



ANN-BASED DIRECT TORQUE CONTROL SCHEME OF AN IM DRIVE FOR A WIDE RANGE OF SPEED OPERATION

Jeyashanthi J.^{*}, BarsanaBanu J.[†]

Abstract: Induction motor (IM) drives with direct torque control (DTC) enable fast torque response without the need for complex orientation conversions or inner loop current loop. In the speed estimation responses, however, there is a significant level of torque ripple. The voltage source inverter adds acoustic noise and needs a high sampling frequency since it operates at a high and variable switching frequency. This work describes an ANN-based DTC technique for controlling the speed of an IM drive over a large speed range. To achieve good dynamic performance of induction motor drive, the ANN-based speed controller will replace the speed controller, switching tables, and hysteresis comparators. The neural network was trained using the back-propagation algorithm. The goal of a neural speed controller is to improve the system ability to respond quickly to changes in process variables while also mitigating the impacts of external perturbations. The projected ANN based DTC considerably and simply tracks the reference speed thus improves the efficiency of speed-torque of induction motors with quicker responses for rapid varying of speed reference and torque as that of Electric Vehicles in any uneven roads circumstances. MATLAB/Simulink software is used to evaluate the drive performance for both transient and dynamic operations. The proposed control performance is simulated and compared to a DTC-based traditional PI speed controller. In comparison to PI, the results show that ANN has better and faster effects. The torque ripple gets reduced by 1.5% in ANN (artificial neural network) controller compared to PI controller. The THD (total harmonic distortion) is reduced by 6.38% from PI controller to ANN controller.

Key words: *artificial neural networks, back propagation algorithm, induction motors, pid controller, torque control, total harmonic distortion*

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1. Introduction

In the recent past, study has been carried out to develop an information processing control scheme to imitate the functions of the human brain. Hence, Neuro-computer has developed parallel processing for information processing instead of

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sequential processing. ANN imitates the functions of the nervous system in the human brain. ANN can model the system like the learning of biological neurons. Non-linear and complex control systems can be easily developed with the ANN algorithm because of its robustness and good learning abilities. The learning in ANN is done with associated input/output patterns of the system. The neural network contains knowledge of the plant dynamics and functional mapping characteristics. Hence, it is considered as a knowledge representation framework. ANN deals with the nonlinear function approximation problem. ANN comprises several interconnected neurons with their weights and it is analogous to synapses of the human brain. ANN does not involve any lookup table and computation. In the ANN training algorithm, the weights of the neuron are regulated iteratively and learning is alleviated. Nowadays, ANN is preferred for power electronics and drives, because of the following features: Offers very fast parallel computation, Input harmonic resistance, fault-tolerant features, devoted excellent signal processing. A predictive model of torque control with the fuzzy logic controller has been proposed in [1] to decrease the flux and torque ripple. Space vector pulse width modulation technique has been used to decrease flux and torque in DTC-IM (direct torque control-induction motor) drives used in [2] and [5]. In [4], the sectors of switching tables are modified and the hysteresis band and stator resistance estimation are employed with a fuzzy logic controller in direct torque. The overall performance of the controller has been improved by this modified approach. In [3] the author has proposed a torque hysteresis band with changeable magnitude FLC (fuzzy logic control) to decrease the torque and flux error. At minimum speed, the presentation is improved by using the fuzzy logic controller and minimizes the torque and flux ripples. Compared to conventional DTC, the inverter duty ratio control method gives good steady-state torque output and minimum torque ripple. A scalar control technique utilizing a fuzzy logic algorithm for the induction motor speed control has developed in [6] and [20].

In [7] the author presented DTC with a 3-level inverter (neutral point clamped (NPC) structure) has been presented to reduce torque ripple as an alternative of 2-level inverter and a PI-fuzzy controller rather than the traditional PI controller. The Conventional PI speed controller is replaced by the FLC to improve the speed response. This will provide a higher power range of drive configuration and it is adequately robust and intellectual for real-time requirements.

To eliminate load unsettling influences consequences for the IM working during sliding, sliding stage DTC-SVM based versatile burden torque control is projected by [8] for the three sorts of burdens such as consistent burden torque, direct burden torque, and quadratic burden torque. This methodology expands the best exhibitions without load unsettling influence impacts. Sliding stage FLC incorporating with the SVM (space vector modulation) has been anticipated by [9] for the IM (induction motor) drives which are utilized in the electric vehicle impulsion configuration. To obtain and withstand the sliding stage and constancy of the configuration, the FLC has been exercised with the Lyapunov direct method. The maximum torque tracking capability can be accomplished during outer unsettling influences. In the absence of speed sensors utilized, a sliding-mode spectator computes the induction motor flux and torque.

Compared to the traditional PI controller and sliding stage control, this strategy provides decreased torque ripple and current distortion along with robust dynamic behaviour. In [10], the cuckoo search algorithm to train the data and test the ANFIS (adaptive neuro fuzzy inference system) to offer appropriate electromagnetic torque which thus alters the switching state of the inverter. The CS-based (current source) ANFIS speed controller performance has been compared with PI, fuzzy, and ANFIS speed controllers. Rotor speed, torque, settling time, steady-state error, and peak overshoot have been analyzed. DTC and finite control state predictive torque control (PTC) for IM drive have been computed by [11]. Both DTC and PTC strategies provide great execution in steady and transient states and modulators is not needed. Numerous control strategies are accessible for IM drive. DTC provides excellent performance in dynamic state.

Compared to FOC (field oriented control), DTC provides minimum reliance on changes of machine parameter, simple implementation, excellent transient outcomes, and ruggedness. DTC does not engage recent regulation and coordinate transformation. The flux linkage and motor torque have been controlled separately and directly by appropriate selection of switching voltage vectors in [12] have proposed a different approach to calculate actual flux by square root function in the direct torque control. A rule-based Mamdani type FLC have proposed in [13] to closed-loop control of IM drive. According to the motor model parameters, membership functions are picked and the motor model has been designed for the new operating point. The definite velocity of an induction motor has been contrasted with the speed reference.

The sensor less control for double fed induction machine drive through two DTC is proposed by [14]. A novel algorithm of PTC has been proposed by [15] for IM based on discrete space vector modulation (DSVM) method. The quantity of voltage vectors is increased by the DSVM configuration and it has been valued in the PTC method. This PTC-DSVM gives minimum sampling frequency. But, the maximum quantity of virtual vectors has augmented the computational burden considerably. To overcome this issue, the switching table of DTC has been presented and the quantity of acceptable voltage vectors is diminished. At any switching frequency, PTC-DSVM has the similar performance as traditional PTC but the sampling frequency is thrice the times lesser.

The minimum sampling frequency procedure makes it feasible for industries to employ minimum expensive hardware or execute a maximum computational examination. To overcome this problem the sensor less induction motor control scheme has been projected by [17] because of the versatile rotor speed observer. PI-based shunt active filter has been introduced in an artificial neural network to diminish the harmonics produced by the non-linear loads in the source current [16]. Improved efficiency of DTC-IM by the golden section method [18], fuzzy logic [19] and ANFIS strategy [20] are discussed.

In this paper, the ANN controller is employed in a speed control loop of the DTC-IM drive to minimize torque and flux ripples in the IM. The speed and torque of the 3Φ induction motor are controlled by the DTC method to accomplish excellent dynamic and transient response characteristics. ANN enhances the efficient operation of the IM drive.

2. Strategy of direct torque control

Unlike vector control, DTC does not depend on the regular switching pattern. Whenever there is a change in load on the DTC drive, there will be a change in the switching pattern of the inverter. Hence, the response is quicker in the DTC drive. This technique gives accurate speed control without involving any feedback device. DTC is also an adaptive control and the major requirement is IM winding resistance. DTC does not involve coordinate transformation, current regulation loop, and position sensor which make the controller simple. In this research work, DTC is operated with a stationary d – q reference frame. The actual values of flux and torque are estimated from the stator line currents, DC input voltage of the inverter, and the present switch position of the inverter.

The measured 3Φ stator phase currents are then changed into 2Φ d – q axes variables as given below.

$$\begin{bmatrix} i_{qs} \\ i_{ds} \end{bmatrix} = \begin{bmatrix} \frac{2}{3} & \frac{-1}{3} & \frac{-1}{3} \\ 0 & \frac{1}{\sqrt{3}} & \frac{-1}{\sqrt{3}} \end{bmatrix} \begin{bmatrix} i_{an} \\ i_{bn} \\ i_{cn} \end{bmatrix}. \quad (1)$$

Stator flux of IM can be obtained from stator voltage, current, and stator resistance as given by the following equations.

$$\frac{d\Psi_s}{dt} = V_s - i_s R_s, \quad (2)$$

$$\Psi_{ds} = \int (v_{ds} - i_{ds} R_s) dt, \quad (3)$$

$$\Psi_{qs} = \int (v_{qs} - i_{qs} R_s) dt. \quad (4)$$

The resultant flux linkage in the stator of IM can be expressed as

$$\Psi_s = \sqrt{(\Psi_{ds}^2 + \Psi_{qs}^2)}, \quad (5)$$

$$\theta_e = \tan^{-1} \left(\frac{\Psi_{ds}}{\Psi_{qs}} \right). \quad (6)$$

Generally, Electromagnetic torque of IM can be formulated as given in Eq. (7). In d – q reference frame, the torque of IM can be expressed as given in Eq. (8).

$$T_e = \frac{3}{2} \left(\frac{P}{2} \right) (\Psi_s \times I_s), \quad (7)$$

$$T_e = \left(\frac{3}{2} \right) \left(\frac{P}{2} \right) (\Psi_{ds} i_{qs} - \Psi_{qs} i_{ds}). \quad (8)$$

These values are compared with their reference values and the error values are processed in the controller.

$$\Delta T_e = T_e^* - T_e, \quad (9)$$

$$\Delta\Psi_e = \Psi_e^* - \Psi_e. \tag{10}$$

The controller output selects the appropriate switching position. The status of voltage source inverter is given by

$$V_i = \frac{2V_s}{3} \left[S_a + e^{j\frac{2\pi}{3}} S_b + e^{j\frac{4\pi}{3}} S_b \right]. \tag{11}$$

3. Limitation of traditional DTC fed IM drives

Numerous drawbacks are there for traditional DTC of 3Φ inverter fed IM drive. For the most part, it incorporates minimum torque dynamics; maximum fluxes changes prompting overshoots or undershoot exterior to the flux hysteresis band, expanded ripple in electromechanical torque, stator current and flux, uncontrolled switching frequency and so forth so it isn't reasonable for changeable speed drive requirements. This paper presents simple structure ANN controller for vector selection procedure has the points of interest like the simplicity of training and generalization, insensitivity toward the network distortion, probability of non-linear function approximations, and inaccurate input data. The motor variables ripples can likewise be diminished to an obvious broaden.

4. Proposed neural network based DTC-IM drive

The block diagram of the DTC-IM drive configuration utilizing a neural network is given in Fig. 1. ANN is utilized to estimate the reference torque for the SVPWM (space vector pulse width modulation) block which thusly generates gate pulses for the 3Φ VSI. The speed error is the input of the ANN controller and the output of the ANN controller is the reference torque. Flux reference is kept at a nominal value. Actual flux and the electromagnetic torque values are computed from the stator current and voltage. These estimated values are utilized by the SVPWM generator to produce firing signals for the power electronic switches of VSI. Finally, variable voltage and variable frequency of VSI direct the motor speed.

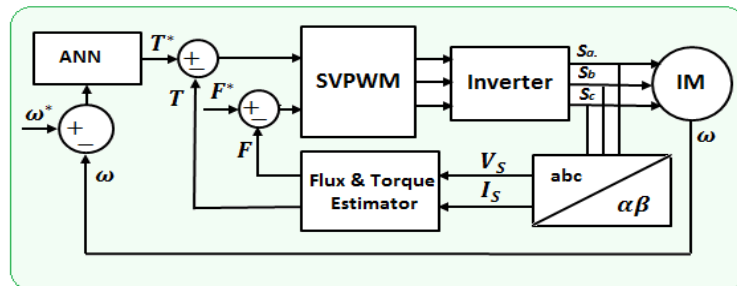


Fig. 1 Block diagram of DTC-IM drive using ANN.

The ANN controller is employed in this paper in the speed control loop of the DTC-IM drive. The steps implicated in the speed control of the DTC induction motor using ANN can be briefed as given below.

- Sample information is gathered from open-loop control of the drive for training.
- Speed error and reference torque are chosen as the input and output of ANN, respectively.
- A back propagation learning algorithm is utilized to train the network.
- Training is stopped, when the desired target achieves mean squared error.

Initially, the network is trained by a definite quantity of input/output data patterns by the MATLAB simulation program to train the network. The sample data for the speed control are generated by simulating the proposed drive system using the PID controller. ANN uses part of these data patterns to train the network and to attain weight and the bias vectors. Then, a new set of input patterns for speed error, output pattern, and torque error are generated and used for further operation of the MATLAB ANN model. The size of the input/output data decides the time of training the data by the back propagation algorithm. ANN is designed with single input layer, single output layer, and five hidden layers for the speed control. The schematic view of the proposed ANN with input, hidden and output layers for the DTC-IM drive are given in Fig. 2.

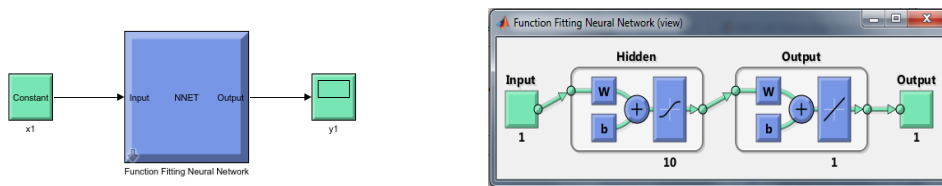


Fig. 2 Schematic of DTC using ANN-based speed controller.

All the initial conditions are to be set appropriately in the ANN block for the simulation since these base values choose the operation of the speed controller. The graphical representation of the neural network for speed control is specified in Fig. 3. In this paper, the Back propagation learning procedure is utilized in

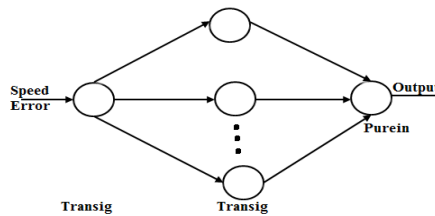


Fig. 3 Neural control design.

ANN training and it is explained in the previous section. The transit function and purely function are selected for the hidden layers and output layer, respectively. The number of epochs used for the neural network training is 1000 to reach the desired outcomes. The working of the proposed ANN-based speed controller is presented as a flow chart in Fig. 4.

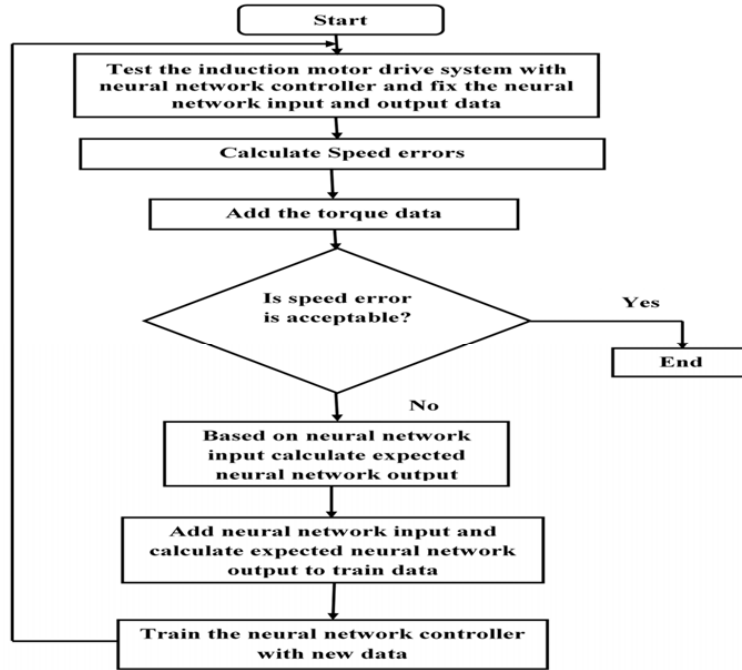


Fig. 4 Flowchart for ANN-based DTC.

Step by step procedure for flowchart

- In the initial step, examine the parameters of the IM drive configuration with the proposed neural network controller values. Then fix the input and output data of the neural network.
- Evaluate the speed error. Speed error is obtained from the comparison of induction motor speed and the nominal reference speed.
- Include the Actual electromagnetic torque data in the neural network controller. This torque data is obtained from the stator voltage.
- Neural network controller stops to train the data when the acceptable speed error is reached.
- If the speed error is unacceptable, add the new neural network input and calculate the neural network output to train data.

- Train the neural network controller with new data.
- This process continues until the acceptable speed error is reached.
- With the help of a neural network controller, finally, reference torque is obtained.

5. Simulation implementation of DTC-IM drive with ANN

Overall Simulink representation of the projected ANN-based DTC configuration is appeared in Fig. 5. The Simulink diagram comprises of three-phase VSI, space vector PWM (pulse width modulation), ANN block and ABC to dq0 (direct quadrature axis) conversion block. The function fitting ANN is opted to compute the reference torque for the SVPWM which in turn generates gate pulses for the 3Φ VSI. The speed error is the input and the output of the ANN controller is the reference torque. Flux reference is kept at a nominal value. Actual electromagnetic torque and the flux values are computed from the stator voltage V_{abc} and stator current I_{abc} . These estimated error values of flux and torque are used by space vector PWM generator to produce gate signals for the power electronic switches present in the VSI (voltage source inverter). At last, variable voltage and variable frequency of VSI control the motor speed. The parameters applied in the simulation for the induction machine and artificial neural network controller are displayed in Tab. I and Tab. II.

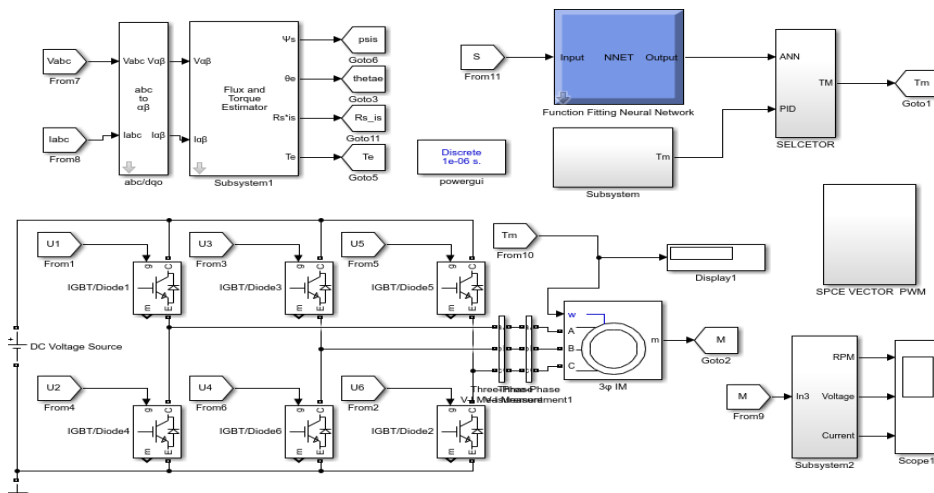


Fig. 5 Simulink model of proposed ANN-based DTC system.

ANN model has one neuron in a single input layer, 10 neurons in the hidden layer and single neuron in the output layer as appeared in Fig. 6(a). After repeating the learning algorithms several times, speed of convergence to the least of the

S.No.	Machine parameters	Values
	Nominal phase voltage, V_{L-L}	400 V
	Nominal speed, N_r	1430 rpm
	Rated shaft power, P_r	4000 W
	Frequency, f	50 Hz
	Pole pair, P	2
	Stator resistance, R_s	11.6 Ω
	Stator inductivity, L_s	0.579 H
	Friction coefficient, K	0.002985
	Rotor inductivity, L_r	0.579 H
	Inertia, J	0.002 kg.m ²
	Rotor resistance, R_r	10.4 Ω
	Mutual inductivity, L_m	0.557 H

Tab. I Induction machine simulation parameters.

Estimator	Speed regulator
Number of neurons in the hidden layer	Single-layer (10)
Input / output	1/1
Activation function	Tansig
Learning algorithm	Back propagation learning algorithm
Number of iteration	1000
Mean squared error tolerance	0.001

Tab. II ANN parameters.

squared error is accomplished quicker. The training results obtained for ANN controller block are illustrated in Fig. 6(b). It finally retained to applied for ANN-DTC strategy. In the proposed ANN controller, root mean square error is used in

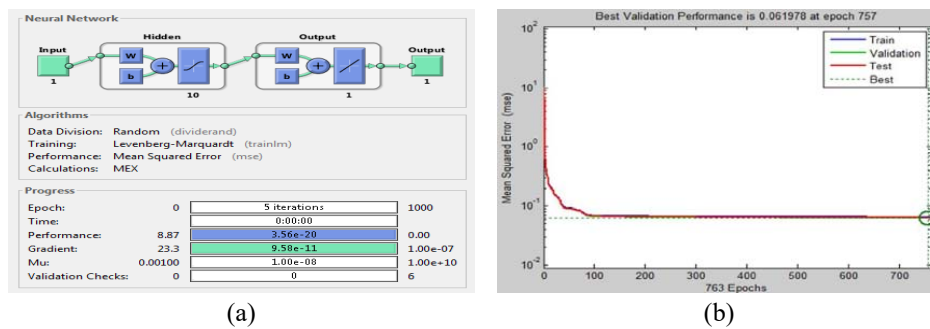


Fig. 6 (a) Parameters setting of the ANN (b) Graphical training results of the ANN.

training. Fig. 6(b) shows the evolution of the root mean square error as a function of the number of epochs for the speed. The loss function, rmse appears in the Fig. 6(b) for the testing and validating of data. It is inferred that the network training has resulted in a significant reduction in the error between the target and predicted output values. The speed control ANN has been trained with nearly 1350 input/output data patterns. Out of these, 945 input data patterns have been utilized for training, 203 data are utilized for validating and 203 data are utilized for testing after all training processes have been ended. The Simulink model for the speed control ANN is observed in Fig. 7. The graphical view of training outcomes is displayed in Fig. 8.

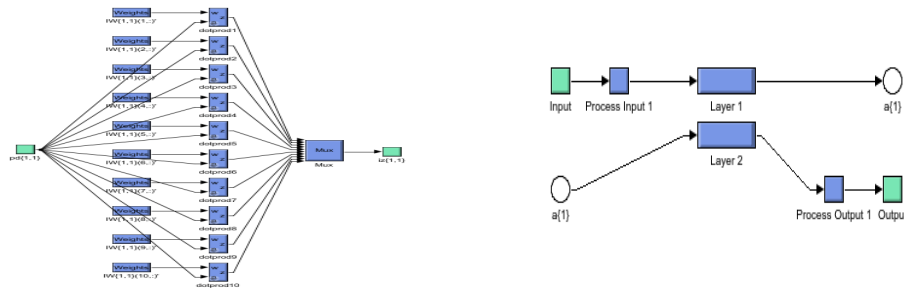


Fig. 7 Simulink model of ANN.

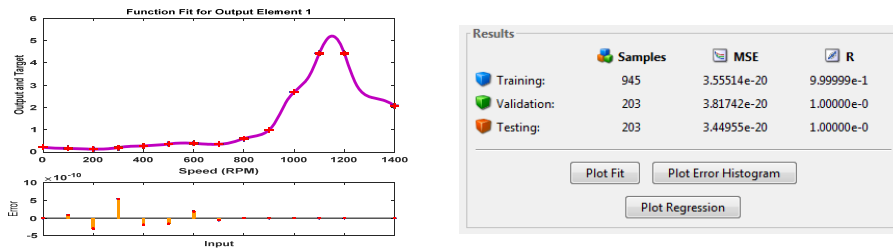


Fig. 8 Graphical training results of the ANN.

6. Results and discussion

The projected DTC-IM drive utilising the ANN controller has been developed and simulated in MATLAB/Simulink 2017 environment. The DTC-IM drive using a traditional PID controller is also simulated for the same machine parameters. Afterward, the drive performance utilizing the proposed ANN controller is analyzed and contrasted with the traditional strategy under various operating conditions.

The simulation time is set as 1s. The direct torque controlled induction motor drive using the PID controller as well as the ANN controller in the speed control loop is evaluated at four different speeds, 800 rpm, 1000 rpm, 1200 rpm, and 1400 rpm, respectively.

6.1 Simulation results for PID controller

The speed responses of the projected drive using the PID controller at 800 rpm, 1000 rpm, 1200 rpm, and 1400 rpm appear in Fig. 10, Fig. 12, Fig. 14, and Fig. 16, respectively. Initially, the drive is beginning at zero load and 0.15s, the reference speed of the motor is changed. The speed response of the DTC-IM takes 0.3s, 0.35s, 0.4s, and 0.45s to reach the set speed of 800 rpm, 1000 rpm, 1200 rpm, and 1400 rpm respectively and they are depicted in Fig. 10, Fig. 12, Fig. 14 and Fig. 16. From Fig. 9, Fig. 11, Fig. 13 and Fig. 15. It could be viewed that during this transition period, the motor torque is increased to near 15 Nm to accomplish the required speed in minimum duration. Also, starting the current gets amplified to augment the drive acceleration. Once the reference speed is reached by the motor, the electromagnetic torque is minimized to zero, and the load current is decreased to no-load value. It could be monitored from the torque curves of the DTC-IM drive for various speeds.

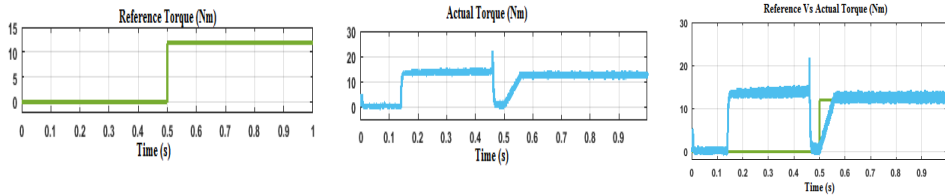


Fig. 9 Torque response curves using PID controller for 800 rpm.

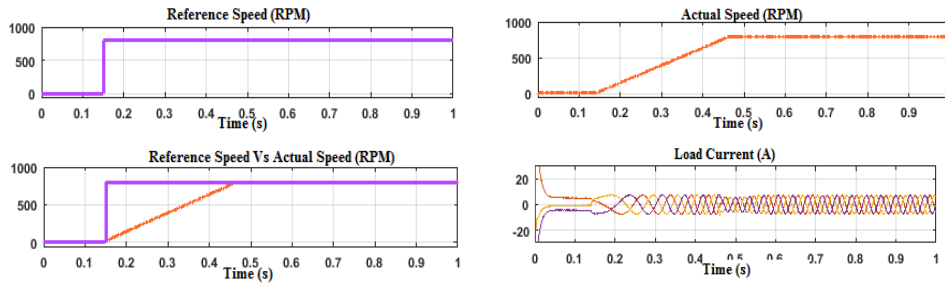


Fig. 10 Speed response characteristics using PID controller for 800 rpm.

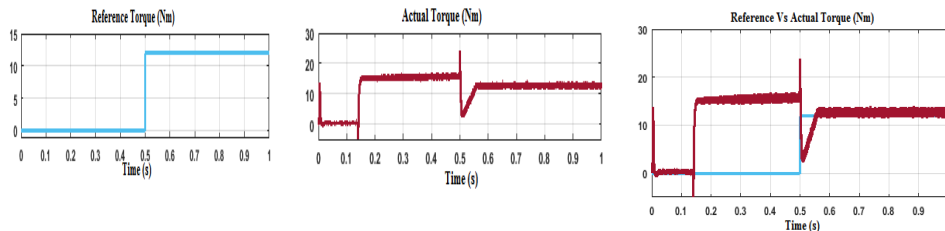


Fig. 11 Torque response curves using PID controller for 1000 rpm.

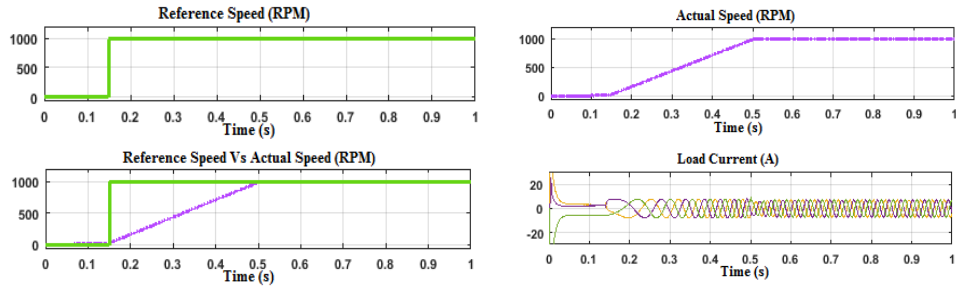


Fig. 12 Speed response characteristics using PID controller for 1000 rpm.

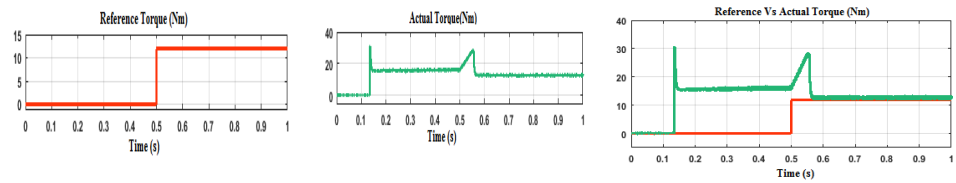


Fig. 13 Torque response curves using PID controller for 1200 rpm.

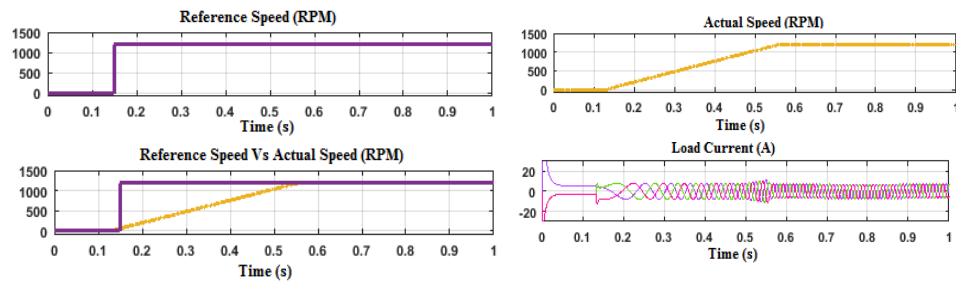


Fig. 14 Speed response characteristics using PID controller for 1200 rpm.

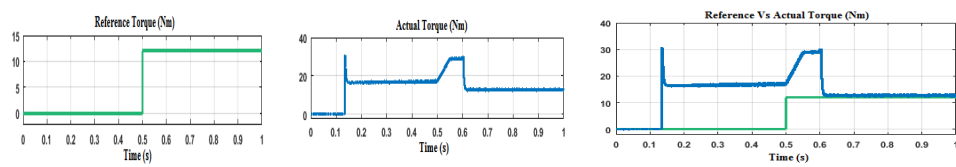


Fig. 15 Torque response curves using PID controller for 1400 rpm.

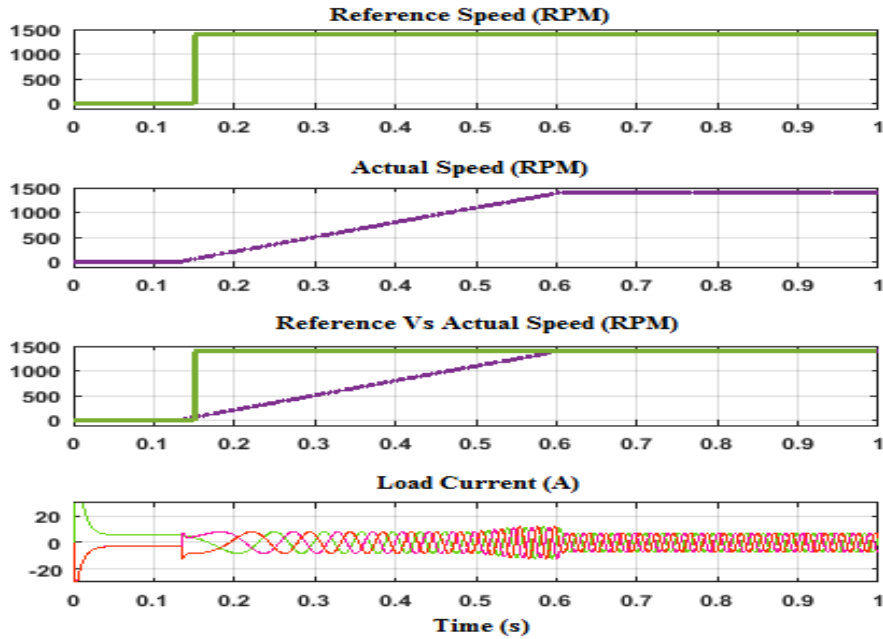


Fig. 16 Speed response and stator current characteristics using PID controller for 1400 rpm.

The torque characteristic curves of the DTC-IM drive using the PID controller for 800 rpm, 1000 rpm, 1200 rpm and 1400 rpm, correspondingly are appeared in Fig. 9, Fig. 11, Fig. 13 and Fig. 15. At first, the machine is started at no load and 0.5 s, load torque is changed from no load to 12 Nm. The motor reaches this reference torque after 0.05 s only. The PID based IM drive is worked at the speed of 800 rpm, and 12 Nm of load torque. Then, the ripple present in the load torque is 2.2 Nm which is about 8.33 % of rated torque as in Fig. 9. When the motor speed reaches near rated value, the ripple content in the load torque gets reduced to 1.4 Nm i.e. 5.28 % of rated torque. Hence, the settling time and torque ripples get reduced with the increase in the speed of the motor, when the conventional PID controller has been utilized.

The percentage of total harmonic distortion analysis for the load current of the DTC-IM drive using a conventional PID controller is given in Fig. 18. When operated at speed of 1400 rpm and the torque of 12 Nm. The corresponding load current of the waveform is given in Fig. 17. The conventional PID controller produces 15.27 % of THD in the load current of the DTC-IM drive.

6.2 Simulation results for ANN controller

The speed response curves of the DTC-IM drive using the ANN controller at 800 rpm, 1000 rpm, 1200 rpm, and 1400 rpm, are appeared in Fig. 20, Fig. 22, Fig. 24 and Fig. 26. Similar to previous work, the drive is beginning at without

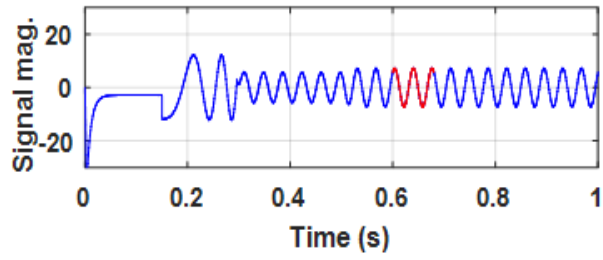


Fig. 17 Single-phase load current for PID controller.

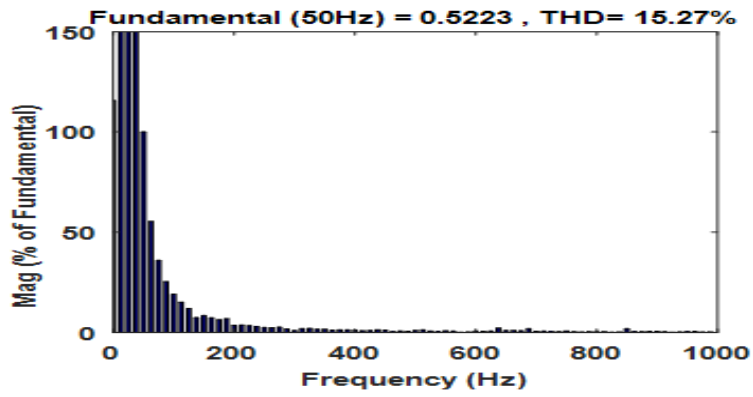


Fig. 18 Load current THD for PID controller.

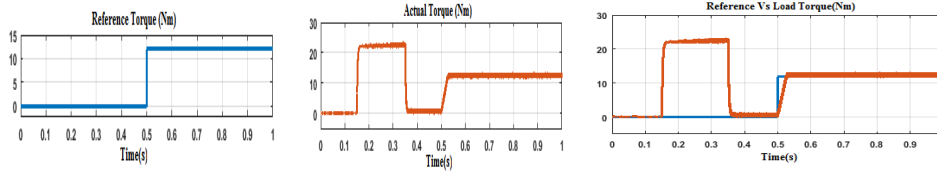


Fig. 19 Torque response curves using ANN controller for 800 rpm.

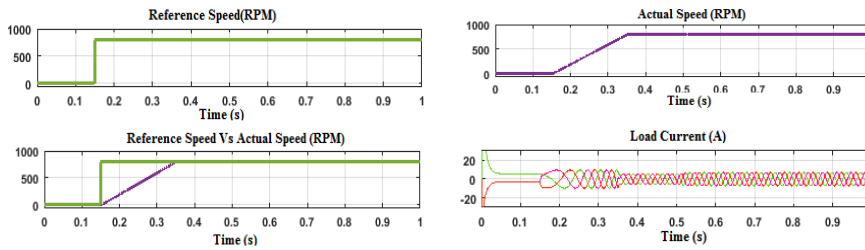


Fig. 20 Speed response characteristics using ANN controller for 800 rpm.

load and 0.15s, the speed reference of the motor is changed. The speed response of the drive takes 0.2s to reach the set speed of 800 rpm which is observed from Fig. 20. On revealing Fig. 20, Fig. 22, Fig. 24 and Fig. 26, the settling time of speed response gets increased with set speed value. During the transient time, the motor torque is raised to nearly 20 Nm and stator current is also increased to a high value to accelerate the motor fast. Once the reference speed is reached by the motor, the electromagnetic torque is reduced to normal value.

The torque curves of the DTC-IM drive using the ANN controller for 800 rpm, 1000 rpm, 1200 rpm, and 1400 rpm, respectively are given in Fig. 19, Fig. 21, Fig. 23 and Fig. 25. Initially, the machine is started at no load and 0.5 s, load torque is changed from no load to 12 Nm. The motor reaches this reference torque after 0.02 s. When the IM drive using the ANN procedure is operated at the speed of 800 rpm and 12 Nm of load torque, the torque ripple is 1.8 Nm which is about 6.79 % of rated torque. When the motor speed reaches near rated value, the ripple content in the load torque gets reduced to 1.1 Nm i.e. 4.15 % of rated torque. Hence, the torque ripples and settling time get decreased with an increase in the speed of the motor, when the ANN controller has been used.

The total harmonic distortion analysis for the ANN controller is displayed in Fig. 28, when operating the machine at 1400 rpm speed and a load torque of 12 Nm. The corresponding load current is given in Fig. 27. The ANN controller produces 8.89% of THD in the load current of the DTC-IM drive.

6.3 Comparative performance analysis of DTC-IM drive

From Fig. 10, 12, 14, 16, 20, 22, 24, and 26, it is understood that the ANN-based direct torque controlled drive has quicker speed responses contrasted to traditional PID controller based drive and it is displayed in Tab. III. While investigating torque attributes (Fig. 9, 11, 13, 15, 19, 21, 23 and 25) of the induction machine under different speeds of operations torque ripples get minimized with the help of the ANN controller as appeared Tab. III.

Parameters	PID controller			ANN controller		
	Torque ripple (Nm)	Torque ripple (%)	Settling time (s)	Torque ripple (Nm)	Torque ripple (%)	Settling time (s)
Speed (rpm)						
800	2.2	8.30	0.30	1.8	6.79	0.20
1000	2.0	7.55	0.35	1.4	5.28	0.25
1200	1.6	6.04	0.40	1.2	4.53	0.30
1400	1.4	5.28	0.45	1.1	4.15	0.35
Transient torque 0–12 Nm	0.05			0.02		
THD %	15.27			8.89		

Tab. III Performance comparison of PID controller vs ANN controller.

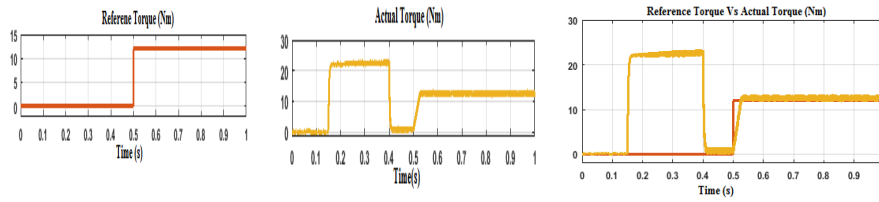


Fig. 21 Torque response curves using ANN controller for 1000 rpm.

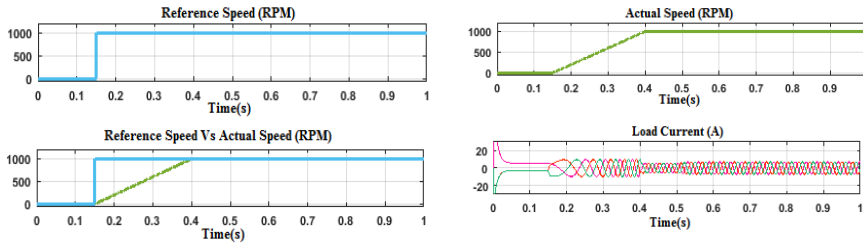


Fig. 22 Speed response characteristics using ANN controller for 1000 rpm.

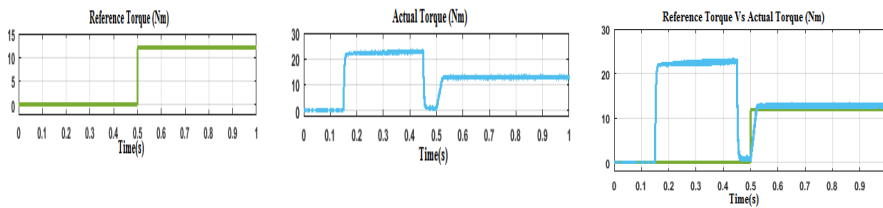


Fig. 23 Torque response curves using ANN controller for 1200 rpm.

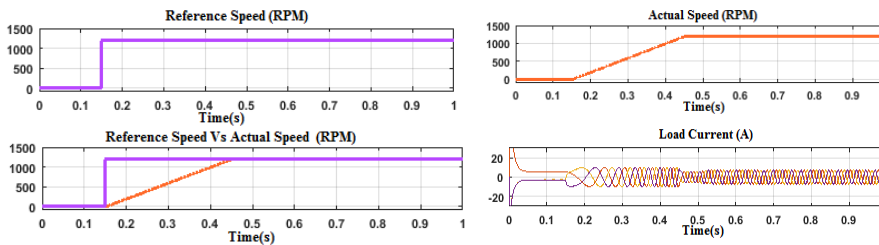


Fig. 24 Speed response characteristics using ANN controller for 1200 rpm.

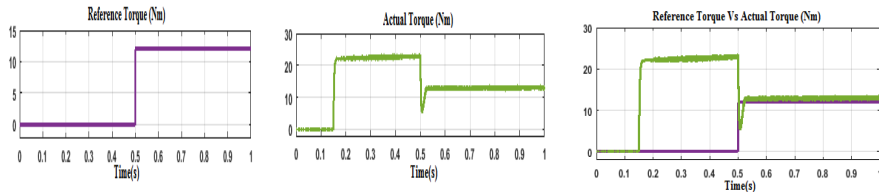


Fig. 25 Torque response curves using ANN controller for 1400 rpm.

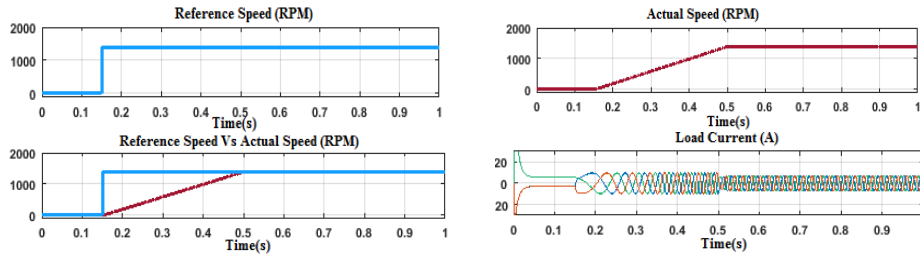


Fig. 26 Speed response characteristics using ANN controller for 1400 rpm.

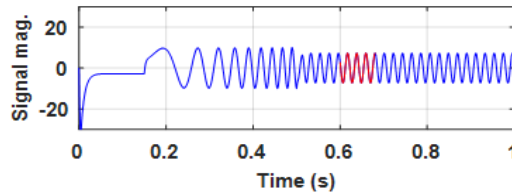


Fig. 27 1Φ load current for ANN controller.

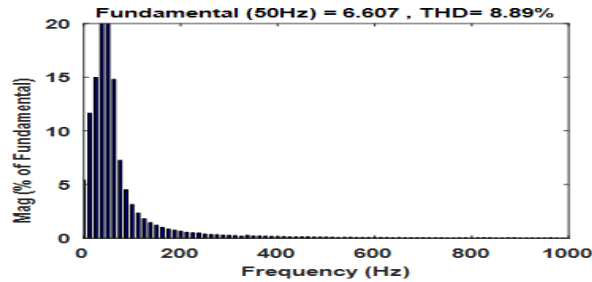


Fig. 28 THD % for ANN controller.

Torque ripple is compared with the load torque of 12 Nm. The settling time is compared for four different speeds at no load and it is given in Tab. III. Moreover, the torque curves reveal that the motor has reached the load torque in minimum time duration when the ANN controller is utilized as given in Tab. III. THD comparison is done and presented in Tab. III for 12 Nm load torque and 1400 rpm speed. As a result, the ANN controller has improved the system performance by minimizing torque ripple and settling time. The performance analysis of the induction motor drive based on torque ripple, settling time and total harmonic distortion is given in Fig. 29(a), (b), (c), and (d). The direct torque controlled induction motor drive ANN controller in speed control loop at four different speeds, 800 rpm, 1000 rpm, 1200 rpm, and 1400 rpm achieves minimum torque ripple, faster response, and minimum THD than the direct torque controlled induction motor drive using PID controller.

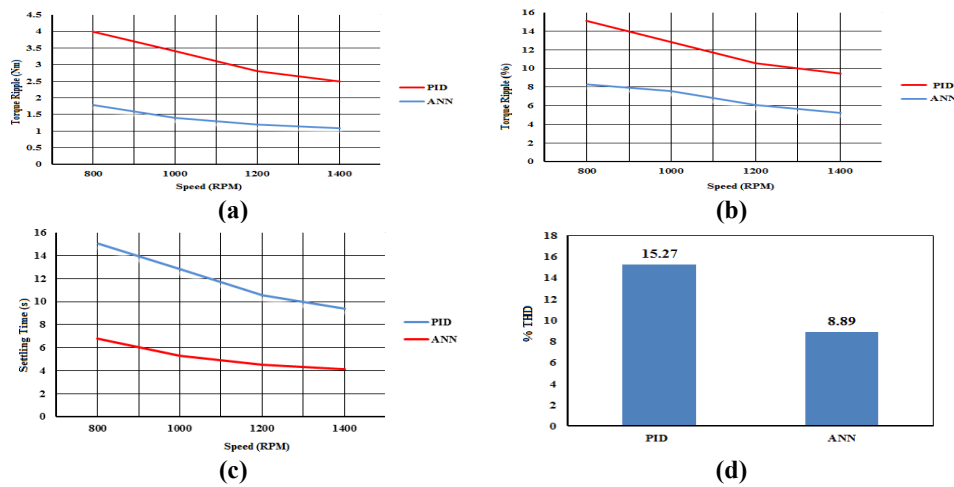


Fig. 29 (a) Performance analysis of DTC-IM drive based on torque ripple in steady-state (b) Performance analysis of DTC-IM drive based on Percentage of torque ripple in steady-state (c) Performance analysis of DTC-IM drive based on settling time and (d) Performance analysis of DTC-IM drive based on % THD.

7. Conclusions

The comparative performance analysis has been investigated using MATLAB/Simulation. The direct torque control employed with the ANN controller has given the best speed tracking capability, good steady-state, transient, and dynamic response contrasted to a traditional controller. The DTC-IM drive system has been studied under various working situations like low speed, no-load, high speed, and medium load torque. The simulation results prove that the ANN controller gives stable operation under all these operating conditions. Mostly, torque ripple and THD have been minimized to some extent and they make the ANN controller as an alternative to conventional PID controller in the direct torque control of IM drive. DTC uses SVPWM to generate a gate pulse for the inverter based on the flux and torque error. Therefore, from the simulation outcomes, it could be said that the whole drive performance has been improved through a neural network. Due to this positive approach and performance, ANN has become popular in recent years.

References

- [1] ABDELKARIM A., BILLEL T., TAREK A., YOUNES A., ABDELAZIZ K. Predictive direct torque control with reduced ripples and fuzzy logic speed controller for induction motor drive, In: Proceedings of the 5th International Conference on Electrical Engineering – Boumerdes, (ICEE-B), 2017, pp. 29–31.
- [2] ABDESSELEM C. Direct torque control of induction motor based on space vector modulation using a fuzzy logic speed controller. Journal of Mechanical and Industrial Engineering, 2014, 8, pp. 169–176.

- [3] ALLIRANI S., JAGANNATHAN V. Torque ripples minimization in dtc based induction motor drive using fuzzy logic technique. *International Journal of Computer Applications*, 2012, 40(1), pp. 25–41.
- [4] AMEUR A., MOKHTARI B., ESSOUNBOULI N., NOLLET F. Direct torque control for permanent magnet synchronous motor drive based on fuzzy logic torque ripple reduction and stator resistance estimator. *Control Engineering and Applied Informatics*, 2013, 15(3), pp. 45–52.
- [5] ANJANA M., JEBIN F. Simulation of direct torque controlled induction motor drive by using space vector pulse width modulation for torque ripple reduction. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 2013, 2(9), pp. 4471–4478.
- [6] ANMOL AGGARWAL J.N., RAI, MAULIK K. Comparative study of speed control of induction motor using pi and fuzzy logic controller. *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, 2015, 10(2), pp. 43–52
- [7] ARCHANA D., KOTYADA, KALYANI, SHANKAR PRASAD B. Efficiency optimization control of induction motor using fuzzy logic. *International Journal of Soft Computing and Engineering (IJSCE)*, 2012, 2(3), pp. 327–332.
- [8] BEN SALEM F., DERBEL N. DTC-SVM-based sliding mode controllers with load torque estimators for induction motor drives, In: Derbel N., Ghommam J., Zhu Q. (eds) *Applications of Sliding Mode Control. Studies in Systems, Decision and Control*, Springer Singapore, 2017, 79, pp. 269–297.
- [9] BOUMEDIENE A., ABDELLAH L. A novel sliding mode fuzzy control based on svm for electric vehicles propulsion system, In: *Terra Green 13th International conference 2013 – Advancements in Renewable Energy and Clean Environment*, Energy Procedia, Published by Elsevier, 2013, 36, pp. 120–129.
- [10] CHANDRA SEKHAR D., MARUTHES WAR G.V. Direct torque control of three-phase induction motor with anfis and cuckoo search algorithms. *International Journal of Pure and Applied Mathematics*, 2017, 114(12), PP. 501–514.
- [11] WANG F., CHEN Z., STOLZE P., KENNEL R., TRINCADO M., RODRIGUEZ J. A comprehensive study of direct torque control (DTC) and predictive torque control (PTC) for high performance electrical drives. *EPE Journal*, 2015, 25(1), pp. 12–21.
- [12] GAO JUNSHAN, LU XINMENG, WANG YUE. Low-speed performance improvement of direct torque control and simulation validation, in: *proceeding of the (ICMIC) International Conference on Measurement Information and Control*, 2013, 02, pp. 906–910.
- [13] ALI J.A., HANNAN M.A., MOHAMED A. Rule-based fuzzy and v/f control for induction motor speed responses using svpwm switching technique. *Przeglad Elektrotechniczny*, 2015, 91(3), pp. 133–136.
- [14] ABDELLATIF M., DEBBOU M., SLAMA-BELKHODJA I., PIETRZAK-DAVID M. Simple low-speed sensor less dual dtc for double fed induction machine drive. *IEEE Transactions on Industrial Electronics*, 2014, 61(8), pp. 3915–3922.
- [15] AMIRI M., MILIMONFARED J., ARAB KHABURI D. Predictive torque control implementation for induction motors based on discrete space vector modulation. *IEEE Transactions on Industrial Electronics*, 2018, 65(9), pp. 6881–6889.
- [16] SIVAKUMAR, MUTHU SELVAN N.B. Reduction of source current harmonics in ANN controlled induction motor. *Alexandria Engineering Journal*, 2018, 57, pp. 1489–1499.
- [17] SOLODKIY E., VARZANOSOV P., BELONOGOV A. Induction motor sensor less vector control with an adaptive speed observer and direct electrical angle correction in coordinate transformations, In: *proceeding of the International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM)*, 2017, pp. 1–4.
- [18] JEYASHANTHI J., SANTHI M. Improved efficiency of direct torque controlled induction motor drive by golden section method. *Revista Facultad de Ingeniería, Universidad de Antioquia* 2019, 91, pp. 31–42.
- [19] JEYASHANTHI J., SANTHI M. Performance of Direct Torque Controlled Induction Motor Drive by Fuzzy Logic Controller. *CEAI 2020*, 22(1), pp. 63–71.

- [20] BARSANA BANU J., JEYASHANTHI J. DTC-IM drive using adaptive neuro fuzzy inference strategy with multilevel inverter. Journal of Ambient Intelligence and Humanized Computing 2021, pp. 1–23. Springer online Published.