Research on Common Fault Diagnosis and Classification Method of Centrifugal Pump Based on ReliefF and SVM

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Abstract

The centrifugal pump is an important rotating machine and it is very critical to identify and differentiate among its common faults as quickly and accurately as possible. Based on the ReliefF algorithm and the sparrow search algorithm (SSA) in conjunction with support vector machine (SVM), an approach for faults classification and diagnosis of centrifugal pumps is proposed, its advantages over traditional fault diagnosis methods include a reduction in the number of characteristic parameters, shorter diagnosis times, as well as improved classification accuracy and robustness. We collected the fault data by designing a centrifugal pump fault test bench that recorded vibration signals for the rotor misalignment fault, the rotor unbalance fault, the seal ring wear fault, and normal operating conditions, and preprocessed the collected signals with Kalman filtering to remove noise interference, the time domain characteristic indexes and the frequency domain characteristic indexes of the filtered signal were extracted, each feature index is given a distinct weight using the ReliefF method, and the eigenvalues with weights less than the threshold are deleted, and the feature indexes that remain create a defect feature matrix. Particle swarm optimization (PSO), genetic algorithm (GA), and simulated annealing algorithm (SA) were used to optimize the SVM for comparison in order to verify the SSA-SVM model's performance for fault diagnosis. The comparison results show that the model has high recognition accuracy, short Classification time, and strong robustness.

Keywords: centrifugal pump, fault diagnosis, ReliefF algorithm, SSA algorithm, SVM.

1. Introduction

The centrifugal pump, as the most common pump product, is widely utilized in all aspects of life and industry, and plays a vital role in water conservancy engineering, mining engineering, agricultural irrigation, and other sectors. If the centrifugal pump breaks while in operation, it will have a huge impact on engineering and life, causing property damage and possibly even casualties. As a result, it is critical to conducts an accurate and effective diagnosis for centrifugal pump failures that occur frequently[1].

Due to the huge amount of fault information included in vibration signals, they are frequently used in rotating machine fault detection research in terms of fault signal extraction and processing[2]. The centrifugal pump faults can be effectively diagnosed by extracting the characteristic quantities from the vibration signal, there have been numerous methods for processing vibration signals, including time domain index statistical methods, spectrum analysis, wavelet analysis, Kalman filtering, and so on[3]. Zhu, et al[4], used continuous wavelet transform to extract the fault features of the vibration signal of the hydraulic piston pump, and realized the fault diagnosis of the piston pump; Li, et al. [5]used Kalman filter combined with IVKF-MSSSE to realize the signal processing of planetary gearbox under non-stationary working conditions; Tan et al.[6] used quadratic Kalman filtering (TSKF) to solve the problem of difficult diagnosis of multi-precision redundant sensor faults caused by changes in background noise.

The identification and classification of frequent centrifugal pump problems has been a study topic for relevant scientists both at home and abroad. The Support Vector Machine (SVM) is a supervised learning approach for classifying data with a solid theoretical foundation, basically, it uses the kernel method to embed the low-dimensional raw data into the high-dimensional mapping space, and then classifies the data in the high-dimensional space. SVM is widely used in fault diagnosis and classification due to its good classification performance and few support vectors that determine the final result and insensitivity to outliers. Ye Tao [7] has developed a method for analyzing cavitation state of a centrifugal pump based on fault-characteristic parameters extracted from the pump and using the SVM model to identify the cavitation state. Nie, et al[8] proposed a SVM model method for diagnosing...
centrifugal pump faults, which is capable of diagnosing the occurrence of centrifugal pump rotor and bearing faults.

Optimization problems of fluid machinery are commonly solved with intelligent optimization algorithms. Bashiri et al. [9] combined the ANN and PSO algorithms to optimize the shape of the impeller, the centrifugal pump can be made more efficient and its head improved, and the experimental data is used to verify the effectiveness of the proposed method; Chen, et al. [10] used BP neural network and GA algorithm to optimize the hydraulic performance and axial force performance of a double-shell segmented multi-stage centrifugal pump, pump efficiency and head have been improved, and bearing temperature and vibration speed have been reduced. The intelligent optimization algorithm is applied to the field of fluid machinery fault diagnosis, due to the problem of low classification accuracy in artificially determining the parameters of SVM, the combination of intelligent optimization algorithm and SVM for fluid machinery fault diagnosis can effectively improve the diagnostic accuracy of SVM. Ye [11] proposed using VMD-MPE and PSO-SVM to improve the accuracy of fault detection for rolling bearings by automatically identifying different fault modes for the rolling bearing, and two experimental studies provide proof of its effectiveness. Wang, et al. [12] established a model for the diagnosis of rolling bearing minor faults by using convolutional neural network and PSO-SVM, which improved the detection accuracy of related rolling bearing faults. Ke, et al. [13] used wavelet transform to extract fault characteristic values and the artificial fish swarm algorithm to optimize support vector machine to determine impeller damage of centrifugal pumps. Chen, et al. [14] used the energy value of the vibration signal and the mean value of the pressure signal as the fault parameters, and after comparing the performance of several optimization algorithms and classifiers, a fault diagnosis method of the airborne fuel pump based on EMD and GA-SVM was proposed. Feng, et al. [15] proposed a bearing fault diagnosis method based on energy diffusion spectrum and genetic algorithm to optimize SVM, which significantly improved the diagnosis accuracy of rolling bearing faults. Based on the foregoing analysis, this study proposes a ReliefF-SSA-SVM fault diagnosis method to address the current research's issues, including signal noise's large influence, low diagnostic accuracy, a large number of fault feature parameters, long SVM training time, and low classification stability. By building a fault simulation test bench to capture vibration signals from the machine’s feet in four different operating states: normal, rotor misalignment, unbalanced rotor and seal ring wear, the collected signal is processed with the Kalman filter, after that its time domain parameters and frequency domain parameters are extracted to form a fault characteristic matrix, as a result of the ReliefF algorithm, characteristic parameters are weighted and the characteristics with heavier weights are selected to form a new fault characteristic matrix, the new fault characteristic matrix will be input to the SVM model optimized by the Sparrow Search Algorithm (SSA) for faults identification. The result show that the method can be significantly more accurate and quicker in faults identification.

2. Kalman Filter

As a result of the operating environment and mechanical load of the centrifugal pump, the acquired vibration signals contain a large amount of noise components. The Kalman filtering has the benefits of processing dynamic positional data, removing random interference noise, and collecting usable information that approximates the signal’s genuine condition. As a result, Kalman filtering can efficiently analyze the collected vibration signal, ensuring fault characteristic parameters extraction and faults identification. The principle of applying Kalman filtering to vibration signals is shown in Fig. 1 below.

![Fig. 1 Principle of Kalman filter denoising](image)

3. Fault characteristic parameters

A failure of the centrifugal pump unit will also change the vibration signal of the machine foot in regard to its time domain waveform and frequency domain characteristics. Thus, it is advisable to use the time domain characteristic parameters and frequency domain characteristic parameters in faults classification and identification of centrifugal pumps. To avoid the limitations of single
index or single-type characteristic parameters for faults analysis, this study opts to use a multi-domain multi-category fault feature set that consists of ten time-domain indicators and four frequency-domain indicators. Listed below are ten time domain indicators: ME, KUR, P, Var, RMS, SHA, I, CRE, CLE, SKE; The following four frequency domain indicators are: MF, FC, RMSF, RVF. The calculation formulas of the above indicators are shown in Tab. 1 below.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Number</th>
<th>Calculation Formula</th>
<th>Abbreviation</th>
<th>Number</th>
<th>Calculation Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>ME</td>
<td>p₁</td>
<td>( \frac{1}{N} \sum_{n=1}^{N} x(n) )</td>
<td>CRE</td>
<td>p₈</td>
<td>( \frac{p₈}{p₅} )</td>
</tr>
<tr>
<td>KUR</td>
<td>p₂</td>
<td>( \frac{1}{Np₅} \sum_{n=1}^{N} (x(n))^4 )</td>
<td>CLE</td>
<td>p₉</td>
<td>( \frac{p₅}{N} \sum_{n=1}^{N}</td>
</tr>
<tr>
<td>P</td>
<td>p₃</td>
<td>( \max(</td>
<td>x(n)</td>
<td>) )</td>
<td>SKE</td>
</tr>
<tr>
<td>Var</td>
<td>p₄</td>
<td>( \frac{1}{N} \sum_{n=1}^{N} (x(n) - p₁)^2 )</td>
<td>MF</td>
<td>p₁₁</td>
<td>( \sum_{i=1}^{m} U(i) )</td>
</tr>
<tr>
<td>RMS</td>
<td>p₅</td>
<td>( \frac{1}{\sqrt{N}} \sum_{n=1}^{N}</td>
<td>x(n)</td>
<td>^2 )</td>
<td>FC</td>
</tr>
<tr>
<td>SHA</td>
<td>p₆</td>
<td>( \frac{p₅}{p₁} )</td>
<td>RMSF</td>
<td>p₁₃</td>
<td>( \sqrt{\frac{\sum_{i=1}^{m} (f_i)^2 \times U(i)}{\sum_{i=1}^{m} U(i)}} )</td>
</tr>
<tr>
<td>I</td>
<td>p₇</td>
<td>( \frac{Np₅}{\sum_{n=1}^{N}</td>
<td>x(n)</td>
<td>} )</td>
<td>RVF</td>
</tr>
</tbody>
</table>

\( x(n) \) in the table is the time domain sequence of the signal, \( n=1,2,3,..,N \), \( N \) is the number of sample points; \( U(i) \) represents the spectrum of the signal \( x(n) \), where \( i=1,2,3,..,m \), where \( m \) is the number of spectral lines; \( f_i \) represents the frequency value of the \( i \)-th spectral line.

4. ReliefF Algorithm and Sparrow Search Algorithm

4.1 The basic principle of ReliefF algorithm

As a feature weighting algorithm, the Relief algorithm allocates weights to feature values based on their correlation with data types and features, the heavier the weight, the larger the contribution of that feature value to the classification, based on the characteristics of the Relief algorithm, a weight threshold can be used to filter the eigenvalues, and eigenvalues with a weight less than the threshold will be discarded. However, the Relief algorithm is limited to problems involving two types of data, whereas the ReliefF algorithm can handle multiple types of data, in the subsequent analysis, multiple types of feature parameters will be used, so the ReliefF algorithm will be utilized. The process of the ReliefF algorithm is as follows[16] :

1. Set the training set size \( D \), the sampling times \( m \), the weight threshold index \( \delta \), and the number of nearest neighbor samples \( k \).
2. Reset all feature weights to zero, randomly select a sample set \( R \) from \( D \), find the \( k \) nearest samples \( H \) of \( R \) from the same sample set of \( R \), and find the \( k \) nearest samples \( N \) of \( R \) from the different sample sets of \( R \).
3. Calculate the weight \( W(i) \) (\( i=1,2,3,... \)) of each feature parameter according to the weight calculation formula repeat the above process according to the set sampling 100 times \( m \), continuously update \( W(i) \), and finally get the weight of each feature parameter.
4. Sort \( W(i) \) and filter feature parameters according to the threshold \( \delta \).

By using the ReliefF algorithm with a weight threshold of a reasonable size, the number of feature parameters can be reduced, the training time for the SVM classification model can be reduced, and the classification performance can be enhanced.

4.2 Sparrow Search Algorithm

The sparrow search algorithm is a swarm intelligence optimization algorithm proposed by Jiankai Xue and Bo Shen in 2020...
based on the behavior of sparrows foraging and evading predators [17]. The algorithm divides the sparrow population into seekers, followers and alarms:

1. The seekers is responsible for finding food for the entire population and provides the followers with the direction of foraging. Its position is updated as follows:

\[
X_{i,j}^{t+1} = \begin{cases} 
X_{i,j} \exp \left(-\frac{i}{a_j \alpha T} \right) & R < T \\
X_{i,j} + QL & R \geq T 
\end{cases}
\]  
(1)

In eq. (1), \(i\) represents the current number of iterations, \(j=1, 2, ..., d, d\) represents the dimension of the optimization variable, \(a_j\) represents the maximum number of iterations, \(X_{i,j}\) represents the position information, \(R\) is the warning value, \(R \in [0, 1]\), \(T\) is a safe value, \(T \in [0.5, 1]\), \(Q\) is a random number conforming to a normal distribution, and \(L\) is a 1*d all-one matrix. When \(R < T\), there are no predators around, and the seekers can search in a large area at this time, when \(R \geq T\), seekers have spotted a predator and will lead the population to a safe place to forage.

2. The position of the followers is updated as follows:

\[
X_{i,j}^{t+1} = \begin{cases} 
Q \exp \left(\frac{X_w - X_{i,j}^t}{i^2}\right) & i > n/2 \\
X_{p}^{t+1} + |X_{i,j} - X_{p}^{t+1}| A^t L & \text{otherwise} 
\end{cases}
\]  
(2)

In equation (2), \(X_w\) represents the global worst position, \(X_p\) represents the optimal position of the searcher, \(A\) represents a 1*d matrix, and the elements in \(A\) are randomly assigned to 1 or -1, \(A^t = A^t (AA^t)^{-1}\). when \(i > n/2\) indicates that the \(i\)-th follower with low fitness has not obtained food and needs to go to other places for food.

3. The part of the population that is aware of the danger is called the alarms, and the position of the alarms is updated as follows:

\[
X_{i,j}^{t+1} = \begin{cases} 
X_{i,j} + \beta |X_{i,j}^t - X_{best}^t| & f_i > f_g \\
X_{i,j} + K \frac{|X_{i,j}^t - X_{best}^t|}{(f_i - f_w) + \epsilon} & f_i = f_g 
\end{cases}
\]  
(3)

In equation (3), \(X_{best}\) is the global optimal position, \(\beta\) is a random number obeying a normal distribution with mean 0 and variance 1, \(K \in [-1, 1]\), \(f_i\) is the fitness value of the current sparrow, \(f_g\) and \(f_w\) are the current global best and worst fitness values respectively. \(\epsilon\) is a constant, avoiding a denominator of 0.

The Sparrow search algorithm shows strong local search ability and fast convergence speed, by applying the SSA algorithm to optimization of the support vector machine model, classification accuracy can be improved and training times can be reduced.

5. Test and Analysis

5.1. Test description

To verify the effectiveness of the proposed method, a centrifugal pump fault simulation test bench was designed to simulate rotor misalignment, rotor imbalance, and wear of the seal ring during centrifugal pump operation. The main equipment includes horizontal centrifugal pump, variable frequency motor, three phase asynchronous motor, electromagnetic flowmeter, uniaxial acceleration vibration sensor, data acquisition box and other equipments, the schematic diagram of the fault simulation test bench is shown in Fig. 2, and the test pump is shown in Fig. 3.

We modified the flow and rotational speed conditions during the test by adjusting the valve and the variable frequency motor, simulating the actual operation of the centrifugal pump. The rotor misalignment fault tests are mainly aimed at parallel misalignment, and the offset distance is adjusted by the dial indicator; The rotor unbalance fault is realized by the simulation of the counterweight, the centrifugal pump operation is shown in Fig. 3. During the test, the vibration acceleration sensor was placed at the foot of the centrifugal pump.

The sampling frequency of this experiment is 25600Hz, the sampling time is 1s, \(n\) of the test pump is 2900r/min, and \(Q_n\) is 10.6m³/h. According to the similarity law, the speed and flow rate are selected from three speed conditions of 0.7n, 0.85n and 1.0n, and three flow conditions of 0.7Qn, 0.85Qn and 1.0Qn. The test collected the vibration signals of the machine foot in four states, including the normal state, the rotor misalignment state, the rotor unbalanced state, and the wear state of the seal ring.
Table 2 Fault simulation test scheme

<table>
<thead>
<tr>
<th>Fault type</th>
<th>degree of failure</th>
<th>Fault Simulation Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>rotor misalignment</td>
<td>0.3mm</td>
<td>degree of offset</td>
</tr>
<tr>
<td></td>
<td>0.4mm</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.5mm</td>
<td></td>
</tr>
<tr>
<td>Unbalanced rotor</td>
<td>2.6g</td>
<td>Mass weight</td>
</tr>
<tr>
<td></td>
<td>6.3g</td>
<td></td>
</tr>
<tr>
<td></td>
<td>9g</td>
<td></td>
</tr>
<tr>
<td>seal ring wear</td>
<td>0.15mm</td>
<td>Orifice clearance</td>
</tr>
<tr>
<td></td>
<td>0.25mm</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.35mm</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 2 Schematic diagram of simulated fault test rig: 1-water tank 2-inlet valve 3-electromagnetic flowmeter 4-soft joint 5-machine foot vibration sensor 6-centrifugal pump 7-three-phase asynchronous motor 8-outlet valve

Fig. 3 Failure simulation test pump

Fig. 4 Rotor misalignment fault simulation

Fig. 5 Rotor unbalance fault simulation

Fig. 6 Port ring wear fault simulation

5.2. Analysis of test results

5.2.1. Time and frequency domain plot analysis

Prepare the time-domain diagram and the frequency-domain diagram for the vibration signal of the machine foot under normal operating conditions and under different failure conditions for the centrifugal pump, and compare the results. Comparative analysis in the time domain diagram is limited to 1s, and in the frequency domain diagram, comparison is restricted to 0-5000Hz. Fig. 7 shows the time domain diagrams in the four states, and Fig.8 shows the frequency domain diagrams.

There are obvious differences between the time domain diagram and frequency domain diagram of the vibration signal of the centrifugal pump foot in the normal state and the time domain diagram and frequency domain diagram under the rotor misalignment fault, rotor unbalance fault, and seal ring wear fault. Therefore, It is feasible to combine characteristic parameters and frequency
domain characteristic parameters as fault diagnosis indicators.

To eliminate the influence of noise, the original vibration signal is preprocessed by the Kalman filter, and the rotor misalignment fault state vibration signal under rated speed and rated flow conditions is selected for comparative analysis. Figure 9 is the original waveform diagram of the vibration signal, and Fig. 10 is the waveform diagram of the vibration signal after filtering. Comparative analysis shows that the original vibration signal contains a large number of clutter components, the filtered signal graph has significantly reduced clutter, the overall curve becomes smooth, and the amplitude decreases.

**Fig. 7** Time domain diagram analysis and comparison

**Fig. 8** Analysis and comparison of frequency domain maps

**Fig. 9** Original waveform of vibration signal

**Fig. 10** Waveform of vibration signal after filtering

### 5.2.2. Feature extraction and ReliefF algorithm

The data sets consist of 90 sets of signals for the normal state, 270 sets in the rotor misaligned state, 270 sets in the rotor unbalanced state, and 270 sets in the wear state of the seal ring, a total of 900 sets of data, each set of data has 2560 data points. We calculated 14 characteristic parameters for each group of signals and normalized them through Z-score processing, and we uniformly converted different characteristic parameters into the same magnitude to ensure that the data was comparable. The calculation formula of Z-score standardization is as follows shown:

\[ z = \frac{(x - \mu)}{\delta} \]  \hspace{1cm} (4)

In Equation (4), \( x \) is a specific eigenvalue, \( \mu \) is the mean, \( \delta \) is the standard deviation, and the calculation result \( z \) is the distance between \( x \) and \( \mu \), and \( \delta \) is used as the unit to measure.

In order to calculate the 14 eigenvalues' weights, the ReliefF algorithm is applied. Based on the principles of the ReliefF algorithm and the size of the sample data set, the sampling times \( m \) is set to 90, the weight threshold index \( \delta \) is 0.5, and the number of nearest neighbor samples \( k \) is 8. The ten calculations were performed to eliminate the possibility of chance, and the feature parameters with the average value of the 10 calculation weights greater than 0.5 were chosen, and the others were eliminated. The calculation results are shown in Fig. 11, and the average value of each feature parameter weight is recorded in Table 3.
Table 3 Weight average of characteristic parameters

<table>
<thead>
<tr>
<th>Name</th>
<th>Result</th>
<th>Name</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>ME</td>
<td>0.67</td>
<td>CRE</td>
<td>0.42</td>
</tr>
<tr>
<td>KUR</td>
<td>1.05</td>
<td>CLE</td>
<td>0.37</td>
</tr>
<tr>
<td>P</td>
<td>0.79</td>
<td>SKE</td>
<td>0.44</td>
</tr>
<tr>
<td>VAR</td>
<td>0.85</td>
<td>MF</td>
<td>0.96</td>
</tr>
<tr>
<td>RMS</td>
<td>0.83</td>
<td>FC</td>
<td>0.02</td>
</tr>
<tr>
<td>SHA</td>
<td>-0.25</td>
<td>RMSF</td>
<td>-0.10</td>
</tr>
<tr>
<td>I</td>
<td>0.70</td>
<td>RVF</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Seven characteristic parameters, such as ME, KUR, P, Var, RMS, I, and MF, are selected according to the weight threshold and input into the SVM for fault diagnosis and classification.

5.2.3. SSA-SVM classification

The SVM uses the RBF function as the kernel function, and the Sparrow search algorithm (SSA), the Particle swarm algorithm (PSO), the Genetic algorithm (GA), and the Simulated annealing algorithm (SA) as optimization algorithms to determine the best penalty coefficient $c$ and the best kernel parameters $g$, so as to achieve the best classification effect. The selected eigenvalues are processed into a feature matrix and input to the SSA-SVM, PSO-SVM, GA-SVM, and SA-SVM models for fault classification and diagnosis, and their classification accuracy and training time are compared. The normal status label is 0, the rotor misalignment label is 1, the rotor unbalance label is 2, and the seal ring wear fault label is 3. Fig. 12 shows the single classification result of the SSA-SVM model, Fig. 13 shows the single classification result of the PSO-SVM model, Fig. 14 shows the single classification result of the GA-SVM model, and Fig. 15 shows the single classification result of the SA-SVM model. The red stars in the figure are the predicted classification of the data by SSA-SVM, and the blue circles represent the real fault categories represented by the data, if the red star coincides with the blue circle, the prediction is correct. Table 4 shows the single classification accuracy and time of the four models. Through comparative analysis, it can be known that the SSA-SVM model can greatly shorten the model training time and the model classification accuracy compared with the other three models.

![Fig. 11 Calculation results of ReliefF algorithm](image1)

![Fig. 12 Classification results of SSA-SVM](image2)

![Fig. 13 Classification results of PSO-SVM](image3)
In order to avoid the appearance of chance, the four models were trained for 30 times respectively. Each classification time and classification accuracy are shown in Figs. 16 and 17, and the average time and diagnosis accuracy of the four models for 30 times of diagnosis are recorded in Table 5.

Table 5 shows the SSA-SVM model is significantly better than the other three models in the diagnosis of common rotor misalignment, rotor imbalance, and seal ring wear faults in centrifugal pumps, which can considerably shorten the classification time and improve the classification accuracy. More importantly, the SSA-SVM model is relatively stable, and the recognition accuracy fluctuates less, while the PSO-SVM model and the GA-SVM model have poor stability.

6. Conclusion

In this study, We built a centrifugal pump fault simulation test bench to simulate the operating state of the pump under several common fault conditions. A single-axis acceleration sensor was used to collect the vibration signal of the machine foot, and the Kalman filter was applied to denoise the original signal, by using the ReliefF algorithm and the SSA-SVM, diagnostic and
classification models are constructed for centrifugal pumps, allowing for diagnosis and classification of a variety of common faults. According to the test analysis results and model diagnosis results, the following conclusions are obtained:

1. The time domain and frequency domain parameters of the vibration signal of the centrifugal pump foot can be effectively used for the classification of rotor misalignment, rotor imbalance and wear of the seal ring. Use the ReliefF algorithm to calculate the weight of the feature parameters. The feature parameters that contribute more to fault diagnosis and classification include: ME, KUR, P, Var, RMS, I, MF. The fault classification accuracy of the eigenmatrix established by the above eigenvalues averages 90.12% in several diagnostic models.

2. Compared with the classic PSO-SVM, GA-SVM and SA-SVM, SSA-SVM has the highest accuracy in identifying and diagnosing several faults of centrifugal pumps, the shortest diagnosis time, and has strong robustness. The accuracy of multiple identifications does not fluctuate much. The average accuracy of 30 identifications can reach 96.67%, and the average identification time is 0.78s. With the new diagnosis method, the efficiency of diagnosing centrifugal pump faults can be significantly increased, providing a theoretical basis for the application of the diagnostic method in the field of engineering.

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Nomenclature

<table>
<thead>
<tr>
<th>Qn</th>
<th>the rated flow[m³/h]</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>the rated speed [r/min]</td>
</tr>
<tr>
<td>Var</td>
<td>Variance</td>
</tr>
<tr>
<td>RMS</td>
<td>Root Mean Square</td>
</tr>
<tr>
<td>SHA</td>
<td>Waveform index</td>
</tr>
<tr>
<td>I</td>
<td>Impulse index</td>
</tr>
<tr>
<td>CRE</td>
<td>Peak index</td>
</tr>
<tr>
<td>RVF</td>
<td>Frequency standard deviation</td>
</tr>
<tr>
<td>ME</td>
<td>Mean</td>
</tr>
<tr>
<td>KUR</td>
<td>Kurtosis</td>
</tr>
<tr>
<td>P</td>
<td>Peak</td>
</tr>
<tr>
<td>CLE</td>
<td>Fluid Density</td>
</tr>
<tr>
<td>SKE</td>
<td>Skewness index</td>
</tr>
<tr>
<td>MF</td>
<td>Mean frequency</td>
</tr>
<tr>
<td>FC</td>
<td>Center of gravity frequency</td>
</tr>
<tr>
<td>RMSF</td>
<td>Root mean square frequency</td>
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</tbody>
</table>

References