International Journal of Systems Signal Control and Engineering Application

MEDWELL PUBLICATIONS

Classification Model using Neural Network for Centrifugal Pump Fault Detection

Eslam Sayed, Ahmed A. Abdelsamee and Nouby M. Ghazaly
Department of Mechanical Engineering, Faculty of Engineering, South Valley University, 83523 Qena, Egypt

Key words: Centrifugal pump, fault detection, vibration fault classification, neural network and multi-layer perceptron

Corresponding Author:
Eslam Sayed
Department of Mechanical Engineering, Faculty of Engineering, South Valley University, 83523 Qena, Egypt

Page No.: 120-126
Volume: 13, Issue 4, 2020
ISSN: 1997-5422
International Journal of Systems Signal Control and Engineering Application

Abstract: The different utilities of centrifugal pumps made the potential for fault occurrence inevitable thus early fault diagnosis is essential for such machines to prevent further losses in different demands. In this study, a vibration-based condition monitoring with the development of the Artificial Neural Network (ANN) model for fault classification and detection. The Multilayer perceptron network with the back-propagation algorithm model is that the most ordinarily used network nowadays. The neural network ability to internally learn from examples makes them more engaging and exciting in the data mining scientific field, rather than following a collection of rules such that by human consultants. This paper deals with the evaluation and development of the ANN model for fault recognition in a centrifugal pumping system with two faults simulated which were seal and particle impurities hitting the impeller. Data required to feed the network extracted from the time-domain vibration raw signal. Results showed great potential for using ANN as a fault diagnosis; the recognition rate of the network was 0.958.

INTRODUCTION

Centrifugal pumps reserves a significant space in several crucial demands, so mechanical elements fault detection became completely essential[1]. The pumps are an essential part of the food industry, wastewater plants, hydraulic power plants, petrol industry, paper industry, sugar cane. Etc. As bearing and impeller are the critical components during a pump that directly affects the specified pump characteristics[2]. Hence, defects by these elements were taken for analyzing Vibration monitoring and analysis are applicable for fault detection of pumps and rotating machines as all machines vibrate accelerometers can be used to extract vibration signals from machines which are then analyzed using software. A vibration signal is processed to get helpful information concerning the condition of the machine. Used to interpret the vibration signal starting from the conventional ones using time-domain analysis and frequency domain analysis where methods such as the Fast Fourier Transform (FFT) are applied. More recently, a powerful multi-resolution technique called wavelet analysis different methods have traditionally been has been applied to fault detection in rotating machines and has demonstrated the ability to analyze non-stationary signals Automatic fault detection methods made use of Artificial Intelligence (AI) Artificial intelligence systems have been applied for centrifugal pump fault diagnosis using different methods[3]. Recently Artificial Neural Networks (ANNs) have attracted the interests of engineers to develop fault detection systems. The advantage of the neural network approach is the generalization capability that lets them influence the information that it's not seen before. An ANN Model developed and designed to detect 20 faults in pumps by Rajakarunakaran *et al.*[4]. A survey made by Selvakumar and Natarajan[5] on problems commonly encountered by pumps. ANN Model proposed to diagnose cavitation, seal and impeller faults of the water pump by Farokhzad *et al.*[6]. The Network system prohibits the processing units which are the neurons. They try to simulate the behavior of the natural neurons. A neuron as a processing unit processes inputs (via. dendrites in biological neuron) and one output (synapse across axon) the neuron did that with a function that determines the activation of the neuron[7] to scale back the neural network complexity[8], the statistical of vibration time-domain analysis contains various parameters. If the activation function of network is continuous, bounded and non constant, then continuous mappings can be learned uniformly over compact input sets[9]. Hinton *et al*.[10] proved how to use "complementary priors"to eliminate the explaining-away effects that make inference difficult in densely connected belief nets that have many hidden layers. One-Dimensional Ternary Pattern (1D-TP) methodology is applied to the vibration signals that obtained from the bearing that artificial faults were generated in specific sizes that uses patterns received from comparisons between every fee on vibration indicators The length of the error is set (mm) of the fault with the help of deciding the bearing part (inner ring, outer ring, ball) from that the faults within the bearings are caused[11]. As it is the so-called activation function. By using images LBP (Local Binary Pattern) Bearing vibration signals were converted to grayscale images whereas the images that the signals of different bearing failures form different Materials[12].

Byusing vibration signals new methods for fault diagnosis are suggested. The Local Binary Patterns (1D-LBP) method was used to the vibration signals that we collected from the bearing on which synthetic faults and a new signal whose values ranged among 0-255 the coexistence matrices have been obtained from those signals. The correlation, energy, homogeneity and comparison properties have been extracted from these matrices. Numerous machine learning strategies were used with these options to implement the classification[13]. Based on the 1D-LBP technique, the F-1D-LBP technique was utilized to build feature vectors to work out the vibration signal velocities of various fault sizes and kinds[14]. The using of the Adaptive Neuro-Fuzzy Inference System (ANFIS) version is diagnosed the scale of the defects occurring within the bearings Vibration signals are obtained from several sizes of synthetic faults are generated via. the laser beam on inner earrings of bearing and by applying[15].

By using wavelet transformer the signals collected are decomposed from noise accordingly vibration signal ensuing from normal operation of the system is obtained. The power of noisy and noise-free signal is calculated and the wavelet coefficients with a purpose to be utilized in classifying are obtained[16].

Smart controllers utilize two sorts of ship maneuvering which are ship berthing and way point controlling. Where, the optimization technique is used to train the multi-layer ANN controller. Whereas, some simulations are conducted to detect the durability of the control unit under wind turbulence and after work and found successful.

As for the move in the way points, a double-loop control unit is used way point navigation. The outer loop belongs to fuzzy that generates the aspired course for the inner loop for important course correction. Here, the navigation path plan is done based on the supplied set points called WayPoints (WP) to be transferred. Near the turning point, the fuzzy thought system will determine to choose the suitable course defined and after choosing a suitable course by fuzzy thought, the course is fixed using a PD controller[17]. ANNs techniques are applied in medical sciences for diagnosis such as to develop the medicine prescription and keeping records for patients by managing the patient's account, so that, it is easy to predict diseases[18].

MATERIALS AND METHODS

Experimental work: In this experimental work, the steps branched at three stages, experimental setup for different fault free and faulty pump, preparation and pre-processing using raw time-domain vibration signal for statistical extraction and optimize for a suitable network. The main targets of the experimental work are to determine whether the centrifugal pump is in good or faulty condition with the best accuracy and simple model for the MLP network. If the pump is in faulty condition then the aim is to classify the faults into leakage and metal chip contaminants in water to test network recognition and ability to generalize trained statues.

Experimental test rig setup: Faults pump classification system using vibration signal and the statistical feature extraction technique with the ANN system is the aim of the study. Features from the time-domain signal were adapted to introduce different faults of the pump to the network. The experimental setup to collect datasets consists of a centrifugal water pump an electrical motor, an accelerometer. The setup is shown in Fig. 1. An electrical motor-driven pump was used. All vibration data were registered from the experimental rig of the centrifugal pump using an accelerometer. Seal fault and metal chip and one fault-free conditions adapted.

Fig. 1: Experimental test pump and sensor position

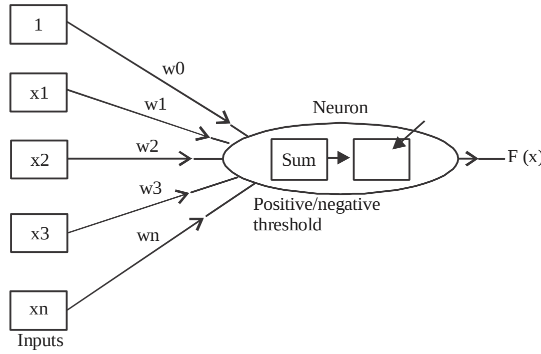

Fig. 2: Artificial neuron model[3]

Table 1: Centrifugal pump data

Pump type	Capacity (l/min)	Head (m)	Speed (rpm)	Electric motor power (hp)
Jet-505b	75	66	2860	2

Table 2: Data acquisition specification

Data acquisition type	i/o channels	Channels used as an input
Bruel&Kjaer3560-b-140	5/1	1

Table 3: Accelerometer specification

Accelerometer type	Sensitivity	Mounting	Position
Bruel and Kjaer 4514-001	10 mv/ms^-2	Magnetic	Vertical near discharge side

Table 4: Data acquisition information

Variables	Values
Sampling Frequency (Hz)	12500
Number of data Points	8192
Sampling period (seconds per sample)	0.00008
Duration of samples (s)	0.655
Filter	Anti-aliasing filter (analog) Finite Impulsive Response (FIR) Band-pass digital filter (10 Hz-25 kHz)

The vibration was measured for the pump at normal conditions at a constant operating speed of 2860 rpm. The flow rate was 24 lpm. Centrifugal pump specification is provided in Table 1, data acquisition, specification is in Table 2 and accelerometer specification is provided in Table 3.

In Table 4 sampling frequency: the number of samples per second (or per another unit) taken from a continuous signal to make a discrete or digital signal. Number of data Points: The appropriate number of samples in which these samples must be taken in order for us to process the samples. The sampling period: is the time difference between two consecutive samples in a Sound. It is the inverse of the sampling frequency. Duration of samples (s): how much seconds it takes to sample 8192 point which specifies the signal length.

Anti-aliasing filters used in data acquisition before sampler to restrict frequency band in order to satisfy Nyquist-Shannon theory. Finite impulsive response filter implemented by means of convolution to smooth-DC removal in time domain signal. Band-pass filter rejects frequencies less than lower band 10 Hz and more than higher band 25 kHz and passes frequencies in between. The pump part which is used to regulate discharge is the seal (packing). It has to be examined once in three months also performance Leakage rate of 60 drops per minute is permitted[3]. Without this leakage the chilling of the pump becomes an issue although more leakage than usual in a pump results from improper selection of material, wear or even misalignment. Loss of 2 drops per second simulated in this work and Suspended solids like particles of sand or chips of metal of blades or vanes inhabited cavitation results in wired liquid cause abrasive wear of vane and shaft. A 120-micrometer aluminum chip particles injected in the suction line to simulate this fault.

Artificial neural network setup: In Fig. 2: x1, ..., xn were the inputs to the neuron (processing unit) that does some math with the input to produce output. Bias was added to the neuron with inputs to stimulate the neuron processing. Usually bias value is initialized to 1. W0, .., Wn are the weights. A weight which responsible for the network learning (synaptic junction) is the connection to the signal. The product of weight and input vectors represents the strength of the signal. The neuron processes multiple inputs from different sources and has a single output there are various functions used for activation:

$$F(x) = \frac{1}{1+e^{-x}} \quad (1)$$

The ANN consists of layers which are the input layer that senses the input values, it has no processing just elevate the input to the ANN system, then the hidden layer(s) that is a set of neurons between input and output layers and It has no interaction in the environment with physical quantities like the first and last layers, so, the name is hidden, finally here comes the output layer that is usually has determined number of neurons and its output ranges usually but not always between zero and one.

Back-propagation has proved an algorithm with success. Network training through iteration. As the iteration payoff, General error unremarkably approaches zero to learn from error. The Mean Square Error (MSE) is the loss or cost function that is calculated and propagated backward across the Network. The Back Propagation Network (BPN) works with the MSE to adjust the value of the weights on the neural connection in the multiple layers so that error decreases. This process is repeatable until the cost function minimized as soon as practical to the acceptable value determined by the validation test data which would be suitable to classify the test set correctly. The mean square error loss function F(x) at iteration i is given by:

$$F(x)=\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\hat{x}_i\right)^2 \qquad (2)$$

The algorithm usually but not always uses different methods, the steepest descent method is one of them and the goal is to adjust the weights and biases (network parameters). The adjusted weights and biases of the layer at iteration i are calculated by:

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

$$b_{i,j}^{m}(i+1)=b_{i,j}^{m}(i)-\alpha\frac{\partial f}{\partial b_{k,j}^{m}} \qquad (4)$$

Where α is the learning rate and represents weights of connection between neuron k and neuron j[6].

Pre-processing setup: The pre-processing step is that which aims to figure out features that condition the discerning ability of the network between the pump conditions. Features were extracted from the pump vibration signal with time analysis. As statistical parameters, computed from the raw signal, provide important information; it's primarily within the signal wherever fault affects measure higher expressed in terms of energy and distribution within the knowledge measure. To scale back the neural network complexity[8], the Statistical of vibration time-domain analysis contains various parameters. A good set of them were elected because of the study. They were mean, variance, standard deviation, kurtosis, skewness, root mean square, crest factor, maximum, minimum, mode and median those features extracted from the signal. These features of statistical parameters can describe the trend of the faults[6]. Maximum and minimum may seem to indicate similar information but it introduce range into network that won't to exceed and not to get down below. Standard deviation: Measure of the effective content of the vibration signal:

$$S=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i-\bar{x}\right)^2} \qquad (5)$$

Variance: Indication of significance in the data set also it may appear that it has the same information as standard deviation but it represents power of vibration signal as it is units (m/s^2)^2 but with its mean removed:

$$S^2=\frac{1}{N}\sum_{i=1}^{N}\left(x_i-\bar{x}\right)^2 \qquad (6)$$

Kurtosis: Indication of the signal impulsiveness:

$$\text{kutosis}=\frac{\sum_{i=1}^{N}\left(x_i-\bar{x}\right)^4}{S^4} \qquad (7)$$

Skewness: Indication of the signal's degree of asymmetry:

$$\text{Skewness}=\frac{\sum_{i=1}^{N}\frac{\left(x_i-\bar{x}\right)^3}{N}}{S^3} \qquad (8)$$

Root mean square: Information from RMS differs from mean as the mean value is a center of set of values that data dispersed around it, where rms is important factor when values ranges between positive and negative values like sinusoids and used along with calculation of crest factor used in time domain analysis:

$$\text{RMS}=\sqrt{\frac{\sum_{i=1}^{N}\left(x_i\right)^2}{N}} \qquad (9)$$

Crest factor:

$$\text{Crest factor}=\frac{\text{MAX}}{\text{RMS}} \qquad (10)$$

Where:

x_i = The data point of the sample
N = The sample size
$\bar{x}$ = The mean
S = The standard deviation

Table 5 illustrates the names, description and use the variables in the data set. The numbers of inputs were eleven, targets were three and no unused variables:

In Table 5 the maximum value the value of the function at a maximum point. The minimum value is the

Table 5: Dataset variables

Factors	Names	Use
1	Max	Input
2	Min	Input
3	Mean	Input
4	Median	Input
5	Mode	Input
6	Stdev	Input
7	Var	Input
8	RMS	Input
9	Crestf	Input
10	Skew	Input
11	Kurt	Input
12	Normal	Target
13	Fault1	Target
14	Fault2	Target

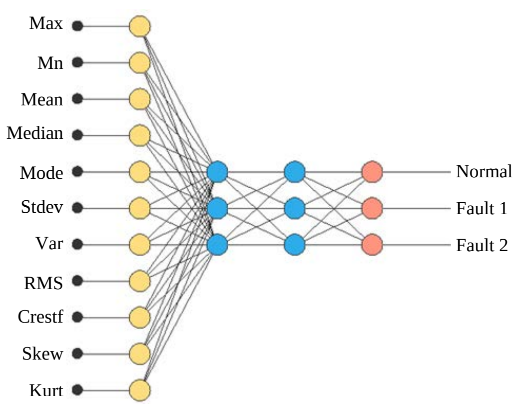

Fig. 3: Network architecture

value of the function at a minimum point. Meanit is the average of all signal point values. A median is a value separating the higher half from the lower half of a data sample. The mode of a sample is the element that occurs most often in the collection. Standard deviation Measure of the effective content of the vibration signal or this is a measure of the amount of variation or dispersion of the vibration signal.Variance: is a measure of how far each value inthe data set is from the mean. Root mean square is defined as the square root of the mean square. Crest Factor is the peak amplitude of the waveform divided by the RMS value of the waveform. Skewnessis an asymmetry in a statistical distribution in which the curve appears distorted or skewed either to the left or to the right. Skewness can be quantified to define the extent to which a distribution differs from a normal distribution. Kurtosis is a statistical measure used to describe the degree to which scores cluster in the tails or the peak of a frequency distribution. or is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.

In Fig. 3, the proposed network architecture shows the network of 2 layers the first layer in yellow cells is the input one and the one with blue are the hidden layer which simulates the absence of interaction with the

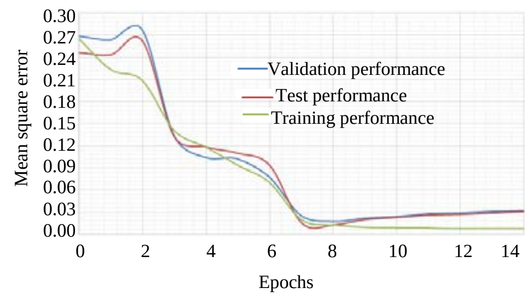

Fig. 4: Error history of training

environment and perform as a conduit for the input and the output layer also important calculations and processing in it.

The number of samples is 120 instances and divided into training samples 72 instances or observations (60%) of the total, the number of selected samples of 24(20%) of the total and the number of testing data is 24 instances (20%) of the total data samples. The Number of hidden Neurons was 10 as two-thirds of the input layer size plus the size of the output layer.

The advancements of the events during the learning process governed by the training strategy.Applied in order to obtain the best possible loss value. Training data used to train the network then and selection to validate and stop the optimization algorithm from further update the weights. Finally, the test instances were used to test the network before final deployment. The quasi-Newton method is used here for training. It is based on Newton's method but does not require the calculation of second derivatives. Instead, the quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm by only using gradient information (Fig. 4).

RESULTS AND DISCUSSION

The following plot shows the training, selection (validation) and test errors in each iteration (epoch). The blue line represents the validation mean squared error and the red line represents the mean squared error on the test data where the green line represents the training performance of the network by MSE error. The parameters of the network (weights) selected at an epoch which has minimum validation error that shall result in higher classification accuracy at which the test data error rate represents the networkability of generalization. At initially random starting conditions the initial validation and training error rate was 0.27 MSE where test error rate was 0.24 MSE the network continues evaluation by the back-propagation algorithm until one of the following stopping criteria occur (maximum number of estimated epoch reached, limit time reached or number of failing in

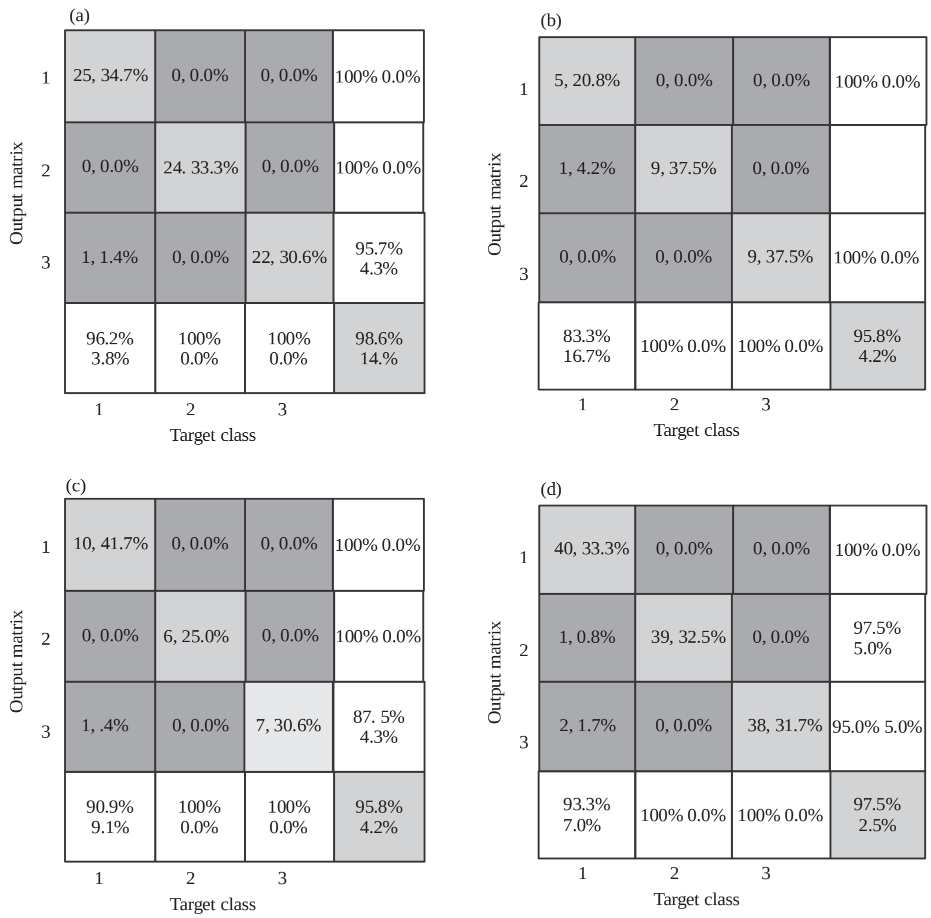

Fig. 5(a, b): Confusion matrices (a) Training confusion matrix (b) Validation confusion matrix (c) Test confusion matrix and (d) All confusion matrix

validation check), after 6 validation check failure the network stopped at epoch 14 releasing the error history shown in Fig. 4. The best validation error rate was the minimum which was 0.0124 MSE, the training error rate was 0.0123 MSE where test performance was 0.0174 MSE at epoch 8.

Figure 5 represents the confusion matrices which can indicate the classification power and the ability of the network in generalization. Generalization means the recognition of the fault class with data that have never considered in the training process. 1, 2 and 3 are the classes normal, leaking seal fault and impurities of metal chip particles fault, respectively. Total test data were 24 observations selected randomly to test the network after the end of the training process. Vertical classes numbering for predicted classes from the network and the horizontal order of classes illustrate the real classes. About 0 of 24 test samples were reserved for class 1 and network predicts all of them as class 1, 6 of the 24 test observations were reserved for class 2 and the network predicted all 6 data as class 2 correctly where 8 of the 24 data were for class 3 but network managed to correctly predict 7 of them as class 3 where one wrong prediction was for class 1. So, Network accuracy was 95.8% (Fig. 5c for test confusion matrix on test data) and error was 4.2%, so, the recognition rate of the network was 0.958 at which 100% recognition for fault-free and fault 1 and 87.5% recognition for fault 2 condition. In Fig. 5a illustrates confusion matrix on training data where 1 misclassified condition fails thus final training error was 1.4%. Where in Fig. 5b which indicates the confusion matrix for validation data (random 21 data selected to stop network from over fitting) error 4.2% and recognition was 95.8%. Figure 5d for all data confusion matrix which aggregates all before three confusion matrices to indicate overall accuracy of 97.5% for all 120 samples of data.

CONCLUSION

The fault recognition and classification of the centrifugal pump by using data acquired from the vibration signal. In the present work, fault pump classification system based on a vibration signature. This technique can be used to detect the changing signals of fault in this centrifugal pump. The main goal of the work is to illustrate the potential of artificial intelligence at which the centrifugal pump is in a fault-free or faulty case with the classification of the fault. If the pump is in faulty condition then the system must be capable of classifying the fault. The measured vibration values of signal were collected to obtain the most significant features by feature extraction. Artificial neural networks are algorithms for cognitive feature tasks such as learning and optimization. They have the power to be told and generalize from examples while not data of rule. Also, the model predicted the data with 95.8% accurately and was 10 hidden neurons only with simple features 11 for centrifugal pump fault detection with vibration signal. Difference of this study in other stated is that it used simple computations which gave high accuracy with less number of hidden neurons with 11 input features in order to detect this type of pumps that has leakage with and particles impurities hitting impeller 2 drops per second leak and 120 micrometer aluminum chip which is difficult to detect using signal processing techniques to detect faults than using data driven method like ANN but it comes with the cost of requirement much more data than signal processing techniques. Finally, the more the data samples the greatest the network for generalization.

REFERENCES

01. Farokhzad, S., 2013. Vibration based fault detection of centrifugal pump by fast fourier transform and adaptive neuro-fuzzy inference system. J. Mech. Eng. Technol., 1: 82-87.
02. Muralidharan, V. and V. Sugumaran, 2013. Rough set based rule learning and fuzzy classification of wavelet features for fault diagnosis of monoblock centrifugal pump. Measurement, 46: 3057-3063.
03. Al Tobi, M.A.S., G. Bevan, K.P. Ramachandran, P. Wallace and D. Harrison, 2017. Experimental set-up for investigation of fault diagnosis of a centrifugal pump. Int. J. Mech. Aerospace Ind. Mechatronic Manuf. Eng., 11: 481-485.
04. Rajakarunakaran, S., D. Devaraj and S.K. Rao, 2008. Fault detection in centrifugal pumping systems using neural networks. Int. J. Mod. Identif. Control, 3: 131-139.
05. Selvakumar, J. and K. Natarajan, 2015. Failure analysis of centrifugal pumps based on survey. ARPN J. Eng. Applied Sci., 10: 1960-1965.
06. Farokhzad, S., H. Ahmadi, A. Jaefari, M.R.A.A. Abad and M.R. Kohan, 2012. 897. Artificial neural network based classification of faults in centrifugal water pump. J. Vibroengineering, 14: 1734-1744.
07. Kukreja, H., N. Bharath, C.S. Siddesh and S. Kuldeep, 2016. An introduction to artificial neural network. Int. J. Adv. Res. Innov. Ideas Educ., 1: 27-30.
08. Zouari, R., S. Sieg-Zieba and M. Sidahmed, 2004. Fault detection system for centrifugal pumps using neural networks and neuro-fuzzy techniques. Surveillance, 5: 11-13.
09. Hornik, K., 1991. Approximation capabilities of multilayer feedforward networks. Neural Networks, 4: 251-257.
10. Hinton, G.E., S. Osindero and Y.W. Teh, 2006. A fast learning algorithm for deep belief nets. Neural Comput., 18: 1527-1554.
11. Kuncan, M., K. Kaplan, M.R. Mi?naz, Y. Kaya and H.M. Ertunc, 2019. A novel feature extraction method for bearing fault classification with one dimensional ternary patterns. ISA. Trans., 100: 346-357.
12. Kaplan, K., Y. Kaya, M. Kuncan, M.R. Mi?naz and H.M. Ertunc, 2020. An improved feature extraction method using texture analysis with LBP for bearing fault diagnosis. Applied Soft Comput., Vol. 87, 10.1016/j.asoc.2019.106019
13. Kaya, Y., M. Kuncan, K. Kaplan, M.R. Minaz and H.M. Ertunc, 2020. A new feature extraction approach based on one dimensional gray level co-occurrence matrices for bearing fault classification. J. Exp. Theor. Artif. Intell., Vol. 1, 10.1080/0952813X.2020.1735530
14. Kaya, Y., M. Kuncan, K. Kaplan, M.R. Minaz and H.M. Ertunc, 2020. Classification of bearing vibration speeds under 1D-LBP based on eight local directional filters. Soft Comput., Vol. 1, 10.1007/s00500-019-04656-2
15. Kaplan, K., M. Kuncan and H.M. Ertunc, 2015. Prediction of bearing fault size by using model of adaptive neuro-fuzzy inference system. Proceedings of the 2015 23nd Signal Processing and Communications Applications Conference (SIU), May 16-19, 2015, IEEE, Malatya, Turkey, pp: 1925-1928.
16. Bayram, S., K. Kaplan, M. Kuncan and H.M. Ertunc, 2014. The effect of bearings faults to coefficients obtaned by using wavelet transform. Proceedings of the 2014 22nd Signal Processing and Communications Applications Conference (SIU), April 23-25, 2014, IEEE, Trabzon, Turkey, pp: 991-994.
17. Adnan, A.Y., H.M. Abdul and M.K. Iwan, 2020. Intelligent control for ship manoeuvering. J. Adv. Res. Applied Mech., 67: 1-9.
18. Parveen, R., M. Nabi, F.A. Memon, S. Zaman and M. Ali, 2016. A review and survey of artificial neural network in medical science. J. Adv. Res. Comput. Appl., 3: 7-16.