897. Artificial neural network based classification of faults in centrifugal water pump

Saeid Farokhzad[1], Hojjat Ahmadi[2], Ali Jaefari[3], Mohammad Reza Asadi Asad Abad[4], Mohammad Ranjbar Kohan[5]
[1, 2, 3]Department of Mechanical Engineering of Agricultural Machinery
Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran
[4, 5]Department of Mechanical Engineering, Buinzahra Branch, Islamic Azad University, Buinzahra, Iran
E-mail: [1]*Saeidfarokhzad@ut.ac.ir*, [2]*hjahmadi@ut.ac.ir*, [3]*jafarya@ut.ac.ir*, [4]*Asadi_reza2007@yahoo.com*, [5]*ranjbarkohan@gmail.com*

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Abstract. The detection and diagnosis of faults are of great practical significance for the safe operation of a plant. Early detection of fault can help avoid system shutdown, breakdown and even catastrophe involving human fatalities and material damage. This paper presents the design and development of ANN-based model for the fault detection of centrifugal water pump using a back-propagation learning algorithm and multi-layer perceptron neural network. The centrifugal pump conditions were considered to be healthy pump and faulty impeller and faulty seal and cavitation, which were four neurons of output layer with the aim of fault detection and identification. Features vector, which is one of the most significant parameters to design an appropriate neural network, was extracted from analysis of vibration signals in frequency domain by means of FFT method. The statistical features of vibration signals such as mean, standard deviation, variance, skewness and kurtosis were used as input to ANN. Different neural network structures are analyzed to determine the optimal neural network with regards to the number of hidden layers. The results indicate that the designed system is capable of classifying records with 100 % accuracy with one hidden layer of neurons in the neural network.

Keywords: centrifugal pump, fault diagnosis, condition monitoring, artificial neural network, back propagation, classification.

1. Introduction

Centrifugal pumps are one of the most common and most important machines in almost any production process. They play a significant role in industrial plants and need continuous monitoring to minimize loss of production [4]. They are the key elements in food industry, waste water treatment plants, agriculture, oil and gas industry, paper and pulp industry, etc. [10].

Centrifugal pumps are sensitive to:

(1) variations in liquid condition (i.e., viscosity, specific gravity, and temperature);

(2) suction variations, such as pressure and availability of a continuous volume of fluid;

(3) variations in demand.

Several reasons cause mechanical failures. Some are induced by cavitations, hydraulic instability, or other system-related problems. Others are the direct result of improper maintenance, maintenance-related problems, improper lubrication, misalignment, unbalance, seal leakage, bearing damages, wear in the pump housing [9]. Pumping costs within industry are enormous, with the potential for considerable financial savings through fault diagnosis and condition-based maintenance [4]. Therefore, faults on pumps need to be detected and located rapidly, classified correctly and cleared as fast as possible**.** Unexpected downtime due to machinery failure has become more costly than ever before. Therefore, condition monitoring is gaining importance in industry because of the need to increase machine availability and health trending, to warn of impending failure and or to shut down a machine in order to prevent further damage. It is required to detect, identify and then classify different kinds of failure modes that can occur within a machine system. Often several different kinds of sensors are employed at different positions to sense a variety of possible failure modes. Two basic approaches have been used: the use of a single feature to assess a very general indication of the existence of a fault without any indication of the nature of the fault and, alternatively, the use of more detailed frequency derived indicators [11].

Among the various methods for condition monitoring of rotating machinery, artificial neural networks (ANN) have become in the recent decades the outstanding method exploiting their non-linear pattern classification properties, offering advantages for automatic detection and identification of pump failure conditions, whereas they do not require an in-depth knowledge of the behavior of the system. Vibration signals which have been widely used in the condition monitoring and fault diagnosis systems of rotating machinery. They are often used for fault signals diagnosis in mechanical systems since them often carry dynamic information from mechanical elements. However for fault detection and identification issues, the frequency ranges of the vibration signals are often wide; and according to the Shannon's sampling theorem, a high sampling rate is required, and consequently, large-sized samples are needed for the pump fault detection purposes [5]. However, the human skills required to transform monitored data into maintenance information are often unavailable. ANNs are proposed for automation of this skill in the development of a pumping system decision support tool, the key requirement of which is accurate pump fault diagnosis [4]. Therefore due to existence of superfluous data and their large dimensionality, there is a requirement to preprocessing for extracting an appropriate and economized feature vector which is necessarily used to train a well-educated ANN [5].

Rajakarunakaran [6] used two different ANN techniques back propagation algorithm and adaptive resonance network for fault detection of a centrifugal pump. Alfayez and et al [1] discussed acoustic emission for detecting incipient cavitation and determining the best efficiency point (BEP) of a centrifugal pump based on net positive suction head (NPSH) and performance tests. However, this method using acoustic emission as a means of detecting cavitation is not useful in detecting other faults. Application of ANN to preprocess, compress and classify vibration spectrum for bearing faults have been demonstrated by Alguindigue [2].

Heydarbeygi and et al used ANN techniques back propagation algorithm and a multi-layer network for condition monitoring of massy Ferguson tractor gearbox [3]. Youshang [16] presented a method for classification of bearing faults by ANN that was fed from DWT preprocessed signals. More recently various researchers have applied ANN [4, 12, 15].

2. Experimental studies

In this research, the procedure consists of three stages, namely experimental setup for different faulty and faultless pump, preprocessing using FFT for feature extraction and design of an appropriate neural network. The main objective of the study is to determine whether the centrifugal pump is in good or faulty condition. If the pump is in faulty condition then the aim is to segregate the faults into impeller, seal and cavitation.

2.1. Experimental setup

This research experimentally presents a fault recognition and classification system for centrifugal water pump using a non-destructive method exploiting artificial neural networks (ANN). Vibration condition monitoring technique is used for diagnosis of centrifugal pump and presence of defect in system was known with variation in vibration values and acquaintance manner of any common faults of pump was considered from vibration spectra of each measurement points. The experimental setup to collect dataset consists of centrifugal water pump, an electrical motor, an accelerometer. The setup is shown in Fig. 1.

Fig. 1. Experimental setup

The electro motor is used to drive the pump. The flow at the inlet and the outlet of the pump can be adjusted using flow control valve. The valve at the inlet of the pump is used to create pressure drop between the suction and at the eye of the impeller to simulate cavitation. All vibration signals were collected from the experimental testing of centrifugal pump using the mono-axial accelerometer which was mounted on the pump inlet. For each configuration different fault conditions were tested that were impeller faulty, seal faulty, cavitation and one faultless condition. The signals from the accelerometer were recorded in a portable condition monitoring signal analyzer.

The frequency domain signal can be used to carry out fault diagnosis by analyzing vibration signals obtained from the experiment. We take a set of consecutive samples of the vibration signal at some time during a certain interval and determine with FFT the frequency spectrum of the signal at that particular time interval. By analyzing the frequency spectrum of the vibration signal for a short time interval at different moments, we can monitor the condition of the machine or its parts. The frequency spectrum during a certain time interval can be represented by a vector with components equal to the coefficients of the spectrum Features to apply as input to ANN were extracted from analysis of vibration signals in frequency domain by means of FFT method. The classified network outputs are healthy, impeller faulty, seal faulty and cavitation. In developing the ANN models, different ANN architectures, each having different numbers of neurons in hidden layer, were evaluated. The optimal model was selected after several evaluations based on minimizing of mean square error (MSE), correct classification rate (CCR) and coefficient of correlation (r).

2.2. Experimental procedure

The vibration signals are measured from the centrifugal pump working under normal condition at a constant rotation speed of 1450 rpm. Centrifugal pump specification is provided in Table 1.

Table 1. Centrifugal pump specification

Pump type	Capacity $\left(m^3/h\right)$	Head (m)	Impeller diameter (mm)	Speed (rpm)	Electromotor power (kW)
Centrifugal pump 40-250 (Ø220) 1450	18	15	220	1450	1.5

In the present study the following faults were examined (Figs. 2(a, b)):
(i) defect impeller;
(ii) defect seal (leakage);

(iii) cavitation.

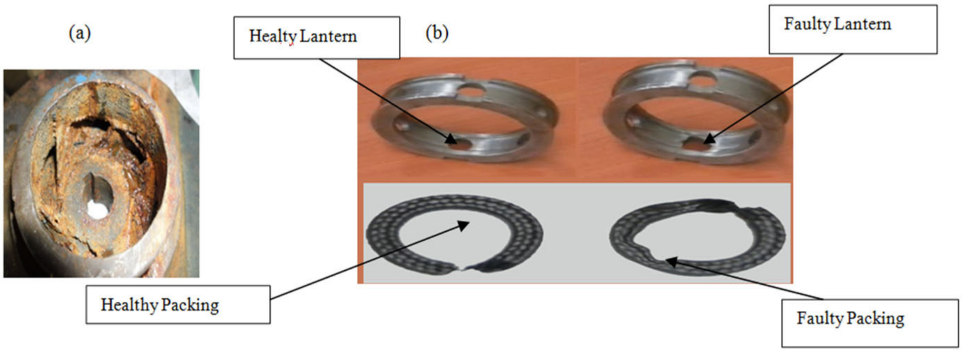

Fig. 2. (a) Faulty impeller, (b) healthy (left) and faulty (right) seal

2.2.1. Impeller faulty

In the study two impellers of diameter 220 mm made up of cast iron were used. One impeller was assumed to be free from defects. In the other impeller, a defect was created by removing a small portion of metal through a machining process.

2.2.2. Seal faulty

Pump users relied primarily on braided style packing to achieve a seal around the shaft. A series of pieces or ring were installed into the pump stuffing box and they were compressed tightly so that they created a difficult leak path for the liquid negotiate in order to leak to atmosphere. Braided packing style required varying amount of leakage for lubrication. If leakage was not permitted to occur the packing would literally burn up and often cause severe damage to the pump shaft. Lantern rings are widely used in order to keep packing lubricated, cool and flushed of abrasives and chemicals. The use of lantern rings greatly increases the life of compression packing, resulting in less maintenance and downtime over the life of the equipment. A seal may fail or leak when the pump runs under dry condition over a period of time or use of heavy oil or lubricant on the seal during installation or extreme. Vibration signals with defective seal were the other recorded keeping all other components in good condition.

2.2.3. Cavitation

At a particular suction head there was abnormal noise, high vibration in the pump and vapor bubbles were formed. This simulates the cavitation condition of the pump. It is to be noted that all components in the pump are in good condition [10].

3. Design network

3.1. Artificial neural network

Artificial neural networks (ANN) are simplified models of biological neuron system. It consists of a massively parallel distributed processing system made of highly interconnected neural computing elements called as Neurons, which has the ability to learn and thereby acquire knowledge. ANN comprises of number of neurons which forms the basic processing unit. Each neuron is further connected to other neurons by links. Every neuron receives number of inputs which are modified by weights. The synaptic weights would either strengthen or weaken the signal which is processed further. To generate the final output the sum of the weighted output is passed on to a non-linear filter called as Transfer function plus a threshold value called bias which releases the output. The function of neural network is determined by structure of neurons, connection strengths, and the type of processing performed at elements. In classification tasks, the output being predicted is a categorical variable, while in regression problems the output is a quantitative variable. Neural network uses individual examples, like set of inputs or input-output pairs, and appropriate training mechanism to periodically adjust the number of neurons and weights of neuron interconnections to perform desired function.

The learning methods for NN can be classified as [7]:

- ✓ Supervised learning, wherein the input and output patterns are provided. A teacher is assumed to be present during learning process, when a comparison is made between network output and correct expected output, so as to determine the error.
- ✓ Unsupervised learning, wherein the target output is not presented to the network. The system learns by itself by adapting to the structural features in input patterns.
- ✓ Reinforced learning, a teacher though available does not present the expected answer but only indicates if the computed output is correct or incorrect.

ANN consists of a number of interconnected artificial processing neurons called nodes, connected together in layers forming a network. A typical ANN is schematically illustrated in Fig. 3(a). The number of nodes within the input and output layers are dictated by the nature of the problem to be solved and the number of input and output variables needed to define the problem. The number of hidden layers and the nodes within each hidden layer is usually a trial and error process.

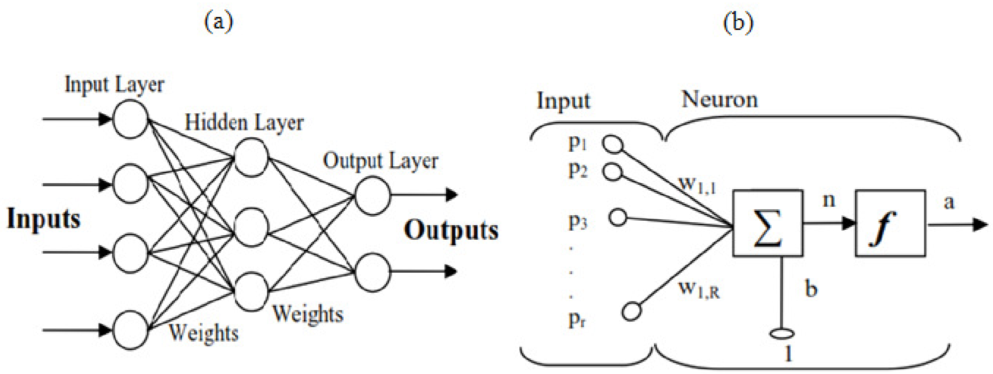

Fig. 3. (a) ANN model, (b) a neuron

As illustrated in Fig. 3(b) each node in a layer provides a threshold of a single value by summing up their input value p with the corresponding weight value w_i. Then the neuron's net input value n is formed by adding up this weighted value, with the bias term b. The bias is added to shift the sum relative to the origin. The net input value then goes into transfer function f, which produces the neuron output a:

$$a = f\left[\sum_{i=1}^{r} w_i \cdot p_i + b\right] \tag{1}$$

The transfer function f, that transforms the weighted inputs into the output a, is usually a nonlinear function. The sigmoid (S-shaped) or logistic function is the most commonly used transfer function which restricts the nodes output between 0 and 1 [13].

3.2. Learning algorithm

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion so as to attain a desired design objective. Back-propagation (BP) learning algorithm is the most commonly used to train ANN and it has been adopted in the present study [8]. This is a supervised method of learning mainly used to train multilayer neural networks. In supervised learning, a set of inputs are applied to the network, then the resultant outputs produced by the network are compared with that of the desired ones [13].

The architecture shown in Fig. 4 consists of one or more number of hidden layers, where input signals are given to the input layer of the network for further processing. The synaptic weights are generated with the help of a random number sub-routine. The transfer function may be sigmoid, hyperbolic tangent, etc. [8].

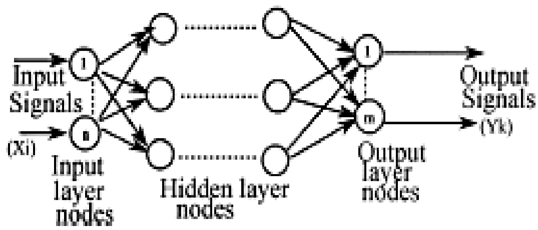

Fig. 4. Architecture of a back-propagation neural network

BP has already been successfully applied by several workers to solve some difficult and diverse problems by training ANNs in a supervised manner. With regard to the BP method a training set is applied to the input of the network, signals propagate through the network and emerge as a set of output states. An error term is derived from the difference between the desired and actual output values and synaptic weights are then adjusted in accordance with an error correction rule. As the iteration proceeds, the overall error normally approaches zero [14]. The normalized mean square error (MSE) is calculated and propagated backwards via the network. Back propagation network (BPN) uses it to adjust the value of the weights on the neural connection in the multiple layers. This process is repeated until the MSE is reduced to an acceptably low value, which would be suitable to classify the test set correctly. The mean square error function $F(x)$ at iteration k is given by:

$$F(x)=\left[(t_1 k-\alpha_1 k)\uparrow 2\right] \tag{2}$$

BPN uses steepest descent method to adjust the weights and biases. The adjusted weights and biases of m^{th} layer at iteration k are estimated by:

$$w_{i,j}^m(k+1)=w_{i,j}^m(k)-\alpha\frac{\partial F}{\partial w_{i,j}^m} \tag{3}$$

$$b_i^m(k+1)=b_i^m(k)-\alpha\frac{\partial F}{\partial b_i^m} \tag{4}$$

where α is learning rate and $w_{i,j}$ represents weights of connection between neuron i and neuron j [13].

3.3. Feature selection

The frequency domain signal can be used to perform fault diagnosis by analyzing vibration signals obtained from the experiment. The measured FFT values of signal were calculated to obtain the most significant features by feature extraction. Statistical methods have been widely used to provide the physical characteristics of frequency domain data. Statistical analysis of vibration signals yields different descriptive statistical parameters. A wide set of parameters were selected as the basis for the study. They are mean, standard deviation, sample variance, kurtosis, skewness, Root Mean Square, Crest Factor, Slippage and Fourth, Fifth and Sixth Central Moment. These features were extracted from vibration signals. The statistical features are explained below. These features can thoroughly describe the characteristics of the faults.

Mean. It is the average of all signal point values in a given signal.

Standard deviation. This is a measure of the effective energy or power content of the vibration signal. The following formula was used for computation of standard deviation:

$$Stdv = \sqrt{\frac{n\sum x^2 - \left(\sum x\right)^2}{n(n-1)}} \tag{5}$$

where n is the sample size.

Sample variance. It is variance of the signal points and the following formula was used for computation of sample variance:

$$Variance = \frac{n\sum x^2 - \left(\sum x\right)^2}{n(n-1)} \tag{6}$$

Kurtosis. Kurtosis indicates the flatness of the signal. Its value is very low for normal condition of the pump and high for faulty condition of the pump due to the spiky nature of the signal:

$$Kurtosis = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i - \bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{7}$$

where ‘s’ is the sample standard deviation.

Skewness. Skewness characterizes the degree of asymmetry of a distribution around its mean. The following formula was used for computation of skewness:

$$Skewness = \frac{n}{(n-1)}\sum\left(\frac{x_i - \bar{x}}{s}\right)^3 \tag{8}$$

Root Mean Square. It is the root of mean square of all signal point values in a given signal and the following formula was used for computation of root mean square:

$$RMS = \sqrt{\frac{\sum_{n=1}^{N}\left(x(n)\right)^2}{N}} \tag{9}$$

where N is the sample size.

Crest Factor. It is the ratio between the peak value of a waveform to its root mean square (RMS) value:

$$Crest\ Factor = \left(Max\left(\left| x(n) \right| \right) \right) \Big/ RMS \tag{10}$$

Slippage. It is calculated according to the following formula:

$$Slippage = \frac{\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-F_1\right)^3}{\left(\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-F_1\right)^2}\right)^3} \tag{11}$$

Fourth, Fifth and Sixth Central Moment. Central moments form one set of values by which the properties of a probability distribution can be usefully characterized. The fourth, fifth and sixth central moment are calculated according to the corresponding formulas.

3.4. Creation of training, validation and test vectors

75 % of data were used for training and validation the ANN. The remaining 25 % of data, which have not been seen by the ANN, were used for testing. As there were 11 features, therefore a training matrix of 11×100, validation matrix of 11×50 and test matrix of size 11×50 are used.

3.5. Training of artificial neural network

The neural network consisting of an input layer, one hidden layers and an output layer was used. The input layer has nodes representing the features extracted from the measured vibration signals. The number of neurons in the hidden layer was 10. The number of output nodes was varied between 1 and 2. The target values of two output nodes can have only binary values 1 or 0 representing normal and failed pump. The ANN was trained using the MATLAB 7.11 neural network toolbox using back propagation with Levenberg–Marquardt algorithm [13].

The ANN was trained iteratively to minimize the performance function of MSE between the network outputs and the corresponding target values. For training, a MSE of 10^{-8}, a minimum gradient of 10^{-10} and maximum iteration number (epoch) of 1000 were used. The training process would stop if any of these conditions were met. The initial weights and biases of the network were selected randomly. The multilayer perceptron is one of the most widely implemented neural network topologies. MLPs are normally trained with the back-propagation algorithm [1, 8]. Error data at the output layer is back propagated to earlier ones, allowing incoming weights to these layers to be updated. It is most often used as training algorithm in current neural network applications. Since its rediscovery, the back-propagation algorithm has been widely used as a learning algorithm in feed-forward multilayer neural networks. In general, the difficulty with multilayer perceptrons is in calculating the weights of the hidden layers in an efficient way that result in the least (or zero) output error; the more hidden layers there are, the more difficult it becomes. To update the weights, one must calculate an error. Weights $w_{j,i}$ are updated by equation (3). At the output layer this error is easily measured; this is the difference between the actual and desired (target) outputs. At the hidden layers, however, there is no direct observation of the error; hence, some other technique must be used. To calculate an error at the hidden layers that will cause minimization of the output error, as this is the ultimate goal. The back-propagation algorithm is an involved mathematical tool; however, execution of the training equations is based on iterative processes, and thus is easily implementable on a computer. MATLAB 7.11 was used for design and testing of ANN models. Each node has a weighted connection to every node in the next layer, and each performs a summation of its inputs passing the results through a transfer function. This is a linear function at the input layer and a non-linear hyperbolic tangent function, TANH, at every other layer. Each unit computes the weighted sum of its inputs, and passes this through TANH nonlinearity. The topology of final MLP neural network is given in Fig. 5. This figure shows a three layer network incorporating a single hidden layer of nodes.

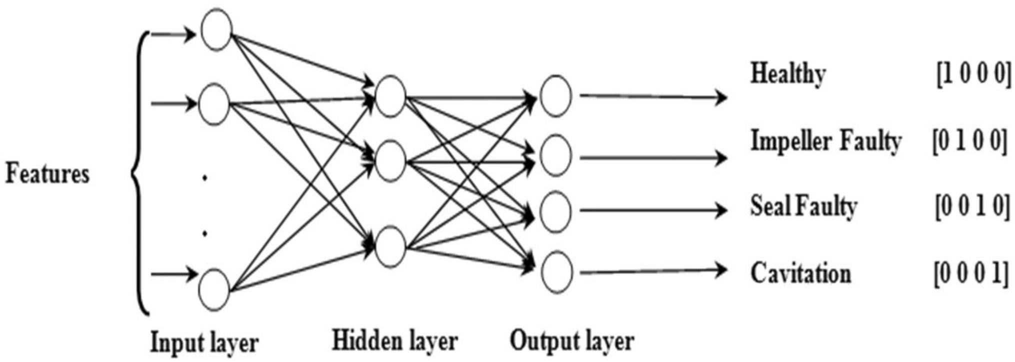

Fig. 5. The topology of final MLP neural network

The input layer had 11 processing elements (PE). Each of them is related to an input feature that is extracted from the frequency spectrum. The number of nodes in the hidden layer was varied according to the number of inputs and network performance. A learning rate $\alpha = 0.9$ was used throughout the momentum learning rule. Considering pump condition, output layer had four nodes. Numbers of nodes for hidden layer were selected based on trial and error. In order to minimize ANN training time, only one hidden layer was considered. By using information about mean square error (MSE) of cross validation (CV) different ANN models, the number of nodes in hidden layer was selected to be 10. For this purpose cross validation, MSE for different numbers of hidden PE's at various epochs were investigated. Based on data these considerations, a network with 10 PE's in hidden layer was observed to have the least standard deviation error as well as a very high stability. Therefore optimal selected model had 11-10-4 structure for classification.

4. Results

Performance evaluations of different designed models were compared based on mean square error (MSE) and correlation coefficient (r). After training and validation, the generalization performance of the network is evaluated with the test data that contains the combination of both normal as well as all types of fault categories. An ANN of structure 11-10-4 was developed for the purpose. Correct Classification Rate of four pump condition output (healthy, impeller faulty, seal faulty and cavitation), were found to be 100, 100, and 100 %, respectively (Table 2 lists the results obtained for such test). Performance of the ANN during training, validation and testing is shown in Fig. 6. Confusion matrix for the training data, testing data, validation data and all data is shown in Fig. 7. The mean square error achieved during training is $1.63810e^{-7}$. During testing, the mean square error achieved by the network is $9.48827e^{-8}$.

Table 2. Classification confusion matrix showing % of correctly classified pump condition with 11-10-4 structure predicted classification

		Healthy	Impeller faulty	Seal faulty	Cavitation
Desired classification	Healthy	21	0	0	0
	Impeller faulty	0	6	0	0
	Seal faulty	0	0	11	0
	Cavitation	0	0	0	12
	CCR	100	100	100	100

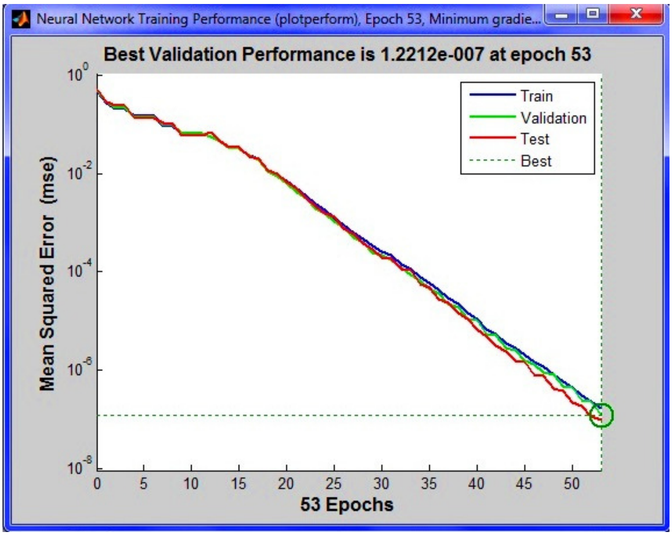

Fig. 6. Network performance for 10 neurons in hidden layer based on MSE

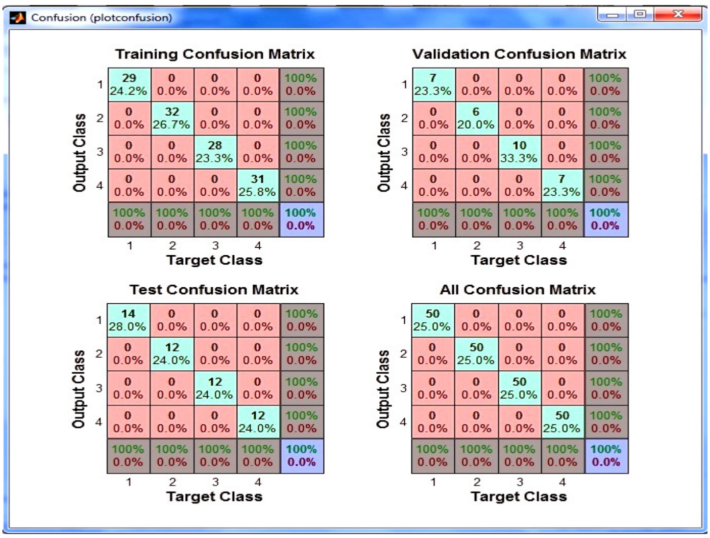

Fig. 7. Confusion matrix

5. Conclusion

A method is presented to identify centrifugal pump condition by using simple features such as mean, standard deviation, variance, skewness, kurtosis, crest factor, slippage, root mean square and 4^{th} – 6^{th} central moments of frequency domain vibration signal. The MLP network was developed using MATLAB 7.11 Neural Network Toolbox. In total, 4 faults in centrifugal water pump were considered in the developed model. All the input features are continuous variables while the output is represented as [1 0 0 0] for Healthy, [0 1 0 0] for Impeller Faulty, [0 0 1 0] for Seal Faulty and [0 0 0 1] for cavitation. Best training performance is $1.63810e^{-7}$ at epoch 53. An ANN of structure 11-10-4 was developed for the purpose of soft fault analysis and detection. The presented model works on the basis of vibration differences, therefore is not restricted to a particular applications and therefore can be used in other applications.

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