HAIWF-based fault detection and classification for industrial machine condition monitoring

T. Sathish*
Vesta Educational and Charitable Trust,
Pudukkottai, Tamil Nadu, 622001, India
Email: sathish.sailer@gmail.com
Email: sathishtphd@gmail.com
*Corresponding author

S. Karthick
Department of Electronics & Communication Engineering,
Satyam College of Engineering & Technology,
Kanyakumari, Tamil Nadu, 629301, India
Email: karthicksuyam@gmail.com

Abstract: Fault detection and classification is based on the idea that can detect changing conditions within equipment. The techniques for detecting faults can be distinguished as a pattern matching from the values of a sensor and the difference between the sensor readings and expected value. Researchers also interested in the field of fault detection of rotating machinery using artificial neural networks (ANNs). But, ANN suffer from data diversity and training complexity. In this paper, an approach is presented to prevent the complexities of ANN. The proposed system uses the inertia weight firefly (IWF) algorithm for training the neural network. The efficiency of the Hybrid ANN IWF (HAIWF) in detecting and classifying machine faults is compared with conventional techniques. The proposed techniques achieved 11–14% more than the conventional techniques. Ultimately the proposed IWF based ANN is suggested to effectively predict the industrial machine fault detection.

Keywords: industrial machine maintenance; fault detection; artificial neural networks; ANNs; particle swarm optimisation; genetic algorithm.


Biographical notes: T. Sathish completed his BE in Mechanical Engineering from Panimalar Engineering College, Chennai and he completed his MTech in Manufacturing Technology from Prist University, Thanjavur. Currently, he is working as a Dean (R&D) in Vesta Institutes.

S. Karthick has completed his Bachelor of Engineering in Electronics and Communication Engineering from Anna University in 2013 and he completed his Master of Engineering in Communication Systems from Anna University.
in 2017. He is currently working as an Assistant Professor in Satyam College of Engineering and Technology an Anna University affiliated college. He has published more than seven research papers in sci/scopus journals.

This paper is a revised and expanded version of a paper entitled ‘HAIWF-based fault detection and classification for industrial machine condition monitoring’ presented at International Conference on Recent Advances in Mechanical Engineering, Vellore, India, 01–02 September, 2017.

1 Introduction

The industrial revolution in 1760s is one of the most critical periods in the modern era. In this time only the machinery industry was born. It has paved the way to the invention of various devices that have helped human (Zarei and Poshtan, 2007). These industries still play a huge role when it comes to business. The machines are mattered to some form of catastrophes in spite of the dependability can be progressed considerably. These breakdowns may be intrinsic to the machine itself or due to working conditions (Yang et al., 2004a). The basis of distinctive failures is due to the mechanical or electrical forces acting in the machine field. By using an appropriate condition watching go with dominant signal processing method, the machine problem and its abnormality can be identified at an early stage (Singh and Kazzaz, 2003).

To give information for the choice of switchgear, setting of relays and constancy of system operation, the error study of a machine’s system is necessary (He, 2013). On most circumstances, mainly when the error is small, these pulses can minute, and they can bury in noise and much higher energy low-frequency components of the calculated acceleration signal. These errors may either be three phases in nature connecting all three phases in a balanced manner or may be unbalanced where typically only one or two phases may be engaged (Li et al., 2005). That is the cause why ball bearing errors are not simple to identify (Sikorsk and Mba, 2006; Sugumaran et al., 2007). Due to insulation breakdown errors happen in a power system, flashover, physical spoil or human fault (Lei et al., 2007). Fault study is performed in per-unit quantities as they give results which are slightly reliable over different voltage and power ratings and work on values of the order of accord (Zhang et al., 2005). Investigators have revised a variety of machine errors, such as winding faults, unbalanced stator and rotor parameters, broken rotor bars, eccentricity and bearing errors (Yang et al., 2004b). Rotor errors are of considerable importance among different imperfections happened in machines because they cause secondary breakdowns that direct to a severe motor failure.

Condition monitoring helps to set right such errors when going with other computer-aided solutions as declared earlier. Condition monitoring concerns to offer data about the state of the plant so that it can be sustained appropriately (He et al., 2009). We can forecast incipient malfunctions by having such information of machine state, and stop the plant for repairs in a designed manner so that the minimum loss of output happens and so that the maintenance can be performed as competently as feasible (Peng et al., 2010; Hameed et al., 2009). The related knowledge obtained from different sensors is examined in machine condition monitoring, to evaluate the health condition of the machine components, which are unattainable not including dismantling the machines (Li et al.,
2006a). In above all, vibration and sound signals are directly associated with structural dynamics of the machine, so they have full knowledge about the machine health condition (Subrahmany et al., 2010). Furthermore, the understanding of the attributes may vary significantly under different operating conditions. In the condition monitoring and error study of rotating machinery, fault-related machine vibration is damaged by the vibration from the structured machine itself and noise from interfering machinery (Hua et al., 2007; Sugumaran et al., 2007). Hence it is essential to find an efficient technique of redundancy reduction (Peng and Chu, 2004; Li et al., 2006b). Consequently, it is favourable but challenging to remove the dynamic characteristics again from the unique characteristics for efficient machine condition monitoring (Jiang and Liu, 2011; Loutas et al., 2011). Thus pattern recognition techniques take parts a pivotal position to decide such problems.

Even though the machinery industry has the significant role in today’s lifestyle, it has some drawbacks and complexity for users. Hence the researchers involved in the research based on the machines to resolve those problems. In this sense, our system also planned to overcome a problem in machines. One of the significant research is to detect the fault in rotating machines. For this purpose of fault detection, ANN is used in any case. ANN is a novel artificial intelligence technique applied in many fields (Sankar et al., 2017). Still, it faces some problem in training of ANN. In our work, we propose a method for training the ANN by IWF. Subsequent sections in this document explain about the efforts associated with fault detection, suggested the method for fault detection, result from analysis and the conclusion.

2 Related work

Few recent works related to the fault detection of rotating machines by using various techniques are reviewed as follows.

Banerjee and Das (2012) have suggested a hybrid model for an onboard fault tolerant control system. They considered a hybrid method for fault signal classification based on sensor data fusion by using support vector machine (SVM) and short term Fourier transform (STFT) techniques. From the opinion of evidence theory, knowledge acquired from every sensor could be regarded as a piece of proof, and as such, the multi-sensor based motor error diagnosis could be analysed as the problem of proof fusion. They suggested and examined a hybrid technique for fault signal classification based on sensor data fusion using the SVM and STFT methods. They accounted a practical function of this hybrid model and assessed its presentation.

Wu et al. (2010) have proposed an online adaptive condition-based maintenance method for mechanical systems. They have utilised a subtype of neural network methods called self-organising map (SOM) in this suggested technique. Also, distance examination and statistical pattern recognition (SPR) on neurons of the SOM were united to launch rules and criteria for performing and controlling the invention and learning process so continuous process as purging prototypes on the map could be evaded.

Wang et al. (2012) have suggested a system for effectual categorisation of a rolling bearing fault location and particularly its degree of presentation degradation. By joining empirical mode decomposition (EMD) with the autoregressive copy, they have removed
characteristics of the rolling bearing vibration signal, whose copy parameters and differences of the remainder could be attained using the Yule-Walker or Ulrych–Clayton technique. Thus, multi-status original diagnosis of conventional rolling bearings and fault rolling bearings at various positions and the degrees of performance degradation of the fault rolling bearings could be accomplished concurrently. Prieto et al. (2013) have presented a novel monitoring scheme applied to diagnose bearing faults. Zarei et al. (2014) have proposed an intelligent method based on artificial neural networks (ANNs) to detect bearing defects of induction motors. Guasp et al. (2015) have presented an analysis of state of the art in condition monitoring and fault detection.

Trendafilov (2010) has identified and categorised errors based on pattern recognition and principal components study of the calculated vibration signals. That was pursued by pattern recognition (PR) procedure applied to distinguish among signals coming from good bearings and those produced from different bearing faults. The PR method employs first six principal elements removed from the signals after a proper principal component analysis (PCA). In the suggested technique, an adapted PCA was proposed, which was much more suitable for specific information. The mixture of the adapted PCA and the PR technique makes sure that the error is routinely identified and classified to one of the measured fault categories.

3 Proposed HAIWF technique

Machines take the significant role in the modern world for making the lifestyle ease. However, the problems while using the machines are enormous. Hence, many researchers have involved in the research to rectify the problems in machine one of such interest is resolving the problems in the rotating machines. For this purpose, ANN was used to solve such a problem before it occurring. One of the most used ANN models is the multi-layer perceptron (MLP) and trained by the back propagation algorithm. Every MLP network has one input layer, one output layer and one or more hidden layers. All nodes are composed of neurons except the input layer. The number of nodes in each layer varies depending on the problem. The complexity of the architecture of the MLP depends upon the number of hidden layers and nodes. Training an MLP is to find a set of weights that would give desired values at the ANN’s output when presented with different patterns at its input Figure 1 shows an example of an MLP.

In Figure 1, \( X_i, X_1, X_2, \ldots, X_f \) are the input neurons, \( Y_i = Y_1, Y_2, \ldots, Y_o \) are the output neurons, is ‘\( w_1 \)’ the weight between the input neuron and hidden neuron, ‘\( w_2 \)’ is the weight between the hidden neuron and output neuron, and ‘\( f_i \)’ is the activation function.

The ANN with back propagation has slow convergence and data deficiency. Hence to overcome the issue in training of ANN, optimisation techniques are used. Hence in this work, ANN is trained with the aid of IWF to overcome the drawbacks of the backpropagation training algorithm. In this proposed technique the inertia weight firefly (IWF) trained ANN is used for the detection of rotating machine. Hence the weights for the ANN is considered as the input value of this IWF. The following sections describe the IWF.
3.1 Inertia weight firefly training

The IWF based ANN is used in this work to detect rotating machine faults; it overcomes the drawbacks like data deficiency and training difficulties in ANN using the backpropagation algorithm. In this ANN, the weight is considered as the input data. In this proposed technique, the separate neural network is used for each weighted input. In this method by using an individual neural network for individual input weight makes the training process more efficient and also the issue of data deficiency can be reduced to an extent.

Initially, the input weights are assigned to begin the training process by our proposed IWF technique. The individuals are selected as per the ranking of the individuals, and the ranking is based on their calculated fitness value. The individual has 1 (one) is considered to be the fittest individual for the next iteration of training. That is the individuals whose fitness value is low getting the highest rank and individuals having following fitness values are assigned with consecutive fitness values.

An individual with lowest fitness value, i.e., less error is the fittest individual. So, we are considering the fitness values in the previous iterations and based on that; the rank is assigned using equation (1). An individual may have the lowest fitness value in the current iteration, but while considering the fitness value of that individual in current iteration with its fitness value in the previous iteration and if the fitness value has increased in the current iteration, then that individual has degraded in its fitness. Hence it is a wrong idea to consider an individual as the fittest individual only based on its fitness value in the current iteration. On the other hand, if an individual has the lowest fitness value and the difference between its current fitness value and previous iterations fitness value is less than the difference between the current fitness value and previous iterations fitness value of another individual, then the individual whose fitness values difference can get the highest rank.
3.1.1 Inertia weight firefly algorithm

The critical objective is to minimise the greatest of support value and minimise the base of support value. For that, we have utilised some control parameters such as Initial brightness \( b = 0.4 \); Randomisation parameter \( \eta = 0.5 \); Coefficient of light absorption \( \gamma = 0.5 \).

A multi-objective function is mathematically formulated as,

\[
\text{obj}(i) = \min \{ x \}
\]  

In equation (1), \( x \) denoted data rate value.

Calculation of the fitness function:

\[
F(j) = \left\{ \begin{array}{ll}
\frac{1}{1 + \text{obj}(i)} & \text{if} (\text{obj}(i)) \geq 0 \\
\end{array} \right. 
\]  

(2)

\( \text{obj}(i) \) – separate objective functions.

Numbers of iterations are used for calculating the Fitness function. This iteration continues until the best-optimised value is as received. The objective function should be high in our work.

As attractiveness of fireflies’ is directly proportional to the light intensity seen by adjacent firefly, we can now define the attractiveness \( \beta \) a firefly by

\[
\beta(r) = \beta_0 e^{-r/c} \quad ; \quad m \geq 1
\]  

(3)

where \( \beta_0 \) is the attraction per \( c = 0 \) and \( \gamma \) is the illuminated saturation immersion coefficient, and \( \gamma = [0, \infty] \), by and large \( \gamma = 1 \), some circumstance \( \beta_0 \) is taken as \( \beta_0 = 1 \), and \( m = 2 \) because of the most fireflies are visible just to a constrained separation. Consume arrangement room to be n-dimensional, the distance between any two fireflies \( i \) and \( j \) at \( x_i \) and \( x_j \), here for separation count, utilised Cartesian separation as:

\[
c = \sqrt{\sum_{k=1}^{n}(x_i - x_j)^2}
\]  

(4)

Here, time-varying adaptive weight is developed for updating the position of fireflies. The AW linearly decreases concerning time. Following equation is used for updating AW:

\[
S_{new}(t+1) = w(t)S_{old} + \beta_0 e^{-r/c}(x_j - x_i) + \alpha \epsilon_i
\]  

(5)

where \( S_{new}(t+1) \) stands the position of the \( i \)th firefly, after \( t + 1 \)th movement; \( \alpha \) being the randomisation parameter, \( \alpha \in [0,1] \) for most problems, we can use a fixed value of \( \alpha = 0.1 \). Here \( \epsilon_i \) is a vector of random numbers, which is come from Gaussian distribution.

Adaptive weight (inertia weight linearly decreasing)

Most of the firefly variants use time-varying adaptive weight (AW) strategies in which adaptive weight value are determined based on iteration number. Time-varying inertia
weight approaches have essential applications in numerous fields; these procedures can be either increasing or decreasing and linear or non-linear. In a linear decreasing AW is introduced to improve the delicate tuning firefly's characteristics.

Many works have been done by researchers to increase its efficiency while handling optimisation problems. Such work is introduced in original firefly characteristics to control its misuse and analysis for better performance. Still, adaptive weight firefly algorithm is known to have premature limitation convergence by solving difficult (multipeak) problems due to the lack of adequate energy. The addressing challenge has been incurred in a long time and has concerned much researcher's attention in global optimisation field.

In principle that a significant inertia weight simplifies a global search although a small inertia weight simplifies a local search, a linearly reducing inertia weight was used with an initial value 0.9 and final value 0.4. By these values, inertia weight can be inferred as medium flexibility in which a firefly moves, showing that setting it to a comparatively high initial value (e.g., 0.9) makes fireflies performs efficiently and move in a low viscosity medium. Progressively decreasing it to a much lower value, e.g., 0.4 makes firefly execute more exploitation and moves in a high viscosity medium.

In this method, $\omega$ the value is linearly decreased from an initial value ($w_{\text{max}}$) to final value ($w_{\text{min}}$) according to following equation:

$$w(t) = \frac{w_{\text{max}} (w_{\text{max}} - w_{\text{min}}) \cdot t}{\text{MaxG}}$$

where $w(t) \in [0,1]$ is the inertia weight at $t$ iteration, $w_{\text{max}}$ is the initial values of inertia weight, $w_{\text{min}}$ is the final value of inertia weight, $t$ is current iteration and MaxG is the maximum number of allowable iterations.

Thus the update of the $i$th firefly is formulated as follows,

$$S_{\text{new}} = S_{\text{old}} + S_{\text{new}} (t+1)$$

Equations (4) and (5) shows that the $i$th firefly, will move towards the $j$th firefly and which is more attractive one in the optimisation. Thus the optimisation using AWFA reduces the complexity by achieving better performance. The experimental results demonstrate that the firefly joined quickly towards optimal positions but slowed down it is convergence speed when it is near optimal value. Thus, by using linearly decreasing inertia weight, firefly lacks global search capability at the end of the run even in some cases when global search capability is essential to local minimum jump out. Accordingly, using adapting scheme for altering inertia weight was recommended to increase firefly’s routine local optima.

4 Result and discussion

The proposed IWF training algorithm for the ANN is implemented in the working platform of MATLAB version 7.12. In this section, we are given a detailed description to prove the performance of our proposed IWF trained ANN. The performance of the proposed IWF algorithm is compared with the performance of some other traditional ANN training algorithm like particle swarm optimisation (PSO), genetic algorithm (GA), adaptive PSO (APSO) and adaptive GA (AGA). To analysis, the performance of our fault
HAIWF-based fault detection and classification

detection of rotating machine by the IWF trained ANN algorithm. The initial parameters used in this experimental analysis are ‘velocity’, ‘rpm’ and ‘velocity of the displacement’ of the rotating machine and other initial parameters used in the training process given in Table 1. The performance obtained by various techniques is shown in Tables 2 and 3. Table 2 gives the TP, TN, FP, FN values based on its prediction. Table 3 gives the every observation of ANN with different training strategies.

### Table 1  Parameter setting

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input neuron</td>
<td>3</td>
</tr>
<tr>
<td>Hidden neuron</td>
<td>20</td>
</tr>
<tr>
<td>Output neuron</td>
<td>1</td>
</tr>
</tbody>
</table>

### Table 2  Performance measure of various methods

<table>
<thead>
<tr>
<th>Training method</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>4</td>
<td>16</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td>GA</td>
<td>5</td>
<td>17</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>APSO</td>
<td>3</td>
<td>16</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>AGA</td>
<td>4</td>
<td>15</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>IWF</td>
<td>6</td>
<td>18</td>
<td>6</td>
<td>6</td>
</tr>
</tbody>
</table>

### Table 3  Performance comparison

<table>
<thead>
<tr>
<th>Testing case</th>
<th>Actual</th>
<th>Observed</th>
<th>Actual</th>
<th>Observed</th>
<th>Actual</th>
<th>Observed</th>
<th>Actual</th>
<th>Observed</th>
<th>Actual</th>
<th>Observed</th>
<th>Actual</th>
<th>Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
</tr>
<tr>
<td>2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
</tr>
<tr>
<td>4</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
</tr>
<tr>
<td>5</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>6</td>
<td>T3</td>
<td>T1</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
</tr>
<tr>
<td>7</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
</tr>
<tr>
<td>8</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>9</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
</tr>
<tr>
<td>10</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>11</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>12</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
</tr>
<tr>
<td>13</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
</tr>
<tr>
<td>14</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>15</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
</tr>
<tr>
<td>16</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>17</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
</tbody>
</table>
Table 3  Performance comparison (continued)

<table>
<thead>
<tr>
<th>Testing case</th>
<th>PSO Actual</th>
<th>PSO Observed</th>
<th>GA Actual</th>
<th>GA Observed</th>
<th>APSO Actual</th>
<th>APSO Observed</th>
<th>AGA Actual</th>
<th>AGA Observed</th>
<th>IWF Actual</th>
<th>IWF Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>18</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T1</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
</tr>
<tr>
<td>19</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>20</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>21</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
</tr>
<tr>
<td>22</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>23</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>24</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
</tr>
<tr>
<td>25</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
</tr>
<tr>
<td>26</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>27</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
</tr>
<tr>
<td>28</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>29</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>30</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
</tr>
<tr>
<td>31</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>32</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>33</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
</tr>
<tr>
<td>34</td>
<td>T1</td>
<td>T3</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T1</td>
<td>T1</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>35</td>
<td>T2</td>
<td>T3</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T1</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
<td>T2</td>
</tr>
<tr>
<td>36</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
<td>T3</td>
<td>T2</td>
<td>T3</td>
<td>T3</td>
</tr>
</tbody>
</table>

The graphical representations of sensitivity, specificity, and accuracy are classified under different dataset values. These values can be found out by using the values in Table 1. For all these values, by viewing the graphical representations, it can be stated that this proposed ANN trained using IWF technique has better values than the previous techniques.

Figure 2 shows the sensitivity comparison of IWF with the different training algorithm. From the chart, the sensitivity of the proposed IWF system is 50% which is 17% greater than the AGA method, 23% greater than APSO method, 8% greater than the PSO algorithm and 14% greater than GA algorithm. Thus we can prove that our proposed IWF technique has the very high sensitivity while comparing to the other technique for training the ANN for the detection of machine fault detection.

The specificity comparison chart is shown in Figure 3. It shows that the IWF has the highest specificity of 75%, which is 12%, 11%，11% and 4% higher than the AGA, APSO, GA and PSO respectively.

Figure 4 shows the graphical representation of accuracy in which IWF has 67% of accuracy which is 14%, 14%, 11% and 6% higher than the AGA, APSO, GA and PSO respectively. Hence we can prove that our proposed IWF technique has the highest accuracy.
Figure 2  Graphical representation of sensitivity value for PSO, GA, APSO, AGA and IWF (see online version for colours)

Figure 3  Graphical representation of specificity value for PSO, GA, APSO, AGA and IWF (see online version for colours)

Figure 4  Graphical representation of accuracy value for PSO, GA, APSO, AGA and IWF (see online version for colours)
In Figure 2, the proposed IWF has the highest sensitivity of 50% whereas other techniques have the sensitivity of around 27% to 42%. In Figure 3, which shows the specificity, IWF along with AGA yields 75% whereas remaining techniques yield around 63% to 71%. The accuracy rate is graphed in Figure 4 and IWF has a very high accuracy of 67%. Hence it is clear to the vision that this proposed ANN trained by IWF is the most effective method to detect the faults.

From these discussions, we can easily prove that our proposed IWF method for the training of ANN has the better performance than the other training algorithm like AGA, APSO, AG and PSO. Hence our IWF based ANN is one of the best choices for the detection of rotating machine faults.

5 Conclusion

Condition monitoring of industrial machine is a challenging task to predict the faulty machine before it wholly damaged. Hence it this proposed work a novel approach for the prediction faults in industrial machines. The proposed system ANN with IWF is used for the faults detection of air condition monitoring. The proposed system can instruct the fault condition based on the ‘velocity’, ‘rpm’ and ‘velocity of the displacement’. The set of input data is gathered and which is used for the modelling of the neural network. The proposed technique is tested using Matlab, and the performance is compared with conventional techniques such as GA, PSO, AGA and APSO. The performance is compared regarding prediction accuracy, sensitivity and specificity. The proposed IWF based prediction provides 50%, 75% and 67% of sensitivity, specificity and accuracy, which are better than the conventional techniques. The results were analysed, and they suggest that the proposed technique is more efficient than those existing techniques. In future, a new classifier can pre-developed, because modelling ANN is involved and its execution time is high. Hence a simple high-speed classifier technique for the industrial machine fault detection is encouraged in future.

References


