SPEED CONTROL OF INDUCTION MOTOR USED NOVEL INTELLIGENT CONTROLLER

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ABSTRACT– *This paper presents design and evaluation of a novel approach based on emotional learning to improve the speed control system of stator flux oriented control of induction motor. The controller includes a neuro-fuzzy system with speed error and its derivative as inputs. A fuzzy critic evaluates the present situation, and provides the emotional signal (stress). The controller modifies its characteristics so that the critic's stress is reduced. The comparative simulation results show that the proposed controller is more robust and hence found to be a suitable replacement of the conventional PI controller for the high performance industrial drive applications.*

Keywords–– Induction motor; Speed control; Emotional Learning; intelligent controller; PI controller.

I. INTRODUCTION

AC motor drives are used in multitude of industrial and process applications requiring high performances. In high performance drive systems the motor speed should closely follow a specified reference trajectory regardless of any load disturbances, parameter variations and any model uncertainties. In order to achieve high performance, field oriented control of IM drive is employed [1]. However, the controller design of such system plays crucial role in the system performance. The decoupling characteristics of vector controlled induction motor are adversely affected by the parameters change in the motor.

The motor control issues are traditionally handled by fixed gain proportional integral (PI) and proportional integral derivative (PID) controllers. However, the fixed gain controllers are very sensitive to parameter variations, load disturbances, etc. So, the controller parameters have to be continually adapted. The problem can be solved by several adaptive control techniques such as model reference adaptive control (MRAC) [2], sliding mode control (SMC) [3], variable structure control (VSC) [4] and self tuning PI controllers [5], etc. The design of all of the above controllers depends on the exact system mathematical model. However, it is often difficult to develop an accurate system mathematical model due to unknown load variation, unknown and unavoidable parameter variations due to saturation, temperature Variations and system disturbances. In order to overcome the above problems, recently the fuzzy logic controller (FLC) is being used for motor control purpose.

The mathematical tool for the FLC is the fuzzy set theory introduced by Zadeh [6]. As compared to the conventional PI, PID and their adaptive versions, the FLC has some advantages such as:

- It does not need any exact system mathematical model
- It can handle nonlinearity of arbitrary complexity
- It is based on the linguistic rules with IF-THEN general structure which is the basis of human logic

However, the application of FLC has been facing some disadvantages during hardware and software implementation due to its high computational burden [7]. That is why so far the reported fuzzy logic works in motor drives [8-12] are mainly theoretical and based on either simulation or experimental results at very low speed operating conditions. With referring to above mentioned approaches it is clear up that fuzzy-logic control utilization to design speed control system of induction motor, rapidly increasing because of the good performance of this controller both in nonlinear and complex systems.

A fuzzy system includes a fuzzifier of a deterministic input signal with a membership function, reasoning in a fuzzy rule set using a proper inference method, and defuzzifier process to produce a deterministic output. Fuzzy rule base includes IF-THEN rules representing expert knowledge that makes decisions from input signals. This knowledge is provided by a control engineer who has performed extensive mathematical modeling, analysis, and development of control algorithms for power systems. Thus, fuzzy controllers work well as supervisory controllers in conditions such as severe nonlinearities, time varying parameters and plant uncertainties.

The proposed method in this study is the controlling model based on emotional processing in human beings brain that is latter method from above methods where the Critic gives rewards and punishments with respect to the states reached by the learner and is called "Brain Emotional Learning Based Intelligent Controller" (BELBIC). In real time control and decision systems, Emotional Learning is a powerful methodology due to its simplicity structure, low computational complexity, and independent from system model, online controlling and fast training. For these reasons, recently there is rising tend to intelligent controllers and BELBIC to use in different systems such as [14-16]. Emotional learning based intelligent controllers for Rotor flux oriented control of induction motor has been proposed [17]. This novel approach applied to improve the speed control system of stator flux oriented control of induction motor. The control system combined from a neuro-fuzzy controller and a fuzzy critic which evaluates the motor speed condition and then produces an appropriate signal to controller learning.

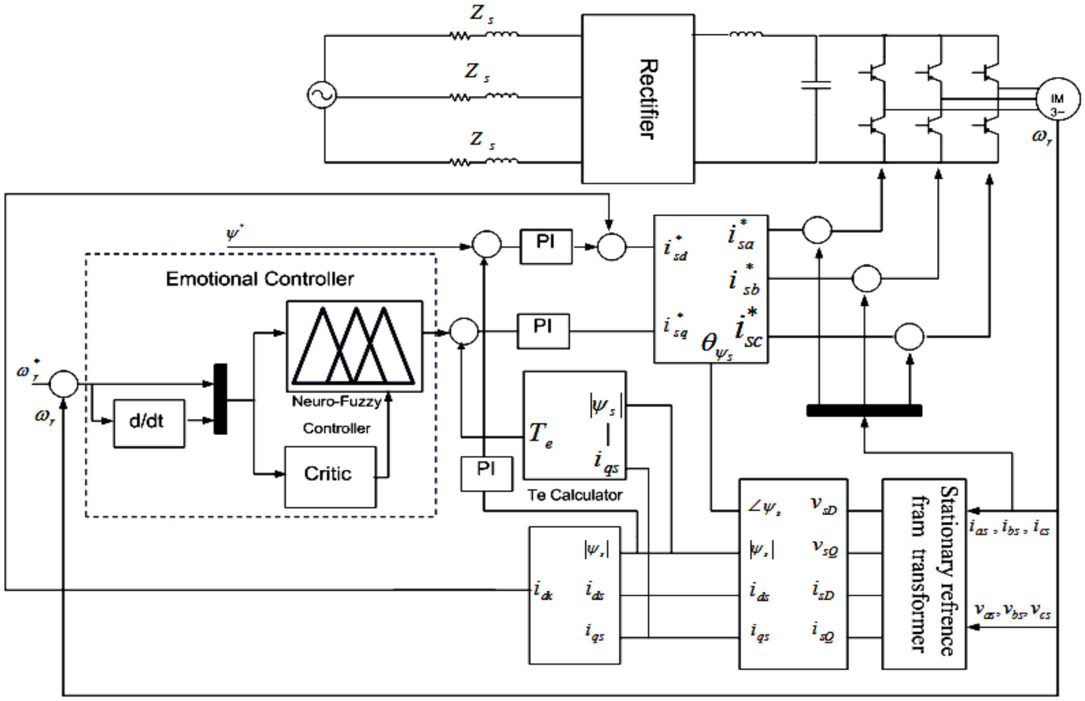

Fig.1. The proposed Emotional Controller based IM drive.

The vestige of this paper is organized as follows. In section 2, an overview about stator flux oriented control of induction motor are explained. Section 3 describes the emotional learning concept. Section 4 characterizes Neuro-fuzzy controller scheme based on brain emotion and some mathematical Fundamentals. Then section 5 presents architecture of emotional learning based intelligent controllers (ELIC) for Stator flux oriented control of induction motor. In section 6 the simulation results that compare the proposed method to PI Controller designs is illustrated And finally, conclusions and viewpoints based on comparing results are exposured in section 7.

II. STATOR FLUX ORIENTED CONTROL OF INDUCTION MOTOR

In this paper stator flux oriented control will be applied to induction motor. The effects of magnetic saturation are neglected. Expressions for the electromagnetic torque of induction machine is proportional to the magnetizing flux (current) and torque producing stator current component (i_{sq}); thus from (1):

$$T_e = \frac{3}{2} P L_m |\varphi_s| i_q \qquad (1)$$

Where P is the number of pole pair and L_m magnetizing inductance of the machine, $|\varphi_s|$ is obtained from (2):

$$|\varphi_s| = L_s i_{ds} \qquad (2)$$

Where L_s, is self inductance of the stator.

II.1. Stator flux estimation

The angle of stator flux doesn't obtain from the terminal of machine directly. The required equation for estimate flux stator obtained as (3) – (6):

$$V_{sD} = R_s i_{sD} + \frac{d}{dt}\varphi_{sD} \qquad (3)$$

$$V_{sQ} = R_s i_{sQ} + \frac{d}{dt}\varphi_{sQ} \qquad (4)$$

$$\varphi_s = \sqrt{\left(\varphi_{sD}^2 + \varphi_{sQ}^2\right)} \qquad (5)$$

$$\theta_s = \angle\varphi_s = \tan^{-1}\left(\frac{\varphi_{sD}}{\varphi_{sQ}}\right) \qquad (6)$$

Where V_{sD} and V_{sQ} are components of stator voltage in stationary reference frame and θ_s is angle of stator flux.

Decoupling of q and d axis current components rotor voltage equation with assumption $\varphi_s = L_s i_{ms}$ is expressed in the stator flux oriented reference frame (7):

$$V_r^s = 0 = R_r i_r^s + L_r \frac{d}{dt} i_r^s + L_m \frac{d}{dt} i_s^s + j(\omega_{ms} - \omega_{mr})(L_r i_r^s + L_m i_s^s) \qquad (7)$$

Where ω_r is the rotor speed and R_r and L_r are the rotor resistance and rotor self inductance.

Expression of magnetizing flux yields simply as (8):

$$L_m i_r^s = \phi_s - L_s i_s^s \qquad (8)$$

By the substitution of (8) into (7) and by considering that, since the rotor winding can be considered as short circuited winding, yields:

$$0 = R_r\left[i_{ms} - \frac{L_s}{L_m} i_s^s\right] + L_r \frac{di_{ms}}{dt} - \left(\frac{L_s' L_r}{L_m}\right)\frac{di_s^s}{dt} + j\omega_{sl}\left[L_r i_{mr} - \left(\frac{L_s' L_r}{L_m}\right) i_s^s\right] \quad (9)$$

Decomposition of (8) into its real and imaginary axis component gives:

$$\frac{L_m}{L_s'}\frac{di_{ms}}{dt} + \frac{L_m}{T_r' L_s} i_{ms} = \frac{di_{sd}}{dt} + \frac{i_{sd}}{T_r'} - \omega_{sl} i_{sq} \quad (10)$$

$$\omega_{sl}\left(\frac{L_m}{L_s} i_{ms} - i_{sd}\right) = \frac{di_{sq}}{dt} + \frac{i_{sq}}{T_r'} \quad (11)$$

Where

$$\omega_{sl} = \omega_{ms} - \omega_r \quad (12)$$

$$L_s' = L_s\left(1 - \frac{L_r L_s}{L_m^2}\right) \quad (13)$$

$$L_r' = L_r\left(1 - \frac{L_r L_s}{L_m^2}\right) \quad (14)$$

From relations (10) and (11) are seen that i_{qs} have undesirable effects on transient component of i_{ds} and so they can't control independently. For removing effects of coupling, i_{sd} is expressed as (15):

$$i_{sd} = \hat{i}_{sd} + i_{dx} \quad (15)$$

So for remove the unintended effect of i_{qs} on the magnetizing current component i_{dx} is obtained from relations (10) and (11) as follow:

$$i_{dx} = \omega_{sl}\frac{T_r'}{1 + sT_r'} i_{sq} \quad (16)$$

$$\omega_{sl} = \frac{(1 + T_r)L_s i_{sq}}{T_r\left(\left|\varphi_s\right| - L_s' i_{sq}\right)} \quad (17)$$

With this separation axis component d and q, the flux controller (PI), only see $\hat{i}_{sd}$ that it does not have any coupling terms (figure 1).

The conventional PI controller is one of the most common approaches for speed control in industrial electrical drives, because of its simplicity, and the clear relationship existing between its parameters and the system response specifications. The conventional PI controller fixed gains may perform well under some operating conditions but not all, because of complexity, time variant, nonlinearity and model uncertainties. In order to improve the performances of the indirect vector control system, a novel approach based on emotional learning is being used to be the speed controller. The schematic diagram of the ELIC-based indirect vector control of IM is shown in Fig.1**.** The motor parameters are given in the Appendix.

III. EMOTIONAL LEARNING

There are three learning methods for neural networks characterized by the information source used for learning and classified with respect to the degree of information of the source. These learning methods are supervisored learning, unsupervisored learning, and reinforcement learning. Emotional learning is a type of reinforcement learning. It is done fuzzily and continuously in human being, in a way that the learning process is done through emotional signals. This signal is produced by the brain based on the person's behavior. Whenever the person's behavior is satisfactory, the stress is reduced in the person and no correction of the behavior is needed and as a result the value of the produced stress signal is small. If the person's behavior is not satisfactory, the stress is increased and as a result, the value of the stress signal is higher in order to improve the person's behavior.

Although, reinforcement learning and emotional learning have many similarities in training the controller systems, there also exist some differences in a way that the critic which is used in emotional learning has a continuous performance producing the learning signal in the range of [-1,1]. If the system operation is satisfactory, the value of this signal will be close to zero and if it is unsatisfactory its value is increased and based on the type of operation it will be close to 1 or -1. But the critic which is used in reinforcement learning just analyzes success and failure in the system operation and based on this analyzing the learning signal is produced in order to train the controller (0 for failure in the system operation and 1 for success in the system operation).

IV. EMOTIONAL LEARNING CONTROLLER

Fig.2. shows the emotional learning controller structure which is used in this paper. The critic produces an emotional signal for the controller by analyzing the system performance. Controller amends its parameters based on this emotional signal and the current error in the system output in order to improve system performance.

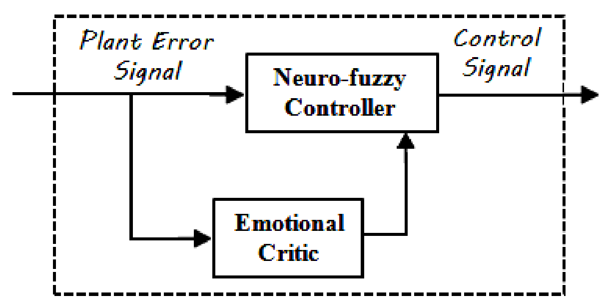

Fig.2. Structure of emotional learning methodology.

In this structure, because updating the controller parameters is based on the emotional signal, the system response is so dependent on the critic performance. Thus, the most important part in the control system is to design the critic. In this section, at first the neuro-fuzzy controller, then the operation of emotional critic, and finally the method of teaching the neuro-fuzzy controller is explained.

IV.1. Neuro-fuzzy controller

Fuzzy systems are *knowledge-based* or *rule-based* systems [13]. The heart of a fuzzy system is a *knowledge base* consisting of the so-called fuzzy IF-THEN rules. A fuzzy IF-THEN rule is an IF-THEN statement in which some words are characterized by continuous membership functions. The starting point of constructing a fuzzy system is to obtain a collection of fuzzy IF-THEN rules from human experts or based on domain knowledge. The next step is to combine these rules into a single system. In fact the fuzzy system can be viewed as performing a real and nonlinear mapping from an input vector $X=[x_1, x_2\ldots x_n]^T \varepsilon R^n$ to an output vector $\tilde{y}=\tilde{f}(X)\ \varepsilon\ R^m$ ($.^T$ denotes transposition; n and m are input and output vector dimensions). Different fuzzy systems use different principles for this combination. There are two types of fuzzy systems that are commonly used in the literature: Takagi-Sugeno-Kang (TSK), and fuzzy systems with fuzzifier and defuzzifier.

The model which is used here to design the neuro-fuzzy controller is of TSK type. Consider a multiple-input single-output (MISO) fuzzy system consisting of N rules as follows:

R_j (jth rule): if(x_1 is F_{j1}) and (x_2 is F_{j1}) and (x_2 is F_{j2}) and and (x_n is F_{jn}) then $c_j=g_j(X)$

Where j=1, 2, . . . , N; x_i(i=1,2, … ,n) are the input variables of the fuzzy system, F_{ji} is characterized by its corresponding membership function $\mu F_{ji}(x_i)$, c_j is the consequence of the jth rule and g_j : $\mathcal{R}^n \rightarrow \mathcal{R}^m$. Each rule R_j, can be viewed as a fuzzy implication by the inference engine.

The antecedent fuzzy set (fuzzy Cartesian product) of each rule $F_1\times F_2\times\ldots\times F_n$ is quantified by the *t-norm* operator which may be defined as (18), the min-operator or the product operator.

(18)

$$\mu F_1\times\mu F_2\times\ldots\times\mu F_n(x_1,\ldots,x_n)\quad \begin{cases}\min[\mu F_1(x_1)\times F_2(x_2)\times\ldots\times\mu F_n(x_n)]\\ or\\ \mu F_1(x_1)\times F_2(x_2)\times\ldots\times\mu F_n(x_n)\end{cases}$$

The defuzzification is performed using (19), where μ_j the firing strength of the antecedent is part of the jth rule and is given by (20).

$$\tilde{y}=\tilde{f}(x)=\frac{\sum_{j=1}^{N} c\mu_j}{\sum_{j=1}^{N}\mu_j}\ ,\ X=[x_1,\ldots,x_n]^T\ \varepsilon\ \mathcal{R}^n \tag{19}$$

$$\mu_j=\mu F_1\times\mu F_2\times\ldots\times\mu F_n(x_1,\ldots,x_n) \tag{20}$$

In TSK fuzzy systems, the consequent part of rules is given by (21).

$$c_j=a_{0j}+\sum_{i=1}^{n}a_{ij}.x_i \tag{21}$$

Where where a_{oj} and a_{ij} are the coefficients that should be set at design stage or tuned during the corresponding learning procedure. Implementing a fuzzy inference system in the framework of an adaptive neural network results in a six layer network in which each layer serves as one part of the equivalent fuzzy system. Fig.3. shows a sample neuro-fuzzy system equivalent to a two-input and one-output TSK fuzzy inference system which has two linguistic labels for each input and therefore four rules in its rule base.

In the first layer, which is shown by I, the input is normalized to the range [-1,1]. In the second layer, which is shown by MF, by using the membership functions the input variables are transformed from real variables into linguistic variables. The third layer which is shown by *c*, multiplies the variables received from layer two and provides the antecedent part of the fuzzy rules $\left(\mu_{F_{j1}}(x_1)\times\ldots\times\mu_{F_{jn}}(x_n)\right)$. In the fourth layer, which is shown by N, the term $\mu_j\Big/\sum_{j=1}^{n}\mu_j$ is calculated which expresses the ratio of firing strength in the *j*th node to the sum of all firing strengths of the rules.

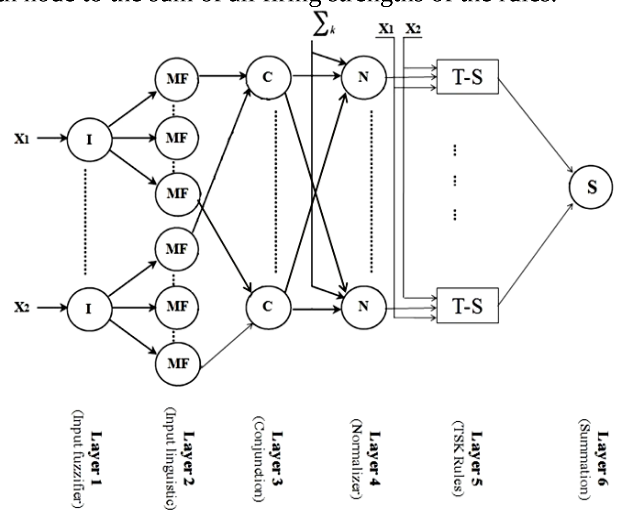

Fig.3. Neuro-fuzzy structure equivalent with a MISO TSK fuzzy inference system.

In the fifth layer, which is shown by T-S, by using the normalized data of the previous layer and the arranged TSK rules in this layer, the output of the above rules are calculated. Finally, the sixth layer is a defuzzifier layer and the output is calculated based on (19).

IV.2. *Emotional Critic*

The performance of the critic is similar to the emotional section of human brain, in a way that it produces a learning signal in order to update the neuro-fuzzy controller weights by analyzing the system performance. This analysis is done by using the system error and its derivation signals. It means that position of system output and also the system behavior are effectual on the emotional signal. The critic is designed by implementing PD behavior via fuzzy systems. The critic which is designed by PD controller has a linear performance and it is not suggested to be used for non-linear systems. But the critic which is designed by neuro-fuzzy controller has a proper performance in non-linear systems. In this article, the expert fuzzy system model is used to design the critic.

Considering the fact that controller performance correction should lead to reduction of critic stress, the cost function is defined as follows:

$E=\sum_{j=1}^{m}k_j\left(r_j^2/2\right)$

In which r_j is the output emotional signal of critic j, k_j is the weight of this signal, and m is the number of system outputs which also defines the number of critics used in the system.

IV.3. Emotional learning

As it is mentioned in section VI-B, the main goal of emotional controller is to update the neuro-fuzzy controller parameters in order to reduce the critic stress based on cost function in equation 22. As a result steepest descent method is used.

$$E=\frac{1}{2}r^2 \qquad (22)$$

$$\Delta\omega=-\eta\frac{\partial E}{\partial\omega} \qquad (23)$$

In which η is controller learning rate and ω is the tunable parameter of the controller. By using the chain rule in order to calculate equation 20 we will have:

$$\Delta\omega=-\eta\frac{\partial E}{\partial r}.\frac{\partial r}{\partial y}.\frac{\partial y}{\partial u}.\frac{\partial u}{\partial\omega} \qquad (24)$$

$$\frac{\partial E}{\partial r}=r \qquad ,\frac{\partial y}{\partial u}=J$$

In which u is the control signal.

TABLE+I CRITIC FUZZY RULE BASE

		Speed Error				
		BN_e	SN_e	Z_e	SP_e	BP_e
Speed Error Derivative	BN_{ed}	VBN	BN	SN	VSN	ZE
	SN_{ed}	BN	SN	VSN	ZE	VSP
	Z_{ed}	SN	VSN	ZE	VSP	SP
	SP_{ed}	VSN	ZE	VSP	SP	BP
	BP_{ed}	ZE	VSP	SP	BP	VBP

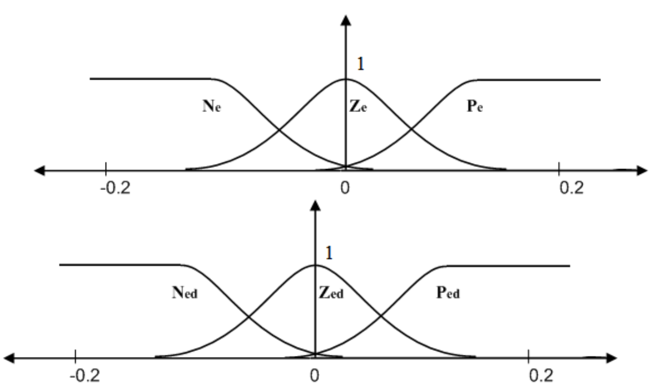

Fig.**4. The membership functions of the corresponding linguistic variables of the Neuro-Fuzzy Controller.**

In the above equation J is system Jacobean. Jacobean of the systems can be replaced by their symbols. As the system input is increased its output will increase too, as a result the system Jacobean sign is positive in this system.

$$\Delta\omega=-\eta.r.\frac{\partial r}{\partial y}.(+1).\frac{\partial u}{\partial\omega}=-\eta.r(\frac{\partial r}{\partial e}.\frac{\partial e}{\partial y}).\frac{\partial u}{\partial\omega} \qquad (25)$$

Because the critic operation is fuzzy $\frac{\partial r}{\partial e}$ value can be repla

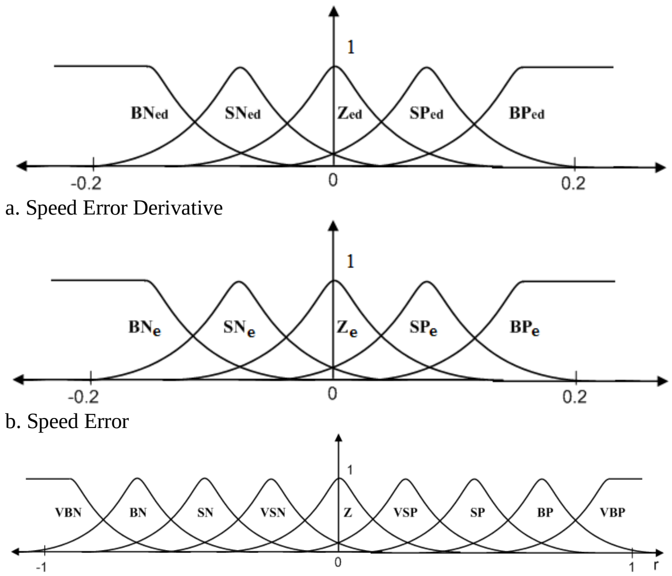

Fig.5. Fuzzy critic membership functions: (a) input membership functions and (b) output membership unctions.

ced by its symbol. Considering the fact that increase in the system error leads to increase in the stress, the sign of the above equation is positive. The system error is also calculated by using $e=y_{ref}-y$.

$$\Delta\omega=\eta.r.\frac{\partial u}{\partial\omega} \qquad (26)$$

In the introduced neuro-fuzzy controller, control signal u of the previous sub-sections is calculated by combining equations 19 and 21 according to equation 27.

$$u=\frac{\sum_{j=1}^{N}(a_{0j}+\sum_{i=1}^{n}a_{ij}.x_i).\mu_j}{\sum_{j=1}^{n}\mu_j} \qquad (27)$$

Now based on equation 26 controller parameters are updated based on equations 28 and 29.

$$\Delta a_{0j}=\eta.r.\frac{\partial u}{\partial a_{0j}}=\eta.r.\frac{\mu_j}{\sum_{j=1}^{N}\mu_j} \qquad (28)$$

$$\Delta a_{ij}=\eta.r.\frac{\partial u}{\partial a_{ij}}=\eta.r.x_i.\frac{\mu_j}{\sum_{j=1}^{N}\mu_j} \qquad (29)$$

V. THE PROPOSED SPEED CONTROL SYSTEM OF STATOR FLUX ORIENTED CONTROL OF INDUCTION

The structure of the designed emotional controller for speed control system of stator flux oriented control of induction is shown in Fig.1. This structure is made of neuro-fuzzy controller and critic sections. The neuro-fuzzy controller section produces command signal in order to speed control system of stator flux oriented control of induction. As it was mentioned earlier the structure of this controller is of TSK type and speed error signal and its derivation are used as the inputs of this controller. In this controller three linguistic variables (Negative (N), Positive (P) and Zero (Z)) are used in each input in order to tune the rules and according to this 9 rules are formed for the controller. Membership functions of linguistic variables are shown in “Fig. 4”**.**

It is obvious that sigmoid functions are used for variables N and P, i.e. $\mu F_{ji}(x_i) = [1+\exp(-a_{ji}(x_i - c_{ji}))]^{-1}$ and Gaussian function, i.e. $\mu F_{ji}(x_i) = [-((x_i - c_{ji})/\sigma_{ji})^2]$ is used for variable Z. In the above equations c_{ij} is the center of function σ_{ji} is the function variance and a_{ij} is the curve inflection function. The main sector in emotional controller is the critic. In this controller expert fuzzy model is used in order to design the critic. Speed error signal and its derivation are used as critic inputs in order to analyze system performance. Five linguistic variables are used for each of the above inputs; their membership functions are shown in Fig. 5-a. and Fig. 5-b. As it is seem in the figure, Gaussian function is used for variables SP, SN and Z and Sigmoid function is used for variables BP and BN. According to the above linguistic variables, 25 different states can be defined in the critic and 25 different rules are tuned based on them in order to form the critic stress in the then part of these rules. The above rules are shown in table 1 and also Fig. 5-c. shows the critic stress signal derived from these rules. For example if the speed error signal and its derivation are BP (Big Positive), the system performance is unsatisfactory and the critic stress will be VBP; contrary to that if the speed error signal is SP (Small Positive) and its derivation is SN (Small Negative) the system performance is satisfactory and the critic stress is also reduced.

Finally by applying the stress signal to the neuro-fuzzy controller, the controller parameters are tuned by using SD method in order to optimize system performance.

VI. RESULTS AND DISCUSSIONS

Several tests were performed to evaluate the performance of the proposed ELIC based vector control of IM drive system simulated. The speed control loop of the drive was also designed, simulated implemented with PI controller, in order to compare the performances to those obtained from the respective FLC based drive system. The speed responses are observed under different operating conditions such as sudden change in command speed, step change in load, etc. Some sample results are presented in the following section. The PI controller is tuned at rated conditions in order to make a fair comparison. Fig.6. show the simulated starting performance of the drive with PI and ELIC based drive systems, respectively. Although the PI controller is tuned to give optimum response at this rated condition, the emotional controller yielded better performances in terms of faster response time. Fig.7. show the speed responses of the drive system using PI and emotional controller, with step change in reference speed. It is evident from Fig.7, that the proposed ELIC based IM drive system can follow the command speed without any overshoot and steady state error. So this intelligent controller is not affected by the sudden change of the command speed. Thus, a good tracking has been achieved for the ELIC. Whereas, the PI controller based drive system is affected with the sudden change in command speed.

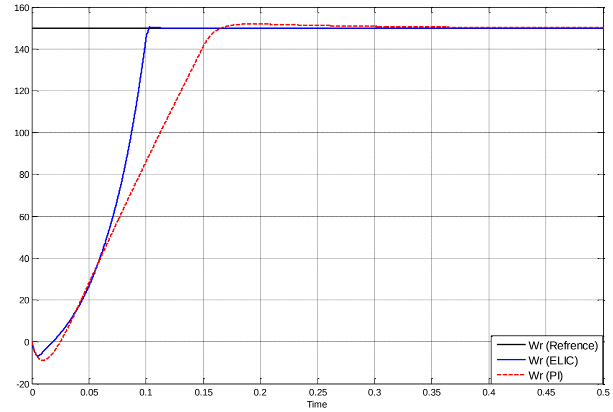

Fig.6. Simulated starting responses of the drive with ELIC and PI

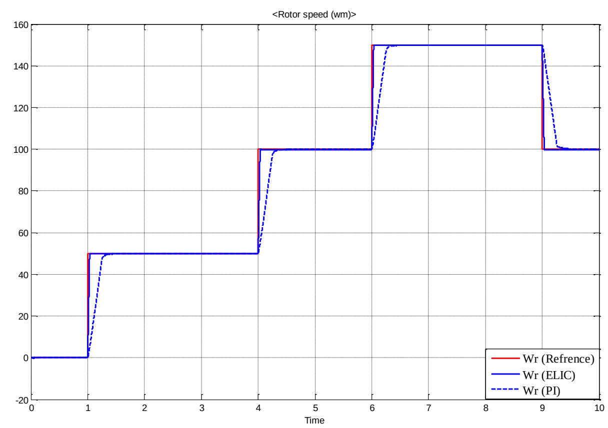

Fig.7. **Simulated speed responses of the drive due to step change of the reference speed ELIC and PI.**

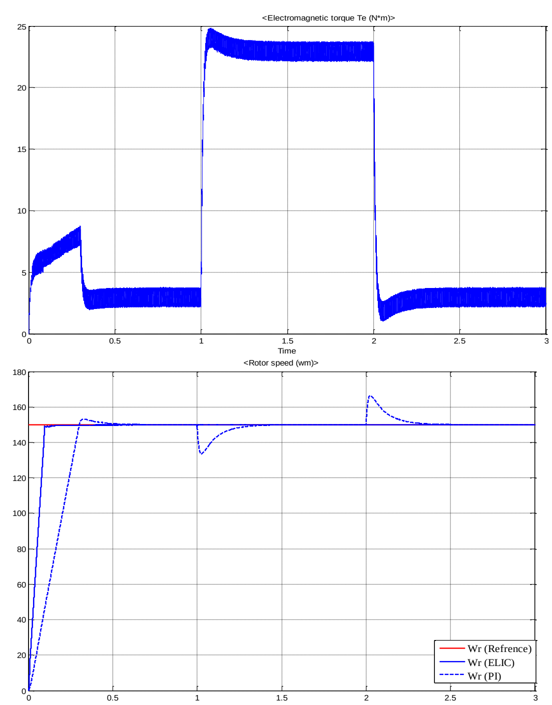

Fig.8. Simulated speed responses of the drive due to applying and removing the full load ELIC and PI.

Fig.8. show the speed responses for step change in the load torque using PI and emotional controller. The motor starts from standstill without load and at t=1 sec, a sudden full load is applied and at t=2 sec, full load is removed. The motor speed follows its reference with zero steady state error and fast response using ELIC. It is to be noted that the speed response is affected by the load conditions. This is the draw-back of PI controller with varying the operating conditions.

These figures also show that the ELIC based drive system can handle the sudden increase in command speed quickly without overshoot, undershoot and stead-state error, whereas the PI controller based drive system has steady-state error and the response is not as faster as compared to the ELIC. Thus, the proposed emotional controller based drive has been found superior to the conventional PI controller based system.

VII. CONCLUSION

A novel Emotional learning based intelligent controllers to improve the speed control system of stator flux oriented control of induction motor has been presented in this paper. The ELIC has been designed for speed control loop. The simulation has been carried out using SIMULINK Toolbox. The above controller is an intelligent controller of reinforcement learning type which uses a fuzzy critic in order to assess the system performance and tuning parameters of the controller. Since exact system parameters are not required in the implementation of the proposed controller, the performance of the drive system is robust, stable and insensitive to parameters and operating condition variations. In order to prove the superiority of the ELIC, a conventional PI controller based IM drive system has also been simulated implemented. It is concluded that the proposed Emotional learning based intelligent controllers has shown superior performances over the PI controller.

Appendix

Specifications of induction motor:

5hp, 3-Phase, 4-Pole, Y-Connected, 460 V, 60 Hz, 1800 rpm, squirrel cage induction motor.

R_s = 1.115 Ω, R_r =1.083 Ω, L_s =0.0059 H, L, = 0.0059 H, L_m = 0.2037 H, J_m = 0.01 Kg.m^2, B_m = 0.02 (N.m.s).

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