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ENACTMENT INVESTIGATION OF INDIRECT VECTOR CONTROL INDUCTION MOTOR USING VARIOUS PREDICTIVE CONTROLLER

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ABSTRACT

In this paper, enactment of an indirect vector control induction motor (IVCIM) has been studied with proportional plus integral (PI), fuzzy logic and neural network (NN) based controllers. Putting into practice of PI, fuzzy logic control and Neural Network predictive control for studies of parameter of speed in IVCIM is termed under dissimilar operating conditions of induction motor. Simulation results of IVCIM have been carried out in MATLAB. Stator currents, electromagnetic torque and rotor speed of IVCIM have been examined using three controllers. A comparative performance analysis of IVCIM with three dissimilar controllers with load has been deliberated.

Keywords: indirect vector control, PI control, fuzzy logic control, neural network predictive control.

I. INTRODUCTION

Smart control has been developing area of investigation to advance the dynamic performance of A.C. drives [1] in modern past. Nonlinear controller based on fuzzy logic, neural networks and other computation intellect proposals to deal the dynamics of great performance flexible frequency Induction drives. Scalar control on induction motor has a modest control structure [2] which compromises a coupled control over torque and speed. To develop speed control performance using scalar control, an encoder or speed tachometer is required which adds an supplementary cost and also abolishes the mechanical toughness of the induction motor. A hybrid system combining fuzzy controller [3-4] with vector-control induction motor has been used for realising variable speed operation, which is the greatest between all the methods. Design [5-6] of fuzzy controllers has been complete without re-establishing the domain knowledge of the plant beneath control. Fuzzy logic [7-9] executions need not involve rigorous information of a system model. A speed model reference adaptive control system [10] for indirect field oriented induction motor drives by fuzzy laws and neuro fuzzy procedure improve the fuzzy rules. In sensor less drives, the speed sensors [11] are exchanged by a flux model which involves two additional voltage sensors along with IVCIM. Squirrel cage induction motors involve of high robustness and low maintenance [12] in various industrial modern processes. An auto tuning based fuzzy reasoning [13] has been castoff for the speed control of vector controlled induction drive system. A hybrid speed controller [14] has quick dynamic response with nearly no overshoot, good robustness and control performance. PI and fuzzy estimators[15-16] had been used for wired tracking of rotor resistance in IVCIM drive. Fuzzy logic controller [17] proposals high enactment dynamics to IVCIM drive. The examination, design and simulation of the fuzzy logic controller based on fuzzy set theory [18] were carried out on IVCIM drive. Fuzzy logic controllers [19] are originate to be robust for high performance industrial drive applications. A proportional-integral and fuzzy logic speed controllers operating in indirect field orientation [20-21] are considered and compared under with load conditions by varying different reference speeds. Speed and flux tracking of an induction motor has been attained using advanced control algorithm [22]. PI based controller can be interchanged by a neural network controller [23] in the indirect field oriented induction machine drive control structure. Speed of induction motor under load torque has been projected by artificial neural networks. The artificial neural network offers a nonlinear modelling of motor drive system [24] without any information of predetermined model and thus marks the drive system robust to noise, parameter variations, load changes. An adaptive neuro-fuzzy inference system (ANFIS) based intelligent control [25-26] for vector controlled induction motor drive includes fuzzy logic algorithm with a five-layer artificial neural network structure [27]. A vector control structure by merging the advantages of two types of field oriented technique has been discussed for the squirrel cage induction motor fed from a PWM based voltage source inverter (VSI). Reference model has [28] been chosen in terms of tracking and disturbance rejection with high robustness. Two speed control techniques, [29] scalar control and indirect field oriented control have been used to compare the performance of the control system with fuzzylogic controller. Fuzzy logic controller is more robust, and found to be suitable to replace the conventional PI controller for the high performance industrial drive applications. This speed controller offers improved torque in IVCIM [30-31] with high dynamic performance.

2. INDIRECT VECTOR CONTROL INDUCTION MOTOR (IVCIM)

In field oriented control (FOC) an induction motor is fed by three phase variable frequency PWM invertors. The motor flux is well-ordered by the direct-axis

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current reference ids*. Block d-qto abc is used to convert id* and iq* into three phase current references i_a*, i_b* and i_c* for PWM current regulator. The induction motor is fed through a voltage source inverter (VSI), which derive its dc bus voltage from a 3 phase rectifier. The VSI is operated in current control mode with the benefit of a hysteresis current converter. The current controller relates the terminal current (i_a, i_b, i_c) of induction motor with an internally generated references current (i_a*, i_b*, i_c*) corresponding to anticipated speed (w_r*) and motor torque. The reference currents are determined using direct axis current i_{ds} and quadrature axis i_{qs} current calculated for required speed &torque condition. The parameters and rating of induction motor measured for simulation studies are shown in Table-1.

Table-1. Induction machine parameters

Rated voltage	440V	Stator resistance	0.09861Ω
Pole pairs	2	Rotor resistance	0.0563 Ω
Rated speed	1775 rpm	Stator inductance	0.954mH
Power	37 KW	Rotor inductance	0.654mH
Inertia	0.4 kg m^2	Mutual inductance	0.2017 H
Frequency	60 Hz	Damping factor	0.0187 Nm/sec

3. PI, FUZZY AND NEURAL PREDICTIVE CONTROLLER

A. PI Controller

The PI control is one common linear control strategy, which is mathematically described as

$$PI_{control} = K_p e + \int e \, dt \quad (1)$$

B. Fuzzy controller

Fuzzy logic is an influential method of sensitive when mathematical formulations are infeasible and input data are vague. Fuzzy Logic implementation involves no exact knowledge of a system model. Fuzzy logic controller (FLC) involves the use of the concept of fuzzy subset, membership function and rule based modelling.

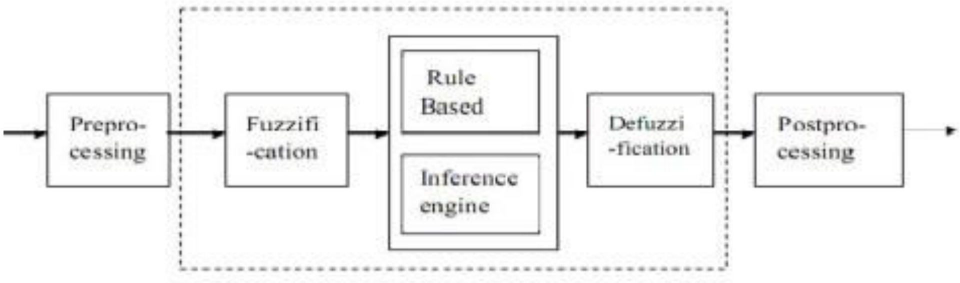

Figure-1. Block diagram of fuzzy logic controller.

C. Neural network predictive control

The initial step in model predictive control is to define the neural network plant model. The plant model is castoff by the controller to predict future act.

a) System identification

The first stage of model predictive control is to train a neural network to represent the forward dynamics of the plant. The prediction error among the plant output and the neural network output is used as the neural network training signal. The process is represented by Figure-2.

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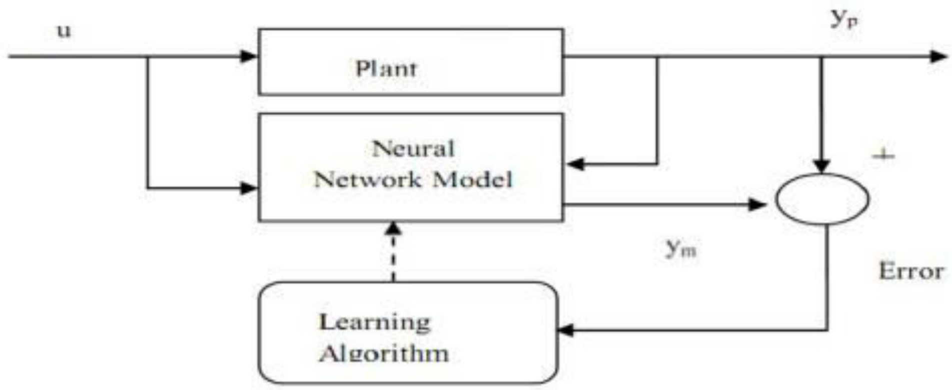

Figure-2. System identification using neural network.

b) Predictive control

The estimates are used by a numerical optimization program to fix the control signal that minimizes the performance standard over the specified prospect in equation (2).

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 + p\sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2)) \quad (2)$$

A block diagram of predictive control is shown in Figure-3. Where N_1, N_2, and N_u define the horizons completed which the tracking error and the control increments are estimated. The *u'* variable is the tentative control signal, Y_r is the preferred response and Y_m is the network model response. The p value determines the impact that the sum of the squares of the control increments has on the performance index. The optimization block regulates the values of *u'* that minimize J, and then the optimal *u* is input to the plant.

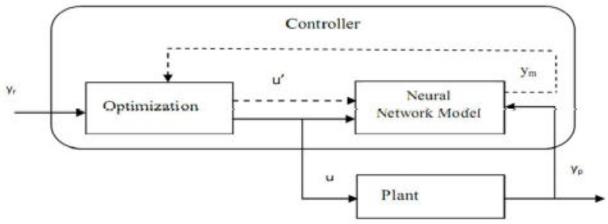

Figure-3. Predictive control using neural network.

4. SIMULINK IMPLEMENTATION OF IVCIM

MATLAB simulation of IVCIM using Proportional plus Integral, Fuzzy logic and Neural Network predictive controllers are developed and shown in Figures 4, 7 and 8 respectively.

A. Implementation of IVCIM using PI Controller

Implementation of IVCIM drive for speed and torque control using PI controllers is shown in Figure-4. PI controller is adjusted for minimizing the error among estimated speed and reference speed. The control strategy in this control is established in simulink, which regulate required reference current for generating gating signals for VSI. The VSI produces required PWM voltage of appropriate frequency for regulation of speed and torque of IM.

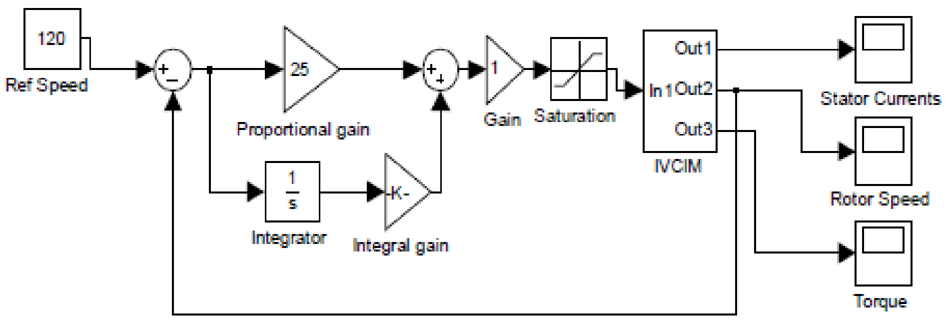

Figure-4. Simulink block diagram of IVCIM using PI controller.

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B. Implementation of IVCIM using fuzzy controller

The simulink implementation of fuzzy logic based IVCIM drive is shown in Figure-7. Figure-5 illustrate the membership functions used for error and variation in errorinputs. Figure-6 shows the membership function for output of the fuzzy logic controller. The fuzzy controller is established to process the speed error and derivative of error as two input membership role and mandatory rule base is defined by using IF AND THEN rule to create magnitude of reference current driving for current controlled VSI. The Table-2 shows the rule based matrix with two inputs of error, change in error and control signal as output used in fuzzy logic controller. This is developed in simulink, and determines required reference current for generating VSI gating signals.

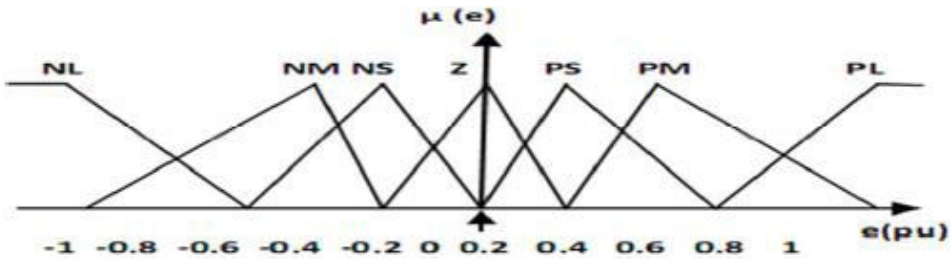

Figure-5. Membership functions for error and change in error inputs.

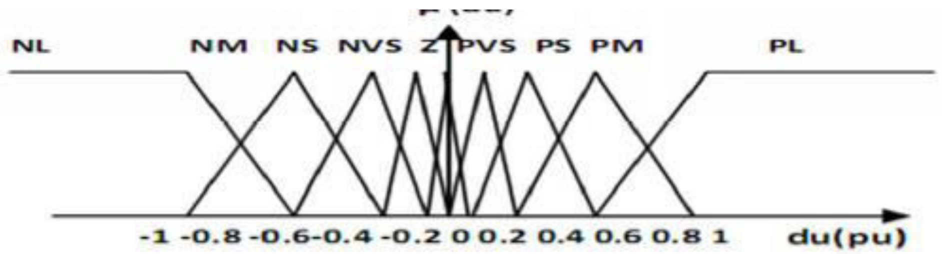

Figure-6. Membership functions for output.

Table-2. Rule based matrix for fuzzy logic controller.

CE/E	NL	NM	NS	Z	PS	PM	PL
PL	Z	PS	PM	PL	PL	PL	PL
PM	NS	Z	PS	PM	PL	PL	PL
PS	NM	NS	Z	PS	PS	PL	PL
Z	NL	NM	NS	Z	PM	PM	PL
NS	NL	NL	NM	NS	Z	PS	PM
NM	NL	NL	NL	NM	NS	Z	PS
NL	NL	NL	NL	NL	NM	NS	Z

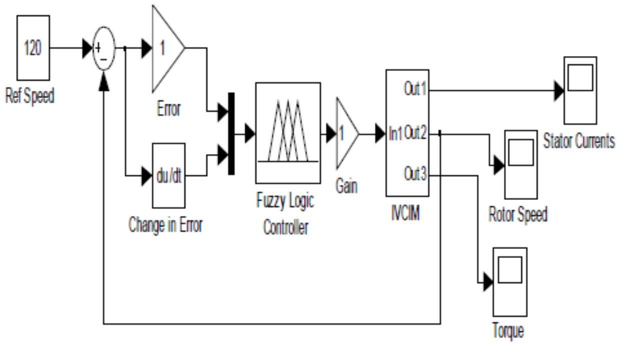

Figure-7. Simulink block diagram of IVCIM using fuzzy logic controller.

C. Implementation of .IVCIM using NN predictive controller

A NN based predictive control strategy for IVCIM drive is also implemented in MATLAB. The developed Simulink diagram is shown in Figure-8.

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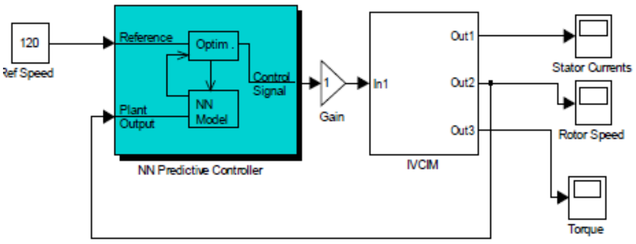


Figure-8. Simulink block diagram of IVCIM using NN Predictive controller.

5. SIMULATION RESULTS AND DISCUSSIONS

The performance of IVCIM using PI, fuzzy and neural controllers are studied and analyzed in detail.

Simulation results of IVCIM using PI controller at load

Figures 9 and 10 shows the performance characteristic of IVCIM drive, when a unexpected change in load torque from 0 to25 N/m is added at time of 2.2 sec. It is detected from the waveforms that motor speed is reduced briefly but controller adjusts the motor speed, close to reference value of 119 rad/sec at 0.76 sec. However, with no overshoot tolerable in speed response, the drive has some finite offset.

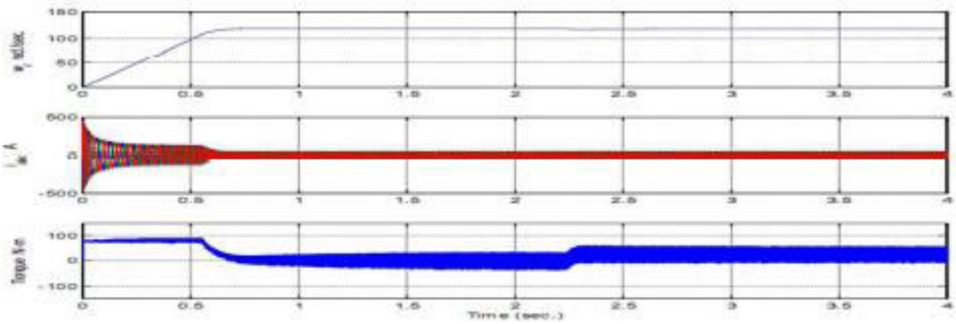


Figure-9. Performance of IVCIM with PI control at load torque 25 N-m.

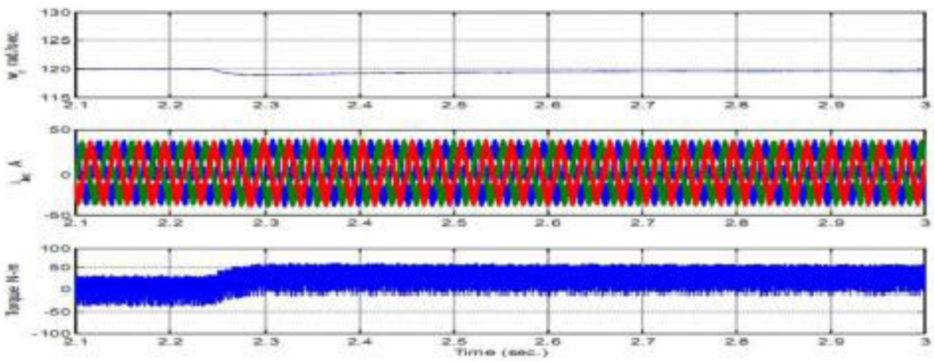


Figure-10. Performance of IVCIM with PI control at load torque 25 N-m (range 2.1 - 3.0 sec).

Simulation results of IVCIM using fuzzy controller at load

Figures 11 and 12 shows the performance of IVCIM with fuzzy logic control when a sudden change in load torque of 25 Nm is applied at 2.2 sec. It is observed that speed dips temporarily and controller effectively regulate the speed, when IM pickups reference speed of 119.5 rad/sec at 0.2sec.

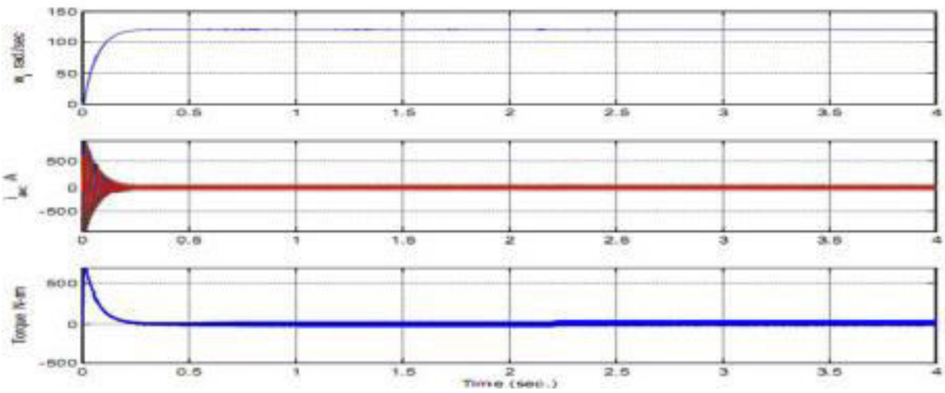


Figure-11. Performance of IVCIM with fuzzy logic control at load torque 25N-m.

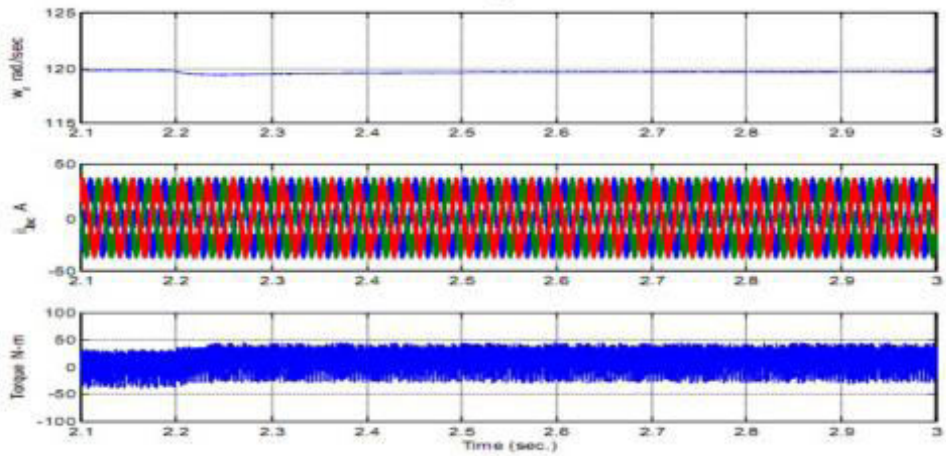


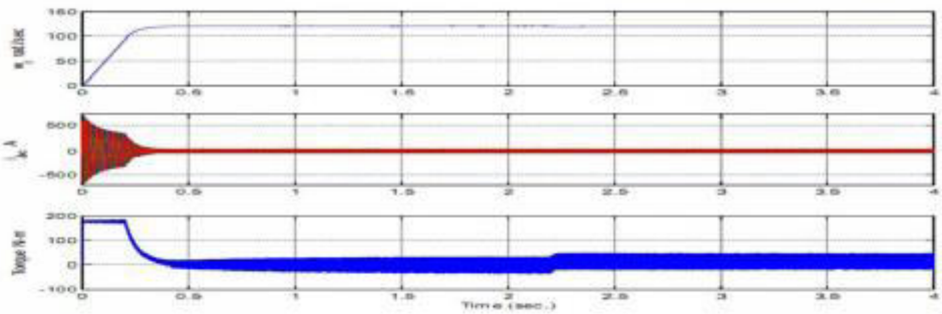
Figure-12. Performance of IVCIM with fuzzy logic control at load torque 25 N-m (range 2.1-3.0 sec).

Simulation results of IVCIM using NN predictive controller

Identification of plant has been performed by Neural Network predictive control in simulink. After identification training data was made and acknowledged, depending on comparison of plant output and Neural Network output, Neural Network was trained using this data to obtain optimum value of weight and biases using trainlmfunction (Levenberg Markquardt back propagation). The weight and bias values were applied to Neural Network Predictive controller. Twenty hidden layers, 8000 training sample and200 epochs are considered for developing Neural Network model. The network has converged after 12 epochs when the sum squared error is $3.23681e^{-005}$ and learning rate is 0.05.

Simulation results of IVCIM using NN predictive control at load

Figures 13 and 14 shows the performance of IVCIM drive, when load torque of 25 N-m is applied at 2.2 sec. It is observed that IM speed drops for few cycles, but the NN controller rapidly permits the drive to restore the reference speed, when IM pickups the reference speed of 119.5 rad/secat 0.2sec.



Figures-13. Performance of IVCIM with NN predictive control at load torque 25N-m.

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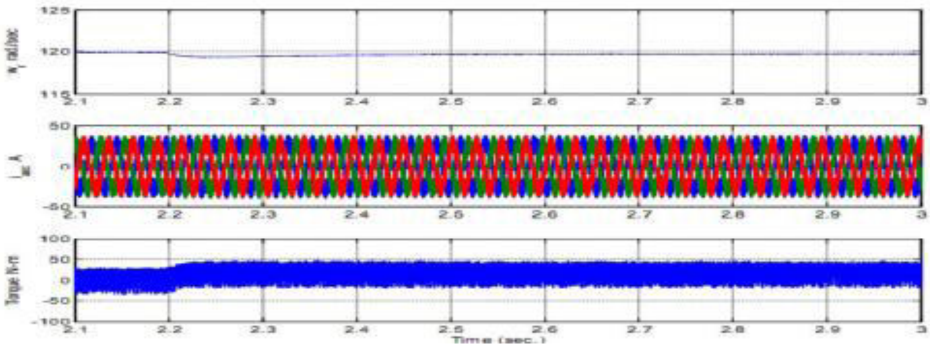

Figure-14. Performance of IVCIM with NN predictive control at load torque 25N-m (range 2.1-3.0 sec).

Speed regulation of IVCIM has been compared with the rotor speed with the load of 25 N/m at 2.2 second. Using PI controller 119 rad/sec at 0.76 sec, For Fuzzy controller 119.5 rad/sec at 0.2 second and finally neural network 119.5 rad/sec at 0.2 sec.

6. CONCLUSIONS

The performance of IVCIM with PI, Fuzzy and Neural Network predictive control has been compared through simulation study. The stator current and electromagnetic torque of the IM is found within the safe limits of the operation. The small ripples in torque and current are detected due to switching in hysteresis PWM current controller. The operations of IVCIM with conventional PI, fuzzy and NN predictive based controllers have been simulated and dynamics of the IVCIM during starting and sudden application of load is presented. The operation of drive with PI control is simple and easy to implement but drive performance weakens during parametric variations. Performance of IVCIM drive with fuzzy controller is observed to be more precise and close to reference speed. The fuzzy controller is capable in recognising the uncertainty in parameter variation and nonlinear performance of IM. However, in steady state there are offset between the reference speed and the actual speed of the drive. The performance of IVCIM drive with Neural Network predictive controller is also observed to be close to the reference speed at load. Transients in currents are low in Neural Network predictive control as compare to fuzzy logic control. Also starting torque of IM is low in Neural Network predictive control as compare to fuzzy logic control.

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