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Comparison of two classifiers; K-nearest neighbor and artificial neural network, for fault diagnosis on a main engine journal-bearing

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Abstract. Vibration analysis is an accepted method in condition monitoring of machines, since it can provide useful and reliable information about machine working condition. This paper surveys a new scheme for fault diagnosis of main journal-bearings of internal combustion (IC) engine based on power spectral density (PSD) technique and two classifiers, namely, K-nearest neighbor (KNN) and artificial neural network (ANN). Vibration signals for three different conditions of journal-bearing; normal, with oil starvation condition and extreme wear fault were acquired from an IC engine. PSD was applied to process the vibration signals. Thirty features were extracted from the PSD values of signals as a feature source for fault diagnosis. KNN and ANN were trained by training data set and then used as diagnostic classifiers. Variable K value and hidden neuron count (N) were used in the range of 1 to 20, with a step size of 1 for KNN and ANN to gain the best classification results. The roles of PSD, KNN and ANN techniques were studied. From the results, it is shown that the performance of ANN is better than KNN. The experimental results dèmonstrate that the proposed diagnostic method can reliably separate different fault conditions in main journal-bearings of IC engine.

Keywords: Fault diagnosis, main journal-bearing of IC engine, power spectral density, K-nearest neighbor, artificial neural network

1. Introduction

Since condition monitoring has substantial impacts in industry, it has received an enormous attention from the expert and practical maintenance [1]. Machine condition monitoring is significant considering system maintenance and process automation [3]. Condition monitoring provides significant information on the health and maintenance requirement of rotary machinery and is applied in many industrial applications [4]. The condition monitoring, diagnostic systems are mainly used to any machines based on vibration and technological parameters measurements [5]. Parameters such as vibration, temperature, lubricant quality and acoustic emission can be applied to monitor the mechanical status of equipment. Fault diagnosis improves the reliability and availability of an existing system. Since various failures degrade relatively slowly, there is potential for fault diagnosis at an early step [11]. It should be stressed that machine fault diagnosis is becoming significant in industry due to the need to have highly reliable machinery. However, many of the techniques available presently need a great deal of expert knowledge to perform

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Table 1
Major causes of journal-bearing defect

Dirt	45.4%
Misassembly	12.8%
Misalignment	12.6%
Insufficient Lubrication	11.4%
Overloading	8.1%
Corrosion	3.7%
Improper Journal Finish	3.2%
Other	2.8%

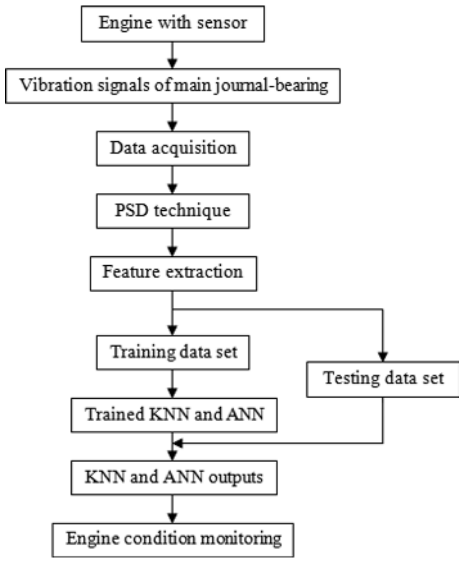

Fig. 1. Flow chart of diagnostic procedure.

them successfully. In real world, there is a demand to combine techniques that can make decisions on the health of the machine [12]. Some of the recent works in condition monitoring and fault diagnosis area are listed in [2,7,8,10, 12,14,16,40].

Journal-bearings are multifunctional components. So as to operate efficiently and provide long service life, journal-bearings often have to satisfy several requirements simultaneously, such as position and support a crankshaft or journal [17]. Journal-bearing performance affects the vibration behavior of internal combustion engine [18]. A crankshaft rotation within a journal-bearing is indeed separated from the journal-bearing's metal facing by an extremely thin film of continuously supplied engine oil that prevents metal to metal contact. Faulty journal-bearing can alter the thickness of oil film. This will lead to change the normal movement of the crankshaft. So, it is obvious that failure journal-bearing increase crankcase vibration at rotational speed of crankshaft [19]. Table 1 shows the eight major causes of premature engine journal-bearing failure. This list is found in Clevite 77 catalogue [20]. Much research has been implemented on journal-bearing due to its importance in industry such as [21–26].

Common techniques used for machine fault diagnosis include time and frequency-domain analyses. Statistical information of the time-domain signal can be applied as trend parameters [19,49,50]. They can indicate the shape of the amplitude probability distributions. Spectrum analysis provides spectrum in the frequency-domain. The spectrum peaks can be compared for normal and faulty conditions to determine whether the machine is experiencing a particular fault. When full knowledge of the under lying probabilities of a class of samples is available, Bayesian theory gives optimal new sample classification rates. In cases where this information is not present, many algorithms make use of the similarity among samples as a means of classification. The nearest neighbor decision rule has often been applied in these patters recognition problems [31,32]. K-nearest neighbor (KNN) decision rule has been a ubiquitous classification method with good scalability. Artificial neural networks (ANNs) are successfully applied for fault diagnosis applications [35–37]. They are developed to mimic humans in decision-making and identification [34,41]. ANNs are efficient for learning the certain status or operation condition of the rotary machines. The well-trained network can identify these various conditions [33].

Recently, there has been an increasing requirement of selecting appropriate techniques for the various stages of fault diagnosis, which have accurate classification and short computing time [30]. In [27], a performance comparison was done between ANN and KNN. In this, ANN technique performed better than KNN method for retrieval in both the speed and accuracy rate because of its ability to generalize information through training. Shintemirov et al. [28] presented an intelligent fault classification approach to power transformer dissolved gas analysis (DGA). In this paper, a comparison was performed between different techniques in classification stage. Genetic programming (GP) was used to construct classification features and Bootstrap preprocessing was applied to improve subsequent fault classification with GP feature extraction. Performance comparisons were made between the combined GP-ANN,

Fig. 2. The experimental system.

GP-support vector machine (GP-SVM) and GP-KNN classifiers and the ones derived from ANN, SVM and KNN classifiers, respectively. Wenhu et al. [15] surveyed the accuracy rate of four techniques, namely, SVM, ANN, KNN and least square SVM (LS-SVM) for transformer fault classification. Bagheri et al. [13] proposed fault gear identification and classification using ANN and KNN classifiers. In this, the frequency-domain vibration signals of the gearbox of a tractor were used. Improved distance evaluation (IDE) method was applied to establish a reduced set of superior features. The performances of classification algorithms based on KNN and ANN were compared in order to search for the best classifier. The accuracy rate of both classifiers was improved by IDE technique. But, the performance of ANN was slightly better than KNN.

The present work carries out a comparative study of two classification methods for fault diagnosis of journal-bearing using vibration signals [30]. The main differences between the present work and Bagheri et al. [13] are in case study, signal processing technique and the number of used features. A flow diagram of the proposed procedure for fault diagnosis is shown in Fig. 1. Three different conditions of the journal-bearing, namely, normal, oil starvation and extreme wear are studied. The effect of PSD technique [6,11,29] and feature extraction, KNN and ANN classifiers in journal-bearing fault detection are determined. Also, the accuracy rate of KNN and ANN with fast Fourier transform (FFT) and PSD technique is thoroughly compared. Finally, the performance of the proposed method is reported.

2. Experimental system

The case study for this work was a four cylinders internal combustion engine with the power of 125 hp. The experimental system is shown in Fig. 2. Vibration signals were collected for normal, oil starvation and extreme wear conditions of main journal-bearing. Failure journal-bearings were selected from the IC engine that was worked for a long time periods and its faults led to reduce of its efficiencies. The working speed of the engine crankshaft was set at 1500 rpm. The vibration signals in frequency-domain were gained by an accelerometer (VMI-102 model). Root mean square (RMS) of vibration acceleration (g) was calculated for these signals. The accelerometer was mounted horizontally on the body of crankcase near to main journal-bearing of engine. The accelerometer was connected to the signal conditioning unit (X-Viber FFT analyzer) where the signal goes through a charged amplifier and an analogue-to-digital converter (ADC). The vibration signal in digital form was saved on computer. SpectraPro-4 software was used for recording the signals. The sampling frequency was 8192 Hz and the number of data in each sample was 12800.

Table 2
The feature parameters

Frequency-domain feature parameters	
$F_1 = \frac{\sum_{k=1}^{K} s(k)}{K}$	$F_{16} = \frac{F_4}{F_1} \times 100$
$F_2 = \max(\lvert s(k)\rvert)$	$F_{17} = \frac{\sum_{k=1}^{K} \lvert s(k)-F_1\rvert}{K-1}$
$F_3 = \sqrt{\frac{\sum_{k=1}^{K} (s(k))^2}{K}}$	$F_{18} = \frac{F_{13}}{(F_5)^2}$
$F_4 = \sqrt{\frac{\sum_{k=1}^{K} (s(k)-F_1)^2}{K-1}}$	$F_{19} = \frac{K}{\sum_{k=1}^{K} \frac{1}{s(k)}}$
$F_5 = \frac{\sum_{k=1}^{K} (s(k)-F_1)^2}{K-1}$	$F_{20} = \left(\frac{\sum_{k=1}^{K} \sqrt{\lvert s(k)\rvert}}{K}\right)^2$
$F_6 = \frac{\sum_{k=1}^{K} (s(k)-F_1)^3}{(K-1)F_4^3}$	$F_{21} = \frac{F_2}{F_{20}}$
$F_7 = \frac{\sum_{k=1}^{K} (s(k)-F_1)^4}{(K-1)F_4^4}$	$F_{22} = \sqrt[K]{\prod_{k=1}^{K} s(k)}$
$F_8 = \frac{F_3}{\frac{1}{K}\sum_{k=1}^{K} \lvert s(k)\rvert}$	$F_{23} = \frac{\frac{1}{K}\sum_{k=1}^{K} (s(k)-F_1)^3}{(\sqrt{\frac{1}{K}\sum_{k=1}^{K} (s(k)-F_1)^2})^3}$
$F_9 = \frac{F_2}{\frac{1}{K}\sum_{k=1}^{K} \lvert s(k)\rvert}$	$F_{24} = \sum_{k=1}^{K} s^2(k)$
$F_{10} = \frac{F_2}{F_3}$	$F_{25} = \frac{3(F_1-\hat{s})}{F_4}$
$F_{11} = \sqrt{\frac{k\sum_{k=1}^{K} s^2(k)-(\sum_{k=1}^{K} s(k))^2}{k(k-1)}}$	$F_{26} = \sum_{k=1}^{K} \log s^2(k)$
$F_{12} = \frac{\sum_{k=1}^{K} (s(k)-F_1)^3}{K-1}$	$F_{27} = \min(\lvert s(k)\rvert)$
$F_{13} = \frac{\sum_{k=1}^{K} (s(k)-F_1)^4}{K-1}$	$F_{28} = \sum_{k=1}^{K} s^2(k)\log s^2(k)$
$F_{14} = \frac{\sum_{k=1}^{K} (s(k)-F_1)^5}{K-1}$	$F_{29} = \frac{K^2\sum_{k=1}^{K} (s(k)-F_1)^6}{(\sum_{k=1}^{K} (s(k)-F_1)^2)^3}$
$F_{15} = \frac{\sum_{k=1}^{K} (s(k)-F_1)^6}{K-1}$	$F_{30} = \frac{K^2\sum_{k=1}^{K} (s(k)-F_1)^8}{(\sum_{k=1}^{K} (s(k)-F_1)^2)^4}$

where $s(k)$ is a spectrum for $k = 1, 2, \ldots, K$, K is the number of spectrum lines; $\hat{s}$ is the median of spectrum lines

3. Background knowledge of applied methods

3.1. Feature extraction

PSD values could not directly used as inputs of classifier and a post-processing step is needed to prepare data for classifiers. In this work, thirty features were extracted from the PSD values of the vibration signals using different parameters. The thirty feature parameters are shown in Table 2. Some of these features are explained below.

Standard deviation: It is a measure of the effective energy or power content of the vibration signal.

Skewness: It characterizes the degree of asymmetry of a distribution around its mean [9,14].

Root Mean Square: It is a measure of the power content in the vibration signature [14,38,53].

Crest Factor: It is calculated from the peak amplitude of the signal divided by the RMS value of the signal [13, 39,53,55].

Shape Factor: It is calculated from the RMS value of the signal divided by the average of signal point values [9, 13,14,54].

3.2. K-nearest neighbor (KNN)

KNN classifier is a simple non-parametric method for classification. Despite the simplicity of the algorithm, it performs very well, and is an important benchmark method. KNN classifier requires a metric d and a positive integer K [42]. KNN rule holds the position of training samples and their class. When decision about new incoming data

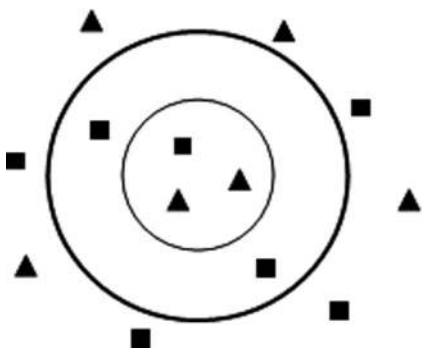

Fig. 3. KNN algorithm for a situation with 2 class and 2 features.

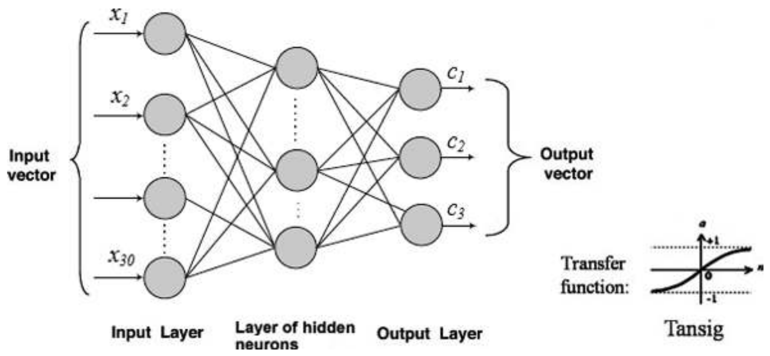

Fig. 4. The architecture of applied neural network.

is needed, distance between query data and training samples is being calculated. Based on the defined threshold for the rule (it is the K number), K samples with least distances are selected and the class with more samples inbound is the result. In other words, for example if there is 2 or 3 features for a classification situation, position of training samples and input sample can be visualized on 2D and 3D Cartesian coordinates. Process to find result is like to draw a circle (Sphere) centered on input location and increase radius until K samples are embed inside the circle (sphere) and then a class with more samples inbound is the result. Figure 3 shows this method. For K = 3, inside small circle there are 2 triangles and 1 square, the result is triangle class. For K = 5, inside large circle there are 3 squares and 2 triangles so the result is square class. KNN is a classifier that its accuracy is always 100% on training data set, because the position of training samples and their class are constant during the classification process. In this work, variable K value is used between 1 and 20.

In KNN classifier, Euclidean distance metric is a simple and easy-to-implement method for computing distances in multidimensional input space which can yield competitive results even compared to the most sophisticated machine learning methods [32,44]. The Euclidean distance between point p and q is the length of the line between them. In Cartesian coordinates, if p_i and q_i are two points in Euclidean n-space, then the distance from p to q is given by

$$d_E = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \tag{1}$$

3.3. *Artificial neural network (ANN)*

Networks are one method for decomposing a complex system into simpler parts so as to realize it. A set of nodes and connections between nodes are components of networks. The nodes are known as computational units of networks and the connections determine the information flow between nodes. ANNs are one of networks that see the nodes as artificial neurons. An artificial neuron is a computational model inspired in the natural neurons.

In artificial neurons, inputs are multiplied by weights and then calculated by an activation function. Another function estimates the output of the artificial neurons. ANNs combine artificial neurons [45]. ANNs are non-linear mapping structure. ANNs can recognize correlated patterns between input data set and corresponding target values. ANNs has huge capacity in prediction, pattern recognition, data compression, decision-making, etc. ANNs are recently used in the classification problem where regression model and other statistical techniques have traditionally been applied [43,51]. Now, there are many different models of ANNs. The differences might be the topology, the functions, the hybrid models, the accepted values, the learning algorithms, etc. However, back-propagation algorithm is one of the most common models of ANNs. In back-propagation algorithm, the network gains inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be several hidden layers. By this work, difference between actual and expected results is estimated (error). Finally, the back-propagation algorithm is to decrease this error, until the ANN learns the training data set [46].

In ANN, input vectors and the corresponding target vectors are applied to train a network until it can approximate a function, associate input vectors with specific output vectors in a proper way as defined by user. Empirical risk minimization (ERM) is used minimizing the error on the training data set for ANN [37,47,48].

Table 3
Description of journal-bearing data set

Journal-Bearing condition	The number of training samples	The number of testing samples	Label of classification
Normal	30	30	1
Oil starvation	30	30	2
Extreme wear	30	30	3

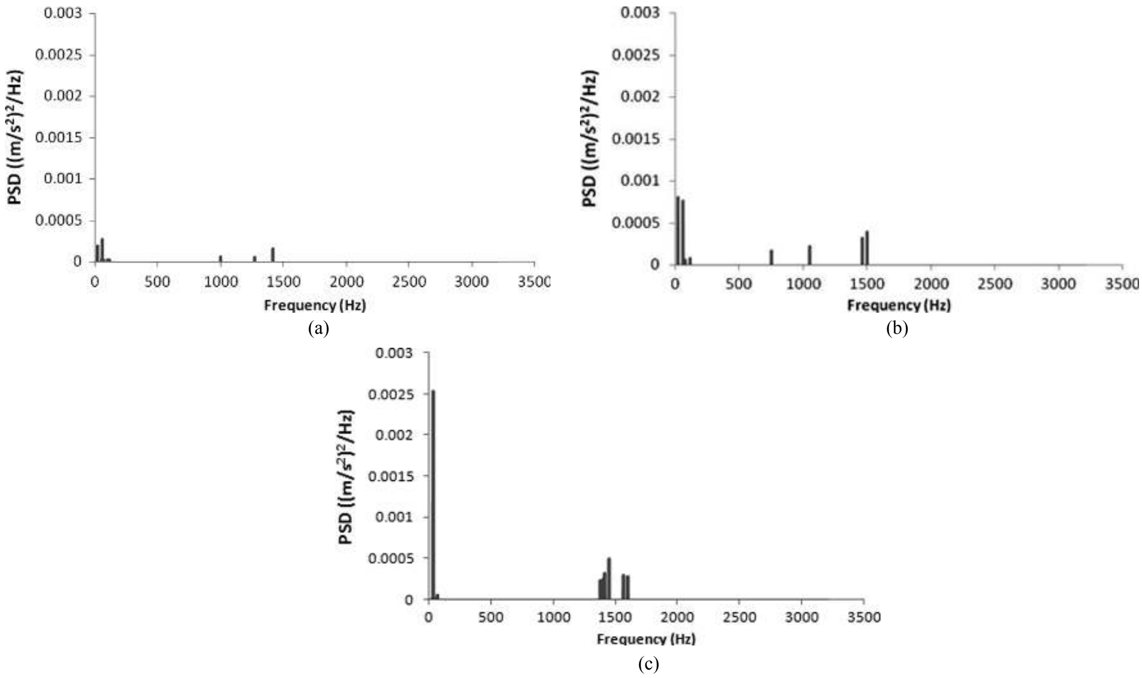

Fig. 5. PSD-Frequency diagrams of journal-bearing in three conditions; (a) normal; (b) oil starvation; (c) extreme wear.

In this paper, the feed forward back-propagation neural network is used, which consists of input layer, hidden layer and output layer. Also, network with 'tansig' transfer function, 'mse' performance function and variable number of hidden layer neurons between 1 and 20 is applied (Fig. 4).

4. Results and discussion

The objective of this study was main journal-bearing fault diagnosis of IC engine using power spectral density, K-nearest neighbor and artificial neural network. The classification of the journal-bearing based on its situation was done using the features extracted from the PSD values of the vibration signals.

Figure 5 shows the samples of PSD diagram of the vibration signals acquired from the different conditions of the journal-bearing. It can be seen that the maximum value of PSD for faulty condition is more than normal condition. Also, PSD value for extreme wear condition is the highest.

Data set consists of 180 data samples of three conditions. Each of the three operating conditions includes 60 data samples. Data set for each class were equally divided into training and testing data set. The detailed descriptions of the three data sets are shown in Table 3 [36,52].

Finally, KNN and ANN were generated by training with training data set and simultaneously simulated by testing data set. The variable K value and hidden neuron count (N) were used between 1 and 20 for KNN and ANN.

Table 4 shows the classification results of KNN and ANN with FFT and PSD techniques. From Table 4, we can see that the best performance of KNN with PSD and FFT is 85.7% and 76.2%, and also the best test success of ANN with PSD and FFT is 90.5% and 85.7%, respectively. So, it can be found easily that the accuracy rate of two

Table 4
The performance of ANN with FFT and PSD technique

K and N	KNN		ANN	
	Test success with FFT (%)	Test success with PSD (%)	Test success with FFT (%)	Test success with PSD (%)
1	76.2	85.7	69.2	47.6
2	76.2	85.7	42.9	57.1
3	57.14	57.14	71.4	71.4
4	61.9	61.9	71.4	47.6
5	52.38	57.14	61.9	90.5
6	42.86	61.9	76.5	71.4
7	28.57	57.14	82.1	81
8	42.86	57.14	57.1	81
9	47.68	52.38	38.1	85.7
10	38.1	52.38	76.3	85.7
11	38.1	52.38	61.9	47.6
12	42.86	47.62	49.2	81
13	52.38	47.62	42.9	76.2
14	42.86	42.86	42.9	66.7
15	42.86	38.1	85.7	76.2
16	42.86	33.33	71.4	71.4
17	42.86	38.1	71.4	66.7
18	47.62	33.33	57.1	47.6
19	52.38	33.33	71.4	61.9
20	52.38	33.33	42.9	66.7

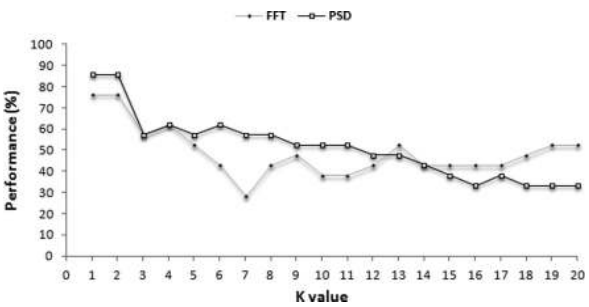

Fig. 6. The difference between FFT and PSD technique in KNN accuracy rate.

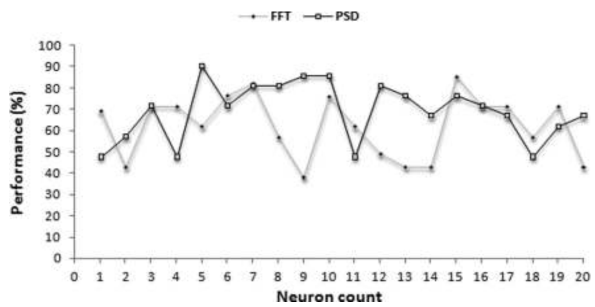

Fig. 7. The difference between FFT and PSD technique in ANN accuracy rate.

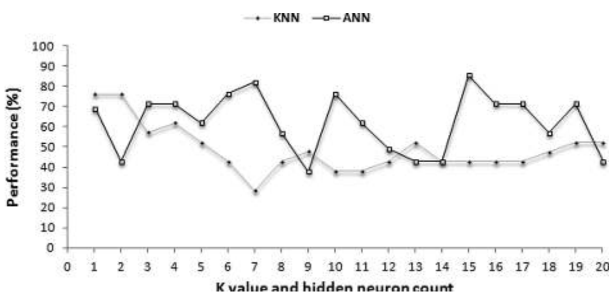

Fig. 8. The performance of ANN and KNN with FFT technique.

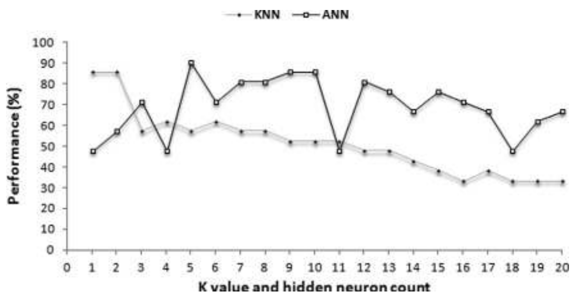

Fig. 9. The performance of ANN and KNN with PSD technique.

classifiers with PSD technique is substantially better. Figures 6 and 7 show the difference between the effect of FFT and PSD on the performance of KNN and ANN.

The best performance was 94.5% and 90.5% on training and testing data set which belonged to the N = 5 for ANN with PSD. Generally, the accuracy rate of ANN was significantly higher than KNN. But computation time for KNN was relatively much lower than the ANN. Figures 8 and 9 show the comparison between the performance of ANN and KNN with FFT and PSD techniques.

5. Conclusion

A procedure was presented for diagnosis of main engine journal-bearing condition using two classifiers, namely, KNN and ANN with PSD technique. The proposed method was evaluated by using vibration data collected from an IC engine with different faulted main journal-bearings installed. Three different conditions of journal-bearing were studied, namely, normal, oil starvation and extreme wear. The vibration signals in frequency-domain were processed by PSD technique. Different parameters were used for the feature extraction stage such as max, min, average, standard deviation, variance, crest factor, kurtosis, skewness, 4th central moment, 5th central moment, etc. It is to be stressed here that feature extraction directly affects final diagnosis results. Therefore, the selection of proper parameters is very important for feature extraction stage. Then, KNN and ANN were trained as the pattern classifiers. The performance of KNN and ANN was computed by using the testing data set. Variable K value and hidden neuron count (N) between 1 and 20 with a step size of 1 were used for KNN and ANN to gain the best diagnosis results. The performance of PSD technique was substantially better than FFT. The best test success was 90.5% which belonged to ANN with the number of hidden neuron of 5 ($N = 5$). The accuracy rate of ANN was actually more than KNN. But the training time was less for KNN than ANN. ANN was an appropriate candidate for this work because of its capability in classification. The results show that the proposed method can be used effectively in diagnosing main engine journal-bearing faults and developing an on-line condition monitoring tests.

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