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Experimental Set-Up for Investigation of Fault Diagnosis of a Centrifugal Pump

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Abstract**—**Centrifugal pumps are complex machines which can experience different types of fault. Condition monitoring can be used in centrifugal pump fault detection through vibration analysis for mechanical and hydraulic forces. Vibration analysis methods have the potential to be combined with artificial intelligence systems where an automatic diagnostic method can be approached. An automatic fault diagnosis approach could be a good option to minimize human error and to provide a precise machine fault classification. This work aims to introduce an approach to centrifugal pump fault diagnosis based on artificial intelligence and genetic algorithm systems. An overview of the future works, research methodology and proposed experimental setup is presented and discussed. The expected results and outcomes based on the experimental work are illustrated.

Keywords**—**Centrifugal pump setup, vibration analysis, artificial intelligence, genetic algorithm.

I. Introduction

NOWADAYS, condition monitoring is increasingly used to anticipate and detect problems in industrial machines. Failures in machines can incur high maintenance or replacement costs, or if neglected, may cause catastrophic accidents leading to production downtime and potential failure to supply, hence affecting profitability. Consequences include loss of availability, cost of spares, cost of breakdown labour, cost of secondary damage and risk of injury to people and the environment. Any company that seeks optimum production at the lowest cost has to adopt a reliability function rather than a repair function for the maintenance strategy [1]. Vibration monitoring and analysis are applicable for fault detection of pumps and rotating machines as all machines vibrate [2]-[5]; accelerometers can be used to extract vibration signals from machines, which are then analysed using software. A vibration signal is processed to present useful information about the condition of the machine.

There are different methods that have traditionally been used to interpret the vibration signal starting from the conventional ones using time domain analysis [6] and frequency domain analysis, where methods such as the Fast Fourier Transform (FFT) are applied [7], [8]. More recently, a powerful multi-resolution technique called wavelet analysis has been applied to fault detection in rotating machines and has demonstrated the ability to analyse non-stationary signals [8]-[11]. Significant advantages of applying wavelet transforms for the signal analysis are the ability to present a high frequency resolution at low frequencies and a high time resolution at high frequencies, as well as reducing noise for some raw signals [12].Wavelet transforms have been applied in diverse industries, including biomedical, civil, and manufacturing engineering [13]. Artificial intelligence (AI) systems for automatic fault diagnosis and classification have been investigated by numerous researchers [12], [14]-[16]. Such automatic fault classification can be used to improve precision and reduce mistakes that might otherwise be caused due to human misinterpretation [14].

Automatic fault detection methods make use of Artificial Intelligence (AI) which seeks to replicate mental capabilities with the support of computational systems [17]. The Artificial neural network (ANN) was first introduced by McCulloch and Pitts [18], and Fuzzy logic was first introduced by Zadeh [19]. Artificial intelligence systems have been applied for centrifugal pump fault diagnosis using different methods for the feature extraction, starting from a simple method of statistical analysis [20]-[23], later FFT [14], [24], [25], and also a wavelet transform has been applied using time-frequency method [12], [26]-[28]. Ilott and Griffiths [29] proposed ANN with Back Propagation (BP) algorithm to diagnose pump faults. Then, Zouari et al. [30] applied ANN and a fuzzy neural network to diagnose centrifugal pump faults; statistical methods of time and spectral analysis were used for the feature extraction.

Experimental setup can play a major role when studying the vibration forces of a machine. Centrifugal pump fault diagnosis studies have been implemented using various experimental arrangements, data acquisition systems and analysis processing methods [12], [14], [16], [17], [31]. Muralidharan et al. [12] used a monoblock centrifugal pump with a constant speed of 2880 RPM, an accelerometer sensor was mounted on the pump suction and signals were processed at sampling rate of 24 kHz and sample length of 1024. Al-Braik et al. [32] used a setup consisting of a centrifugal pump, electric motor with a capacity of 4 kW, a variable speed motor to control the speed up to 2900 RPM and instrumentation including pressure sensors and a flow meter. An accelerometer (YD3-8131 model) was used with a frequency range of 2 Hz-15 kHz. The sampling rate was 96 kHz with 24 bit data resolution.

This paper is divided into four parts including introduction namely, experimental setup, work methodology and

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conclusion.

II. Experimental Setup

The centrifugal pump experiment has been designed and assembled specifically for this research where it consists of 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/M), control panel with speed controller (Schneider model VFD with speed controller and display screen, switch (OFF/ON) and emergency shutdown), digital turbine flow meter (USA-TM model, 2 inch 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 comprises SCXI-1000 and SCXI-1530 models. The accelerometer model is IMI 621B40 with sensitivity of 10 mv/g and frequency range from 3.4 to 18000 Hz for (±10%) and 1.6 to 30000 Hz for (±3 dB). Fig. 1 shows the centrifugal pump experimental setup which includes the products of NI.

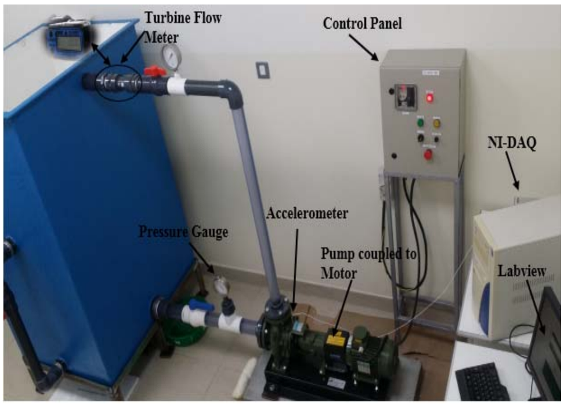

Fig. 1 Experimental setup

The vibration signals will be measured under two conditions, namely healthy and faulty. Firstly, the signal of normal condition is acquired when the pump is healthy, without any faults. Secondly, the faulty conditions will be divided into two main categories; mechanical faults (bearing, seal, misalignment, unbalance, impeller, and looseness), and hydraulic faults (cavitation, water hammer, and turbulence). These faults will be created and simulated one by one. Signals will be acquired from the pump using an accelerometer which is mounted on its bearing housing. This sensor will transfer the vibrational data to the data acquisition device (DAQ) where the signals have to be amplified and filtered out; and then will be moved to a computer which is equipped with a digital/analogue converter card (D/A) in order to convert the analogue signals to digital. Finally, these signals will be captured via LabVIEW software where then signals in form of raw data will be saved in order to use them in the second stage for further processing.

III. Method

The procedure consists of three main stages, namely, data collection, data pre-processing and extraction, and fault classification, as shown in Fig. 2.

Classification and diagnosis of the centrifugal pump condition will be implemented using two artificial intelligence classifiers, namely, MLP and SVM. MLP will be implemented along with its traditional learning algorithm (Back-Propagation) and with GA, for the first time, to investigate and compare the two learning algorithms. SVM will also be used as a classifier and its performance will be compared with MLP. MATLAB software is selected to implement the classification stage, for which tools and codes will be developed. Classifiers consist of two main processes: training of data, and testing, where an automatic classification will be implemented for the different conditions. The performance of the AI classifier will be measured according to the classification accuracy rates (%). Fig. 3 depicts the main concept of the AI classifier processes.

GA and BP algorithms will be investigated and tested for training the MLP where its weights have to be modified and updated. Each training algorithm will be tested alone and then a hybrid training algorithm that combines both GA and BP will be applied. It is remarked that this hybrid training method will be applied with ANN for the first time, as it has not been done before with any fault diagnosis research on centrifugal pumps, or even more generally on any rotating machinery. The general principle of operation of MLP-ANN with learning algorithms of GA and BP is depicted in Fig. 3. MLP consists of three layers, namely, input layer, hidden layer, and output layer. The input layer consists of many neurons which represent the extracted and normalized features that are pre-processed using WT, and the number of neurons (features) will be selected based on the GA-based selection method. The hidden layer consists of a number of neurons in which GA-based optimization is used to minimize the Mean Square Error (MSE) and the number of neurons will be selected accordingly. The output layer consists of a number of neurons according to the tested centrifugal pump conditions, and with the current proposed conditions, there is one neuron for a healthy condition, and nine neurons for nine different fault conditions.

MLP will be trained using GA and BP where the following steps will be applied while training with GA:

1) [$W1$, $W2$, Wn] are bias weights of neural network, and these weights will be coded into individual populations (chromosomes).
2) Train and evaluate each chromosome (previously weight) individually based on the fitness.
3) Rank the chromosomes according to the higher fitness.
4) Select the best and top ranked chromosomes for survival.
5) Use genetic operators of crossover and mutation to recreate a new generation of chromosomes where the weak chromosomes at step 1 are replaced with the new and strong ones.

6) Repeat step 2 by training and computing the new chromosomes and the process is continuous until reaching the desired Mean Square Error (MSE).

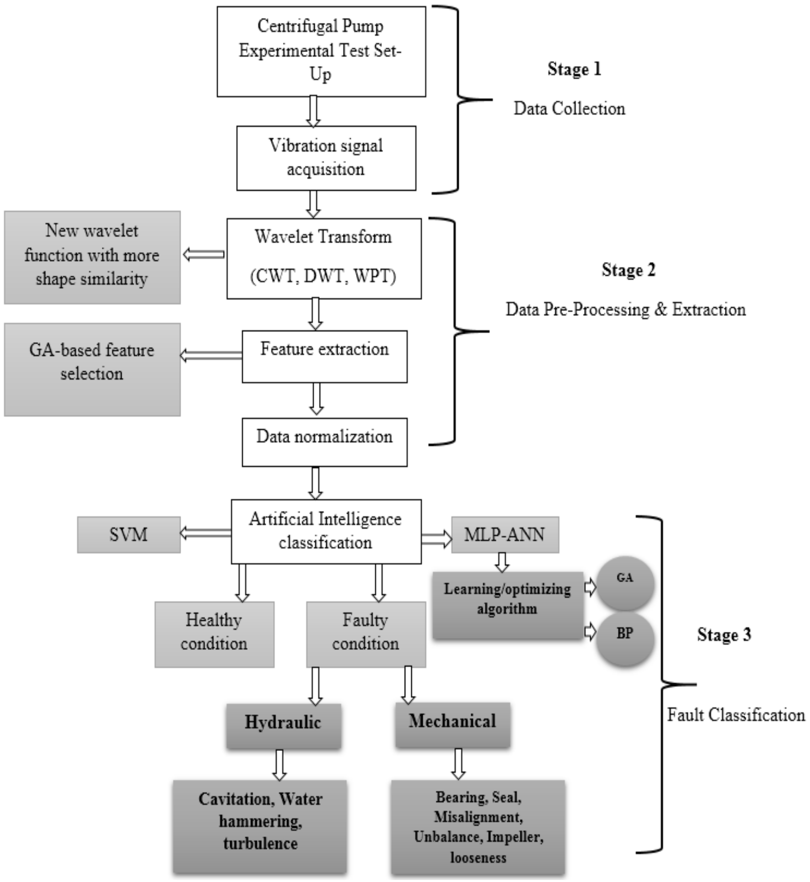

Fig. 2 Research methodology steps

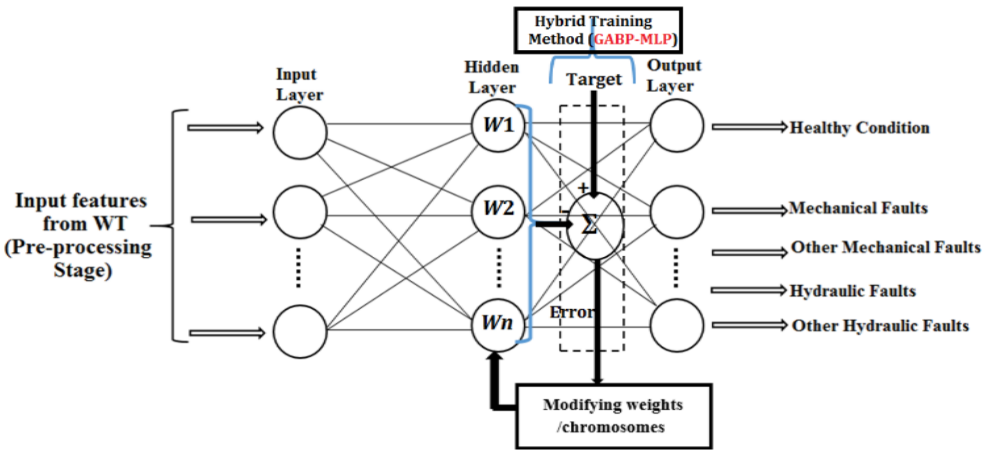

Fig. 3 The proposed methodology of MLP-ANN with learning algorithms of GA and BP

The BP algorithm will then be used after the optimization of GA. BP is based on a gradient descent method that it works to modify the neural network weights which have been optimized through GA.

IV. Conclusion

Many experimental works can be conducted using the centrifugal pump experimental setup including the investigation of the vibrational behaviours which can be measured, monitored and analysed through the vibration analysis methods. This work presents a novel experimental setup which is made specifically to study mechanical and hydraulic vibrations of the centrifugal pump and it offers different vibrational monitoring options. Future work would be implementations of vibration artificial intelligence techniques that for the first time in the machinery condition monitoring field; genetic algorithm would be investigated as a learning algorithm for the neural networks.

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