Sigma J Eng & Nat Sci 36 (4), 2018, 1235-1253

Sigma Journal of Engineering and Natural Sciences
Sigma Mühendislik ve Fen Bilimleri Dergisi

Research Article

A COMBINED DECISION ALGORITHM FOR DIAGNOSING BEARING FAULTS USING ARTIFICIAL INTELLIGENT TECHNIQUES

Hüseyin Metin ERTUNÇ*[1]

[1]*Kocaeli University, Department of Mechatronics Engineering, KOCAELI;* ORCID: 0000-0003-1874-3104

Received: 02.02.2018 Revised: 03.10.2018 Accepted: 01.11.2018

ABSTRACT

The condition monitoring of bearings has gained great importance in recent years to increase reliability and reduce production loss. Many monitoring techniques have been proposed based on different intelligent techniques and feature extraction schemes. In this study, a combined decision algorithm has been developed based on feature set that composed of statistical variables and linear prediction coefficients of time domain vibration signals. Artificial intelligent techniques, namely artificial neural networks, adaptive neuro-fuzzy inference systems and support vector machine were employed together to develop a decision making algorithm that classify the type and severity of bearing faults. Although each method can be used alone for data classification in the developed models with a limited performance, the proposed decision algorithm combines decision of each method with a synergy according to the majority of the decisions. Based on the experimental results, the proposed scheme outperformed the three methods when used alone.
Keywords: Condition monitoring, bearing fault detection, ANN, ANFIS, SVM, combined decision algorithm.

1. INTRODUCTION

Machine automation and condition monitoring of the rotating machines have become crucial as the technologies of modern manufacturing industry have been rapidly developed. Vast majority of rotating machines such as motor systems absolutely need rolling element bearings that provide an interface between the stationary and moving parts of the mechanical equipment for proper operation of rotating parts. Because of their functions, rolling element bearings have to bear not only high loads in the system but also harsh operating conditions in spite of their delicate structures [1]. Thus, severe operating conditions may frequently cause defects on the parts of bearing. If these defects are developed, they lead up to fault or malfunctions of the bearing mechanism that deteriorate the machine running condition; and eventually the roller bearing with faults may cause fatal break down of the rotating machines and even catastrophic personal casualties [2]. Subsequently, these phenomena may result in catastrophic accidents and unexpected downtime of all processes in manufacturing companies employing critical rotating machinery such as large motors and pumps in power generation plants [3]. On the other hand, although the prices of bearing elements are low, economical cost due to bearing failures are huge [4]. It was reported that, motor failures are often linked to bearing failure [5]. Therefore, condition

[*] Corresponding Author: e-mail: hmertunc@kocaeli.edu.tr, tel: (262) 303 32 17

monitoring of the bearing and other rotating parts is a real problem in modern production plants. There are extensive amount of research related to the procedures of condition monitoring based on fault detection and diagnosis that are an important part of preventive maintenance in industrial applications [6].

Over the last few decades, different methods of fault diagnosis have been developed for rotating machinery systems based on vibration analysis to classify the extracted feature parameters [7–11]. Vibration occurs as an output of the impacts between mechanical components. The faults or defects at the subcomponents of bearings such as inner race and outer race generate impulses as the roller elements, balls, impact the defects during the operation of bearing. Not only inner race and outer race but also the balls may have cracks or spalls as bearing faults. The amplitude and frequency spectrum of the vibration signals depends on the size and location of the defects on the bearing local parts [12,13].

All the methods based on vibration signals can be aggregated in three classes: time domain analysis, frequency domain analysis, and time–frequency domain analysis. Time domain analysis is at first the simplest and cheapest way for diagnosing based on feature extraction using statistical parameters such as mean, root-mean square (rms), median, standard deviation, skewness, kurtosis, etc [5]. It was reported that statistical investigation of time domain vibration signals displays different characteristics features for healthy and defected bearings [3]. Shao and Nezu examined the relations fault/defect level, the kurtosis value and the learning ratio of adaptive noise cancellation for faulty bearing signals [14]. Williams et al. used multiple sensors for bearing condition monitoring in the run-to-failure test [15]. They showed that statistical parameters such as rms value, kurtosis and crest factor calculated from the time series data collected by multiple sensors increase as the size of the bearing faults grows.

Diagnosis requires to locate and to determine exact causes of the bearing faults. Using the extracted features based on vibration analysis, artificial intelligent techniques such as Artificial Neural Networks (ANN) [2,16,17], Fuzzy Logic [9], Genetic Algorithms [18], Support Vector Machines [19] have been developed for condition monitoring of rotating machines, and have been successfully applied to classification to bearing fault classification. These techniques have largely improved the reliability and automation of fault diagnosis systems for bearings. In general, these data-driven soft computing techniques make possible the development of diagnostic models if they are supported with suitable feature extraction scheme [20]. To apply intelligent techniques for classification problems, they need to be trained from empirical data to build models; then they can be tested for unseen data that are not used in training procedure. Among them, the ANNs have been widely used to identify faulty and normal machine conditions. By combining the benefits of learning capability of neural networks and human-like reasoning style of fuzzy logic, Lei et al. used Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and they gave the most superior features as input to the network [21]. Thus they showed that the importance of selecting feature set so that the classifier can improve the classification success rate and generalization performance.

Yet Support Vector Machine (SVM) is one the most successful and widely used intelligent technique in recent years as considering the classification performances reported by the researchers [22]. Yang et al. applied SVM for fault classification based on time domain signals with fractal dimension method in order to increase classification performance [23]. Hu et al. proposed an SVM ensemble approach that can successfully diagnosis much higher than single SVMs [24]. They reported the success rate of SVMs ensemble is higher than 90% even if the percentage of noise exceeds 35%. This means that the SVMs ensemble has more capacity of reliability and robustness, and shows an excellent generalization performance.

In this study, a combined decision algorithm was developed based on the time vibration signals using intelligent methods such as ANN, ANFIS and SVM for bearing fault detection. The inputs to the methods are the statistical values and linear prediction coefficients of the signals in the sense of the feature extraction procedure. Each of the intelligent methods evaluates the signals to determine both the type of fault and the severity or level of fault of the roller element bearing. It was observed that if three intelligent techniques are used together, the decision algorithm uses the synergy of all and shows better performance for condition monitoring.

2. EXPERIMENTAL SETUP (VIBRATION DATA)

The vibration data used in this study have been obtained (downloaded) from the web site so-called Bearing Data Center supported by the Case Western Reserve University (CWRU). This data set has been analyzed by many researchers and has become a standard data set of the roller bearings as a benchmark for various developed techniques [25]. The data was acquired from rolling element bearings under different operating loads and bearing conditions. As can be seen from Fig. 1, the ball bearings are installed in an induction motor driven by a mechanical system.

The test rig consists of a 2 hp, three-phase induction motor, a dynamometer and a torque sensor. Different torque load levels are obtained by controlling the dynamometer. An accelerometer is mounted on the motor housing at the drive end of the motor to acquire the vibration signals from the bearing. The data was collected by a 16 channel DAT recorder with the 12 K/s sample rate per channel.

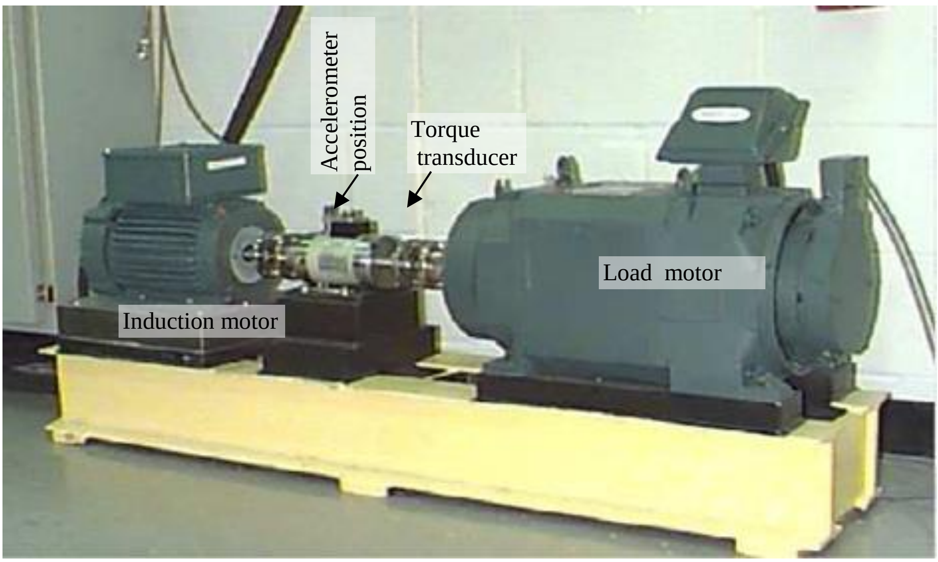

Figure 1. Experimental setup.

The bearings used in this work are type of SKF 6205, deep groove ball bearings. Artificial defects with single point faults were introduced into the drive-end bearing of the motor using an electro erosion process so-called ‘electro-discharge machining (EDM)’. The fault diameters are namely 0.1778, 0.3556 or 0.5334 mm which correspond to incipient, moderate and heavy faults. EDM is a machining method for processing hard metals or mechanical components which could not be penetrated with conventional methods. Each bearing was tested under four different loads (0, 1, 2 and 3 hp). For each kind of working condition, signals were measured under the rotating speeds of 1730, 1750, 1772 and 1797 rpms, respectively. The bearing data set was obtained from the experimental system under four different operating conditions: normal condition, inner race fault condition, ball fault condition and outer race fault condition. Fig. 2 shows sample vibration signals for normal and faulty bearings in time axis.

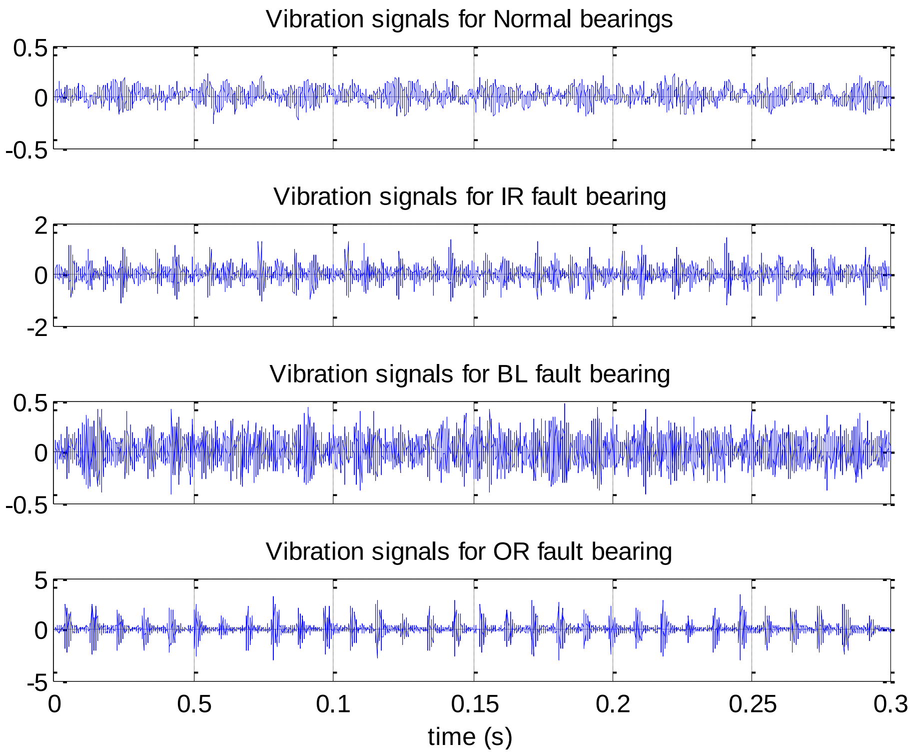

Figure 2. Sample vibration signals for normal and faulty bearings.

3. FEATURE EXTRACTION

During the operation of a rotating machine that consist of many components such as gears, bearing and shafts, a valuable data can be acquired via sensors for developing condition monitoring techniques. But the data that contains useful information about the machine and component conditions may consist of a large number of samples like vibration signals used in this study. Therefore, the acquired data in the form of raw signals are not appropriate to be directly instructed as inputs to the intelligent techniques for diagnostic operation. To process the data and get rid of the 'curse of dimensionality', feature extraction is an essential step for abbreviation and consequently usage of the raw data. On the other hand, a feature set with appropriate number and relevant elements that represent the collected data must be given as input into the intelligent techniques without both increasing computer computation burden and reducing classification accuracy.

There have been many feature extraction techniques in the literature developed for the bearing fault diagnosing [26]. While some of them require complicated signal processing procedure, a relatively simple approach based on calculating the statistical parameters and linear prediction coefficients of vibration signals in time domain is employed in this study. 9 statistical parameters were extracted by taking the mean, median, maximum, minimum, root mean square, standard deviation, skewness, kurtosis and crest factor of the raw signals. Besides, the first 10 linear predictive coefficients are used in the feature set. Linear prediction coefficients (lpc) are used to encode the vibration signals similar to the applications in filter design and speech recognition. In this study, the last 10 samples are used to predict the current value of the vibration signals, therefore, 10 linear predictive coefficients (lpc) are employed in the feature set. Thus, total number of elements in the feature set was determined as 19.

In the data set obtained from the web site of Bearing Data Center, the raw vibration data were acquired with 12 kHz sampling frequency. Then, the features that represent the vibration signals are extracted for determining the inputs of the intelligent methods, ANN, ANFIS and SVM. All methods were employed using the same features as input parameters in the present work.

4. A COMBINED DECISION ALGORITHM

The fault diagnosing and classification schemes for bearing consist of data acquisition from the process, feature extraction from the acquired data, and diagnostic algorithm for decision making. Since the acquired and feature extracted data contains information not only about the type of mechanical fault such as inner race (IR), ball element (BL) and outer race (OR), but the fault severity can also be assessed using a proper decision algorithm.

Various intelligent techniques have been used for constructing decision algorithms and they can successfully perform the diagnostic of the bearing faults to some extent. Thus, a combined decision making algorithm was proposed based on ANN, ANFIS and SVM to obtain a better diagnosing performance. The basic idea is to exploit the ability of each method individually, and then to combine the decisions of separate methods for more accurate results. The developed combined decision making algorithm has two stages, as illustrated in Fig. 3 and Fig.4. At the first stage, a decision of bearing fault type is made whether the bearing is normal or has an IR, OR or BL damage. When the type of damage is determined at this stage, the algorithm proceeds to the second stage to determine the severity of the fault, namely incipient, moderate and heavy fault. Obviously, the decision making process is ceased at the first stage for a normal bearing.

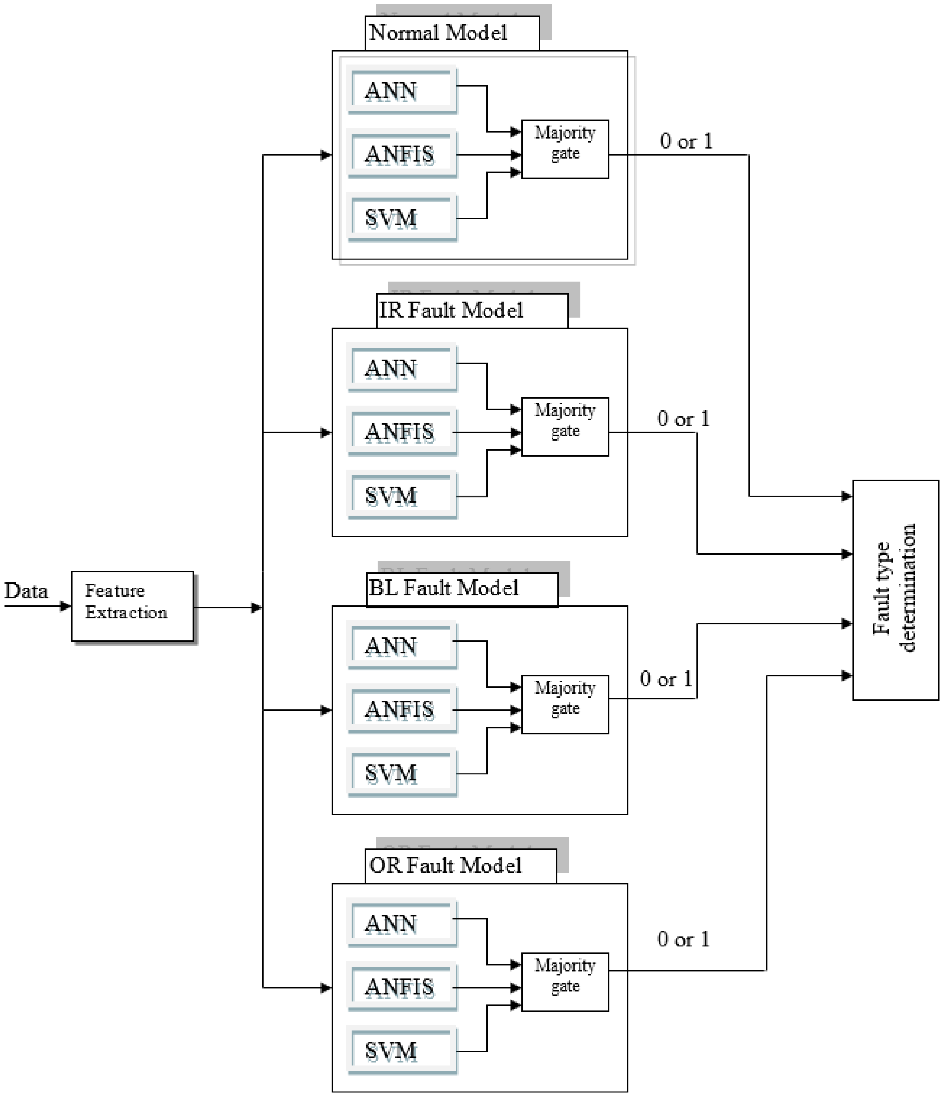

Figure 3. The first stage of the combined decision making algorithm.

ANN, ANFIS and SVM methods were separately used at each step of the decision algorithm. The methods inside the models at each stage were trained to output 0 or 1 for input features from the corresponding data set. For instance, the intelligent methods in the normal model used in the first stage were trained to generate 1 for normal bearings and 0 for others. The decisions of these methods with a feature set were combined based on the logical majority gate principle shown in Figs. 3 and 4. The majority gate principle means that it generates 1(0) as an output if the majority of the inputs are logic 1(0), otherwise the output is logic 0(1). In other words, if two out of three methods lead the same result for a given feature set input, then the decision is determined according to those outputs.

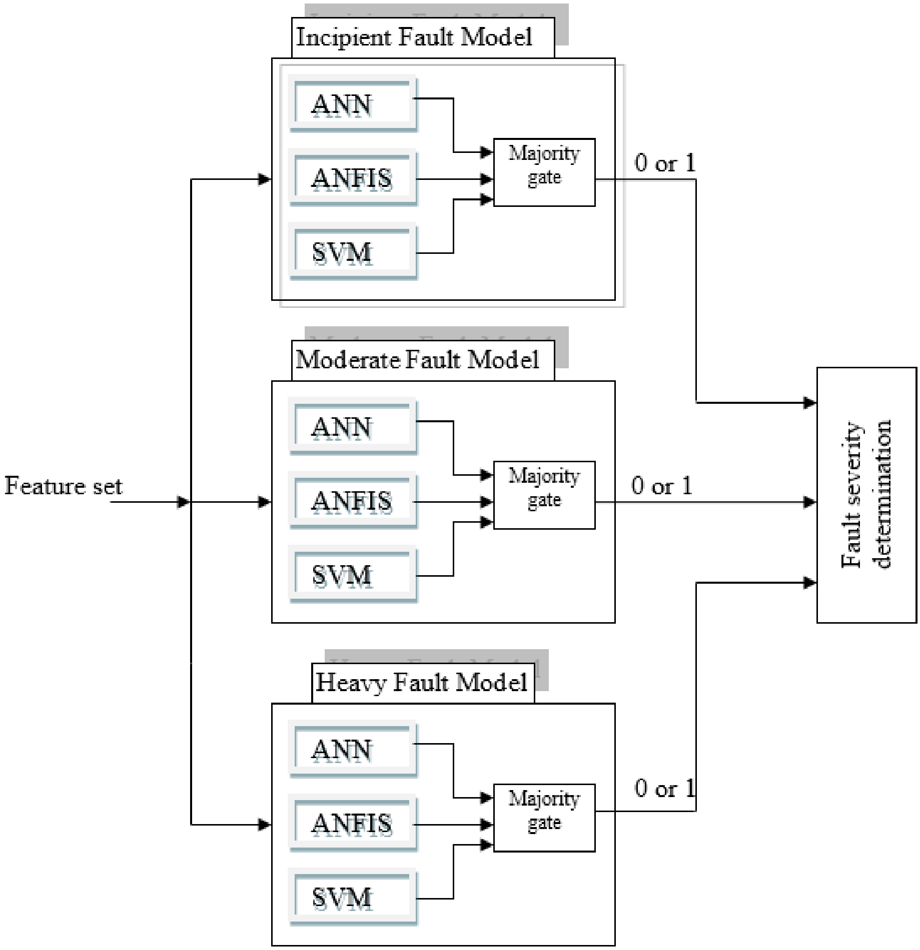

Figure 4. The second stage of the combined decision making algorithm (one per each fault type).

The second stage of the combined decision algorithm consists of separate incipient, moderate and heavy fault models for all three fault types (IR, BL and OR). The faults severity models were trained using only the data for the corresponding fault type. For instance, the incipient fault model for the IR fault case was trained using the IR faulty data only. For training the model, the IR faulty data was divided into two groups: incipient vs. not incipient. The model was trained to output 1 for the IR incipient fault and 0 for the IR fault with other severity levels. The remaining models in the second stage were trained in a similar fashion.

The final decision of the model is again made by logical majority gate operation, i.e., if the majority of three intelligent methods inside the model generate the same result, then final decision of the fault model, say incipient fault model, is reached. At the last step, all the decisions from models are unified to determine the severity of fault. On the contrary to logical majority gate principle, only one model out of three must generate 1 and the others must generate 0 for an accurate final decision about the fault severity. If more than one fault type models generate 1, then it corresponds to a 'conflicting decision' that shows failure of the proposed algorithm.

When utilizing the intelligent methods in the algorithm, a circumstance must be pointed out that the ANN and the ANFIS methods were trained to generate 0 or 1. But these methods can generate any arbitrary values at the outputs. Since the models were forced to generate 0 or 1 for decision making, a threshold value was used to separate the two states of the method. The outputs of the ANN and ANFIS methods below the threshold value were considered to be 0, while the outputs above the threshold were considered to be 1.

5. EXPERIMENTAL RESULTS

In order to assess the proposed combined decision making algorithm, we applied the data [27] to predict the type and severity of the faults for rolling element bearings. The detailed description of the data set is shown in Table 1.

Table 1. Experimental conditions

Data index	Fault type	Fault level (mm)
1-40	IR	0.1778
41-80	IR	0.3556
81-120	IR	0.5334
121-160	BL	0.1778
161-200	BL	0.3556
201-240	BL	0.5334
241-280	OR	0.1778
281-320	OR	0.3556
321-360	OR	0.5334
361-500	Normal	-

Before applying the proposed algorithm, a data set was prepared from Case data [27]. The data set comprises the vibration signals acquired for the roller element bearing under four different operating conditions (normal condition, inner race fault, ball fault and outer race fault). The data was collected at 12,000 samples/second with different time durations. While all the data for faulty cases was collected for 10 seconds, the time duration of normal bearing data was 20 seconds for unloaded case and 40 seconds for other motor loads (1, 2 and 3hp). In order to get a rich data set, we divide the data into 1 second windows. Then, the features of each signal window were extracted in order to avoid the difficulties of long data sets for intelligent methods. 9 statistical parameters and 10 linear predictive coefficients were used to represent the data that is divided into one second parts. Finally, we obtained a feature set with dimension of 19 rows and 500 columns where each column represents the features of one second of vibration signals.

The proposed algorithm, a combined decision making algorithm, employs intelligent methods inside the models at two stages. In the first stage of the decision algorithm shown in Fig.3, four models (normal, IR, BL and OR) are developed that have ANN, ANFIS, SVM systems and a logical majority gate. These intelligent systems were trained for either 0 or 1using the 50 % of data for the corresponding case. For instance, 120 column of the feature set belongs to IR fault case. 50 % columns out of it (corresponding 60 columns) and 50 % of the rest (corresponding 190 columns) were selected randomly to give as input for training process of the intelligent methods. The rest of the data in feature set was used to test the developed system in training. The decision of the model, say IR fault model, is determined after the logical majority gate operation.

The test scores of each intelligent system developed for the fault type models are shown in Figs. 5-8, separately. In these figures, the blue circles show the actual state of the bearing and red crosses represent the predicted state of the bearing, whereas the green stars imply the modified prediction values after threshold. Because the ANN and ANFIS systems may generate any value rather than 0 and 1 in test process, their outputs must be modified according to the threshold. In the experiments, a reasonable threshold value was chosen as 0.5.

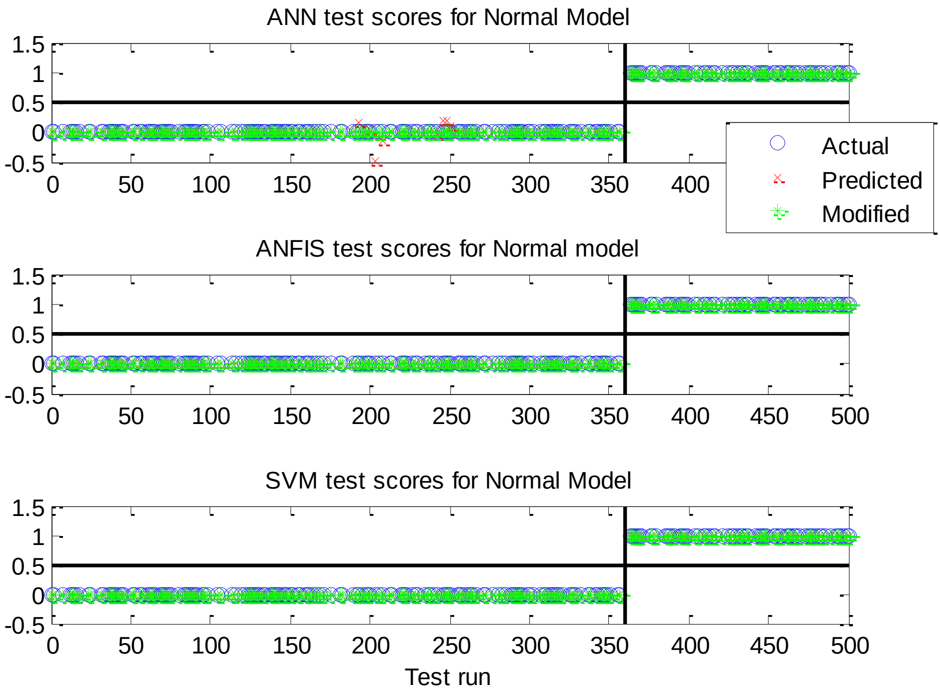

Figure 5. Test scores at the first stage of the combined decision algorithm for Normal model.

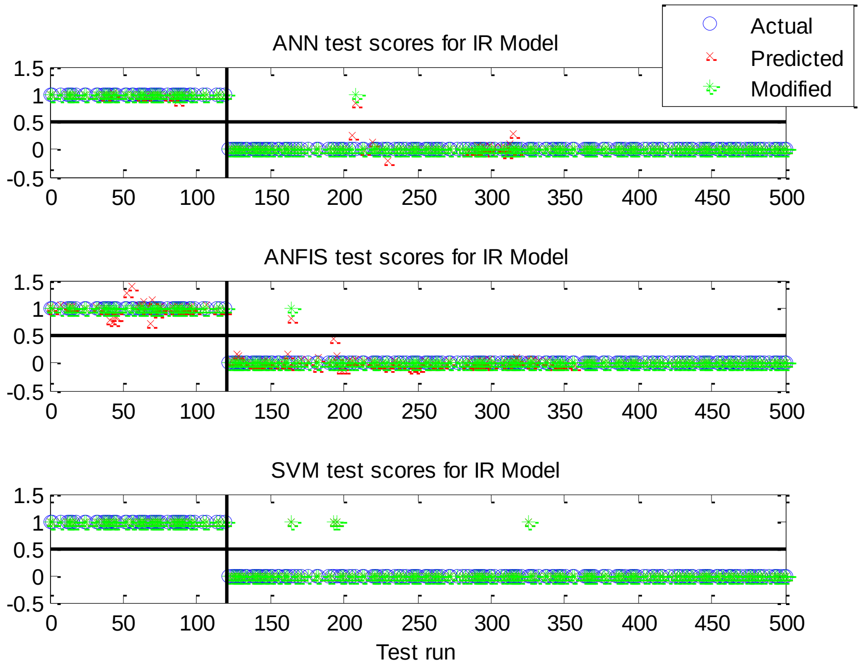

Figure 6. Test scores at the first stage of the combined decision algorithm for IR fault model.

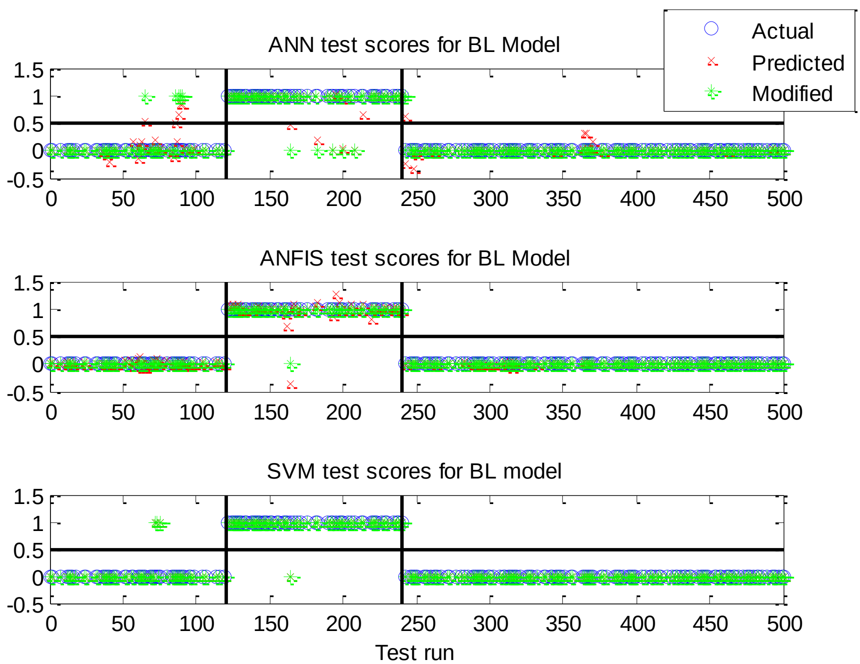

Figure 7. Test scores at the first stage of the combined decision algorithm for BL fault model.

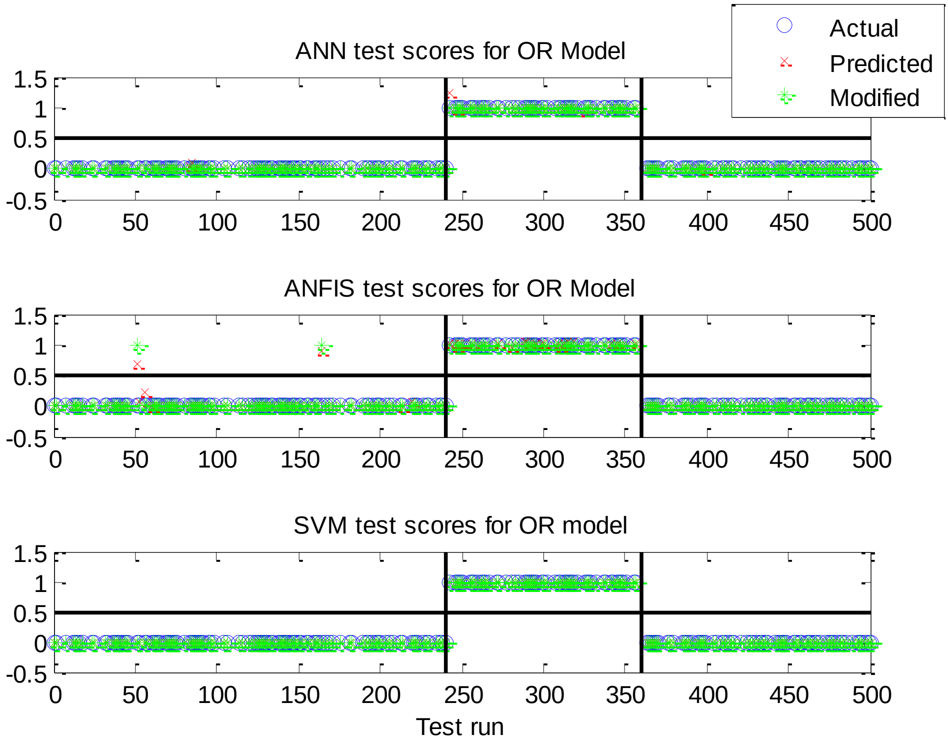

Figure 8. Test scores at the first stage of the combined decision algorithm for OR fault model.

To evaluate the performance of the developed models for classification accuracy with numerical values, true positives and true negatives are used. For a two-class prediction problem, i.e. binary classification, the outcomes are labeled either positive (1) or negative (0). There are four possible outcomes from a binary classifier. If both the actual value and the prediction outcome are 1, then it is called a *true positive* (TP); however, if the actual value is 0 when the prediction outcome is 1, then it is said to be a *false positive* (FP). Conversely, a *true negative* (TN) has occurred when both the prediction outcome and the actual value are 0, and *false negative* (FN) is when the prediction outcome is 0 while the actual value is 1. The idea explained with four outcomes of a binary classification can be formulated in a 2×2 contingency table as illustrated in Table 2.

Table 2. The contingency table for binary classification

	Actual	
Prediction	1	0
1	TP	FP
0	FN	TN

The detailed prediction percentages of each intelligent system for the first stage of the proposed algorithm are given in Table 3 using the TP and TN representations explained above. Again in this table, TP shows the prediction performance in percentage when the actual value and the model prediction outcome are 1, while TN shows the performance when both the actual value and prediction outcome values are 0. Recall that the IR, BL, OR and normal models were trained with randomly selected features using half of the whole feature data set. During the test procedure, the rest of the data that is not used for the training process are given the intelligent methods inside the models. Therefore, the model may generate either 0 or 1 as prediction outcomes.

Table 3. The prediction performance in percentage for the first stage of the combined decision algorithm

	Methods	**TN**	**TP**	**Total**
IR Model	ANN	99.47	100	99.60
	ANFIS	99.47	100	99.60
	SVM	97.89	100	98.40
BL Model	ANN	96.84	91.67	95.60
	ANFIS	100	98.33	99.60
	SVM	97.89	98.33	98
OR Model	ANN	100	100	100
	ANFIS	98.94	100	99.20
	SVM	100	100	100
Normal Model	ANN	100	100	100
	ANFIS	100	100	100
	SVM	100	100	100

In general, ANN presents the worst performance when compared the other intelligent methods. For IR and BL fault type models, ANFIS outperforms the SVM. On the other hand, SVM outperforms the ANFIS for the OR fault type and normal models. Because the intelligent methods have different performances for different fault type models, their outputs were combined using the logical majority gate operation. As explained in the previous section, majority gate generate logic 1 (0) output if at least two of the inputs are 1 (0). When we apply this operation, the proposed algorithm predicts the type of the fault with an accuracy of 100%. To show the utilization of this operation, the outputs the three methods for a selected data set are given in Table 4. ANN_IR, ANFIS_IR and SVM_IR refer to the decisions of the ANN, ANFIS and SVM methods for the IR fault model at the first stage, respectively. The similar representations were used for the BL and OR fault models. It can be seen from the table that the proposed algorithm makes a correct decision about the state of the bearing while the other individual methods make prediction errors. The prediction errors are pointed by bold numbers in the table. For instance, for the data with index 51, ANN_, ANFIS_ and SVM_IR models all output 1 signaling an IR fault. The three models for the BL fault case all generate 0 meaning there is not a BL fault in the bearing. For the same data, ANN_, ANFIS_ and SVM_OR models generate 0, 1, and 0, respectively. Although, the ANFIS model produced an incorrect decision, the majority gate outputs a 0 which eliminates the individual error made by the ANFIS model. As a result, the proposed algorithm accurately gives a final decision of IR fault for the data.

Table 4. The results of the first stage for determining the bearing fault types

Data Index	ANN_IR	ANFIS_IR	SVM_IR	Decision_IR	ANN_BL	ANFIS_BL	SVM_BL	Decision_BL	ANN_OR	ANFIS_OR	SVM_OR	Decision_OR	ANN_Nor	ANFIS_Nor	SVM_Nor	Decision_Nor	Final Decision	Actual state
1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	'IR'	'IR'
51	1	1	1	1	0	0	0	0	0	**1**	0	**0**	0	0	0	0	'IR'	'IR'
65	1	1	1	1	**1**	0	0	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
72	1	1	1	1	0	0	**1**	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
73	1	1	1	1	0	0	**1**	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
75	1	1	1	1	0	0	**1**	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
76	1	1	1	1	0	0	**1**	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
86	1	1	1	1	**1**	0	0	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
88	1	1	1	1	**1**	0	0	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
89	1	1	1	1	**1**	0	0	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
91	1	1	1	1	**1**	0	0	**0**	0	0	0	0	0	0	0	0	'IR'	'IR'
164	0	1	1	1	0	0	0	0	0	**1**	0	**0**	0	0	0	0	'BL'	'BL'
183	0	0	0	0	**0**	1	1	**1**	0	0	0	0	0	0	0	0	'BL'	'BL'
193	0	0	1	0	**0**	1	1	**1**	0	0	0	0	0	0	0	0	'BL'	'BL'
195	0	0	**1**	**0**	1	1	1	1	0	0	0	0	0	0	0	0	'BL'	'BL'
208	**1**	0	0	**0**	**0**	1	1	**1**	0	0	0	0	0	0	0	0	'BL'	'BL'
242	0	0	0	0	**1**	0	0	**0**	1	1	1	1	0	0	0	0	'OR'	'OR'
325	0	0	**1**	**0**	0	0	0	0	1	1	1	1	0	0	0	0	'OR'	'OR'
500	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	'Nor'	'Nor'

When the fault type is predicted at the first stage of the algorithm, the severity of the fault is attempted to predict at the second stage as shown in Fig. 4. The test scores for the methods inside the models are illustrated in Figs. 9−11, and the prediction percentages of the scheme are summarized in Tables 5−7. Note that the figures represent the test scores for determining the fault level developed for IR fault case. The incipient, moderate and heavy fault models at the second stage are developed separately for each IR, BL and OR fault type. Note that only the data for corresponding fault type is feed to the models at this stage.

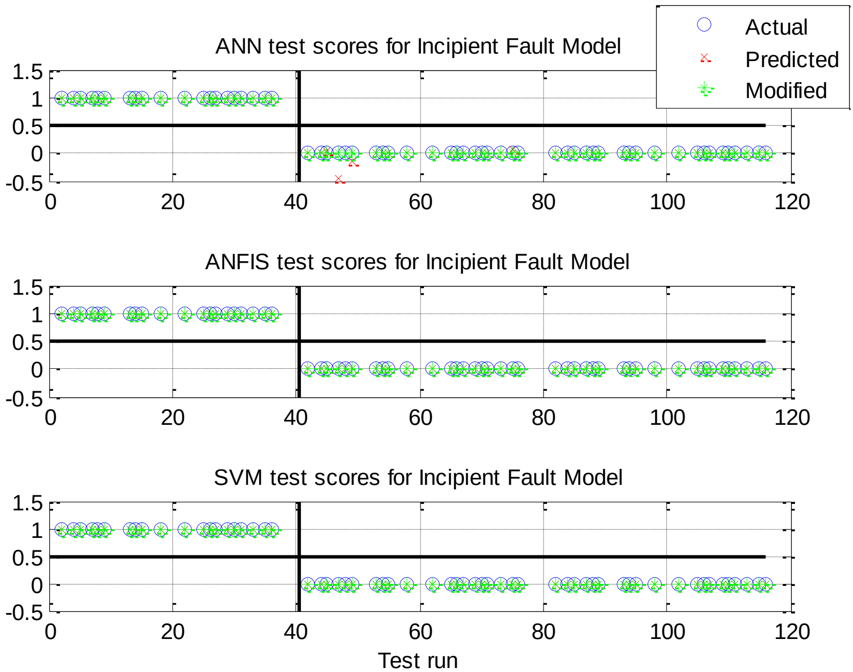

Figure 9. Test scores of Incipient model at the second stage developed for BL fault.

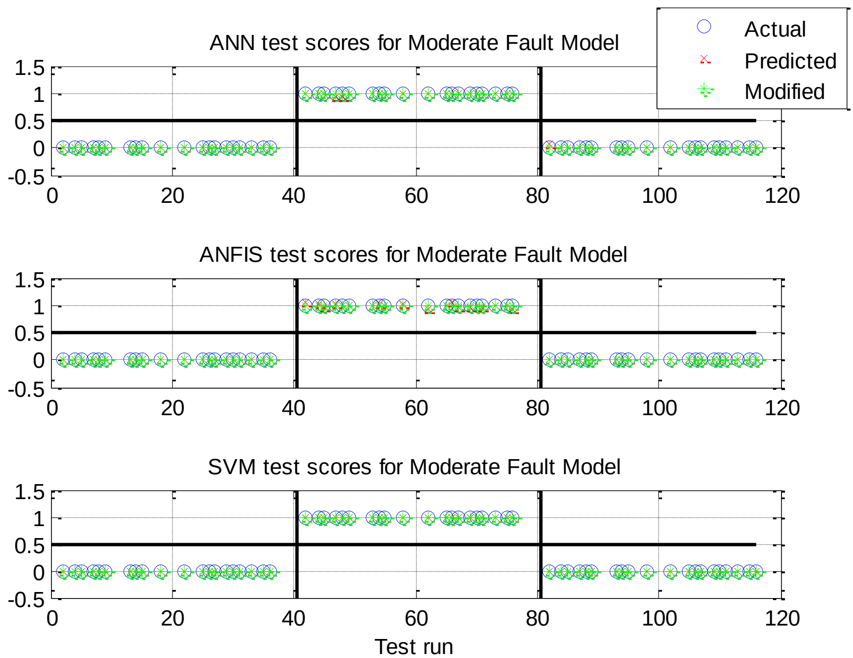

Figure 10. Test scores of Moderate fault model at the second stage developed for BL fault.

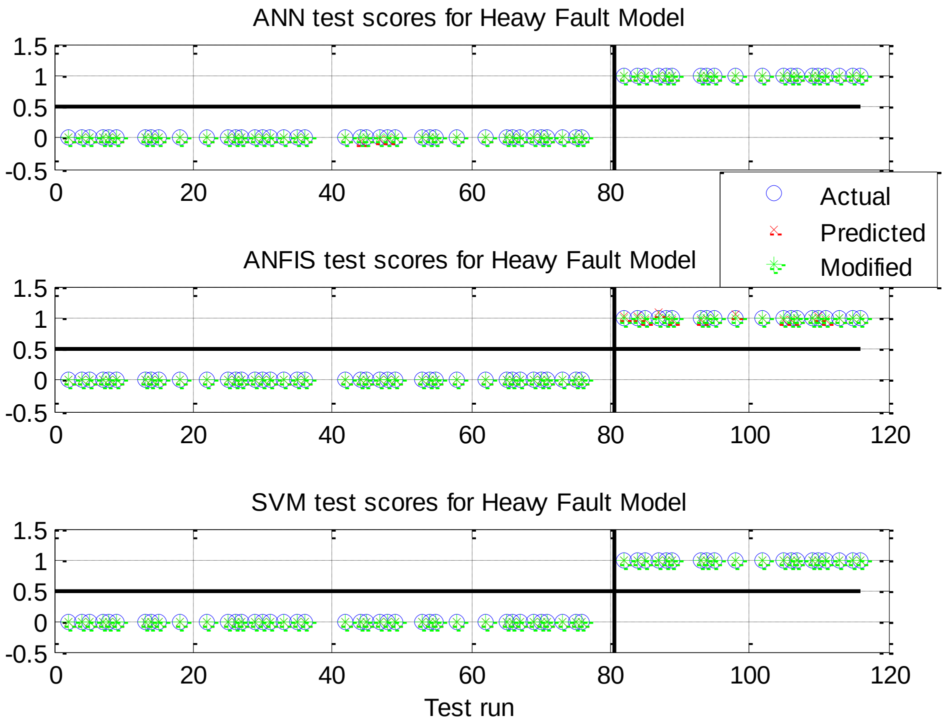

Figure 11. Test scores of Heavy fault model at the second stage developed for BL fault.

Similar to the first stage, each one of the intelligent methods predicts the severity of the fault at the models. Again, the majority of the decisions in one model, say incipient fault model, is the decision of the model. After generating own decision of each model, the final decision can be reached about the severity of fault. If more than one model generates 1, then it means that the models couldn't predict properly. Tables 5−7 present the performance of the intelligent methods for the IR, BL and the OR fault case, respectively. The tables provide the TN, TP and the total prediction percentages. It can be observed from the tables that, performances for each intelligent method are different.

Table 5. Test scores of intelligent methods for IR model

IR	**Methods**	**TN**	**TP**	**Total**
Incipient Fault Model	ANN	100	100	100
	ANFIS	100	100	100
	SVM	100	100	100
Moderate Fault Model	ANN	100	85	95
	ANFIS	100	100	100
	SVM	100	100	100
Heavy Fault Model	ANN	100	100	100
	ANFIS	100	100	100
	SVM	100	100	100

Table 6. Test scores of intelligent methods for BL model

BL	**Methods**	**TN**	**TP**	**Total**
Incipient Fault Model	ANN	97.5	100	98.33
	ANFIS	100	100	100
	SVM	100	100	100
Moderate Fault Model	ANN	100	80	93.33
	ANFIS	100	100	100
	SVM	100	100	100
Heavy Fault Model	ANN	90	100	93.33
	ANFIS	100	100	100
	SVM	100	100	100

Table 7. Test scores of intelligent methods for OR model

OR	**Methods**	**TN**	**TP**	**Total**
Incipient Fault Model	ANN	100	90	96.67
	ANFIS	100	100	100
	SVM	100	100	100
Moderate Fault Model	ANN	100	95	98.33
	ANFIS	100	100	100
	SVM	100	100	100
Heavy Fault Model	ANN	100	100	100
	ANFIS	100	100	100
	SVM	100	100	100

When the decision of each method is combined based on majority gate operation, the fault severity of each feature set is predicted perfectly. As an example, Table 8 is composed of the outcomes of each model that was run for BL (Ball Fault) data set. This table presents the usefulness of the proposed algorithm using some of the prediction cases. At the 1st, 2nd and 13th lines, all the intelligent methods at each model predict the actual status of the fault severity accurately so that final decision of the algorithm coincides the actual states. At the other lines of the table, some methods do not predict the fault severity properly as happened in the 3rd line where ANN method at incipient fault model predicts the fault severity rather than incipient fault. The misclassifications (wrong predictions) were shown with bold number, but fortunately the other two methods predict properly, and two of the methods, i.e. majority of the methods, have correct prediction, the combined decision algorithm determines the actual fault severity without any misclassification.

Table 8. The results of the second stage for determining the fault level of BL model

'No'	'Data No'	'ANN_Incip'	'ANFIS_Incip'	'SVM_Incip'	'Decision_Incip'	'ANN_Moder'	'ANFIS_Moder'	'SVM_Moder'	'Decision_Moder'	'ANN_Heavy'	'ANFIS_Heavy'	'SVM_Heavy'	'Decision_021'	'Final_Decision'	'Actual state'
1	2	1	1	1	1	0	0	0	0	0	0	0	0	Incip	Incip
2	4	1	1	1	1	0	0	0	0	0	0	0	0	Incip	Incip
3	8	**0**	1	1	**1**	0	0	0	0	0	0	0	0	Incip	Incip
4	44	0	0	0	0	**0**	1	1	**1**	0	0	0	0	Moder	Moder
5	48	0	0	0	0	**0**	1	1	**1**	0	0	0	0	Moder	Moder
6	49	0	0	0	0	**0**	1	1	**1**	0	0	0	0	Moder	Moder
7	54	**1**	0	0	**0**	1	1	1	1	0	0	0	0	Moder	Moder
8	58	0	0	0	0	**0**	1	1	**1**	0	0	0	0	Moder	Moder
9	65	**1**	0	0	**0**	1	1	1	1	0	0	0	0	Moder	Moder
10	66	0	0	0	0	**0**	1	1	**1**	0	0	0	0	Moder	Moder
11	82	0	0	0	0	0	0	0	0	**0**	1	1	**1**	Heavy	Heavy
12	87	**1**	0	0	**0**	0	0	0	0	**0**	1	1	**1**	Heavy	Heavy
13	116	0	0	0	0	0	0	0	0	1	1	1	1	Heavy	Heavy

Finally, Table 9 presents a summary for the overall performances of the proposed combined decision algorithm with two stages. Remember that the first stage determines the fault type and second stage is used to predict the severity of fault for the corresponding data. According to the results presented at Table 9, it can be concluded that the proposed combined decision algorithm is an effective tool for detecting the type of a bearing fault and diagnosing its severity. On the other hand, ANFIS has perfect performance except the first stage that is used to determine the fault type of bearing. It can be concluded that ANFIS based decision algorithm outperforms the ANN and SVM. SVM also shows a satisfactory performance in this study. The prediction performances for ANN is the worst compared to other intelligent methods. Its performance can be modified by changing the network structure such as number of hidden layers and neurons. But it can sometimes predict the fault type more accurately than ANFIS at some cases as can be seen from the 2nd and 12th line at Table 4. In these cases, when the ANFIS method is not able to predict the fault type, ANN method has the correct answer. Therefore, a combined decision algorithm that uses the ability of each intelligent method is proposed in this paper, and the algorithm with two stages is an effective means for detecting and diagnosing bearing faults.

Table 9. The overall performances of all models.

	ANN	ANFIS	SVM	Combined model
First stage	96	99.2	97.2	100
Fault IR	95	100	100	100
Fault BL	98.33	100	100	100
Fault OR	95	100	100	100

6. CONCLUSION

There are many research studies considering CWRU bearing data set for fault classification techniques with different feature extraction schemes in the literature. Most of the researches employ intelligent techniques to obtain a better classification performance. ANFIS and SVM perform with higher accuracy in classification than the other methods including ANN, as was the case in this study. Besides, selection of features and/or feature extraction scheme is an important issue that affects the performance of the applied techniques. The feature sets are composed of either statistical characteristic in time domain or features extracted in frequency domain; or features extracted in both time and frequency domain. A combined decision algorithm is developed that employ three intelligent methods, namely ANN, ANFIS and SVM based on the comparatively easy and cheap feature set composed of nine statistical variables and 10 linear prediction coefficients of the time domain vibration signals. The final decision at each model in the algorithm is made according to the logical majority gate, i.e., if two out of three methods lead the same result for a given feature set input, then the decision is determined according to those outputs. Experimental results revealed a 100% success rate for the proposed algorithm whereas the ANN, ANFIS and SVM based methods were not as effective when they were used alone.

REFERENCES

[1] Liang M. and Bozchalooi I.S. (2010) An energy operator approach to joint application of amplitude and frequency-demodulations for bearing fault detection. *Mech Syst Signal Process*, 24(5), 1473–1494.

[2] Yang H, Mathew J and Ma L. (2005) Fault diagnosis of rolling element bearings using basis pursuit. *Mechanical Systems and Signal Processing*, 19(2), 341–356.

[3] Janjarasjitt S, Ocak H and Loparo K.A. (2008) Bearing condition diagnosis and prognosis using applied nonlinear dynamical analysis of machine vibration signal. *J Sound Vib.*, 317(1–2), 112–126.

[4] Ertunc H.M., Ocak H and Aliustaoglu C. (2013) ANN- and ANFIS-based multi-staged decision algorithm for the detection and diagnosis of bearing faults. *Neural Computing & Applications*, 435–446.

[5] Ocak H, Loparo K.A. and Discenzo F.M. (2007) Online tracking of bearing wear using wavelet packet decomposition and probabilistic modeling: A method for bearing prognostics. *Journal of Sound and Vibration*, 302, 951–961.

[6] Yu J. (2011) Bearing performance degradation assessment using locality preserving projections and Gaussian mixture models. *Mechanical Systems and Signal Processing*, 25(7), 2573–88.

[7] Cornell E and Owen E. (1982) Improved motors for utility applications, 2: 6759687.

[8] Konar P and Chattopadhyay P. (2011) Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs). *Applied Soft Computing*, 11(6): 4203–4211.

[9] McFadden P.D. and Smith J.D. (1984) Model for the vibration produced by a single point defect in a rolling element bearing. *J Sound and Vibration*, 96(1):69–82.

[10] McFadden P.D. and Smith J.D. (1984) Vibration monitoring of rolling element bearings by the high-frequency resonance technique - a review. *Tribol Int*. 17(1):3–10.

[11] McFadden P.D. and Smith J.D. (1985) The vibration produced by multiple point defects in a rolling element bearing. *J Sound Vib*. 98(2), 263–273.

[12] Ocak H. and Loparo K.A. (2004) Estimation of the running speed and bearing defect frequencies of an induction motor from vibration data. *Mechanical Systems and Signal Processing*, 18(3), 515–533.

[13] Ertunç H.M., Ocak H, Merdoğlu M. and Bayram S. (2011) Vibration analyses based

localized bearing fault diagnosis under different load. *12th International Workshop on Research and Education in Mechatronics*. 201–208.

[14] Shao Y. and Nezu K. (2005) Design of mixture de-noising for detecting faulty bearing signals. *J Sound Vib*. 282(3–5), 899–917.

[15] Williams T., Ribadeneria X., Billington S. and Kurfess T. (2001) Rolling Element Bearing Diagnostics in Run-To-Failure Lifetime Testing. *Mech Syst Signal Process.* 15(5), 979–993.

[16] Li B., Chow M.Y., Tipsuwan Y. and Hung J.C. (2000) Neural-network-based motor rolling bearing fault diagnosis. *IEEE Trans Ind Electron.* 47(5), 1060–1069.

[17] Kowalski C.T and Orlowska-Kowalska T.(2003) Neural networks application for induction motor faults diagnosis. *Math Comput Simul.* 63(3–5), 435–448.

[18] Zhang L., Jack L.B. and Nandi A.K. (2005) Fault detection using genetic programming. *Mech Syst Signal Process.* 19(2), 271–289.

[19] Saimurugan M., Ramachandran K.I., Sugumaran V. and Sakthivel N.R. (2011) Multi component fault diagnosis of rotational mechanical system based on decision tree and support vector machine. *Expert Syst Appl*. 38(4), 3819–3826.

[20] Randall R.B. and Antoni J. (2011) Rolling element bearing diagnostics-A tutorial. *Mech Syst Signal Process.* 25(2), 485–520.

[21] Lei Y., He Z. and Zi Y. (2008) A new approach to intelligent fault diagnosis of rotating machinery. *Expert Syst Appl.* 35(4), 1593-1600.

[22] Widodo A. and Yang B.S. (2007) Support vector machine in machine condition monitoring and fault diagnosis. *Mech Syst Signal Process.* 21(6), 2560–2574.

[23] Yang J., Zhang Y, and Zhu Y. (2007) Intelligent fault diagnosis of rolling element bearing based on SVMs and fractal dimension. *Mech Syst Signal Process.*, 21(5), 2012–2024.

[24] Hu Q., He Z., Zhang Z., Zi Y. (2007) Fault diagnosis of rotating machinery based on improved wavelet package transform and SVMs ensemble. *Mech Syst Signal Process.* 21(2): 688–705.

[25] Li M., Xu J., Yang J., Yang D. and Wang D. (2009) Multiple manifolds analysis and its application to fault diagnosis. *Mech Syst Signal Process.*, 23(8), 2500–2509.

[26] X.Chen, J. Zhou, J. Xiao, X.Zhang, H Xiao, W. Zhu, W. Fu. (2014) Fault diagnosis based on feature vector and probability neural network for rolling element bearings. *Applied Mathematics and Computation*, 247: 835-847.

[27] shttp://csegroups.case.edu/bearingdatacenter