Failure Prediction of Induction Motors: A Case Study using CSLGH900/6-214, 5.8 MW, 11 kV/3ph/50 Hz Sag Mill Motor at Goldfields, Damang Mine

By C. K. Amuzuvi & H. Warden

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Keywords: *SAG mill induction motor, feed-forward neural network, multilayer perceptron*.

I. Introduction

Damang Gold Mine, a subsidiary of Goldfields International is a world class mining operation consisting of a 25 MTPA open pit mining and a 5.2 MTPA Carbon in Leach (CIL) metallurgical plant. Located in the south western part of Ghana, 300 km by road from the capital of Ghana, Accra, the mine exploits oxide and fresh hydrothermal mineralization in addition to Witwatersrand – style transitional paleo placer gold. The plant is designed to treat 5.2 MTPA of gold ore from a blend of approximately 20% oxide ore and 80% fresh ore sourced from various open pit mining operations.

Process feed for the 12-month period of 2016 comprised 4.3 Mt at a yield of 1.17 g/t for a 148 koz of gold.

The plant has 2×5.8 MW ball mill and sag mill, a 1×600 kW primary gyratory crusher, 1×375 kW pebble crusher, 8×CIL tanks and a secondary crushing plant with a maximum electric power draw of 17.5 MW at peak times. The mine uses a lot if induction motors at the crushing circuit, milling circuit, CIL circuit, elution circuit, tailings, etc., because of its strength, mechanical simplicity and adaptability to a variety of applications [1]. The plant is often faced with issues associated with burnt induction motors. Unfortunately, the exact causes are not clearly known.

Induction motors are the mainstay for every industry. They are widely used in transportation, mining, petrochemical, manufacturing and in almost every other field using electrical power. These motors are simple, efficient, highly robust and rugged, thus, offering a very high degree of reliability. However, like any other machine, they are susceptible to faults, which if left unmonitored, might lead to catastrophic failure of the machine in the long run especially due to heavy duty cycles, poor working environment alongside with installation and manufacturing factors.

In a bid to detect fault and avoid complete breakdown of induction motors with its concomitant production losses, on-line condition monitoring of the induction motors must be implemented for effective operation of these machines. With increasing demands for reliability and efficiency, fault prediction in induction motors has become necessary, particularly in industries that make use of these rotary equipment of which the Damang Gold Mine is no exception [2]. Various fault conditions of induction motors as well as methods of their detection and prediction are presented in this paper.

a) Some Impacts of the Occurrence of Faults

With the mines current maintenance cost of electrical motors on the high, the mine must come up with strategies to bring the overall cost of engineering maintenance down. Figure 1(a) is a graph showing annual motor change-out from 2012 to 2016 and Figure

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1(b) is the probability of occurrence of faults in an operating induction motor [2]. Research has shown that, failures associated with induction motors are often caused by rotor, stator, and bearing failures, etc. [2].

With the current price of gold on the downside, the maintenance department is under intense pressure to efficiently maintain the plant machinery to continue to stay in business. Table 1 show gold prices from 2012 to 2016 respectively. This research work seeks to identify and assess in detail, all the various root causes of induction motor failures in the mine and suggest a means of accurately predicting future failures.
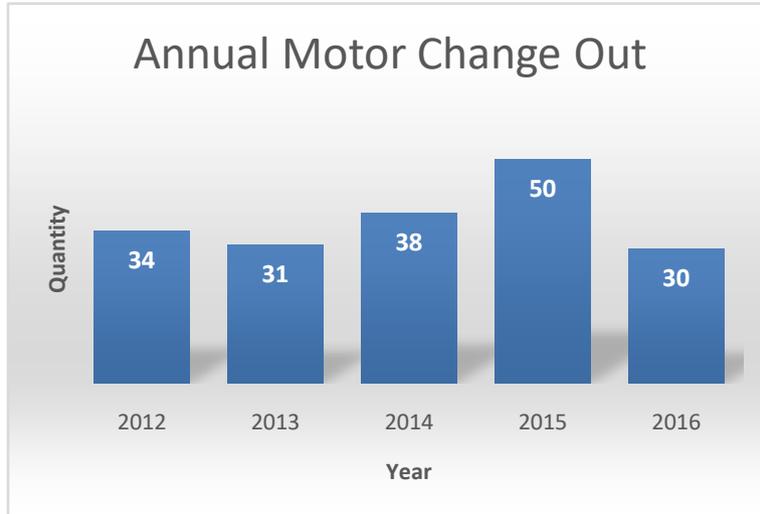
(a)
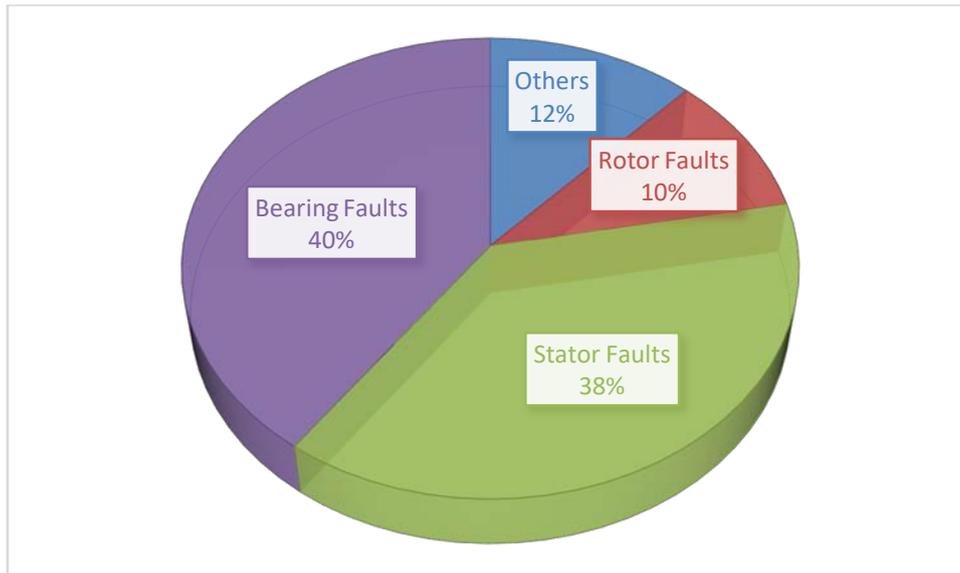
(b)

Figure 1: (a) Graph Showing Number of Annual Motor Change – Out; and (b) Probability of Occurrence of Faults

Table 1: Gold Price from 2012 to 2016 Year

Year	Closing Price	Year Open	Year High	Year Low	Year Close	% Change
2012	$1,668.86	$1,590.00	$1,790.00	$1,537.50	$1,664.00	5.68%
2013	$1,409.51	$1,681.50	$1,692.50	$1,192.75	$1,201.50	−27.79%
2014	$1,266.06	$1,219.75	$1,379.00	$1,144.50	$1,199.25	−0.19%
2015	$1,158.86	$1,184.25	$1,298.00	$1,049.60	$1,060.20	−11.59%
2016	$1,251.92	$1,075.20	$1,372.60	$1,073.60	$1,151.70	8.63%

(Source: [3])

b) Induction Motor

An induction motor is a type of asynchronous alternating current (AC) motor, where power is supplied to the rotating device (rotor) by means of electromagnetic induction. There are two types, namely wound or slip-ring induction motor and squirrel-cage induction motor.

Squirrel-cage induction motors are the preferred choice for industries due to their low cost, high reliability, absence of slip-rings and brushes, which eliminate the risk of sparking thereby, making them explosion proof with high efficiency over a wide range of power outputs.

They also have the ability of speed control. From a constant frequency source, they operate as constant speed drives. For continuous speed control over a wide speed range, a solid-state variable-frequency converter provides an indirect source of supply [4].

c) Induction Motor Failure

Induction motors are rugged, low cost, low maintenance, reasonably small sized, reasonably highly efficient and operating with an easily available power supply. They are reliable in operations but are subject to different types of undesirable faults.
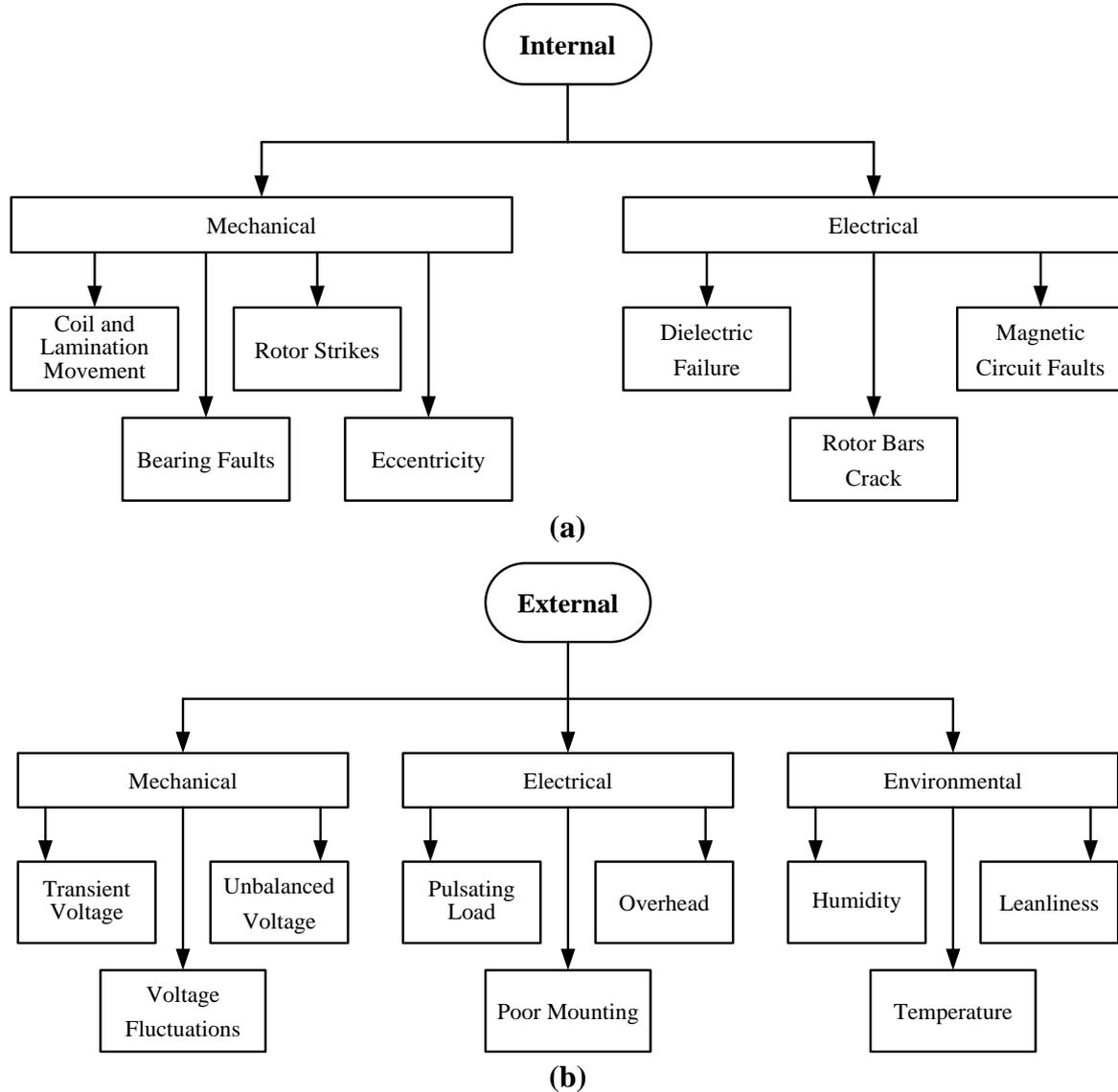

(a)

(b)

Figure 2: (a) Block Diagram Presentation of Internal Faults; and (b) Block Diagram Representation of External Faults

Sources of induction motor faults may be internal or external. In Figure 2(a) and Figure 2(b) [2], block diagrams of internal and external faults are depicted. The most vulnerable parts for fault in the induction motor are bearing, stator winding, rotor bar, and shaft. Besides, due to non-uniformity of the air gap between stator-inner surface and rotor-outer surface, motor faults occur [5]. Faults in induction motors can be categorized as:

1. Electrical-related faults due to unbalance supply voltage or current, single phasing, under or over voltage or current, reverse phase sequence, earth fault, overload, inter-turn short-circuit fault, and crawling;
2. Mechanical-related faults due to broken rotor bar, mass unbalance, air gap eccentricity, bearing damage, rotor winding failure and stator winding failure; and
3. Environmental-related faults such as ambient temperature, external moisture as well as vibrations of machine due to reasons like installation defect and foundation defect affect the performance of induction motor.

Figure 3(a) [5] show the rotor and parts of a broken rotor bar and Figure 3(b) a rotor with mass unbalance fault, with a hole drilled into one bar.
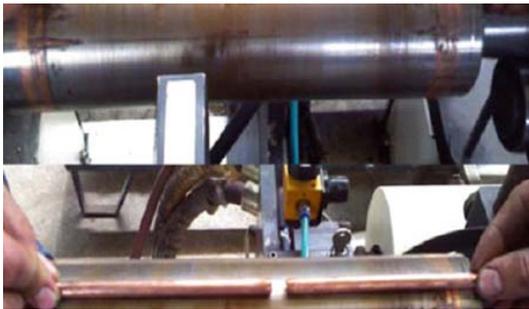
(a)
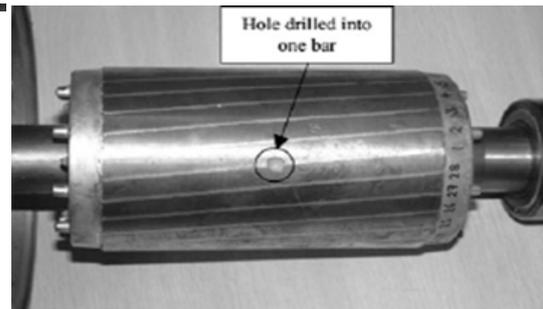
(b)

Figure 3: (a) Photograph of Rotor and Parts of Broken Rotor Bar; and (b) Rotor with Mass Unbalance Fault

Industrial processes make use of a large number of asynchronous motors even in sensitive applications. Consequently, a defect can induce high losses in terms of cost and can be dangerous in terms of security and safety. Motor failures are mostly directly or indirectly caused by insulation breakdown, bearing wear or extensive heating of different motor parts involved in motor operation [6]. Multiple faults may occur simultaneously in an induction motor, which may result in unbalanced stator currents and voltages, oscillations in torque, reduction in efficiency and torque, overheating and excessive vibration. Normally, electric motors do not fail suddenly. It happens over time and regular inspection will detect a problem before a serious situation develops. Three main components of electric motors that experience faults are the stator, rotor and bearings. These faults may be a growing one with only small effects on the operation, a partial non-catastrophic one with emergency operation possible or a catastrophic one with total drive breakdown [6]. Incipient fault detection is preferably done to find faults before complete motor failure in order to avoid service downtime and large losses.

d) Condition Monitoring and Its Necessity

Induction motors are the main workhorse of industrial prime movers due to their ruggedness, low cost, low maintenance, reasonably small size, reasonably high efficiency, and operating with an easily available power supply. About 50% of the total generated power of a nation is consumed by these induction motors[5]. These statistics gives an idea regarding the use of huge number of induction motors, but they have some limitations in their operating conditions. If these conditions are exceeded, then some premature failure may occur in the stator or/and rotor. This failure, in many applications in industry, may lead to a shut down, even, the entire industrial process resulting in loss of production time and money. It is, therefore, an important issue to avoid any kind of failure of an induction motor. Operators and technicians of induction motors are under continual pressure to prevent unscheduled downtime and also to reduce maintenance cost of motors.

Maintenance of electrical motors can be done in three forms: breakdown maintenance, fixed-time maintenance, and condition-based maintenance. In breakdown maintenance, the strategy is 'run the motor until it fails' which means maintenance action is taken only when the motor gets breakdown. In this case, though the motor may run comparatively for a long time before the maintenance is done, when breakdown occurs, it is necessary to replace the entire machine, which is much costlier compared to replacing or repairing the faulty parts of the motor. Also, it causes loss of productivity due to downtime.

In fixed-time maintenance, the motor is required to stop for inspection, which causes long downtime. Also, trained and experienced technical persons are required to recognise each and every fault correctly. All these necessitate the condition-based maintenance of the motor. In this form of maintenance, the motor is allowed to run normally and action is taken at the very first sign of an incipient fault.

In condition monitoring, when a fault has been identified, sufficient data is required for the plant operator for the best possible decision making on the

correct course of action. If the data is insufficient, there remains the chance for wrong diagnosis of fault, which leads to inappropriate replacement of components, and if the root of the problem is not identified properly, the replacement or any other action taken already will succumb to the same fate. In condition monitoring, signals from the concerned motor are continuously fed to the data acquisition system and the health of the motor is continuously evaluated during its operation for which it is also referred as online condition monitoring of the motor, and hence, it is possible to identify the faults even while they are developing. The operator/technician can take preparation for the preventive maintenance and can arrange for necessary spare parts in advance, for repairing. Thus, condition monitoring can optimise maintenance schedule and minimise motors downtime and thereby increase the reliability of the motor. Advantages of using condition monitoring can be mentioned point wise as follows:

1. Prediction of motor failure;
2. Optimisation of the maintenance schedule of the motor;
3. Reduction of maintenance cost;
4. Reduction of the downtime of the machine; and
5. Improvement of the reliability of the motor.

Condition monitoring and fault detection are usually carried out by investigating the corresponding anomalies in the machine current, voltage and leakage flux. Other methods include monitoring the core temperature, bearing vibration level and pyrolysed products. Fault conditions such as insulation defects and bearing degradation may also be diagnosed [2].

e) Failure Prediction Methods or Techniques

According to [7], online failure prediction aims to identify situations that will evolve into a failure. Classification of failure prediction methods are usually based on the type of input data used, namely: data from failure tracking, symptom monitoring, detected error reporting and undetected error auditing. System monitoring, however, is mostly used as it is effective and offers reliable data based on analysis of time series and/or type of symptoms. In order to build high availability systems based on failure prediction, methods are developed not only to capture, select, or interpret essential data and predict future system states but also to provide proactive recovery and failure avoidance schemes, which build on these predictions and help to self-manage the system.

Thus, it has become necessary to diagnose motor faults for effective maintenance plans by management, so as to avoid complete failure of systems or machines in the future. Using baseline characteristics of a healthy motor as a reference data, any deviation in motor operating characteristics obtained from system monitoring may be used to perform fault detection and diagnosis, irrespective of

unavoidable manufacturing defects in the system. Depending on the region of fault occurrence, five main categories of faults, namely: stator faults, eccentricity faults, rotor faults, bearing faults and vibration faults are diagnosed based on various failure prediction methods [2].

i. *Vibration Spectrum Analysis*

This technique is used to detect bearing faults. High frequency components of vibration are created due to friction or forces occurring in the rolling element bearing in electrical machines under normal conditions. In case of a defect in the bearings or breaks in the lubrication layer between the friction surfaces, shock pulses are produced.

The method analyses the vibration spectrum of an induction machine using piezoelectric accelerometer, which works on Fast Fourier Transform to extract from a time domain signal, the frequency domain representation. In diagnosing bearing fault, the harmonic vibration spectrum of the healthy motor and that with defective bearing is analysed individually. Upon comparison, it is realized that the vibration amplitude for faulty motor is larger than that of a healthy motor. Dynamic simulation of motor running with bearing fault to analyse frequency spectrum of electromagnetic torque produced by the faulty motor may provide similar result when compared with its vibration spectrum.

ii. *Park Vector Approach and Complex Wavelets*

Park vector transformation approach is used to diagnose stator faults on a three-phase induction motor due to the impact of fault on the machine current. This technique uses Park's Transform to derive a two-dimensional Park's current vector components, which are expressed as functions of the phase currents of the three-phase induction motor. Thus, the locus of instantaneous spatial vector sum of the measured three phase stator currents forms the basis for Park's vector.

This maps a circle, which has its centre at the origin of the coordinates. This locus is distorted by stator winding faults and thus provides easy fault diagnosis. In other words, a graphical representation of the Park's current vector for a faulty motor gives an elliptical shape, which is a distortion of the circularly shaped Park's current vector representation of a healthy motor. The amount of distortion of the circular shape depends on the level of stator fault of the motor. Simulation and experimental results are finally analysed using complex wavelets.

iii. *Motor Current Signature Analysis (MCSA)*

This technique can be used to detect rotor faults and eccentricity. In case of a fault, current harmonics in the stator current, caused by a backward rotating field in the air gap, are analysed by MCSA. This requires only one current sensor, whose function is based on signal processing techniques like the Fast Fourier Transform (FFT).

An equipment set-up, which comprises current transformer, signal conditioning unit, data collector/analyser and computer, is used for measuring the motor current. Data is acquired by performing FFT on the stator current. The data obtained, is analysed after FFT is normalized as a function of the first harmonic amplitude. Conversely, harmonic contents or percentage amplitude for harmonics, increase with increase in the level of faults, like the number of broken rotor bars and eccentricity.

iv. *Intelligent Techniques*

Several intelligent techniques like Fuzzy logic systems, Artificial Neural Networks and Neuro-Fuzzy Systems usually have three prime steps for induction motor condition monitoring. These are: i) Signature extraction; ii) Fault detection; and iii) Fault severity estimation.

Apart from the above-mentioned techniques, some other methods for incipient fault detection of induction motors are the finite element method, vibration testing and analysis, Concordia transform, external magnetic field analysis, multiple reference frames theory, power decomposition technique, zero crossing time method and modal analysis method. This work, however, makes use of the artificial neural network for failure prediction of induction motors.

f) *Artificial Neural Network*

According to [8], Artificial Neural Network (ANN) is a non-linear mapping structure inspired by observed process in natural network of neurons in the human brain. It consists of highly interconnected simple computational units called neurons. It imitates the learning process of the human brain and can process problems, which involve complex, non-linear, imprecise and noisy data. It is ideally suited for modelling and predicting the outcome of new independent input data after training.

ANNs are parallel computational models consisting of densely interconnected adaptive processing units. They are used for a wide variety of applications where statistical methods are traditionally employed. ANN is therefore being recognised as a powerful tool for data analysis. By their adaptive nature, "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing especially in application domains, where a problem to be solved is not understood fully but training data is readily available. Back propagation algorithm is the most widely used learning algorithm in an ANN. Various types of ANN include Multilayered Perceptron, Radial Basis Function and Kohonen networks. In fact, majority of the networks are more closely related to traditional mathematical and/or statistical models, such as non-parametric pattern classifiers, clustering algorithms, non-linear filters, and statistical regression models than they are to neurobiology models.

ANNs are constructed with layers of units. All units in a particular layer perform similar tasks. The first and last layers of a multilayer ANN consist of input units (independent variables) and output units (dependent or response variables) respectively. All other units (hidden units) make up the hidden layer. The behaviour of a unit is governed by an input function and an output or activation function. These functions are normally the same for all units within the whole ANN. Input into a node is a weighted sum of outputs from nodes connected to it. There exists a threshold term, which is a baseline input to a node in the absence of any other inputs. A weight is termed inhibitory if it is negative as it decreases net input, otherwise it is called excitatory.

Each unit takes its net input and applies an activation function to it. In instances where the inputs and outputs are binary encoded, the threshold function becomes very useful. The activation function mainly maps the outlying values of the obtained neural input back to a bounded interval. The activation function shows a great variety. However, the most common choice is the sigmoid function since it maps a wide domain of values into the interval.

i. *Development of an ANN Model*

A neural network forecasting model is developed by the following steps:

1. Variable selection;
2. Formation of training, testing and validation sets;
3. Neural network architecture; and
4. Model building.

Suitable variable selection procedures are used to select the input variables, important for modelling or forecasting variable(s) under study in the first step. This is followed by the formation of three distinct data sets called training, testing and validation sets. These data sets are used by the neural network not only to learn current data patterns (training set) and evaluate the overall ability of the supposedly trained network (testing set), but also to check the performance of the trained network using the validation set. The third step defines the network structure, which includes a number of hidden layers and hidden nodes as well as the number of output nodes and the activation function. The next step involves model building.

The model of a very popular and frequently used multilayer feed-forward neural network (FFNN) or multilayer perceptron (MLP) learned by back propagation algorithm is constructed based on supervised procedure or on examples of data with known output. The examples presented are assumed to implicitly contain the information necessary to establish the relation for building the model. An MLP allows prediction of an output object for a given input object. Its non-linear elements or neurons are arranged in

successive layers with a unidirectional flow of information from input layer to output layer through hidden layer(s). With adequate data, only one hidden layer is always sufficient for an MLP as it can learn to approximate virtually any function to any degree of accuracy. MLPs are therefore also known as universal approximates. Generally, learning methods in neural networks are classified into three basic types, namely; supervised learning, unsupervised learning or reinforced learning. A neural network learns off-line if the learning phase and the operation phases are distinct. On-line learning occurs when it learns and operates at the same time. Supervised learning is usually performed off-line based on training data, whereas unsupervised learning is performed on-line based on given data. In reinforced learning, data is usually not given, but generated by interactions with the environment.

ii. *Architecture of Neural Networks*

The two most widely used ANN architecture are the feed-forward networks and the feedback or recurrent networks. Other types of ANN architecture include stochastic network, physical network, bi-directional network, Elman and Jordan network, Hopfield network, self-organising map and long short-term memory networks. Feed-forward networks have no feedback loops and are extensively used in pattern recognition. Thus, signals are allowed to travel one way only; from input to output. The output layer does not affect that same layer. In feedback networks however, signals do not travel in one way only due to the presence of a feedback loop. In addition, their state changes continuously (dynamic) until an equilibrium point is reached. They remain at this point until the input changes and a new equilibrium needs to be found.

The MLP network is trained using a supervised learning algorithm like the backpropagation algorithm. The backpropagation algorithm uses data to adjust the network's weights and thresholds so as to reduce the error in its prediction on the training set. It computes how fast the error, which is the difference between the actual and the desired activity, changes due to an alteration in:i) the activity of an output unit; ii) the total input received by an output unit; iii) weight on the connection into an output unit; and iv) the activity of a unit in the previous layer.

According to [9], some of the uses and applications of Artificial Neural Networks are for; classification, pattern matching, pattern completion, optimisation; control, function approximation/times series modelling, and data mining.

g) Related Works

Lizarraga-Morales *et al.* [10] proposed a novel FPGA-based methodology for early broken rotor bar (BRB) detection and classification through homogeneity estimation. Obtained results demonstrated the high efficiency of the proposed methodology as a deterministic technique for incipient BRB diagnosis in induction motors, which can detect and differentiate among half, one, or two BRBs with very high accuracy.

Kayri [11] did a comparative study on the predictive ability of Bayesian regularization with Levenberg-Marquardt artificial neural networks. Analysis were done by sum squared error (SSE), sum squared weight (SSW) and correlation of regression and concluded that the Bayesian regularization training algorithm shows better performance than the Levenberg-Marquardt algorithm.

Araujo *et al.* [12] provides an analysis about early incipient and recurring failures in three-phase induction motor bearings when driven by pulse width modulation inverters, focusing on a real industrial process. Over the investigation, it was concluded that the presence of common-mode currents at the verified levels could cause damages to the motor bearings, which was confirmed when the machine stopped working due to another bearing failure.

Yu *et al.* [13] developed a model-based remaining useful life (RUL) prediction method for induction motor with stator winding short circuit fault. The induction motor model with stator winding short circuit fault is introduced based on reference frame transformation theory. A particle filter method is used to realize unknown parameter estimation and RUL prediction. Simulation results were provided to validate the proposed method.

Kraleti *et al.* [14] presented a paper on model-based diagnostics and prognostics of three-phase induction motor for vapour compressor applications. Faults under consideration were incipient electrical faults: insulation degradation and broken rotor bars. Two online approximators were used to discover the system parameter degradation and facilitate fault isolation, or root-cause analysis, and a time to failure (TTF) prediction before the occurrence of a failure.

Ghate and Dudul [15] developed the radial-basis- function- multilayer- perceptron cascade connection neural-network based fault detection scheme for the small and medium sizes of three-phase induction motors. Simple statistical parameters of stator current were considered as input features and experimental results showed ability of the proposed classifier for detecting faults such as stator winding inter-turn short and/or rotor eccentricity. The network was tested for good classification accuracy with enough robustness to noises. The classifier was then found to be suitable for real world applications.

The use of ANN's in predicting failure of the 5.8 MW 11 kV motor on nominal load provides a new area of research. The network is a generalised feed-forward network and the input data samples are current, winding temperatures and power all in the time domain.

II. Methods Used

In designing a model for the failure prediction of a 3 phase 5.8 MW, 11 kV slip-ring SAG Mill induction motor at Goldfields Ghana Limited, Damang mine, Artificial Neural Networks was employed in modelling and simulations on the data collected (power, current and winding temperatures) from the company. The materials used in this research for the collection of the motor data was the Citect and Laptop computer with MATLAB software (2017a) for modelling and simulation of the data.

a) Designing and Programming of ANN Models

Figure 4(a) [15] shows a generalized flow chart of ANN–based fault classification of induction motors. Designing ANN models follows a number of systemic procedures. In general, there are five basics steps: (1) collecting data, (2) pre-processing data, (3) building the network, (4) train, and (5) validate and test the performance of model as shown in Figure 4(b).
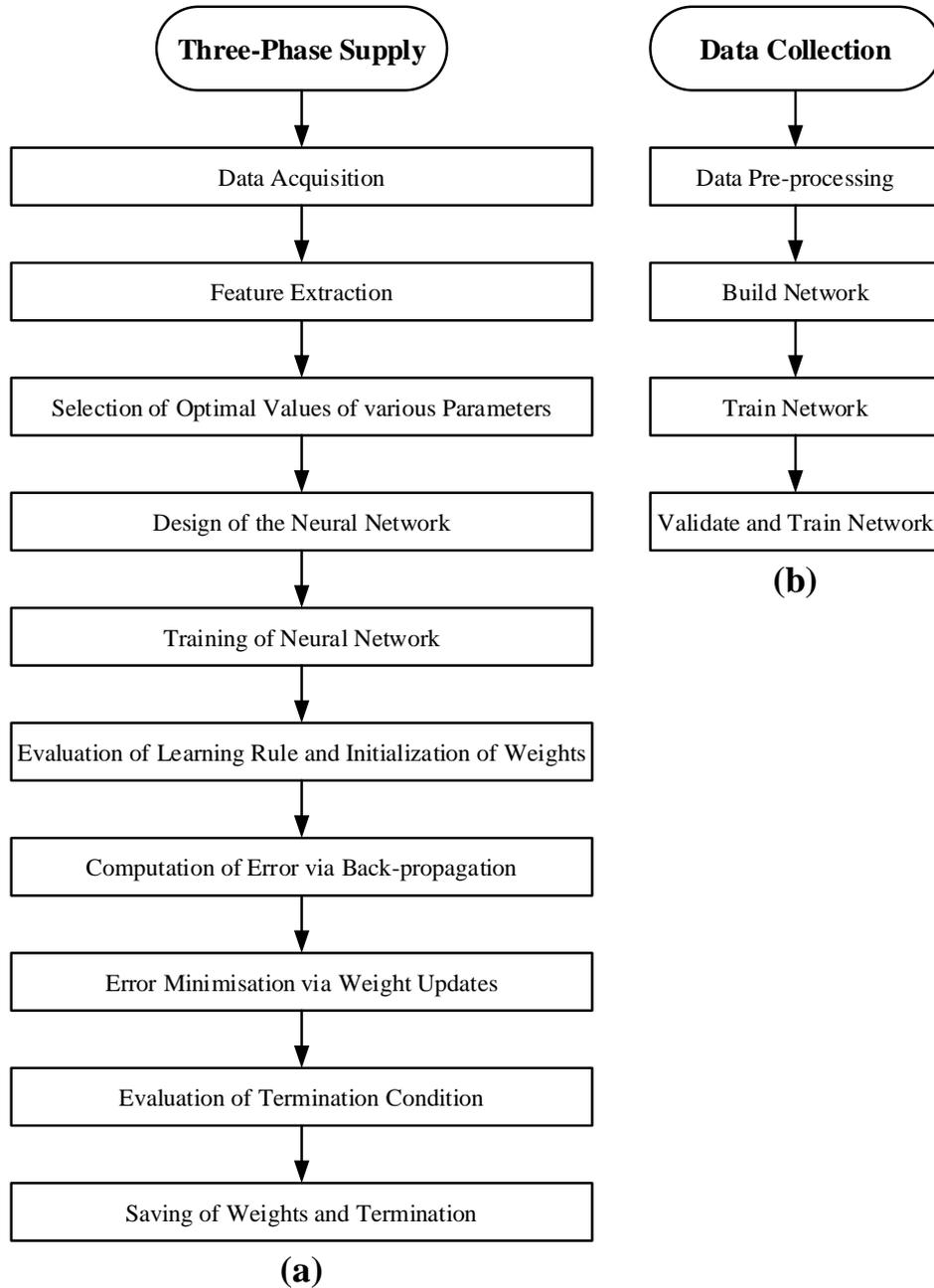
Figure 4: (a) General Flow of ANN–Based Fault Classification of Induction Motors; and
(b) Basic Flow Chart for Designing Artificial Neural Network Model

b) Data Collection

Collecting and preparing sample data is the first step in designing ANN models. As it is outlined in Figure 4(b), measurement data of the SAG Mill motor power (MW), motor current (A), and winding temperatures (°C) with the corresponding motor condition i.e. motor healthy or motor faulty (MH/MF) for the Damang mine for a 93-day period from 6th January, 2019 to 8th April, 2019 was collected through the Citect as shown in Figure 5 (a). A total of 5×879 data samples were collected. Figure 5(b) show graphs of trends of the SAG Mill motor current and power.

(a)
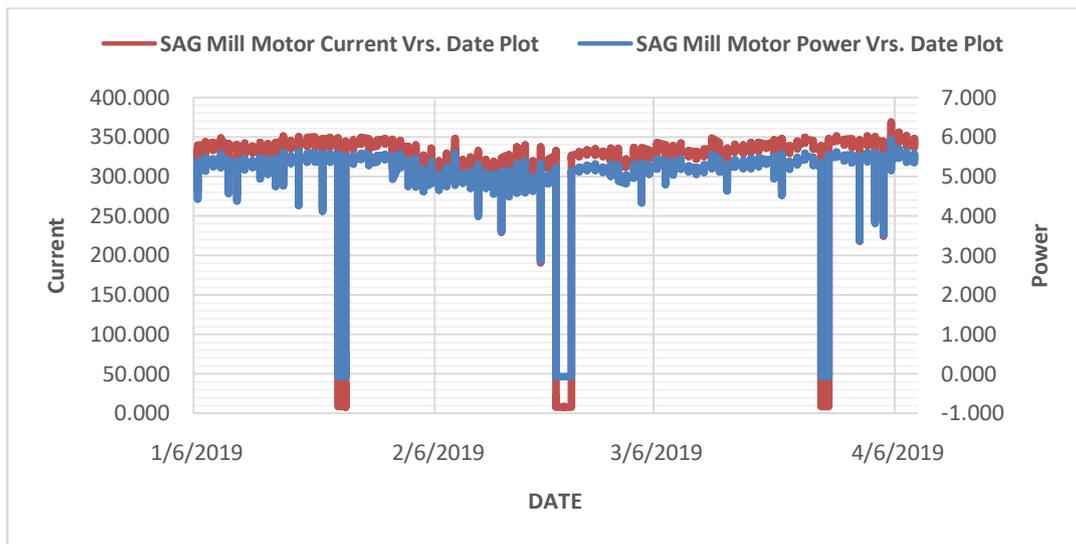
(b)

Figure 5: (a) Trends of SAG Mill Motor Current, Power and Winding Temperatures; and (b) Graph Showing Trends of SAG Mill Motor Current and Power
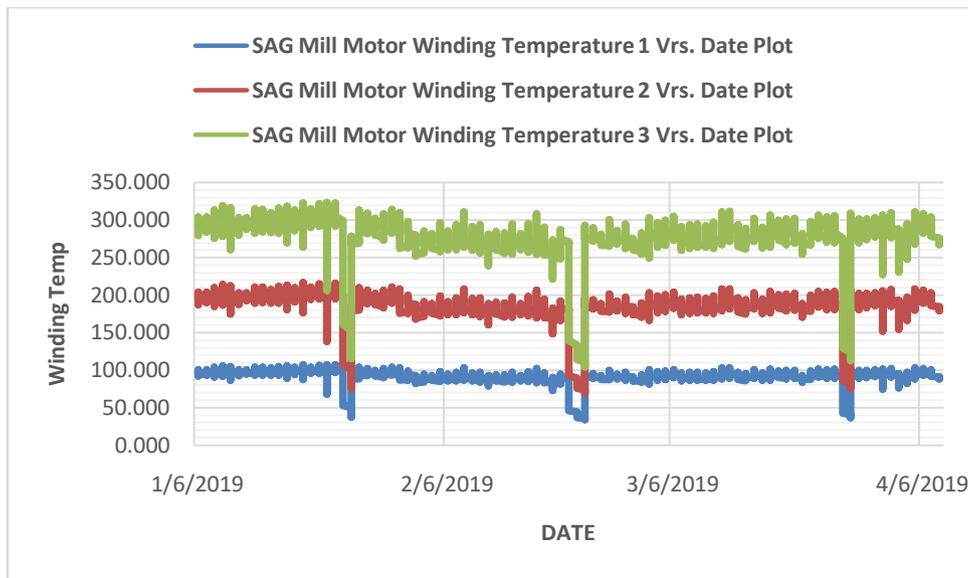
(a)
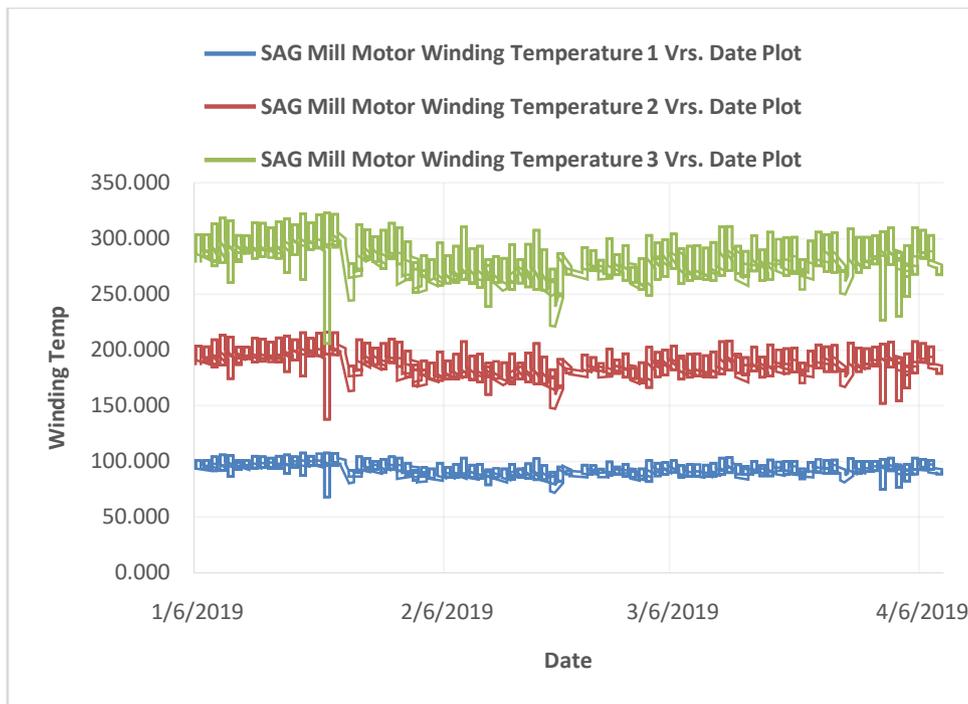
(b)

Figure 6: (a) Graph Showing Trends of SAG Mill Motor Winding Temperatures; and
(b) Graph Showing Trends of SAG Mill Motor Winding Temperatures after Normalisation

c) Data Pre-Processing

After data collection, data pre-processing procedures are conducted to train the ANNs more efficiently. The procedure is normalisation of data. Normalization procedure before presenting the input data to the network is generally a good practice, since mixing variables with large magnitudes and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude [16]. Figure 6(a) and Figure 6(b) are graphs showing SAG Mill motor winding temperatures and winding temperatures after normalisation. A total of 5×837 data samples were considered healthy after normalisation.

Data samples which were out of range after normalisation were taken to be faulty data samples. This data samples totalled 5×42 faulty data samples. Figure 7 is a graph showing faulty data samples.
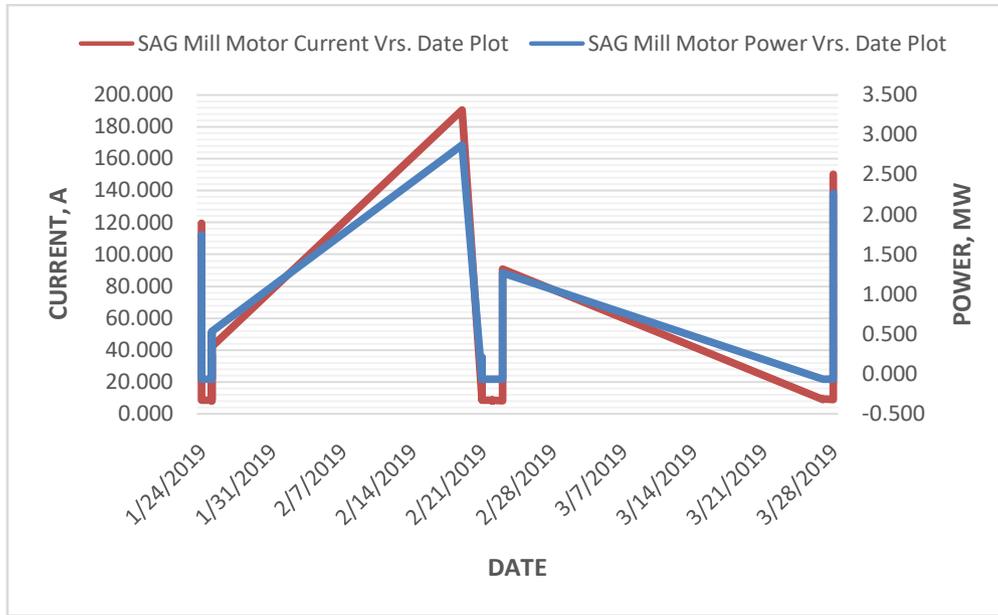
Figure 7: Graph Showing Trends of Faulty SAG Mill Motor Current and Power

d) Building the network

At this stage, the designer specifies the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function. In this work, the generalised feed-forward neural network was used.

Feed-Forward Neural Network with Backpropagation Algorithm

In feed-forward neural networks, otherwise known as multilayer perceptrons, the input vector of independent variables is related to the target (SAG Mill motor condition) using the architecture depicted in Figure8. This figure shows one of the commonly used networks, namely; the layered feed-forward neural network with one hidden layer. Here, each single neuron is connected to those of a previous layer through adaptable synaptic weights. Knowledge is usually stored as a set of connection weights, and then, the weights are adjusted so that the network attempts to produce the desired output. The weights after training contain meaningful information, whereas before training they are random and have no meaning.
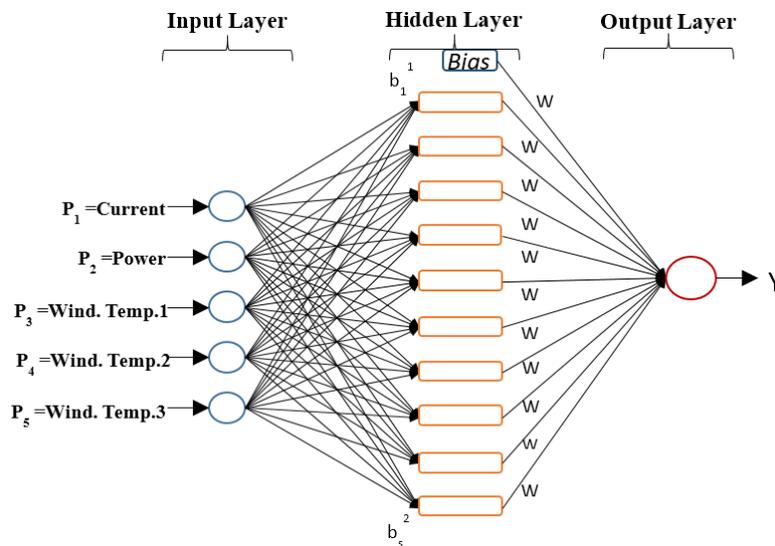

Figure 8: Architecture of Feed-Forward Network

e) Training the network

Training is the process of modifying the network using a learning mode, in which an input is presented to the network along with the desired output. During the training process, the weights are adjusted in order to make the actual outputs (predicated) close to the target

(measured) outputs of the network. In this study, 70% of the data was used for training. Two different types of training algorithms were investigated for developing the feed-forward network. These are Levenberg-Marquardt algorithm and Bayesian Regularisation algorithm. MATLAB provides built-in transfer functions, which are used in this study; Linear (purelin), Hyperbolic Tangent Sigmoid (tansig) and Logistic Sigmoid (logsig).

f) Validating and Testing the Network

The next step is to validate and test the performance of the developed model. At this stage, unseen data are fed to the model. For this case study, 15% of SAG Mill motor data was used for validating and another 15% used for testing the ANN models. Validation data generalise the network validation and stops training before overfitting, which occurs when a network memorises the training data but not learn to generalise new inputs.

In order to evaluate the performance of the developed ANN models quantitatively and verify whether there is any underlying trend in performance of ANN models, statistical analysis involving mean squared error were conducted. MSE provides information on the short-term performance, which is a measure of the variation of predicated values around the measured data. The lower the MSE, the more accurate is the estimation. The expressions for the aforementioned statistical parameter is:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(I_p - I_i \right)^2 \tag{1}$$

where
I_p denotes the predicted power of SAG Mill motor in MW;
I_i denotes the measured power of SAG Mill motor in MW; and
n denotes the number of observations.

On the other hand, regression is a statistical analysis assessing the correlation between two variables. The regression line equation can be written as:

$$y = a + bx \tag{2}$$

$$b = \frac{N\sum XY - (\sum X)(\sum Y)}{\left(N\sum X^2 - \sum X \right)^2} \tag{3}$$

$$a = \frac{\sum Y - b(\sum X)}{N} \tag{4}$$

where
a = the y intercept when x = 0;
b = the slope/gradient of the line;
N = number of data samples;
X = first group; and
Y = second group and regression coefficient.

R is the correlation coefficient and is given as:

$$R = \frac{\sum XY \frac{\sum X \sum Y}{N}}{\sqrt{\left(\sum X \frac{(\sum X)^2}{N} \right)\left(\sum Y \frac{(\sum Y)^2}{N} \right)}} \tag{5}$$

g) Programming the Neural Network Model

MATLAB is a numerical computing environment and also a programming language. It allows easy matrix manipulation, plotting of functions and data, implementation of algorithms, creating user interfaces and interfacing with programs in other languages. The Deep Learning Toolbox (formerly Neural Network Toolbox) provides a framework for designing and implementing deep neural networks with algorithms, pretrained models, and apps. Apps and plots help you visualize activations, edit network architecture, and monitor training progress (The Math Works, 2019).

Figure 9(a) show the screen captions of the FFNN ANN training window obtained using the "nntraintool" GUI toolbox in MATLAB. Figure 9(b) show the flow chart for the development of the feed forward network using MATLAB.
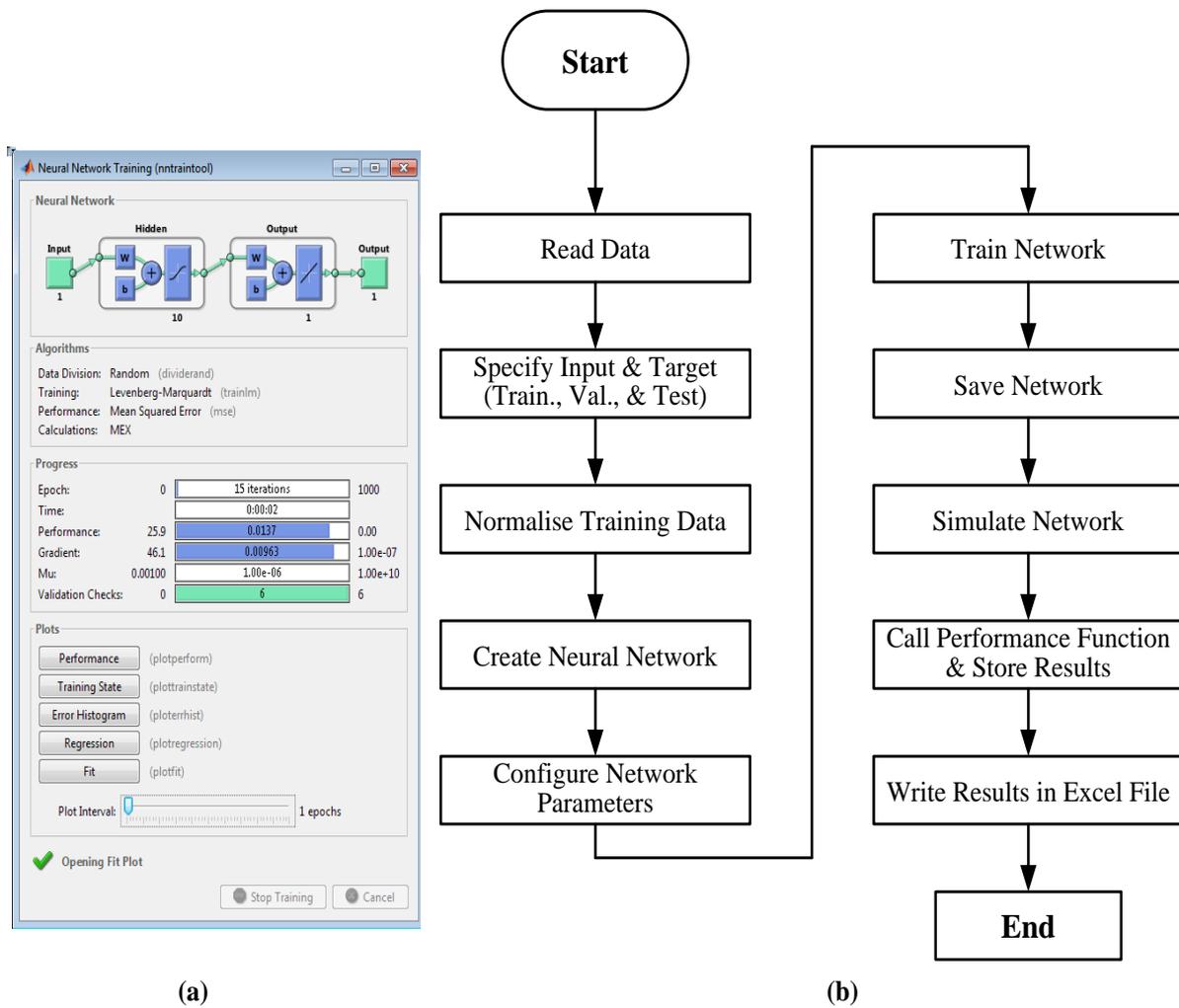
(a) **(b)**

Figure 9: (a) FFNN Network Training Window; and (b) Flow Chart for Developing the Feed-forward Networks Using MATLAB

h) Implementation of Proposed Methodology

The proposed methodology is implemented using a microprocessor to achieve online failure detection. In addition to the cost–effectiveness of the microprocessor implementation, it is flexible and its re-configurability allows changes and refinements while in operation.

Figure 10 show the block diagram of the proposed methodology implementation. The data acquisition system receives current, power and three winding temperature signals from the sensors connected to the power supply to the stator windings of the motor. Signal processing is performed by the microprocessor and the result further analysed by a postprocessor decision-making block that simply states the motor condition in two possible values, i.e., MH (a healthy motor) and MF (a faulty motor), making the process online with no expert technician required for the diagnosis.
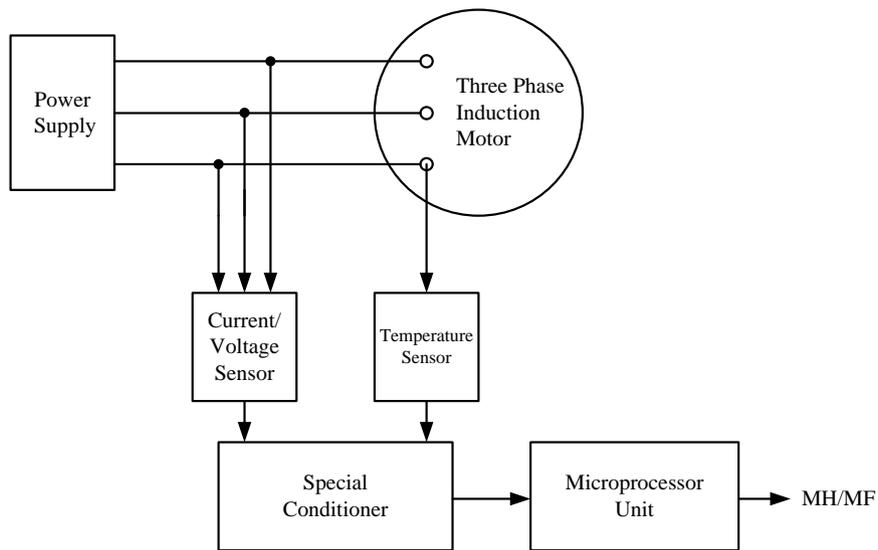
Figure 10: Overall Block Diagram of Implementation of Proposed Methodology

III. RESULTS AND DISCUSSION

The results of MATLAB simulations using Artificial Neural Network tool box of SAG Mill motor current, temperature and power data from Goldfields Damang Mine are presented here.

### a) Simulation Results using Feed-Forward Network

In this section, results of using current and winding temperature readings representing three sides of the SAG Mill motoris used as the input to the network with Mill motor power as the target of the network. Two training algorithms i.e. Levenberg-Marquardt (LM) and Bayesian Regularization (BR) were used in training the network. Simulation results of correlation coefficient for network performance (R), mean squared error (MSE) against epochs, error histograms and training state plot for model validation are presented here.
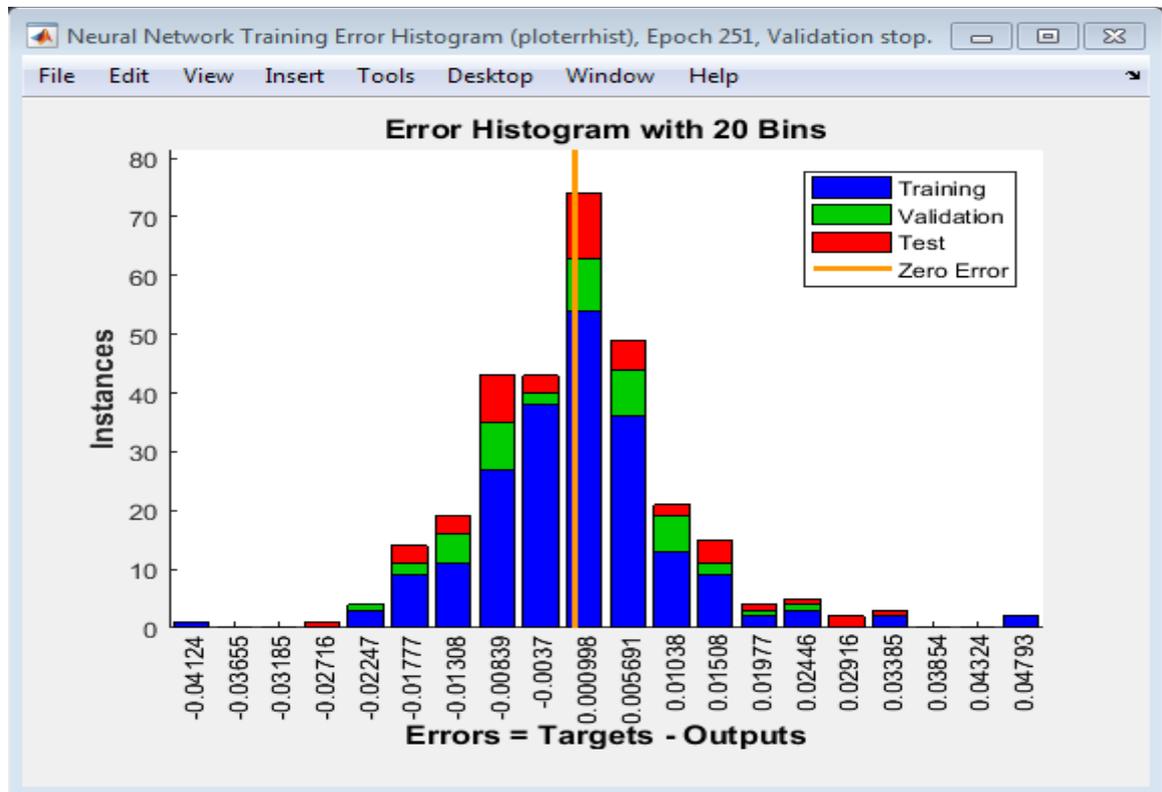
i. *Simulation Results of FFNN Using Levenberg-Marquardt Training Algorithm*
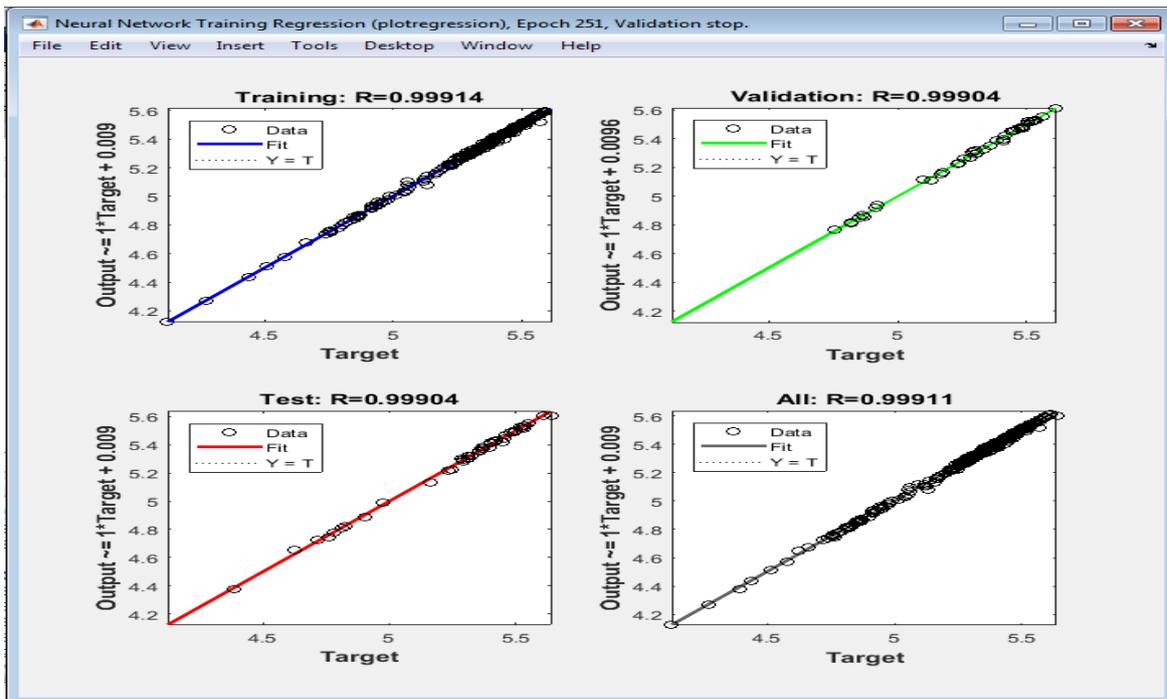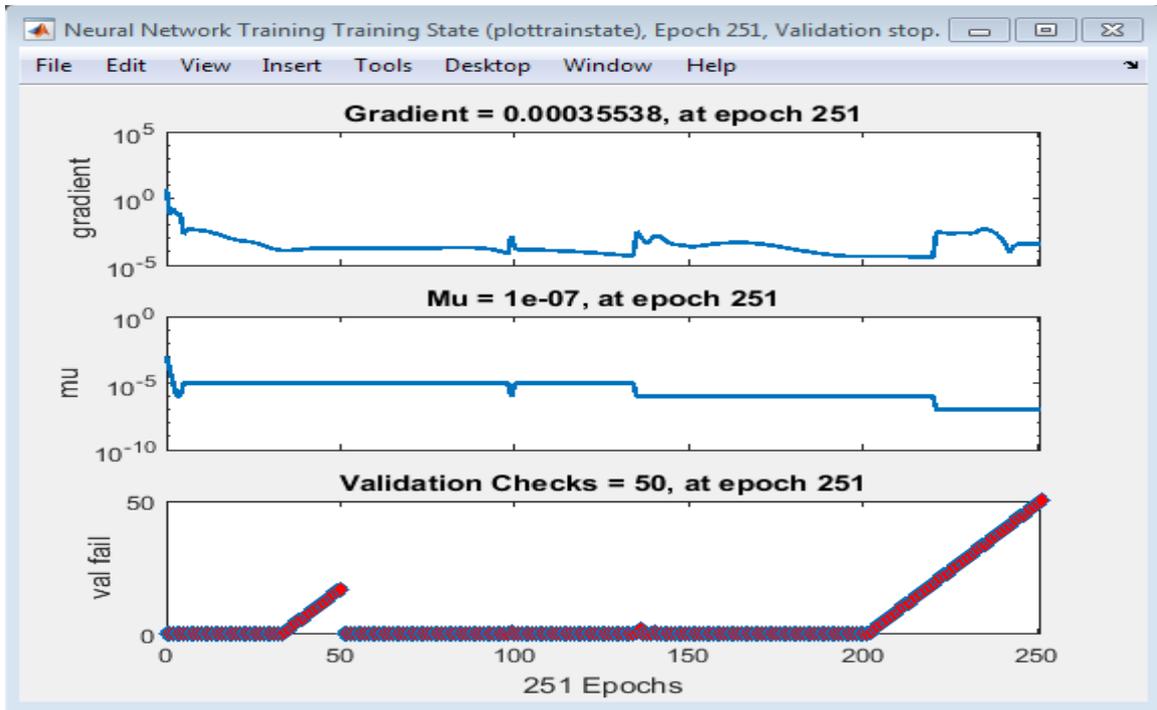

(a)
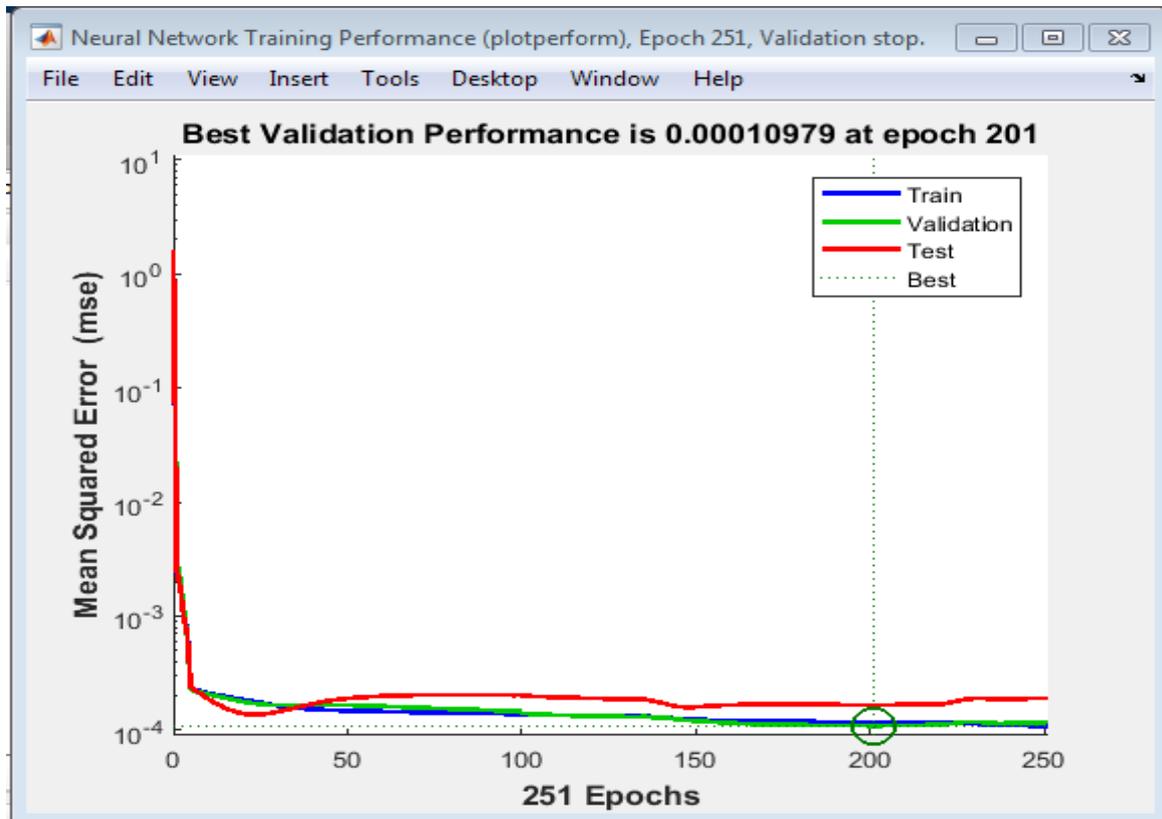
(b)

Figure 11: (a) Correlation Coefficient for Network Performance, R (LM); and (b) Mean Squared Error (MSE) against Epochs (LM)

(a)

(b)

Figure 12: (a) Error Histogram (LM); and (b) Training State Plot for Model Validation (LM)

ii. *Simulation Results of FFNN Using Bayesian Regularisation Training Algorithm*
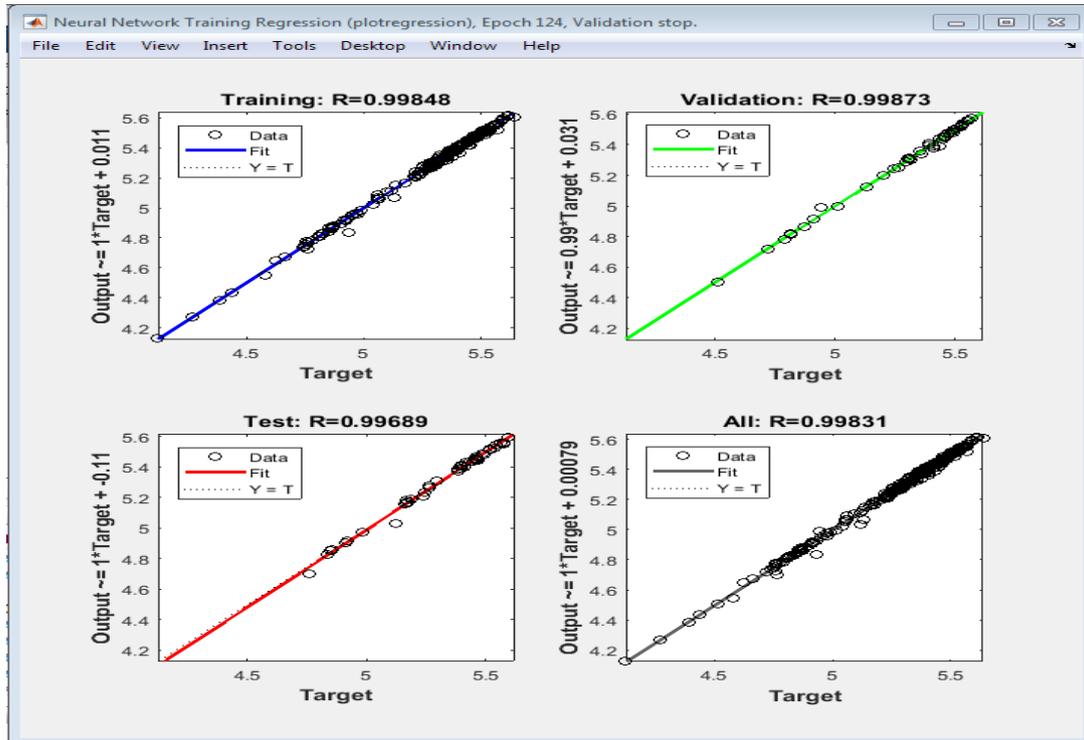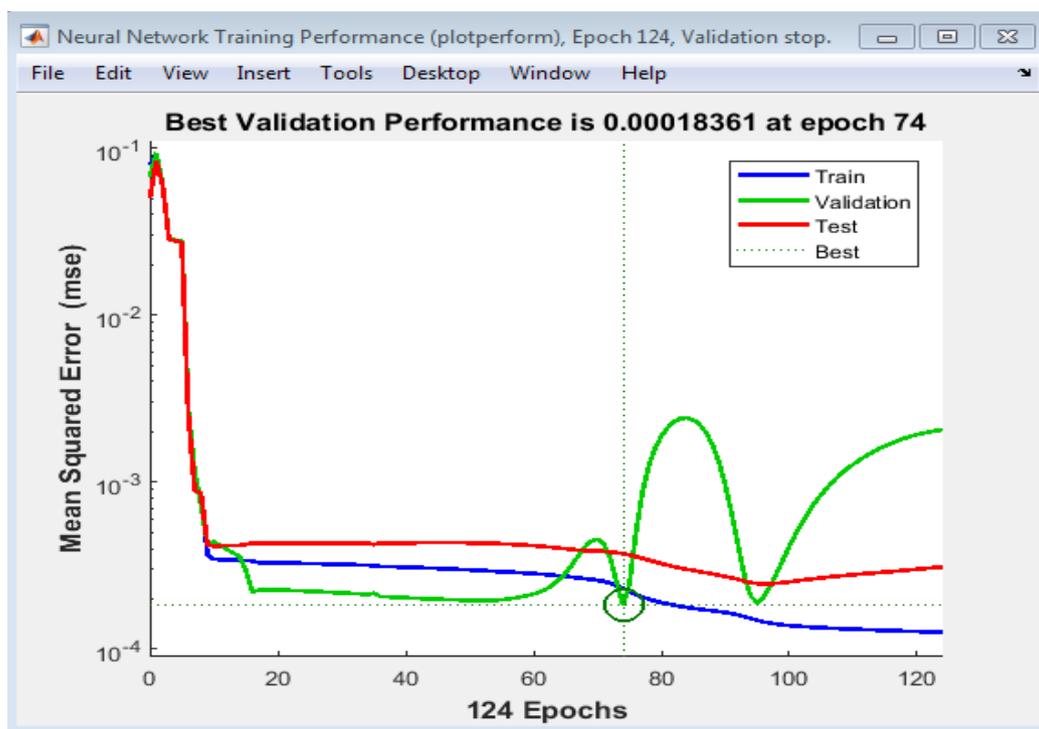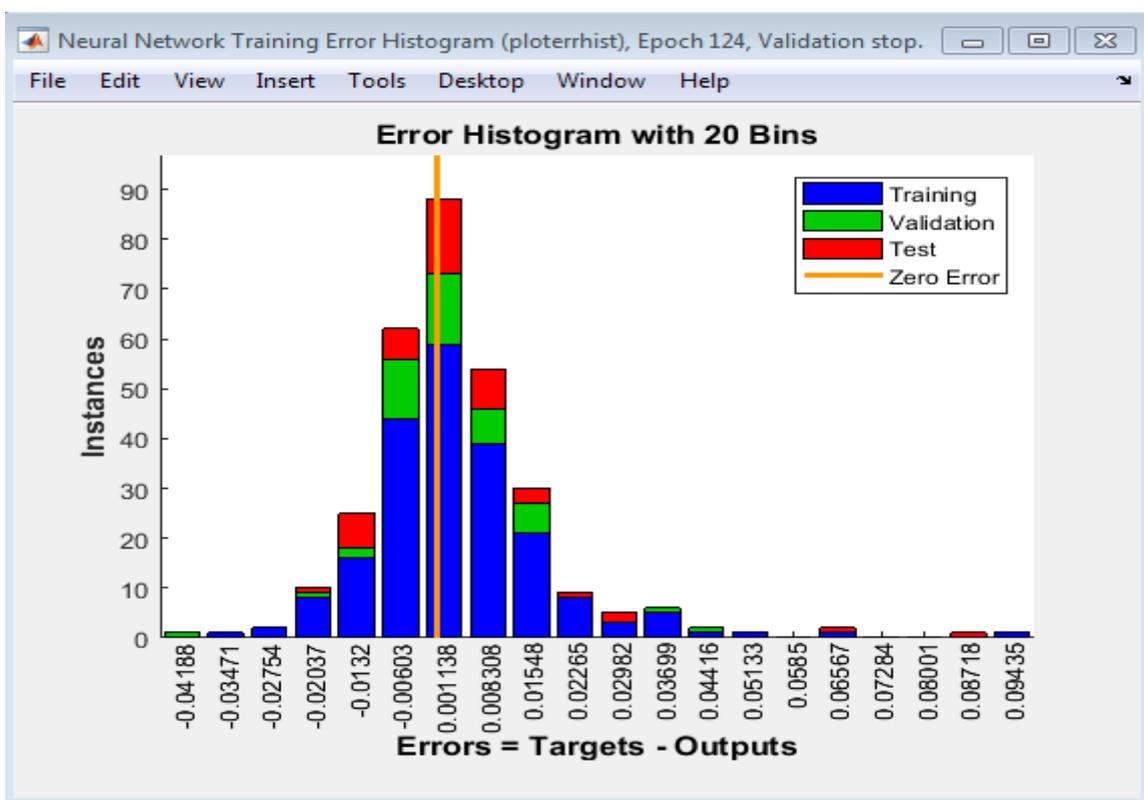

Figure 13: Correlation Coefficient for Network Performance, R (BR)

(a)

(b)

Figure 14: (a) Mean Squared Error (MSE) against Epochs (BR); and (b) Error Histogram (BR)
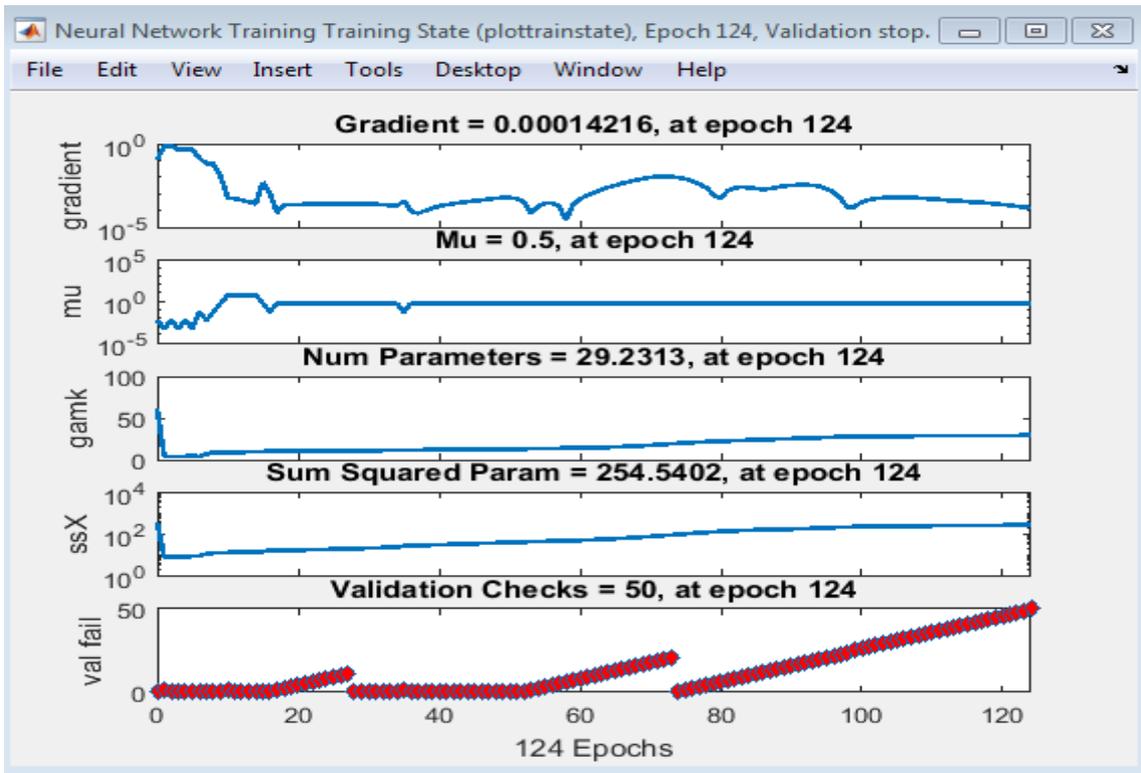
Figure 15: Training State Plot for Model Validation

b) *Discussion of Simulation Results*

This section also presents discussions of the MATLAB simulated results using FFNN. Table 2 shows the computed values of mean squared error MSE and correlation coefficient of network performance, R. It shows values of MSE and R for different number of data samples for training, validation and testing of the generated FFNN. The data samples range from 100, 200, 300, 400 and 500.

Table 2: Statistical Error Parameters of Developed FFNN Models for Different Data Sample Size

Number of Data Samples	Levenberg - Marquardt Algorithm				Bayesian Regularisation Algorithm			
	A/F – LOGSIG		A/F – TANSIG		A/F - LOGSIG		A/F - TANSIG	
	MSE	R	MSE	R	MSE	R	MSE	R
100	1.48E-04	0.99724	2.48E-04	0.99842	2.55E-04	0.99702	2.32E-04	0.99668
200	1.03E-04	0.99894	2.76E-04	0.99751	1.87E-04	0.99812	1.67E-04	0.99843
300	1.33E-04	0.99904	1.74E-04	0.99911	3.70E-04	0.99831	3.03E-04	0.99701
400	8.93E-04	0.99565	4.46E-04	0.99685	5.50E-03	0.9755	5.41E-04	0.99738
500	0.0064	0.96889	6.40E-03	0.96977	6.50E-03	0.96807	6.40E-03	0.96863

In this study, the network was decided to consist of one hidden layer with 10 neurons. The criterion R and MSE were selected to evaluate the networks to find the optimum solution. The complexity and size of the network was also an important consideration and therefore smaller ANN's had to be selected. A regression analysis between the network response and the corresponding targets was performed to investigate the network response in more detail. Thus, LM and BR were selected. The R-values in Table 3 represent the correlation coefficient between the outputs and targets. The R-values did not increase beyond 10 neurons in the hidden layer. Consequently, the network with 10 neurons in the hidden layer would be considered satisfactory. From all the networks trained, few ones could provide the low error condition, from which the simplest network was selected. The results showed that, the training algorithm of LM was sufficient for predicting SAG Mill motor failures. There is a high correlation between the predicted values by the ANN model and the measured values collected from normal real time running of 5.8 MW, 11 kV SAG Mill motor, which imply that the model succeeded in prediction of SAG Mill motor failures.

It can be observed in Figs. (11a, b, 12a, b and 13) that, the ANN provided the best accuracy in modelling induction motor failures with correlation coefficients of 0.999 and 0.998 for LM and BR respectively. Generally, the ANN offers the advantage of being fast, accurate and reliable in the prediction or

approximation affairs, especially when numerical and mathematical methods fail. There is also a significant simplicity in using ANN due to its power to deal with multivariate and complicated problems.

The measured values collected from real time, on load running of the 5.8 MW, 11 kV SAG Mill motor showed some linearity between the current, temperatures and the power. The power of the SAG Mill motor at nominal load ranges from 4 MW – 5.6 MW with the current and temperatures reading 300 A – 349 A and $80^{o}C$ – $109^{o}C$ respectively.

From Table 2, it can be seen that, the ANN showed good R and MSE values when data samples of 300 was used. This was the same for LM and BR, while using log-sigmoid and tan-sigmoid as transfer functions for the hidden layer. The results for R-values for data samples of 300 were 0.99904, 0.99911, 0.99831 and 0.99701 respectively, while MSE values were 1.33E-04, 1.74E-04, 3.70E-04 and 3.03E-04 respectively. This simulation was repeated for data samples of 100, 200, 400 and 500. It was observed that, increasing the number of data samples resulted in bad R-values. Data samples of 100 gave better results than 200, 200 than 400 and 400 than 500 in that order.

Training stops after 251 iterations. At this position, performance of network, 150×10^{-4}, gradient decrease to 3.55×10^{-4} and also the value of mu $= 10^{-7}$ as shown in Figure 12(b). Validation performance reached the minimum at epoch 201. The training continued for 51 more iterations and stopped at epoch 251. The gradient and mu increased gradually as shown in Figure 12(b).

From the error histogram shown in Figure 12(a), most errors occurred between –0.04 to +0.05. Errors also occurred at 0.065, 0.087 and 0.094 of the training data on the histogram, and also represents the point for which output 4.5 – target value 4.6, output 4.8 – target 4.9 and output 5.1 – target 5.2 on the training correlation coefficient for network performance, plot shown in Figure11(a).

c) Discussions on Using the Network for Prediction

Two matrices of 5×669 and 5×31 constructed by power, current and three winding temperature values normalised sample data of SAG Mill motor at healthy and faulty on load condition respectively as input are used to analyse network performance. Among them, 70%, 15% and rest data are used as training, cross validation and testing data. The target of the network is 1 or 0, with 1 indicating healthy motor condition and 0 indicating faulty motor condition. For any output value between 1 and 0 represents the probability of fault condition, in training the network, there was 1 hidden layer with 10 neurons and tansigmoid as the transfer function. The output layer had 1 neuron and the transfer function was logsigmoid.

Fresh data samples consisting of 5×169 and 5×10 healthy and faulty on load power, current and three winding temperatures of the SAG Mill motor were fed into the network to detect health. Table 3, Figure 16(a) and 16(b) show the detection efficiency and confusion plot of network using LM and BR algorithm respectively. Out of the 169 healthy data samples, using LM training algorithm could rightly predict them as true detection (TD) and false detection (FD) of 0. The network could also predict a TD of 10 out of 10 faulty data fed into it. This shows the network with LM training algorithm can detect healthy and faulty conditions of the SAG Mill motor with 100% accuracy. BR training algorithm could detect 169 healthy samples as TD and 9 out of 10 faulty data samples as TD and 1 FD, therefore, network with BR could detect healthy and faulty conditions of the SAG Mill motor with 99.4% efficiency.
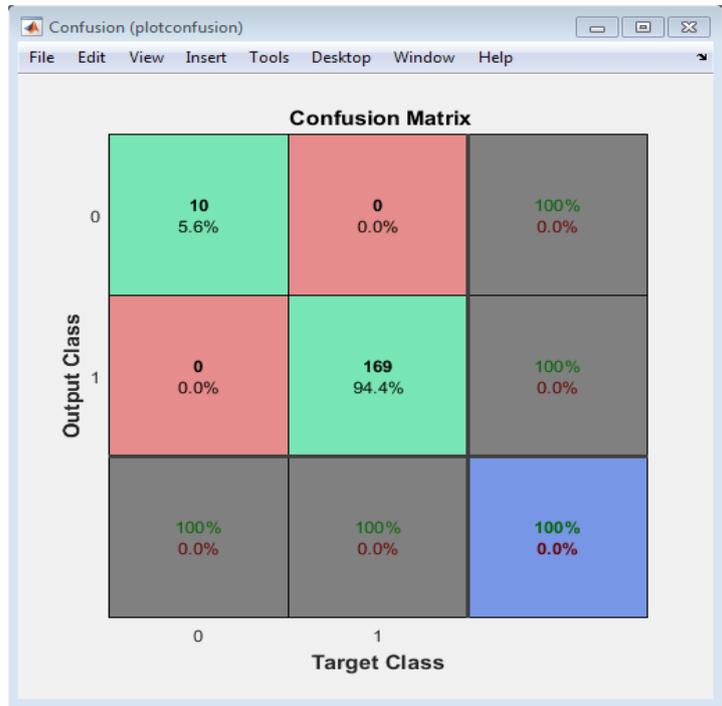
(a)
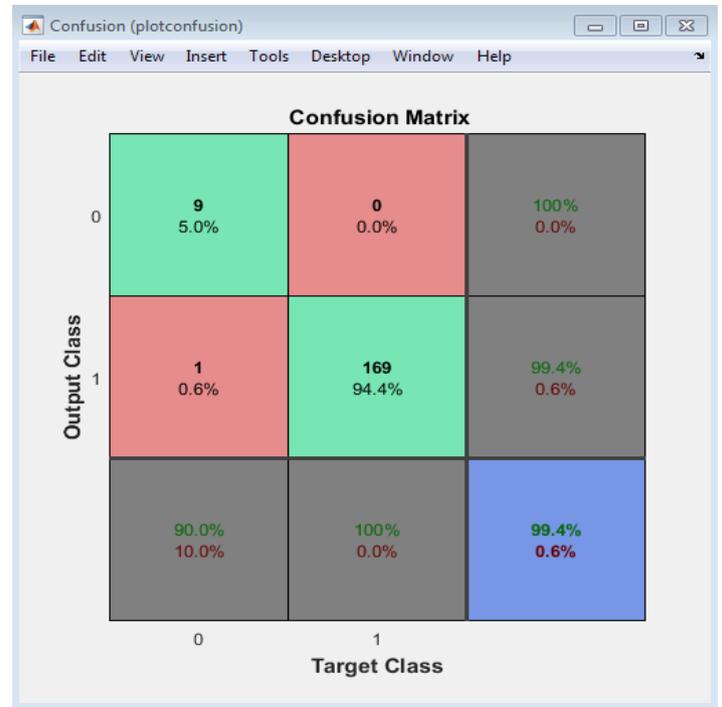
(b)

Figure 16: (a) Plot of Confusion Matrix Using Levenberg-Marquardt Algorithm; and (b) Plot of Confusion Matrix Using Bayesian Regularization Algorithm

Table 3: Detection Accuracy

TOTAL NUMBER DATA SAMPLES	HEALTHY		FAULTY		ACCURACY
	TD	FD	TD	FD	
Levenberg-Marquardt	169/169	0/169	10/10	0/10	100%
Bayesian Regularization	169/169	0/169	9/10	1/10	99.4%

d) Summary of Findings

The findings as regards simulations of data samples measured on the 5.8 MW, 11 kV SAG Mill motor at the Goldfields Ghana Ltd., Damang Mine from 6th January, 2019 to 8th April, 2019 are summarised as follows:

1. A smaller Feed-Forward Neural Network size of 4-10-1 provides optimum performance for prediction of SAG Mill motor failures;
2. Though Bayesian Regularisation training algorithm has not been extensively used in failure prediction of three phase slip-ring induction motor as compared to Levenberg-Marquardt, yet it gives acceptable results in terms of accuracy but at a relatively low efficiency;
3. Data samples of 100, 200, 300, 400 and 500 were used in this work. Data samples of 300 with Levenberg-Marquardt training algorithm and tansigmoid activation function of the hidden layer provided the best results for R-values and MSE;
4. The network stopped training at 251 iterations, a network performance of 150×10^{-4} at this position. The gradient decreases to 3.55×10^{-4} and mu = 10^{-7}. Validation performance reaches minimum at epoch 201; and
5. The network with Levenberg-Marquardt training algorithm can detect healthy and faulty conditions of the SAG Mill motor with 100% accuracy and 99.4% using Bayesian Regularization as the training algorithm.

IV. Conclusions and Recommendations

a) Conclusions

From the results and discussions, the following conclusions can be drawn:

1. The proposed Feed-Forward Neural Network with Levenberg-Marquardt training algorithm is capable of predicting imminent faults ofon load 5.8MW, 11 kV SAG Mill three phase slip-ring induction motor at Goldfields Ghana Ltd., DamangMine with 100% accuracy;
2. Correlation coefficient of network performance, R and mean squared error, MSE proved to be very good statistical tools for artificial neural network model analysis; and
3. Bayesian Regularisation training algorithm proved to be a good alternative to Levenberg-Marquardt algorithm in failure prediction networks.

b) Recommendations

The following are recommended based on the conclusions drawn:

1. Similar research could be carried out on the Ball Mill motor and other important motors at the plant;
2. Since it will be very difficult to set up a prototype for the 3 phase 5.8 MW, 11 kV slip-ring induction motor

taking into consideration the size and cost, MATLAB/SIMULINK and Finite Element Method Magnetics could be considered in generating signals for this research; and
3. Wavelet techniques and Fuzzy logic could be used to find exact location of fault, identification and evaluation of fault severity.

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