

## Control of Induction Motor using Neural Network

B. Gayathri<sup>1</sup>, D. Thivya Prasad<sup>2</sup>

<sup>1</sup>B. Gayathri M.E., Dept of Electrical & Electronics Engineering, Mount Zion College of Engineering & Technology, Tamil Nadu, India.

<sup>2</sup>D.Thivya Prasad M. Tech., HOD, Dept of Electrical & Electronics Engineering, Mount Zion College of Engineering & Technology, Tamil Nadu, India.

\*\*\*

**Abstract** — This paper presents The induction machine has proved to be an appropriate solution for most industrial applications; Moreover, it presents the future of sustainable automotive industry due to the strategies of control and command of which it can be equipped. This paper presents a study of advanced methods applied to the control of induction machine in order to obtain a system satisfying the criterion of robustness. This work has been done as a comparison between the conventional controller and the advanced techniques of control such as fuzzy logic and artificial neural network. The results of various simulation tests highlight the robustness properties of the different control strategies based on orientation of the rotor flux. A relative comparison between the PI controller and the proposed NNM based ANN controller indicates that the ANN mapping controller yields superior performance.

**Keywords:** GA Genetic Algorithm, IM Induction Motor ANN Artificial Neural Network

### 1. INTRODUCTION

A high performance induction motor (IM) drive system is characterized by an efficient intelligent speed controller, causing the drive to follow the command speed over a range of varying operating conditions. This tracking of command speed is achieved rapidly and precisely regardless of system parameter variations and sudden load excursions. The conventional PI model is widely used for steady state performance results. For transient performances this model does not yield good results due to saturation effects, parameter variations, load disturbances, temperature variations, etc. The consequence is that these PI controllers typically perform well for limited range of specific conditions. On the other hand, the traditional artificial neural network controllers require extensive off-line training, incur high computation time and rely on the past characteristic behavior of the motor drive for a specific system. However, if the performance is unpredictable, the drive encounters parameters outside the training set. [1-2,5-

6,9-10]. For the saturated IM drive, an improved ANN mapping model is needed to develop a nonlinear polynomial types PI with more parameters that can give a complex map and provide better fit to responses.

To train a controller based on the integrated squared difference over a set period of time, it is preferable to develop a desired model and train it before uploading the controller to the actual system. For online training it would be best to select the most sensitive parameters based on simulation and adjust only those parameters step by step in time. With fixed weights and biases, these would seem to produce control which is proportional-like and integral type, respectively. However, due to the speed-error based self-tuning of the ANN and the interconnections between layers, the drive, when in closed-loop, will seek command speed even if one of the input weights is fixed. This occurs because the non-fixed weights and biases of any interconnections and neurons remain adaptive and will be continually adjusted as long as speed error exists within limits, if the ANN output command torque differs from the reference torque command. The more complex the network, the less appropriate such a comparison to PI-based control becomes. A network consisting of two neurons is compared to a precise and adaptive PI controller which continually adjusts itself in real-time based on speed error and by comparison to reference torque command.

In applying this technique to this paper, ANN is used only to mimic PI controllers which means fixed suitable weights are needed to follow the desired speed precisely. For comparative evaluation purposes, a PI controller-based IM drive system has also been employed and tested. Furthermore, simulations have been run to assess the performances of both drives at different dynamic operating conditions. Simulation and laboratory results are provided and discussed to validate the efficacy of the proposed improved method.

#### 1.1 Indirect Vector Control By Orientation Of Rotor Flux

The principle of which is based the vector control by orientation of rotor flux is to remove the internal coupling of the

machine and return it to a linear control similar to that of a continuous current machine with a separated excitation.

For the realization of the vector control, there are two methods: the direct method and the indirect method. This study is based on the indirect one; it uses the position of the rotor flux and it requires the use of a speed sensor.

The equations of tensions, fluxes rotor and the electromagnetic torque in a frame of reference (d, q) turning at a speed  $\omega$  in comparison with the stator are:

$$\begin{cases} V_{rd} = R_r \cdot I_{rd} + \frac{d\phi_{rd}}{dt} - \omega_r \cdot \phi_{rq} \\ V_{rq} = R_r \cdot I_{rq} + \frac{d\phi_{rq}}{dt} + \omega_r \cdot \phi_{rd} \end{cases} \quad (1)$$

$$\begin{cases} \dot{\phi}_{rd} = L_r \cdot I_{rd} + M \cdot I_{sd} \\ \dot{\phi}_{rq} = L_r \cdot I_{rq} + M \cdot I_{sq} \end{cases} \quad (2)$$

$$C_{em} = \frac{P.M}{L_r} (\phi_{rd} \cdot I_{sq} - \phi_{rq} \cdot I_{sd}) \quad (3)$$

Where

(Vrd, Vrq): rotor voltage

(φrd, φrq): Rotor flux

(Ird, Irq): Current rotor

(Isd, Isq): Current stator

$\omega_r$ : Rotor pulsation

$\omega_s$ : Stator pulsation

Rr, Lr: Rotor and inductance resistance

P: pole pairs

M: Mutual inductance

The axis mark (d, q) is oriented along the axis carrying the vector of the rotor flux so we have

$$\phi_{rq} = 0 ; \phi_{rd} = \phi \quad (4)$$

With the condition, the expressions of torque and flux simplifies to:

$$C_{em} = \frac{P.M}{L_r} \cdot \phi \cdot I_{sq} \quad (5)$$

$$\phi = \frac{M}{1+T_r s} \cdot I_{sd} \quad (6)$$

Where

Tr: Rotor time constant

The decoupling by compensation is intended to decouple the axes d and q. This decoupling makes it possible to write the equations of the machine and of the regulation part in a simple manner and thus easily calculate the coefficients of the regulators. The expression of the stator voltages in the Laplace form are given as:

$$\begin{cases} V_{sd} = (R_s + \sigma \cdot L_s \cdot s) I_{sd} - \omega_s \cdot (\sigma \cdot L_s \cdot I_{sq}) \\ V_{sq} = (R_s + \sigma \cdot L_s \cdot s) I_{sq} + \omega_s \cdot (\sigma \cdot L_s \cdot I_{sd}) + \omega_s \cdot \frac{M \cdot \phi}{L_r} \end{cases} \quad (7)$$

And it can be simplified to:

$$\begin{cases} V_{sd} = V_{sd\_r} + V_{sd\_c} \\ V_{sq} = V_{sq\_r} + V_{sq\_c} \end{cases} \quad (8)$$

With:

$$\begin{cases} V_{sd\_r} = (R_s + \sigma \cdot L_s \cdot s) I_{sd} \\ V_{sq\_r} = (R_s + \sigma \cdot L_s \cdot s) I_{sq} \end{cases} \quad (9)$$

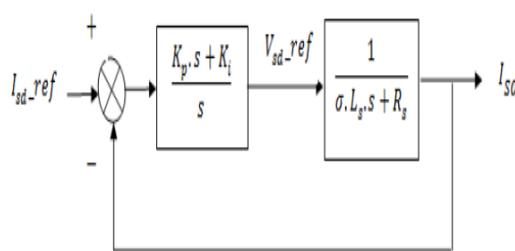
$$\begin{cases} V_{sd\_c} = -\omega_s \cdot (\sigma \cdot L_s \cdot I_{sq}) \\ V_{sq\_c} = +\omega_s \cdot (\sigma \cdot L_s \cdot I_{sd}) + \omega_s \cdot \frac{M \cdot \phi}{L_r} \end{cases} \quad (10)$$

Where

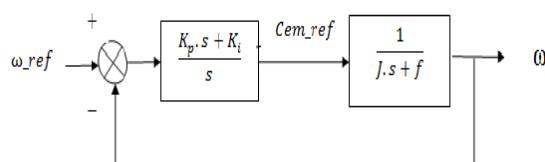
LS: Inductance stator

S: Laplace operator

The system studied in this work is composed of three PI controllers, which one is for speed regulation and the two others for currents regulation ( $I_{sd}$ ,  $I_{sq}$ ). The Figure (1) shows the loop control of current stator during the d axis and the speed control loop is shown on the figure (2).



**Fig. 1. Current stator loop control**



**Fig .2 . Speed loop control**

The parameters were calculated by the method of poles compensation the speed control of the indirect vector controller in Fig. 1 is performed using a Proportional-Integral (PI) regulator. The output of the speed controller is the reference torque to the motor. The reference torque is transferred into the inner current control loop. However, while designing the outer speed loop, the inner current control loop can be treated as, With KP and Ki represent respectively the proportional and the integral gain. The parameters were calculated by the method of poles compensation .

## 2. VECTOR CONTROL BASED ON A FUZZY CONTROLLER

The basic principle of a fuzzy controller approaches the human approach in the sense that the treated variables are not logical in the sense of binary logic (for example) but linguistic variables. Moreover these linguistic variables are processed using rules that refer to certain knowledge of the system behavior.

The design of a fuzzy logic controller starts by assigning the input and output variables. The speed error reference value and its time variation has been selected as the inputs and the electromagnetic torque as the output.

### 2.1a.Fuzzification and Database Preparation

The step of fuzzification is concerned with the processing of digital values to a fuzzy input values using the databases.

The fuzzification must be made a priority. The universe of discourse of all the input and output variables are established as (-1, +1). The suitable scaling factors are chosen to brought the input and output variables to this universe of discourse.

In this study each universe of discourse is divided into five overlapping fuzzy sets: NL (Negative Large), NS (Negative Small), ZE (Zero), PS (Positive Small) and PL (Positive Large). For the choice of the membership functions form, the triangular one has been chosen for all the membership functions with the exception of the extremities of each function whose trapezoidal forms used .The table 1 shows the distribution of the fuzzy sets for speed regulation.

**TABLE I. DISTRIBUTION OF FUZZY SETS FOR THE SPEED REGULATION**

Signification	Symbol	Speed error	Speed error time variation	Electromagnetic torque time variation
Negative Large	NL	[-20 ; 16]	[-2 ; 0.8]	[-120 ; -48 ]
Negative Small	NS	[-12 ; 0 ]	[-1.2; 0 ]	[-72 ; 0 ]
Zero	ZE	[-16 ; 16]	[-0.4;0.4]	[-24 ; +24]
Positive Small	PS	[0 ; 12 ]	[0 ; 1.2]	[0 ; 66 ]
Positive Large	PL	[8 ; 20]	[0.8 ; 2]	[48 ; 120]

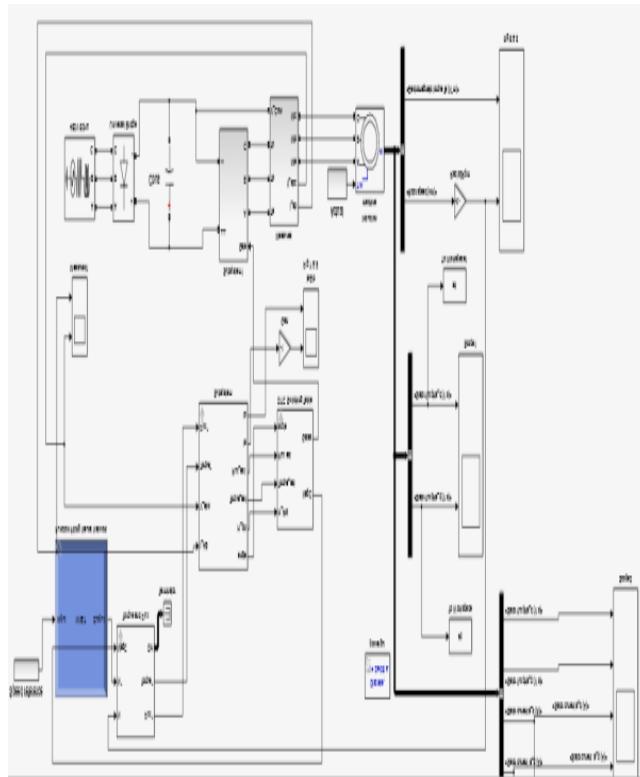
### 2.1b. Rule Base and Inference Matrix

For the inference method, there are too many methods, and the most applied is the Max-min method, the inference matrix of the fuzzy controller is given in the Table 2.

**TABLE II. INFERENCE MATRIX OF THE FUZZY CONTROLLER**

$\Delta E$ E \	NL	NS	ZE	PS	PL
NL	NL	NL	NL	NS	ZE
NS	NL	NL	NS	ZE	ZE
ZE	NL	NS	ZE	PS	PL
PS	ZE	ZE	PS	PS	PL
PL	ZE	ZE	PL	PL	PL

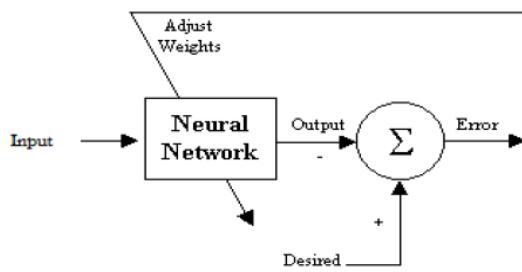
**2.1c.Defuzzification:** When the fuzzy outputs are computed, they must be transformed into a numerical value. There are several methods of defuzzification, and in this study the method used is the center of gravity.



### 3. CONTROL OF ASYNCHRONOUS MACHINE USING THE ARTIFICIAL NEURAL NETWORK

A neural network is composed of several simple elements called neurons working in parallel. By adjusting the values of the connections (or weights) between the elements (neurons), we can train a neural network for a specific task. The ANN are used in many important engineering and scientific applications, some of these are: signal enhancement, noise cancellation, pattern classification, system identification, prediction, and control.

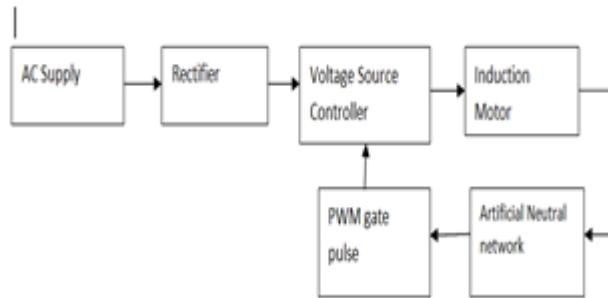
Neural network learning depends on the network architecture and the nature of the problem and there are many learning rules, which are divided to a supervised learning, none supervised learning and learning by reinforcement. The general principle of learning algorithms is based on the minimization of a cost function which can be defined as the quadratic of the differences between the outputs of the network and values desired as it is shown on the figure 3.



**Fig. 3b. Learning principle of neural networks**

To control the asynchronous machine with a neural controller, it had chosen to work with the block "NARMA-L2 (Feedback Linearization) Control", given its ease of use and the results and performances that presents. The block "" NARMAL2 "or "Nonlinear Autoregressive-Moving Average "is a block that converts a nonlinear system to a linear one, for that our block involves first the identification of the system to control. To identify a system there are many methods, that we can find the regression algorithm with a graded step, the genetic algorithm based approach with its binary

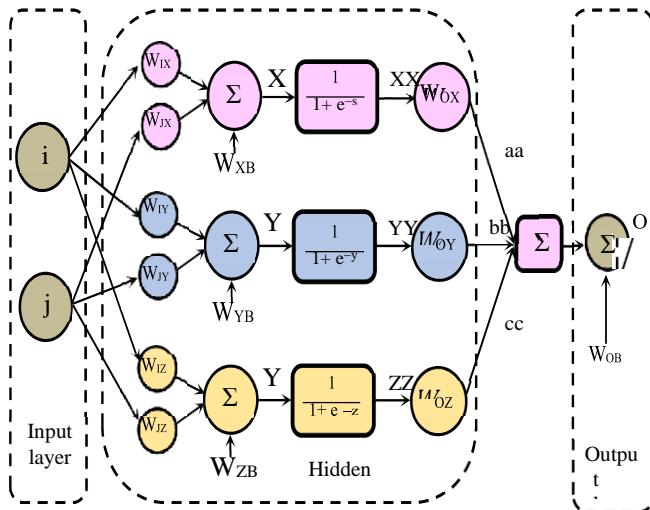
representation and the approach based on the combination of the genetic algorithm in its real representation and the artificial neural network with a polynomial activation function and it's based in this study on the last approach. After identifying system's model to monitor, we train a neural network in order to make system.



**Fig 4.Block Diagram of Neural Network**

### 3. 1.ANN Structure

The amount of nodes in the input layer depends on the number of inputs to the ANN. Since the aim of using the ANN in this application is to mimic the PI controller, the number of nodes required in the input layer is two (i.e.  $i$  and  $j$ ); where one is used to represent proportional gain, and the other is used to represent integral gain. The number of hidden layers,

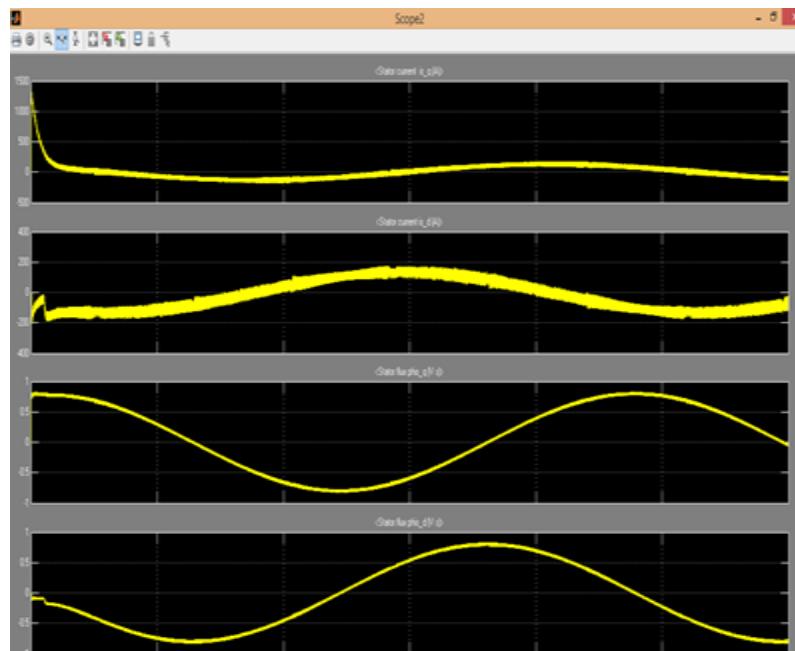


And the number of neurons in the hidden layer(s) were chosen with the goal of achieving the optimal balance between drive performance and computational complexity. The ANN is command torque, requiring only one neuron in the output layer. Fig. 3 shows the ANN structure based speed drive for the field oriented control of IM. This type of structure was chosen because it is the standard one which allows the creation of the controller with dead band and saturation effect in one input direction and saturation in the other direction.

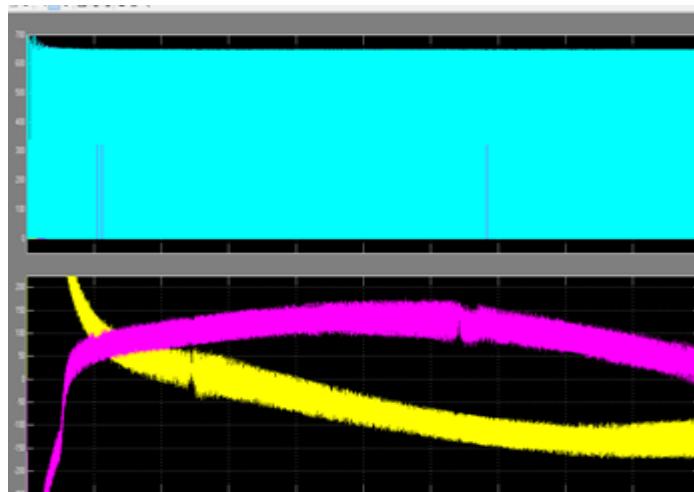
### 4. SIMULATION RESULTS AND DISCUSSION

To validate the efficiency of the ANN based speed controller for the IM drive, hysteresis PWM control algorithms are generated. The aim of using ANN is to create a suitable map. This map has to have more degrees of freedom and a more local character. To train a controller based on the integrated squared difference over a set period of time, it is preferable to develop a model of the system and train it before uploading the controller to the actual system. For online training it is best to select the most sensitive parameters based on simulation and adjust only those parameters step by step in time. However, the ANN controller map must be able to mimic the conventional there is no change in its parameters. From these results, it is clear that the ANN controller has been successfully tuned, via the off-line PI-referenced method presented in this paper, to exhibit performances equal to those obtained with the conventional PI controller upon which it is based. The

results highlight that under the conditions presented here, the ANN controller is, in fact, producing control signals in agreement with the reference PI controller.



**Fig.5:** Simulated response of the ANN maps controller-based IM to step changes of command speed with applying rated load.



**Fig. 6: Simulated response of the PI controller-**

## 5. EXPERIMENTAL RESULTS AND DISCUSSION

The control algorithm for the ANN based IM drive was implemented through software by developing in ANSI. After initializing the required variables, the initial set the results show that the proposed drive system has the ability to follow the reference speed under no load conditions. It should be mentioned that the effect of sudden load impact on dynamic speed response and the evaluation of speed with parameter variation of the ANN map based IM drive were performed solely by computer simulation as depicted in Figs. 6, 7. It can be noted for these experimental results that the performance of the ANN map controller is more accurate in following the command speed compared to that of the PI controller.

The results show that under the conditions the ANN map controller is producing better control signals by 2%, which is in agreement with the reference PI controller of weights and biases gotten from the offline training of the ANN structure was downloaded. This work evaluated the performances of the proposed ANN based drive system.

## 6. CONCLUSIONS

The asynchronous machine is a nonlinear system affected by parameters variation and unknown disturbances .This paper deals with a contribution to induction machine's intelligent control. The work was done in the form of a comparative study between conventional controller and intelligent controllers; it reveals the motivation to realize researches in the field of control by artificial intelligence techniques to the asynchronous machine drive.

It is concluded that the neural controller had a good performances face to parametric variations and to un known disturbances comparing to the other techniques of control, that it can be applied for the electric vehicle motorization and auto mation. It is advisable to examine experimentally the efficiency of neural controller performances to confirm the results found by this study.

## REFERENCES

- (1). Ashutosh Mishra, Prashant Choudhary, "Artificial Neural Based Controller for Speed Control of an Induction Motor using Indirect Vector Control Method", Vol.2, No.4, December 2012, pp. 402~408, Chhattisgarh, Bhili – India.
- (2). Kendar Pratap, Shelja, "Artificial neural network (ANN) inspired from biological nervous system", International Journal of Application or Innovation in Engineering & Management (IJAIE), Volume 2, Issue 1, India January 2013.
- (3). Math Works, Neural Networks Toolbox User's Guide, Math Works, Natick, Mass, USA, 2015.
- (4). T. F. Chan and K. Shi, Applied Intelligent Control of Induction Motor Drives, IEEE Willey Press, 1st edition, 2011.