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Full Length Article

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A R T I C L E I N F O

A B S T R A C T

This paper presents a comparative study of Multilayer Feedforward Perceptron Neural Network which is trained with Back Propagation (MLP-BP) and also using hybrid training using Genetic Algorithm (GA) (MLP-GABP), and Support Vector Machine (SVM) classifiers to classify the fault conditions of a centrifugal pump. Continuous Wavelet Transform (CWT) with three different wavelet functions (Morlet, db8 and rbio1.5) is used to extract the features. GA is also used to optimize the number of hidden layers and neurons of MLP. From the results obtained, MLP-BP has shown better performance than MLP-GABP and SVM using a lower number of features. SVM has performed better using polynomial kernel function using a smaller number of features and parameters. A centrifugal pump test rig has been specifically designed and built for this work in order to create the desired faults.

1. Introduction

Centrifugal pumps at industries are widely used for different and numerous applications and the continuous of production relies on the good condition of the machines. However, faults can still occur and can affect the performance of the machines, and such faults have to be detected at their early stages to avoid any catastrophic failures. The condition monitoring of such machines can be implemented using the traditional methods like the overall vibration analysis and up to the automatic ones, where artificial intelligence get involved for the goal of classifying the different machine faults precisely. In this present work, artificial intelligence is proposed to be integrated along with a feature extraction method based on Continuous Wavelet Transform (CWT) and Genetic Algorithm (GA) based optimization and training.

There have been many previous works on fault diagnosis of rotating machines including centrifugal pumps. By emphasizing on the major works on the fault diagnosis of centrifugal pumps based artificial intelligence, there have been many methods applied for the centrifugal pump based fault diagnosis such as a work by Sakthivel et al. [1] performed an experiment to classify

faults of a mono-block centrifugal pump. Five faults were considered in this work (bearing, seal, impeller, bearing and impeller together, and cavitation faults). Feature extraction was applied using statistical analysis and classification was implemented using four methods, viz. decision tree, Naïve Bayes, Bayes net, and K-Nearest-Neighbor (KNN). The number of features was reduced using a dimensionality reduction technique to reduce data processing load and optimize speed of classification. Results showed that the decision tree classifier outperformed other classifiers, with success rate of 100%. Automatic fault classification has been accepted and investigated by many machinery fault diagnostic methods in order to improve precision and minimize mistakes that were caused by human interpretation [2]. Selection of the error function and optimization method is essential that during training of patterns, the error function is minimized and weights are updated. There are many learning algorithms which can be used for MLP; the most popular ones are Delta and Back Propagation [2]. Muralidharan and Sugumaran [3] presented the application of the decision tree (J48 algorithm) in fault diagnosis of centrifugal pumps. This algorithm was applied as a fault classifier along with the features that were extracted using discrete wavelet transform families (DWT). Different families of DWT have been applied for the classification and it was observed that reverse bio-orthogonal wavelet (rbio1.5) is an appropriate choice for fault diagnosis of centrifugal pumps. In this study, DWT has been tested and applied successfully as a technique for feature extraction. It was concluded that using DWT in feature extraction and using J48 algorithm for

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classification was a successful approach, with success rate of 99.84%. However, it should be noted that this study included only a limited number of faults. Muralidharan et al. [4] proposed support vector machine (SVM) for the classification of healthy and faulty conditions (bearing defect, impeller damage, bearing and impeller damage together and cavitation) of a mono-block centrifugal pump. Different statistical parameters and histogram features were extracted from vibration signals using CWT and different wavelet functions or families were applied at different levels and calculated to identify the best wavelet that would be applied for the fault diagnosis and feature extraction. Farokhzad et al. [5] proposed an AI system for fault classification of centrifugal pumps using a decision tree method for training and linear regression model for classification. Vibration signals of four conditions were extracted, viz. healthy, bearing fault, seal fault, and impeller fault. Using FFT for feature extraction, 10 features were extracted: average, maximum, minimum, range, standard deviation, energy, moment1, moment2, moment3, and moment4. The total classification success rate was 94.16%. Farokhzad [2] presented the application of Adaptive Network Fuzzy System (ANFS) for fault classification of centrifugal pumps. Features were extracted using FFT and the following statistical parameters were obtained: mean, standard deviation, sample variance, kurtosis, skewness and root mean square. A classification success rate of 90.67% was achieved, which is not particularly high compared to other AI systems.

Farokhzad et al. [6] presented application of ANN for the fault diagnosis of a centrifugal water pump. The proposed model was multilayer perceptron neural network (MLP) and back propagation (BP) learning algorithm. Four different conditions were tested which are normal condition, impeller fault, seal fault, and cavitation conditions. Features were extracted from the vibration signals using FFT and eleven statistical features were extracted which are: mean, standard deviation, variance, skewness, kourtosis, crest factor, slippage, root mean square (RMS), and the fourth, fifth and sixth central moments. The BP has already been effectively used by numerous researchers to solve some challenging and various problems by training ANN in a supervised method and this study mentioned that BP has been widely applied as a learning algorithm along with MLP. Chen [7] demonstrated the application of partially-linearized neural network (PNN) for the centrifugal pump conditions classification, wavelet transform using a Reverse Bior wavelet function (rbio2.8) for the feature extraction, and rough set for feature selection. Four conditions were considered in this study: healthy, misalignment, unbalance, and cavitation. Classification success rates ranged from 83.7% for impeller problem to 99.9% for misalignment, depending on the condition and frequency of vibration. Wang and Chen (2007c) [8] presented a study for fault diagnosis of centrifugal pumps, in which a fuzzy neural network known as a partially-linearized neural network (PNN) was proposed for fault classification, wavelet transform was used for feature extraction. Classification success rates of 99%, 99%, more than 98%, and 98% were achieved for the healthy, misalignment, cavitation and impeller conditions using recomposed signals. This study proposed different methods for feature extraction, selection and then classification. Muralidharan and Sugumaran [9] presented a study for a mono-block centrifugal pump fault diagnosis using two classifiers, namely, SVM and Extreme Learning Machine (ELM) to diagnose five different conditions (normal, faulty bearing, faulty impeller, faulty bearing and impeller together, and cavitation). DWT is used to extract the features using different wavelet mother functions. The best performance is achieved using ELM with 99.84%, and SVM with 98.84%.

As per as the previous works, this present work is aiming to contribute with a novel method by integrating genetic algorithm along with AI, as there has been no previous work that has introduced GA with AI based centrifugal pumps fault diagnosis. In addi-

tion, the number and type of faults have considered carefully according to the common faults in industries.

The performance is determined in terms of the number of hidden layers and neurons in the neural network, number of features, and the training and kernel methods. This paper is divided into four parts including this introduction. Section 2 presents materials and methods including MLP-BP, SVM classifiers, GA, the experimental setup, and the method applied, procedures for feature extraction, and the classification methods. Then, Section 3 presents the results and discussion. Finally, a conclusion with remarks and recommendations is given in Section 6.

2. Proposed method

This paper investigates the classification performance of two artificial intelligence methods: MLP-BP along with GA based training and selection and SVM, as they have illustrated good performance with rotating machine fault diagnosis and classification [3,10,11,12] and this present work intends to compare their performance using a greater range of faults with seven centrifugal pump conditions, namely, healthy (non-faulty); five mechanical faults: misalignment, imbalance, faulty bearing, faulty impeller and mechanical looseness; and a hydraulic fault: cavitation. The procedure consists of three main stages, namely, data collection, preprocessing and extraction, and fault classification. Classification and diagnosis of the centrifugal pump condition is implemented using two artificial intelligence classifiers: MLP and SVM. MLP is implemented along with its traditional learning algorithm (Back-Propagation) and is also compared with a hybrid training algorithm (MLP-GABP). The network hidden layers and neurons are selected manually and also optimized using GA with comparable results. The flow chart of the diagnosis methods and training algorithm is shown in Fig. 1.

3. Artificial intelligence

3.1. Multilayer Perceptron with Back Propagation

Multilayer Perceptron (MLP) is inspired initially from the simple artificial neuron network which represents a linear mapping (without a hidden layer) between the input and output [13] as illustrated in Fig. 2.

From Fig. 2, Inputs are denoted by $X_i = [x_0, x_1, x_2, x_3, x_n]$, w_0 is a new input which known as bias = +1, weights are indicated as $W_i = [w_0, w_1, w_2, w_3, w_n]$, and Y_i is the output. S is the sum of product which is given by:

$$S = \sum_1^n XiWi + bias \tag{1}$$

where bias is another input (x_0), and added to the sum of product (S) to provide more freedom and flexibility with the decision boundary. Hence, S can be presented by:

$$S = [x_0 w_0 + x_1 w_1 + x_2 w_2 + x_3 w_3 + x_n w_n] \tag{2}$$

The training process of BP can be started by multiplying the input vectors with the weights, as the biases and weights are summed in order to calculate the actual outputs. The desired outputs have to be determined and then compared with the actual outputs, continuing evaluation and weight modification until the process approaches the desired MSE value.

MSE is also known as training or network error and represented mathematically as:
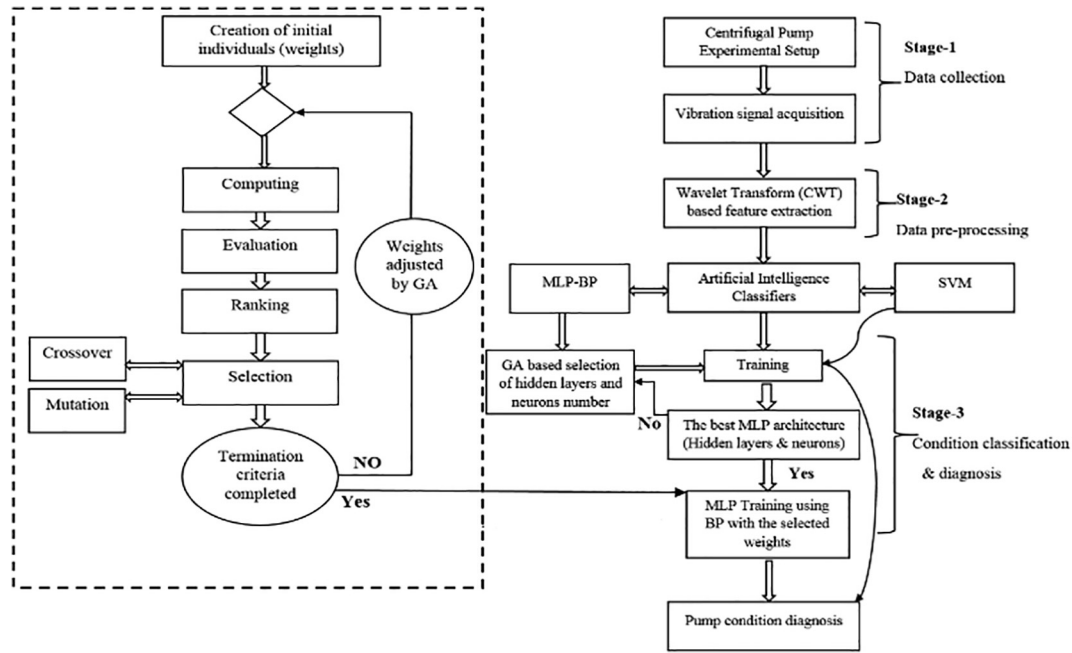
$$E = 1/n \sum_{i=1}^n (t_i - y_i)^2 \tag{3}$$

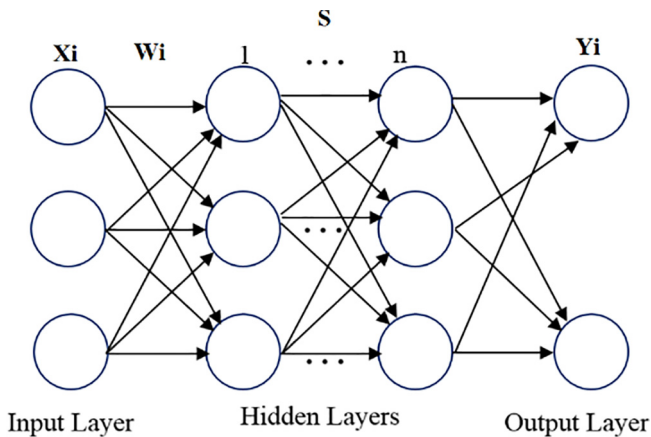**Fig. 1.** Flow chart of diagnosis methods and training algorithms.

Fig. 2. The artificial neural network.

where n is the total number of inputs, i known as the index of summation, t_i is the desired (target) output from the output layer, and y_i is the actual output in the output layer.

3.2. Support vector machine

SVM is a curve square optimization problem which makes it able to provide a globally optimal solution. The linear classifier (hyperplane) is expressed as:

$$W^T X + b = 0 \tag{4}$$

If class A is assumed to be above the hyperplane, then A greater than 0 and indicated as +1 and given by:

$$W^T X + b = +1 \tag{5}$$

And if class B < 0, it is denoted by -1:

$$W^T X + b = -1 \tag{6}$$

where W^T is the weight vector, X is the input and b is the bias.

A decision function can be used to separate two different classes (i.e. A and B) and given by [14]:

$$f(x) = sign((W.X) + b) \tag{7}$$

Using Eq. (4) and Eq. (7), the decision function can be given by:

$$f(x) = sign\left(\sum_{i=1}^{L} vi\,(X.X_i) + b \right) \tag{8}$$

where L is the number of training data and vi is applied as weighting factor to identify the suitable support vectors from the given inputs.

SVM can separate and classify different classes linearly. However, it is not always guaranteed that a linear boundary is able to classify the two different classes. Therefore, in order to classify the two classes with better margin, SVM can map the non-linear training data into a higher dimension level which is known as the feature space s using a transformation $\Phi\,(X)$ and s is given by [15]:

$$s = \Phi(X) \tag{9}$$

where $X \in R^N$ and $s \in R^Q$. Then by substituting Eq. (9) in Eq. (8), the decision function can be defined as:

$$f(x) = sign\left(\sum_{i=1}^{L} vi(\Phi(X).\Phi(X_i)) + b \right) \tag{10}$$

Moreover, to provide such transformation into non-linear classification, a kernel function is used $k(X.Y)$ which is given by [14]:

$$k(X.Y) = \Phi(X).\Phi(Y) \tag{11}$$

where k indicates the kernel.

By substituting Eq. (10) in Eq. (11), the decision function for the non-linear classification can be given by [14]:

$$f(x) = sign\left(\sum_{i=1}^{L} vi\,k\,(X.X_i) + b \right) \tag{12}$$

There are different kernel functions that can be used with SVM for the purpose of non-linear classification, and such kernel functions such as;

Polynomial kernel function and given by [14]:

$$k(X.Y) = k(X.Y)^d \tag{13}$$

where d indicates to the dimension.

RBF and given by [10]:

$$k(X.Y) = \exp(-\|X - Y\|^2/2\sigma^2) \tag{14}$$

where σ is the width parameter of RBF kernel function.

Sigmoid and given by [10]:

$$k(X.Y) = \tanh(\kappa(X.Y) + \Theta) \tag{15}$$

where κ is known as gain parameter and Θ is offset parameter of sigmoid kernel function.

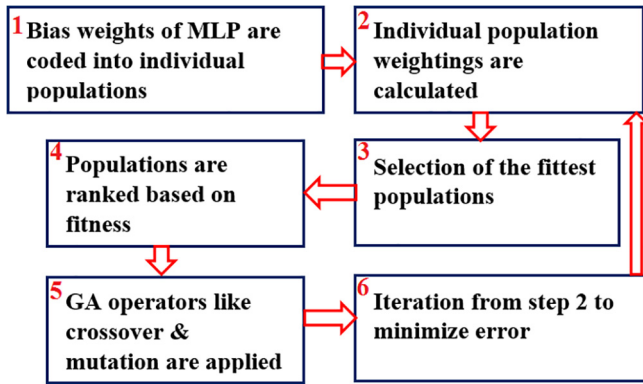**Fig. 3.** The Training steps using GA.

Table 1
Values and parameters of GA based optimization and training.

GA based training			
No. of generations	Size of population	TolFun	Mutation & crossover options
1000	1000	1E-60	Mutation-Gaussian Crossover-scattered
GA based optimization			
No. of generations	Size of population	TolFun	Mutation & crossover options
40	10	1E-60	Mutation-Gaussian Crossover-scattered

3.3. Genetic Algorithm based training and optimization

GA and BP algorithms are tested and investigated for the training of MLP where its weights have to be modified and updated. It is remarked that this hybrid training method is applied with ANN for the first time as it has not been done before with any fault diagnosis research on centrifugal pump.

Firstly, MLP is trained using GA with 1000 generations and 1000 population size, where GA works to minimize the error, and the training can be then terminated after reaching the minimum error (i.e. the best fitness). Training steps using GA can be illustrated in Fig. 3. Secondly, BP completes the training by minimizing the error as well.

GA is also applied to optimize the architecture of the neural network to select the optimal number of hidden layers and neurons using MATLAB. The GA based selection and optimization has been developed where the range of constraints and parameters are searching within the range from 1 to 4 layers with up to 30 neurons per layer, 20 generations, and population size is 10 individuals to avoid long computational time. Table 1 shows the selected values and parameters for the GA based optimization and training.

4. Experimental setup and data collection

The centrifugal pump experiment has been designed and assembled where it consists of several parts including: centrifugal pump which is coupled with a motor (Saer company, Italy, model: NCBZ-2P-50-125C, 2.2 kW, 3-phase, 420 V, head 8–17 m and flow rate 500–1000 L/min), control panel with speed controller (Schneider model Variable Frequency Drive (VFD) with speed controller and display screen, switch (OFF/ON) and emergency shutdown), digital turbine flow meter (USA-TM model, 2 in. diameter), pressure gauges, vacuum pump and clear PVC pipes; and spare parts: a rolling element bearing, mechanical seal, gasket and impeller. A data acquisition system (DAQ) and accelerometers from National Instruments (NI) are used. The DAQ system includes SCXI-1000 and SCXI-1530 models with 4 input channels. The accelerometer model is IMI 621B40 with sensitivity of 10 mV/g and frequency range from 3.4 to 18 kHz for (±10%) and 1.6 to 30 kHz for (±3 dB). Fig. 4 shows the centrifugal pump experimental setup. CPU with 2.20 GHz, RAM 8 GB and MATLAB (version 2012 a).

The vibration signals are measured under healthy and faulty conditions. Firstly, the signal of normal condition is acquired when the pump is healthy, without any faults. The faulty conditions are
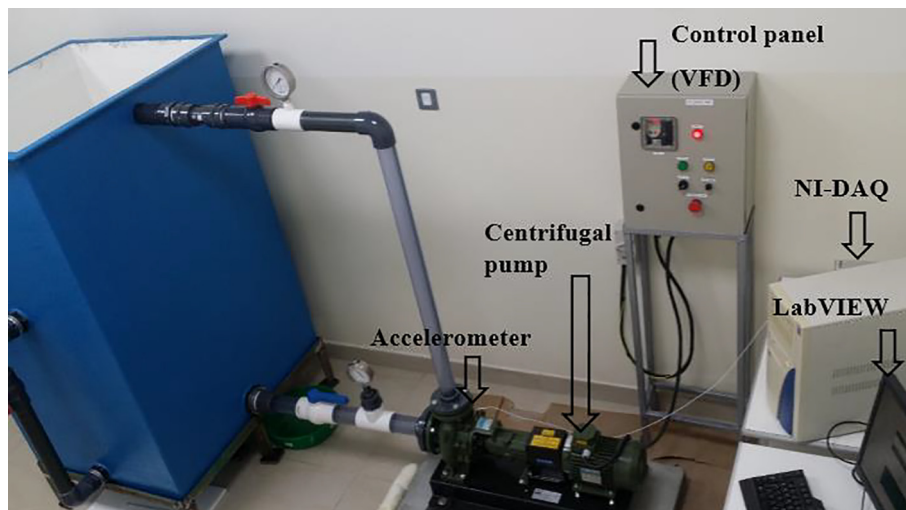

Fig. 4. Experimental test rig.

divided into two main categories: five mechanical faults (bearing, misalignment, unbalance, impeller, and looseness), and a hydraulic fault (cavitation). These faults are created and simulated one by one. Signals are acquired from the pump using an accelerometer which is mounted on its bearing housing. A DAQ is used to read the signals, where the signals are amplified and noise filtered out before digitization and filtering is used with a bandwidth of 2.5 kHz; and then transmitted to a computer which is equipped with a digital/analogue converter card (D/A) in order to convert the analogue signals to digital. Data are acquired for a period of 2.4 s at a sampling rate of 16 kHz, resulting in acquisition of 38,400 samples. Averaging is applied with 10 as number of averages. Finally, these signals are captured via LabVIEW software where raw signals are saved in order to use them in the second stage for further processing. All data of the pump conditions are acquired at a speed of 20 Hz (1200 RPM) [16,17,18,19].

5. Feature extraction

CWT is similar in concept to the Fourier Transform, but uses families of wavelets as its basis functions instead of sine and cosine functions; a family of wavelets consists of two parameters (scale and translation); hence the signal will be represented as a two dimensional time-scale plane, instead of only one dimensional plane, thus addressing an important limitation of the Fourier Transform [20], and CWT is given by:

$$Wx(a + b; \varphi) = a^{\frac{-1}{2}} \int x(t) \varphi^* \left(\frac{t - b}{a} \right) dt \qquad (16)$$

where Wx is the wavelet transform that is linked with the two parameters; a which is the scale parameter, and b is the time parameter, φ is wavelet function, and $x(t)$ is the original signal.

In this work, CWT is applied with Morlet wavelet function, as Morlet is well known for its shape similarity with the rotating machine fault signals [11,12,21]. The vibration data are captured from the pump for seven cases: the healthy pump, and six different fault conditions. In each case, a signal of length 34,800 samples is recorded. These signals are each divided into 8 segments, of length 4800 samples.

From each of the 8 segments, the wavelet transform produced 30 features (the wavelet scale). From these 240 features, 6 parameters (Kurtosis, RMS, Peak, Crest Factor, Shape Factor and Impulse Factor) are computed for the signal from each case. All of these features are used to train the MLP-BP. For the SVM, a smaller number of features and parameters are selected; first using 2 parameters and 240 features; and then with the number of features reduced to just 60 and also 30.

The effectiveness (sensitivity) of each parameter against all conditions are plotted in Fig. 5. Normally, when healthy (blue+) is the lowest, it indicates good effectiveness of the parameter. Peak and RMS illustrate better distribution compared to the other parameters, and they can be selected as inputs for SVM.

6. Classification methods

The extracted features are used as input vectors that were forwarded to the neural network classifier and SVM.
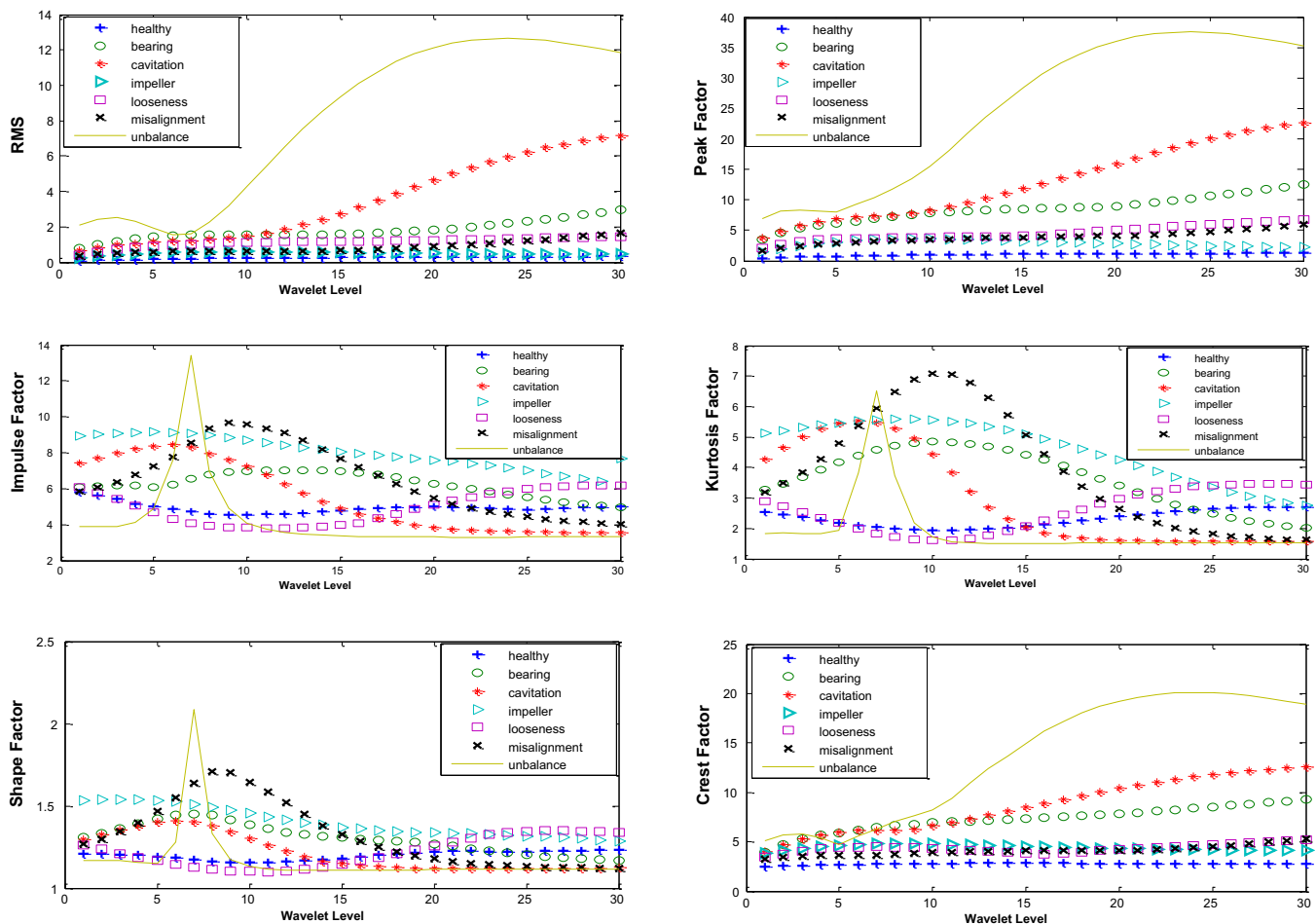

Fig. 5. The effectiveness of each parameter against all conditions.

Different hidden layers and neurons are tested; single layers contain 10, 15, 20 and 30 hidden neurons, and three hidden layers contain 10, 20 and 10 neurons respectively. Subsequently, the number of hidden layers and neurons were optimized using GA.

Three cases are considered based on number of features, (240 normalized and non-normalized features) per condition with a total of 1680 input features for all conditions per parameter were forwarded to the MLP-ANN which results in a matrix of size [6 × 1680], the second case has 60 features (normalized and non-normalized) which results in a matrix of size [6 × 420], and the third one with 30 (normalized and non-normalized) which results in a matrix of size [6 × 210]. The target for training was a Boolean matrix of size [7 × 1680] (240 features) or [7 × 420] (60 features) and [7 × 210] (30 features).

The network is first trained using Levenberg-Marquardt (LM) function which is a back propagation algorithm to update weights and biases. The input vectors are divided into three datasets (training has 70%, test has 15% and validation has 15%). The target consists of rows corresponding to the 7 conditions (cases) in which seven digits-coding and each digit represents a block of size (1xnumber of features) and is given as follows (sources): Healthy [1 0 0 0 0 0 0], Bearing fault [0 1 0 0 0 0 0], Cavitation [0 0 1 0 0 0 0], Impeller fault [0 0 0 1 0 0 0], Misalignment [0 0 0 0 1 0 0], Looseness [0 0 0 0 0 1 0], Imbalance [0 0 0 0 0 0 1].

SVM classification has been applied using three cases which are 240 features (normalized and non-normalized), 60 non-normalized features, and 30 non-normalized features which were extracted using CWT. For the three cases, all seven cases classification conditions are tested (i.e. all seven cases against each other).

For the first case with 240 features (normalized and non-normalized), SVM classification method has been applied for the different centrifugal pump conditions using MATLAB. The SVM has been investigated using three kernels, namely, linear, polynomial and radial basis function (RBF) separately.

The second and third cases of using 60 and 30 features are implemented using a polynomial kernel and penalty parameter C (width) set to 3 since the polynomial kernel was shown from the first case to be the best.

7. Results and discussion

7.1. MLP-BP

Classification rates using the first case (240 features) of 89.6%, 91.1%, 93.3% and 95.3% are obtained using manually selected single layers of 10, 15, 20 and 30 neurons respectively, and an overall success rate of 98% is scored using the three hidden layers containing [20 10 20] neurons. However, the best overall success rate of 99.3% and 98.2% using non-normalized and normalized features respectively is achieved using GA based selection which suggested four hidden layers containing [24 21 24 23] neurons.
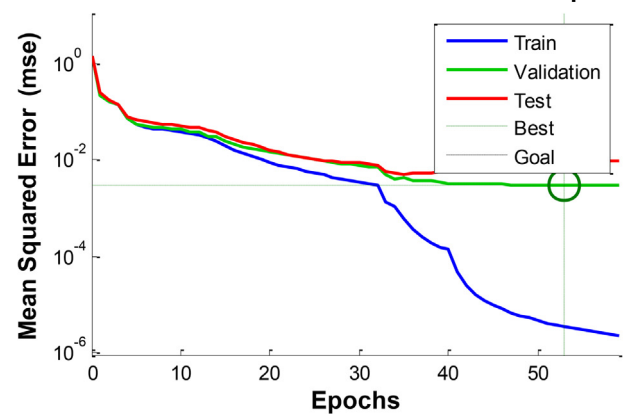
Classification rates using the second case (60 features) of 98.3% are obtained using manually selected three hidden layers containing [20 10 20] neurons, and with GA based selection as four hidden layers containing [24 21 24 23] neurons, the best overall rate are 99.5% using non-normalized features as illustrated in Figure 7, and 99.3% with normalized ones.

As shown in Fig. 6(a), the lower right blue square shows the overall classification rates, where overall, 99.5% (in green) of the classifications are correct and 0.5% are incorrect classifications. Taking each classes' accuracy rate (pump conditions) individually; healthy (case 1) has an accuracy rate of 98.4%, bearing fault (case 2) has an accuracy rate of 100%, cavitation (case 3) scored 100%, impeller fault (case 4) has an accuracy rate of 100%, misalignment

(a)

(b)

Fig. 6. (a) Matrix confusion of classification rates of 60 non-normalized features, (b) the mean square error diagram for MLP network of 60 non-normalized features.

(case 5) has 100%, mechanical looseness (case 6) has 100% and imbalance (case 6) has shown an accuracy rate of 98.4%.

Classification rates using the second case (30 normalized features) of 99% are obtained using three manually selected hidden layers containing [20 10 20] neurons, and with GA based selection as four hidden layers containing [24 21 24 23] neurons, the best overall rate are 99.5% using normalized features and 99.5% with non-normalized ones.

7.2. MLP-GABP

MLP-GABP illustrated lower performance comparing MLP-BP in terms of computational time and classification accuracy rate which is 88.5%, where as an overall, 88.5% of the classifications are correct and 11.5% are incorrect classifications. Taking each classes' accuracy rate (pump conditions) individually; healthy (case 1) has the accuracy rate of 95.2%, bearing fault (case 2) has an accuracy rate of 74.9%, cavitation (case 3) scored 81.9%, impeller fault (case 4) has an accuracy rate of 91.3%, misalignment (case 5) has 91.4%, mechanical looseness (case 6) has 94.3% and imbalance (case 6) has shown an accuracy rate of 92.1%.
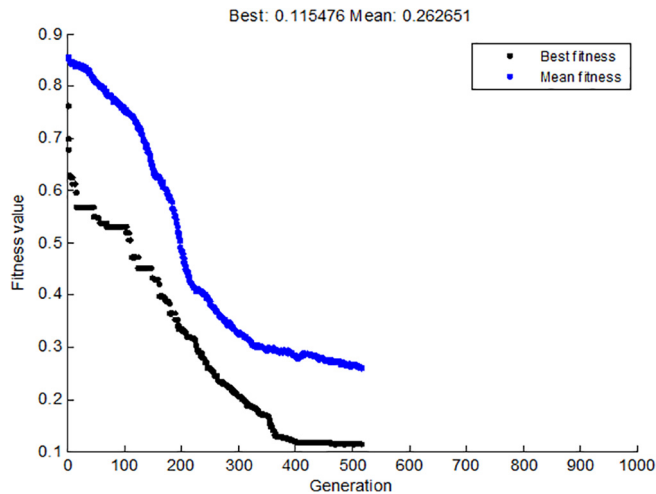
Fig. 7. Best score value and mean score versus generation.

Four hidden layers containing [24 21 24 23] neurons are used in MLP as per as selection of GA and weights of neural network have been adjusted and selected using GA and optimization is terminated after 515 generations with best fitness function of 0.115476 as shown in Fig. 7. Table 2 shows a comprehensive performance of all MLP-BP/GABP cases.

7.3. SVM

The classification accuracy rates using the three kernels showed that polynomial kernel is the best in terms of hyper plane with wider margin and better classification accuracy rates. From the results obtained from the first case (240 non-normalized and normalized features), it is shown that non-normalized features outperformed the normalized features in terms of overall accuracy rate, and polynomial kernel function shows better performance than linear and RBF kernel functions as shown in Table 3. Therefore, it was decided to use non-normalized features for the second and third cases (60 and 30 features).

Table 4
SVM overall performance based CWT.

Method	Features	Overall classification rate (%)
SVM (polynomial)	60 (non-normalized)	96.77
SVM (polynomial)	240 (non-normalized)	95.88
SVM (polynomial)	240 (normalized)	95.48
SVM (RBF)	240 (non-normalized)	94.93
SVM (RBF)	240 (normalized)	94.54
SVM (linear)	240 (non-normalized)	87.45
SVM (linear)	240 (normalized)	77.38

In the second (60 non-normalized features) and third (30 non-normalized features) cases, The classification performance has been improved using lower number of features with an overall classification rate of 96.77% and 98.8% respectively. Table 4 illustrate a comprehensive classification rates of all SVM applied methods and cases.

8. Conclusion

The feature extraction and classification of the pump conditions using MLP-BP, MLP-GABP and SVM were conducted successfully where 99.5% of the best overall classification rate is scored with MLP-BP and 98.8% with SVM, where MLP-BP slightly outperformed SVM in terms of overall classification accuracy rate. It has been remarked that MLP-BP and SVM performed better using non-normalized fewer parameters and features. Polynomial kernel function outperformed the other two kernel functions (linear and Radial Basis Function (RBF)) as it gives better accuracy rates. Therefore, polynomial has been selected and used for the other SVM classifications.

GA has shown a good ability in optimizing and selecting the number of hidden layers and neurons, as the best performance is scored using 4 hidden layers containing 24, 21, 24 and 23 neurons respectively. However, GA needs longer computational time and the risk of getting stuck in a local minimum. On the other hand, GA along with BP based MLP training, presented lower performance comparing MLP-BP of 88.5% an overall rate. Finally, this work showed that MLP-BP classification accuracy can be improved

Table 2
MLP overall performance based CWT.

Method	Features	Hidden layers & neurons	Training time (hh:mm:ss)	Test rate (%)	Validation rate (%)	Training rate (%)	Overall classification rate (%)
MLP-BP & GA selection	30 (normalized)	[24 21 24 23]	00:00:28	96.9	100	100	99.5
MLP-BP & GA selection	30 (non-normalized)	[24 21 24 23]	00:00:18	96.9	100	100	99.5
MLP-BP & GA selection	60 (non-normalized)	[24 21 24 23]	00:01:11	96.8	100	100	99.5
MLP-BP & GA selection	60 (normalized)	[24 21 24 23]	00:01:04	95	100	100	99.3
MLP-BP & GA selection	240 (non-normalized)	[24 21 24 23]	00:02:12	98.4	99.9	97.2	99.3
MLP-BP & GA selection	30 (normalized)	[10 20 10]	00:00:03	93.8	100	100	99
MLP-BP	60 (normalized)	[10 20 10]	00:00:06	93.7	98.4	100	98.8
SVM (polynomial)	30 (normalized)	____	____				98.8
MLP-BP & GA selection	240 (normalized)	[24 21 24 23]	00:02:06	93.3	100	94.4	98.2
MLP-BP	240 (normalized)	[10 20 10]	00:00:20	94.4	95.6	98.6	97.5
MLP-GABP & GA selection	240	[24 21 24 23]	MLP: 00:02:17, GA: 20:00:00				88.5

Table 3
The overall SVM classification accuracy rates for case-1.

Overall Classification	Kernel function					
	Linear (%)		Polynomial (%)		RBF (%)	
%	240 normalized	240 non-normalized	240 normalized	240 non-normalized	240 normalized	240 non-normalized
	77.38	87.45	95.48	95.88	94.54	94.93

if the neural network architecture is optimized using GA and with the suitable selection of features.

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