International Journal of Electrical Engineering.
ISSN 0974-2158 Volume 6, Number 3 (2013), pp. 339-349

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A Responsive Neuro-Fuzzy Intelligent Controller via Emotional Learning for Indirect Vector Control (IVC) of Induction Motor Drives

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Abstract

The principle of a new adaptive Neuro-Fuzzy Controller (NFC) is introduced and used for indirect vector control of induction motor drives. The proposed algorithm has advantages of neural and fuzzy networks and uses a supervised emotional learning process to train the NFC. This newly developed design leads to a controller with minimum hardware and improved dynamic performance. System implementation is relatively easy since it requires less calculation as compared with the conventional fuzzy and/or neural networks, used for electrical drive applications. The proposed controller is used for speed and torque control of an induction motor drive. In order to demonstrate the NFC ability to follow the reference speed and to reject undesired disturbances, its performance is simulated and compared with that of a conventional PID controller.

Keywords: Neuro-Fuzzy Controller, EmotionalLearning, Indirect Vector control

1 Introduction

In an indirect vector controlled induction motor drive, the speed controller impacts the drive performance in several important ways. In particular, the q- axis of stator current generated by speed (or torque) controller not only commands the current regulator, but also determines the slip calculation. Therefore, a desired speed controller should not only deliver a satisfactory torque signals, but also generate accurate slip commands to guarantee the independent control of torque and flux. In effect, if the speed controller is intelligently designed, it will have the ability to minimize de-tuning effects and the drive performance will be verystong. [1].

Traditionally, a PID controller is often used as the speed controller; the PID controller generally offers fair performance if it is well tuned. However, there are several drawbacks in using PID as the speed controller. For example a set of fixed PID gains cannot satisfy requirements of different speed commands. Moreover, tuning PID gains is tedious and time-consuming [2].

Recently the intelligent algorithms have been used to control highly nonlinear systems complex models and time varying uncertainties. To get the advantages of both fuzzy logic and neural networks, it is demonstrated that the neural-fuzzy systems can be used. So the learning abilities of neural networks and fuzzy inference of fuzzy systems is achieved simultaneously [3-6].

In this paper a new adaptive, responsive neural-fuzzy controller is introduced and used for the vector control of induction motor drives. To train the proposed NFC, instead of the traditional back propagation technique, the emotional learning procedure is used. The proposed controller is used for speed and torque control of an induction motor drive. Simulation results are used to show the abilities and shortcomings of the proposed algorithm as compared with the conventional PID controller.

2 Neuro-Fuzzy Systems

In parallel to development of the technology and complexity of the industrial plants, their modeling and control, by using the conventional techniques has become more difficult. Therefore, the conventional mathematical-model-based analysis techniques have become very complex or

in rare cases they have become impossible to apply. On the other hand, human abilities in controlling the complex systems, has encouraged scientists to pattern from human neural network and decision making systems. The researches began in two separate fields and resulted in establishment of the fuzzy systems and artificial neural networks.

There are primarily three concepts prevailing over the intelligent control:

- Fuzzy Logic Control
- Neural Network based Control
- Neuro-Fuzzy Control (Hybrid Control)

In the first concept, the controller is represented as a set of rules, which accepts the input in the form of linguistic variables and gives the output in the form of linguistic variables. The main advantages of such a controller are:

- Approximate knowledge about the plant is required (unlike most optimal and adaptive strategies that require an accurate system model).
- Knowledge representation and inference is relatively simple.
- Implementation is fairly easy.

The fuzzy controller is one rule-based control system. One of the main advantages of using a fuzzy approach is that the fuzzy logic provides the best techniques for knowledge representation that could possibly be devised for encoding knowledge about continuous variables. Figure 1, shows the general model of a fuzzy system, which is composed of four major components [3].

Figure 2 shows a sample of membership functions of input and output variables, which has been used in this paper. Three sets NE, ZE and PO represent negative, zero and positive sets, respectfully. More detailed descriptions of the concepts and definition of a fuzzy logic controller can be found in [3,4]. In the second concept, the controller is represented as a nonlinear map between the inputs and outputs. Depending on a specific plant, the map (in the form of a network) can be trained to implement any kind of control strategy.

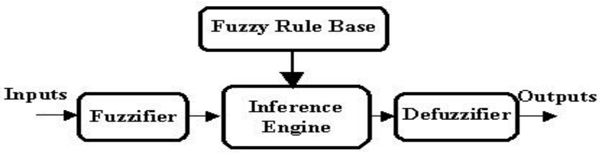

Figure 1: General Model of a Fuzzy System

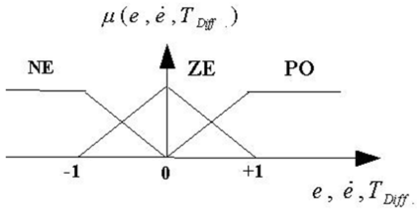

Figure 2: Membership Functions for the Inputs/Outputs

Artificial neural networks with their massive parallelism and ability to learn any type of nonlinearity are used nowadays to address some of the very practical control problems. A neuro-controller (neural networks based control system) performs a specific form of the adaptive control with the controller taking the form of a multi layer network and the adaptable parameters being defined as the adjustable synaptic weights. The main advantages of this controller are:

- Parallel architecture
- Any kind of nonlinear mapping is possible
- Training is possible for various operating conditions, therefore it can be adapted to any desired situation.

The simple fuzzy controller represents a good nonlinear controller; however, it cannot adapt its structure whenever the situation demands. Sometimes the fuzzy controllers with fix structures fail to stabilize the plant under wide variations in the operating conditions. These types of controllers also lack the parallelism of neural controllers. On the other hand the Neural Networks are very much adaptive to situations by adjusting their weights accordingly. The parallel architecture enables faster implementation of the control algorithm. However in the presence of noise and other uncertainties the performance may deteriorate. Some times in certain neural controller structures the model of the plant is required. But in case of plants whose model becomes uncertain it is difficult to use neural networks with fixed structures. To get the advantages of fuzzy and neural networks and to overcome their shortcomings, it is wised to use the combination of both, which leads to Neuro-Fuzzy Controllers (NFC). In other words the new hybrid structure can be named as an Adaptive responsive Fuzzy Controller. This is the approach used in this paper.

Figure 3, shows the structure of the NFC, which has been used for motion control. The on -line supervised learning algorithm performs very well when the training data are available on-line. In this paper,the error E between the reference and plant output is used to adjust the weights. This controller is an Adaptive Network-based Fuzzy Inference System (ANFIS) [5].

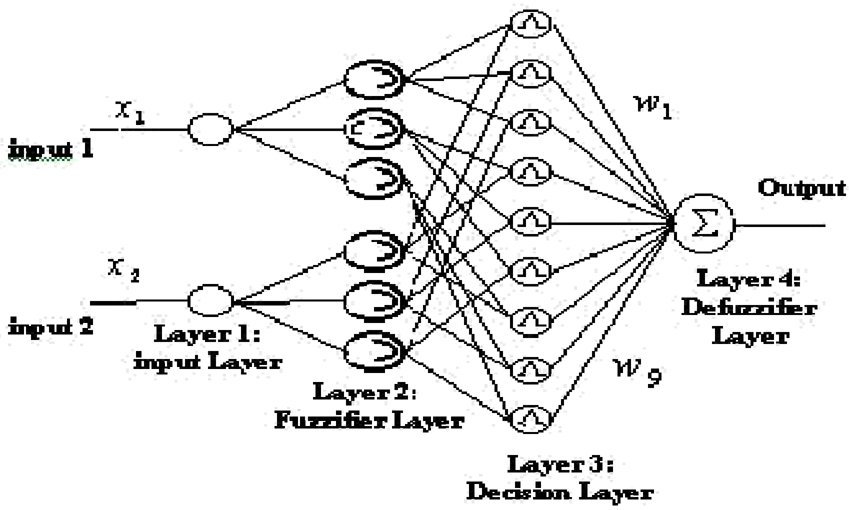

Figure 3: Neuro-Fuzzy Network Structure

2.1 Supervisory Learning in ANFIS

In some situations it may be desirable to design an automatic controller, which mimics the action of the human. This has been called supervised control(Teacher learner method). A neural network provides one possibility for this. Training the network is similar in principle to learning a system forward model. In this case, however, the network input corresponds to the sensory input information received by the human. The network target outputs used for training correspond to the human control input to the system. Figure 4 shows the NFC as a supervisory controller.

The Error Back Propagation Through Plant (EBP-TP) technique is one of the general approaches for training neural networks [6-7]. In EBP-TP technique, output error of the controller is passed through the plant, and updating law of the weights is achieved. However, this technique has some defects, such as sensivity to noise, disturbance and learning rate coefficient. To develop the learning, emotional learning ability can be added to EBP-TP algorithm. In this supervisory learning algorithm, one supervisor (as a teacher) controls the network behavior and reminds it the correct operation. Figure 5 shows a NFC controller by using a critic. Therefore, critic which shows amount of the system stress, can be described like a simple PD control system as:

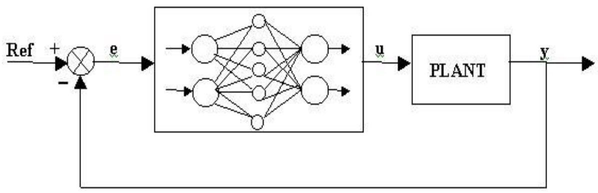

Figure 4: Supervisory Controller

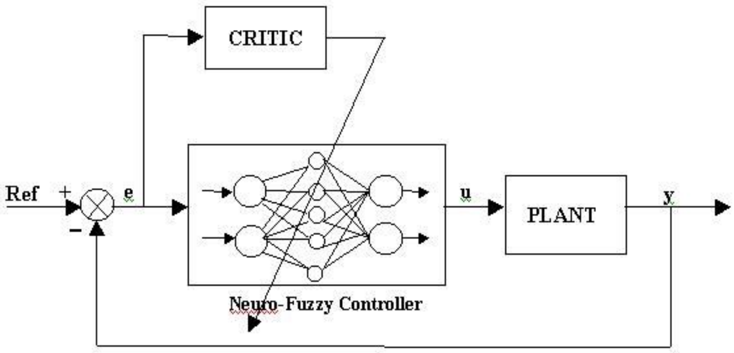

Figure 5: Supervisory Controller by using one Critic

$$S = k_1 \cdot e + k_2 \cdot e \qquad (1)$$

Where k_1, k_2 are critic coefficients and should be set suitable. For training the neuro-fuzzy system with linear PD critic, the criterion is selected as:

$$E(W_i) = \frac{1}{2} S^2 \qquad (2)$$

The parameter W_i should be adjusted in the direction of negative gradient of E . Thus, for the last layer, we have

$$\Delta W_i \propto -\frac{\partial E}{\partial W_i} \tag{3}$$

By using the chain differential law

$$\Delta W_i \propto -\frac{\partial E}{\partial S}\cdot\frac{\partial S}{\partial u}\cdot\frac{\partial u}{\partial W_i} \tag{4}$$

or

$$\Delta W_i \propto -S\frac{\partial S}{\partial y}\cdot\frac{\partial y}{\partial u}\cdot\frac{\partial u}{\partial W_i} \tag{5}$$

Thus:

$$\Delta W_i \propto -\eta\cdot S\cdot\frac{\partial u}{\partial W_i} \tag{6}$$

Therefore, the online updating law of weights is written as:

$$W_{i,new} = W_{i,old} + \eta\cdot S\cdot e\cdot\frac{u_i^4}{\sum_{i=1}^{9} u_i^4} \tag{7}$$

Where η is the learning rate coefficient of the network. It is possible to generalize training to previous layers. But in the sense of practical remarks, it has some defects and therefore, we content learning only for the last layer [8].

It is possible to use another teacher in parallel to error critic (1'Th teacher). This can limit the control effort. Simultaneous operation of critics makes it possible to lower following error and control effort.

3 Indirect Vector Control via Rotor Flux Orientation

Induction motors have been used for over a hundred years. Because of their simplicity, ruggedness, reliability, low cost, induction motors with a squirrel-cage rotor are the most widely used motors. Also because of their highly non-linear dynamic structure with strong dynamic interactions, they require more complex control schemes compared with DC motor control. Vector control can be applied to an induction motor supplied using VSI or CSI inverters. The vector-controlled induction motor can achieve four-quadrant operation with high dynamic response. In this section indirect vector control via rotor flux orientation has been briefly proposed.

Stator voltage equation is obtained in the reference frame fixed to the rotor flux-linkage space pharos, which rotates at the speed ω_{mr} as:

$$T_s'\frac{d\bar{i}_{s\psi_r}}{dt} + \bar{i}_{s\psi_r} = \frac{\bar{u}_{s\psi_r}}{R_s} - j\omega_{mR}T_s'\bar{i}_{s\psi_r} - (T_s - T_s')\left(j\omega_{mR}\left|\bar{i}_{mR}\right| + \frac{d\left|\bar{i}_{mR}\right|}{dt}\right) \tag{8}$$

By resolving Eq.11 into its real (x) and imaginary (y) components, the following two-axis differential equations are obtained for the stator currents:

$$T_s' \frac{d\bar{i}_{Sx}}{dt} + \bar{i}_{Sx} = \frac{u_{Sx}}{R_s} - \omega_{mR} T_s' i_{Sy} - (T_s - T_s') \frac{d|\bar{i}_{mR}|}{dt} \quad (9)$$

$$T_s' \frac{di_{Sy}}{dt} + i_{Sy} = \frac{u_{Sy}}{R_s} - \omega_{mR} T_s' i_{Sx} - (T_s - T_s') \omega_{mr} |\bar{i}_{mR}| \quad (10)$$

The stator current components can be independently controlled if the decoupling rotational voltage components (defined by equations11-12) are added to the outputs ($\hat{u}_{Sx}$,$\hat{u}_{Sy}$) of the current controllers that controli_{sx}andi_{sy}respectively [2].

$$u_{dx} = -\omega_{mR} L_s' i_{Sy} \quad (11)$$

$$u_{dy} = \omega_{mR} L_s' i_{Sx} + (L_s - L_s') \omega_{mR} |\bar{i}_{mR}| \quad (12)$$

We can summarize equations:

$$\hat{u}_{Sx} = R_s i_{Sx} + L_s' \frac{di_{Sx}}{dt} \quad (13)$$

$$\hat{u}_{Sy} = R_s i_{Sy} + L_s' \frac{di_{Sy}}{dt} \quad (14)$$

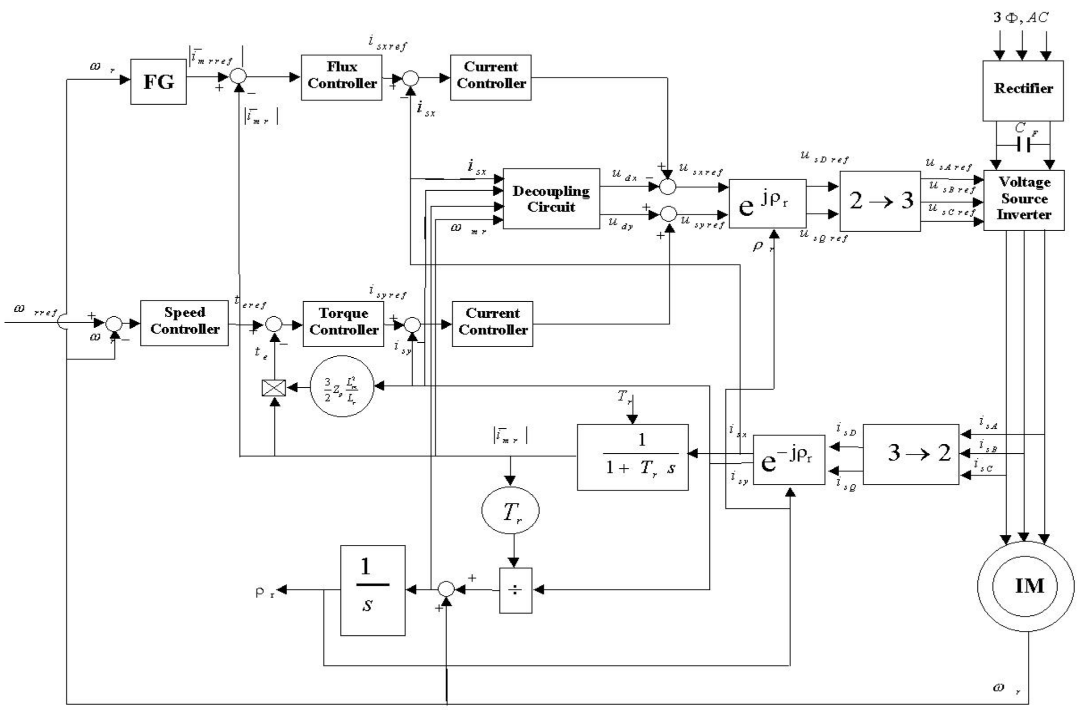

Figure 6: Overall Block Diagram of the proposed Indirect Vector-Controlled Induction Motor Drive

Therefore, $\hat{u}_{Sx}$ and $\hat{u}_{Sy}$ directly control the stator currents i_{sx} and i_{sy} through a simple time delay element. The overall block diagram of the indirect vector controlled induction motor drive has been shown in Figure 6. In this drive system, the current controllers, flux controller, and torque controller can be designed as PID controllers, where as the Emotional Neuro-Fuzzy controller can be used to control the speed at velocity loop [2, 9,10].

4 Simulation Results

In this section some simulation results are used to explore the proposed NF controller and compare its performance with the conventional PID controller. The Critic in the neuro-fuzzy controller has been selected as $S_{1=\cdot 5\cdot e\cdot+50\cdot e,}$ and the learning rate coefficient is set on set to η=0.6 . PID Controller is assigned by k_P=20, k_I=5
Usually PID controller parameters are adjusted by trial and error. It should be noted that the inner loop controllers (current controllers) should be faster than outer loops. Simulations are performed using a three phases squirrel cage induction motor with P_{rated}=15KW . Motor nominal parameters are given in the appendix. In Figures 7 and 8 show the speed tracking with NFC and PID controllers, respectively. With NFC, speed follows its reference with better dynamic. At t=1 sec and t=3 sec, load torque is applied to the motor and as expected, NFC demonstrates a better rejection ability as compared with the PID controller. Figures 9 and 10 show the developed torque and rotor flux tracking. In Figures 11 and 12, the x, y components of stator current are shown. Figure 13 shows the stress signal of the critic.

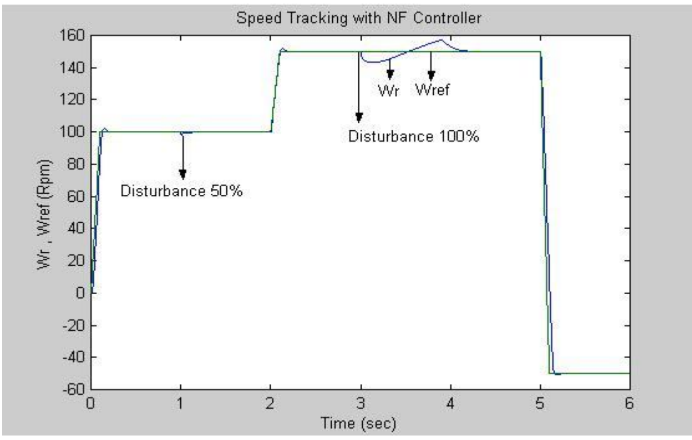

Figure 7: Speed Tracking with NFC

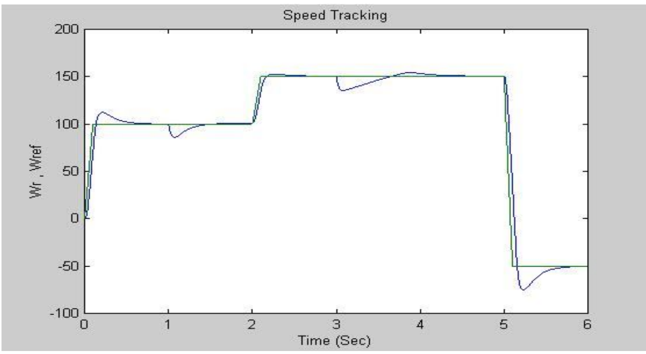

Figure 8: Speed Tracking with PID controller

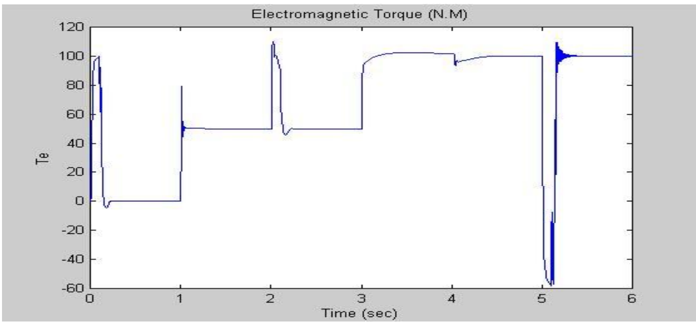

Figure 9: Developed Torque with NFC

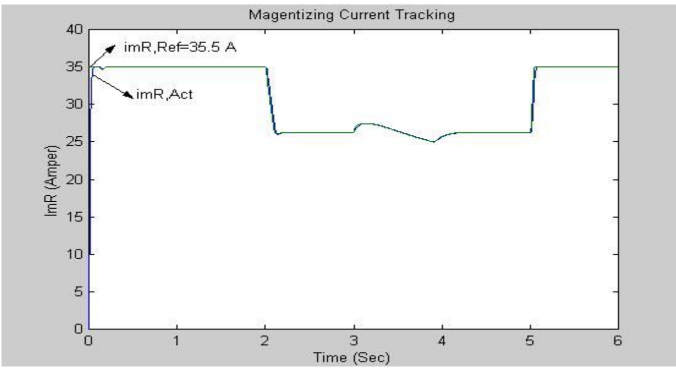

Figure 10: Reference Rotor Flux Following

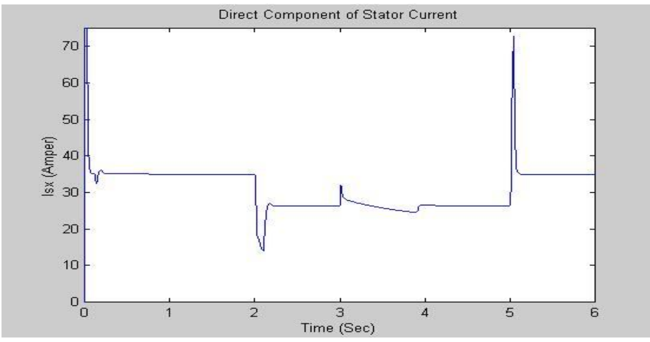

Figure 11: i_{Sx} (Flux Component of Stator Current

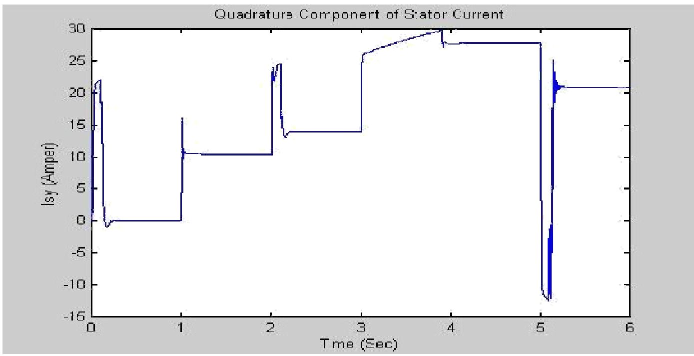

Figure 12: i_{Sy} (Torque Component of Stator Current)

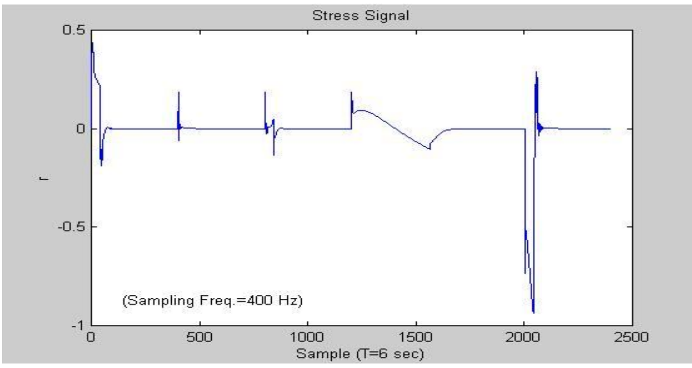

Figure 13: Stress Signal of the Critic

5 Conclusion

In this paper, an adaptive Neuro-Fuzzy Controller (NFC) based on emotional learning has been proposed and investigated. To improve controller performance a critic has been defined and used to supervise the learning of neural network. In addition, other critics are used to lower amount of control effort. Performance of the proposed NFC is analyzed and compared with the conventional PID controllers. Base on the simulation results, the following main conclusions can be stated about the proposed NFC:

- It enjoys the fine abilities and advantages of both the fuzzy and the neural networks.
- It is more robust against the uncertainties compared with the PI and PID controllers.
- Due to its non-model base, it can be used to control a wide range of complex and nonlinear systems.
- It does not require an accurate model of the induction motor, its knowledge representation and interface description is relatively simple and therefore its construction and implementation is fairly easy.
- It doesn't require knowledge of expert man to obtain and set its rule bases since less number of adjustable parameters is involved (as compared with fuzzy and/or neural systems).

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Appendix: Motor Parameters:

U_n=380*volt*
P_n=15*Kw* f_n=50*Hz*
J_{nomi}=0.1
Z_P=3
L_m=32.2 $e-3H$ L_r=34.1$e-3H$ L_s=34.3$e-3H$ R_r=0.023Ω
R_s=0.324Ω