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Development of an Adaptive Neuro-Fuzzy Inference Strategy (ANFIS) for speed control of Induction Motor

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Abstract— **The paper proposes to develop an Adaptive Neuro Fuzzy Inference Strategy (ANFIS) to control the speed of an induction motor. Speed control of an induction motor is significant aspect to produce maximum torque and efficiency. Induction motors exhibit highly non-linear properties, makes it difficult to control. Artificial Neural Network (ANN), Fuzzy logic based controllers are potential candidates for such applications, due to their flexible nature of operation. The basic structure of the ANFIS coordination controller consists of fuzzification, knowledge base, neural network and de-fuzzification. The fuzzification unit converts the crisp data into linguistic variables, as inputs to the rule based block. The set of rules are written on the basis of previous knowledge / experiences in rule based block and are provided to neural network block. Back propagation algorithm is used to train neural network to select proper set of rule base. After rules are selected and fired, control signal is obtained and the optimal outputs are generated. The output of the ANN unit is applied to the de-fuzzification unit and the linguistic variables are converted back into crisp form. By comparing ANFIS controller with other models, it is evident that the addition of learning algorithm to the control system will reduce the rise time and improves performance.**

Index Terms— **Adaptive Neuro Fuzzy, Fuzzy Inference Strategy, Fuzzy Knowledge Base, Speed control of Induction Motor.**

I. INTRODUCTION

In conventional control methods, the system parameters are assumed to be linear. But in practical, the systems parameters are purely non-linear and time-dependent. It uses an accurate mathematical model, which is very difficult to obtain. The performance of conventional control system drops off for non-linear systems. Hence, proper control through the conventional techniques may not yield appropriate results [1-2]. Various advanced and intelligent control techniques have been explored by researchers in the recent past. Fuzzy logic based controllers are considered as potential candidates for such an application. The Fuzzy Logic controllers don't require a mathematical model which makes it popular in the area of electromechanical devices control [3-5]. These controllers develop a control signal which yields on the firing of the rule base. These rules are written on the previous experiences & are fired which is random in nature. Hence the outcome of the controller is also random & optimal results may not be obtained [8]. Thus the major concern with Fuzzy controllers is that the parameters associated with the membership functions and the rules depend on the intuition of the experts. Also the Fuzzy Logic controllers are less sensitive to system parameters variation and it may be difficult to obtain robustness for the various system parameters. The most recent intelligent techniques are based on neural networks. A neural network can be trained to emulate fuzzy controller. Artificial Neural Network (ANN) controller is one of the intelligent controllers, which is usually utilized for two purposes, for constructing non-linear controllers and for adding human intelligence to controllers. These controllers are less sensitive to system parameters variation. Thus it would be difficult to obtain robustness for the various system parameters. Neural Network has the learning capability, but does not have any knowledge of the system (adaptability) [6-7]. An alternative method would be to combine the capabilities of Fuzzy logic and neural network. Such a combination is thus believed to be an effective method to control the speed of motors. Designing of a robust System with "Adaptive Neuro Fuzzy Inference Strategy (ANFIS) for Speed Control of Induction Motor" is the main focus of this paper.

II. MODELLING OF AN INDUCTION MOTOR

The dynamic model of an Induction motor is essential for transient analysis. When the motor is placed in a feedback control loop for controlling its speed, the dynamics of the machine model dictate the stability of the system. The dynamics of an induction motor are complex because the rotor windings move with respect to stator windings, creating a transformer with time-changing coupling coefficient.

A. The dynamic d-q model

A three-phase motor with three stator windings and three rotor windings can be substituted by an equivalent two-phase machine with two stator (in ds -qs axes) and two rotor windings (in dr-qr axes). This technique is called dynamic dq model. If a two-phase power supply with 90° phase difference is fed to the stator, a rotating magnetic field will be created as in a three phase machine. The stationary frame ds-qs axes windings can be transformed into fictitious windings mounted on synchronously rotating de-qe axes at speed 'we'. "Fig. 1" shows the transformation of three-phase into two-phase frame.

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This transformation eliminates time-changing coupling coefficients between the two sets of windings. The variables in the ds-qs frame can be transformed into de-qe axes variables, and vice versa, by resolving the variables into the respective axes components. It can be easily shown that if the ds-qs variables are sinusoidal variables, then de-qe variables are dc values. This transformation is of great advantage because transient analysis with dc variables is very convenient. In the two-phase machine, first the stator winding voltages are transformed into synchronous frame (de-qe) equations. Then, the rotor voltage equations are transformed into the de-qe frame and merged into the respective equivalent circuits shown in "Fig. 2". The expression of developed torque and mechanical load equation with constant load torque are included in the "Fig. 3". The machine model is nonlinear and is given by a 5th-order system.

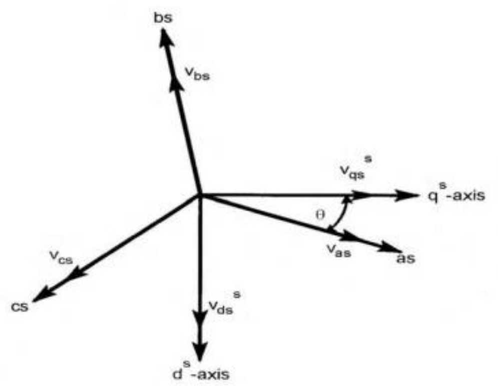

Figure 1: Stationary frame (as-bs-cs to ds-qs) transformation. The 3-phase frame as-bs-cs are converted into 2-phase ds-qs frame.

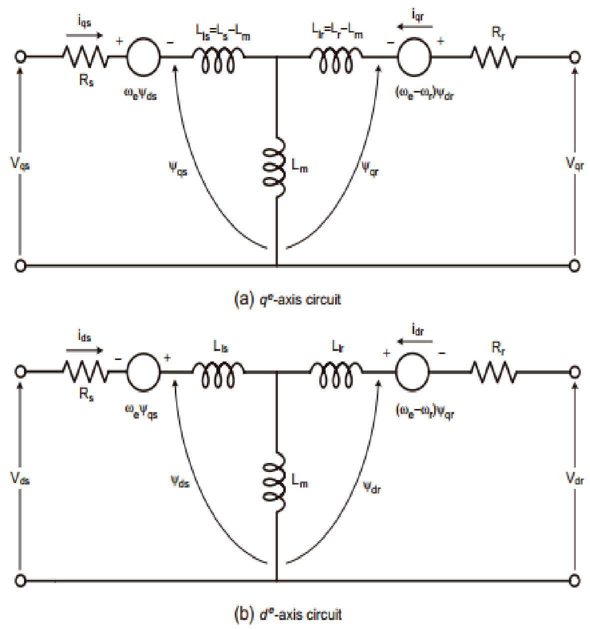

Figure 2: Synchronous frame (de-qe) dynamic model equivalent.

"Fig. 2" shows the transient equivalent circuits of an induction motor in a synchronously rotating de-qe frame, where the frame is moving at speed we with respect to the stator.

$$\begin{bmatrix} v_{qs} \\ v_{ds} \\ v_{qr} \\ v_{dr} \end{bmatrix} = \begin{bmatrix} R_s+L_s & \omega_e L_s & SL_m & \omega_e L_m \\ -\omega_e L_s & R_s+SL_s & -\omega_e L_m & SL_m \\ SL_m & (\omega_e-\omega_r)L_m & R_s+SL_m & (\omega_e-\omega_r)L_r \\ -(\omega_e-\omega_r)L_m & SL_m & -(\omega_e-\omega_r)L_r & R_s+SL_m \end{bmatrix} \begin{bmatrix} i_{qs} \\ i_{ds} \\ i_{qr} \\ i_{dr} \end{bmatrix} \text{......(1)}$$

$$T_e = \frac{3}{2}\left|\frac{p}{2}\right| (\psi_{ds} i_{qs} - \psi_{qs} i_{ds}) \text{ ...... (2)}$$

$$T_L + \frac{2}{p}\left|\frac{p}{2}\right| JS\omega_r = T_e \text{ .... (3)}$$

Figure 3: Dynamic model (de-qe) equations of an induction motor with voltages and currents.

B. Modelling of the 3-Phase Inverter

The 3-Phase balanced sinusoidal voltages are given through the 3-Phase bridge inverter as shown in "Fig. 4". This inverter has eight permissible switching states. These eight permissible switching states and the corresponding phase-to-neutral voltages of the induction machine are shown in "table I".

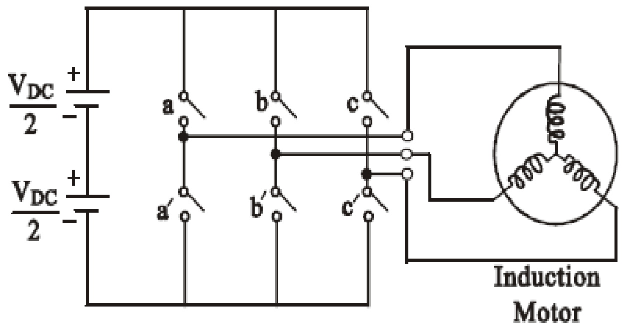

Figure 4: Power circuit connection diagram for the Induction motor.

Table I: Inverter switching states

V_i	a	b	c	V_{An}	V_{Bn}	V_{Cn}
V_0	0	0	0	0	0	0
V_1	1	0	0	$2V_{DC}/3$	$-V_{DC}/3$	$-V_{DC}/3$
V_2	1	1	0	$V_{DC}/3$	$V_{DC}/3$	$-2V_{DC}/3$
V_3	0	1	0	$-V_{DC}/3$	$2V_{DC}/3$	$-V_{DC}/3$
V_4	0	1	1	$-2V_{DC}/3$	$V_{DC}/3$	$V_{DC}/3$
V_5	0	0	1	$-V_{DC}/3$	$-V_{DC}/3$	$2V_{DC}/3$
V_6	1	0	1	$V_{DC}/3$	$-2V_{DC}/3$	$V_{DC}/3$
V_7	1	1	1	0	0	0

III. SYSTEM MODEL

A controller is a device which controls each & every operation in the system making decisions. From the control system point of view, it brings stability to the system when there is a disturbance or variation in

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the parameters. The controller may be hardware based or software based or a combination of both. The development of the control strategy for control the speed of an induction machine is presented using the concepts of ANFIS control scheme.

A. The ANFIS Scheme

Neural networks can learn from data and poses an ability to train with various parameter of an induction motor. As a non-linear function, they can be used for identifying the extremely nonlinear system parameters of an induction motor with high accuracy. But it is difficult to get an insight about the meaning associated with each neuron and each weight. Fuzzy logic can be used to control various parameters of the IM. Fuzzy rule based models are easy to understand as it uses linguistic terms and the structure of IF-THEN rules. Unlike neural networks, fuzzy logic lacks learning capability. The combination of Fuzzy logic and neural networks yields very significant results. This technique of merging the learning capability of the NNs and the knowledge representation of Fuzzy Logic has given rise to the neuro fuzzy networks [9-10].

The ANFIS is basically a neural network-based training of a fuzzy system. If the desired input–output data sets are available for a fuzzy system, the MFs and rule table for a fuzzy model can be designed using the Neural Network training method. The structure of the network is composed of a set of units (and connections) arranged into five connected network layers as shown in "Fig. 5".

Layer 1: This layer consists of input variables (membership functions), input 1 & input 2. Here, triangular or bell shaped MF can be used. This layer just supplies the input values to the next layer, where I = 1 to N.

Layer 2: This layer is called as membership layer. It checks for the weights of each MF. It receives the input values from the 1st layer and act as MFs to represent the fuzzy sets of the respective input variables. Further, it computes the membership values which specify the degree to which the input value belongs to the fuzzy set, which acts as the inputs to the next layer.

Layer 3: This layer is called as the rule layer. Each node in this layer performs the pre-condition matching of the fuzzy rules, i.e., they compute the activation level of each rule, the number of layers being equal to the number of fuzzy rules. Each node of these layers calculates the weights which are normalized.

Layer 4: This layer is called as the defuzzification layer & provides the output values y resulting from the inference of rules. Connections between the layers 3 & 4 are weighted by the fuzzy singletons that represent another set of parameters for the neuro fuzzy network.

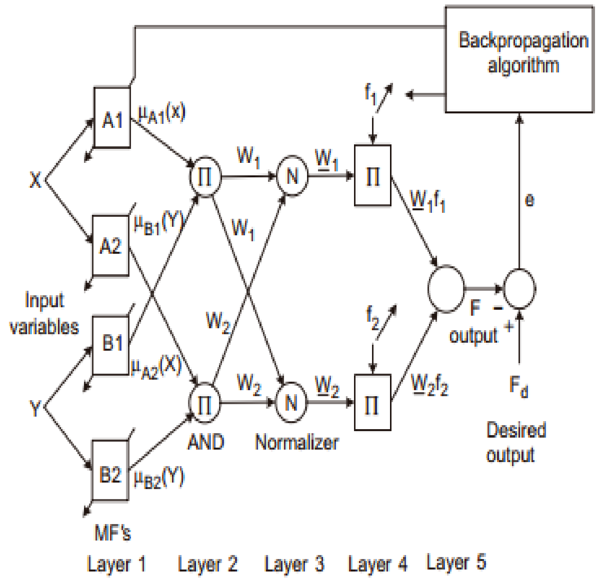

Figure 5: The Adaptive Neuro Fuzzy Inference System (ANFIS).

Layer 5: This layer is called as the output layer which sums up all the inputs coming from the layer 4 and transforms the fuzzy classification results into a crisp (binary). The calculated output F is compared with the desired value Fd, and the error signal is used to train the network parameters.

The ANFIS structure is tuned automatically by least- square estimation & the back propagation algorithm. The algorithm shown above is used in the next section to develop the ANFIS controller to control the various parameters of the induction motor. Because of its flexibility, the ANFIS strategy can be used for a wide range of control applications. The MATLAB/Fuzzy Logic Toolbox can be used to design the ANFIS. The network can be trained off-line or on-line. "Fig. 5" shows the feedforward ANFIS structure, where the functions A1, A2, B1, B2, f1, and f2 are being tuned by a backpropagation algorithm for the desired output Fd.

B. Control Strategy

The development of control strategy for controlling the speed of an induction machine is shown in "Fig. 6". The basic structure of developed ANFIS controller consists of fuzzification, knowledge base, neural network and the de-fuzzification blocks. A training data set that contains the desired input / output data pairs of target system to be modeled are required. The inputs to the ANFIS controller, the error & the change in error are modeled using "(4)".

$$e(k) = \omega_{ref} - \omega_r$$
$$\Delta e(k) = e(k) - e(k-1) \quad (4)$$

Where ω_{ref} is the reference speed, ω_r is the actual speed, $e(k)$ is the error and $\Delta e(k)$ is the change in error.

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In the fuzzification process, the speed error & the change in error are converted from crisp variables into fuzzy or linguistics variables. The fuzzification maps the 2 input variables to linguistic labels of the fuzzy sets. Each fuzzy label has an associated membership function. The membership function of triangular type is used. The inputs are fuzzified using the fuzzy sets & are given as input to ANFIS controller.

The Knowledge base consists of rule base. The set of 49 rules are written on the basis of previous knowledge / experiences in the rule based block. The rule base block is connected to the neural network block. Back propagation algorithm is used to train the neural network to select the proper set of rule base. Once the proper rules are selected & fired, the control signal required to obtain the optimal outputs is generated. The distributed weights in the network contribute to the distributed intelligence of the network. Initially with the untrained network, random weights are selected. The output generated is also random in this case and may mismatch the desired output pattern for a given input. The actual output is compared with the desired output and the weights are adjusted by the supervised back-propagation training algorithm until pattern matching occurs. Then the error becomes acceptably small.

Table II: Rule base for controlling the speed.

E / ΔE	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

There are two input variables and seven fuzzified variables. The controller has a set of 49 rules for the ANFIS controller. Out of these 49 rules, the proper rules are selected by the training of the neural network with the help of back propagation algorithm & these selected rules are fired.

Further the output from the neural network block has to be converted into crisp output. This process is called as defuzzification. The defuzzifcation transforms fuzzy set information into numeric data information. There are so many methods to perform the defuzzifcation. In our work, we will be using the centre of gravity method. The output of the defuzzification unit will generate the control command which is given as input to the plant through the 3-phase inverter. If there is any deviation in the controlled output (crisp output), this is fed back & compared with the set value & the error signal is generated which is given as input to the ANFIS controller. The ANFIS controller brings back the output to the normal value thus maintaining stability in the system. This controlled output is the weighted average of the proper rule based outputs.

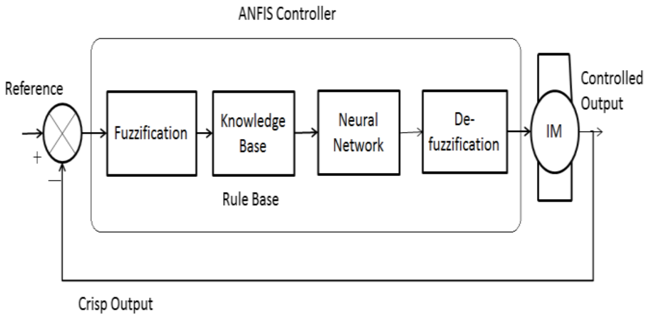

Figure 6: Block diagram of the ANFIS control scheme for the speed control of the IM.

The inputs to the ANFIS controller, the error & the change in error are modeled. The fuzzification unit converts the crisp data into linguistic variables, which is given as inputs to the rule based block. The set of rules will be written on the basis of previous knowledge / experiences in the rule based block. The rule base block is connected to the neural network block. Back propagation algorithm is used to train the neural network to select the proper set of rule base. For developing the control signal, the training is a very important step in the selection of the proper rule base. Once the proper rules are selected & fired, the control signal required to obtain the optimal outputs is generated. The output of the NN unit is given as input to the de-fuzzification unit and the linguistic variables are converted back into the numeric form of data in the crisp form.

CONCLUSIONS

By comparing ANFIS controller with other models, it is evident that the addition of learning algorithm to the control system will decrease rise time and improves the performance. For variable loads, when there is a sudden change in load, the ANFIS controller is expected to reach its steady state value faster without any overshoots. The transient response of an induction machine is expected to improve greatly. The main advantage of ANFIS controller is that the designs of these controllers do not depend on accurate system mathematical model and its performance is robust. The knowledge base controlled by back propagation algorithm makes the system adaptive to the changes in the parameter.

Simulation results of the induction motor will be presented in Matlab to validate the proposed architecture. The comparison between the performance of an induction motor drive with Conventional controller, Fuzzy controller and developed Adaptive Neuro Fuzzy (ANFIS) controller will be presented. The performance of the Induction motor drive will be analyzed for no load, constant and variable loads.

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