Dynamic Simulation of Induction Motor Drive using Neuro Controller

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Abstract— Induction Motors are widely used in Industries, because of the low maintenance and robustness. Speed Control of Induction motor can be obtained by maximum torque and efficiency. Apart from other techniques Artificial Intelligence (AI) techniques, particularly the neural networks, improves the performance & operation of induction motor drives. This paper presents dynamic simulation of induction motor drive using neuro controller. The integrated environment allows users to compare simulation results between conventional, Fuzzy and Neural Network controller (NNW). The performance of fuzzy logic and artificial neural network based controller’s are compared with that of the conventional proportional integral controller. The dynamic Modeling and Simulation of Induction motor is done using MATLAB/SIMULINK and the dynamic performance of induction motor drive has been analyzed for artificial intelligence controller.

Index Terms— Neuro Network(NNW), PI Controller, Fuzzy Logic Controller(FLC), Sugeno Fuzzy Controller

I. INTRODUCTION

Three phase Induction Motor have wide applications in electrical machines. About half of the electrical energy generated in a developed country is ultimately consumed by electric motors, of which over 90% are induction motors. For a relatively long period, induction motors have mainly been deployed in constant-speed motor drives for general purpose applications. The rapid development of power electronic devices and converter technologies in the past few decades, however, has made possible efficient speed control by varying the supply frequency, giving rise to various forms of adjustable-speed induction motor drives. In about the same period, there were also advances in control methods and Artificial Intelligence (AI) techniques. Artificial Intelligent techniques mean use of expert system, fuzzy logic, neural networks and genetic algorithm. Researchers soon realized that the performance of induction motor drives can be enhanced by adopting artificial-intelligence-based methods. The Artificial Intelligence (AI) techniques, such as Expert System (ES), Fuzzy Logic (FL), Artificial Neural Network (ANN or NNW), and Genetic Algorithm (GA) have recently been applied widely in control of induction motor drives. Among all the branches of AI.
the NNW seems to have greater impact on power electronics & motor drives area that is evident by the publications in the literature. Since the 1990s, AI-based induction motor drives have received greater attention. Apart from the control techniques that exist, intelligent control methods, such as fuzzy logic control, neural network control, genetic algorithm, and expert system, proved to be superior. Artificial Intelligent Controller (AIC) could be the best controller for Induction Motor control [1-6]. Since the unknown and unavoidable parameter variations, due to disturbances, saturation and change in temperature exists; it is often difficult to develop an accurate system mathematical model. High accuracy is not usually of high importance for most of the induction motor drive. Controllers with fixed parameters cannot provide these requirements unless unrealistically high gains are used. Therefore, control strategy must be robust and adaptive. As a result, several control strategies have been developed for induction motor drives within last two decades. Much research work is in progress in the design of hybrid control schemes. Fuzzy controller conventionally is totally dependent to memberships and rules, which are based broadly on the intuition of the designer. This paper tends to show Neuro controller has edge over fuzzy controller. Sugeno fuzzy controller is used to train the fuzzy system with two inputs and one output [10-12]. The performance of fuzzy logic and artificial neural network based controllers is compared with that of the conventional proportional integral controller.

II. DYNAMIC MODELING & SIMULATION OF INDUCTION MOTOR DRIVE

The induction motors dynamic behavior can be expressed by voltage and torque which are time varying. The differential equations that belong to dynamic analysis of induction motor are so sophisticated. Then with the change of variables the complexity of these equations decrease through movement from poly phase winding to two phase winding (q-d). In other words, the stator and rotor variables like voltage, current and flux linkages of an induction machine are transferred to another reference model which remains stationary[1-6].

![Figure 1 d q Model of Induction Motor](image)

In Fig.1 stator inductance is the sum of the stator leakage inductance and magnetizing inductance \((L_{s}=L_s+L_{m})\), and the rotor inductance is the sum of the rotor leakage inductance and magnetizing inductance \((L_{r}=L_r+L_{m})\). From the equivalent circuit of the induction motor in d-q frame, the model equations are derived. The flux linkages can be achieved as:

\[
\frac{1}{\omega_p} \frac{d\psi_{qs}}{dt} = v_{qs} - \frac{\alpha_p}{\omega_p} \psi_{qs} - R_s i_{qs} \quad (1)
\]

\[
\frac{1}{\omega_p} \frac{d\psi_{qs}}{dt} = v_{qs} - \frac{\alpha_p}{\omega_p} \psi_{qs} - R_s i_{qs} \quad (2)
\]

\[
\frac{1}{\omega_p} \frac{d\psi_{qt}}{dt} = v_{qt} - \left(\frac{\omega_p}{\omega_p} \psi_{qt}\right) - R_s i_{qt} \quad (3)
\]

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By substituting the values of flux linkages in the above equations, the following current equations are obtained as:

\[
\frac{1}{\omega_0} \frac{d\psi_{\phi q}}{dt} = v_{\phi q} + \left( \frac{\omega_b - \omega_p}{\omega_0} \right) \psi_{\phi q} - R_{\phi \phi q}
\]  

(4)

Where \( \omega_b \) and \( \omega_p \) are the flux linkages over \( L_m \) in the q and d axes. The flux equations are written as follows:

\[
i_{qs} = \frac{\psi_{qs} - \psi_{m0q}}{X_{is}}
\]

(5)

\[
i_{ds} = \frac{\psi_{ds} - \psi_{m0d}}{X_{is}}
\]

(6)

\[
i_{qr} = \frac{\psi_{qr} - \psi_{m0r}}{X_{is}}
\]

(7)

\[
i_{dr} = \frac{\psi_{dr} - \psi_{m0d}}{X_{is}}
\]

(8)

In the above equations, the speed \( \omega_b \) is related to the torque by the following mechanical dynamic equation as:

\[
T_v = T_{i0sd} + \frac{d\omega_{0q}}{dt} T_{i0sd} + \frac{I^2}{p} \frac{d\omega_r}{dt}
\]

(12)

then \( \omega_b \) is achievable from above equation, where:

\[p\]: number of poles.

\(J\): moment of inertia (kg/m²).

In the previous section, dynamic model of an induction motor is expressed. The model constructed according to the equations has been simulated by using MATLAB/SIMULINK as shown in Fig.2 in conventional mode of operation of induction motor. A 3 phase source is applied to conventional model of an induction motor and the equations are given by:

\[
V_a = \sqrt{2} V_{rms} \sin(\omega t)
\]

(13)

\[
V_b = \sqrt{2} V_{rms} \sin\left(\omega t - \frac{2\pi}{3}\right)
\]

(14)

\[
V_c = \sqrt{2} V_{rms} \sin\left(\omega t + \frac{2\pi}{3}\right)
\]

(15)

By using Parks Transformation, voltages are transformed to two phase in the d-q axes, and are applied to induction motor. In order to obtain the stator and rotor currents of induction motor in two phase, Inverse park transformation is applied in the last stage [6].

III. FUZZY LOGIC CONTROLLER

The speed of induction motor is adjusted by the fuzzy controller. The following equation is used to represent the fuzzy triangular membership functions:
In Fig. 3, the membership function of $\Delta \alpha$, $e$ and three scalar values of each triangle that are applied into this controller are shown.

In Table-I, the fuzzy rules decision implemented into the controller are given. The center of area method yields the following

$$
\Delta U_q(k) = \sum_{d=7.8,12.15,18} \frac{(\Delta U_R) \Delta \alpha(R)}{\sum_{d=7.8,12.15,18} \Delta \alpha_d}
$$

(17)
Where, \( \Delta u(R_i) \) is the crisp value corresponding to the maximum membership degree of the fuzzy set that is an output from the rule decision table for the rule \( R_i \). The conventional simulated induction motor model as shown in Fig. 2 is modified by adding Fuzzy controller and is shown in Fig. 4. Speed output terminal of induction motor is applied as an input to fuzzy controller, and in the initial start of induction motor the error is maximum, so according to fuzzy rules FC produces a crisp value. Then this value will change the frequency of sine wave in the speed controller. The sine wave is then compared with triangular waveform to generate the firing signals of IGBTs in the PWM inverters. The frequency of these firing signals also gradually change, thus increasing the frequency of applied voltage to Induction Motor [12]. As discussed earlier, the crisp value obtained from Fuzzy Logic Controller is used to change the frequency of gating signals of PWM inverter. Thus the output AC signals obtained will be variable frequency sine waves. The sine wave is generated with amplitude, phase and frequency which are supplied through a GUI. Then the clock signal which is sampling time of simulation is divided by crisp value which is obtained from FLC. So by placing three sine waves with different phases, one can compare them with triangular waveform and generate necessary gating signals of PWM inverter. So at the first sampling point the speed is zero and error is maximum. Then whatever the speed rises, the error will decrease, and the crisp value obtained from FLC will increase. So, the frequency of sine wave will decrease which will cause IGBTs switched ON and OFF faster. It will increase the AC supply frequency, and the motor will speed up. The structure of PWM inverter is shown in Fig 5. The inputs to these blocks are the gating signals which are produced in speed controller block. The firing signals are applied to IGBT gates that will turn ON and OFF the IGBTs according to the following logics.

![Fuzzy Control Induction Motor Model](image)

The logics are applied to generate firing signals applied to speed controller block as shown in Fig. 4. The output of the PWM inverter is shown in Fig. 6. The flow chart of simulation of fuzzy logic controller is shown in Fig. 7.
Figure 5: PWM Inverter Circuit

Figure 6 (a): IGBTs gating signals

Figure 6 (b): PWM inverter output
TABLE I: MODIFIED FUZZY RULE DECISION

<table>
<thead>
<tr>
<th>e</th>
<th>NB</th>
<th>NS</th>
<th>ZZ</th>
<th>PS</th>
<th>PB</th>
</tr>
</thead>
<tbody>
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<td>PB</td>
<td>ZZ</td>
<td>NS</td>
<td>NS</td>
<td>NB</td>
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<tr>
<td>PS</td>
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<td>ZZ</td>
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<td>NS</td>
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<td>ZZ</td>
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<td>PS</td>
<td>ZZ</td>
<td>NS</td>
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<td>NB</td>
<td>PB</td>
<td>PB</td>
<td>PS</td>
<td>PS</td>
<td>ZZ</td>
</tr>
</tbody>
</table>

IV. NEURO CONTROLLER

The most important feature of Artificial Neural Networks (ANN) is its ability to learn and improve its operation using neural network training [7-8]. A neuron is the connecting block between asummer and an activation function. The mathematical model of a neuron is given by:

\[ y = \Phi(\sum_{i=1}^{N} w_{ij} x_i + b) \]  

where \((x_1, x_2, \ldots, x_N)\) are the input signals of the neuron, \((w_{1}, w_{2}, \ldots, w_{N})\) are their corresponding weights and \(b\) is bias parameter. \(\Phi\) is a tangent sigmoid function and \(y\) is the output signal of the neuron. The ANN can be trained by a learning algorithm which performs the adaptation of weights of the network iteratively until the error between target vectors and the output of the ANN is less than a predefined threshold. The most popular supervised learning algorithm is back-propagation, which consists of a forward and backward action. In the forward step, the free parameters of the network are fixed, and the input signals are propagated throughout the network from the first layer to the last layer. In the forward phase, a mean square error is computed:

\[ E(k) = \frac{1}{N} \sum_{i=1}^{N} (d_i(k) - y_i(k))^2 \]  

where \(d_i\) is the desired response, \(y_i\) is the actual output produced by the network in response to the input \(x_i\), \(k\) is the iteration number and \(N\) is the number of input-output training data. The second step of the backward phase, the error signal \(E(k)\) is propagated throughout the network in the backward direction in order to perform adjustments upon the free parameters of the network in order to decrease the error \(E(k)\) in a statistical sense[9]. The weights associated with the output layer of the network are therefore updated using the following formula:

\[ w_{ij}(k+1) = w_{ij}(k) - \eta \frac{\partial E(k)}{\partial w_{ij}(k)} \]  

where \(w_{ij}\) is the weight connecting the \(i^{th}\) neuron of the output layer to the \(j^{th}\) neuron of the previous layer. \(\eta\) is the constant learning rate. The objective of this NNC is to develop a back propagation algorithm such that the output of the neural network speed observer can track the target. Fig. 8 depicts the network structure of the NNC, which indicates that the neural network has three layered network structure. The first is formed with five neuron inputs \( \Phi(\omega_{ANN}(K+1)), \Phi(\omega_{ANN}(K)), \Phi(\omega_{ANN}(K-1), \Phi(\omega_{ANN}(K-2)) \). The second layer consists of five neurons. The last one contains one neuron to give the command variation \( \omega_{ANN}(K) \). The aim of the proposed NNC is to compute the command variation based on the output variation \( \omega_{ANN}(K+1) \). Hence, with this structure, a predictive control with integrator has been realised. At time \( k \), the neural network computes the command variation based on the output at time \( (k+1) \), while the later isn’t defined at this time. In this case, it is assumed that \( \omega_{ANN}(K+1) \equiv \omega_{ANN}(K) \). The control law is deduced using the recurrent equation given by:

\[ \phi_{ib} = G(s)v_{ds} \]

\[ \phi_{iq} = G(s)v_{qs} \]
Large values of $\eta$ may accelerate the ANN learning and consequently fast convergence but may cause oscillations in the network output, whereas low values will cause slow convergence. Therefore, the value of $\eta$ has to be chosen carefully to avoid instability. The proposed Neural network controller is shown in Fig. 9[8-9].
V. SIMULATION RESULTS & DISCUSSION

Modeling and simulation of Induction motor in conventional, fuzzy and adaptive neuro fuzzy are done on MATLAB/SIMULINK. A complete simulation model for inverter fed induction motor drive incorporating the proposed FLC, adaptive neuro fuzzy controller and Neuro controller has been developed. The dynamic performance of the proposed Conventional, FLC, and neuro controller based induction motor drive is investigated. The proposed neuro controller proved to be more superior as compared to FLC and Conventional Controller by comparing the response of conventional and FLC based IM drive. The results of simulation for induction motor with its characteristics are listed in Appendix 'A'. Fig.10, Fig 11 and Fig.12 show the torque–speed characteristics, torque and speed responses of conventional, and FLC and neuro controller respectively. It appears the rise time drastically decreases when neuro controller is added to simulation model and both the results are taken in same period of time. In neural network based simulation, it is apparent from the simulation results shown in Fig. 10(b) and Fig. 10 (c), torque-speed characteristic converges to zero in less duration of time when compared with conventional Controller and FLC, which is shown in Fig. 10(a) and Fig 10(b). Neuro controller has no overshoot and settles faster in comparison with FLC and conventional controller. It is also noted that there is no steady-state error in the speed response during the operation when neuro controller is activated as shown in Fig.12. In conventional controller, oscillations occur, whereas in neuro controller and FLC, no oscillations occur in the torque response before it finally settles down as shown in Fig. 11. Good torque response is obtained with Neuro controller as compared to conventional, and FLC at all time instants and speed response is better than conventional controllers and FLC controller. There is a negligible ripple in speed response with neuro fuzzy controller in comparison with conventional controller, FLC and adaptive neuro controller under dynamic conditions which are shown in Fig.11. With the neuro controller, speed reaches its steady state value faster as compared to Conventional and FLC controller as shown in Fig. 12. The speed comparison between the three artificial intelligent controller is given in Table-II.

![Figure 9 Neuro control of induction motor drive](image)

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At No Load Condition
At Load Condition:

Induction motor drive with conventional controller speed response has small peak, but in case of fuzzy controller, neural network speed response, it is quick and smooth response which is shown in Fig.13. Fig.14, Fig. 15 and Fig. 13 show the waveforms of torque –speed, torque and speed characteristics with four controllers. Fig.15 shows the speed response with load torque using the conventional, fuzzy and neuro controller respectively. The time taken by the conventional controlled system to achieve steady state is much higher than neuro controlled system. The motor speed follows its reference with zero steady-state error and a fast response using a neuro controller. On the other hand, the conventional controller shows steady-state error with a high starting current. It is to be noted that the speed response is affected by application of load. This is the drawback of a conventional controller with load. It is to be noted that the neuro controller gives better responses in terms of overshoot, steady-state error and fast response when compared with conventional and fuzzy. It also shows that the neuro controller based drive system can handle the sudden increase in command speed quickly without overshoot, under- shoot, and steady-state error, whereas the conventional and fuzzy.
controller-based drive system has steady-state error and the response is not as fast as compared to neuro. Thus, the proposed neuro based drive has been found superior when compared with the conventional controller and FLC controller based system.

Figure 12(b) Speed Response of Fuzzy Controller

Figure 12(c) Speed Response of Neuro Controller

Figure 13(a) Torque-Speed Characteristics with Conventional Controller
Figure 13 (b) Torque-Speed Characteristics with Fuzzy Controller

Figure 13 (c) Torque-Speed Characteristics with Neuro Controller

Figure 14 (a) Torque Response of Conventional Controller

Figure 14 (b) Torque Response of Fuzzy Controller
Figure 14 (c) Torque Response of Neuro Controller

Figure 15 (a) Speed Response of Conventional Controller

Figure 15 (b) Speed Response of Fuzzy Controller

Figure 15 (c) Speed Response of Neuro Controller
TABLE-II. SPEED COMPARISON BETWEEN CONVENTIONAL, FLC AND NN

<table>
<thead>
<tr>
<th>Speed Time line</th>
<th>Speed in conventional Simulation (rpm)</th>
<th>Speed in FLC based simulation (rpm)</th>
<th>Speed in ANN controller based simulation (rpm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>65</td>
<td>400</td>
<td>410</td>
</tr>
<tr>
<td>1</td>
<td>150</td>
<td>800</td>
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</tr>
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<td>8</td>
<td>1460</td>
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<tr>
<td>10</td>
<td>1640</td>
<td>1710</td>
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VI. CONCLUSION

In this paper, comparison of simulation results of the induction motor are presented with different types of controller such as conventional, fuzzy and neuro controller. From the speed waveforms, it is observed that with neuro controller the rise time decreases drastically, in the manner which the frequency of sine waves are changing according to the percentage of error from favourite speed. The frequency of these firing signals also gradually changes, thus increasing the frequency of applied voltage to Induction Motor. According to the direct relation of induction motor speed and frequency of supplied voltage, the speed will also increase. With results obtained from simulation, it is clear that for the same operation condition of induction motor, fuzzy controller has better performance than the conventional controller. By comparing neuro controller with FLC model, it is apparent that by adding learning algorithm to the control system will decrease the rising time more than expectation and it proves neuro controller has better dynamic performance as compared to FLC and conventional controller.

APPENDIX A INDUCTION MOTOR PARAMETERS

The following parameters of the induction motor are chosen for the simulation studies:

\[ V = 220 \quad f = 60 \quad HP = 3 \quad R_s = 0.435 \quad R_r = 0.816 \quad X_{ls} = 0.754 \quad X_{lr} = 0.754 \quad X_m = 26.13 \quad p = 4 \]

\[ J = 0.089 \quad \text{rpm} = 1710 \]

REFERENCES