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Pruned Ann Model for Three Phase Induction Motor Operating Conditions Classification

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ABSTRACT - The Artificial Neural Networks (ANN) have become a very useful tool in a wide range of engineering applications. In this paper, feed forward neural network Optimal Brain Surgeon (OBS) pruned model is proposed to classify the operating conditions of three phase induction motor. The proposed model had been trained with error back propagation training algorithm using frequency and voltage as input signals with nine possible operating conditions (faulty and healthy) acting as output neurons of the neural network model. The simulation results show that the pruned ANN model can perform perfect classification for the operating conditions of three phase induction motor.

Keywords: Neural Networks, Optimal Brain Surgeon, Induction Motor.

1. INTRODUCTION

Condition monitoring has been used in rotating machines fault diagnosis and classification for decades due to its importance in identifying early stages of faults to avoid machine breakdown [(1)]. The induction machines are known as work horse of modem industries because of various technical and economical reasons. These machines face various conditions during their operation, which may lead to some modes of failures. Hence the operating condition classification becomes necessary in order to avoid catastrophic failures [(2)]. Recently, neural networks have attracted a lot of attention from the research community. Its application has grown beyond control system theory into a wider sphere including biomedical, engineering, financial and operation research [(3)]. In industries 3-phase induction motors have been used extensively with the growing use of electric cookers for domestic purposes, air conditioners and sensitive electronics equipments like TV sets, computer …etc. and increasing demands have become a matter of concern due to either a serious damage to the equipment or heavy production loss. Among the worst affected consumers apparatuses are the single phase fractional horse power motors used in refrigerators, home freezers and water systems. For example, in the case of refrigerators, reduced frequency result in a reduced efficiency and high consumption as the motor draws larger current at reduced power factor. On the other hand, when the voltage is low the motor draws less current and the current relay may fail to disconnect the starting winding. The current may be too low to operate the over-load rely, but may be high enough to damage the starting winding and thus lead to burn out of the motors. In many large interconnected systems having inherently low rate of frequency decay, low voltage may be more objectionable than low frequency.

This work presents a feed forward neural network OBS pruned model for classification of operating conditions of three phase induction motor. Thus, a supply voltage variation of ±10% from the rated voltage and supply frequency variations of ±3% from the rated frequency have been considered in this work to form a set of operating conditions (faulty and healthy) which would be classified via OBS pruned feed forward neural network model. This work is presented into seven parts. Starting with an introduction, the second section covers a brief theory of three-phase induction motor, the third section discuss the artificial neural networks and its architecture, the error back propagation training algorithm has been covered with OBS pruning algorithm at the fourth section, the neural network model for operating conditions classification has been proposed at the fifth section, the last two sections present results and discussion and conclusions.

2. MODEL DESCRIPTION

The induction motor essentially consists of two main parts: stator and rotor. For analysis purposes, the induction motor can be treated basically as a transformer [(4)]. The induction motor has stator leakage reactance, stator copper loss and magnetizing inductance as shunt elements. The rotor circuit likewise has rotor leakage reactance, rotor copper (aluminum) loss and shaft power as series elements. The transformer in the center of the equivalent circuit can be eliminated by adjusting the values of the rotor components in accordance with the effective turn's ratio of the transformer [(4)]. From the equivalent circuit and a basic knowledge of the operation of the induction motor, it can be seen that the magnetizing current component and the iron loss of the motor are voltage dependant, and not load dependant. Additionally, the full voltage starting current of a particular motor is voltage and speed dependant, but not load dependant. The magnetizing current varies depending on the design of the motor. For small motors, the magnetizing current may be as high as 60%, but for large two pole motors, the magnetizing current is more typically 20-25% at the rating voltage of 220V, the iron is typically near saturation, so the iron loss and magnetizing current do not vary linearly with voltage, with small increase in voltage resulting in a high increase in magnetizing current and iron loss. On the other hand, the resistance and reactance of the equivalent circuit depend proportionately upon the frequency of operation. Thus, three voltages (200, 220, and 240V) with three frequencies (48.5, 50, and 51.5Hz) for a given slip (0.01) have been used in this work to form the nine operating conditions (faulty and healthy) of the induction motor. The power factor and the efficiency decreased as the frequency reduced from 51.5Hz down to 48.5Hz. Table (1) illustrates the efficiency of the motor for various frequencies and voltages[4]. From Table(1), it is obvious that the best operation condition (with respect to efficiency) for the motor occurs at the faulty case of normal frequency (50 Hz) and over voltage (240 V) at which the efficiency equals to (87.424 %), whereas at the normal operating condition (50 Hz and 220 V) the efficiency is (86.065) and this means an increase of (1.58%), because when the input voltage increases during the operation, the actual speed of the rotor will increase, and in turn the efficiency will also increase.

Table (1): Efficiency with different frequencies and different voltages

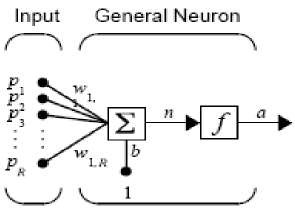
Efficiency %		Voltage		
		200 V	220 V	240 V
Frequency	51.5 Hz	83.873	85.776	87.224
	50 Hz	84.278	86.065	87.424
	48.5 Hz	84.081	85.926	87.330

3. ARTIFICIAL NEURAL NETWORKS (ANNs)

Artificial neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. Artificial neural networks were developed using the principles of operation of the human brain. It resembles the brain in two respects [5]:

A- Knowledge is acquired by the network through a training process.

B- Interconnection strengths known as synaptic weights are used to store the knowledge.



Figure(1).: Single Neuron

The advantages of neural networks are [6]:-

1. Neural networks can learn (identify) any system from its input-output data.
2. They offer versatile input-output mapping capabilities.
3. Neural network models have a considerable tolerance for noise.

Basically, ANN consists of interconnected network of elementary unit, called neurons, which are arranged in layers and operate in parallel. Each neuron in the network operates by taking the sum of its weighted inputs and passing the result through a nonlinear activation function. The single neuron model is shown in Fig. (1). A feed forward network is made up of an input and output layers, having one or more layers of neurons in between called the hidden layers, which propagate the inputs forward to the output layer. The optimization process for calculating the weights of the neural network is called training. During training, weights are continuously modified until the neural network is able to predict the outputs from the given set of inputs within an acceptable user-defined error level. Fig. (2) shows the general architecture of a multilayer, (fully connected) feed forward neural network. In this work, a network with only one hidden layer is considered because a network with one hidden layer (of nonlinear activation function) and a linear output layer can approximate any continuous function (7). Two input neurons had been considered representing the frequency and voltage which drives the induction motor with nine output neurons of linear activation function representing the (faulty and healthy) operating conditions of the motor.

4 .BACKPROPAGATION ALGORITHM

The neural network model of this study has been trained using error back propagation algorithm. Initially, weights connecting input and hidden neurons and weights connecting hidden and output neurons are assigned random values. The outputs of the hidden neurons are calculated by (8):

$$h_j = f\left(\sum_i p_i w_{ij} + b_j\right) \tag{1}$$

where h_j is the actual output of hidden neuron j. p_i is the input signal of input neuron i. w_{ij} is the weight between input neuron i and hidden neuron j. b_j is the bias of hidden neuron j. f is the tangent sigmoid activation function. The output of the output layer is calculated by:

$$a_k = f\left(\sum_j h_j w_{jk} + b_k\right) \tag{2}$$

where a_k is the actual output of output neuron k. w_{jk} is the weight between hidden neuron j and output neuron k. b_k is the bias of the output neuron k. The error at the output layer back propagated using the relation:

$$\delta_k = (t_k - a_k) f'\left(\sum_j h_j w_{jk} + b_k\right) \tag{3}$$

where f' is the derivative of the activation function. t_k the target of output neuron k. The weights and biases are adjusted between the hidden layer and output layer (equations 4 and 5) and between the input and hidden layer (equations 6 and 7) where the learning rate is denoted by α and momentum factor by μ ;

$$\Delta w_{jk}(n) = \alpha\, \delta_k h_j + \mu\, \Delta w_{jk}(n-1) \tag{4}$$

$$\Delta b_k(n) = \alpha\, \delta_k h_j + \mu\, \Delta b_k(n-1) \tag{5}$$

$$\Delta \mathrm{w}_{\mathrm{ij}}(\mathrm{n}) = \alpha\, \delta_{\mathrm{j}}\, \mathrm{p}_{\mathrm{i}} + \mu\, \Delta \mathrm{w}_{\mathrm{ij}}(n-1) \tag{6}$$

$$\Delta \mathrm{b}_{\mathrm{j}}(\mathrm{n}) = \alpha\, \delta_{\mathrm{j}} + \mu\, \Delta \mathrm{b}_{\mathrm{j}}(n-1) \tag{7}$$

Finally, the weights and biases are updated according:

$$w_{jk}(n) = w_{jk}(n-1) + \Delta w_{jk}(n) \tag{8}$$

$$b_k(n) = b_k(n-1) + \Delta b_k(n) \tag{9}$$

$$w_{ij}(n) = w_{ij}(n-1) + \Delta w_{ij}(n) \tag{10}$$

$$b_j(n) = b_j(n-1) + \Delta b_j(n) \tag{11}$$

Once the network is sufficiently "trained", a general model is created for the relationship between inputs (frequency and voltage of the 3-phase induction motor) and outputs (the nine operating conditions of the motor). When the training patterns are very limited, (such the present case of the nine operating conditions in this work) it is important that the network architecture is chosen wisely in that it should contain only the most essential weights. The most popular procedure for optimizing the neural network architecture is the *Optimal Brain Surgeon (OBS)* algorithm. The basic idea in this algorithm is that one initially finds a fully connected network architecture which (in principle) is large enough to perform classification among different operating conditions. Starting with this architecture, the weights and biases are then eliminated one at a time according to a specified criterion until the optimal architecture has been reached [9]. Removing single weight or bias is not the whole story. The (new) network must be retrained up to 50 iteration using Levenberg-Marquardt training algorithm (for its superiority in convergence) to adjust the remaining weights in order to compensate the effect of eliminated weight or bias. The flow chart of the OBS algorithm is shown in Fig.(3).

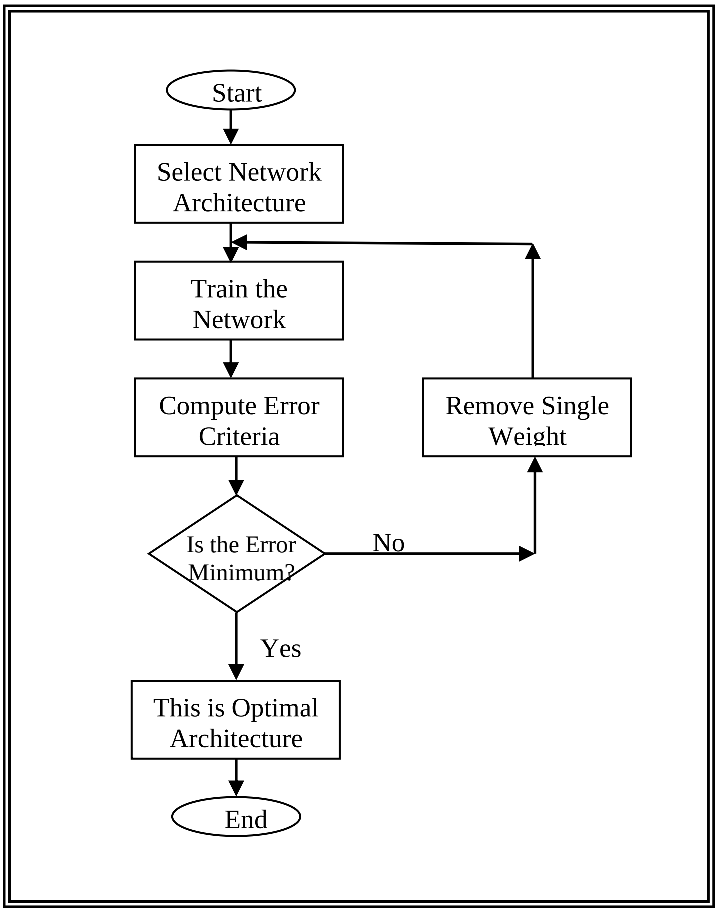


Figure (3): Flow Chart for the OBS Algorithm

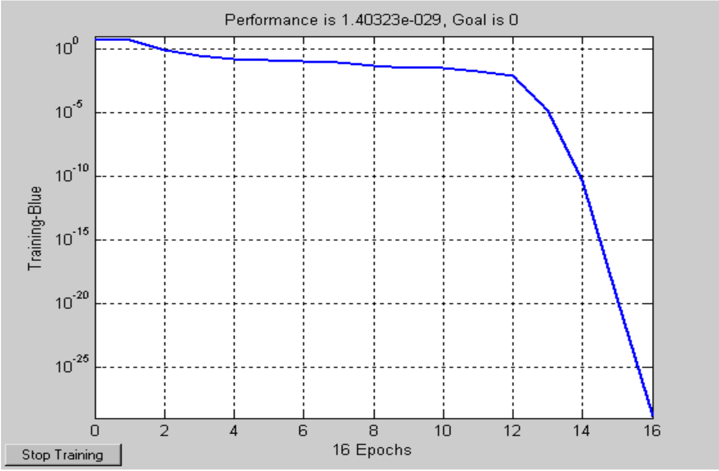
5. THE PROPOSED NEURAL NETWORK MODEL

The main objective of this research is to develop a network model with high generalization ability to classify the operating conditions of 3-phase induction motor when some variation happened in the rated voltage and/or frequency of the motor. A supply voltage variation of ± 10% from the rated voltage and a supply frequency variation of ± 3% from the rated frequency are considered to form the operating conditions (training patterns) of the neural network model as shown in Table (2).

Table (2): Training Patterns

	Frequency (Hz)	Voltage (v)	Operating Condition
1	48.5	200	Under Frequency / Under Voltage **(UU)**
2	48.5	220	Under Frequency / Normal Voltage **(UN)**
3	48.5	240	Under Frequency / Over Voltage **(UO)**
4	50	200	Normal Frequency / Under Voltage **(NU)**
5	50	220	Normal Frequency / Normal Voltage **(NN)**
6	50	240	Normal Frequency / Over Voltage **(NO)**
7	51.5	200	Over Frequency / Under Voltage **(OU)**
8	51.5	220	Over Frequency / Normal Voltage **(ON)**
9	51.5	240	Over Frequency / Over Voltage **(OO)**

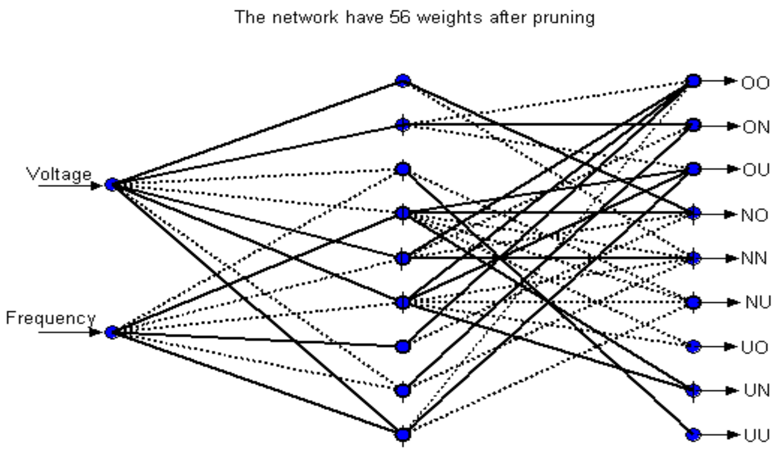
Thus, the architecture of the neural network model consists of two input neurons (one for voltage and the other for frequency), nine hidden neurons with nonlinear activation function (hyperbolic *tansig*), and nine output neurons with linear activation function (*purelin*) representing the nine possible operating conditions of the motor. After the architecture of the network has been selected, the training session is running as shown in Fig. (4).It is important to note that the network training can be made more efficient if certain preprocessing steps are performed on the network inputs and targets(7). In this work, we scaled the inputs and targets so that they always fall within the range [-1,1].



Figure(4): Training Session

6. RESULTS AND DISCUSSION

MATLAB (R2006b) based computer programs was developed to train the network using Levenberg-Marquardt training algorithm. The OBS pruning algorithm considered in this work to optimize the network architecture and to improve the network performance resulting with a *partially connected* network as shown in Fig. (5). The aim of OBS pruning algorithm is to capture the optimal network size by gradually reducing (a large trained) network's parameters (weights and biases) according to specified criteria(11). The algorithm is based on the idea of iteratively removing single parameter and then adjusting the remaining weights and biases with a view to maintain the original input-output behavior(10). After pruning accomplished, a network with 56 weights and biases have been obtained as illustrated in Table(3) and Table(4) which represents the networks parameters. Thus, the network is ready to classify the operating conditions, for a given set of inputs (voltage and frequency), the output neuron corresponding to that operating condition would be one while other eight neurons go to zero, the same is true for the other operating condition and so on. Simulation results of the neural network model showed perfect classification of the operating conditions (with an error about 1.0e-15 of the specified operating conditions) as shown in Table (5).



Figure(5): NN Model for Operating Condition Classification of 3-phase Induction Motor

Table (3): Input to Hidden Layer Weights and Biases

Hidden Neurons	Input Layer Neurons		Hidden Layer Biases
	Frequency	Voltage	
1	0	1.972	0
2	0	3.4692	3.4458
3	-8.8816	-8.6356	-13.2412
4	11.9352	-8.0721	11.9456
5	-6.2451	6.2657	6.1483
6	-15.3243	7.8363	-14.6344
7	0.3211	0	0
8	-0.6532	-7.9384	-8.2978
9	11.5307	17.6493	8.2599

Table(4): Hidden to Output Layer Weights and Biases

Output Neurons	Hidden Neurons									Output Biases
	1	2	3	4	5	6	7	8	9	
1	0	-1.6219	0	0	1.8325	1.027	6.5277	0	-0.1991	0
2	0	4.3284	0	0	-1.8373	0	0	3.489	0	0
3	0	-2.0111	0	3.3119	0	3.3275	0	0	1.0196	0
4	2.0821	0	0	1.9823	-1.9415	0	-6.4086	0	0	-1.0002
5	-2.0915	0	0	-3.298	1.688	-3.2831	0	-3.1176	0	-3.8084
6	0	0	-1.0001	-3.2908	0	-3.2878	0	0	-1.0029	-1.0002
7	0	0	0	-2.6272	0	-1.6269	0	0	0	0
8	0	0	0	3.2878	0	3.2876	0	0	0	-0.9998
9	0	0	1.0001	0	0	0	0	0	0	0

Table(5): Output Neurons Response

OO	ON	OU	NO	NN	NU	UO	UN	UU
1	-1.776e-15	1.665e-16	-1.554e-15	-2.220e-16	6.161e-15	9.436e-16	1.054e-15	-5.107e-15
-2.220e-16	**1**	2.775e-16	6.661e-16	-1.110e-15	-3.996e-15	-3.330e-16	-7.771e-16	3.608e-15
1.110e-16	2.220e-16	**1**	1.110e-16	5.551e-16	-1.443e-15	1.110e-16	0	7.771e-16
3.885e-16	2.220e-16	-4.440e-16	**1**	-2.220e-16	-2.220e-16	8.326e-16	-1.110e-15	1.110e-16
-2.220e-16	1.110e-15	-4.440e-16	6.661e-16	**1**	-2.220e-15	8.881e-16	-5.551e-16	1.998e-15
-7.771e-16	7.771e-16	6.661e-16	1.221e-15	1.110e-16	**1**	-1.332e-15	1.665e-16	3.330e-15
2.220e-16	-6.661e-16	8.881e-16	4.99e-16	4.99e-16	0	**1**	2.775e-16	-5.551e-16
-1.998e-15	2.886e-15	1.110e-16	1.998e-15	-1.221e-15	-7.771e-15	-6.661e-16	**1**	6.328e-15
5.551e-16	5.551e-16	-1.110e-16	1.221e-15	7.771e-16	-2.775e-15	-3.330e-16	-6.661e-16	**1**

7. CONCLUSIONS

An efficient neural network-based model for classifying operating conditions of three phase induction motor have been proposed. The OBS pruning algorithm has been used in this work to optimize network architecture and improve model performance, the result of this work shows that ANN is applicable, easy and reliable for classification purposes and able to indicate the presence of faults using instantaneous voltage and frequency values for various cases including normal case as well as over/under frequency and/or voltage.

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تصنيف حالات العمل لمحرك حثي ثلاثي الطور باستخدام نموذج الشبكة العصبية الاصطناعية المهذبة

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الخلاصة

أصبحت الشبكات العصبية الاصطناعية أداة مفيدة جدا في مدى اسع من التطبيقات الهندسية. في هذا البحث, تم تقديم نموذج لتصنيف حالات العمل لمحرك حثي ثلاثي الطور باستخدام تقنية الشبكات العصبية الاصطناعية ذات التغذية الأمامية والمهذبة بخوارزمية جراحة الدماغ المثلى. تم تدريب النموذج المقدم بخوارزمية انتقال الخطأ الخلفي باستخدام التردد وفرق الجهد كإشارات إدخال للشبكة العصبية لتصنيف تسع حالات عمل (خاطئة وصحيحة) تمثل أشارات الإخراج لنموذج الشبكة العصبية. بيّنت نتائج المحاكاة إن نموذج الشبكة العصبية المهذب بإمكانه تصنيف حالات العمل للمحرك الحثي ثلاثي الطور بصورة مثالية.

الكلمات الدالة : شبكات عصبية، جراحة الدماغ المثلى، محرك حثي.