DESIGN OF A THREE-PHASE INDUCTION MOTOR RPM CONTROLLER USING NEURAL ESTIMATOR-FUZZY CONTROLLER IN THE ABSENCE OF SPEED SENSOR

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ABSTRACT- In this paper, various methods of speed estimation including speed calculation by open-loop method, Model Reference Adaptive System and use of the extended Kalman filter are explained and then scalar and vector control of induction motor have been investigated and implemented. In the following, many types of the neural estimator of speed were analyzed and implemented and the application of fuzzy controller is discussed in this respect. Finally, the proposed method consisting of neural estimator-fuzzy controller was modeled and compared with conventional techniques. Three-phase induction motor has 4 poles and its nominal values are 220 V, 10 hp, 60 Hz and 1725 rpm. Comparison of the simulation results and reference articles shows the validity of the work.

Keywords- scalar and vector control, neural estimator, fuzzy controller, induction motor

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INTRODUCTION

Three-phase induction machines are the machines with asynchronous speed which operate below synchronous speed in motor mode and above synchronous speed in generator mode [1]. Due to the complexity of the dynamic behavior of such motors, control of induction motors, variable frequency power supply and the nonlinear dependence of the speed and torque on the input parameters, controlling induction motors is much more difficult than controlling DC machines [2].

Different methods have been proposed in this regard. Motor equations are directly used to estimate the speed in open-loop method which has lower accuracy and higher sensitivity to machine parameter change. This method is not robust and rarely used to control induction motors.

The MRAS[1] method utilizes two models of motor with the same outputs. The output of the two models (speed, flux, power, etc.) are compare with each other, and the error between them is used to determine the speed such that the resulting error rate tends to zero [3-5]. The accuracy of speed estimation depends on the validity of machine information which is not desirably accurate owing to the change of machine parameters including the variation of rotor resistance because of heat and skin effect.

Recently, extended Kalman filter techniques is used to estimate flux and speed of induction machines. Due to the high degrees of Kalman filter, this technique requires complicated mathematical calculations that limits its application. The idea of Kalman Algorithm is based on determining 5 state variables for motor equations and using filter to view these variables. This method is sensitive to the parameters of the motor and the estimation speed is low [6, 7]. Other ways such as estimating the speed by sliding observer is also used in this area [8, 9].

In all the above methods, the induction motor model is used to build a flux-speed observer. The problems of these methods include low estimation, non-robustness against changes of the machine parameters, and inappropriate performance for a full range of speed and transient states.

Recently, the use of neural networks has been suggested to estimate speed more accurately, this method has a high speed and is robust against the changes in machine model parameters. A classic controller, such as PI, is typically used to improve the efficiency of induction motor closed-loop control system. While in the transient states, such as rapid change of load or reference speed, the classic controller may lead to the elimination of high efficiency of control system. Thus, the use of fuzzy controllers due to the simple structure and ease of implementation is considered in place of the classic-controller.

I. SCALAR CONTROL OF INDUCTION MOTOR

Scalar control method only includes controlling the amplitude of the control parameters [10]. In scalar control of induction machine, motor model is considered only in steady state, thus scalar controls do not express appropriate performance and function in motor transient states. It is the most important and basic limitation of scalar control for induction machines.

For voltage source inverters, scalar control can be done in two ways: 1) Control of V/Hz; 2) control of torque and flux. Control of V/Hz can also be set up by three methods: open-loop or closed-loop, or slip regulation. The block diagram of the V/Hz control method and slip regulation is provided in Fig. 1. It is observed that the speed control loop generates the slip control command through a PI controller and a limiter. Then slip is added to the speed signal to generate voltage command through the V/Hz generator function. Changes in the ratio of V/Hz lead to a change in air gap flux and produced torque. Reduction of air gap flux improves the efficiency in low loads because of reduced dissipation of the core. But the deficiency is that the machine might be unstable due to the sudden increase of load. V/Hz arrangement with slip regulation is shown in Fig. 2 and simulation results in Fig. 3.

[1] Model Reference Adaptive System

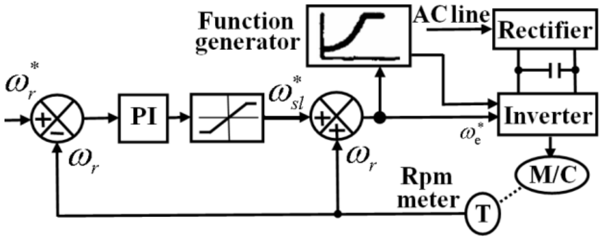

Fig. 1. Block diagram of speed control by V/Hz method with slip regulation [10]

According to the results, it is observed that the controller has followed the reference speed well but a bit slow. The float of torque and flux is evident in the figures, so that the controller performance has been successful to control and fix the flux. The constant flux is made because of the stator voltage change proportional to the supply frequency.

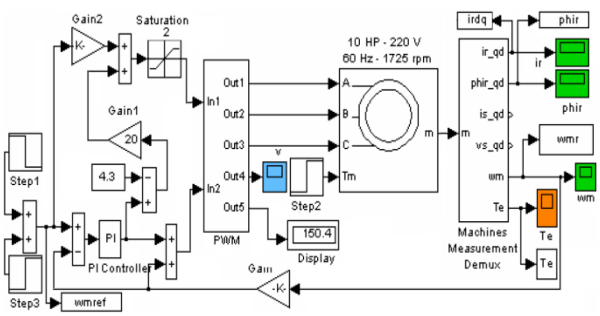

Fig. 2. V/Hz method with slide regulation

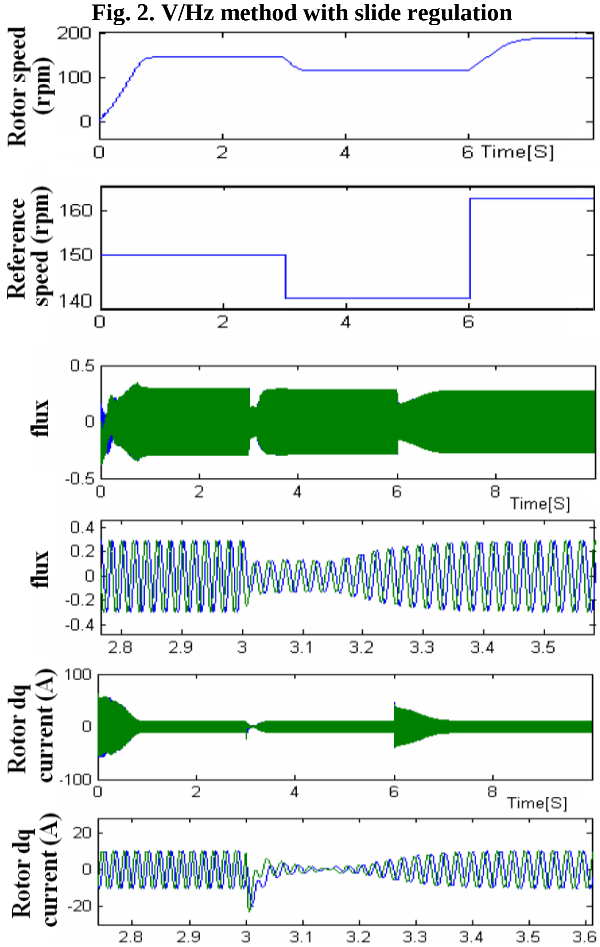

Fig. 3. Diagram of the rotor speed, reference speed, rotor dq current and flux in V/Hz.

III.VECTOR CONTROL OF INDUCTION MOTOR

Vector control method includes controlling the amplitude and phase of variables simultaneously [10]. In vector control method, motor model is valid both for steady state and transient state, thus vector control method is recommended for the applications with high accuracy and efficiency.

In scalar control methods, basic variables of induction motors on which there is a control include voltage, current or frequency. Furthermore, air gap flux and torque are the functions of voltage and frequency and this dependence is the main cause of slow response of induction motors. The above limitation can be resolved using vector control methods. These methods are applicable to the induction machines and synchronous machines. In fact, AC machine is controlled as like as an independent stimulation DC machine using vector control [12].

Vector control is divided into two types: direct and indirect. Block diagram of the direct vector control method for a current source inverter is shown in Fig. 4. The main parameters of controlling i_{qs}^* and i_{ds}^* are first inverted into the signals corresponding to the stationary reference system and then to the commands of the inverter three-phase current. For more precise control of flux, a flux control loop is added. Reference current i_{qs}^* is made by the torque control loop.

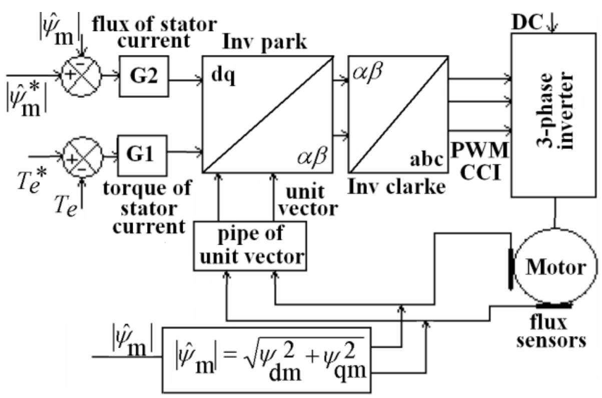

Fig. 4. Block diagram of direct vector control for a current source inverter [12, 13]

It can be observed in direct vector control method that, the building unit vectors depends on the condition of machine terminal. Hence, indirect vector control would be proposed in which there is no limitation, so that the problem of distortion will be eliminated. The block diagram of this method is shown in Fig.5 in which the relations (1) and (2) are used for indirect vector control.

$$\omega_{sl} = \frac{L_m}{\hat{\psi}_r}\left(\frac{R_r}{L_r}\right)i_{qs} \tag{1}$$

$$\frac{L_r}{R_r}\frac{d\hat{\psi}_r}{dt} + \hat{\psi}_r = L_m i_{ds} \tag{2}$$

Where i_{ds} is the component of the current flux, $\hat{\psi}_r$ rotor flux, i_{qs} the component of current torque, ω_{sl} slip regulation, L_m magnetizing inductance of the motor, R_r and L_r are the resistance and leakage inductance of the rotor coils.

The component of current flux i_{ds}^*, can be obtained from equation (2) to achieve the desired rotor flux, which is held constant. Normally, the torque current i_{qs}^*, is obtained from the speed control loop. The value of slip regulation ω_{sl}^*, is related to the current i_{qs}^* by equation (1). Using indirect vector control, as with the direct method, machine can be controlled in 2 working area, and adjust the speed from zero to nominal value [12].

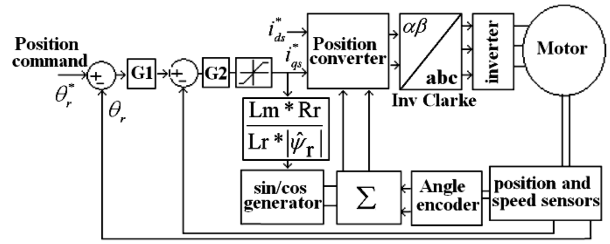

Fig. 5. Block diagram of the indirect vector control method [10, 12]

An indirect vector control arrangement is provided in Fig. 6, in which torque stepper was applied to the motor at the moment of 1.1 second to study the dynamic performance of the controller.

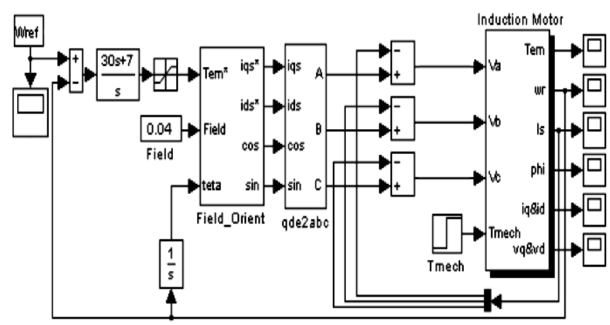

Fig. 6. indirect vector control of induction motor

The results of applying torque steps are provided in Fig. 7. According to the results, it is shown that the controller follows the reference speed well enough. To evaluate the performance of the control system in brake and generator cases, motor speed was changed from 50 radians per second to -50 radians per second and the corresponding graphs are provided in Fig. 8. It can be inferred from the graphs that, the vector control method has better performance rather than scalar control method in dynamic and transient states.

IV. ESTIMATION OF THE INDUCTION MOTOR SPEED BY MODEL REFERENCE ADAPTIVE METHOD

The block diagram of speed estimation by MRAS method is provided in Fig. 9 which is based on a repeated method for the estimation of speed and rotor angle from magnetizing current. Both voltage and current observers estimate magnetizing current of the motor based on equation (3), this estimation with voltage model depends on the accuracy of speed [3].

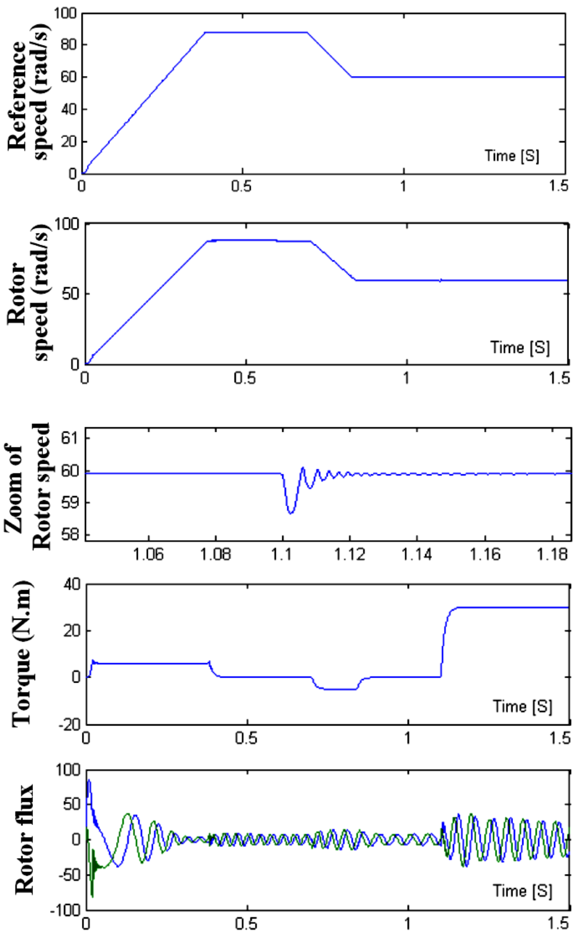

Fig. 7. Diagram of reference speed, electric torque, speed and flux of rotor by applying torque step at 1.1 second (using the indirect vector control)

$$p\begin{bmatrix} i^s_{dmr} \\ i^s_{qmr} \end{bmatrix} = \frac{L_r}{L_m^{\,2}}\left\{\begin{bmatrix} V^s_{ds} \\ V^s_{qs} \end{bmatrix} - \begin{bmatrix} R_s+\sigma L_s p & 0 \\ 0 & R_s+\sigma L_s p \end{bmatrix}\cdot\begin{bmatrix} i^s_{ds} \\ i^s_{qs} \end{bmatrix}\right\} \qquad (3)$$

$$p\begin{bmatrix} i^s_{dmr} \\ i^s_{qmr} \end{bmatrix} = \begin{bmatrix} -\dfrac{1}{T_r} & -\omega_r \\ \omega_r & -\dfrac{1}{T_r} \end{bmatrix}\cdot\begin{bmatrix} i^s_{dmr} \\ i^s_{qmr} \end{bmatrix} + \frac{1}{T_r}\begin{bmatrix} i^s_{ds} \\ i^s_{qs} \end{bmatrix}$$

Where V^s_{ds} and V^s_{qs} are respectively d and q components of the stator voltage, $T_r = \dfrac{L_r}{R_r}$ rotor time constant, L_r and R_r inductance and resistance of each phase of the rotor transferred to the stator, i^s_{ds} and i^s_{qs} d and q components of the stator current, L_s and R_s respectively inductance and resistance of each phase of the stator, L_m magnetizing inductance, $\sigma = 1-\left(L_m^{\,2}/L_sL_r\right)$ the leakage factor, ω_r angular speed of the rotor, finally $i^s_{dmr} = \lambda^s_{dr}/L_m$ and $i^s_{qmr} = \lambda^s_{qr}/L_m$ that λ^s_{dr} and λ^s_{qr} are d and q components are the rotor flux [3].

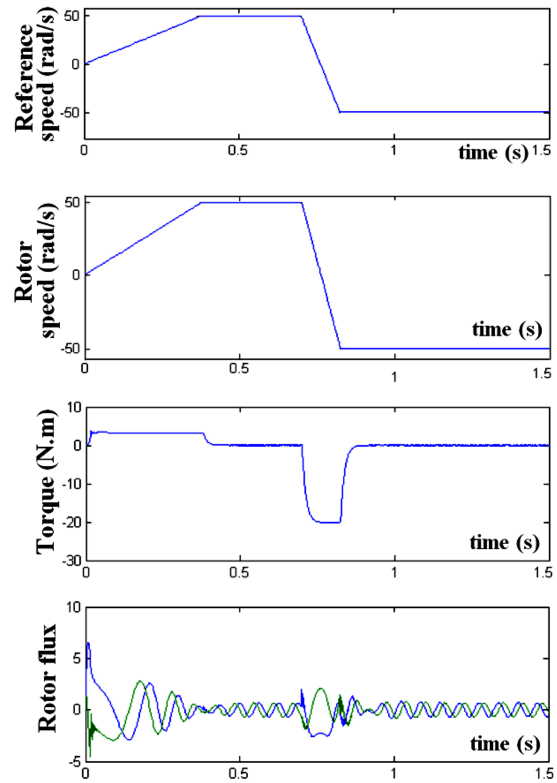

Figure 8: Diagram of reference speed, torque, speed and flux of rotor in Brake and generator states (indirect vector control method)

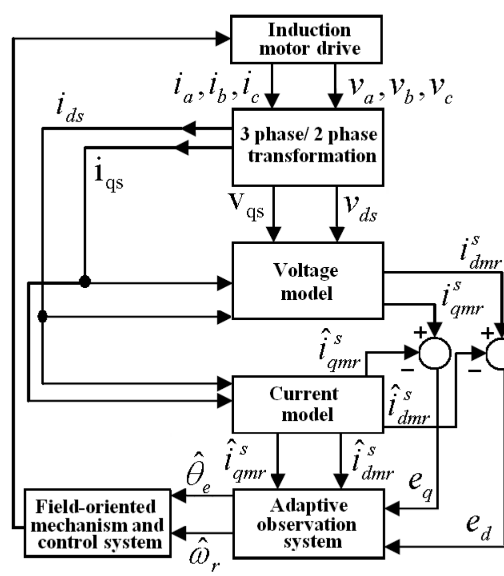

Fig. 9. Block diagram of speed estimation by MRAS method

Equation (3) can be rewritten as follows:

$$p\begin{bmatrix}\hat{i}^{s}_{dmr}\\ \hat{i}^{s}_{qmr}\end{bmatrix}=\begin{bmatrix}-\dfrac{1}{T_r} & -\hat{\omega}_r\\ \hat{\omega}_r & -\dfrac{1}{T_r}\end{bmatrix}\cdot\begin{bmatrix}\hat{i}^{s}_{dmr}\\ \hat{i}^{s}_{qmr}\end{bmatrix}+\frac{1}{T_r}\begin{bmatrix}i^{s}_{ds}\\ i^{s}_{qs}\end{bmatrix} \qquad (4)$$

By subtracting the equation (3) and (4), we obtain equation (5):

$$p\begin{bmatrix}e_d\\ e_q\end{bmatrix}=\begin{bmatrix}-\dfrac{1}{T_r} & -\omega_r\\ \omega_r & -\dfrac{1}{T_r}\end{bmatrix}\cdot\begin{bmatrix}e_d\\ e_q\end{bmatrix}+\left(\omega_r-\hat{\omega}_r\right)\begin{bmatrix}-\hat{i}^{s}_{qmr}\\ \hat{i}^{s}_{dmr}\end{bmatrix} \qquad (5)$$

Where $e_d = i^{s}_{dmr} - \hat{i}^{s}_{dmr}$ and $e_q = i^{s}_{qmr} - \hat{i}^{s}_{qmr}$. Speed estimator is obtained from equation (6), in which η is a positive constant.

$$\dot{\hat{\omega}}_r = \eta.\left(\hat{i}^{s}_{dmr}.e_q - \hat{i}^{s}_{qmr}.e_d\right)/\left(\hat{i}^{s\ 2}_{dmr} + \hat{i}^{s\ 2}_{qmr}\right) \qquad (6)$$

According to the above equations, changing the motor parameters is not significantly effective on the motor speed estimation in the steady state. But it is necessary to hold the parameters constant for the speed estimation at transient states.

An arrangement of induction motor control system using MRAS estimator is shown in Fig. 10. As seen, a PI controller is used to increase the reliability of speed loop in sensorless drive system. To further evaluate the performance of above estimator, torque stepping was applied to the motor at the moment of 0.7 seconds and the simulation results are provided in Fig. 11. MRAS method is seen to have a good performance at low speeds, but the steady speed estimation error is zero due to the PI controller at the estimator output. It is also a method for estimating the speed in transient and stable times, but the estimated time will have some errors at the time of rapid change in speed or estimator load.

V. NEURAL NETWORKS AS EDUCABLE DYNAMICAL SYSTEMS

Neural networks as educable dynamical systems are able to learn from the past, experience and environment and also improve their behavior during learning. The improvement criteria models the objective of learning system. Learning rules are expressed by recursive relations, commonly differential equations. Neural estimator of the speed is both online and offline.

Neural estimator of the speed with online .A training

At this estimator, shown in Fig. 12, the rotor speed is considered as the output of the neural network. Multi-layer and recursive structure of neural network reinforce it against parameter change and system noise. The weight of neurons is continuously and immediately modified during the operation of motor drive; so that the neural network is not to be trained offline. As with the MRAS method, this method also utilizes two voltage and current models of the flux to estimate the speed of induction motor by the help of neural network. Voltage and current of the induction motor is measured at static reference. According to equation (7), they are used to determine the rotor flux [14].

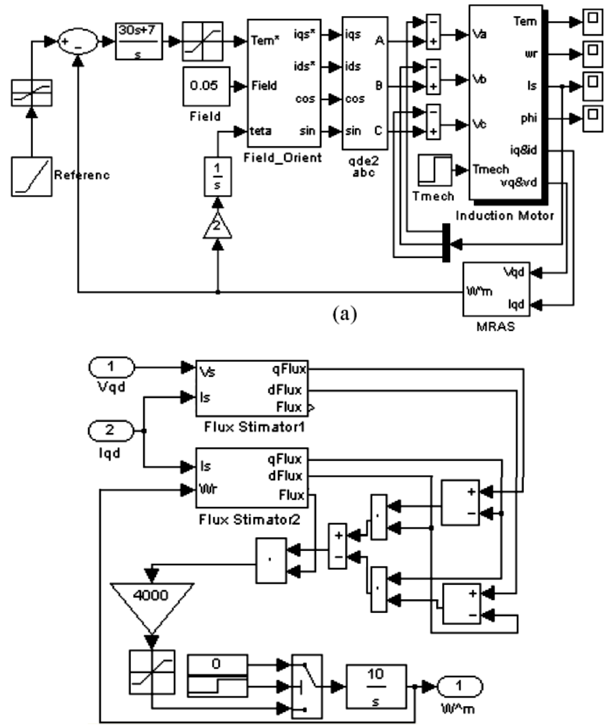

Fig. 10: (a) Vector control with MRAS estimator, (b) estimator structure

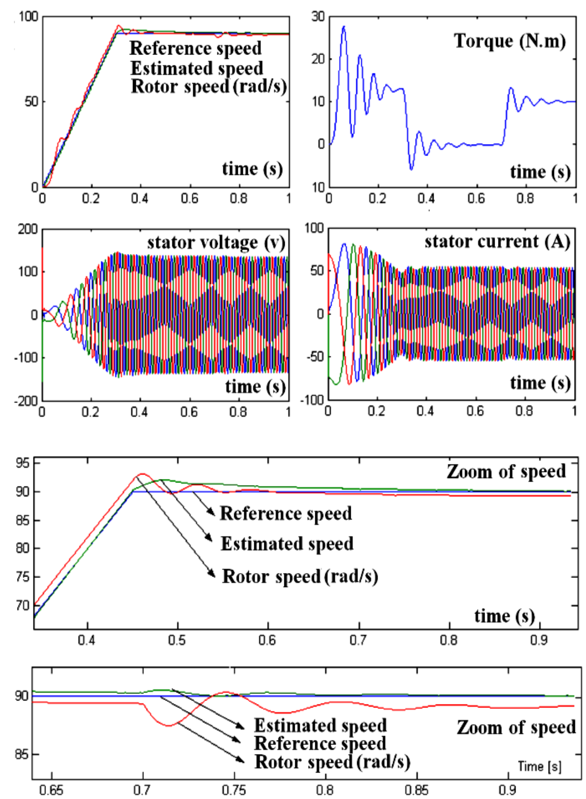

Fig. 11. Diagram of speed, torque, voltage and current of the stator in estimator simulation with MRAS method (with torque step at a time 0.7 seconds)

$$p\begin{bmatrix}\lambda_{dr}^{s}\\ \lambda_{qr}^{s}\end{bmatrix}=\frac{L_r}{L_m}\left\{\begin{bmatrix}V_{ds}^{s}\\ V_{qs}^{s}\end{bmatrix}-\begin{bmatrix}R_s+\sigma L_s p & 0\\ 0 & R_s+\sigma L_s p\end{bmatrix}\cdot\begin{bmatrix}i_{ds}^{s}\\ i_{qs}^{s}\end{bmatrix}\right\} \tag{7}$$

$$p\begin{bmatrix}\lambda_{dr}^{s}\\ \lambda_{qr}^{s}\end{bmatrix}=\begin{bmatrix}-\dfrac{1}{T_r} & -\omega_r\\ \omega_r & -\dfrac{1}{T_r}\end{bmatrix}\cdot\begin{bmatrix}\lambda_{dr}^{s}\\ \lambda_{qr}^{s}\end{bmatrix}+\frac{L_m}{T_r}\begin{bmatrix}i_{ds}^{s}\\ i_{qs}^{s}\end{bmatrix}$$

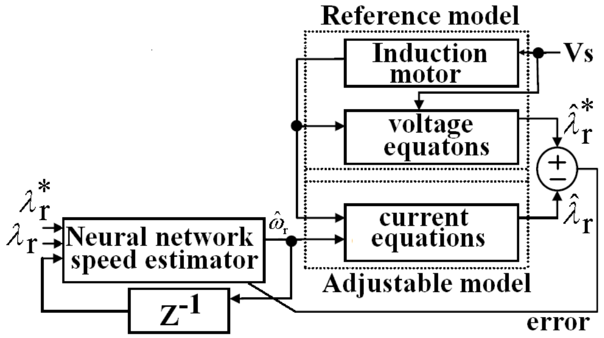

Fig.12. Structure of the neural speed estimator [14]

If there is difference between $\hat{\omega}_r$ and the actual speed value, there will be an error between the flux of adjustable model and the flux of reference model. This error is used to adjust the weights of neurons in the neural network in order to minimize training error and ultimately, the output of the neural network follows the actual speed of the motor. The proposed neural network consists of three layers including input layers, hidden layers and output layers, where Sigmoid and linear functions are respectively used in hidden and output layers [14]. The steps of training neural network to estimate the speed of induction motor include [15]:

A) Calculation of $\hat{\lambda}_r$: To make use of the equation (7) in the neural network calculations, we should convert it to a recursive relationship. This is achieved by taking some approximation as follows:

$$\hat{\lambda}_r(k+1)=e^{-(T/T_r)}*(\cos(\theta_r)\underline{I}+\sin(\theta_r)\underline{J})*\lambda_r(k) \tag{8}$$
$$+BTi_s(k)$$

Where $\theta_r=\omega_r T$, $B_m=L_m/T_r$, and $T_r=L_r/R_r$.

B) Calculation of the error: it is defined as the difference between the amounts of two fluxes as $E(k)=\hat{\lambda}_r^{*}(k)-\hat{\lambda}_r(k)$.

C) Calculation of the weights: weight coefficients of the neural network layers are as follows $W_1=1-(T/T_r)$, $W_2=\omega_r.T$, $W_3=(L_m/T_r)T$. Thus only the weight of W_2 is changed by changing the speed and this weight will normally be trained. Weight change of W_2 is performed by the least squares error method $\Delta W_2(k)=(\lambda_r^{*}(k)-\hat{\lambda}_r(k))^T\underline{J}\hat{\lambda}_r(k-1)$ and the new weight will be $W_2(k)=W_2(k-1)+\eta\Delta W_2(k)$ (J is the transposed of unit matrix I).

An arrangement of neural speed estimator with online training is shown in Fig. 13, in which to further evaluate the performance of estimator, torque stepping was applied to the motor at the moment of 0.7 second and the simulation results are provided in Fig. 14.

In the next, the applied reference speed is considered as step and the results are provided in Fig. 15. It can be seen according to the results that, in the early moments of the simulation, neural estimator has 20% error in estimating the speed and this is one of the biggest problems of neural estimator with online training. However, changing the training algorithm can improve the current situation. After transient period, the network is well trained and the error is reduced by about 1%.

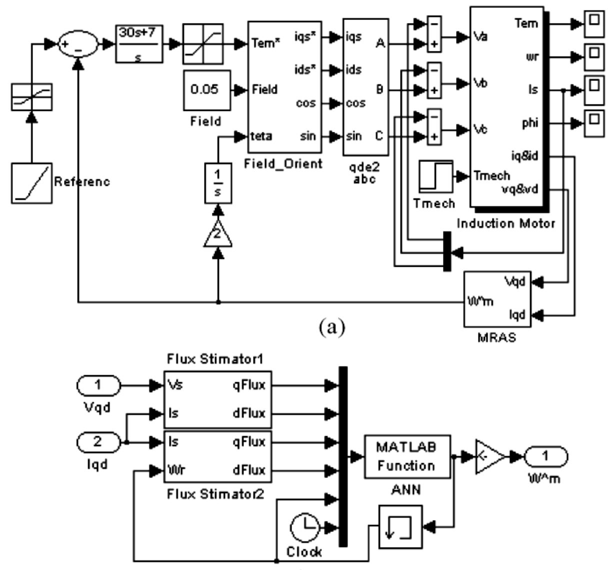

Fig. 13. a) Block diagram of induction motor control system using neural speed estimator with online training b) estimator structure

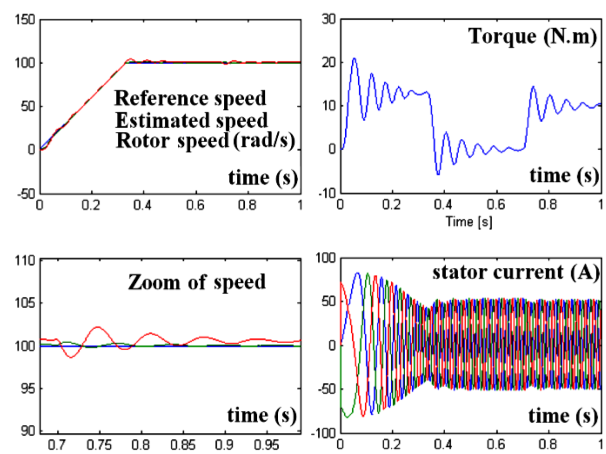

Fig. 14. Diagram of speed, torque, stator current in the simulation of neural speed estimator with online training (torque step at the time 0.7 seconds)

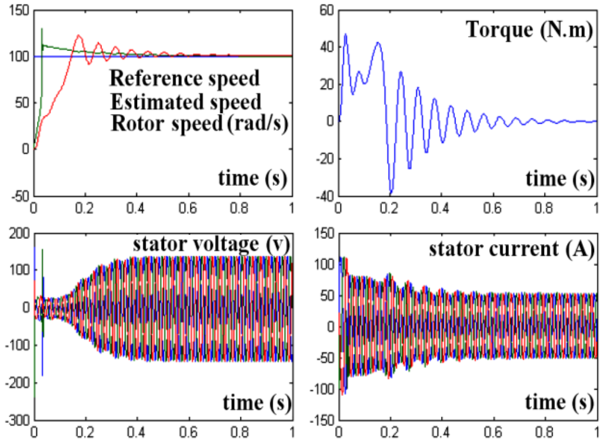

Fig. 15. Diagram of speed, torque, stator current and voltage in the simulation of neural speed estimator with online training (applying step reference speed)

B. neural speed estimator with offline training

A certain dynamic system model can be stored in the neural network and predict the output of the system using neural networks training with real data. The estimation accuracy of this method depends on numerous factors; so that the first important factor in this method is the neural network structure. The second factor is the training style of the network; so that different loading states have to be considered during the training. The data should be also trained by sufficient times. Hence, the design and training a neural estimator is time-consuming and accurate operation.

The structure of induction motor control system is provided in Fig. 16 to collect training data. As it is observed, first the three-phase voltage and current of the induction motor is converted into dq two-point reference and then stored in the MATLAB workspace. This data will be used with motor speed as the training data.

The block diagram of the simulation neural estimator with offline training is provided in Fig. 17. At first, only one state of motor function is trained to the network and then it will be generalized to all operating states of the system. Structures [4 7 4 1], [8 12 10 1] and [8 16 8 4 1] are considered for neural network and the results have been shown in Fig. 18.

It is shown in Figs (18-a) and (b) that the estimated speed is not accurate in the transient moments. This error is resulted from the neural network structure, so that the proposed structure is not able to fully store training data. Hence, the estimator with structure [8 16 8 4 1] will be obtained by adding a layer to the existing structure and the results are provided in Fig (18-C). It can be said that, we have to consider an appropriate structure for neural estimator to have a proper estimation, such that it has the capability to store motor dynamic system and the calculations wouldn't be complicated in real time operation.

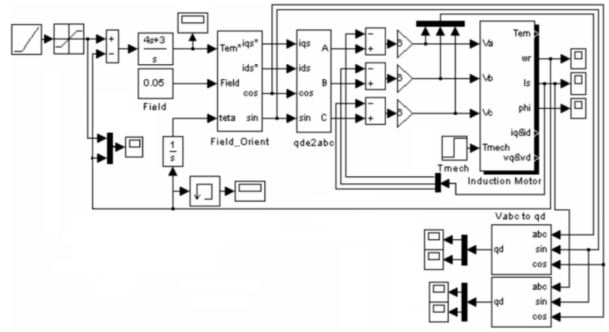

Fig. 16. Block diagram of induction motor control system to collect training data

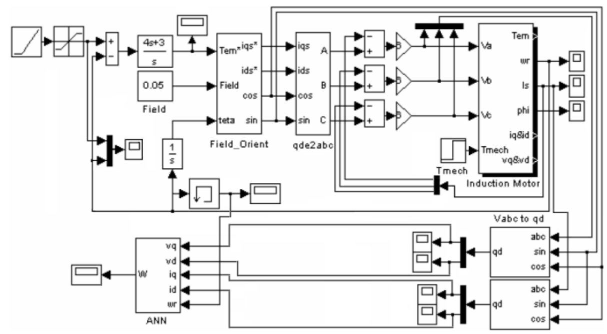

Fig. 17. Block diagram of induction motor control system using neural estimator with offline training

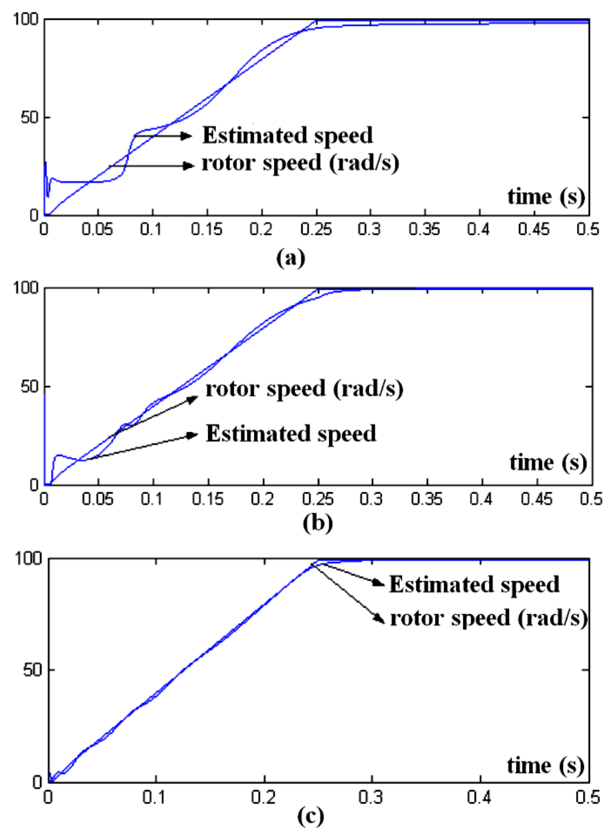

Fig. 18. Diagram of induction motor speed and estimated speed of neural network, structure a) [4 7 4 1] b) [8, 12, 10, 1] c) [8 16 8 4 1]

VI. Induction Motor Control Using Fuzzy Controller

Normally, a PI controller is used to improve the efficiency of the closed-loop control system of induction motor. This controller causes the steady error of the system to be zero, but it leads to the elimination of high performance of control system in transient states such as rapid change of load or reference speed. Hence, the use of fuzzy controller has been studied and investigated. Fuzzy controllers are often used in vector control systems of induction motors by two ways. In the conventional way, error and the derivative of the speed loop error are considered as the inputs of fuzzy system, and reference current changes as the output. While in the second method, which is more under consideration, reference current command is considered as the fuzzy controller output. An arrangement of induction motor control system using fuzzy controller is provided in Fig. 19 and fuzzy rules governing it are shown in Fig. 20. In the fuzzy rules above, e and de are respectively error and derivative error, and the definition of abbreviations are as follows:

PB: positive big, P: positive, PZ: positive small, Z: Zero, NB: negative big, N: negative, NZ: negative small.

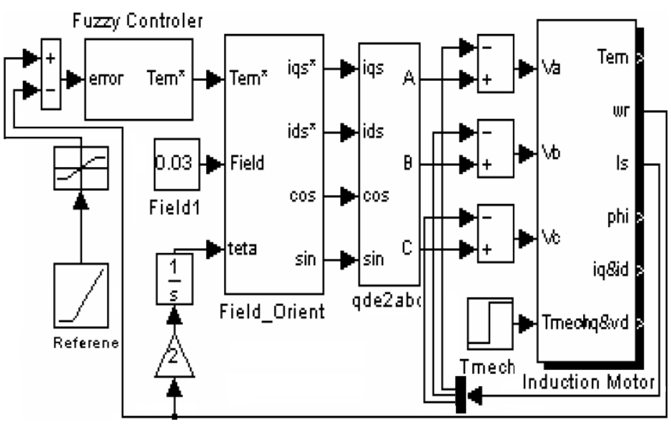

Fig. 19. Block diagram of speed estimation of induction motor using fuzzy controller

	de	NB	N	NZ	Z	PZ	P	
e								
NB		NB	NB	NB	N	N	N	N
N		NB	NB	N	N	N	N	NZ
NZ		N	N	N	NZ	NZ	Z	Z
Z		N	N	NZ	Z	PZ	P	P
PZ		Z	Z	NZ	NZ	P	P	P
P		PZ	P	P	P	P	PB	PB
PB		P	P	P	P	PB	PB	PB

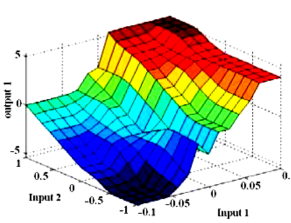

Fig. 20. the fuzzy rules governing the system

The arrangement of Fig. 19 is simulated by fuzzy controller and PI controller separately and the results have been provided in Fig. 21. According to the simulation results, we can say that the fuzzy controller has better dynamic response rather than PI controller.

One of the important parameters of induction motor speed control system is how the rotor flux control operate. This fuzzy controller controls the rotor speed and flux appropriately, but there will be inappropriate changes in the flux during transient moments that lead to inaccurate estimation of flux and speed. It can be observed in the simulation of Fig. 22.

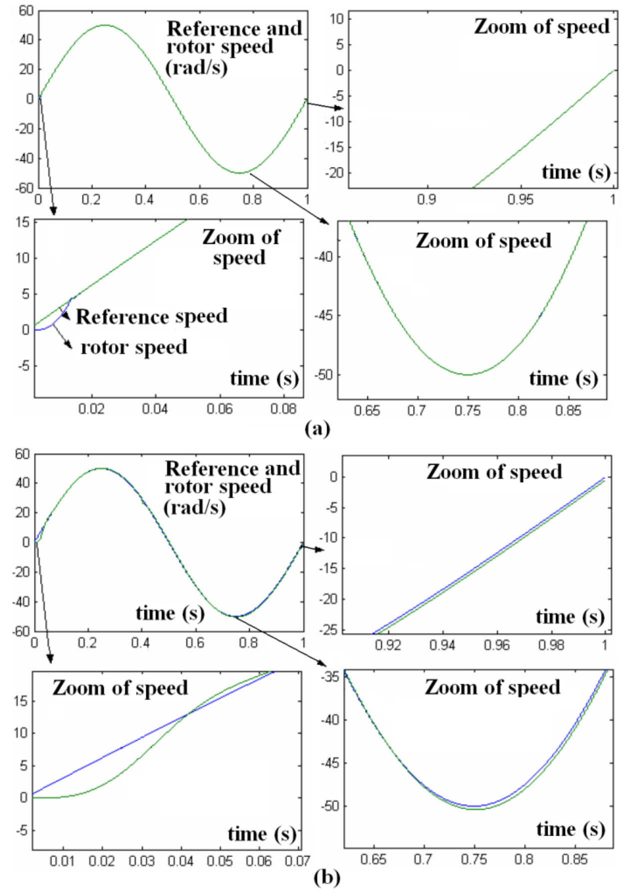

Fig. 21. Graph of speed over time, a) with fuzzy controller b) with PI controller

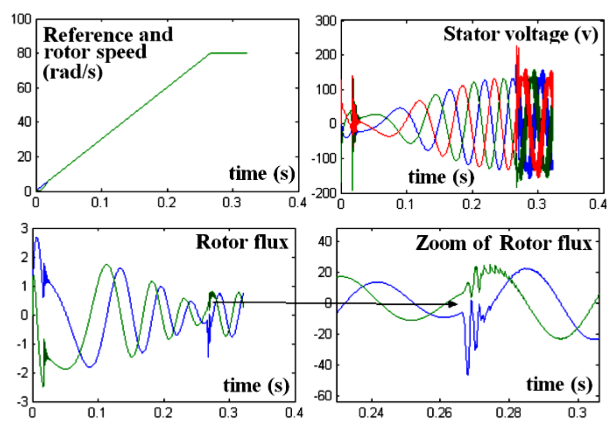

Fig. 22. Graph of speed, stator voltage and rotor flux from simulation with Fuzzy Controller

VII. Induction Motor Control Using the Proposed Method of Neural Estimator-Fuzzy Controller

In order to use companion speed estimator with fuzzy controller, some changes have to be made on the fuzzy controller for overcoming the problem of adverse changes in the flux during transient times. Therefore, given the structure of fuzzy logic, some changes were made on the

proposed fuzzy controller in accordance with Fig. 23 in the method of fuzzification and defuzzification of input and output parameters, and the results of simulation by applying step torque at the time of 0.3 second are provided in Fig. 24.

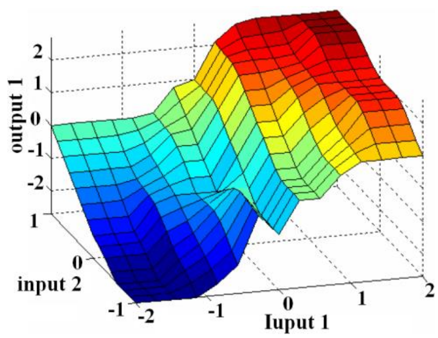

Fig. 23. Three-dimensional diagram of the proposed fuzzy controller input and output

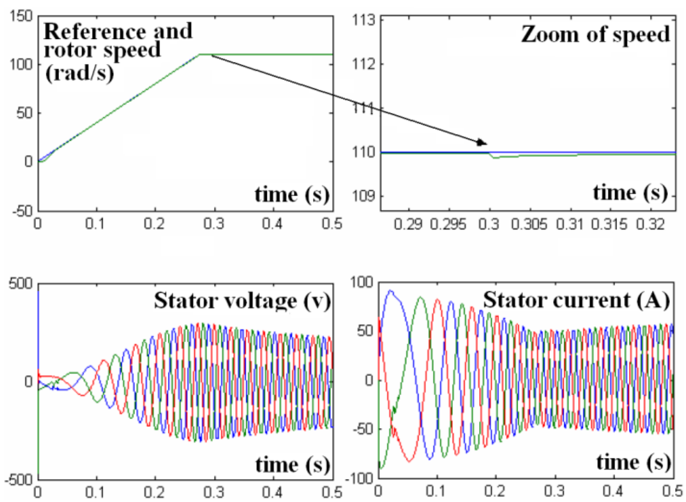

Fig. 24. Diagram of speed, voltage and current of the stator by applying the torque at the time of 0.3s using the proposed fuzzy controller

It can be observed in Fig. 24 that the motor speed is accurately estimated in loaded and no-loaded states.

The proposed fuzzy controller with .A neural estimator

In this section, the drive system of induction motor is implemented using the proposed fuzzy controller and neural estimator, it is also shown in Fig. 25. In this drive system, neural estimator with online training estimates the induction motor speed for each step of the simulation. Estimated speed, as the rotor speed, is compared with the reference speed. The error and its derivative are also the inputs of the fuzzy system.

The results of the simulation by applying step torque at the time of 0.4 second are provided in Fig. 26. According to the results, it can be said that the proposed fuzzy controller with neural estimator performs well in all circumstances (operation, loaded and no-loaded states), estimates the rotor speed accurately.

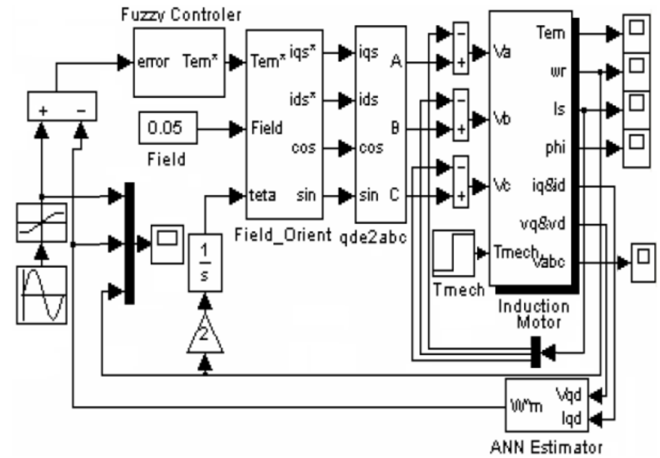

Fig. 25. Block diagram of the speed control system of induction motor using neural estimator and proposed fuzzy controller

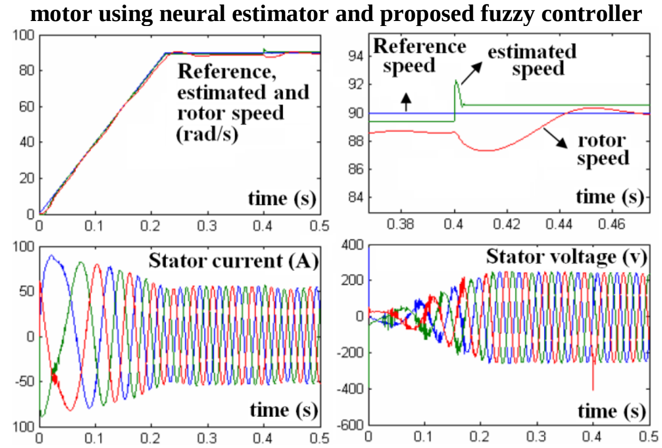

Fig. 26. Diagram of speed, voltage and current of the stator by applying the step torque at the time of 0.4s (using the proposed fuzzy controller and neural estimator)

IIX. Conclusion

In this paper, scalar and vector control methods were introduced and implemented. According to the simulation results, we can say that despite simple calculation of scalar method, it has a poor dynamic response and slow control system response. Meanwhile, despite the complex calculations of vector method, it benefits from high stability, good dynamic response and independent control of flux and torque.

Then, neural network with online training was investigated. It was observed that this method is appropriate to estimate the induction motor speed, but its main limitation was inaccurate estimation in transient moments due to the numerous time delays between calculations. For each sample of current and voltage in this estimator, the network must be trained once. There is also the possibility of loss of control in case of slow training.

The calculations in the neural estimators with offline training are reduced because of no training during motor operation; but it must be considered that all the states of induction motor performance have to be trained for the neural network in order to have an accurate estimation. Hence, selecting the type of estimator is totally dependent on the type of control system hardware.

Then, the fuzzy controller was simulated and analyzed. The results show that deals with the appropriate control of speed and simplicity of structure, lack of proper control on the rotor flux is a disadvantage.

Finally, by changing the method of fuzzification and defuzzification of input and output parameters, a new fuzzy controller was proposed and was used simultaneously with neural estimator in the induction motor drive system. Simulation results show that this method, despite of complex calculations, controls the flux and speed very well and does not require a speed sensor.

IX. References

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