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THE IMPLEMENTATION OF ARTIFICIAL NEURAL NETWORKS IN DESIGNING INTELLIGENT DIAGNOSIS SYSTEMS FOR CENTRIFUGAL MACHINES USING VIBRATION SIGNAL

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Abstract
It is important to maintain every machine affecting the process of making sugar to ensure excellent product quality with minimal losses and to accelerate productivity and profitability targets. The centrifuges are widely used in industry today with some being very difficult and critical for surgery, and the collapse of the engine has the ability to cause expensive damage. One of these is the centrifugal machines, and they are expected to be efficient to produce high-quality sugar. Meanwhile, an efficient diagnostic tool to predict the correct time for centrifugal repair is vibration signal analysis namely by attaching the accelerometer sensor to the location of the centrifugal bearing to produce vibration data that is ready to be analyzed. Still, the process requires sufficient insight and experience. The manual method usually used is complicated and requires a lot of time to obtain results of a centrifugal diagnosis. Therefore, this study was conducted to design an intelligent system to diagnose centrifugal vibrations using Artificial Neural Networks (ANN). The situation is involved in applying and training the concept of vibration analysis from spectrum data to ANN to produce diagnostic results according to the spectrum diagnosis reference. The results obtained were quite good with the largest cross-entropy value of 10.67 having 0% error value with the largest Mean Square Error value being 0.0023 while the smallest regression was 0.993. The test conducted on nine new spectrums produced eight true predictions and one false. The system can provide fairly accurate results in a short time. Classification quality improvement can be made by adding training data.

Keywords:
Artificial Neural Network;
Centrifugal;
Sugar industry;
Vibration analysis;

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INTRODUCTION

It is important to maintain every machine affecting the process of making sugar to ensure superior product quality with minimal losses and to accelerate productivity and profitability targets. The goal of all sugar mills is to have a product with high-quality standards and good results, and one of the machines used in ensuring this is centrifugal, which is shown in Figure 1.

Conical continuous centrifuges complete the step of separating the remaining sugar from the process. The Centrifuges operate at a single speed of around 2000 RPM. The material enters the conical centrifugal base through a pipe which passes through the centrifugal center from above. Around the pipe is a steam jacket, which increases the temperature, thereby reducing viscosity to aid cleaning. The material flows into a centrifuge in the shape of a cone with the molasses continuously extracted as it moves. About two thirds of the centrifuge receive the clean sugar product before final drying the remaining third from the centrifuge. The solid is discharged to the centrifugal lip into the solids discharge chamber then falls into the solids processing system. The centrifugal involves separating crystals in massecuite from molasses using centrifugal force after which the raw sugar is sent to the drying or refining unit depending on the type of product and the desired packing section [1]. There is, however, the need for predictive maintenance of the centrifuges using reliable methods to ensure their continuous and effective functioning, especially due to their role in producing sugar with good quality and minimal losses [2].

Several rotating machines such as centrifuges are widely used in industry today with some being very difficult and critical for surgery, and the collapse of the engine can cause expensive damage. There is, therefore, a need for an efficient diagnosis system to predict conditions and consistent engine repair times and this means it is very suitable to emulate effective and efficient condition monitoring and fault diagnosis systems in the industry. Meanwhile, the method mostly used for fault detection in rotating machines is vibration analysis [3, 4, 5].

The condition is very important for the health of the engine and, even in the best operating conditions, there are vibrations due to minor defects with each machine having a level considered to be normal. There are times this level increases or becomes excessive probably due to some mechanical issues such as imbalance, misalignment, gears or wear pads, slack, etc. which are measured using a sensor such as proximity sensor, speed transducer, and accelerometer. Meanwhile, an accelerometer is widely used for vibration analysis while the fault diagnosis on a spinning machine is usually conducted through stages including data acquisition, feature extraction, and error detection. Moreover, noise signals are often contained in the vibration signals collected, and these are not suitable for fault diagnosis. It is, however, impossible to detect vibration or signature features without the help of certain techniques such as feature extraction which has the ability to determine certain components in a signal to help in detecting machine errors [6]. Other methods, according to Yang [7] and Bruand [8], include classical non-parametric spectral analysis, principal component analysis, joint time-frequency analysis, and discrete wavelet transforms.

Figure 1. Sugar Centrifugal

The studies by Acquarelli [9] showed the development of new scientific and technical solutions, especially based on the classification of neural networks for vibrational measuring spectrums, promises to create intelligent systems to diagnose centrifugal states [10]. There is, however, the need for diagnostic information on the technical condition of the system to resolve the problem. The situation is usually obtained based on certain measurement parameters monitored from systems characterizing the conditions, for example, vibration amplitude, vibration acceleration, etc. which are compared with the permitted values. This monitoring and diagnostic method make it possible to detect sudden failures in equipment operation effectively. It is possible to determine centrifugal conditions and damage using vibration data in the form of an overall vibration value and vibration spectrum.

The condition is involved determining the requirements by comparing the overall vibration with the ISO standards while the damage location was detected using the spectrum or frequency domain [11].

It is, however, possible for a system being monitored to have the parameters within their tolerance field but with the tendency to drift to the limits due to several reasons such as mechanical wear or ageing, gradual failure of equipment and electronic components, etc. These problems make the controlled parameters exceed seemingly unexpected tolerance limits leading to the failure of the equipment [12]. Meanwhile, the damages caused are usually gradual and not detectable by measuring the controlled parameters directly as long as they are within their tolerance limits. This means there is a need to develop necessary methods to detect these gradual damages due to their significantly higher rate. It is possible to solve this problem by obtaining diagnostic information by analyzing the output signal from the system under study. This approach allows diagnosis without additional information on the status of individual elements in the system and the study of intermediary signals. The successful implementation of the method, therefore, depends on the choice of a mathematical model for the system being diagnosed and it's level of adequacy, which ultimately determines the reliability of the diagnosis.

Moreover, the information on the technical status of a test input signal sent to the system for diagnosis is contained in its output signal [13] [14]. It is, however, very often possible for the object being diagnosed to be the source of diagnostic signals. For example, it possible to use the characteristics of vibration signals to assess the technical conditions of a centrifugal machine [15, 16, 17].

Artificial Neural Network (ANN) has received great attention in recent times due to its strong capability in speech recognition, image processing, natural language processing, etc. The performance of its models is, however, highly dependent on the quantity and quality of data, computational power, and algorithm efficiency [18] [19]. Moreover, the traditional ANN model trains by iteratively aligning all weights and minimizing the loss function which is defined as the difference between the model predictions and real observations whose derivatives are propagated back to each layer to guide the adjustment of parameters [20] [21]. ANN has been used by several researchers to identify the location and severity of damage to different types of input and output variables due to its ability to provide efficient features for pattern recognition [12, 22, 23]. Several studies have also concluded that it has the capability to provide correct identification of damage, especially when the engine damage and related changes in vibration properties are numerically and Fourier simulated [24] [25].

Many methods can be used in the classification of machine failure based on the vibration spectrum. However, most methods cannot perform classification system updates by themselves. ANN is a classification method that can update the level of classification quality. In addition, by utilizing existing data and supported by programming packages, ANN is very easy to make with a fairly fast time and accurate results. The ANN approach is very suitable for application in recognition of vibrational spectrum patterns. The backpropagation architecture was chosen because it can simultaneously display various types of centrifugal damage as output so that alternative identifications can be seen in the form of correlation factors. Other architectures such as Hebb, heteroassociative, and autoassociative only specify output that states whether a pattern being tested is a network-stored class pattern or not. Therefore, ANN backpropagation was applied to diagnose centrifugal vibrations in this study due to its pattern recognition ability as a solution to the problem previously mentioned.

METHOD

This research was divided into several stages and these generally include preparing centrifugal data, measuring, designing ANN according to the principles of vibration analysis, training the network, and testing the system developed. Vibration data is obtained from centrifugal measurements using a vibration measurement tool called VIBXpert, which is shown in Figure 2. The centrifugal has a power of 90 kW with a motor rotating speed of 1500 RPM. The measurements are made using an accelerometer type sensor that is attached to the location of the centrifugal bearing in the radial and vertical directions. Data transfer was carried out using a companion software tool, namely Omnitrend and then was processed using MATLAB. Moreover, the data prepared in the form of vibration and spectrum were used as input and for training while creating the system.

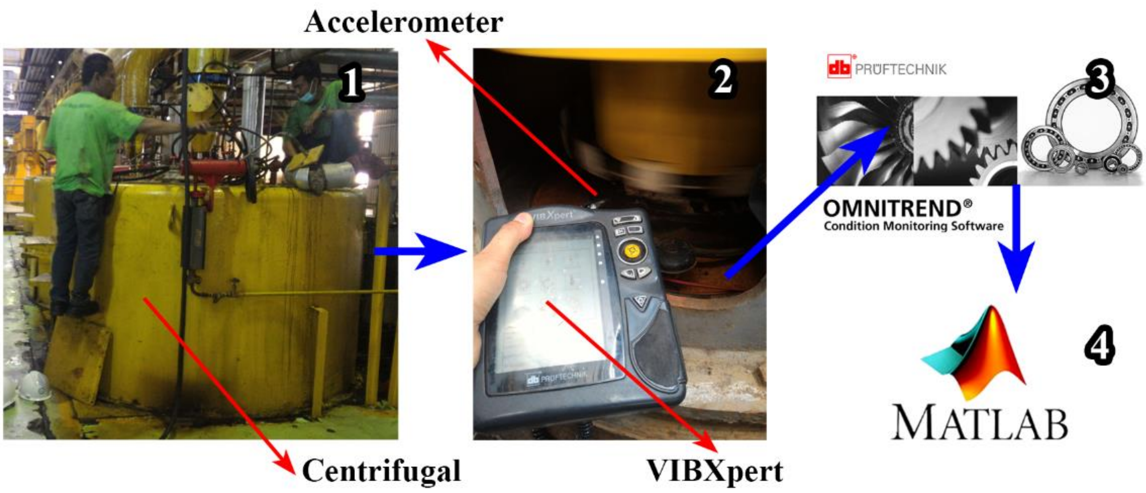

Figure 2. Data Collection and Analysis

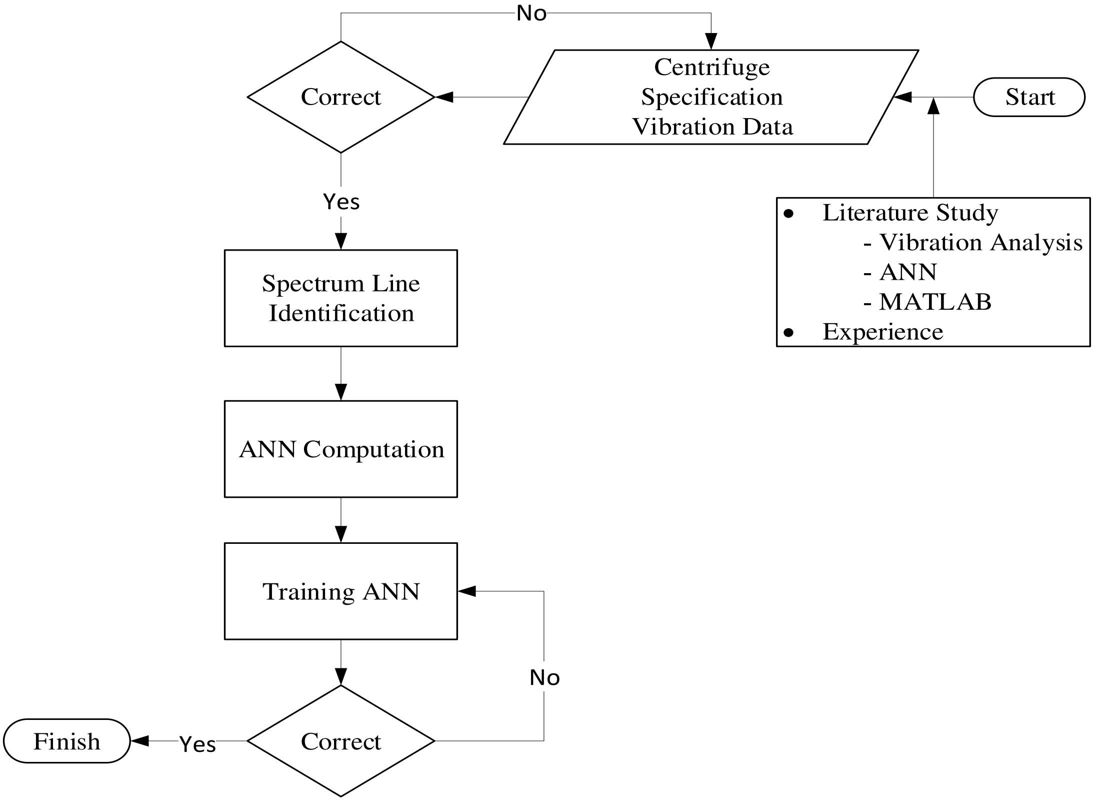

Figure 3. Research Flowchart

The initial step for the system algorithm is identifying the frequency of each centrifugal machine component to be used as input and this was followed by outlining the components of the vibrational spectrum to obtain output data which were to be read by the ANN as input. One of the ANN training algorithms widely used in pattern recognition field is backpropagation, especially in multilayer feed-forward ANN which is composed of several layers and signals transmitted from the direction of the input to the output. The broad outline of the research is, however, presented in Figure 3.

In general, a network like this consists of a number of neuron units as the input layer, one or more layers of hidden computation neuron nodes, and a layer of output computational neuron nodes. The input signal is propagated forward, layer by layer. This type of network is the result of a generalization of the one-layer perceptron architecture, so it is commonly referred to as a multilayer perceptron.

Error backpropagation is a multilayer perceptron algorithm that uses the principle of supervised learning. Backpropagation occurs after the network has produced an output containing an error. In this phase, all synaptic weights in the network will be adjusted to correct or minimize errors that occur. For network training, the forward and backpropagation phase pairs are repeated for a set of training data, then repeated for some epochs until the error reaches a certain tolerance threshold or zero.

There is also the need for spectrum data in addition to the overall vibration value in determining centrifugal conditions. The spectrum is the frequency domain obtained from the Fast Fourier Transform method which is required to locate the cause of the magnitude of vibration and also presented in the form of an amplitude and frequency graph as shown in Figure 4. It, however, has a total frequency of 400 Hz. The centrifugal vibration spectrum has 1600 frequencies and amplitudes in the form of text used as input data in ANN and the details of one of the original data are shown in Table 1. The capacity of the spectrum as the training data is also limited. Therefore, it is important to make the input data simpler by displaying the components of the main centrifugal frequencies through the extraction of the frequency and amplitude values based on calculations.

Table 1. Details of the Vibration Spectrum

Path of Location : PT. Berkah Manis Makmur 09-11-2019\Continuous Centrifugal (Before)\4H\1H.FFT
Number of Meas. Values : 1600
Meas. Task : Machine
Meas. Type : Spectrum
Unit: mm/s (0P)

Date	Time	f (Hz)	Value
11/9/2019	12:25:18 AM	0	0.56
11/9/2019	12:25:18 AM	0.25	0.62
11/9/2019	12:25:18 AM	0.5	0.51
11/9/2019	12:25:18 AM	0.75	0.08
11/9/2019	12:25:18 AM	1	0.11
11/9/2019	12:25:18 AM	1.25	0.16
11/9/2019	12:25:18 AM	1.5	0.07
11/9/2019	12:25:18 AM	1.75	0.06
11/9/2019	12:25:18 AM	2	0.08
11/9/2019	12:25:18 AM	2.25	0.13
11/9/2019	12:25:18 AM	2.5	0.09
11/9/2019	12:25:18 AM	2.75	0.08
11/9/2019	12:25:18 AM	3	0.08
11/9/2019	12:25:18 AM	3.25	0.09
11/9/2019	12:25:18 AM	3.5	0.07
11/9/2019	12:25:18 AM	3.75	0.07
11/9/2019	12:25:18 AM	4	0.08
11/9/2019	12:25:18 AM	4.25	0.09
11/9/2019	12:25:18 AM	4.5	0.08
⋮	⋮	⋮	⋮
11/9/2019	12:25:18 AM	400	0.01

Table 2. Details of the Vibration Spectrum

No.	Component/Attribute		Frequency 1 (Hz)	Frequency 2 (Hz)
1	0.5X		13	15
2	1X		25	30
3	2X		50	60
4	3X		75	90
5	4X		100	120
6	5X		125	150
7	**Bearing**	BPFI	23.5	268.25
		BPFO	176.75	211.75
		FTF	11	13.25
		BSF	209.75	251.5
8	**Pulley**		12	-

The components are detailed in Table 2 and two frequencies were identified with Frequency 1 referring to the motor RPM while Frequency 2 focuses on the centrifugal bowl rotation. This round was sourced from the motor after it has passed through pulley transmission.

The input and target data determined were later used to train the system in order to achieve the desired output. Meanwhile, five types of centrifugal damage were classified and they include unbalance, misalignment, looseness, bearing damage, and pulley damages each with 50 input data consisting of 8 attributes as shown in Table 3.

There is also the need to prepare target data in addition to the input data and these were observed to be consisting of numbers 1 and 0 with the same 50 units as the training data but each consisting of 5 attributes. The target weights were, however, found to be 10 for each type of damage as presented in Table 4.

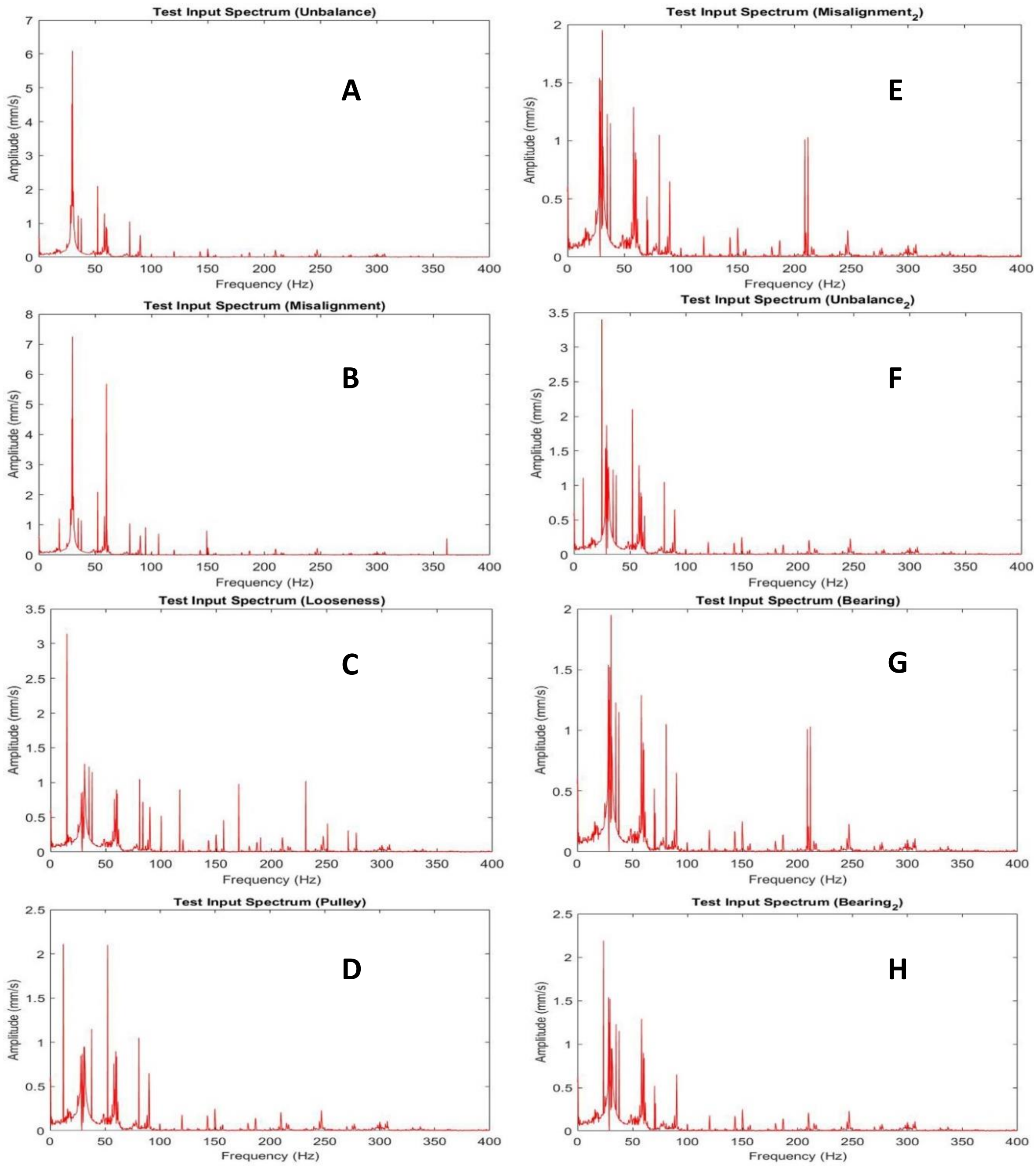

Figure 4. Testing Spectrum

Table 3. Training Data Input

Atribute	0.5X	1X	2X	3X	4X	5X	Pulley	Bearing
Unbalance	0.69	4.25	0.53	0.83	0.6	0.34	0.3	0.45
	0.42	3.75	0.56	0.74	0.42	0.43	0.12	0.02
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.39	8.74	0.32	0.81	0.79	0.85	0.51	0.64
Misalignment	0.95	3.56	3.65	1.24	0.63	0.36	1	0.22
	0.65	6.74	4.58	0.08	0.03	0.42	0.18	0.73
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.41	9.73	8.56	0.68	0.99	0.77	0.34	0.66
Looseness	4.34	0.3	0.68	0.53	0.41	0.6	0.75	0.58
	5.97	0.58	0.51	0.08	0.72	1	0.35	0.97
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	3.15	3.17	0.71	0.62	0.34	0.94	0.12	0.73
Bearing	0.65	0.83	0.4	0.75	0.84	0.32	0.55	3.74
	0.55	0.33	0.62	0.36	0.76	0.41	0.49	4.31
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.88	0.09	0.93	0.4	0.05	0.34	0.74	4.25
Pulley	0.54	0.69	0.89	0.05	0.3	0.05	3.65	0.72
	0.72	0.88	0.58	0.07	0.92	0.8	4.58	0.54
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.99	0.86	0.39	0.45	0.25	0.78	8.56	0.91

Table 4. Target

Unbalance	1	0	0	0	0
	1	0	0	0	0
	⋮	⋮	⋮	⋮	⋮
	1	0	0	0	0
Misalignment	0	1	0	0	0
	0	1	0	0	0
	⋮	⋮	⋮	⋮	⋮
	0	1	0	0	0
Looseness	0	0	1	0	0
	0	0	1	0	0
	⋮	⋮	⋮	⋮	⋮
	0	0	1	0	0
Bearing	0	0	0	1	0
	0	0	0	1	0
	⋮	⋮	⋮	⋮	⋮
	0	0	0	1	0
Pulley	0	0	0	0	1
	0	0	0	0	1
	⋮	⋮	⋮	⋮	⋮
	0	0	0	0	1

In pattern recognition problems, ANN classifies inputs into the target categories with the location of centrifugal damage recognized based on the spectrum analysis contained in Tables 3 and Table 4. Moreover, the Neural Pattern Recognition application helped in selecting data, creating and training networks, and evaluating its performance using cross-entropy and confusion matrices.

A two-layer forward feed network as shown in Figure 5 with sigmoid hidden and softmax output neurons (patternnet) randomly classified the vectors 16 neurons found to be located in the hidden layer aster which the network was trained with backpropagation gradient conjugates (scainscg). Moreover, the number of neurons was determined after repeated trials to obtain optimal outputs.

The number of validation and test data was also determined before the ANN was trained to be 15% for each sample, while 70% was used as training samples. Moreover, the training samples were presented to adjust the network according to the samples' mistakes while the validation samples were used to measure network generalizations and also to stop the training when the generalizations stop improving. However, there was no effect of the test sample on the training and this means it provided an independent measure of the network performance during and after training.

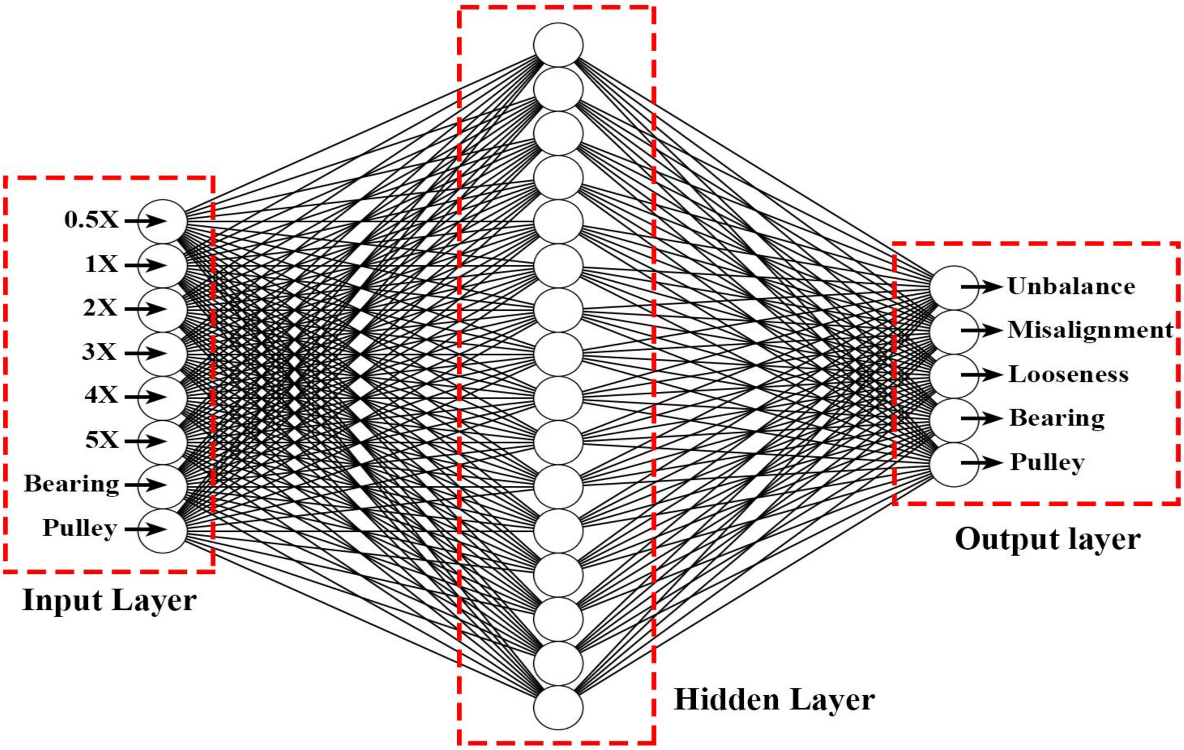

Figure 5. ANN Architecture

RESULTS AND DISCUSSION

The neural networks were trained using backpropagation gradient conjugated scales (trainscg) and the training was observed to have automatically stopped when generalizations stop improving as shown by the increase in cross-entropy errors from the validation sample presented in Figure 6.

The pattern recognition-based ANN was able to minimize the cross-entropy result and placed it in a good classification due to the fact that a lower value is considered better. Moreover, the 0 value means the absence of errors while the % Error value indicates the incorrect classification of the sample fraction such that 0 means there is no misclassification while 100 represents maximum misclassification. Moreover, different results were produced from the training conducted at different times due to the variations in the initial conditions and sampling.

The histogram of the error between the targeted and predicted values after the feed-forward neural network has been trained is presented in Figure 7. It is important to note that there is a possibility of negative results because the error values are meant to show the difference between the predicted and targeted values. The total errors were divided into 20 bins as observed on the number of vertical bars located on the X-axis while the number of samples from the dataset located in a particular bin is presented on The Y-axis. Moreover, a bin with an error value of -0.00234 is located at the middle of the plot, bin height for the training dataset is below 60 while validation and test datasets are between 50 and 70.

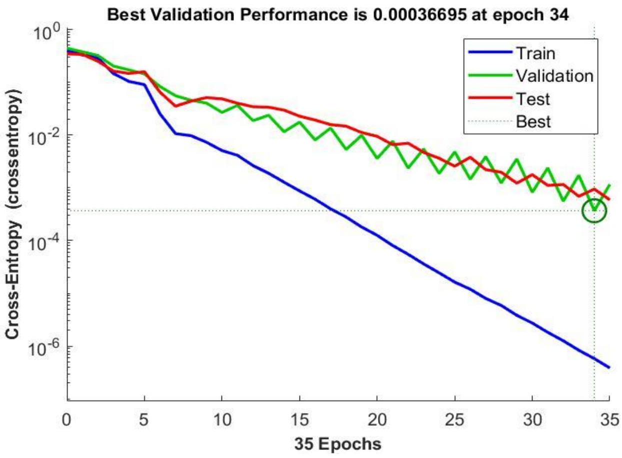

Figure 6. Cross-Entropy

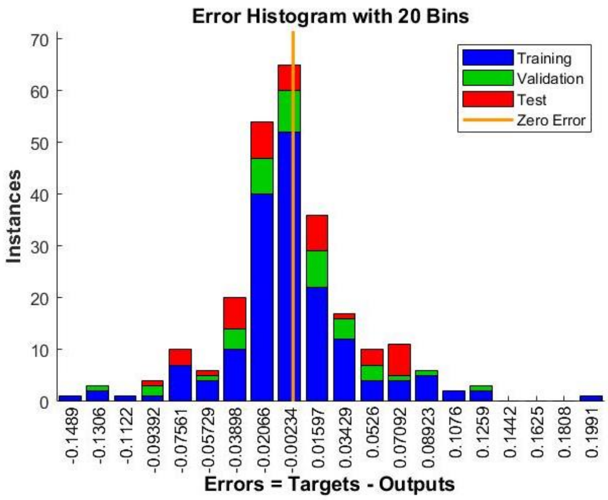

Figure 7. Error Histogram

This, therefore, means the errors for several samples from different datasets are within this range. Meanwhile, the zero-error line corresponds to the zero-error value on the error or X-axis and the zero-error point is observed to above the center bin with -0.00234. The confusion matrix presented in Figure 8 shows the accuracy of the trained ANN, while the 5 × 5 matrix corresponds to the number of centrifugal damage types used as targets. It also lists the correct classifications as 'true positive' or 'true negative' while the incorrect classifications were labelled as 'positive false' or 'negative false', but all the sample data were correctly detected.

The ROC curves shown in Figure 9 are based on the values between the False Positive Rate and True Positive Rate obtained from the confusion matrix and the results showed the ANN system performance in classifying the targets was correct. This table serves to simplify the confusion matrix in determining the best threshold for a classification machine. The higher the True Positive Rate and the smaller the False Positive Rate, the threshold is better. Moreover, the regression graph in Figure 10 measures the correlation between the output and the target, and good results were obtained with all samples recorded to have values close to 1. Meanwhile, the comprehensive results of the ANN training are presented in Table 5.

The output data for the ANN after training presented in Table 6 shows the weight values are in accordance with the target data and all the samples were correctly classified. This was followed by a trial run using the new data and eight vibrational spectrums were produced as shown in Figure 4 and another trial was conducted to determine the ANN performance with the inclusion of the new vibration spectrums. The results shown in Table 7 indicate the ANN system detected seven centrifugal damage correctly with one spectrum predicted to be damaged due to the frequency of 1X components and bearings in the spectrum.

Figure 8. Confusion Matrix

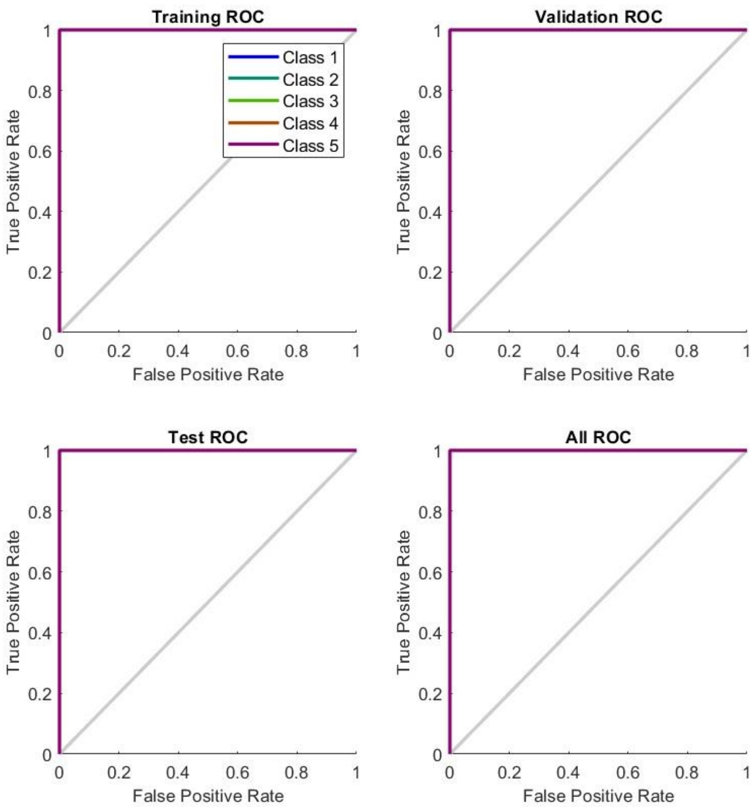

Figure 9. Receiver Operating Characteristic

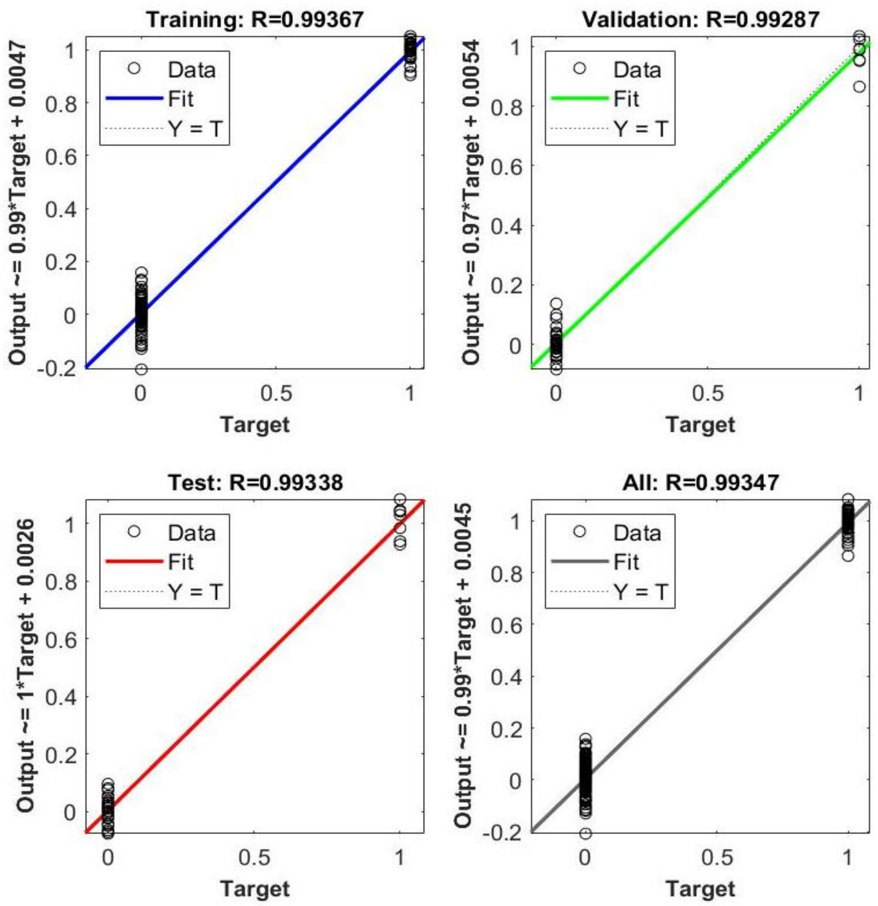

Figure 10. Regression

Table 5. ANN Training Results

Sample	Cross-Entropy	%Error	MSE	Regression
Training	3.796	0	0.0020	0.994
Validation	10.666	0	0.0023	0.993
Testing	10.63	0	0.0021	0.993

Table 6. ANN Output

Unbalance	1.00	0.02	-0.02	0.02	0.01
	1.01	0.02	-0.02	0.02	0.01
	⋮	⋮	⋮	⋮	⋮
	1.01	0.02	-0.01	0.01	-0.02
Misalignment	0.04	0.97	0.02	0.01	-0.05
	0.06	0.94	0.10	0.03	-0.10
	⋮	⋮	⋮	⋮	⋮
	0.00	1.02	0.06	0.01	-0.08
Looseness	0.07	0.01	0.94	0.02	0.00
	0.10	0.01	0.95	-0.01	-0.07
	⋮	⋮	⋮	⋮	⋮
	0.13	0.01	0.90	0.02	0.00
Bearing	0.01	-0.01	0.00	0.98	0.00
	0.00	-0.01	0.02	0.99	-0.01
	⋮	⋮	⋮	⋮	⋮
	-0.05	-0.02	0.07	1.03	0.02
Pulley	0.00	0.02	-0.01	0.00	1.02
	0.00	0.04	-0.05	-0.04	1.04
	⋮	⋮	⋮	⋮	⋮
	0.04	0.01	-0.06	0.00	1.05

Table 7. New Spectrum Testing Results

No.	Spectrum Input	Output	Target	Testing Result	Result
1.	A	0.9118 0.0263 0.0100 0.0263 0.0726	Unbalance	Unbalance	Correct
2.	B	0.0661 1.0108 0.0623 0.0109 -0.1327	Misalignment	Misalignment	Correct
3.	C	0.4349 0.0221 0.4624 0.0311 0.1006	Looseness	Looseness	Correct
4.	D	0.1752 0.0287 -0.0352 0.0081 0.8587	Pulley	Pulley	Correct
5.	E	0.3144 1.0144 -0.0544 0.0490 -0.3032	Misalignment	Misalignment	Correct
6.	F	0.9118 0.0263 0.0100 0.0263 0.0726	Unbalance	Unbalance	Correct
7.	G	0.6342 0.0179 0.0397 0.2141 0.1431	Bearing	Unbalance	Wrong
8.	H	0.1549 -0.0180 0.0502 0.8470 -0.0555	Bearing	Bearing	Correct

Meanwhile, the ANN did not recognize the spectrum pattern with more than one damage because the spectrum with conditions such as spectrum G is not provided in the training data.

CONCLUSION

ANN was successfully applied to diagnose the centrifugal vibrations by utilizing the spectrum data by extracting the spectrum into the main frequencies of the centrifugal components to produce eight attributes used as input data for the training process.

The length of time the vibration analysis process can be handled using this system. It only takes a few seconds for the system to produce fairly accurate results. The ANN training results were observed to be fairly good with the largest cross-entropy value of 10.67 having 0% Error value while the largest MSE value was 0.0023 and the smallest regression was 0.993. Moreover, the accuracy of selecting the appropriate type of neural network also affected the predicted results accuracy as observed in the eight centrifugal spectrums tested and seven spectrums successfully predicted correctly. It was impossible to predict the spectrum correctly due to the fact that it has more than one high amplitude in the main centrifugal frequency as well as due to the unavailability of spectrum data during the training process.

It is better to use a lot of training data in constructing ANN in order to produce accurate outputs and test values and the training needs to be repeated up to when the targeted results are achieved. It is, however, necessary to change the number of attributes to the overall vibration value (RMS), number of neurons, or modify the training data in case the target was not achieved. It is recommended that further research adds the number of attributes and target classification to the condition of the engine when it has good performance.

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