve the efficiency of the model training [16]. The feature vector extracted by WPD is utilized as the input of OCSVM model.

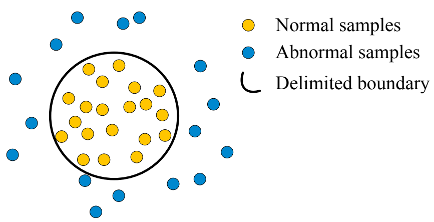


Fig. 5. Illustration of the OCSVM model.

3. System test and experiment

3.1. Experiment deployment

Constrained by the experiment environment, a small fan is used to simulate and test the condition monitoring system. As described in the previous section, pattern recognition is the core of fault diagnosis. The large fan and the small fan have similar mechanical structures, and the faults are basically the same. Therefore, the vibration signal has many similarities, which makes it feasible to use a small fan to verify the system and diagnosis model. The experimental deployment is demonstrated as Fig. 6. The acceleration sensor is mounted on the back of the motor. Considering the rotational frequency of the fan is around 25 Hz, the sampling frequency is designed as 80 Hz to meet the Shannon's sampling theorem. Ultimately, the real sampling frequency is about 76 Hz due to the delay of I2C communication between the sensor and the MCU.

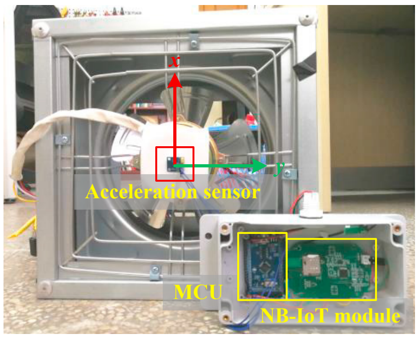
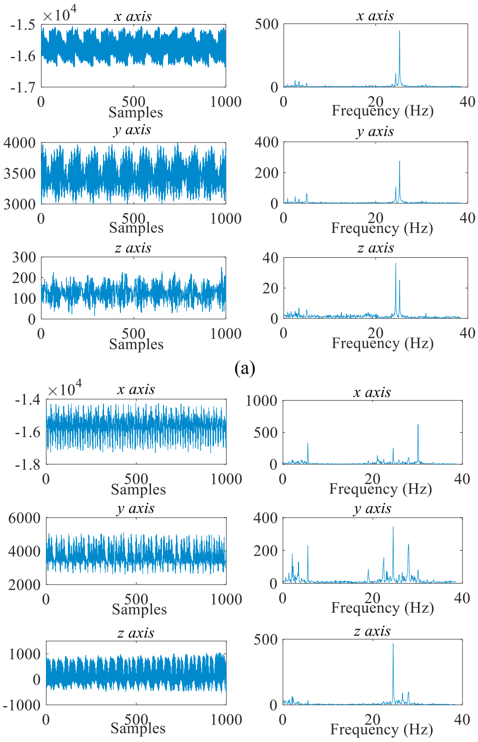


Fig. 6. Illustration of the experimental deployment.

3.2. TD and FD analysis

The analysis mainly focuses on two working conditions: normal running and the imbalance of the fan blade. And the imbalance of the fan blade is manmade by sticking a block on the fan blade so that the blade with the block is out-of-balance compared with other blades. After preprocessed by subtracting the mean value of the single, the zero-centered vibration signal of normal and anomalous data is processed by FFT, and the waveforms in TD and FD are drawn in Fig. 7. It can be seen from the waveforms that the fan blade imbalance results in an obvious change in the FD. And the vibration signal can represent the machine working condition, which provides the theoretical basis for the fault diagnosis using OCSVM.

The abnormal vibration signal is decomposed to five layers by WPD, as shown in Fig. 8, the darker the color, the greater the energy of the sub-band. A distinct frequency component can be observed, which differs from the main rotational frequency of the experimental fan. The sub-band width is 1.1875 Hz, and thus the feature of the normal and abnormal data can be effectively distinguished by means of the energy of the 32 terminal nodes.



(a)
(b)

Fig. 7. Waveforms in TD and FD at different conditions (a) Normal working condition; (b) Fan blade imbalance condition.

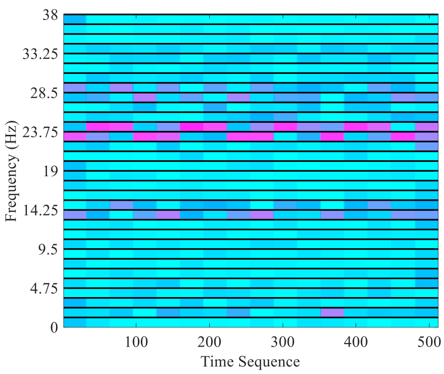


Fig. 8. The WPD of abnormal vibration data (*x*-axis).

3.3. Terminal duration estimation

Power consumption is a major consideration of the IoT device. Hence, the STM32L0 MCU and NB-IoT module are applied in the condition monitoring terminal for energy efficiency. The total power consumption of the three main components was measured by the oscilloscope, and Table I is given combined the theoretical value with the measurements showing the energy consumption of each component in different working states. The total operating current of the terminal in the working state is about 16.6 mA, the transmitting current is about 90.6 mA, and the total current in the sleep state is about 22.7 μA.

Table 1. Estimated power consumption.

Component	Working current	Transmitting current	Sleep current
STM32L0	7 mA	7 mA	10 μA
MPU6050	3.6 mA	3.6 mA	6 μA
NB-IoT	6 mA	80 mA	6.7 μA

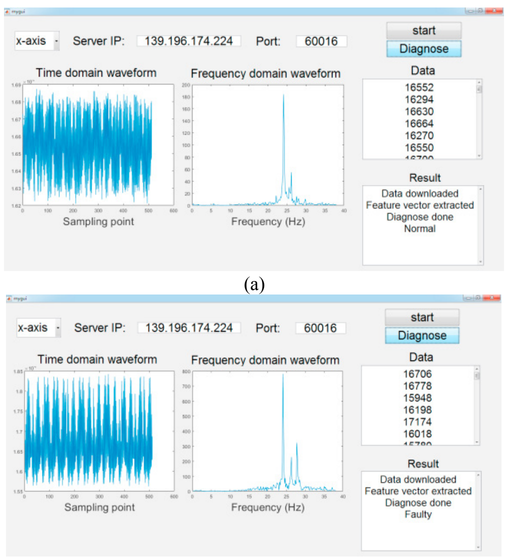
The terminal works in intermittent mode, the data is collected every five minutes. During each period, the terminal works 7 s, and the connection status for data transmission lasts 16 s. Then, the NB-IoT module enters the PSM mode 2s after the MCU sleeps. Supposing the terminal battery mounted is 10000mAh regardless of the self-discharging effect. The terminal duration can be estimated by the average power and battery capacity:

$$\begin{aligned} Duration &= \frac{10000\times 300\mathrm{s}}{16.6\times 7+90.6\times 16+6.016\times 2+0.0227\times 275} \\ &\approx 1894h \end{aligned} \quad (3)$$

The calculated terminal duration is around 79 days, which basically meets the requirement of practical applications. If the data is uploaded once an hour, the terminal will work longer, about 904 days, which can meet the requirement of the long life cycle.

3.4. System verification

As shown in Fig. 9, a MATLAB GUI is designed as the local interface to verify the performance of the system online. Aforementioned OCSVM model is trained offline using the normalized WPD energy as the input feature vector. The connection between the NB-IoT module and the server is established in advance. The server starts the data receiving program and receives the vibration data transmitted by the



(a)
(b)

Fig. 9. Client local interface (a) Identified as normal condition; (b) Identified as abnormal condition.

NB-IoT module. The server converts the received binary data stream into string format and waits for the client's data request. After clicking the "Start" button, the data request is sent to the server. Then, the real-time vibration data is downloaded to the client. Click the "Diagnose" button, the received data is processed by the implanted diagnosis model. At last, the detection results and the waveforms in TD and FD are displayed in the GUI. Through repeated experiments, the stability and accuracy of the whole system are verified. The system can realize full-automatic and lifelong condition monitoring and diagnosis.

4. Conclusion

An anomaly detection system is proposed in this paper for machinery equipment based on NB-IoT, WPD, and OCSVM. The feature extraction of the vibration signal is performed using WPD, and the trained OCSVM is implemented on a local interface programmed by MATLAB GUI. Testified by a small fan, the presented system works stably with correct the data transmission and satisfactory identification precision, thereby meeting the requirements of real fault detection. The greatest strength of the system is that it can realize lifelong condition monitoring because of the introduction of NB-IoT technology. In future research, a more integrated terminal will be developed and an extended data set of more faults types, larger amount, and different sensor signals will be collected to optimize the diagnosis model.

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References

[1] Tavner PJ. Review of condition monitoring of rotating electrical machines. IET Electr Power Appl 2008;2:215–247.
[2] Xu LD, He W, Li S. Internet of Things in Industries: A Survey. IEEE Trans Ind Informatics 2014;10:2233–2243.
[3] Korkua S, Jain H, Lee1 W, Kwan C. Wireless health monitoring system for vibration detection of induction motors. In: 2010 IEEE Industrial and Commercial Power Systems Technical Conference; 2010. p. 1–6.
[4] Sen M, Kul B. IoT-based wireless induction motor monitoring. In: 2017 XXVI International Scientific Conference Electronics (ET); 2017. p. 1–5.
[5] Wei X, Hou L, Hao J. Machine fault diagnosis using IIoT, IWSNs, HHT, and SVM. In: 18th International Conference on Communication Technology Proceedings (ICCT); 2018. p. 978–982.
[6] Chan JC, Tse PW. A Novel, Fast, Reliable Data Transmission Algorithm for Wireless Machine Health Monitoring. IEEE Trans Reliab 2009;58:295-304.
[7] Yuan H, Wang H, Qi H, Ke X. A ZigBee wireless sensor network for fault diagnosis of pump. In: 2010 Sixth International Conference on Natural Computation. 2010. p. 3778-3782.
[8] Huang QQ, Tang BP, Deng L. Development of high synchronous acquisition accuracy wireless sensor network for machine vibration monitoring. Measurement 2015;66:35-44.
[9] Mangalvedhe N, Ratasuk R, Ghosh R. In: NB-IoT deployment study for low power wide area cellular IoT. In: 2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC); 2016. p. 1–6.
[10] Lauridsen M, Krigslund R, Rohr M, Madueno G. An Empirical NB-IoT Power Consumption Model for Battery Lifetime Estimation. In: 2018 IEEE 87th Vehicular Technology Conference (VTC Spring); 2018. p. 1–5.
[11] Yan R, Gao RX, Chen X. Wavelets for fault diagnosis of rotary machines: A review with applications. Signal Process 2014;96:1–15.
[12] Zhao M, Kang M, Tang B, Pecht M. Multiple Wavelet Coefficients Fusion in Deep Residual Networks for Fault Diagnosis. IEEE Trans Ind Electron 2019;66:4696–4706.
[13] Yan R, Gao RX. Base Wavelet Selection for Bearing Vibration Signal Analysis. Int J Wavelets Multiresolution Inf Process 2009;7:411–426.
[14] Yan R, Gao RX. An efficient approach to machine health diagnosis based on harmonic wavelet packet transform. Robot Comput Integr Manuf 2005;21:291–301.
[15] Schölkopf B, Williamson R, Smola A, Shawe-Taylor J, Platt J. Support Vector Method for Novelty Detection. In: Proceedings of the 12th International Conference on Neural Information Processing Systems; 1999. p. 582–588.
[16] Domingues R, Filippone M, Michiardi P, Zouaoui J. A comparative evaluation of outlier detection algorithms: Experiments and analyses. Pattern Recognit 2018;74:406–421.