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Optimal Control to Sensor less Vector Control of Induction Motor using AI Techniques

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***Abstract-* this paper deals with a new design optimal control to Sensor less Vector Control of Induction Motor using Artificial Intelligent (AI) Techniques. This study discusses a method to control the speed of three phase induction motor based on sensor less Control using Neural Network (NN). With this method, it is expected to produce accurate steady-state speed response for the motor parameters (electromagnetic torque and stator flux) can be set directly. The analysis is done with PI, Fuzzy & ANN controllers. An optimal SIMULINK/MATLAB model has been designed in order to achieve the speed control of three phase induction motor based on sensor less control method.**

***Index Terms*– Artificial Intelligent (AI), ANN, speed estimator, induction motor, and efficiency optimization,**

I. INTRODUCTION

Induction motor is the work horse in industry due to its rigid construction & can work under all conditions of environment. But due to the factor that flux & torque cannot be controlled individually as the stator current is a combination of both it is not popular like D.C. Motor. But with the development of power electronics & Vector control concept the three phase stator current can be resolved into two phase components by orthogonal transformation by using Clarke's transformation& to rotor reference frame by parks transformation. To do this the position of flux vector is important. This position of flux vector can be found by direct & indirect methods where direct method employs sensors incorporated in stator which adds to cost, size & induction of harmonics. Hence in indirect control this flux vector can be found by machine parameters & modeling equations governing its performance. Hence sensor less vector control has gained importance. Basically there are various methods of indirect vector control of which Kalman filter, MRAS, sliding mode observer are in major use in earlier days, and hence these methods are prone to numerical & steady errors due to large calculations involved. Hence with the development of software's like Matlab/Simulink, & computer methods like fuzzy logic, neural networks the complications have been resolved.

The Indian power sector has come long way in power generation from 1300MW capacity during independence to 102907MW at present. However in spite of government's plans, the present power availability is not good enough to cater to the needs of the country, as there is a peak shortage of the power of around 10,000MW (13%) and 40,000 million units deficit (7.5%). Unless the system efficiency improves in terms of technical improvements, the crisis will still continue. Energy savings possible due to some major energy equipments such as transformers, motors etc.

The present paper deals with calculation of torque, speed of induction motor without optimization controller & comparing it with after installing controller using ANN approach.

II. MODELING OF INDUCTION MOTOR

A. Dynamic Modeling of induction motors

This section presents the dynamic model of the induction motor as shown in the below fig.1, it is derived by transforming the three-phase quantities into two phases direct and quadrature axes quantities. The equivalence between the three-phase and two-phase machine models is derived from the concept of power invariance [16].

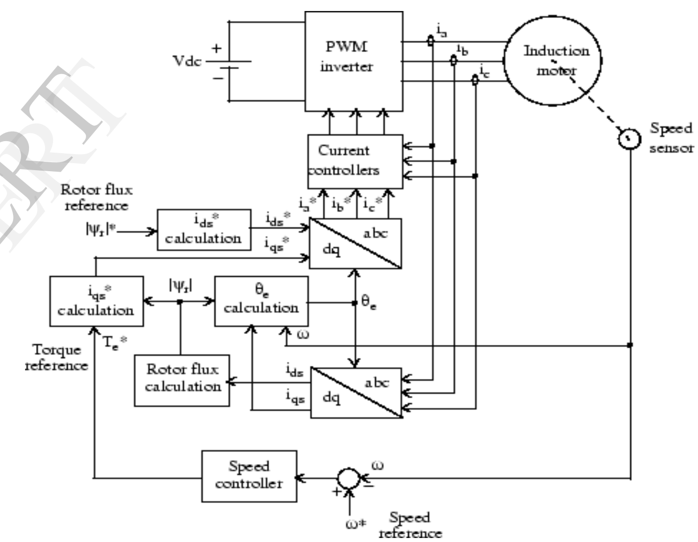

Fig.1.Block diagram of the dynamic model of the induction motor

Electromagnetic Torque:

$$T_e = \frac{3}{2}\frac{P}{2}L_m\left(i_{qs}\ i_{dr} - i_{ds}\ i_{qr}\right) \tag{1}$$

The dynamic equations of the induction motor in synchronous reference frames can be represented by using flux linkages as variables. This involves the reduction of number of variables in dynamic equations, which greatly facilitates their solution. The flux-linkages representation is used in motor drives to highlight the process of the decoupling of the flux and torque channels in the induction machine. The stator and rotor flux linkages in synchronous reference frame are shown in equations (2)-(7)

$$\lambda_{qs} = L_s i_{qs} + L_m i_{qr} \quad (2)$$

$$\lambda_{ds} = L_s i_{ds} + L_m i_{dr} \quad (3)$$

$$\lambda_{qr} = L_r i_{qr} + L_m i_{qs} \quad (4)$$

$$\lambda_{dr} = L_r i_{dr} + L_m i_{ds} \quad (5)$$

$$\lambda_{qm} = L_m \left(i_{qs} + i_{qr}\right) \quad (6)$$

$$\lambda_{dm} = L_m (i_{ds} + i_{dr}) \quad (7)$$

B. State Space model of induction motor

The space phasor model of the induction motors can be presented in state space equations from previous equation, so it can be expressed in the synchronously rotating *d-q* reference frame as shown in equations (8) to (16).

$$\dot{X} = AX + Bu \quad (8)$$

$$\boldsymbol{X} = [\boldsymbol{i_{ds}} \quad \boldsymbol{i_{qs}} \quad \boldsymbol{\lambda_{dr}} \quad \boldsymbol{\lambda_{qr}}]^T \quad (9)$$

$$u = [\boldsymbol{V_{ds}} \quad \boldsymbol{V_{qs}}]^T \quad (10)$$

$$A = \begin{pmatrix} \boldsymbol{a_1} & \boldsymbol{w_e} & \boldsymbol{a_2} & \frac{\boldsymbol{L_m w_r}}{\boldsymbol{\sigma L_s \quad L_r}} \\ -\boldsymbol{w_e} & \boldsymbol{a_1} & \frac{\boldsymbol{L_m w_r}}{\boldsymbol{\sigma L_s \quad L_r}} & \boldsymbol{a_2} \\ \frac{\boldsymbol{L_m R_r}}{\boldsymbol{L_r}} & \boldsymbol{0} & \frac{-\boldsymbol{R_r}}{\boldsymbol{L_r}} & \boldsymbol{w_e - w_r} \\ \boldsymbol{0} & \frac{\boldsymbol{L_m R_r}}{\boldsymbol{L_r}} & -\boldsymbol{w_e} + \boldsymbol{w_r} & \frac{-\boldsymbol{R_r}}{\boldsymbol{L_r}} \end{pmatrix} \quad (11)$$

$$B = \begin{pmatrix} a_3 & 0 \\ 0 & a_3 \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \quad (12)$$

$$a_1 = \frac{-R_s}{\sigma L_s} - \frac{(1-\sigma)R_r}{\sigma L_r} \quad (13)$$

$$a_2 = \frac{L_m \quad R_r}{\sigma L_s \; L_r 2} \quad (14)$$

$$a_3 = \frac{1}{\sigma L_s} \quad (15)$$

$$\sigma = 1 - \frac{L_m 2}{L_S \; L_r} \quad (16)$$

III. SENSOR LESS VECTOR CONTROL TECHNIQUES

A. Sensor less vector control techniques by using fuzzy control

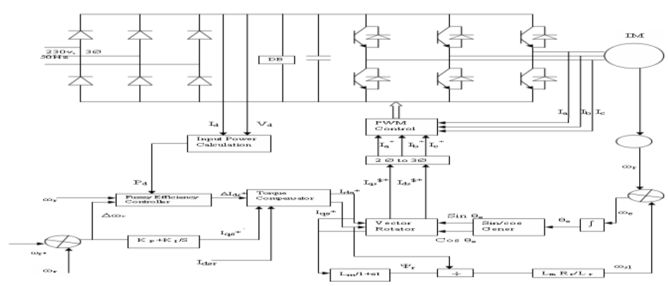

Fig. 2. The indirect vector controlled induction motor with efficiency optimization controller block diagram

The principle of efficiency optimization control with rotor flux programming at a steady-state torque and speed condition is explained in Fig.: 2 The rotor flux is decreased by reducing the magnetizing current, which ultimately results in a corresponding increase in the torque current (normally by action of the speed controller); such that the developed torque remains constant. As the flux is decreased, the iron loss decreases with the attendant increase of copper loss.

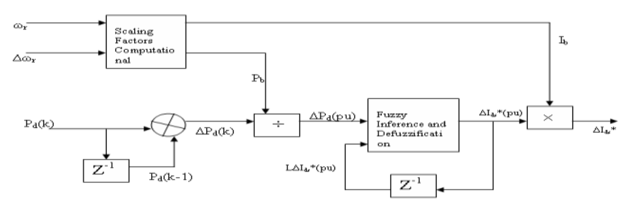

Fig.3.Efficiency optimization control block diagram

The above figure3 explains the fuzzy efficiency controller operation. The input dc power is sampled and compared with the previous value to determine the increment ΔPd. In addition, the last excitation current decrement (L Δi_{ds}) is reviewed. On these bases, the decrement step of Δids* is generated from fuzzy rules through fuzzy inference and defuzzification. The adjustable gains P_b and I_b, generated by scaling factors computation block, convert the input variable and control variable, respectively, to per unit values so that a single fuzzy rule base can be used for any torque and speed condition. The input gain Pb as a function of machine speed w_r can be given as P_b=a w_r+b Where the coefficients a and b were derived from simulation studies. The output gain I_b is computed from the machine speed and an approximate estimate of machine torque T_e $I_b=c_1 w_r - c_2 T_e + c_3$ Again, the appropriate coefficients c1, c2, and c3 were derived from simulation studies. In the absence of input and output gains, the efficiency optimization controller would react equally to a specific value of ΔP_b resulting from a past action Δids*(k-1), irrespective of operating speed. Since the optimal efficiency is speed dependant, the control action could easily be too conservative, resulting in slow convergence, or excessive, yielding an overshoot in the search process with possible adverse impact on system stability. As both input and output gains are function of speed, this problem does not arise. The above equation also incorporates the a priori knowledge that the optimum value of Δids* is a function of torque as well as machine speed. In this way, for different speed and torque conditions, the same Δids*(p.u) will result in different Δids***,** ensuring a fast convergence. One additional advantage of per unit basis operation is that the same fuzzy controller can be applied to any arbitrary machine, by simply changing the coefficients of input and output gains.

The membership functions for the fuzzy efficiency controller are shown below. Due to the use of input and output gains, the universe of discourse for all variables are normalized in the [-1, 1] interval. It was verified that, while the control variable Δids***,** required seven fuzzy sets to provide good control sensitivity, the past control action L Δi_{ds}* (i.e. Δi_{ds}* (k - 1)) needed only two fuzzy sets, since the main information conveyed by them is the sign. The small overlap of the positive (P) and negative (N) membership functions is required to ensure proper operation of the height defuzzification method, i.e., to prevent indeterminate result in case L Δi_{ds}* approaches zero. The rule base for fuzzy control is given below. The basic idea is that if the last control action indicated a decrease of dc link power, proceed searching in the same direction and the control magnitude should be somewhat proportional to the measured dc link power change. In case the last control action resulted in an increase of Pd (ΔPd > 0), the search direction is reversed, and the Δids*, step size is reduced to attenuate oscillations in the search process.

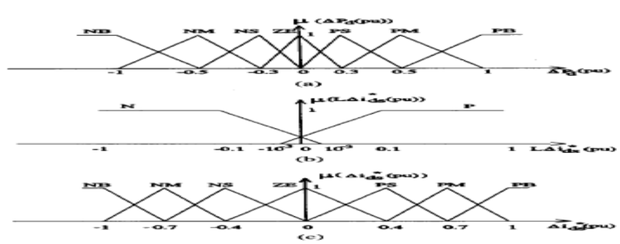

Fig.4a,b&c Membership functions for efficiency controller change of DC link power (ΔP_d(pu)) ,Last change in excitation current (LΔids*(pu)) & Excitation current control increment(Δids*(pu)).

Depending on the member ship functions for efficiency controller change of dc link power,Last change in excitation current,& excitation current control increment shown in Fig.4a,b&c the rule base for fuzzy controller is framed and is shown in table 1

Table I

$\Delta_{pd(pu)}/\Delta_{ids(pu)}$	**N**	**P**
PB	**PM**	**NM**
PM	**PS**	**NS**
PS	**PS**	**NS**
ZE	**ZE**	**ZE**
NS	**NS**	**PS**
NM	**NM**	**PM**
NB	**NB**	**PB**

Rules base for Fuzzy Efficiency Controller:

As the excitation current is decremented with adaptive step size by the fuzzy controller, the rotor flux Ψ_{dr} will decrease exponentially which is given by equation (17)

$$\frac{d}{dt}\psi_{dr} = \frac{L_m i_{ds} - \psi_{dr}}{T_r} \tag{17}$$

Where λ_r = L_r/R_r is the rotor time constant and L_m the magnetizing inductance. The decrease of flux causes loss of torque, which normally is compensated slowly by the speed control loop. Such pulsating torque at low frequency is very undesirable because it causes speed ripple and may create mechanical resonance. To prevent these problems, a feed forward pulsating torque compensator has been proposed.

Under correct field orientation control, the developed torque is given by equation (18)

$$T_e = K_t i_{qs} \psi_{dr} \tag{18}$$

For an invariant torque, the torque current I_{qs}**,** should be controlled to vary inversely with the rotor flux. This can be accomplished by adding a compensating signal ΔI_{qs}* to the original I_{qs}*' to counteract the decrease in flux $\Delta\Psi_{dr}$ (t) where t € [0, T] and T is the sampling period for efficiency optimization control. Let i_{qs} (0) and Ψ_{dr} (0) be the initial values for i_{qs} and Ψ_{dr}**,** respectively, for the k-th step change of ids*. For a perfect compensation, the developed torque must remain constant, and the following equality given by equation (19) holds good.

$$[\psi_{dr}(0) + \Delta\psi_{dr}(t)]\left[i_{qs}(0) + \Delta i_{qs}(t)\right] = \psi_{dr}(0) i_{qs}(0) \tag{19}$$

Solving for ΔI_{qs} (t) yields

$$i_{qs}(t) = \frac{\psi_{dr}(t) i_{qs}(0)}{\psi_{dr}(0) + \psi_{dr\,(t)}} \tag{20}$$

Where $\Delta\Psi_{dr}$ (t) is governed by above equation with, substituted for Δids***.** To implement such compensation, above equations are adapted to produce ΔI_{qs} (t)**,** using flux estimate Ψd**r** and command in I_{qs}* place of actual signals. A good approximate solution for ΔI_{qs}(t) can be obtained by replacing the denominator of the above equation by its steady-state value estimate $\Delta\Psi_{dr}$ (t).In this case the compensation can be implemented in two steps as shown in Fig. 4. First, the value for the compensated torque current step is computed by discrete$i_{qs}{}^{*}(k)$ given by equation (20) as

$$i_{qs}{}^{*}(k) = \frac{\psi_{dr}{}^{*}(k-1) - \psi_{dr}(k)}{\psi dr^{*}} \quad i_{qs}(k-1) \tag{21}$$

Next, the current step is processed through a first order low pass filter of rotor time constant, and then added to the previous compensating steps. This current is added to the original speed loop generated current I_{qs}*' so that, at any instant, the product **Iqs** Ψ_{dr} remains essentially constant

B. Sensor less vector control techniques by using Artificial Neural Network method

An Artificial Neural Network (ANN), often just called a "neural network" (NN), is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

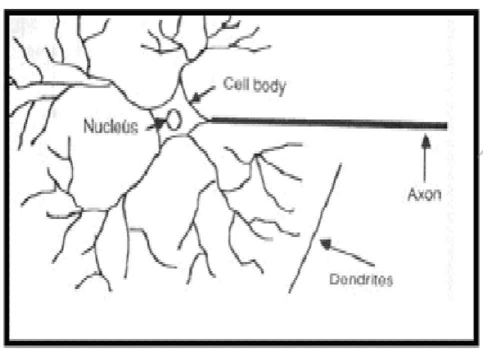

Fig. 5. Basic Neuron network model

An artificial neuron consists of five major components, They are Weighing factors, summation function, transfer function, scaling& limiting function, output function. A neuron usually receives many inputs simultaneously. Each input has its own relative weight which gives the input the impact that it needs on the processing element's summation Weights are a measure of an input's connection strength. These strengths can be modified in response to various training sets and according to a network's specific topology or thought its learning rules.

The first step in a processing element's operation is to compute the weighted sum of all of the inputs. Mathematically, the inputs and the corresponding weights are vectors which can be represented as (i_1, i_2 … i_n) and (w_1, w_2 … w_n). The total input signal is the dot, or inner, product of these two vectors. This simplistic summation function is found by multiplying each component of the 'i' vector by the corresponding component of the w vector and then adding up all the products. Input 1 = i_1 * w_1, input 2 = i_2 * w_2 etc., are added as input 1 + input 2 + … + input *n.*

The result of the summation function, the weighted sum, is transformed to a working output through an algorithmic process known as the transfer function. In the transfer function the summation total can be compared with some threshold to determine the neural output. If the sum is greater than the threshold value, the processing element generates a signal. If the sum of the input and weight products is less than the threshold, no signal (or some inhibitory signal) is generated. Both types of response are significant. The threshold, or transfer function, is generally non-linear. Linear (straight-line) functions are limited because the output is simply proportional to the input. Linear functions are not very useful.

After the processing element's transfer function, the result can pass through additional processes which scale and limit. This scaling simply multiplies a scale factor times the transfer value, and then adds an offset. Limiting is the mechanism which insures that the scaled result does not exceed an upper or lower bound.

Each processing element is allowed one output signal which it may output to hundreds of other neurons. This is just like the biological neuron, where there are many inputs and only one output action. Normally, the output is directly equivalent to the transfer function's result. Some network topologies, however, modify the transfer result to incorporate competition among neighboring processing elements. Neurons are allowed to compete with each other, inhibiting processing elements unless they have great strength. Competition can occur at one or both of two levels. First, competition determines which artificial neuron will be active, or provides an output. Second, competitive inputs help determine which processing element will participate in the learning or adaptation process.

a) ANN Controller for induction motor

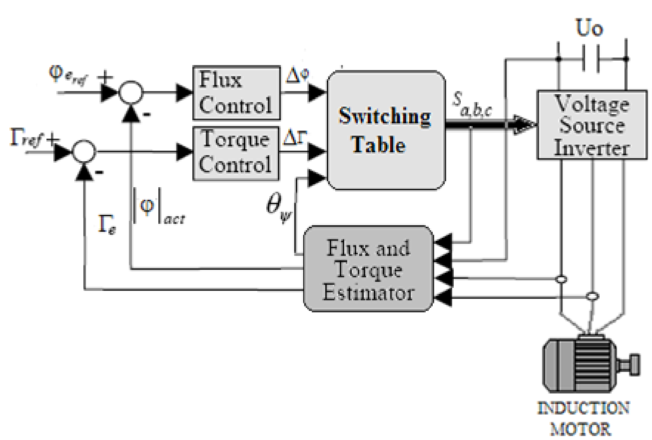

Fig 6 ANN Controller for induction motor

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Fig. 6 shows the control mechanism. If either the estimated flux or torque deviates from there reference more than allowed tolerance, the transistors of the variable frequency drive are turned off and on in such away that the flux and torque will return in their tolerance band as fast as possible.

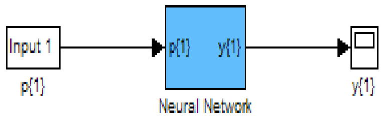

Fig. 7. Simulink block diagram of ANN Controller switching table

Figure 7 shows the switching table for ANN controller at which the controller varies various parameters to get steady state response.

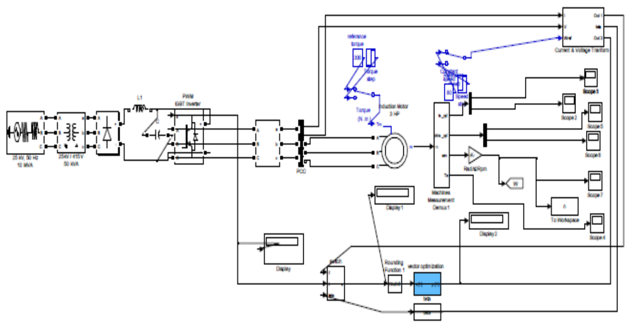

Fig.8 . The block diagram of induction motor with ANN Controller for sensor less vector control.

The above figure8 shows the block diagram of induction motor incorporating ANN controller for sensor less vector control. The drive uses a PWM IGBT inverter fed from a DC source. The speed error is processed through a neural network. Neural Network is used to adjust the motor parameters when the induction motor speed reference changes and also to produce accurate steady-state speed response.

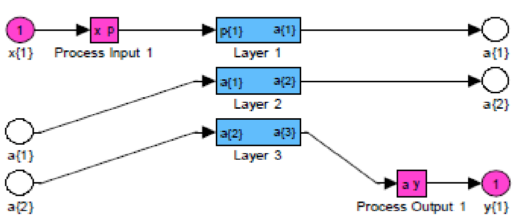

Fig. 9. Simulink block diagram of the multi-layer neural network

Fig. 9 shows multilayer neural network. A network can have several layers. Each layer has a weight matrix W, a bias vector b, and an output vector the layers of a multilayer network play different roles. A layer that produces the network output is called an output layer. All other layers are called hidden layers. Multiple-layer networks are quite powerful. For instance, a network of two layers, where the first layer is sigmoid and the second layer is linear, can be trained to approximate any function

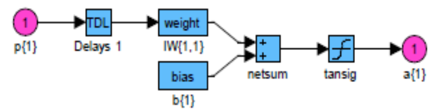

Fig.10.Weights sub block

Fig.10 .shows A neuron usually receives many inputs simultaneously. Each input has its own relative weight which gives the input the impact that it needs on the processing element's summation Weights are a measure of an input's connection strength

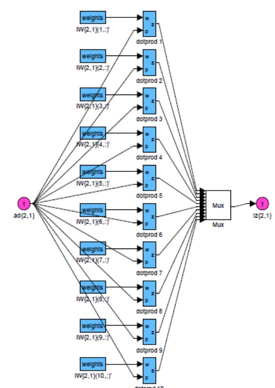

Fig.11. inputs for a neuron

Figure 11 shows the weights sub block & inputs for a neuron which are inter connected. A neuron usually receives many inputs simultaneously. Each input has its own relative weight which gives the input the impact that it needs on the processing element's summation Weights are a measure of an input's connection strength.

IV. SIMULATION RESULTS

A step increase in reference speed W_{ref} produces a positive speed error. The drive accelerates at a permissible inverter current, producing maximum available torque, until the speed error is reduced to small value. The drive finally settles at a speed for which the motor torque balances the load torque. A step decrease in reference speed W_{ref} produces a negative speed error. The speed command is set at the maximum negative value. The drive has fast response because the speed error is corrected at the maximum available torque. The error between the set speed and actual speed is calculated. In order to operate induction motor with variable speed, power converter devices are used with the power supply. A conventional way to control the induction motor speed is by using a PID controller, but tuning the PID controller to work under various speed references is very time consuming. The wave forms for speed ,Torque & voltages with PI Controller & ANN Controller are analyzed & it is true that ANN controller gives better response.

TABLE II

HP=5	Power rating of motor
V=440v	Voltage applied
F=50HZ	Frequency
N=1500RPM	Speed in RPM
P=4	No of poles
R_s = 0.406Ω	Stator Resistance
R_r = 0.478 Ω	Rotor Resistance
L_{ls} = 2.13mH	Stator Leakage Resistance
L_{lr} = 2.13mH	Rotor Leakage Resistance
L_m = 49.4mH	Mutual Inductance

Case A: Sensor less vector control techniques by using PI Controller

The simulation of the induction motor for sensor less vector control method was done with PI controller for a simulation time of 2 seconds & the graphs for voltage ,speed & torque are as shown in figure12 to figure14..

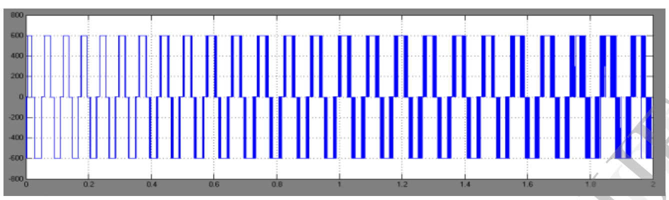

Fig.12. The voltage wave form using PI controller

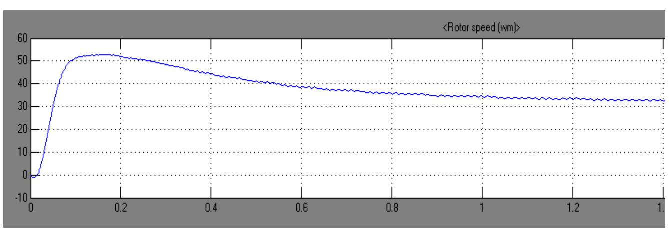

Fig.13. The speed wave form using PI controller

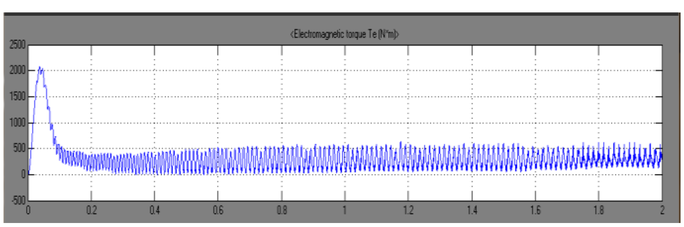

Fig.14 The Torque wave form using PI controller

Case B: Sensor less vector control techniques by using fuzzy control

The simulation of the induction motor for sensor less vector control method was done with Fuzzy controller for a simulation time of 2 seconds & the graphs for voltage ,speed & torque are as shown in figure15 to figure17.

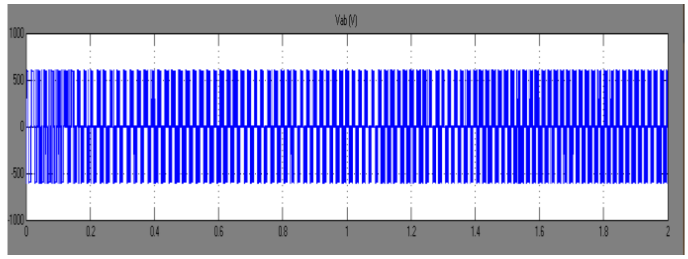

Fig.15. The voltage wave form using fuzzy controller

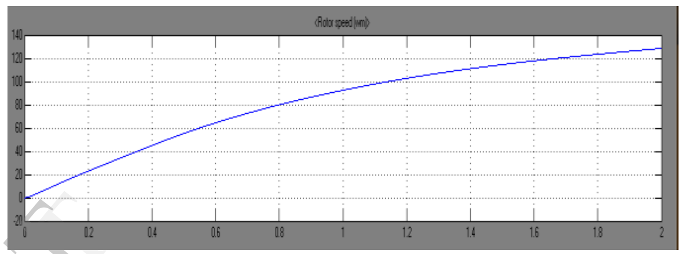

Fig.16. The speed wave form using fuzzy controller

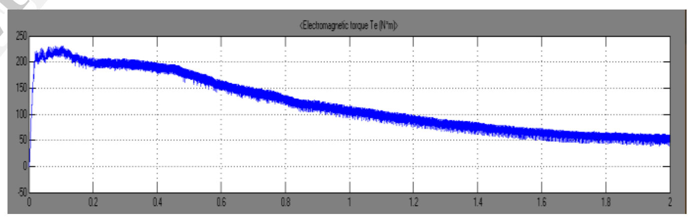

Fig.17 The torque wave form using fuzzy controller

Case C: Sensor less vector control techniques by using Artificial Neural Network method

The simulation of the induction motor for sensor less vector control method was done with ANN controller for a simulation time of 2 seconds & the graphs for voltage ,speed & torque are as shown in figure18 to 20

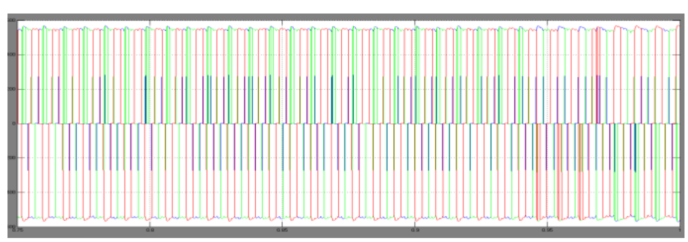

Fig.18. The voltage wave form using ANN controller

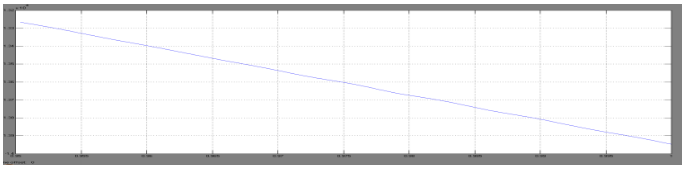

Fig.19. The speede wave form using ANN controller

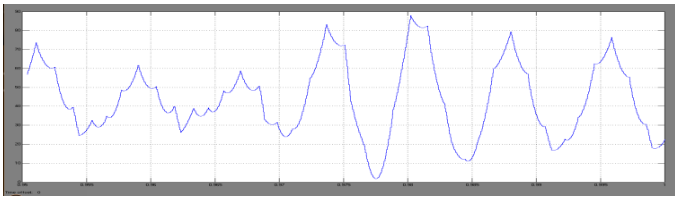

Fig.20 The Torque wave form using ANN controlle

From the simulation studies of voltage wave forms it can be concluded that the voltage is smooth & ripple free with more pulses in a given interval. Hence by using ANN controller the voltage is maintained at highest value with less distortion hence better performance

From the analysis of rotor speeds it is observed that the maximum speed that can be attained is more with controller & it is found that this speed is maintained constant. Whereas without controller the maximum speed attained is less & after a short while speed drops drastically . Hence with ANN controller maximum speed can be increased & maintained constant.

The above simulation wave forms for torque show that the behavior of induction motor ie as torque decreases speed increases. The torque with controller is less distorted, almost all constant without jerky operation. Hence torque is improved & almost all constant with ANN controller.

V. CONCLUSION

In this paper a new MATLAB/SIMULINK model is proposed for speed control of three phase induction motor based on neural network approach. The proposed model gives accurate steady state response for the motor parameters (electromagnetic torque and stator flux). From the simulation results, it can be observed that the proposed model gives accurate steady state response. But owing to the stability and learning capability of neural networks, the proposed method can be considered as better technique.

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