Scientific Research and Essays Vol. 6(7), pp. 1596-1606, 4 April, 2011
Available online at http://www.academicjournals.org/SRE
DOI: 10.5897/SRE10.1103
ISSN 1992-2248 ©2011 Academic Journals

Full Length Research Paper

A novel model for predicting nonlinear response of advanced V/F drive induction motor in maximizing motor efficiency

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Accepted 26 January, 2011

The squirrel-cage induction motors (SCIM) are the largest electrical energy consumption in the world. The efficiency of SCIM is very poor if traditional constant voltage control is used and their efficiency is further lowered as they operate other than rate condition. Therefore, the efficiency improvement of SCIM which consequently improve the power factor can play an important role in energy conservation, especially in the low-load operating periods.In this paper, VI_RBFNN, a new intelligent control strategy using Radial Based Function Neural Network (RBFNN) based on voltage/current (V/I) for maximum efficiency was proposed. Through this strategy, the SCIM performance can be improved both in terms of efficiency and power factor, regardless of the load torque and speed. The proposed VI_RBFNN utilizes the advanced voltage/frequency (V/F) controller to control SCIM operation. The optimum V/I expression of the motor is used in the optimization process, which is derived, based on standard per phase equivalent circuit and its value is obtained by performing the standard induction motor parameters determination tests. The VI_RBFNN which uses RBF Neural Network with six inputs and three outputs to operate as maximum efficiency control variables estimators of V/I controller are designed. The input data used to train the RBF networks are motor phase voltage (V_1), current (I_1), maximum voltage (V_m), synchronous speed (f), the modulation index (m), and the voltage (V_{boost}); while the output data are maximum voltage (V_m*), synchronous speed (f*), modulation index (m*) and boost voltage (v_{boost}*). The neural network were trained to learn their inverse dynamics and then configured as RBFNN controller to the motor drive, based on the set of nonlinear input-output responses. The proposed approach is simple in structure and has the straightforward goal of maximizing the SCIM efficiency for a given load torque.The results show that the function of VI_RBFNN control scheme is fast and properly driving the SCIM at optimum V/I, hence the entire drive system is working at maximum efficiency.

Key words: Radial based function neural network (RBFNN), i induction motor, efficiency, v/i, V/F drive.

INTRODUCTION

According to the latest survey, more than half of the electricity generated is consumed by electric motors and since most of the power-generating systems produce AC, a majority of the motors used throughout the globe are designed to operate on AC, specifically induction motor (Mohan, 1980; Hariram et al., 2005). The vast majority of the motors used in industry are squirrel-cage induction motors (SCIM) due to their low cost and high reliability. SCIM are available in various sizes; from small size at fractional horse power (hp) up to 500 hp. Although SCIMs are generally efficient, idling, cyclic, lightly loaded or oversized motors consume more power than required even when they are not working. Studies conducted by the Electric Power Research Institute reveals that over 60% of industrial motors are operating below 60% of their rated load capacity (Bin et al., 2006; Zahedi and Vaez-Zadeh, 2009; Xiuhe et al., 2010).

Over the past 30 years, concern for effective use of energy resources has grown in response to increased fuel cost, increased demand upon energy supply systems

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Table 1. SCIM design category and maximum efficiency operating condition.

SCIM category	Efficiency level	Maximum efficiency operating condition
Premium Efficient Motor	Highest	75 % of full load
High Efficient Motor	High	75 % of full load
Standard Efficient Motor	Medium	Rated load
Other	Low	Rated load

Table 2. SCIM control types and efficiency level.

SCIM control	Efficiency Level at below 75% of rated load
Constant voltage	Very poor
Variable voltage	poor
VVVF	good
Advanced VVVF	good
Field oriented control	Very good
Intelligent Control	Very good

and concern that growing energy use may be causing irreparable damage to the environment. In response to these concerns, there has been a desire to increase the efficiency of electrical motors, since these devices constitute a significant fraction of the total use of electrical energy. A considerable amount of research has been done in the area of the design of SCIM itself as well as the control for the purpose of optimizing the efficiency (Lin and Yang, 2003; Ta and Hori, 2001; Ferreira et al., 2008). As a result, the market for energy efficient electrical motors has expanded. It has been shown that when such motors are properly applied, the savings in energy use over the lifetime of the motor can offset the higher initial investment required to purchase premium and high efficiency motors. Furthermore, the energy saving is more significant if modern variable voltage variable frequency (VVVF) control is used rather than conventional v/f control or direct online control. The VVVF control is integrated with efficiency control scheme which promise greater energy saving already available since 90’s. Today, the SCIM drive controllers integrated with artificial intelligent maximum efficiency technique scheme are already in the market.

This paper will give attention to Radial Based Function Neural Network in predicting the maximum efficiency condition of nonlinear response of advanced v/f control SCIM drive for a given load. The sequences of this research works are as follows: First, maximum efficiency V/I expression is derived; second, the SCIM drive controller, based on advanced v/f control scheme, powered by MC3PHAC AC motor controller is designed and hardware implemented; third, the control software to run the SCIM drive controller with V/I maximum efficiency scheme is designed and coded; fourth, the laboratory experiment is set up to test the V/I maximum efficiency scheme; fifth, the experimental works to; i) validate the proposed V/I maximum efficiency scheme for SCIM, and ii) to collect the data and use the data to train the proposed neural network; sixth, the design of VI_RBFNN SCIM control system, which consist of the train neural network (NN), PWM generator and SCIM; seventh, design, train and test the NN based on hardware input and output signals; eighth, simulate the VI_RBFNN. Simulation showed that the proposed VI_RBFNN SCIM controller successfully predicts the maximum efficiency condition for any load attached to the motor shaft.

BACKGROUND

Approaches for maximizing efficiency operation of SCIM

Two approaches that have been identified to increase the efficiency of induction motor are; i) optimum design of the SCIM, and ii) optimum operation of SCIM by using intelligent maximum efficiency SCIM drive controller. Table 1 shows the SCIM design and their efficiency operating condition (Famouri and Cathey, 1991). Table 2 shows the control types of SCIM and their efficiency level. Replacing the existing motors with premium or high efficient motors will reduce the energy consumption (Famouri and Cathey, 1991). Obviously, using intelligent drive system based on appropriate maximum efficiency control scheme coupled with premium efficient motor will maximize energy saving.

Maximizing SCIM using maximizing SCIM drive control system approach

Many control schemes of SCIM efficiency improvement drives under partial load have been reported previously. These schemes can be separated into three categories (Lin and Yang, 2003; Ta and Hori, 2001; Ferreira and de Almeida, 2008).

Methods based on search controllers of minimum input power

The controller measures the input power and then searches for the

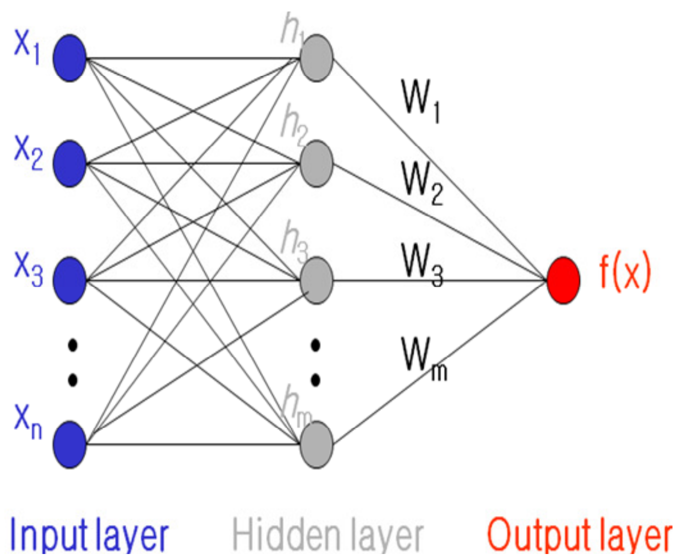

Figure 1. RBFNN architecture.

operating point where the input power is at a minimum while keeping the motor output power constant.

Loss model method

The efficiency of SCIM can be maximized if the losses could be minimized. Loss minimization technique is aimed at reducing the iron core loss and copper loss during low load operation of SCIM. A loss model is required for loss calculation and a feedback controller is used to force the motor to operate at its minimum-loss point.

Power factor method

When the motor is operating at constant speed, the power factor is adjusted such that the operating loss is minimal.

All methods require real-time searching for efficiency and comparing the efficiency before the IM drive system is operated at maximum efficiency. However, real-time searching for maximum efficiency operating condition requires lengthy and complicated mathematical calculation (Bose, 1994). Also, as the flux is reduced for many steps, the drive experience unhealthy pulsating torque, reducing the motor bearing lifetime and is prone to unstable motor operation. The right approaches to overcome the drawbacks are; i) avoiding the variable input voltage/flux methods; ii) avoiding using on-line searching however; iii) immediately drive the motor to maximum efficiency operating condition upon receiving the feedback signals, and; iv) avoiding using sensors (sensorless) as this will affect the drive robustness and reliability. Thus, researchers found that sensorless artificial intelligent (AI) control VVVF drive have great improvement in energy consumption (Bose, 1994).

Intelligent control for maximizing efficiency IM

AI techniques, such as fuzzy logic, neural networks and genetic algorithms have been extending its frontier and bringing new challenge to power electronic industries since 1990 (He et al., 2010; Gan and Ojo, 2006; Ebrahim et al., 2010). For example, the artificial neural network (ANN) based on online efficiency optimization controllers for induction motor drive have been reported in the 1990s (Bose, 2004, 2007). The ANN has the following features; i) nonlinear input-output signal mapping characteristics; ii) knowledge is acquired by learning (or training) through example input-output data sets and; iii) high speed parallel computation - with fault-tolerance and noise filtering property. Therefore, the ANN is suitable application for pattern recognition, pattern classification and associative memory based problems (Bose, 2007). A typical engineering application of ANN includes control and estimation in power electronic system, general industrial process control, robot vision, online diagnostics, etc. The ANN play important roles in data acquisition in laboratory and field environments, data processing and analysis, data searching and data presentation in under-standable and useful formats (Bose, 2004). Furthermore, ANN can handle continuous as well as discrete data and have good generalization capability (Bose, 2007).

In the field of SCIM drive systems, the ANN is not only restricted to final step in optimizing the process, that is, optimizing efficiency, but ANN can also be applied at the beginning of the process such as, tracking and analysis of data. The researchers conclude that the ANN-based controllers have been proven more robust and fault tolerant compared to classical adaptive controllers which have slow learning process and have more complex structures (Pajchrowski et al., 2005; Tsai et al., 2006).

Also, ANN-based techniques show a great enhancement in accuracy of online efficiency optimization in comparison with the conventional techniques (Bose, 2007; Neema et al., 2009). The interest among researchers to achieve maximum efficiency operation of SCIM drive system based on ANN is a continuous effort and keeps growing. This includes the use of Radial Based Function Neural Network (RBFNN) in the drive system (Aziz, et al., 2009; Zhanyou et al., 2009).

Radial based function neural network (RBFNN)

RBFNNs are essentially a combination of the ideas found in multi-level perceptrons (MLPs). In addition to interpolation, they can also be used for function approximation. As shown in Figure 1, the standard (regression-type) RBFNN model uses the 3 layer topology (including bias nodes), an input layer, a hidden layer and an output layer, as the MLP, but the output is modeled as a linear combination of basic functions, of the form:

$$y = \sum_{j=1}^{m} w_j \varphi() \tag{1}$$

where y is the set of matching output vectors, mis the hidden nodes, wis the weight and φ() is a radial basis function. This function operates not on the input data vectors, but on the distance of input data vectors, from a pre-selected ‘center’.

The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the center of the neuron. RBF networks have a variable number of neurons that is usually much less than the number of training points. The basic idea of RBFNN operation is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables. Thus, the predictions for new data items are made by assuming that they are of the same type as the nearest cluster center (Alanzi, et al., 2007). Furthermore, an RBF network also identifies the centers of clusters, and makes predictions by considering the Gaussian-weighted distance to all other cluster centers rather than just the closest one (Ali, 2008; Guill´en et al., 2008).

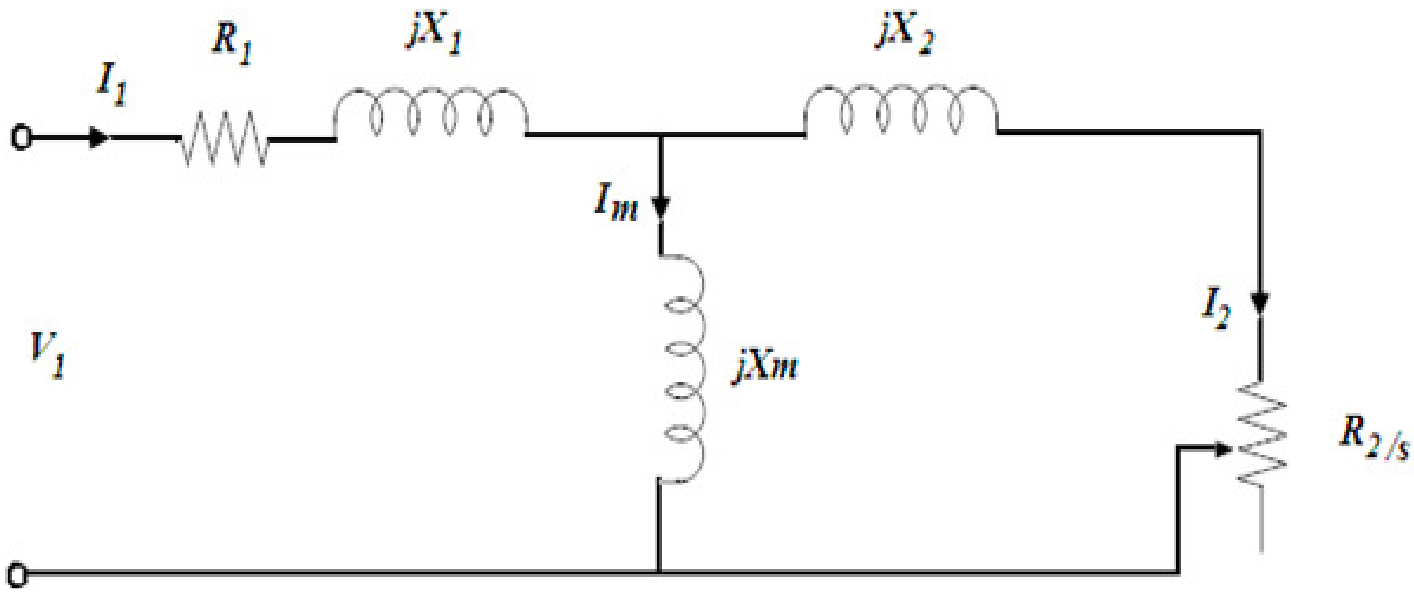

Figure 2. Induction motor per phase model.

SYSTEM DESCRIPTION

The efficiency of SCIM is maximal only when the system operates at its nominal operating point. Below this point, the excessive stored energy in the coil inductances will unnecessarily decrease the efficiency of the machine. In many electrical drives applications, the SCIM does not operate at the nominal point since the desired torque may change as a function of position or load velocity. It is then interesting to decrease flux in order to optimize system performance. The efficiency gain by application of optimal flux in comparison with the conventional constant voltage to frequency control (VVVF) is significant.

VI_RBFNN control strategy for IM efficiency optimization

In this paper, the online maximum efficiency operation of SCIM drive control algorithm is structured using the Radial Basis Functions Neural Network (RBFNN). The main focus is to operate the SCIM drive closest to voltage/current (V/I) reference value which corresponds to the nominal operating point. Then the control signals for maximum efficiency operation of SCIM are recorded and the associated control variables are used to train the RBFNN. Subsequently, the trained NN or VI_RBFNN will predict the value of control variables based on the input and feedback signals. The PWM generator will then generate the control signals based on predicted control variables and the 3-phase inverter will shape the spectrum of power supply to produce maximum efficiency power and frequency supplied to the SCIM. The V/I reference value used in the above algorithm will be explained in the next section. It includes the derivation of V/I, efficiency and slip based on SCIM equivalent circuit.

Maximum efficiency expression and derivation

A steady state equivalent circuit of an SCIM which is used to find out the strategy for maximum efficiency is shown in Figure 2. In Figure 2, if $V = V_1$ and $I = I_1$, V/I and efficiency expression can be written as follows :

$$\frac{V}{I} = R_1 + \frac{X_m^2 \frac{R_2}{s}}{\left(\frac{R_2}{s}\right)^2 + (X_2 + X_m)} + \cdots$$

$$j\left[(X_1 + X_m) + \frac{X_m^2\left[\frac{R_2}{s} - (X_2 + X_m)\right]}{\left(\frac{R_2}{s}\right)^2 + (X_2 + X_m)^2}\right] \quad (2)$$

the efficiency can be written as:

$$\eta = \frac{(s - s^2)X_m^2 R_2}{sR_2X_m^2 + R_1X_m^2s^2 + R_2^2R_1} \quad (3)$$

By taking the derivative of (3) with respect to s, and let $d\eta / ds = 0$, and since $X_2 \gg 2s/X$ is at rated speed, without considering constant losses, the slip with maximum efficiency expression can be written as :

$$s_{\eta,max} = \frac{R_2}{X_m}\sqrt{\frac{R_1}{R_1 + R_2}} \quad (4)$$

Equation (2) shows that all motor parameters are constant and replacing,s in (2) with value calculated using (4), will obtain maximum efficiency reference value for V/I. Maintaining theratio at the setslip at any load and at certain ranges of speed will ensure the SCIMs drive operates at maximum efficiency.

Estimation of slip of IMD on real-time operation

This section describes briefly on method of acquiring data through online data acquisition and then performing necessary

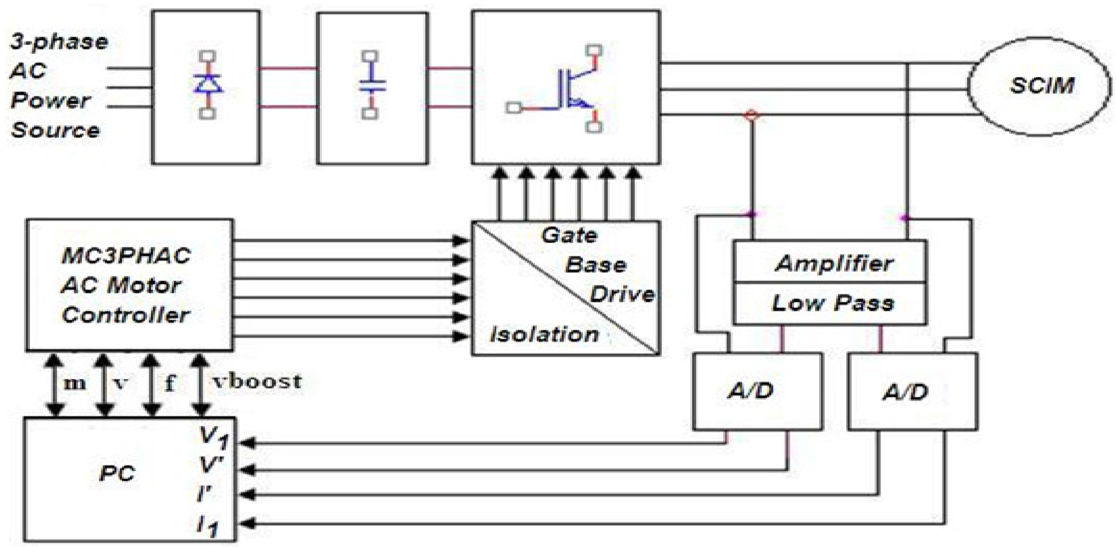

Figure 3. Experiment setup for maximum efficiency control.

Table 3. SCIM parameters.

Poles(p)	4
PF	0.8
Stator Resistance(R_1)	31.09Ω
Rotor Resistance(R_2)	40.56Ω
Stator Leakage Inductance (L_1)	186.9mH
Rotor Leakage Inductance (L_2)	186.9mH
Magnetizing Inductance (L_m)	944.1mH

mathematical operation for tracking maximum efficiency operating condition. From (2), V/I in general form can be written as:

$$\frac{V}{I} = R_e + jX_e \tag{5}$$

Further development of (2) and (5) and solved for slip, s, the online estimation can be written as:

$$s = \frac{R_2(L_e - L_1 - L_m)}{(R_e - R_1)(L_2 + L_m)} \tag{6}$$

Then, the V/I reference value can be calculated based on the fundamental values of V and I which are obtained through online. Furthermore, the motor constants for a particular motor can be pre-determined, which in turn, the efficiency and slip in (3) and (6) respectively can finally be extorted in real-time.

Experimental setup and control software

The laboratory experimental setup to test V/I maximum efficiency scheme is shown in Figure 3. The controller used a commercial 3-phase IGBTs PWM voltage source inverter, commercial AC motor controller MC3PHAC from Motorola controlled by PC, and 3-phase, 400V, 0.34 kW IM. The motor used in the experiment was specifically designed for undergraduate laboratory experiments and their parameters are listed in Table 3.

The control software to control MC3PHAC's variables and maximum efficiency operation of Figure 3 were developed using Microsoft Visual Basic 6.0 running on PC with Pentium IV processor. The algorithms in (2), (3), (4) and (6) were used to calculate the reference values of V/I ratio, efficiency, and slip in real time. The PC, through the control software, performs the following tasks; 1) online calculation as mentioned above and online monitoring of V/I value; 2) online control of the motor operation by controlling the MC3PHAC's control variables, and; 3) provide an online user interface control. The full flow of the control software is shown in Figure 4. Once the experiments were successfully carried out and the V/I was confirmed working accordingly, the experiments data for various load condition and speed was properly collected. This data was used to train the proposed RBFNN intelligent control of maximum efficiency SCIM.

Proposed maximum efficiency SCIM drive system based on RBFNN

The SCIM intelligent controller was designed specifically to meet the requirements for low-cost, variable-speed, open loop V/F 3-phase SCIM motor control system either in stand-alone mode or external master mode (Figure 5). The proposed controller uses RBFNN as the control variables estimator. The design for the RBFN networks which operates as maximum efficiency control signals estimators of V/I controller is shown in Figure 6. The output layer consists of three output nodes where two nodes are for two independent output control signal and the other is single node but share with two control signals. Since the training data is based on V/I maximum efficiency scheme, the controller is name as VI_RBFNN. The input data used in the trained RBF networks are motor fundamental phase voltage (V_1), currents (I_1), synchronous speed (f), modulation index (m), maximum voltage (Vmax), and boost voltage (Vboost). The outputs from the RBFNN estimator are the control signals for the PWM generator which corresponds to maximum efficiency for any determined load and speed. These control signals are synchronous speed (f*), modulation index (m*), maximum voltage (Vmax*) and boost voltage (Vboost*).

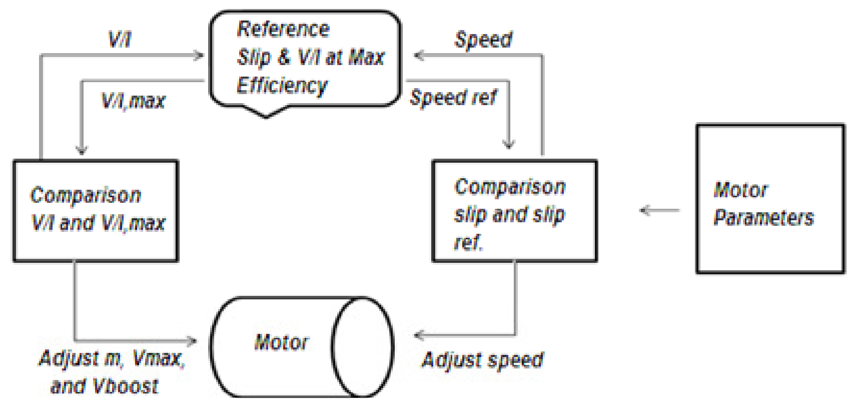

Figure 4. V/I Control software flow diagram.

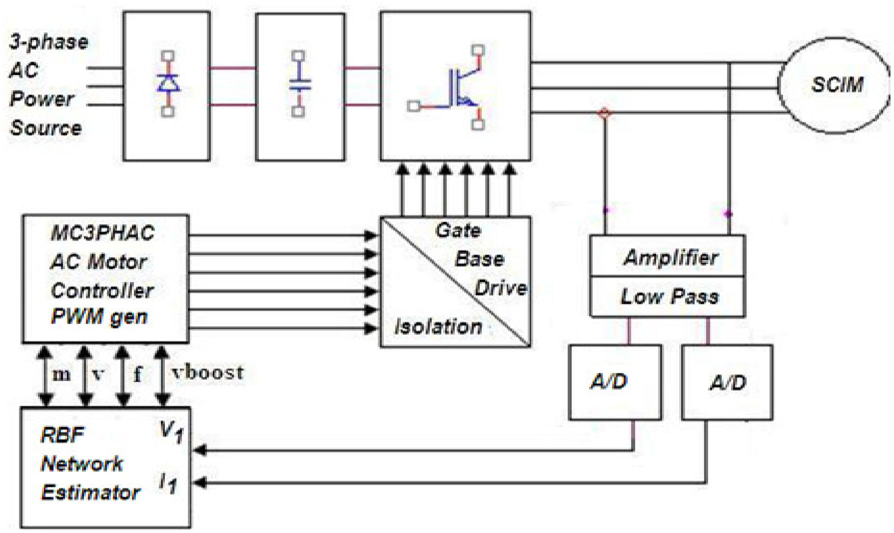

Figure 5. VI_RBFNN SCIM intelligent control model.

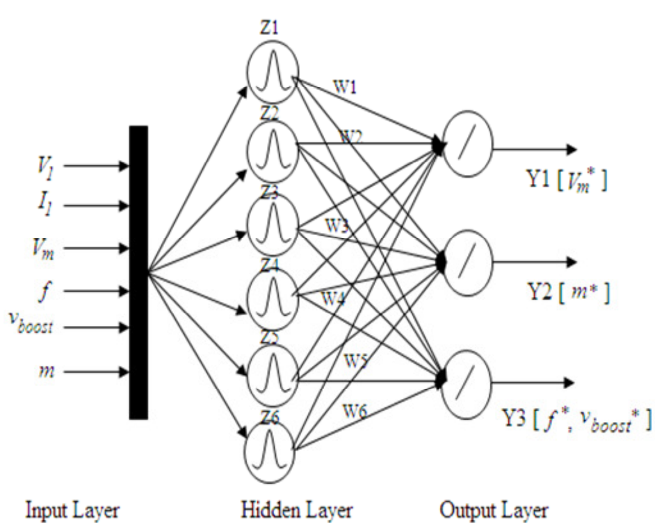

Figure 6. VI_RBFN networks with 6 input and 3 output ; 3 NN

RESULTS AND DISCUSSION

Reference values

The V/I reference values are calculated and listed in Table 2 for the motor mentioned before. As the motor is not an industrial grade but used for the laboratory under-graduate experiments, the maximum efficiency seem to be low. The maximum efficiency of the motor is considered low as the motor used in the experiment in category D of Table 1.

Maximum efficiency control variables

The V/I maximum efficiency SCIM system in Figure 3 and control software in Figure 4 was run online successfully. The controller automatically decreased or increased the values of the MC3PHAC's controlled variables upon

Table 4. Referenced values.

V/I ratio	Efficiency (%)	Slip
308.91	76	0.0822

Table 5. Experimental results :maximum efficiency control variables for f=45 Hz (1350 RPM).

V_1(V)	I_1(A)	M (per unit)	V_m (per unit)	f (Hz)	V_{boost} (per unit)
140.1	0.411	0.90	0.90	45	0.1
141.98	0.419	0.88	0.90	45	0.1
137.38	0.421	0.84	0.90	45	0.1
137.95	0.43	0.82	0.90	45	0.1
139.1	0.465	0.78	0.90	45	0.1
132.72	0.467	0.76	0.90	45	0.1

Table 6. Performance SCIM drive system integrated with V/I maximum efficiency scheme.

Load	Speed (RPM)	Efficiency with V/I (%)	Efficiency w/o V/I (%)	Efficiency Difference (%)
	1350	72.7	63.8	8.9
75% of full load	1200	68.4	56.2	12.2
	1050	65.2	48.4	16.8
	1350	68.3	54.4	13.9
50% of full load	1200	65.9	48.5	17.4
	1050	62.6	40.7	21.9
	1350	63.7	49.1	14.6
25% of full load	1200	69.3	50.1	19.2
	1050	55.6	32.4	23.2

receiving the voltage and current in real-time from multifunction card. Then, the controller run the motor with the control variables (as discussed earlier) closest to values listed in Table 4, which corresponds to maximum efficiency. The experiments were run several times for the similar setup and load. Some of the experimental resultsfor synchronous speed 1350 RPM (f=45Hz) are listed in Table 5.

A selectable acceleration feature of MC3PHAC ensured smooth transition as the controller searching the maximum efficiency point. The method is fast and accurate, and the result meets the steady state and the transient performance requirement.

Performance V/I maximum efficiency scheme

Experiments on VVVF SCIM drive system without V/Imaximum efficiency scheme was also carried out for different load condition at variable speed. The results for both experiments and the differences between the two are shown in Table 6. It is obvious that from the last column of Table 6, the performance of SCIM drive system was far better when V/I maximum efficiency is used. As the speed is reduced, the efficiency is also reduced. Therefore, it is observed that for any constant speed, regardless of load torque, there is a maximum efficiency operating point.

Training and testing of NN

Data collected from the laboratory experiments as shown in Table 5 is used to train the proposed NN. The training process of NN is shown in Figure 6. The training was done using NN tool available in Matlab 7.1. Once the NN is trained, the NN is tested to study the proposed NN performance in predicting the maximum efficiency control variables for a given load and speed. Table 7 shows the tests results of 50% of full load, which are grouped

Table 7. Proposed NN performance.

Speed (RPM)		V_1(V)	I_1(A)	M (per unit)	V_m (per unit)	f (Hz)	V_{boost} (per unit)
1350	Test	145.5	0.43	0.90	0.90	47	0.3
	Exp			0.90	0.90	45	0.1
	NN			0.9	0.878	45	0.1
	Error			0.0	0.022	0	0.0
1200	Test	145.5	0.43	0.90	0.90	47	0.3
	Exp			0.80	0.80	40	0.15
	NN			0.776	0.80	40	0.15
	Error			0.024	0.00	0	0.00
1050	Test	190.5	0.72	0.90	0.99	38	0.4
	Exp			0.70	0.70	35	0.3
	NN			0.667	0.70	35	0.3
	Error			0.033	0.00	0	0.0

according to their operating speed. As shown, the error which is the difference between the experiment and the trained NN represents the accuracy of proposed NN. The test data was selected randomly to show a fair difference from the trained values. The error is very small for the V_m* and m* and the rest of the control signals remain constant, without error.

The experiment proved that the PWM generator was producing the required control signals upon receiving the values from the control variables. The proposed NN also has predicted precisely the speed f,* which is the most critical control variable in this control scheme. The results shown in Table 6 prove that the proposed NN is very precise in predicting the maximum efficiency control variables for a given load and speed.

VI_RBFNN simulation results

The control model in Figure 6 is embedded in the feedback system to form the VI_RBFNN SCIM intelligent control model. The model is shown in Figure 5. This model is used to determine the control variables for maximum efficiency operation of the SCIM for any load and speed. Once the simulation was started, the feedback circuit fed the signals, V_1 and I_1while the PWM generator fed the control signals, V_m, n, f and V_{boost} to the RBFNN estimator. The RBFNN estimator then produced the control variable values as shown in Table 7. The PWM generator produced the control signals to the 3-phase inverter which then shapened the power waveform fed to the SCIM. Three speeds have been selected from the simulation for the analysis. The model was run successfully and the data analysis is depicted in Figures 7, 8, 9 and 10.

In Figures 7 and 8, the load is fixed at 400 mN while the speed is varied starting from 750 to 1350 RPM. Once the feedback signals has been received by the RBFNN estimator, the motor immediately drove the SCIM to the maximum efficiency operation by avoiding several times supply regulations as was done in the online control as described earlier. Figures 7 and 8 show that the maximum efficiency occurs when V/I ratio is in the range of 308 to 310 and slip is in the range of 0.07 to 0.12 respectively, for the speed at above 1050 RPM. However, at speed lower then 1050 RPM, the maximum efficiency values occurred lower than v/i reference value. These figures clearly showed that for different speeds (1200 RPM, and 1050 RPM), but with the same loading condition (200 mN), the maximum efficiency conditions are achieved at almost the same V/I and slip reference values.

In Figures 9 and 10, at fixed speed of 1200 RPM (f = 40 Hz), but with different loading conditions, the maximum efficiency occurred when v/i value is in the range of 0.81 to 0.87 and slip is in the range of 0.07 to 0.12. The significant finding from this figure is that for a constant speed (at 1200 RPM) but with different loading condition (200, 400 and 500 mN), the maximum efficiency are achieved at almost the same V/I and slip reference values. Figures 7, 8, 9 and 10 show that; i) for a particular load with different operating speed, the maximum efficiency is always at v/i and slip in the reference table and; ii) at a particular operating speed with different loading condition, the maximum efficiency is also always at v/i and slip in the reference table.

CONCLUSION

In the present study, the radial basis function has been explored as a new technique for maximizing efficiency of SCIM for partial load through the implementation of the VI_RBFNN strategy. The proposed method successfully

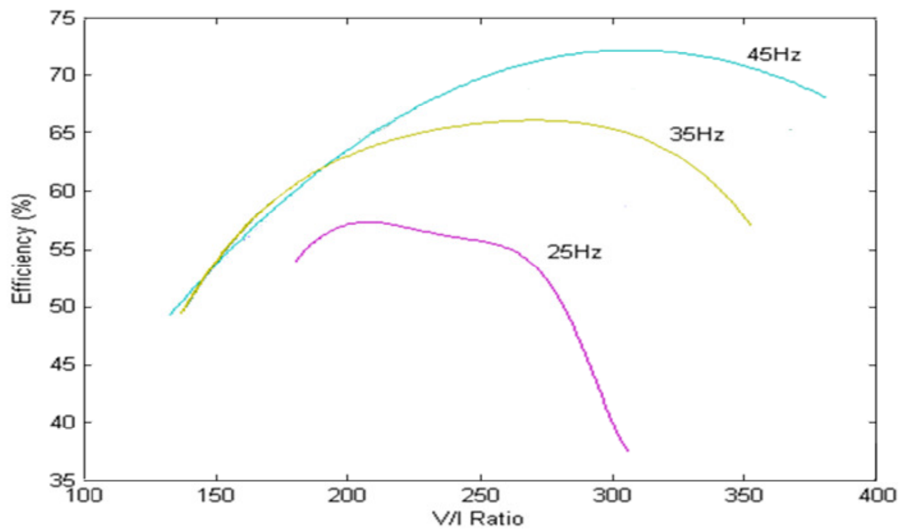

Figure 7. V/I ratio vs. efficiency at different speed.

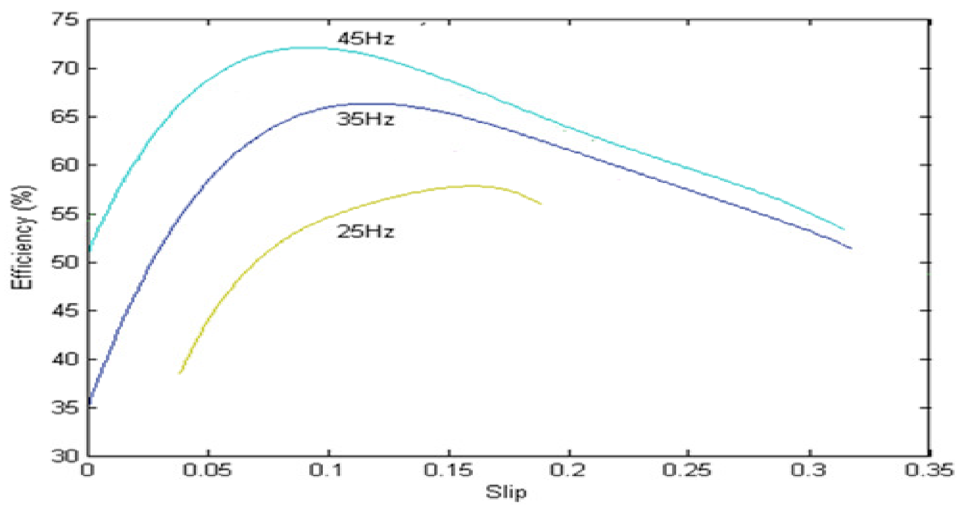

Figure 8. Slip vs. efficiency at different speed.

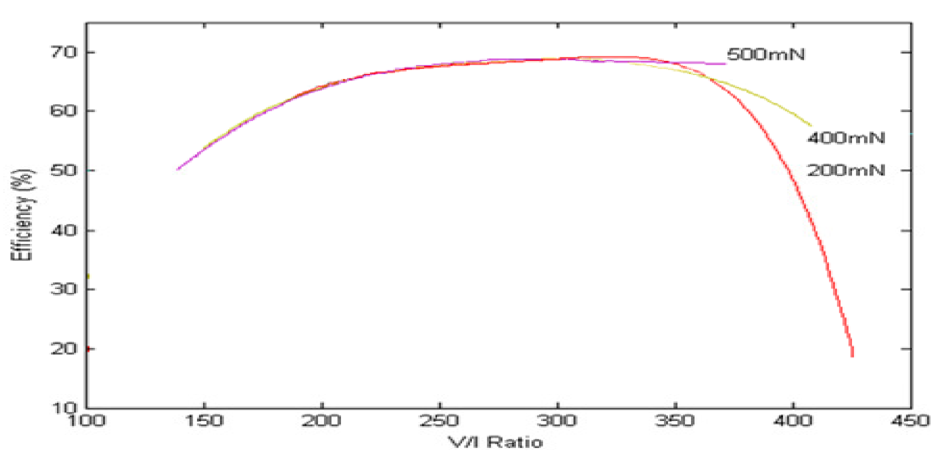

Figure 9. V/I vs. efficiency at fm = 40Hz with different load.

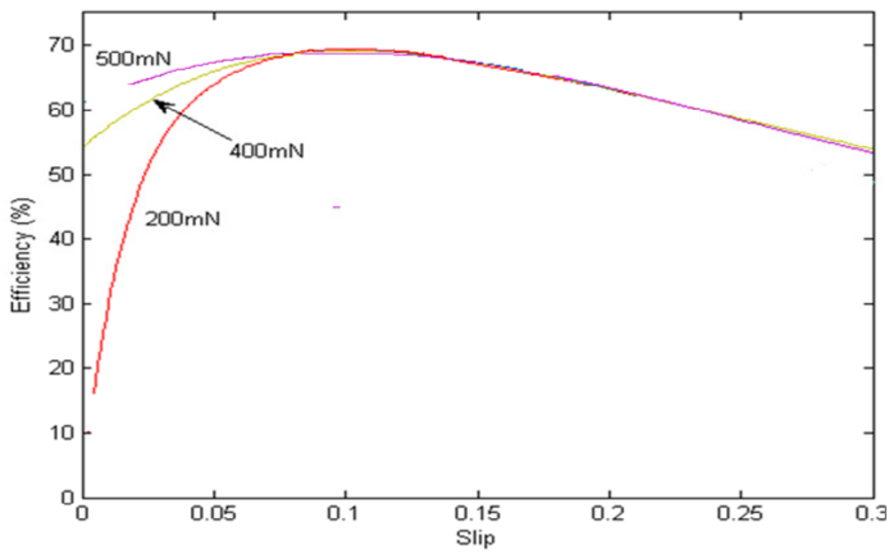

Figure 10. Slip vs. efficiency at fm = 40Hz with different load.

predicts the control variables values based on nonlinear SCIM input-output response data set. VI_RBFNN has the following advantages; 1) avoid the power input calculation and minimum input power searching; 2) avoid the loss calculation and minimum loss searching, 3) avoid the minimum current and minimum power search and; 4) trial and error in power factor method and therefore avoiding unhealthy pulsating torque. Furthermore, by using the proposed VI_RBFNN scheme, the maximum efficiency is easily achieved by operating the SCIM at V/I and slips reference values for any loading conditions and speed. The results show that during steady state operation, the VI_RBFNN scheme has successfully reduced the effort and time required to determine the SCIM maximum efficiency condition.

Finally, it is worth mentioning that the proposed speed control system methodology utilizes slip for maximum efficiency. It is known that the maximum torque of SCIM depends on slip for maximum torque. Further research can be conducted on the determination of maximum torque using RBFNN.

ACKNOWLEDGEMENT

The authors thank University Malaysia Pahang for their support in finishing this project.

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