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MISALIGNMENT AND UNBALANCE DEFECTS DETECTION USING POWER SPECTRAL DENSITY, SUPPORT VECTOR MACHINE AND K-NEAREST NEIGHBOR

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Abstract- The aim of this publication is to develop an adequate approach to control unbalance and misalignment defects in a motor pump unit using a combination of power spectral density (PSD) based frequency analysis, and two supervised learning classifiers such as the KNN and SVM. To achieve this objective, an approach articulated on the frequency processing of the signal, the extraction of significant data and the classification of the defects were operated. The vibration signals were acquired from an experimental smart tool to monitor the normal, unbalanced and misaligned state of the pump unit. Frequency analysis was applied that based on Power Spectral Density (PSD). In total, eight significant characteristics were obtained from the signal spectrum amplitude, precisely 511 samples are measured along the radial (vertical and horizontal) and Axial directions during the operation of the machine. The used classifiers are applied to categories the studied states. The performance of the chosen classifiers was evaluated. The obtained results indicate the efficacy of SVMs in diagnosing faults affecting rotating machines, adding that the method used successfully detects unbalance and misalignment. In this research, our method focuses on supervised learning was proposed to detect and classify imbalance and misalignment defects. The comparison of the different results obtained, concludes that the combination of frequency analysis with KNNs and SVMs classifiers is a reliable and applicable method for monitoring unbalance and misalignment faults. The proposed method can be used to monitor various faults affecting rotating machines.

Keywords: Vibration Control, Detection, Diagnosis and Classification, PSD, KNN, SVM, Unbalance Fault, Misalignment Fault, Rotating Machine.

1. INTRODUCTION

Meet increased use of electricity in Morocco, it is important to ensure its continuous production. For this reason, it is essential to make the strategic installations of the reliable production units and to keep them in good working order, especially the feed pumps. Maintaining these units aims to achieve three important points: the safety of people, the good working order of the machines and the other is economic, by limiting undesirable stoppages. It can be noted that a stoppage in electricity production causes a loss of thousands of dollars [1].

Vibration analysis is the technique applied to monitor the condition of rotating machinery. Not only does it provide information on the health of the functional group, but it also identifies the faulty component and often the nature of the fault. The analysis of these measured signals can therefore give a fairly accurate diagnosis of the machines. Many research results include machine learning in the diagnosis of faults affecting rotating machines [2], as machine learning methods are more competitive than those based on signal analysis. The characteristics extracted to train the classifiers are more significant. In addition, research shows that frequency characteristics are more robust for training ML models [3]. Research has validated that the KNN method is capable of detecting all defect samples [4]. There are various techniques of signal analysis, e.g., spectral analysis, phase analysis, cepstral analysis, envelope analysis, time-frequency analysis, etc.). These processes are frequently complementary to confirm the identification of the faults being monitored. In this paper, we applied spectral analysis association with KNN and SVM to optimize the control feed pump, specifically to control misalignment and unbalance faults, which are considered among the most responded faults in the industry and which are the causes of severe vibration, can cause serious problems in rotating machines [5, 6].

Vibration signals from unbalance and misalignment faults are measured under normal and faulty conditions. By comparing these signals, fault detection is possible. Eight significant features are considered to classify unbalance and misalignment faults using SVM and KNN classifiers.

2. METHODS

Vibration analysis is focused on the analysis acquired vibration signal. There are several analysis techniques, including time, frequency and time-frequency analysis, to which we can integrate the intelligent ML (Machine Learning) approach. These techniques are applicable and complementary to obtain a more accurate diagnosis [7], in this section; we just recall the principle of the techniques used in our paper.

2.1. The Power Spectral Density (PSD)

The measured spectrum Y(F) is calculated by the Fourier transform. As the acquired signals are often random, it is recommended to calculate the PSD defined by Equation (1) [8]:

$$DSP(F) = \left| TF(Cy(t)) \right| \tag{1}$$

The autocorrelation Cy(t) , computed by Equation (2) [8]:

$$Cy(t) = \lim_{t \to \infty} \int_0^t y(t) y(t+\tau) dt \tag{2}$$

It should be remembered that all faults affecting rotating machines, such as unbalance, misalignment, fixing, electromagnetic faults, etc., give rise to vibration signals. A profound analysis of the spectrum, taking into account the characteristic frequencies of the organs that constitute the controlled system, can perfectly identify the type of fault. Phase analysis is a complementary analysis technique to other treatments [7], which is recommended when some faults have the same spectral signature, e.g., the unbalance fault and the fixation fault.

For this reason, two signals should be measured at the same time with two collectors vertically positioned on the same landing. The signal frequency for each measurement is calculated and the phase at the rotational frequency is deduced. If this phase shift is almost 90°, then fault associated with rotational force. If it's close to 0° or 180°, the fault associated with a directional force. This is a commonly used analysis technique to distinguish between faults that have the same spectral signature.

2.2. The K-Nearest Neighbor KNN

KNNs are classified as powerful machine learning tools [10, 11], calculating distances between two features [12]. Is a simple to use technique [9, 18], often used for a limited number of features. It is part of a non-parametric regression and classification technique. To make a prediction, the *KNN* uses the dataset to produce a result [9], it calculates the distance between two features, the closer the two features are, the more similar they are and vice versa.

The calculation of the distance considered is done by several methods, for example: the Euclidean method [13], the Manhattan method [13], the Minkowski method and the Jaccard method, etc. The technique applied depends on the type of data manipulated. However, in our paper, we use the Euclidean method, as it is the most frequently used of all these methods cited, it can be defined by Equation (3) [23]:

$$D_E = \sqrt{\sum_{i=1}^{N} (m_i - n_i)^2} \tag{3}$$

The features *m*, *n* belong to the Euclidean space of *N* dimensions, the accuracy of *KNN* depends on the number of neighbors *K* which will give a reduced error and an accurate prediction.

2.3. The Support Vector Machine SVM

SVMs were published in 1995, proposed by Corinna Cortes and Vapnik [9, 14], widely used due to their promising performance. SVMs, founded on statistical learning theory are an appropriate approach to resolve a diverse range of learning problems. It should be noted that image identification, pattern classification and text detection are among the most widely used applications based on SVMs have been created for binary and multi-class classification [15]. We identify the features of formation $\{u_i, s_i\}$, $i = 1.....n$ and $s_i \in \{-1,1\}$, $u_i \in R^d$.

The interest of hyperplanes is to separate positive and negative classes. The vector u placed on the line of separation satisfies Equation (4) [23]:

$$w.u + b = 0 \tag{4}$$

where, *W* is the vertical vector at the separation line.
all data satisfy the following limits [23]:

$$w.u_i + b \geq +1 \;,\; s_i = 1 \tag{5}$$

$$w.u_i + b \leq -1 \;,\; s_i = -1 \tag{6}$$

These can be assembled in the present inequality [23]:

$$s_i (w.u_i + b) - 1 \geq 0 \qquad \forall i \tag{7}$$

l_+ and l_- are respectively the shortest distances separating the decision hyperplane and the nearest positive and negative training data.

The difference $l_+ + l_-$ is the margin of a separation hyperplane, taking into account Equations (5) and (6), we obtain the equality indicated in the following Equation (8) [23]:

$$l_+ = l_- = \frac{1}{\|w\|^2} \tag{8}$$

Then, the margin is simply defined as: $\frac{2}{\|w\|^2}$ To obtain a separation line that gives a maximum margin, it is necessary to minimize $\|w\|^2$, under the limitations of Equation (7). To achieve the desired objective, the Lagrangian formulation defined by Equation (9) should be minimized [23]:

$$L_p = \frac{1}{2}\|w\|^2 - \sum_{i,j=1}^{n} \alpha_i s_i (wu_i + b) + -\sum_{i=1}^{n} \alpha_i \;,\; \alpha_i \geq 0 \tag{9}$$

where, $\alpha_{i.}$ is the positive Lagrange coefficient [16]. SVMs use kernels to convert a non-linear system into a linear system we give the formulation of three kernels, presented in the Equations (10), (11) and (12) [23]:

• Linear:

$$k(u_j, u_j) = u_j . u_j \tag{10}$$

• Polynomial:

$$k(u_j, u_j) = (\gamma u_j . u_j + 1)^d \ , \ \gamma \geq 0 \tag{11}$$

• Gaussian RBF:

$$k(u_j, u_j) = e^{\frac{\left\| u_i - u_j \right\|^2}{2\sigma^2}} \tag{12}$$

In this paper, the polynomial kernel has been used.

3. COMPONENT AND KINEMATIC CHARACTERISTICS

The controlled feed pump is constituted by Figures 1and 2:

• A high power three-phase electric motor (2 Mw), its rotation speed is 3000 tr/min, so a rotation frequency Fr = 50 Hz. The number of rotor slots is Ne= 38, resulting in a slot frequency Fe = 1900 Hz.

• Two cooling fans.

the number of blades in each ventilator is Np= 8, so the blade frequency is Fp = 400 Hz;

• A rigid coupling couples pump to the motor;

• Centrifugal pump, multistage, horizontal, coupled to the motor, its rotation frequency Fr = 50 Hz;

the number of stages is ten, each stage contains Np=9 blades, i.e., a blade frequency Fp = 450 Hz;

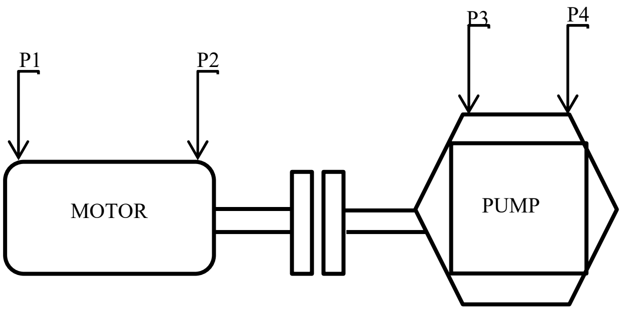

Figure 1. Synoptic diagram of the feed pump

Figure 2. The motor-pump unit [1]

4. CHARACTERISTICS OF THE FEED PUMP

The technical characteristics of the feed pump are illustrated in Table 1.

Table 1. Feed pump characteristics [8, 1]

Aspiration pressure	7 bars
Backflow pressure	170 bars
Pump flow rate	150 m²/h
Temperature	Between 150 °C and 160 °C
Motor power	2 MW
Motor voltage	6. KV
Speed of rotation	3000 tr/min
Frequency of rotation (RPM)	50 Hz

5. FEED PUMP VIBRATION MONITORING

The measurement points (P1, P2, P3 and P4) chosen to monitor the operating state of the feed pump are shown in Figure1. After a global analysis, the measured *RMS* values compared with those of the ISO 10816 standard reveal that the moto-pump system is degraded. We applied frequency analysis, phase analysis, KNN and SVM classifiers.

5.1. Frequency Analysis

For point P1, the signals are measured in a frequency group [0-2.5 KHz] to control the defects that appear in the bass and medium frequencies, for example: unbalance, backlash, fixation, misalignment, etc.

At point P2, under the same conditions, we controlled the misalignment fault and again the faults mentioned previously at point P1. Concerning point P3, the measurements are carried out in a frequency group [0-2 KHz] in different directions (axial, horizontal and vertical). Under these conditions the defects that may appear are those of the shaft, the coupling and the pump. For point P4, we controlled the defects affecting the pump, specifically the cavitation defect.

5.1.1. Results and Discussions

For the monitoring of the feed pump, we acquired the signals by an intelligent tool called Vibxpert, while the visualization and processing were obtained by the software V_System [17]. In the following, we present only the significant results.

5.1.1.1. Failure Mode Unbalance

For points P1 and P2, the spectra obtained under the measurement conditions are illustrated in Figures 3 and 4. It can be noted that:

The line at the 50 Hz frequency is predominant, the possible failures are: unbalance and fixation. Confirm hypothesis, we applied phase analysis. The phase measured is equal to 90°, proving presence an unbalance.

Comparing the unbalance fault detected at the two measurement points P1 and P2, it can be seen that the unbalance fault at point P2 is more advanced than that detected at point P1. The vibration response under the healthy/defect operating conditions shows that the largest amplitude occurs at 1×RPM. It is observed that the amplitudes at the fundamental (1×RPM) and its harmonics, exactly from (3×RPM) to (7×RPM) have a remarkable influence on the classification of the machine's operating states.

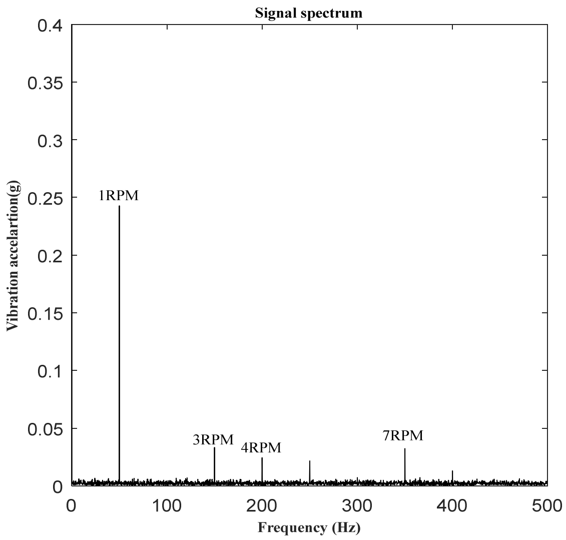

Figure 3. Spectrum measured at point 1

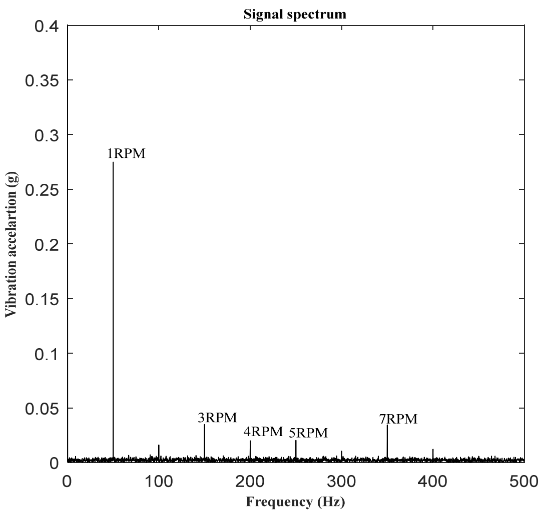

Figure 4. Spectrum measured at point 2

However, the most significant difference occurs at 1×RPM, the amplitude value at 1×RPM would be the relevant indicator to identify the unbalance condition, consequently the fault that occurs in the controlled feed pump will be identified as an unbalance fault.

5.1.1.2. Failure mode Misalignment

For point P3: the frequency plot obtained in the horizontal radial direction is presented in Figure 5. It can be remarked that:

The harmonics of the fundamental frequency attain 10x RPM, note that the 2×RPM line is dominant, the faults generating such a spectrum are absolutely the parallel misalignment fault and the air gap variation or the stator current variation [7, 8]. To confirm the fault monitoring and identification, we zoomed in around the notch frequency Fe = 1900 Hz.

No bandwidth is observed, indicating that there is no modulation phenomenon [8]. To argue the control, we applied phase analysis, the measured phase shift is equal to 0°, clearly indicating presence a parallel misalignment [19].

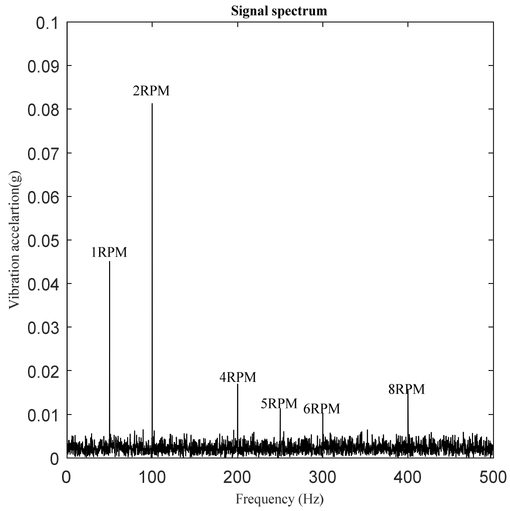

Figure 5. Spectrum measured at point P3

5.1.1.2.1. Misalignment Comparison

A comparison between the last two measured spectra illustrates in Figure 6, we detect a preponderant line at 2×RPM, let us add that the harmonics precisely from 4×RPM to 8×RPM have important amplitudes, symptom of mechanical backlash. Therefore, the defect detected is severe misalignment.

The amplitudes of the harmonics precisely 2×RPM and 4×RPM to 8×RPM, have a remarkable influence on the classification of the machine's operating conditions for misalignment. Therefore, the amplitude value at 2×RPM would be the relevant indicator to distinguish the Parallel misalignment state [7].

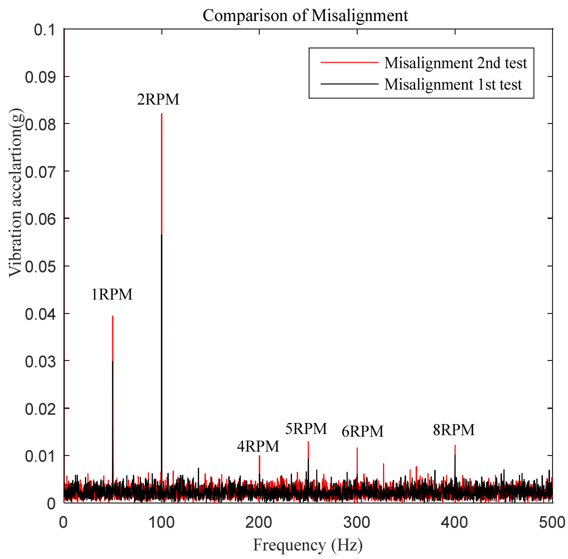

Figure 6. Comparison of the spectra of the last two measurements

5.2. KNN and SVM Classifiers

After signal processing, we focus in this section on extracting the features needed to evaluate the precision of the classifiers used. The classifiers were informed with training features, their capabilities were evaluated with test features [20]. Their accuracy rates were also compared.

5.2.1. Generating a Training Dataset

The choice of classifier depends on the training characteristics. The dataset selected in this research to perform an evaluation of the capability of the models used in the classification of feed pump faults, namely: unbalance fault and misalignment fault. The 511 measured samples, each comprising 2048 points, resulting in 511 assembled data.

5.2.2. Extraction of Defect Features

From a database of 511 samples, each comprising 2048 points, measured on different measurement directions, a total of 8 frequency domain features extracted such as 1×RPM, 2×RPM, 8×RPM, are manipulated to estimate the reliability of the classifiers considered in the classification of misalignment and imbalance categories. The characteristics are manipulated and ranked to train the *KNN* and *SVM* classifiers. The feature extraction influences the definitive diagnostic results [20, 21]. the processing mechanism used is described in Table 2.

Table 2. Description of training and test data for each operating state

Class	Number of training models	Number of test models	Overall
Healthy	70	53	123
Unbalance	140	93	233
Misalignment	90	65	155
Overall	300	211	511

The accuracy results are evaluated to select the most appropriate classifier.

5.2.3. Algorithm

The used structure in this part of the research is shown in Figure 7. Firstly, the data corresponding to the monitored defects are collected, 8 features are extracted and classified. Finally, these features are selected to form the classifiers to conclude the classification efficiency of the considered defects.

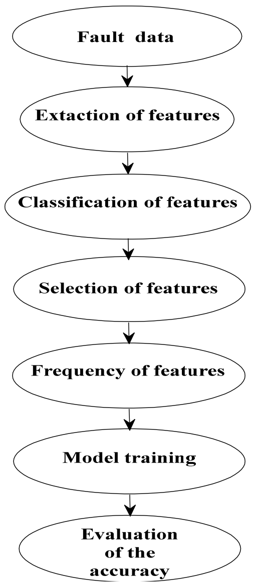

Figure 7. Protocol used for classification of unbalance and misalignment

5.2.4. Result and Discussion

The classifiers were evaluated using the test data. In addition, their accuracy was rigorously examined.

We examined capabilities of the classifiers taking into account the variation of the kernel width (σ) for *SVM* [21], and the number of neighbors K for *KNN*. For the *SVM*, we applied the quadratic programming (QP) method, the value of the penalty factor C is 10^3.

We chose the multi-class method and RBF kernel, noting that the RBF kernel is one of the kernels applied to SVMs to obtain excellent results in fault diagnosis [21, 22]. The bounds of σ are 0.1 to 1.

The *KNN* is accurate, with an efficiency close to 100%, so the *KNN* keeps the location of the training data and their category [23]. Its validity is related to the *K* value. In this paper, the values of *K* are tested from 1 to 10 with a step of 1. The Euclidean method was used to calculate the distance.

The sensitivity (*TPR*, specificity (*FNR*), area of convergence (*AUC*) and overall accuracy of the classification are the factors that explain the power of the classifier. These criteria are explained as follows:

- Sensitivity (*TPR*): the capacity of the approach to detect that an element is positively classified in its category [24].
- Specificity (*FNR*): the capacity to know that a data item is not classified in its category [24].
- *AUC*: This is the measure that quantifies the ability of the classification model. The closer the *AUC* is to 1, the more accurate the classifier is.

The *AUC* is the mean of sensitivity and specificity, calculated manually by Equation (13) [28]:

$$AUC = \frac{TPR + FNR}{2} \tag{13}$$

Overall classification accuracy: this is the quotient positive decisions to the overall number of items studied [20]. Overall accuracy is maintained in fault identification [20, 25]. Table 3 shows the overall accuracy of the two classifiers used.

Table 3. The overall classification accuracy for SVM and KNN

Processing Number	KNN (*k*), overall accuracy	SVM (σ), overall accuracy
01	(1), 97.6%	(0.1), 98.1%
02	(2), 95.6%	(0.2), 96.7%
03	(3), 94.6%	(0.3), 96.5%
04	(4), 90.3%	(0.4), 91.6%
05	(5), 85.3%	(0.5), 91.6%
06	(6), 84.3%	(0.6), 87.4%
07	(7), 84.2%	(0.7), 84.3%
08	(8), 74.8%	(0.8), 84.3%
09	(9), 68.8%	(0.9), 83.3%
10	(10), 59.8%	(1), 82.3%

The performance of *KNN* ranged from 59.8% to 97.6%, while for *SVM* the accuracy rate ranged from 82.3% to 98.1% on the training and test data. Figures 8 and 9 illustrate the accuracy evolution of the two classifiers *KNN* and *SVM*, respectively.

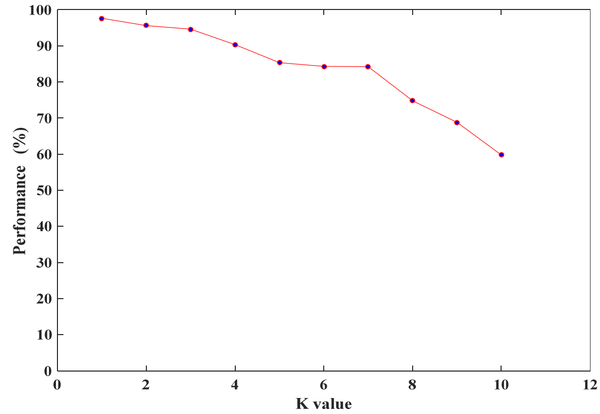

Figure 8. *KNN* overall accuracy as a function number of neighbors

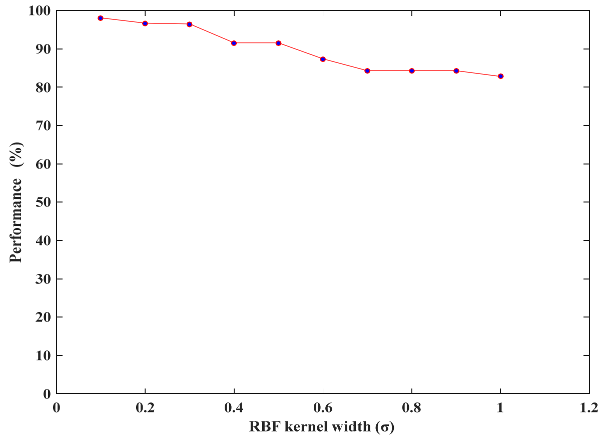

Figure 9. *SVM* overall accuracy rate as a function of *RBF* kernel width values

The overall classification accuracy of the *SVM*, depending on the width σ, decreased for values above 0.1 (σ>0.1), so that it became about 82.3%, the best classification accuracy of the SVM was 98.1% obtained for σ = 0.1. Figures 10 and 11 illustrate the confusion matrices obtained for a better defect's classification (Table 3), respectively, for the *KNN* and *SVM* classifiers.

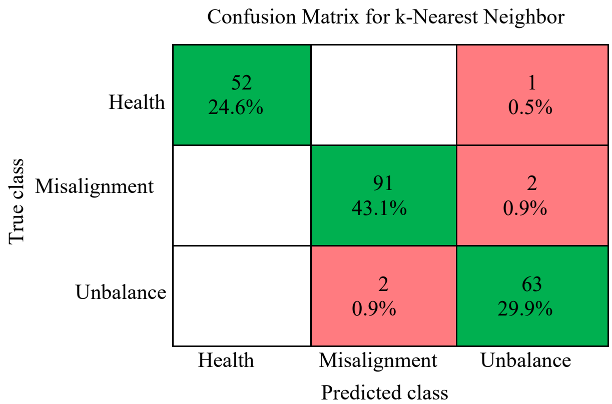

Figure 10. Confusion matrix of testing data for k-Nearest Neighbor

The confusion matrix is a matrix that represents true classes as a function of predicted classes to detect true and false objects [26]. Tables 4 and 5 present the true and predicted class mentioned by confusion matrix (Figures 10 and 11), respectively for the case of *KNN* and *SVM*.

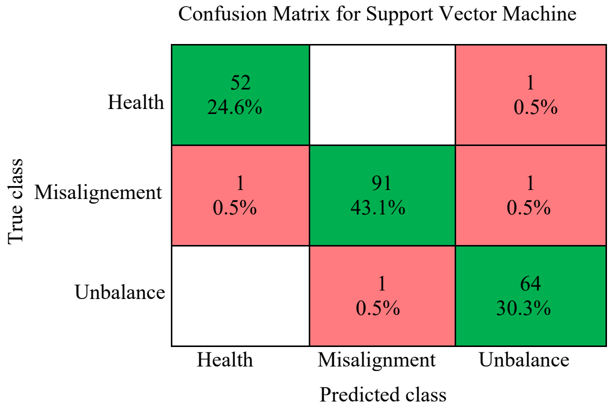

Figure 11. Confusion matrix of testing data for Support Vector Machine

Table 4. Confusion matrix for KNN of testing data

Output/desired	Healthy	Misalignment	Unbalance
Healthy	52	0	1
Misalignment	0	91	2
Unbalance	0	2	63

Table 5. Confusion matrix for *SVM* of testing data

Output/desired	Healthy	Misalignment	Unbalance
Healthy	52	0	1
Misalignment	1	91	1
Unbalance	0	1	64

By studying the more accurate classification cases obtained for *KNN*s and *SVM*s (Table 3), considering prediction criteria such as Sensitivity and Specificity, the total classification accuracy for each method can be determined, the results are presented in Tables 6 and 7.

Table 6. The values of classification *KNN* accuracy criteria

Fault conditions	Statistical parameter		
	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
Healthy	100	99.37	97.6
Misalignment	97.84	98.30	
Unbalance	95.45	98.62	

Table 7. The values of classification SVM accuracy criteria

Fault conditions	Statistical parameter		
	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
Healthy	98.11	99.37	98.1
Misalignment	98.91	98.32	
Unbalance	96.96	99.31	

From the statistical parameter values (Tables 6 and 7), it can be noted that:

- *KNN* classified the healthy, misaligned and unbalanced sets at 100, 97.84 and 95.45%, respectively. Thus, the total classification accuracy of *KNN* was achieved at 97.6%.
- The *SVM* classified the healthy, misaligned and unbalanced sets as 98.1, 100 and 95.5%, respectively. Therefore, the total classification accuracy of *SVM* was obtained as 98.1%.

To confirm the overall accuracy obtained by the *SVM* compared to the *KNN*, we highlight the obtained performances by the area under convergence (*AUC*) in Figure 12.

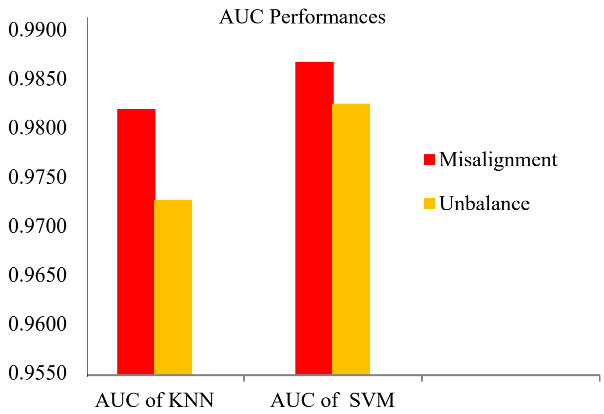

Figure 12. AUC Performances

Exploiting the Figure 12, we see that:

- For the *SVM*, the *AUC* values obtained when classifying the misalignment and the unbalance are 0.9861 and 0.9813, respectively.
- For the *KNN*, the *AUC* values obtained during the misalignment and unbalance classification are respectively: 0.9807 and 0.9703.

By comparing the *AUC* values obtained for the two classification methods considered, we see that the *SVM* classifies the controlled states perfectly. From the curves obtained, it is remarkable that *SVM* (Figure 9) is more accurate than *KNN* (Figure 8), whose execution and processing time of *KNN* is relatively short compared to that of the *SVM*. Finally, considering the accuracy rates and *AUC* values determined for each method, it can be seen that the *SVM* classifies unbalance and misalignment faults perfectly. This result confirms the reliability of *SVM*s classification, hence its popularity and celebrity in the machine learning community [27].

6. CONCLUSIONS

A combination of frequency analysis with both machine learning classifiers *KNN* and *SVM* has been proposed to improve reliability of feed pump diagnosis. The monitored states are unbalance and misalignment.

First, a frequency treatment is evaluated perfectly. Then, 8 features were extracted to train the proposed classifiers. The overall accuracy was evaluated by the test dataset. The Euclidean distance calculation, the multi-class One-At-All (OAA) method and the RBF kernel were applied.

Highest accuracy was 97.6% and 98.1%, respectively on the test data for *KNN* and *SVM*, adding that the execution and processing time for *KNN* is more significant than that of *SVM*. Finally, the results prove that *SVM* is a more accurate and practical technique for diagnosing faults affecting rotating machines. In addition, the results highlight capability and confidence of the proposed PSD-KNN-SVM approach to diagnose unbalance and misalignment faults. This approach can be used to diagnose other mechanical defects.

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