Journal of Thai Interdisciplinary Research
Volume 13, Number 4, Pages 18 - 25

Detection and classification of induction motor faults using feed-forward backpropagation network

Kreangsuk Kraikitrat*, Sittpong Pengpraderm, and Sompornru Ruangsinchaiwanich

Department of Electrical and Computer Engineering, Faulty of Engineering, Naresuan University, Thailand

Abstract

For this paper artificial neural networks technique is applied to identify broken rotor bar fault of single phase induction motor. Since artificial neural networks can be able to deal with non-linear problem, it is capable for apply to many applications in particular for recognizing patterns positively. Furthermore, fast Fourier transform (FFT) is employed for converting original stator current waveform, which is time domain, to stator current signal, which is frequency domain, that is labeled as motor current signature analysis for collecting essential data in order for sending into artificial neural networks later. Although performance of artificial neural network is related as many factors, three different multilayer neural network with several training algorithms are researched in this paper. Also three training algorithms are focused to study for exempla gradient descent algorithm, Levenberg-Marquardt algorithm and resilient back propagation algorithm. Consequently, the Levenberg Marquardt algorithm can perform very well for every different multilayer of neural networks in term the network mean squares errors (MSE) which having 5.25E-07 percent that comparing with other results of training algorithms.

Keywords: fast Fourier transform, artificial neural network, broken rotor bar, induction motor

Article history: Received 16 November 2017, Accepted 25 April 2018

1. Introduction

The squirrel cage induction motor been widely used for many electric drive applications for example fans and pumps, since it has several advantages over other electrical machines. Also for industrial process, majority of induction motor is frequently used for long period of time, therefore the preventing maintenance is recommended for the operating the induction motor to avoiding the serious damage. The faults of induction motor can be categorized normally for example mechanical fault and electrical fault. According to the statistical surveys performed on induction motors revealed that 41 percent of failures are resulted from bearing faults, 37 percent of them are from stator faults, 10 percent of are from rotor faults, and 12 percent are from other faults such as unbalanced phase supply [20]. With advancements in digital electronics and reduced component costs in recent years, monitoring technology for use in condition-based maintenance programs have become more importance. Also the induction motor not need to be taken out of service as many tests are done online, and in many cases very little expertise is required for testing and data interpretation. This enables the user to make well-informed decisions for planning maintenance and repairs, which ultimately leads to increased productivity.

Recently artificial intelligence (AI) is recognized as novel assistance methodology for either researching or developing to several scientific areas. For fault detection in electrical motor, it has been also recommended by several researchers in particular artificial neural networks (ANN) [8-12, 21-25]. The artificial neural network is one of the artificial intelligence methods. Moreover, it is recognized as reasonable and powerful algorithms. Since the artificial neural networks can be trained by supervisor and can be able to deal with non-linear problem, it is capable positively to realize the relationship between the input and output data from experimental work. Therefore, it can be applied to many applications in particular for recognizing patterns. Moreover, it can be supervised for improving classifying performance. Thus the feed forward back-propagation neural network is selected in this research for aiming to recognize the harmonics of the broken rotor bar fault.

For this paper artificial neural networks technique is applied to identify the broken rotor bar fault of single phase induction motors which are 1, 3, 5 and 7 broken rotor bars. Additionally, main parameters for example lower side band frequency (fLSB), upper side band frequency (fUSB), magnitude of lower side band frequency (LSB), magnitude of upper side band frequency (USB) and the distance frequency between lower side band are elected for input to neural networks and many training algorithms are studied.

* Corresponding author; e-mail: kreangsuk_k@hotmail.com

DOI 10.14456/jtir.2018.36

Rated power (Hp)	1/4
Rated voltage (V)	220
Rated current (A)	2.4
Number of poles	4
Number of stator	32
Number of rotor	44
Speed (rpm)	1,450

Figure 1 Stator fame and main parameters of prototype motor

1BB 3BB 5BB 7BB

Figure 2 Photograph of broken rotor bars

2. Induction Motor, fault detection, and classification

A. Motor current signature analysis

Motor current signature analysis (MCSA) is found a highly valuable predictive maintenance tool for metering fault diagnosing particularly in induction motor [1, 2, 5, 7, 21, 22]. In case of the broken rotor bar condition, fundamental sidebands in the amplitude spectrum of the stator currents can be reviewed as:

$$f_{sb} = (1 \pm 2ks)\, f_e \quad (1)$$

where f_e is supply frequency

s is slip of the induction motor

Recently fast Fourier transform (FFT) is widely used for many applications in engineering, science, and mathe-matics. Fundamentally FFT can convert a signal from its original domain (often time or space) to a representation in the frequency domain. For the motor current signature, the typical stator current waveform which has time domain is converted by FFT in order to displaying with the stator current frequency domain. Since a rotor of induction motor has broken rotor bar condition, their sideband frequencies are apparently established as $(1-2s)\, f_s$, which can be labeled as lower-sideband (LSB) and $(1+2s)\, f_s$, which can be called as upper-sideband (USB). Therefore, their sideband frequencies are key parameters for using to recognize into several techniques of the broken rotor bar monitoring.

B. Induction motor with rotor broken bars condition

A single phase squirrel cage induction motor is selected as prototype motor for studying in this research that shows Stator fame and main specific parameters of prototype motor in figure 1. Also figure 2 shows these experimental rotors which are 1, 3, 5 and 7 broken rotor bars condition.

C. Methodology for fault detection and classification

For collecting induction motor data, a scheme is presented in Fig. 3 that consists of such as a prototype induction motor (1), an analog-to-digital converter (2), a computer (3) and an oscilloscope (4). Since the original stator current waveform is difficult to detect the fault of the broken rotor bar conditions, the frequency analysis is recommended to identify problematic frequency bands. According to using FFT, for example, figure 4 shows the stator current spectrum of healthy rotor bar (0BB line) comparing with the stator current spectrum of unhealthy rotor bar (from 1BB, 3BB, 5BB and 7BB lines). Since the rotor has broken rotor bar condition, their sideband frequencies that are apparently established at $(1-2s)\, f_e$, which can be named as lower-sideband (LSB), and at $(1+2s)\, f_e$,which can be named as upper-sideband (USB), are occurred in the stator current spectrum.

Furthermore, for fault detection and classification, the feature extraction process exposes fault frequencies in signal data through a series of signal processing

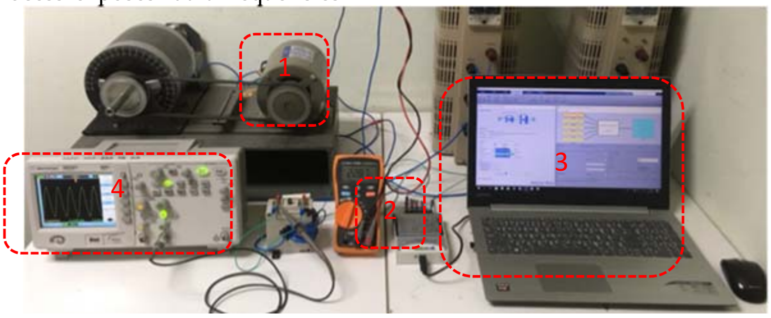

Figure 3 Block diagram for determining current spectrum

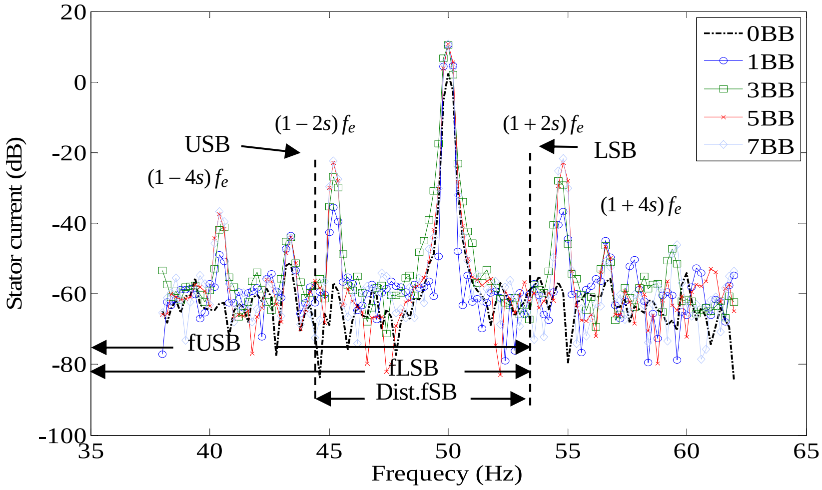

Figure 4 Stator current spectrum waveform of the induction motors

Figure 5 Process of this fault detection and classification

techniques (FFT). Also the approach is based on signal analysis in the frequency domain. For this work, the induction motors, which have broken rotor bar and healthy rotor bar are studied. Main parameter for example lower side band frequency (fLSB), upper side band frequency (fUSB), magnitude of lower side band frequency (LSB), magnitude of upper side band frequency (USB) and the distance frequency between lower side band and lower side band frequency (Dist.fSB), are collected in order to classifying rotor fault by using artificial neural network later. Overall a flow diagram of this fault detection and classification is shown in Fig. 5.

3. Artificial neural network fault classifier

A. Architecture

Artificial neural network is learning systems inspiration from massively dense connected of neurons system in the brain. Typically, the neural network may consist of input layer, hidden layers and an output layer for example as shown in Fig. 6. Also each neuron can link to each other in order to add some weights that transfer the information from one neuron to another. Normally designer can use numerical technique to function desired weight for expressing the strength of each neuron input. For benefiting full artificial neural network, teaching process can repeat for adjusting the preferred weight. In order to construct a neural network, numbers of neurons that to be used must decide first, how many neurons are connected in a network which means network architecture need to determine. In this paper a feed-forward neural network is studied with the purpose of classifying broken rotor bar fault of induction motor. Also a supervised network of back-propagation is decided to apply, since it is extensively recognized for pattern classification nowadays.

The Multilayer Perceptron is a type of supervised network. Multilayer Perceptron is learning process was

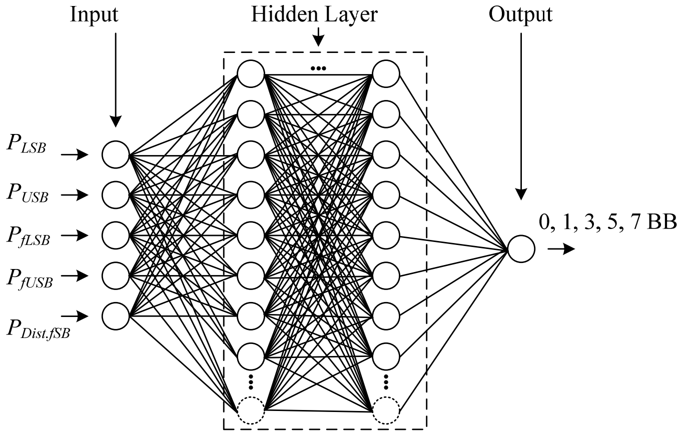

Figure 6 the proposed structure of multilayer perceptron (MLP)

Table 1 Data for training in ANN

Position	0BB	1BB	3BB	5BB	7BB
LSB	-59.54	-35.97	-26.40	-23.31	-22.28
USB	-73.60	-36.88	-27.44	-23.24	-21.43
fLSB	45.20	45.20	45.20	45.20	45.20
fUSB	54.80	54.80	54.80	54.80	54.80
Dist.fSB	9.60	9.60	9.60	9.60	9.60

first developed by Werbos in 1974 [17]. In Fig. 6, the structure of Multilayer Perceptron consists of input layer, one or more hidden layer and an output layer. The input layer provides the input signals where transmit in a forward direction and then distribute these signals to each of neurons in the hidden layer. Finally, the output layer recognized the pattern output of the network. In each neuron associated with activation functions. Multilayer perceptron is normally used for sigmoidal activation function. Weight in hidden layer expressed the strength of each neuron input. The computation of incremental value of weight is depends on training algorithm.

A feed forward back propagation is selected for this investigation, and a hidden layer used activation function of tan-sigmoid transfer function ('tansig') given in equation (2). Characteristically the tansig transfer function is a type of non-linear function where the output can be varied between 1 and -1. For the output layer, linear transfer function ('purelin'), $f(x) = x$ is used properly for fault detection and classification purposes.

$$f(n) = \frac{2}{1+\exp(-2n)} - 1 \tag{2}$$

Table 1 shows the correcting data for the input parameters for the artificial neural network, and there are lower side band frequency (fLSB), upper side band frequency (fUSB), magnitude of lower side band frequency (LSB), magnitude of upper side band frequency (USB) and the distance frequency between lower side band and lower side band.

B. Training Algorithms [15]

The multilayer perceptron network training can be viewed as a function approximation problem in which the network parameters (weights and biases) are adjusted during the training, in an effort to minimize (optimize) error function between the network output and the desired output. The issue of learning algorithm is very important for multilayer perceptron neural network. Although training algorithms have many methodologies, for paper only three training algorithms are studied for example gradient descent (GD) Algorithm, Levenberg-Marquardt (LM) algorithm and resilient back propagation (Rp) algorithm.

Gradient Descent Algorithm (GD)

The standard training process of the MLP can be realized by minimizing the error function E defined by:

$$E = \sum_{p=1}^{p} \sum_{j=1}^{N_M} \left(y_{j,p}^{M} - t_{j,p} \right)^2 = \sum_{P=1}^{P} E_P \quad (3)$$

where $y_{j,p}^{M} - t_{j,p}$ is the squared difference between the actual output value at the j^{th} output layer neuron for pattern p and the target output value. The scalar *p* is an index over input–output pairs. The general purpose of the training is to search an optimal set of connection weights in the manner that the errors of the network output can be minimized [16].

In order to simplify the formulation of the equations, let w be the n-dimensional weight vector of all connection weights and biases. Accordingly, the weight update equation for any training algorithm has the iterative form. In each iteration, the synaptic weights are modified in the opposing direction to those of the gradient of the cost function. The on-line or off-line versions are applied that use the instantaneous gradient of the partial error function, E_P, or on the contrary the gradient of the total error function E respectively.

The procedure in the mode off-line sums up as follows

$$w(k+1) = w(k) + \alpha_k d_k \quad (4)$$

where, $w(k) = \left(w_1(k), ..., w_n(k) \right)^T$ is the weight vector in *k* iterations, n is the number of synaptic connections of the network, *k* is the index of iteration, α_k is the learning rate which adjusts the size of the step gradient, and d_k is a search direction which satisfies the descent condition.

Levenberg-Marquardt Algorithm

The Levenberg-Marquardt (LM) algorithm [18] is the most widely used optimization algorithm. With similar to the quasi-Newton methods, the LM algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. The LM algorithm provides a solution for nonlinear least squares minimization problems. When the performance function has the form of a sum of squares, then the Hessian matrix can be approximated as:

$$H = \mathrm{J}^{\mathrm{T}}\mathrm{J} \quad (5)$$

where J is the Jacobian matrix that contains the first derivate of network errors and the gradient can be computed as:

$$g_w = \mathrm{J}^{\mathrm{T}} e \quad (6)$$

where the Jacobian matrix contains the first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors.

The Levenberg–Marquardt (LM) algorithm uses the approximation to the Hessian matrix in the following Newton like update:

$$w_{k+1} = w_k - \left[\mathrm{J}^{\mathrm{T}}\mathrm{J} + \mu I \right] \mathrm{J}^{\mathrm{T}} e \quad (7)$$

where I is the identity matrix
μ is a constant.

μ decreases after each successful step (reduction in performance function) and increases only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm.

Resilient back Propagation (Rp) Algorithm

Mainly goal of the resilient back propagation (Rp) algorithm is to eliminate the harmful effects of the magnitudes of the partial derivatives. Therefore, only the sign of the derivative is used to determine the direction of the weight up-date. Indeed, the Rp modifies the size of the weight step that is adaptively taken. The adaptation mechanism in Rp does not take into account the magnitude of the gradient ($g_w(k)$) as seen by a particular weight, but only the sign of the gradient (positive or negative) [19].

The Rp algorithm is based on the modification of each weight by the update value (or learning parameter) in such a way as to decrease the overall error. The update value for each weight and bias is increased whenever the derivative of the performance function with respect to that weight has the same sign for two successive iterations. The principle of this method is as follows:

$$w_k - w_{k+1} = -sign\left(g_w(k-1) \right) \Delta_k \quad (8)$$

$$\Delta_k = n^{+} \Delta_{k-1} \ if \ g_w k - 1 * g_w(k) > 0 \quad (9)$$

$$\Delta_k = n^{-} \Delta_{k-1} \ if \ g_w k - 1 * g_w(k) < 0 \quad (10)$$

Else $\Delta_k = \Delta_{k-1}$ where $0 < n^{-} < 1 < n^{+}$

Δ_k is the update value of the weight, which evolves according to changes of sign of the difference ($w_k - w_{k-1}$) of the same weight in k iterations. The update values and the weights are changed as each iteration. All update values are initialized to the value D0. The update value is modified in the following manner: if the current gradient ($g_w(k)$) multiplied by the gradient of the

Table 2 Performance comparison of hidden layer

Number hidden layers	2 INPUT			5 INPUT		
	Layer	Training MSE (%)	Classification Accuracy (%)	Layer	Training MSE (%)	Classification Accuracy (%)
1	2-2-1	3.00E-03	66.67	5-2-1	9.89E-04	66.67
1	2-3-1	1.79E-05	66.67	5-3-1	8.68E-04	73.33
1	2-4-1	1.65E-05	66.67	5-4-1	9.26E-05	73.33
1	2-5-1	1.19E-06	80.00	5-5-1	6.35E-06	73.33
1	2-6-1	2.16E-06	80.00	5-6-1	7.19E-08	73.33
1	2-7-1	4.12E-05	86.67	5-7-1	8.40E-04	73.33
1	2-8-1	1.19E-04	80.00	5-8-1	1.29E-04	60.00
2	2-5-2-1	8.88E-04	66.67	5-6-2-1	1.75E-04	66.67
2	2-5-3-1	2.25E-04	66.67	5-6-3-1	1.53E-04	60.00
2	2-5-4-1	1.53E-04	66.67	5-6-4-1	1.31E-04	60.00
2	2-5-5-1	3.41E-09	80.00	2-6-5-1	4.23E-06	80.00
2	2-5-6-1	1.79E-04	66.67	2-6-6-1	3.87E-07	73.33
2	2-5-7-1	4.52E-04	66.67	2-6-7-1	1.64E-06	73.33
2	2-5-8-1	4.67E-03	66.67	2-6-8-1	2.77E-05	73.33

Table 3 Performance Comparison of Training Algorithm with three Training Algorithm

Training Algorithm	Number hidden layers	2 INPUT		5 INPUT	
		Training MSE (%)	Classification Accuracy (%)	Training MSE (%)	Classification Accuracy (%)
GD	1	7.36E-05	80.00	1.78E-06	73.33
LM	1	2.17E-05	80.00	2.40E-07	73.33
RP	1	2.04E-04	80.00	5.15E-06	73.33
GD	2	5.55E-04	80.00	6.53E-04	73.33
LM	2	5.25E-07	80.00	5.90E-06	73.33
RP	2	2.79E-04	80.00	7.19E-04	66.67

previous step is positive (that is the gradient direction has remained the same), then the update value n^+ is multiplied by a value (which is greater than one). Similarly, if the gradient product is negative, the update value n^- is multiplied by the value (which is less than one).

4. Result

Regularly, the feed forward back-propagation neural network requires core parameters such as input data. target output, the weights, and the bias value. Generally, the network mean squares errors (MSE), which is the performance function for training process, can be expressed as

$$MSE = \frac{1}{K}\sum_{k=1}^{K}\left\|e_k\right\|^2 = \frac{1}{K}\sum_{k=1}^{K}\left\|t_k - a_k\right\|^2 \qquad (11)$$

where e_k is error of the process [$e_k = (t_k - a_k)$]

a_k is resultant output.

Table 2 shows comparison of hidden layer type between 1 and 2 layer in the multilayer perceptron training algorithm, 1 hidden layer which is having the best result in terms of accuracy and MSE is 5 layer for 2 input ((80.00%) and (1.19E-06%)) and 6 layer for 5 input ((73.33%) and (7.19E-08%)), 2 hidden which is having the best result in terms of accuracy and MSE is layer is 5-5 layer for 2 input ((80.00%) and (3.41E-09%)) and 6-6 layer for 5 input ((73.33%) and (3.87E-07%)).

Table 3 and Fig. 7 shows that the multilayer perceptron training algorithm which is having the best result in terms of accuracy for Classification (80.00%) and MSE for training (5.25E-07%) is the LM training algorithm. The second best training algorithm is GD, while RP accuracy for Classification (66.67%) and MSE for training (7.19E-04%) is the least suitable training algorithm.

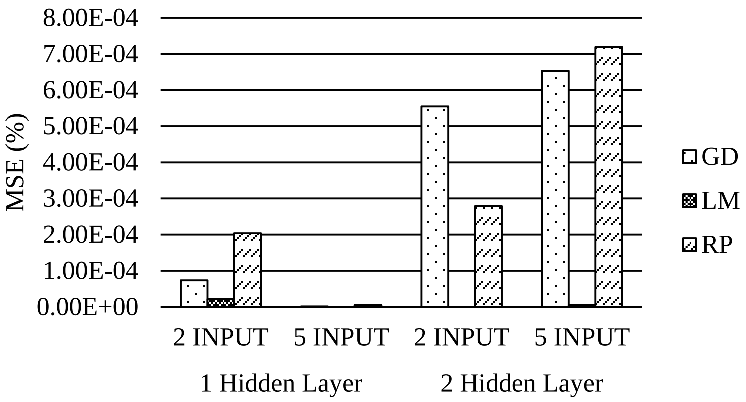

Figure 7 Mean squares errors of training

5. Conclusions

In this paper, the detection and classification of induction motor faults using MCSA and multilayer perceptron neural network is presented. MCSA method has been utilized to obtained data collection of the one phase stator current. Comparison in terms of accuracy and MSE for training the neural network is demonstrated. The result obtained show that multilayer perceptron neural network with Levenberg - Marquardt training algorithm is the best MLP training algorithm having the best accuracy (80.00%) and MSE (5.25E-07) compared with others training algorithms.

Acknowledgements

The authors would like to thanks Naresuan University particular that such as Faculty of Engineering, the graduate school and Department of Electrical and Computer Engineering for supporting the finance for research, material and equipment, advising staffs in this project.

References

[1] Thosmson TW, Mark F. Current signature analysis to detect induction motor faults. **IEEE Industry Application Magazine**, 2001;**7**(4):26-34.

[2] Ashish K, Mohit S. A new burg method based approach to MCSA for broken rotor bar detection. **2012 IEEE International Conference on Power Electronics Drives and Energy Systems;** 2012.

[3] Gennadi YS, Ahmed S, Analysis and diagnostics of adjacent and nonadjacent broken-rotor-bar faults in squirrel-cage induction machines. **IEEE Transactions on Industrial Electronics**. 2009;**56**(11): 4,627-4,641.

[4] Sittisrijan N, Ruangsinchaiwanich S. Synthesis of stator current waveform of induction motor with broken bar conditions. **International Conference on Electrical Machines and Systems;** 2013.

[5] Sittisrijan N, Wangngon B, Ruangsinchaiwanich S. Synthesis of stator current waveform of inverter-fed induction motor with broken bar conditions **International Conference on Electrical Machines and Systems;** 2014.

[6] Sittisrijan N, Ruangsinchaiwanich S. Analysis of stator current waveforms of induction motor with broken bar conditions. **International Conference on Electrical Machines and Systems**; 2011.

[7] Khalaf SG, Hew WP, Mustafa K, Atheer LS. Fault Diagnosis of Induction Motor Using MCSA and FFT. **Electrical and Electronic Engineering.** 2011; **1**(2): 85-92

[8] Sri RK, Shawn DA. Artificial neural network based fault identification scheme implementation for a three-phase induction motor. **International Society of Automation Transactions.** 2007;**46**(2): 261-266.

[9] Dragan M, Filip K. Artificial neural networks broken rotor bars induction motor fault detection. **IEEE Symposium on Neural Network Applications in Electrical Engineering**; 2010.

[10] Rao KSR, Yahya MA. Neural networks applied for fault diagnosis of AC motors. **International Symposium on Information Technology;** 2008.

[11] Moradian M, Ebrahimi M, Danesh M, Bayat M. Detection of broken bars in induction motors using a neural network. **IEEE Journal of Power Electronics**, 2006;**6**(3): 245–252.

[12] Wangngon B, Ruangsinchaiwanich S. Multiple fault detection technique for identifying broken rotor bars. **International Conference on Electrical Machines and Systems**. 2013.

[13] Drira A, Derbel N. Classification of rotor fault in induction machine using Artificial Neural Networks. **International Multi-Conference on Systems**; 2011.

[14] Wangngon B, Sittisrijan N, Ruangsinchaiwanich S. Fault detection technique for identifying broken rotor bars by artificial neural network method. **International Conference on Electrical Machines and Systems**; 2014.

[15] Samira C, Abdelouhab Z, Jilali A. Identification and Prediction of Internet Traffic Using Artificial Neural Networks. **Journal Intelligent Learning Systems & Applications**, 2010: 147-155.

[16] Kostopoulos AE, Grapsa T. Self-Scaled Conjugate Gradient Training Algorithms. **Neuro-computing**, 2009;**72**: 3,000-3,019.

[17] Werbos PJ. **Beyond Regression: New Tool for Prediction and analysis in the Behavioural sciences.** Ph.D. Thesis, Harvard University, Cambridge, MA; 1974.

[18] Hagan MT, Menhaj MB. Training Feedforward Networks with the Marquardt Algorithm. **IEEE Transaction Neural Networks**, 1994;**5**(6): 989-993.

[19] Ramesh J, Vanathi PT, Gunavathi K. Fault Classification in Phase-Locked Loops Using Back Propagation Neural Networks. **ETRI Journal**, 2008;**30**(4): 546-553.

[20] Nandi S, Toliyat H, Xli. Condition monitoring and fault diagnosis of electrical motors – a review. **IEEE Transactions on Energy Conversion,** 2005;**20**(4) :719-729.

[21] Wangngon B, Sittisrijan N, Chaina K, Kondee S, Kaewieow T, Kraikitrat K, Ruangsinchaiwanich S. Fault analysis of induction motor 3 phase by measuring temperature and stator current signal. **RMUTI Journal**, 2016;**9**(2): 76-87 (In Thai).

[22] Wangngon B, Sittisrijan N, Chaina K, Kondee S, Kaewieow T, Kraikitrat K, Ruangsinchaiwanich S. Fault analysis of induction motor 3 phase by measure heat and stator current signal. **Naresuan University Engineering Journal**, 2015;**10**(2): 1-7 (In Thai).

[23] Wangngon B, Ruangsinchaiwanich S. Study and analysis performance of 18.5 KW induction motor by finite element model. **Naresuan University Engineering Journal,** 2013;**8**(1): 30-36 (In Thai).

[24] Kaewkunsri K, Ruangsinchaiwanich S. Study vibration in induction motor by finite element method. **Naresuan University Engineering Journal**, 2012; **7**(1): 29-36 (In Thai).

[25] Kraikitrat K, Ruangsinchaiwanich S, Pookpunt S. Study effect of natural frequency in rotor shape induction motor by finite element model. **Naresuan University Engineering Journal**, 2011;**6**(1): 12-19 (In Thai).