International Journal of Innovative
Computing, Information and Control
Volume **10**, Number **6**, December **2014**

ICIC International ©2014 ISSN 1349-4198
pp. 2277–2293

NEURAL NETWORK BASED REAL TIME DETECTION OF TEMPORARY SHORT CIRCUIT FAULT ON INDUCTION MOTOR WINDING THROUGH WAVELET TRANSFORMATION

Dimas Anton Asfani[1], Syafaruddin[2], Mauridhi Hery Purnomo[1] and Takashi Hiyama[3]

[1]Electrical Engineering Department
Institut Teknologi Sepuluh Nopember
Kampus ITS Sukolilo, Surabaya 60111, Indonesia
anton@ee.its.ac.id

[2]Electrical Engineering Department
Universitas Hassanudin
Tamalanrea, Makassar 90245, Indonesia

[3]Department of Computer Science and Electrical Engineering
Kumamoto University
2-39-1 Kurokami, Kumamoto 860-8555, Japan

Received January 2014; revised May 2014

Abstract. *In this paper, a new detection system for early stage short circuit fault in stator winding of induction motor is proposed. The early stage of stator winding short circuit is represented by a low magnitude current and a very short duration that is defined as temporary short circuit. The proposed method is based on transient current recognizing when short circuit fault starting occur and cleared. The transient current during fault is recognized by high frequency signal energy trending of wavelet transform. Three energy of high frequency signal from three consecutive current signal sampling are used as detection variables. Three wavelet types and five levels transformation are evaluated using linear discriminant analysis (LDA) to get the most suitable wavelet transform. The Elman neural network is designed as detection system. The proposed method is applied to laboratory experiment. As a result, the proposed method can clearly detect the temporary short circuit fault even though the fault has very fast occurrence and the current magnitude is lower than full load current. with the good accuracy and the ability to provide time information of fault, the proposed method is suitable for monitoring system.*
Keywords: Fault detection, Induction motors, Stators, Digital signal processing, Short circuit currents, Discrete wavelet transforms, Wavelet coefficients, Linear discriminant analysis, Recurrent neural networks

1. **Introduction.** Induction motor is known as a robust design with failure rate up to 0.064 failures/unit-years. However, the failure case of this motor is easily found because it has high population in industrial plant [1]. Stator winding deterioration is known as one of most common faults in induction motors. Considering industrial survey, stator contributes up to 66% of motor faults [2]. Moreover, stator insulation is one of the weakest parts [3] and causes approximately 80% stator failures. Induction motor failure in industrial plants can produce massive losses. For instance, in offshore oil plants, downtime losses due to motor failures can reach $25.000 per hour [4]. To avoid those losses, early fault detection system has been widely developed. Advanced methods of signal processing, sensor technology and detection systems are being proposed as innovative tools. Most of them are focused on detecting the early stage of winding deterioration while the

machine is still rotating normally. The insulation systems of electrical machines can be monitored online by considering variables such as capacitance, dissipation factor and/or insulation power factor [5, 6, 7], impedance [8], and sift phase [9] as an insulation failure indicator. Signal injection is also proposed to detect the fault [10]. Some signal processing techniques such as frequency spectrum analysis based on Fourier transform [11, 12, 13], wavelet transform [14, 15, 16], combination the Park's transform and Cross wavelet [17] are proposed to increase detection performance. Moreover, artificial intelligence is widely used for detection systems because of its ability to recognize nonlinear problem. Neural network is proposed as automatic fault diagnostic in induction machine. In this method, frequency spectrum is used as the input to detect the fault and speed of the machine [18]. Moreover, improvement of Feed forward neural network (FFNN) with preprocessing signal input can reduce a significant learning error. The post processing of FFNN fault classification system yields the sensitive classification for slight defect such as two-turn shorted winding [19]. A fault classification system that combines fuzzy systems, neural networks, and the decision tree is designed to distinguish motor operation states that are classified into normal, broken rotor, rotor eccentricity and unbalance voltage. Adaptive neuro fuzzy inference system (ANFIS) is proposed as machine prognosis system. Historical failure data is trained in ANFIS and high order of hidden Markov model is designed as noise model. The combination of this model is used as fault propagation proses to predict the fault [20]. In order to improve classification performance, a cascade connection of neural network systems that combines radial basis function and multi-layer perceptron is proposed. This network is tested and gives better results than single network structures only [21]. Another research work focused on designing robust fault detection is proposed filter to anticipate unknown disturbance and parametric uncertainties. This property is resulting sensitive fault detection and robust to disturbance [22]. Beside the advantages of the recently proposed methods, the electric machine diagnostic system still has some other future challenges. One of the challenges of stator fault detection research is to provide time estimation from symptoms fault to disaster or broken machine [23]. Moreover, a simple, non-invasive and effective fault detection system at an early stage of winding deterioration is still needed to be continuously developed [24]. All in all, the detection of fault in an exact location will be a more interesting challenge in the future [25]. This paper proposes a method to detect incipient of short circuit in stator winding that can be implemented as online condition monitoring of electric machine. By identifying the symptoms of fault inside the machine, the catastrophic failure can be avoided. In this paper, the symptom of fault is defined as low current magnitude and temporary occurrence representing the initial stage of short circuit fault. The detection focuses on the starting and ending points of fault. The fault is selected as the point detection because it results in a higher transient current than other normal operating condition such as load change [26, 27]. Wavelet transform is used as a feature extraction of the current signal because it is more superior than frequency analysis for temporary fault analysis [28, 29]. For optimal selection of a wavelet filter, linear discriminant analysis (LDA) is used as a wavelet filter evaluator. LDA is se1lected because it can simply measure the separation between predefined group of data, while neural network has advantages to recognize nonlinear data pattern and can avoid the complexity of determining a detection threshold [30]. An Elman neural network is used in this paper because it has context layer that can memorize the previous state of motor operation. Effectiveness of the proposed methods is tested in laboratory experiment. The result shows that, the proposed method successfully detects the fault including a very short time of fault that is defined as a spike short circuit.

2. **Temporary Short Circuit as Initial Failure of Stator Winding.** Induction motors are recognized for strength and robustness which have been designed to operate continuously for long periods. However, sometimes it is failure during operation as the result of the ageing and deterioration inside the machine part. In this section, one of the initial faults of this machine is defined as a low current magnitude and a short period of short circuit. This fault occurs as an effect of insulation winding deterioration such as turn-to-turn stator insulation. This fault case will produce thermal hotspot and progressive insulation degradation [12]. In the certain level of insulation deterioration, the insulation capability is decreasing. When the operating stress such as over voltage suddenly occurs or increases to the capability level, the short circuit can be occurred. When the stresses are increasing temporarily, for example voltage surge [31], the short circuit is also occurring temporarily. The current is back to the normal with stress clearance. Therefore, this fault is categorized into two parts based on its time duration. The first type is a spike short circuit and the second is a temporary short circuit, which has a longer duration.

2.1. **Spike current short circuit.** At the beginning of a short circuit fault, the current has low magnitude with a very short duration. This is called a spike fault in this paper. This fault has a fast rise time [32] as the results of partial discharge activity in several locations of winding insulation, indicating the intermittent failure of stator winding [33, 34, 35]. Short circuit duration is in a few milliseconds and captured as a spike current as shown in Figure 1.

2.2. **Temporary short circuit.** A longer period of short circuit is defined as a temporary short circuit as shown in Figure 2. In this case, the short circuit current is not shown as a spike. The motor operation state is changed from normal to fault when a short

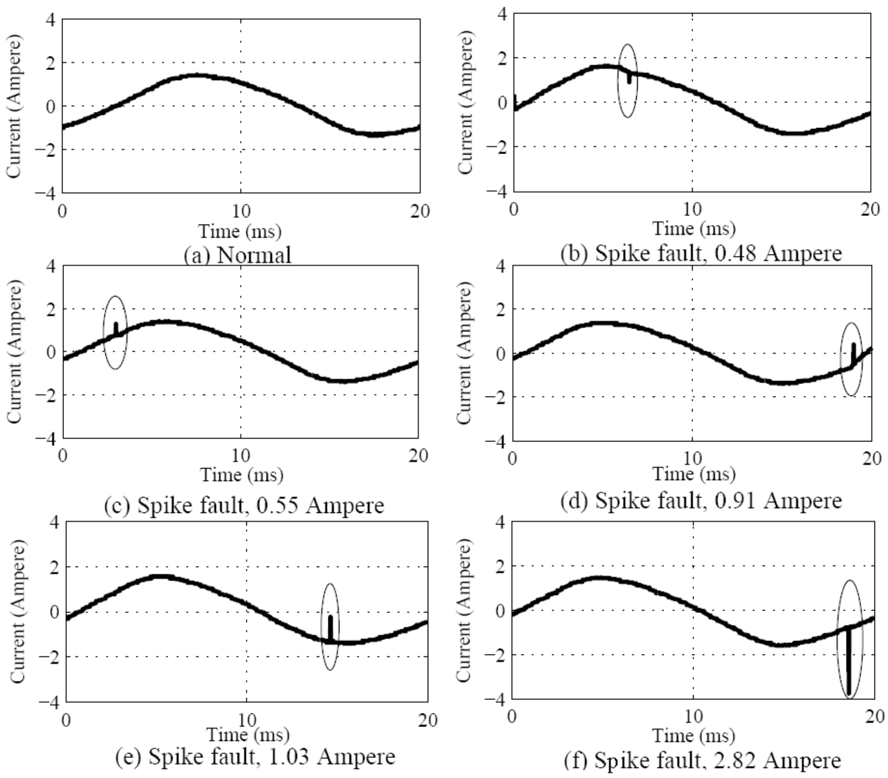

FIGURE 1. Spike short circuit fault

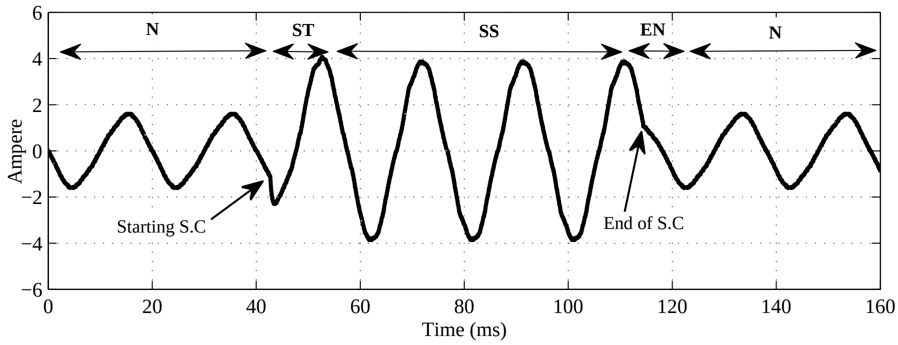

Figure 2. Temporary short circuit fault

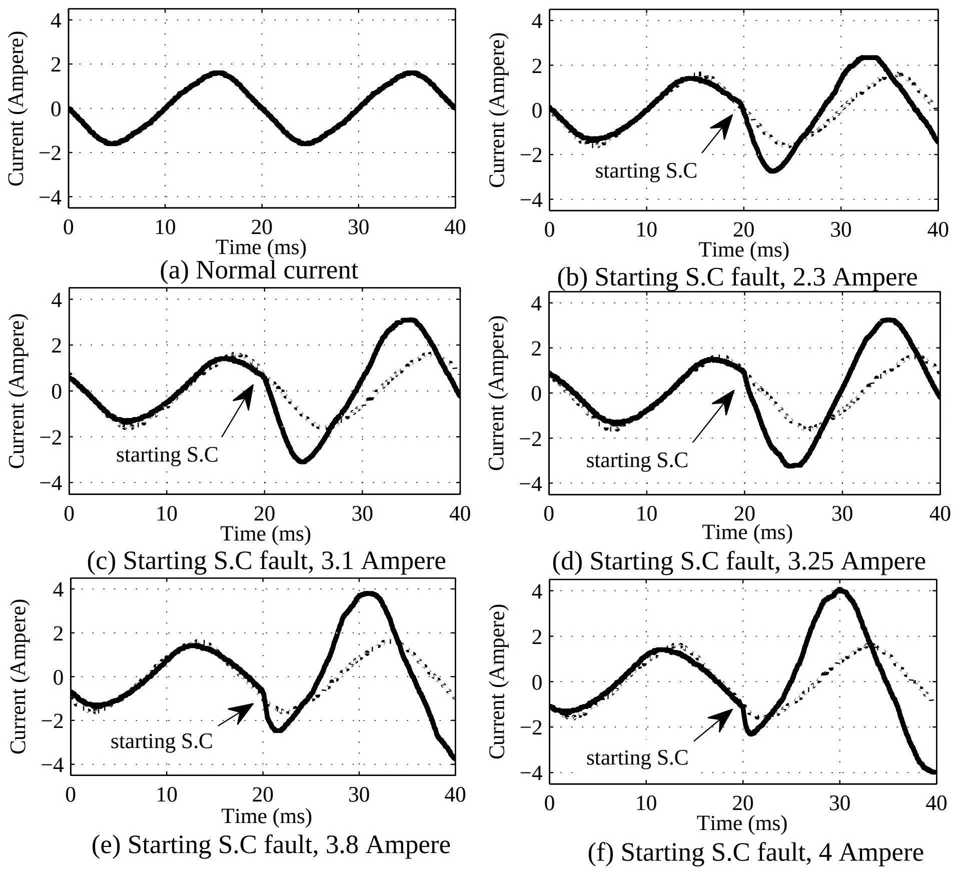

Figure 3. Starting short circuit

circuit starts to appear. Therefore, the current pattern is changed at the point where the short circuit starts. As the result of these changes, the gradient of current is changed. Basically, the gradient can be obtained from the different values of the consecutive data. In this paper, the gradient is represented by a high frequency signal of wavelet transformation. The gradient is higher at the starting point of the short circuit. Conversely, it is lower at the end of the short circuit when the motor is back to normal operation due to a temporary short circuit.

2.3. **Short circuit occurrence.** The main idea of this paper is to detect the temporary short circuit by identifying the transient current pattern when a short circuit starts and ends. The pattern changes are quite different to the load changes. In the case of load

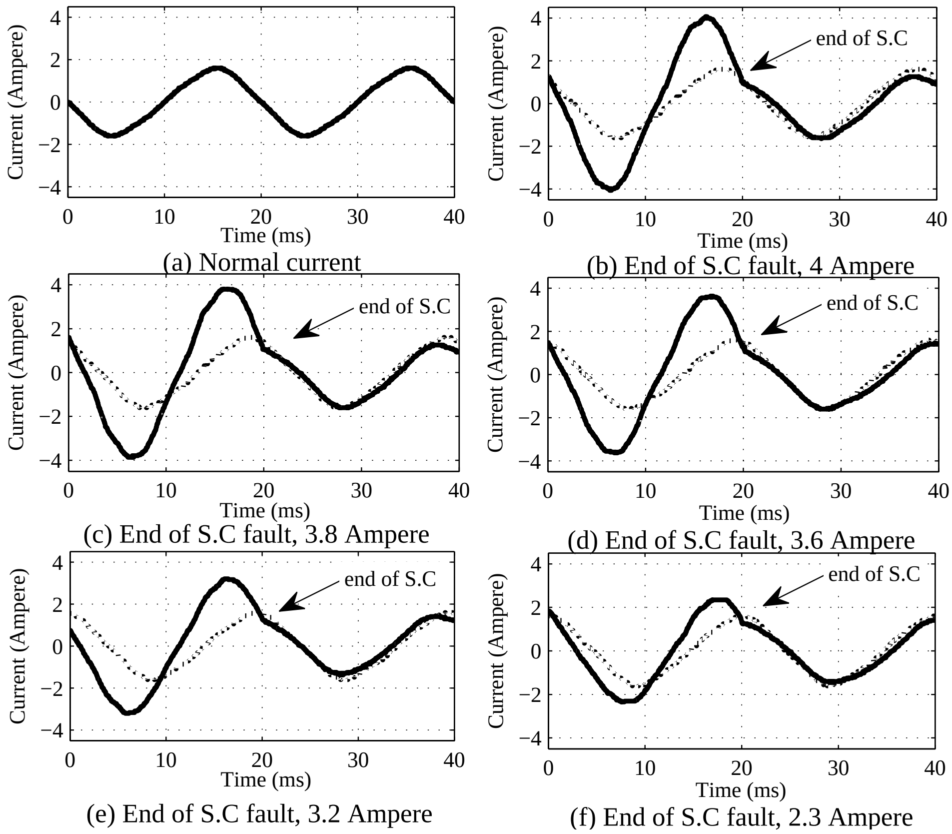

FIGURE 4. End of short circuit

changes, the current pattern changes smoothly in magnitude such as sinusoidal function with linear magnitude [26, 27]. When the short circuit begins and ends, it looks like the turn or the cessation of the current pattern as shown in Figures 3 and 4. These figures show the current pattern changes during the beginning and end of the short circuit at different magnitudes. Each short circuit waveform also compared with a normal operating current. In order to detect the moment when faults start and end, the other operating conditions need to be recognized as normal operations, steady state short circuits and spike short circuits. Furthermore, those five operating conditions are defined as short circuit occurrences. For industrial application purposes, if all defined operating conditions can be detected using online monitoring system based on proposed method, more specific time information can be provided such as when the fault starts, how often and how long this fault strikes. This information can be used as diagnostic and condition assessment of electric machine. Providing this information is also one of the future challenges in the condition monitoring of induction machines [21, 22, 23, 24].

3. **Proposed Method for Occurrence Detection Temporary Short Circuit.** The proposed detection method for temporary short circuit fault occurrence is described in this section. The main contribution of the proposed method not only can detect temporary short circuit [28] but also be able to classify the short circuit occurrence. Moreover, the short circuit duration and time occurrence can be identified. This result will improve the other proposed work that only considers fault detection not time occurrence [12, 13, 14, 15]. The detection system development is shown in Figure 5. This system is divided into three steps: current signal processing using wavelet transform, evaluation wavelet filter using LDA to obtain the most appropriate one, and designing the neural network

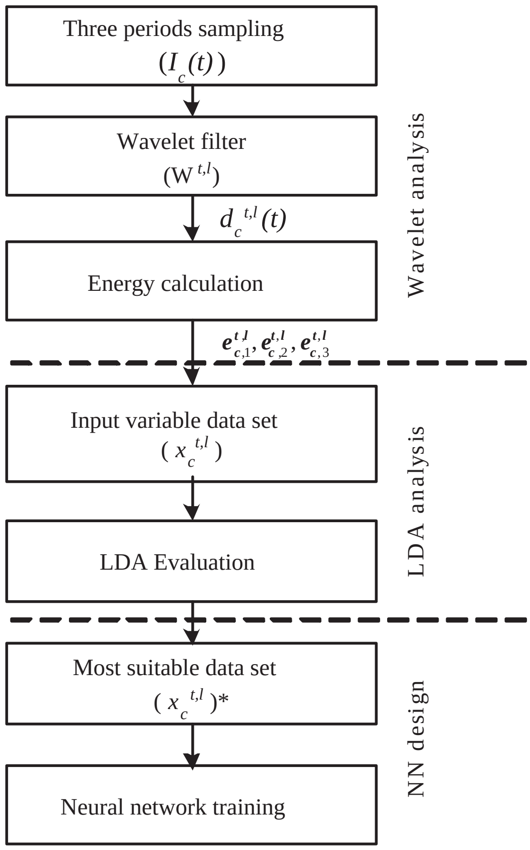

FIGURE 5. Flowchart of designing detection system

detection system for distinguishing the operation state of a motor. In this paper, the wavelet filter is intended as the coefficient of scaling function. These coefficients are also called as decomposition high-pass filter. The convolution between the originals signal and this coefficient is resulting high frequency filter.

3.1. **Feature extraction using discrete wavelet transform.** The current signal is measured and recorded using a current transformer and analog to digital converter respectively. Current signal is stored in n number data and expressed by $I(t) = [i_1\ i_2\ i_3\ \cdots\ i_n]$. Current signal $I(t)$ is applied to the wavelet filter W in order to obtain a high frequency or detail signal $d(t)$ using the following equation.

$$d(t) = I(t) \cdot \mathrm{W} \tag{1}$$

Wavelet filter W is defined as follows.

$$\mathrm{W} = \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 & \cdots & \alpha_k & 0 & 0 & \cdots & 0 \\ 0 & 0 & \alpha_1 & \cdots & \alpha_{k-2} & \alpha_{k-1} & \alpha_k & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & \alpha_k \end{bmatrix} \tag{2}$$

where α is the filter coefficient of each wavelet type. The matrix W has $\left(n/2^L\right) \times n$, where L is the wavelet level transformation and n is the size of transformed signal. Energy of high frequency signal within the determined period is obtained as follows:

$$e = \sum_{t=1}^{n=k} |d(t)|^2 \tag{3}$$

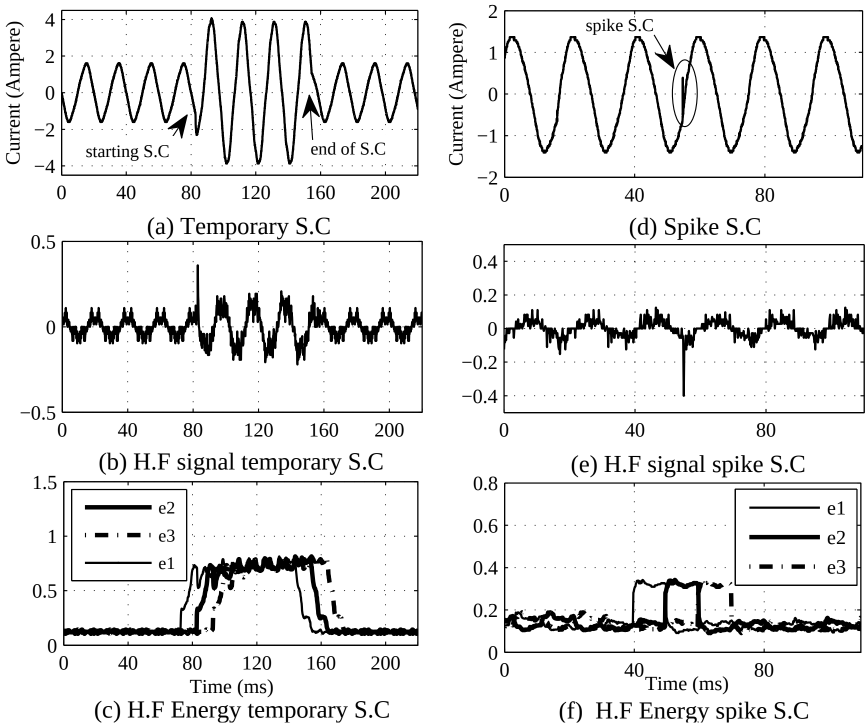

FIGURE 6. Current signal treatment using wavelet transform

Considering three periods sampling of the current signal (Figure 5), the energy of each period can be expressed as:

$$x = [e_1 \; e_2 \; e_3] \tag{4}$$

Three consecutive energy values are then used as detection variables and defined as x. Figure 6 shows the current signal processing to obtain a high frequency signal energy using a wavelet filter. In the case of a temporary short circuit, the fracture of the current signal pattern during the start or end of a short circuit can produce a high value of high frequency signal. As with a spike short circuit, the higher value of a high frequency signal due to a spike is more noticeable. Moreover, all operating states can be identified using three consecutive energy measurements. In this paper, there are three wavelet types: Haar, Daubechies and Meyer. The first to fifth levels are evaluated to obtain the best result. In order to do the evaluation analysis, our dataset of motor current consists of all of motor state operations that can be expressed as follows.

$$I_c(t) = [i_{c,1} \; i_{c,2} \; \cdots \; i_{c,n} \;] \quad c : case\ number \tag{5}$$

By using a wavelet filter matrix, the detail signal can be obtained as in (6).

$$d_c^{t,l}(t) = I_c(t) \, W^{t,l} \tag{6}$$

where t is wavelet type and l is the wavelet level. Moreover, the data set for the energy of the current signal can be calculated as follows:

$$e_c^{t,l} = \sum_{t=1}^{t=k} |d_c^{t,l}(t)|^2 \tag{7}$$

where k is the length of signal in one period. The detection variables of all data set signals can be expressed as in (8).

$$x_c^{t,l} = \left[e_{c,1}^{t,l} \; e_{c,2}^{t,l} \; e_{c,3}^{t,l} \right] \tag{8}$$

TABLE 1. Energy trend of motor states

State of motor	Energy level of each input variable		
	e_1	e_2	e_3
Normal operation	Low	Low	Low
Steady short circuit	High	High	High
Starting short circuit	High	Medium	Low
End of short circuit	Low	Medium	High
Spike short circuit	Low	High	Low

3.2. **Evaluating wavelet filter using LDA.** Discriminative analysis measurement is one of statistical methods used to obtain the differences between the groups in the data set or the signal [40]. Certain groups have been determined beforehand. Moreover, the linear combination of the variable is then calculated to find the optimal separation of the groups with means as close as possible within the groups and as far as possible between other groups [41]. This method is one of the simple algorithms used to measure discrimination of the groups of data even if the groups are not a function of its variables [42].

Figure 6 shows that all operation states of an induction motor can be divided into five states: normal operation, steady state short circuit, starting of short circuit, end of short circuit and spike short circuit. These states follow the trend of having three measurements of consecutive energy of high frequency signal. During normal operation, all of three variables have low energy levels while the beginning is a fault that is represented by high level of e_1, a medium level of e_2 and a low level of e_3. A steady state fault results in a high level of those three variables, and the last state, end of fault is characterized by a low level of e_1, a medium level of e_2 and a high level of e_3. Spike fault has a low level of e_1, a high level of e_2 and a low level of e_3. Table 1 summarizes the five basic trends of three variable inputs which correspond to the states. Based on this trend, the data set is divided into five groups or clusters, Clusters 1-5, correspond to the state of motor operation.

The data point in the k-th column vector of data set e is represented by a_k, the average point of the i-th cluster is $c^{(i)}$, and the global average is c. The scatter matrix within the i-th cluster $S_w^{(i)}$, the within-cluster scatter matrix S_w, the between cluster scatter matrix S_b and the total (or mixture) scatter matrix S_t, are defined, respectively as follows [43]:

$$S_w^{(i)} = \sum_{k \in N_i} \left(a_k - c^{(i)}\right)\left(a_k - c^{(i)}\right)^T \tag{9}$$

$$S_w = \sum_{i=1}^{p} S_w^{(i)} \tag{10}$$

$$S_b = \sum_{i=1}^{p} \sum_{k \in N_i} \left(c^{(i)} - c\right)\left(c^{(i)} - c\right)^T \tag{11}$$

$$S_t = \sum_{i=1}^{p} \sum_{k \in N_i} (a_k - c)(a_k - c)^T \tag{12}$$

$$S_t = S_w + S_b \tag{13}$$

Optimum cluster separation can be obtained by maximizing the ratio between-class to within-class scatter.

$$J(G) = \frac{G^T S_b G}{G^T S_w G} \tag{14}$$

In order to obtain the best training data set corresponding to the wavelet filter, performance classification based on error classification is defined as follows:

$$error = \frac{EC}{TC} \times 100\% \tag{15}$$

where EC is the misclassification cases and TC is the total number of all cases.

3.3. **Neural network detection system.** Artificial neural networks (ANNs) are known as a good classifier system because of features such as robustness, adaptive learning, generalization capability and self-organization [41]. If the amount of data is enough for training, the ANN methods are very useful and suitable for the detection system [42]. This paper uses the Elman neural network (ELNN) to detect short circuit occurrences, specifically to distinguish the state of induction motor operation defined as normal, steady state fault, starting fault, ending fault, and spike fault.

ELNN is used in this paper because it considers the previous state that is stored in the context layer. This design is appropriate with the detection system design requirements. As shown in Figure 6, the state of motor operation has a strong relation to the previous operating state. Normal operation has several previous states that are normal, end of short circuit and spike short circuit. Starting short circuit is initiated by normal operation. Steady state short circuit is initiated by starting short circuit. The preliminary state of the end of a short circuit is a steady state short circuit. The previous state of a spike short circuit is normal operation. This pattern is considered in the training and testing process. This network mainly consists of four layers: input layer, hidden layer, context layer and output layer (Figure 7). In this paper, the three nodes are represented by three input variables, e_1, e_2 and e_3. The input layer nodes are expressed as follows.

$$e_i(k) = f_i(net_i) = net_i, \quad i = 1, 2, 3 \tag{16}$$

The hidden layer has two variable inputs from the input layer and the context layer. The node input inside the hidden layer is expressed as follows:

$$net_j = \sum_r x_r^c(k) + \sum_i W_{ij}^1 \times net_i, \quad r = 1, 2 \ldots, r \tag{17}$$

The output of this layer is calculated based on the node input and the sigmoid activation function as follows.

$$x_j(k) = S(net_j) = \frac{1}{1 + e^{-net_j}}, \quad j = 1, 2 \ldots, j \tag{18}$$

The context layer stores information about previous operating conditions and is used to determine the present state. It can be expressed by:

$$x_r^c(k) = x_j(k-1) \tag{19}$$

The input and output of the output layer are expressed respectively as:

$$net_o(k) = \sum_j W_{jo}^2 \times x_j(k) \tag{20}$$

$$y_o(k) = f(net_o(k)) = net_o(k) \tag{21}$$

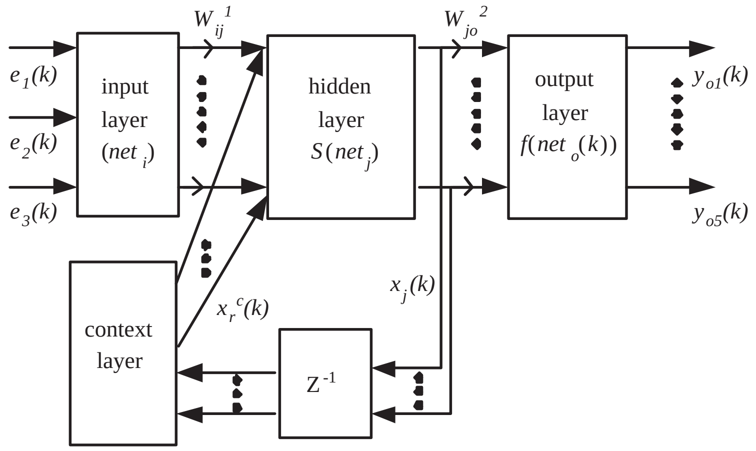

Figure 7. Elman neural network structure

During the training process the mean square error (MSE) is used as a performance index, expressed as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{22}$$

This network presents a back propagation algorithm with a feedback connection from the output of the hidden layer to the input layer. Two hidden layers with tangent sigmoid ($tansig$) activation function are designed inside the networks. Meanwhile, the output layer uses the $purelin$ activation function. The five output nodes represent the five states of the motor operating condition. Each output node is defined with a series value of 0 and/or 1. Five outputs are designed to represent the state of motor operation, defined as: (1 0 0 0 0), (0 1 0 0 0), (0 0 1 0 0), (0 0 0 1 0), and (0 0 0 0 1) for normal, steady state fault, starting fault, ending fault, and spike fault respectively. The training process of the ELNN is based on the $Levenberg$-$Marquardt$ back propagation algorithm. The validation data for this network is defined as a 105% deviation from the training data for the input variable and 100% for target data.

3.4. **Detection performance.** Several methods were used to measure performance of the proposed detection system. These methods consist of detection positive predictive value, confusion matrix and detection efficiency [43]. The proposed method comprises the combination between the wavelet, LDA and the neural network. The next sub-sections will describe these methods. The positive predictive value (PPV) represents the number of cases detected as absolutely true. This value is expressed in percent (%) as the result of the ratio of true positive and summation of true positive and false positive. This value can be obtained using the following equation:

$$PPV = \frac{TP}{TP + FP} \times 100\% \tag{23}$$

True positive (TP) is the case that detects a similar state to the actual state. For example, Case Number 1 is normal operation and detected as normal operation. A false positive (FP) is the case detected as belonging to one of the operational states when actually this case belongs to other states. For example, Case Number 20 is detected as the normal operation states, but it is actually the starting point of a short circuit. The confusion matrix is used to illustrate the result of a classification or detection system. This matrix is expressed as a table with each row representing the prediction result, while the column represents the actual condition of the data or cases. Using this table, it is very easy to analyze the result of the detection system such as confusion between two classes or wrongly detecting one for another state. This paper presents training data and testing data separately in different columns and compares two detection systems consisting of the proposed method (wavelet-LDA-neural network) and wavelet-LDA.

4. Implementation.

4.1. Experimental setup.

The laboratory experimental setup is established to obtain the current signal waveform in different cases of temporary short circuit which has low current fault and temporary occurrence. A single phase motor 1/4 hp, 1400 rpm, 50 Hz, 110/220 Volt 4.8/2.4 Ampere with external winding extension at 25%, 50%, and 75% of total winding is used to model the machine under temporary fault. This machine is also coupled by mechanical load as shown in Figure 8. In order to simulate a temporary fault with high impedance, the short circuit switch is connected to a series with a variable resistor. The resistor is adjusted to simulate the low fault current magnitude. The electronic switch is used to perform a very short duration of short circuit. The current spectrum is recorded using an analog-to-digital converter with a 50 kHz sampling frequency. Current signal consisting fault case is recorded in data storage. Each case has 1.5 cycle current waveform or 30 millisecond of 50 Hz power frequency. The waveform consists of three consecutive current sampling periods, and each period is half cycle or 10 ms. Although the single phase is used in the experiment, the proposed method is also subjected to the high power three phase induction machines because it has similar behavior of short circuit occurrence. When the short circuit occurs, the increasing current is much faster than other normal operation.

4.2. Data collection and signal processing.

Several cases of short circuit can be performed using this experimental setup. The data are made up of 355 cases which represent 290 datasets used for training and 65 cases for testing. These data are varied by current magnitudes as shown in Table 2. The next step is calculating the high frequency signal of the motor current and obtaining the energy level using Equations (6) and (7) respectively. In this step 15 wavelet filters are used that are varied by three wavelet types and five level transformations. This process results in 15 data sets based on the filter. Each data set consists of five groups based on the operating state of the motor. The next step is evaluating data sets using LDA based on Equations (9)-(14). Classification error is calculated based on Equation (15) and is used as a performance index.

The result of the LDA evaluation is summarized in Table 3. The third level Haar wavelet yields the best performance that gives smallest classification error, 22.1%. The scatter plot of dataset groups is shown in Figure 9. The current signal data for a motor

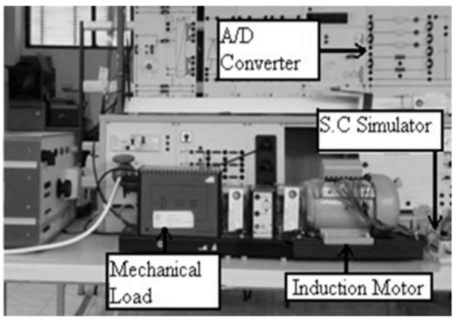

Figure 8. Laboratory experimental setup

TABLE 2. Motor current data set

Operation Case	Training and validation		Testing	
	Number of cases	Variation (Ampere)	Number of cases	Variation (Ampere)
Normal	40	1; 1.3	10	1.2; 1.5
Steady state S.C	100	2.75; 3.2; 3.6; 3.8; 4	10	3.5; 4.5
Starting S.C	50	2.3; 3.1; 3.25; 3.75; 4	15	2.4; 3.2; 4.5
Ending S.C	50	2.3; 3.1; 3.6; 3.8; 4	15	3.1; 3.6; 3.86
Spike S.C	50	0.48; 0.55; 0.91; 1.03; 2.82	15	0.48; 0.55; 0.91; 1.03; 2.82
Total	290		65	

TABLE 3. Evaluation of wavelet filter using LDA

Wavelet type	LDA classification error using wavelet Level 1-5 (%)				
	1	2	3	4	5
Haar	39.7	24.8	22.1	28.3	33.4
Daubechies	56.6	46.9	40.0	60.0	44.1
Meyer	50.3	39.0	42.1	65.9	51.7

under normal operation is marked using number 1 that gathers around the origin of the variable axis. Data represented by number 2 represents the steady state of short circuit. This data is linear and higher for every variable axis. Data numbers 3 and 4 have a similar trend for the input-2 axis, medium, and have the opposite trend for the input-1 and input-3 axes. Furthermore, number 5 has a small value for input-1 and input-3 but being higher for input-2. Several data is close to data number-1 when input number-2 is not too high.

4.3. **Detection system training and testing.** Based on the result from the wavelet filter evaluation, the third level of the Haar wavelet filter is selected as a signal processor. The data set from this filter is used as training data for the neural network detection system. The network used in this system has two hidden layers. Moreover, the numbers of hidden-node from 2 until 9, are evaluated in order to get the best performance detection system. In total, 81 networks are evaluated based on mean square error as shown in Figure 10. The best training performance is given by the network with five and six nodes for the first and second hidden layer respectively. The mean square error for the training process is 9.17×10^{-12} and 4.45×10^{-7} for validations. In order to check the performance, the detection system is tested using a non-trained data set. The testing data set consists of 65 cases, including all operation states of a motor as shown in Table 2. The data consists of normal operation (case number 1-10), steady state short circuit (case number 11-20), starting of short circuit (case number 21-35), end of short circuit (case number 36-50)

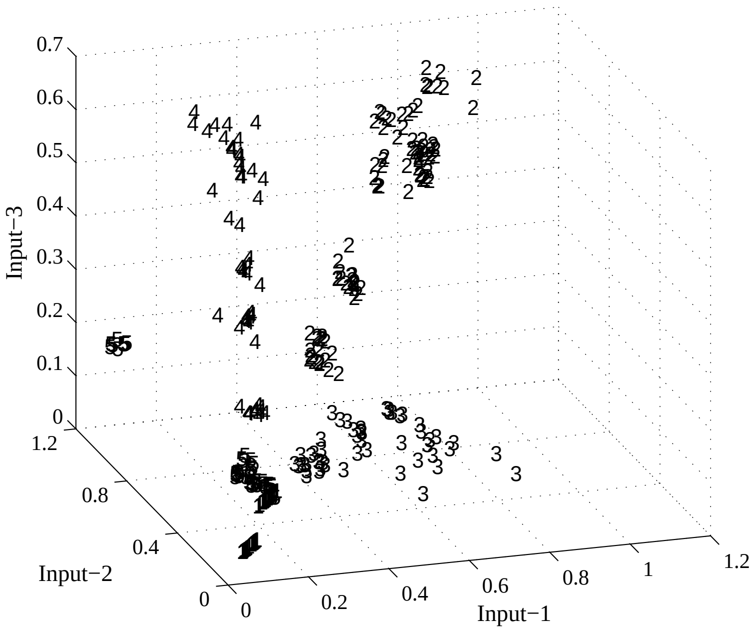

Figure 9. Scatter plots of three input variables

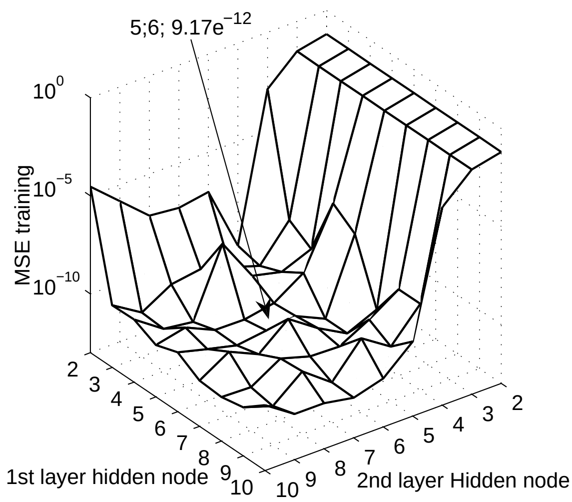

Figure 10. Network design evaluation

and spike short circuit (case number 51-65). Moreover, the fault cases are also varied by current fault magnitude. Some of fault cases have fault magnitude below the motor full load current.

Figure 11 shows the testing results. The first output indicates normal operations. If the motor operates in normal conditions, the first output will equal 1; otherwise it is 0 for other operating conditions. This rule is also applied to the other outputs; output-2 is a steady state short circuit, output-3 is a starting short circuit, output-4 is the end of short circuits and output-5 is a spike short circuit. Based on the test results, all the cases are successfully detected.

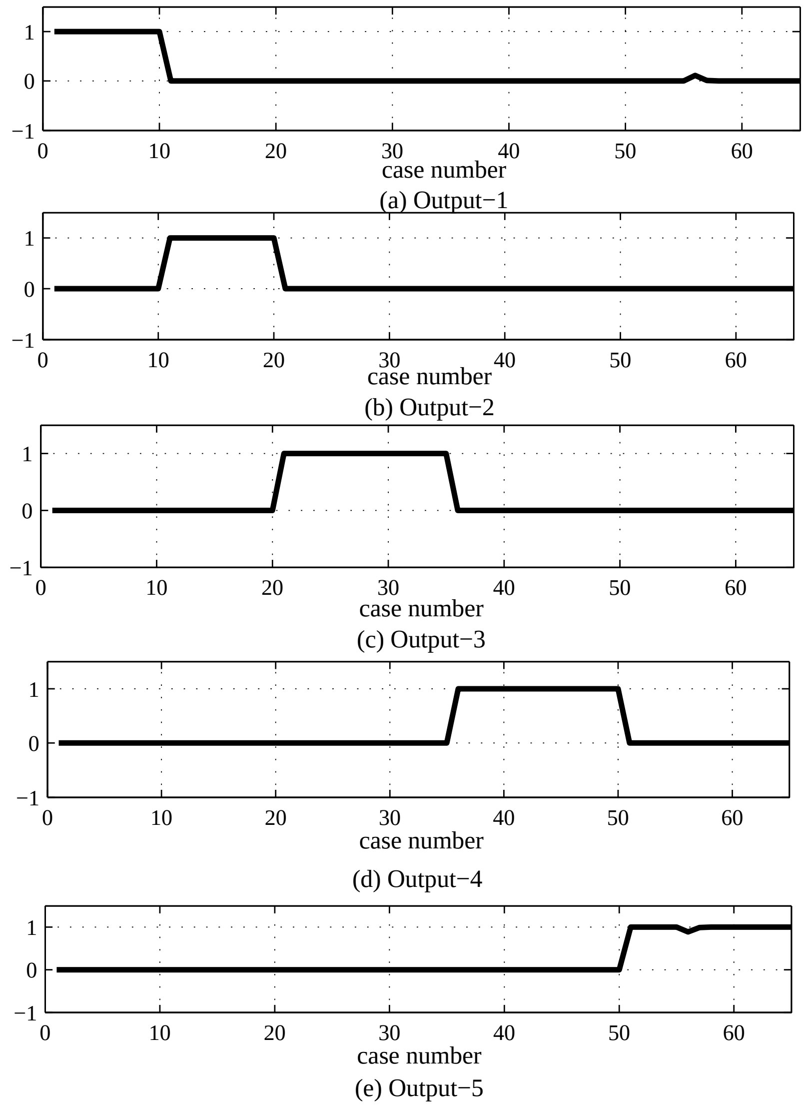

Figure 11. Detection result of testing data

5. **Result and Discussion.** The neural network detection system is trained, tested, and gives satisfactory results. In order to confirm the performance of the proposed methods, a comparison between wavelet and the LDA method is provided. The positive predictive value and confusing matrix are used to evaluate the result as shown in Table 4. The evaluation of training and testing data using the wavelet-LDA method shows that false detection happens most often in normal (N) and spike short circuits (SP). False detections occur because those two states are only differentiated by e_2, while the other input variables, e_1 and e_3, have similar values. Since the LDA method basically uses linear function as a classifier, this method will detect low spike faults as a normal operation. Similar false detection cases happen between the end of short circuit cases with normal operation, the end of a short circuit with spike fault and a steady state with a spike fault. Based on PPV analysis, normal conditions and spike faults contribute to the low level value. It can be concluded that the system cannot discriminate normal operation and spike faults well. The proposed method gives 100% detection results for training and testing. In this case, the neural network can recognize the pattern of variable input as a function of the operating state of the motor, even though the pattern is not absolutely linear. The advantages of the proposed method are emphasized by the efficiency of detection. The overall results

Table 4. Positive predictive value analysis

Detection Method		Actual training cases					Actual testing cases					Positive predictive value
		N	SS	ST	EN	SP	N	SS	ST	EN	SP	
Wavelet-LDA -NN (proposed method)	N	40	–	–	–	–	10	–	–	–	–	100%
	SS	–	100	–	–	–	–	10	–	–	–	100%
	ST	–	–	50	–	–	–	–	15	–	–	100%
	EN	–	–	–	50	–	–	–	–	15	–	100%
	SP	–	–	–	–	50	–	–	–	–	15	100%
Wavelet-LDA	N	40	–	–	8	21	10	–	–	–	6	59%
	SS	–	96	–	–	–	–	10	–	–	–	100%
	ST	–	–	50	–	–	–	–	5	–	–	100%
	EN	–	–	–	37	–	–	–	–	15	–	100%
	SP	–	4	–	5	29	–	–	10	–	9	67%

show that the proposed method gives the efficiency of training and testing data as 100%, while wavelet-LDA are 85.6% and 75.4% for training and testing, respectively.

6. Conclusion.

A new approach to intelligent detection of early stage short circuit fault in induction motor winding has been proposed in this paper. The sensitivity and accuracy of proposed methods is confirmed by successfully detecting the very short time occurrence and low current fault. The optimal design utilizes LDA to evaluate 15 wavelet filters to get the most suitable filter. Moreover, the Elman neural network structure is analyzed by modifying the combination of hidden node number. The design analysis yields the most suitable detection system that uses the third level Haar wavelet as signal processing and Elman network with five and six numbers of hidden nodes for the first and second hidden layers respectively. This system is successfully recognizing all of data training and detecting all of testing cases. In addition, the utilization of wavelet transforms in the proposed methods to detect transient current of fault is potential applied as continues monitoring system because it can provide time information of the fault cases. The advantages of Haar wavelet is easy to be implemented to embedded system due to the simple calculation. Moreover, the development of micro controller technology allows to build NN system in embedded system. However, one of the disadvantages of this method is that it need very high speed processor and large memory for calculating the energy of signal.

Acknowledgment. The authors gratefully acknowledge to the Directorate General for Higher Education (DGHE or DIKTI), Ministry of National Education of Republic Indonesia and JICA Joint Research PREDICT Program (B-2-4) for supporting this research.

REFERENCES

[1] O. V. Thorsen and M. Dalva, A survey of faults on induction motors in offshore oil industry, petrochemical industry, gas terminals, and oil refineries, *IEEE Trans. on Ind. Appl.*, vol.31, no.5, pp.1186-1196, 1995.

[2] P. Zhang, Y. Du, T. G. Habetler and B. Lu, A survey of condition monitoring and protection methods for medium-voltage induction motors, *IEEE Trans. on Ind. Appl.*, vol.47, pp.34-46, 2010.

[3] M. Levesque, E. David, C. Hudon and M. Belec, Effect of surface degradation on slot partial discharge activity, *IEEE Trans. on Dielectr. Electr. Insul.*, vol.17, pp.1428-1440, 2010.
[4] S. Grubic, J. M. Aller, B. Lu and T. G. Habetler, A survey on testing and monitoring methods for stator insulation systems of low-voltage induction machines focusing on turn insulation problems, *IEEE Trans. on Ind. Electron.*, vol.55, pp.4127-4136, 2000.
[5] K. Younsi, P. Neti, M. Shah, J. Y. Zhou, J. Krahn, K. Weeber and C. D. Whitefield, On-line capacitance and dissipation factor monitoring of AC stator insulation, *IEEE Trans. on Dielectr. Electr. Insul.*, vol.17, pp.1441-1452, 2010.
[6] S. B. Lee, J. Yang, K. Younsi and R. M. Bharadwaj, An online ground wall and phase-to-phase insulation quality assessment technique for AC-machine stator windings, *IEEE Trans. on Ind. Appl.*, vol.42, 2006.
[7] H. D. Kim, J. Yang, J. Cho, S. B. Lee and J.-Y. Yoo, An advanced stator winding insulation quality assessment technique for inverter-fed machines, *IEEE Trans. on Ind. Appl.*, vol.44, pp.555-564, 2008.
[8] S. Cheng, P. Zhang and T. G. Habetler, An impedance identification approach to sensitive detection and location of stator turn-to-turn faults in a closed-loop multiple-motor drive, *IEEE Trans. on Ind. Electron.*, vol.58, pp.1545-1554, 2011.
[9] M. Bouzid, G. Champenois, N. M. Bellaaj, L. Signac and K. Jelassi, An effective neural approach for the automatic location of stator interturn faults in induction motor, *IEEE Trans. on Ind. Electron.*, vol.55, pp.4277-4289, 2008.
[10] C. Concari, G. Franceschini and C. Tassoni, Induction drive health assessment in DSP-based self-commissioning procedures, *IEEE Trans. on Ind. Electron.*, vol.58, pp.1490-1500, 2011.
[11] C. Seungdeog, B. Akin, M. M. Rahimian and H. A. Toliyat, Implementation of a fault-diagnosis algorithm for induction machines based on advanced digital-signal-processing techniques, *IEEE Trans. on Ind. Electron.*, vol.58, pp.937-948, 2011.
[12] M. Sahraoui, S. E. Zouzou, A. Ghoggal and S. Guedidi, A new method to detect inter-turn short-circuit in induction motors, *Proc. of ICEM*, Rome, Italy, pp.1-6, 2010.
[13] M. Drif and A. J. M. Cardoso, Discriminating the simultaneous occurrence of three-phase induction motor rotor faults and mechanical load oscillations by the instantaneous active and reactive power media signature analyses, *IEEE Trans. on Ind. Electron.*, vol.59, pp.1630-1639, 2012.
[14] J. Pons-Llinares, J. A. Antonino-Daviu, M. Riera-Guasp, M. Pineda-Sanchez and V. Climente-Alarcon, Induction motor diagnosis based on a transient current analytic wavelet transform via frequency B-splines, *IEEE Trans. on Ind. Electron.*, vol.58, pp.1530-1544, 2011.
[15] A. Bouzida, O. Touhami, R. Ibtiouen, A. Belouchrani, M. Fadel and A. Rezzoug, Fault diagnosis in industrial induction machines through discrete wavelet transform, *IEEE Trans. on Ind. Electron.*, vol.58, pp.4385-4395, 2011.
[16] Y. Gritli, A. Stefani, C. Rossi, F. Filippetti and A. Chatti, Doubly fed induction machine stator fault diagnosis under time-varying conditions based on frequency sliding and wavelet analysis, *Proc. of IEEESDEMPED*, Cargese, France, pp.1-7, 2009.
[17] S. Das, P. Purkait, D. Dey and S. Chakravorti, Monitoring of interturn insulation failure in induction motor using advanced signal and data processing tools, *IEEE Trans. on Dielectr. Electr. Insul.*, vol.18, pp.1599-1608, 2011.
[18] C. Demian, G. Cirrincione and G. A. Capolino, A neural approach for the fault diagnostics in induction machines, *Proc. of IEEE Industrial Electronics Conference*, Sevilla, Spain, 2002.
[19] L. Capocchi, S. Toma, G. A. Capolino, F. Fniaech and A. Yazidi, Wound-rotor induction generator short-circuit fault classification using a new neural network based on digital data, *Proc. of IEEEDEMPED*, Bologna, Italy, pp.638-644, 2011.
[20] C. Chen, B. Zhang, G. Vachtsevanos and M. Orchard, Machine condition prediction based on adaptive Neuro-fuzzy and high-order particle filtering, *IEEE Trans. on Ind. Electron.*, vol.58, pp.4353-4363, 2011.
[21] Y. Yin, P. Shi, F. Liu and K. L. Teo, Robust fault detection for discrete-time stochastic systems with non-homogeneous jump processes, *IET Control Theory and Appl.*, vol.8, no.1, pp.1-10, 2014.
[22] V. N. Ghate and S. V. Dudul, Cascade neural-network-based fault classifier for three-phase induction motor, *IEEE Trans. on Ind. Electron.*, vol.58, pp.1555-1563, 2011.
[23] R. M. Tallam, S. B. Lee, G. C. Stone, G. B. Kliman, J. Yoo, T. G. Habetler and R. G. Harley, A survey of methods for detection of stator-related faults in induction machines, *IEEE Trans. on Ind. Appl.*, vol.43, pp.920-933, 2007.
[24] A. Bellini, F. Filippetti, C. Tassoni and G. A. Capolino, Advances in diagnostic techniques for induction machines, *IEEE Trans. Ind. Electron.*, vol.55, pp.4109-4126, 2008.

[25] A. Gandhi, T. Corrigan and L. Parsa, Recent advances in modeling and online detection of stator interturn faults in electrical motors, *IEEE Trans. on Ind. Electron.*, vol.58, pp.1564-1575, 2011.
[26] H. Douglas and P. Pillay, The impact of wavelet selection on transient motor current signature analysis, *IEEE International Conference on Electric Machines and Drives*, pp.80-85, 2005.
[27] F. S. Moreira, M. F. S. V. D. Angelo, R. M. Palhares and W. M. Caminhas, Incipient fault detection in induction machine stator-winding using a fuzzy-Bayesian two change points detection approach, *The 9th IEEE/IAS International Conference on Industry Applications*, pp.1-6, 2010.
[28] D. A. Asfani, S. Syafaruddin, M. H. Purnomo and T. Hiyama, Temporary short circuit detection in induction motor winding using second level Haar-wavelet transform, *IEEJ Transactions on Industry Applications*, vol.131, pp.1-10, 2011.
[29] D. A. Asfani, S. Syafaruddin, D. N. Wardana, M. H. Purnomo and T. Hiyama, Characterization of temporary short circuit in induction motor winding using wavelet analysis, *International Conference on Modelling, Identification and Control*, Okayama, Japan, pp.477-482, 2010.
[30] J. Lian, Z. Feng and P. Shi, Observer design for switched recurrent neural networks: An average dwell time approach, *IEEE Trans. on Neural Networks*, vol.22, no.10, pp.1547-1556, 2011.
[31] S. M. Tetrault, G. C. Stone and H. G. Sedding, Monitoring partial discharges on 4-kV motor windings, *IEEE Trans. on Ind. Appl.*, vol.35, no.3, pp.682-688, 1999.
[32] D. A. Asfani, S. Syafaruddin, M. H. Purnomo and T. Hiyama, Wavelet-LDA-neural network based short circuit occurrence detection in induction motor winding, *Proc. of IEEE SDEMPED*, Bologna, Italy, pp.330-336, 2011.
[33] S. K. Dhali and I. Sardja, Dielectric-barrier discharge for the removal of SO2 from flue gas, *IEEE International Conference on Plasma Science*, p.150, 1989.
[34] B. G. Moffat, M. P. Y. Desmulliez, K. Brown, C. Desai, D. Flynn and A. Sutherland, A micro-fabricated current sensor for arc fault detection of aircraft wiring, *Proc. of the 2nd Electronics System-Integration Technology Conference*, Greenwich, UK, pp.299-304, 2008.
[35] N. S. Midi and R.-I. Ohyama, Distribution of discharge current in stratified seawater under impulse discharges, *Proc. of Electrical Insulation and Dielectric Phenomena*, West Lafayette, IN, USA, pp.1-4, 2010.
[36] L. M. R. Oliveira and A. J. M. Cardoso, Intermittent turn-to-turn winding faults diagnosis in power transformers by the on-load exciting current park's vector approach, *Proc. of ICEM*, Algarve, Portugal, pp.1-6, 2008.
[37] J. Ilonen, J. K. Kamarainen, T. Lindh, J. Ahola, H. Kalviainen and J. Partanen, Diagnosis tool for motor condition monitoring, *IEEE Trans. on Ind. Appl.*, vol.41, pp.963-971, 2005.
[38] B. Ayhan, M.-Y. Chow and M.-H. Song, Multiple discriminant analysis and neural-network-based monolith and partition fault-detection schemes for broken rotor bar in induction motors, *IEEE Trans. on Ind. Electron.*, vol.53, pp.1298-1308, 2006.
[39] E. G. Strangas, S. Aviyente and S. S. H. Zaidi, Time and frequency analysis for efficient fault diagnosis and failure prognosis for interior permanent-magnet AC motors, *IEEE Trans. on Ind. Electron.*, vol.55, pp.4191-4199, 2008.
[40] M. A. S. K. Khan, T. S. Radwan and M. A. Rahman, Real-time implementation of wavelet packet transform-based diagnosis and protection of three-phase induction motors, *IEEE Trans. on Energy Conv.*, vol.22, pp.647-655, 2007.
[41] P. Haesun, C. Jaegul, B. L. Drake and K. Jinwoo, Linear discriminant analysis for data with sub-cluster structure, *The 19th International Conference in Pattern Recognition*, pp.1-4, 2008.
[42] F.-J. Lin, Y.-C. Hung and S.-Y. Chen, FPGA-based computed force control system using Elman neural network for linear ultrasonic motor, *IEEE Trans. on Ind. Electron.*, vol.56, pp.1238-1253, 2009.
[43] J. H. Shin, B. Lee et al., Detection of abnormal living patterns for elderly living alone using support vector data description, *IEEE Trans. on Inf. Technol. Biomed.*, vol.15, pp.438-448, 2011.