Efficiency Optimization of Variable Speed Induction Motor Drive Using Online Backpropagation

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Abstract-- Development of an efficiency optimization control for variable speed drive system is important not only from the viewpoints of energy saving but also from the broad perspective of greenhouse emission. In this paper the designs of a back propagation based efficiency optimization control (BPEOC) for variable speed compressor induction motor drive is described. The controller is designed to generate signal voltage and frequency references simultaneously. This technique allows for control of both the speed and efficiency. In order to achieve a robust BPEOC from variation of motor parameters, an online learning algorithm is employed. Simulation of the BPEOC and laboratory experimental set up has been developed using TMS320C60 digital signal processor. The result demonstrated a significant increase in efficiency and an improvement in speed performance.

Index Terms—Variable speed induction motor drive, efficiency optimization control, neural network control

I. INTRODUCTION

Induction motors are extensively used in industrial and household appliances consume about 54% of the total consumed electrical energy [1]. In air conditioning system, the induction motors are oftenly used to drive a compressor at constant speed operation. However, because the typical load profile of this load is that the load torque varies with speed, therefore implementation of a variable speed drive for it is potential to increase energy saving [2].

The efficiency of induction motor when operate at rated speed and load torque is high. Unfortunately for variable load operation the application of the motor at rated flux will cause the iron losses to increase excessively, hence its efficiency will reduce dramatically [3,4]. In order to reduce the iron losses the flux level should be set lower than rated flux, but this will increase the copper loss. Therefore, to optimize the efficiency of the induction motor drive system at partial load, it is essential to obtain the flux level that minimizes the total motor losses [3,5,6].

A number of methods for optimizing the efficiency commonly known as energy or efficiency optimization control have been proposed in literature. In general there are two different approaches of efficiency optimization in induction motor drive [5]. The first approach, named losses model controller uses analytical computation of the motor losses to optimize the efficiency. The optimum flux is determined by deriving the motor power losses against flux. From this derivation, the unique value of flux achieved. The main advantage of this method is that it does not require extra hardware but it needs an accurate knowledge of motor parameters. Because the motor parameters vary against temperature and magnetic saturation and also some of the motor losses such as stray losses and iron losses are very complex to be determined, hence this method is difficult to be implemented [7,8].

The second approach is named as online or search efficiency optimization control method. This is based on an input power measurement. The online control method will search the flux level gradually to obtain the maximal efficiency of the motor drive. Therefore, it does not depend on the knowledge of motor parameters. This technique is also known as online energy optimization control method. The main advantage of this method is that it is completely insensitive to motor parameters variation. Some implementations of the intelligent control method such as fuzzy logic and neural network control in this method have many advantages over classical search control methods proposed in literature [8,9,10,11,12].

The development of neural network for searching efficiency optimization control method has been considered due to their various advantages over conventional ones. Based on a scalar control model, a simulation of the neural network control for efficiency optimization of induction motor drive was introduced in [9,10], while the simulation of neural efficiency optimization control in vector control method was proposed [11]. To compensate the variation of resistance iron core loss against to the change of flux and frequency, in vector control model the variation of iron core loss resistance is taken into consideration [12]. All of these methods implement an offline learning algorithm.

Even though simulation results of the neural network efficiency optimization control showed an increase in efficiency of the induction motor drive [9,10,11,12], the

implementation of the offline learning algorithm could reduce the superiority of the online efficiency optimization control method. This is due to the training data employ fixed motor parameters. Consequently, for a real time application the performance of the controller will decrease, because the motor parameters vary against the temperature and magnetic saturation.

This paper proposes an improvement of the neural network control design for efficiency optimization of the variable speed induction motor drive. The neural network controller model is developed based on online learning algorithm using Back propagation scheme. The controller is designed to generate signal voltage and frequency reference simultaneously. The design of the controller is verified by simulation and laboratory experiment.

In the following section the control system of the proposed neural network efficiency optimization based on scalar control method is described. Development of the neural network control online learning algorithm will be explained in section III. Simulation and experimental results is given in section IV. The last section will be a discussion and conclusion.

II. System control description

A. Scalar Control Model

According to the principle of a scalar control method, the speed and electromagnetic torque of the induction motor can be controlled by adjusting voltage and frequency. It can be achieved with different combination of voltage and frequency. In scalar control model usually the motor flux level is assumed by volt per hertz (V/f).

Operation of the induction motor at rated flux results in good utilization of the motor iron hence a high torque per stator ampere can be achieved. At rated flux the nominal electromagnetic torque can be developed at all frequencies. For these reasons the constant V/f control has been often regarded as an optimal control scheme. However, at light load the flux may be greater than necessary for development of required load torque, hence the total losses become high and decrease the efficiency.

B. Search Efficiency Optimization Control Model

The principle of search efficiency optimization control with scalar control at steady state is described in Fig.1. By reducing the voltage stator, the flux and the iron loss will decrease. Although the copper losses increase, the total power loss will decrease hence the dc link power reduces. The search decreases gradually until the system settles down at the minimum input power point P, as indicated. At any operating point the controller will generate an optimum flux level for achieving a minimum input power.

Based on the aforementioned principle, direct inverse neural control is developed. In this model the controller is trained to capture the inverse dynamics of the system. The block diagram of the proposed BPEOC of induction motor drive for variable speed compressor is shown in Fig. 2. From this figure the development of the controller in the digital signal processor is indicated by dashed outline.
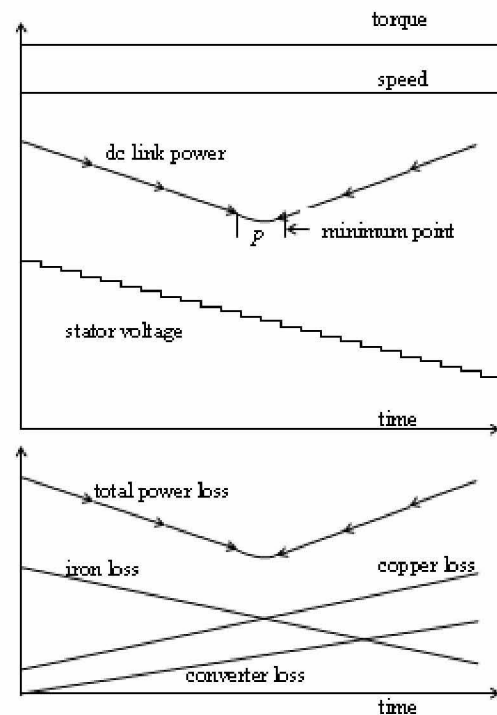

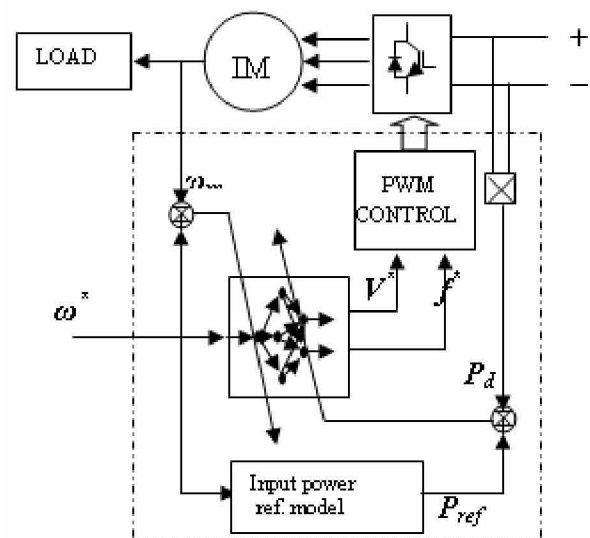Fig. 1. Principle of the efficiency optimization control search

Fig. 2. Scalar controlled induction motor drive for efficiency optimization model

In this scheme the controller recieves command from the speed reference signal (ω_{ref}). While the speed error signal ($\omega_{ref} - \omega_m$) and input power error signal ($P_{ref} - P_d$) are used to supervise the neural network training of the controller. Output of the BPEOC generate two signal controls, voltage reference (m_i) and frequency references (m_f).

III. Neural Network Efficiency Optimal Control Design

Inspired by the successful function of the human brains, the artificial neural network (ANN) was developed for solving many large scale and complex problems. Based on ability to

process some information and also to analyze the input and output simultaneously, it makes ANN suitable for dynamic and nonlinear system. Referring to the classical search EOC system, the development of the structure and learning algorithm of the BPEOC is explained as follows.

A. Structure of BPEOC

To design the neural network control some information about the plant is required. Basically, the numbers of input and output neuron at each layer are equal to the number of input and output signals of the system respectively. Further the number of hidden layers and the total neurons is depended on the complexity of the system and the required training accuracy [9]. To implement search efficiency optimal control of an induction motor drive, a multilayer perceptrons neural network control is developed. Based on the type of the task to be performed, the structure of the proposed BPEOC is as shown in Fig.3.
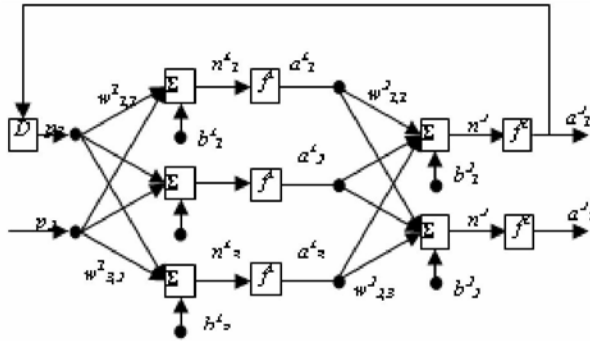

Fig. 2. Diagram block of neural network efficiency optimization control for induction motor drive

The controller consists of input layer, hidden layer and output layer. Based on number of the neuron in the layers, the BPEOC is defined as a 2-3-2 network structure. In this design one of the output signals $a^2{}_1$ is fed back to the first layer as an input signal. The first neuron of the output layer is used as a reference signal frequency ($a^2{}_1=m_f$) and the second neuron is used as a reference signal voltage ($a^2{}_2=m_i$). The speed command of the controller is represented by p_2. The connections weight parameter between j^{th} and i^{th} neuron at m^{th} layer is given by $w^m{}_{ij}$, while bias parameter of this layer at i^{th} neuron is given by $b^m{}_i$. Transfer function of the network at i^{th} neuron in m^{th} layer is defined by:

$$n_i^m = \sum_{j=1}^{S^{m-1}} w_{ij}^m a_j^{m-1} + b_i^m \qquad (1)$$

The output function of neuron at m^{th} layer is given by:

$$a_i^m = f^m(n_i^m) \qquad (2)$$

Where f is activation function of the neuron. In this design the activation function of the output layer is unity and for the hidden layer is a tangent hyperbolic function given by:

$$f^m(n_i^m) = \frac{2}{1 + e^{-2n_i^m}} - 1 \qquad (3)$$

Updating of the connection weight and bias parameters are given by:

$$w_{ij}^m(k+1) = w_{ij}^m(k) - \alpha \frac{\partial F(k)}{\partial w_{ij}^m} \qquad (4)$$

$$b_i^m(k+1) = b_i^m(k) - \alpha \frac{\partial F(k)}{\partial b_i^m} \qquad (5)$$

where k is sampling time, α is learning rate, and F performance index function of the network.

B. Online Learning Algorithm of BPEOC

After the neural network architecture is modelled, the next stage defines the learning model to update network parameters. By this learning capability, it makes the ANN suitable to be implemented for the system with motor parameters which are difficult to define and vary against with environment. The training process minimizes the error output of the network through an optimization method. Generally, in learning mode of the neural network controller a sufficient training data input-output mapping data of a plant is required. Since the motor parameters of the induction motor drive vary with temperature and magnetic saturation, the online learning Back propagation algorithm is developed.
Based on first order optimization scheme, updating of the network parameters are determined. The performance index sum of square error is given by:

$$F(k) = \frac{1}{2} \sum_i e_i^2(k) \qquad (6)$$

$$e_i(k) = t_i(k) - a_i(k) \qquad (7)$$

where t_i is target signal and a_i output signal on last layer.

The gradient descent of the performance index against to the connection weight is given by:

$$\frac{\partial F}{\partial w_{ij}^m} = \frac{\partial F}{\partial n_i^m} \frac{\partial n_i^m}{\partial w_{ij}^m} \qquad (8)$$

The sensitivity parameter of the network is defined as:

$$s_i^m = \frac{\partial F}{\partial n_i^m} \qquad (9)$$

$$s_i^m = \frac{\partial F}{\partial a_i^m} \frac{\partial a_i^m}{\partial n_i^m} \qquad (10)$$

Gradient the transfer function again to the connection weight parameter is given by:

$$\frac{\partial n_i^m}{\partial w_{ij}^m} = a_i^{m-1} \qquad (11)$$

From substitution equation (9) and (11) into (4) the updating connection parameter is given by:

$$w_{ij}^{m-1}(k+1) = w_i^{m-i}(k) - \alpha s_i^m(k) a_i^{m-1}(k) \qquad (12)$$

With the same technique the updating bias parameter is given by:

$$b_i^{m-1}(k+1) = b_i^{m-i}(k) - \alpha s_i^m(k) \qquad (13)$$

IV. SIMULATION AND EXPERIMENTAL RESULTS

A. Simulation Results

Simulation was carried out to investigate the performace of the BPEOC. In this section the dynamic model of a three-phase induction motor, space vector PWM and neural network control model have been developed. The simulation is developed using Borland C++, and then embedded as S-function in Simulink-Matlab. The parameters for the motor are given by:

- Power, frequency and pole are 0.25 Hp, 50 Hz and 4.
- Stator and rotor resistances, $R_s = 5.1\ \Omega$. and $R_r = 4.0\ \Omega$.
- Stator and rotor self inductances are 0.211and 0.211 H.
- Mutual inductance is 0.199 H.
- Combined of inertia is 0.003kg-m^2.

To represent a compressor load, equation of the load torque proportional to the square of the speed is approached by:

$$T_{load} = c_l \omega_m^2 \qquad (14)$$

where ω_m is the rotor speed in rpm and c_l is the compressor load coefficient ($c_l = 6.5 \times 10\text{-}7$).

To verify performance of the proposed BPEOC, the simulation results for a conventional neural network (NN) constant volt/hertz and the proposed controller are compared. With the same speed reference, the simulations of both methods are run simultaneously. The speed trajectory of the motor when the reference is decreased from 700 to 500 rpm is shown in Fig.4.
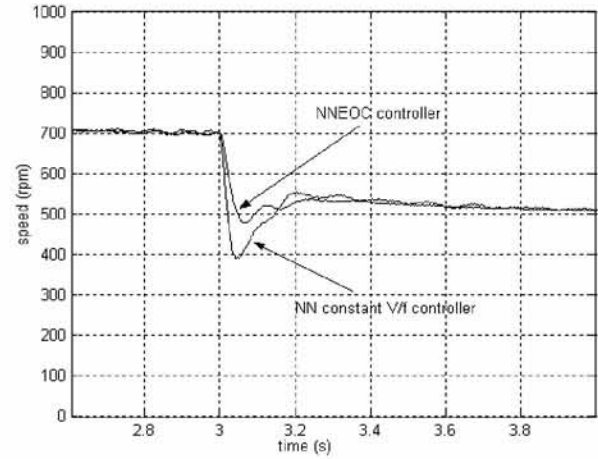

Fig.4. Speed response comparison between BPEOC and NN constant V/f controller with speed reference is varied down.

Based on speed command variations the consumed power of the compressor motor using neural network NN constant V/f and BPEOC controller can be shown through the input power trajectory. The input power searching is captured from maximum overshoot to steady state value. Fig. 5 shows the input power search curve when the speed reference varies down from 700 rpm to 500 rpm.
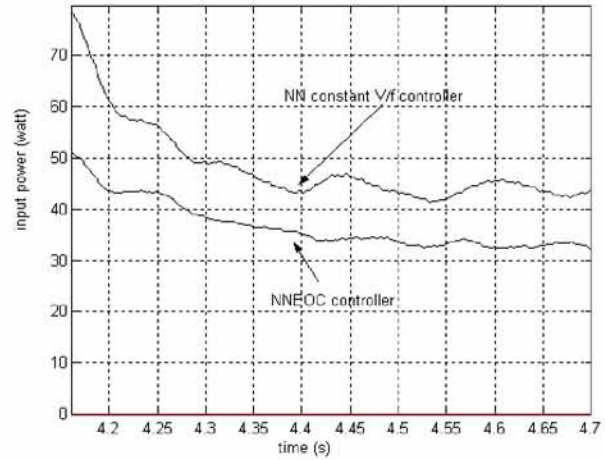

Fig.5. Input power search curve between BPEOC and NN constant V/f controller with speed reference is varied from 700 to 500 rpm.

B. Experimental Results

Based on the simulation model, the experimental setup of the proposed efficiency optimization control using neural network was developed. The BPEOC on the test system was implemented using the digital signal processor control board DS1102. The DSP board consists of TMS320C31 and TMS320P14 DSPs. The first processor implements the space vector PWM scheme, whereas the second provides the BPEOC controller. The rotor of the induction motor was coupled with a dynamometer system as a compressor load simulator. The three phase space vector PWM inverter was implemented using IGBTs.

Fig. 6 shows the experimental response, when the speed command varying downs from 700 to 500 rpm. From this figure, it shows that the overshoot and ripple of the speed decrease. Therefore it is clear that the speed dynamic responses of the proposed method have improvement.
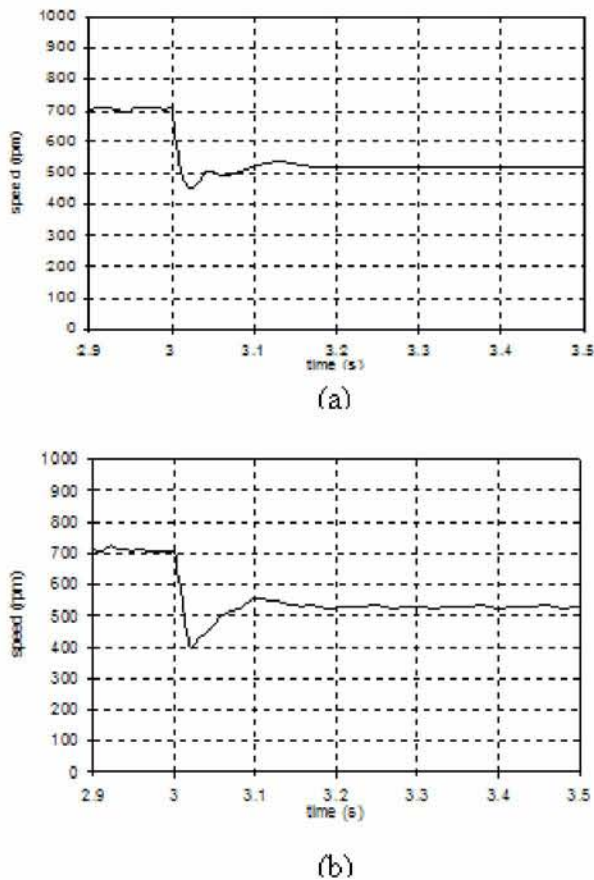

(a)

(b)

Fig.6. Speed response measurement between (a) BPEOC and (b) NN constant V/f controller with speed reference is varied down from 700 to 500 rpm.

Measurement of the input power of the motor when the speed command was varied from 700 to 500 rpm is shown in Fig.7. From this figure, it shows that the same speed reference and load condition the input power of the motor reduce. Beside that ripple of the input power also reduce.
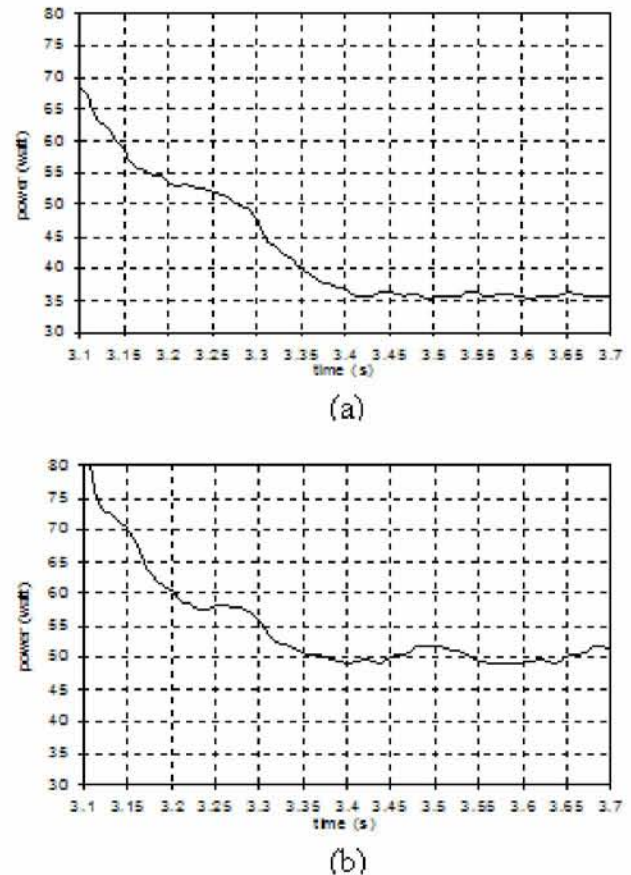

(a)

(b)

Fig.7. Measurement input power search curve between (a) BPEOC and (b) NN constant V/f controller with speed reference is varied from 700 to 500 rpm.

Based on the input and output power measurement at steady state, efficiency of the motor drive for various speed oeration is depicted in Fig.8
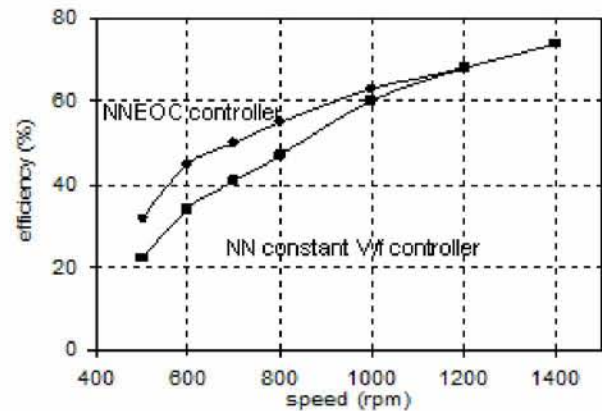

Fig.8. The efficiency measurement between BPEOC and NN constant V/f controller for various speed operation.

From figure 8 it shows that at near nominal speed operation the efficiency of both methods are quite the same, while for low speed operation the efficiency of the proposed method increase.

V. CONCLUSION

The neural network controller for efficiency optimization of variable speed compressor motor drive system has been presented in this paper. The proposed method employs a first order online learning Back propagation algorithm to generate the stator voltage and frequency references simultaneously. The controller does not require motor parameters data. Experimental and simulation results validate the effectiveness of the method. The results show that at low speed operation the speed performance and efficiency of motor drive can be increased.

VI. REFERENCES

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