CHAPTER 7

DEVELOPMENT OF NEURO-FUZZY ESTIMATOR FOR
ENERGY EFFICIENT OPERATION OF VOLTAGE
CONTROLLED INDUCTION MOTOR DRIVES

7.1 INTRODUCTION

It has been proved that the efficiency improvement with reduced voltage operation of the lightly loaded induction motor drive is an attractive scheme for energy conservation. The concept is simple and many researchers have focused on it. Even though elaborate studies have been carried out in the performance optimization of voltage controlled induction motor drives (Xue et al (2006), Nafesa (2010)), a few major drawbacks are noticed and are listed below:

1. The best efficiency point is obtained by gradually changing the SCR firing angle $\alpha$. This search algorithm is similar to trial and error based one and hence in the previous works no clear cut design procedure for the controller is presented.

2. The search technique consumes more time for reaching the optimum point than can be reasonably be allowed. More the time spent, less will be the energy saved.

3. The stepwise change in stator voltage results in poor dynamic response of the drive system. This is more predominant in motors with low moment of inertia.
4. In search technique, the exact point of minimum current may be missed if the change in voltage is large since the voltage-current characteristics curve is more flat in optimum efficiency region. Further by this method, this minimum current point is never reached and only persistent oscillations about this point are observed which requires an additional controller.

This chapter describes the application of fuzzy logic based approach for performance enhancement of voltage controlled induction motor drive. It is shown that the conventional search method for reaching the best efficiency point has got many drawbacks. These demerits are overcome using artificial neutral network based techniques. It is observed that while neutral network based methods are effective in energy saving aspects, the following disadvantages are noted:

1. The information base requirement for training the neutral network is larger.

2. The training epochs required are found to be larger and hence training consumes more time.

An open loop experimental set up suitable for ac voltage controller fed induction motor drive operation is designed and fabricated in the laboratory. The induction motor is subjected to variable load operation with the above configuration and various input-output variables are measured. These variables are used for formation of membership functions and decision making rule base for optimum voltage estimation. The fuzzy membership functions and rule base are iterated manually many times to fall in line with the experimentally observed results. Extensive simulation is carried out for performance optimization of lightly loaded induction motor drive with the
fuzzy logic estimator for optimum voltage identification. Simulation results clearly verify the validity of the proposed method.

The experimental set up for soft starting developed in the chapter 2 is used for experimental study. After soft starting is completed, the mechanical switches are not closed. For different load conditions, the microcontroller is programmed to vary SCR firing angle so that least current is drawn from the source. The following variables are measured:

1. Optimum SCR firing angle, $\alpha_{opt}$ prior to load change
2. Optimum steady state motor current, $I_o$ prior to load change
3. Steady state motor current, $I_{new}$ after load change.

With these variables, the new value of SCR firing angle for best efficiency after load change, $\alpha_{opt(new)}$ is obtained by varying the program in the microcontroller. The experiment is performed for all possible values of the above variables in the entire operating domain of the drive. The relationship between these variables is then written as

$$\alpha_{opt(new)} = f(\alpha_{opt}, I_o, I_{new})$$  \hspace{1cm} (7.1)

The above relationship can be simplified as

$$\alpha_{opt(new)} = f(I_o, I_{new})$$  \hspace{1cm} (7.2)

The relationship in equation 7.2 is obtained through fuzzy variables and an appropriate decision table is formed. Membership functions and rule base are shown in figure 7.1(a),(b),(c) and 7.2. The membership functions are chosen as triangular in shape and they are represented in the following way:
1. The universe of discourse of $I_o$ is characterized by 11 subsets and are grouped between $I_{o1}$ (Optimum 1) to $I_{o8}$ (Optimum B).

2. The universe of discourse of $I_{new}$ is described by 8 fuzzy subsets and are labeled as IN1 (New current 1) to IN8 (New current 8).

3. The membership functions of $\alpha_{opt,new}$ are depicted by 7 subsets with names $\alpha_1$ to $\alpha_7$.

After defining all subsets, the rule base is iterated to cope up with the experimentally derived results.

**Figure 7.1 (a)Membership function of optimum current**

![Membership function of optimum current](image1)

**Figure 7.1 (b)Membership function of new load current**

![Membership function of new load current](image2)
In order to gain both the advantages of fuzzy systems and neural networks—fuzzy logic allows a reasonable amount of approximations and uncertainties, while neural network is computationally compact and fast—a neuro-fuzzy system is now developed. In the present case there are two inputs namely, \( I_{opt} \), \( I_{new} \) and a single output, \( \alpha_{opt} \). Hence there should be two input
neurons and a single output neuron. No attempt has been made to optimize the number of hidden neurons and is obtained by trial and error. It is found that five neurons are sufficient for mapping the input-output relationship obtained through fuzzy logic system. The fuzzy logic estimator developed earlier, is fed with numerous inputs and outputs are obtained. This information base thus obtained is used to train the neural network. The training of the network is carried out using the neural network toolbox in Matlab. The structure of designed neural network is shown in the figure 7.3. The input and output neurons employ linear activation function, while the output neurons make use of typical sigmoid transfer functions. The weights and biases are included in the figure 7.3.

Figure 7.3  Topology of 2-5-1 feed forward neural network
Weights:

\[ w^{1,1} \text{-weight to layer 1 from input 1.} \]

\[ [3.79 \ -4.9835; 5.7849 \ -2.3948; -2.4844 \ 5.747; -6.2583 \ -0.1827; -4.6137 \ 4.2325] \]

\[ w^{2,1} \text{-weight to layer 2.} \]

\[ [-0.3374 \ -0.35085 \ -0.35836 \ -0.099944 \ 1.1374] \]

Biases:

\[ b^{(1)} \text{-Bias to layer 1.} \]

\[ [-2.5342; -3.2604; -1.635; 1.635; -2.9367] \]

\[ b^{(2)} \text{-Bias to layer 2.} \]

\[ [0.20805]. \]

7.3 SIMULATION RESULTS

In order to verify the proposed approach, the neural network is now integrated with ac voltage controlled fed drive model and the complete system is shown in the figure 7.4.
Figure 7.4 Matlab model of induction motor drive with neuro-fuzzy estimator.

The simulation results are shown in the figures 7.5.

Figure 7.5 Dynamic response of the drive with neuro-fuzzy estimator
In figure 7.5, at t=0, the motor is driving a load torque of 5 N-m with an optimum SCR firing angle of 63.2 degrees. The rms value of optimum current, $I_{opt} = 1.3$ amperes. At t = 5 seconds, the load torque is decreased to 1.0 Nm. As can be seen, the new value of the motor current reduces to 0.8 amperes. The neural network estimates the value of the optimum SCR firing angle to be 93.9 degrees and the ac voltage controller is now fired at this optimum angle. The optimum value of voltage and current waveforms before and after load change are shown in the figures 7.6(a) and 7.7(b) respectively.

Figure 7.6(a) Voltage and current waveforms prior to load change (prior to optimization)

Figure 7.7 (b) Voltage and current waveforms after optimization
7.6 CONCLUSION

A fuzzy logic based optimum SCR firing angle identification is developed for efficiency maximization of variable-voltage partly loaded induction motor drive. The rule base is derived from experimental values. In order to benefit the dual advantages of neural networks and fuzzy systems, a neural network is then developed. From the simulation results it is evident that the proposed neuro-fuzzy controller works well and the motor always operates in the energy efficient region.