Speed control of 3-phase induction motor with modified DTC using HTAF-ANN

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Article Info

Article history:

Received Mar 13, 2025
Revised Jul 26, 2025
Accepted Sep 2, 2025

Keywords:

Artificial neural network
Direct field-oriented control
Direct torque control
Hyperbolic tangent activation function
Induction motor
Mean square error
PI controller

ABSTRACT

In this research paper, an artificial neural network (ANN) algorithm is implemented with modifications to enhance the performance of a direct torque controlled (DTC) induction motor drive. Since the main challenge in the conventional DTC technique is to tune the PI controller appropriately therefore in this work, an ANN technique is incorporated in place of the conventional PI controller. Sudden changes in speed and loading in induction motor drives lead to sharp fluctuations and disturb the motor performance. In order to overcome these issues, a trained ANN controller is initially used here to enhance motor drive performance. Subsequently, the performance is further improved by modifying the activation function in the ANN controller. Here, motor parameters at rated and variable speed with various loading conditions have been analyzed and compared for the DTC with a conventional PI controller with ANN, and a proposed ANN controller. Simulation of the complete model with the conventional and proposed controllers is done using MATLAB/Simulink platform to observe the various speed responses for different conditions, and the experimental setup is used to demonstrate the effectiveness and performance of the proposed system.

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1. INTRODUCTION

In recent years, induction motors (IMs) have replaced DC machines in industrial drive applications with its properties like low cost, easy maintenance, and robust structure [1], [2]. But the non-linear behaviour of IM necessitates various types of control strategies to be implemented for obtaining better performance from the motor. Various researchers have discovered the fact that IM performs better with the vector control technique than scalar control, which are the two major control techniques in control engineering [3]. In IM the major function of vector control theory is to determine the phase angle and magnitude of voltages and currents. This vector control method operated on the basis of Park and Clarke transformations, which generates flux and torque of the motor, respectively [4]. The two leading high-performance control techniques for IM drive in recent years are field-oriented control (FOC) and direct torque control (DTC). The result in [5], [6] provide good dynamic and steady state torque responses, and also because of the ability of decoupling control between flux and torque. In the DFOC technique which was proposed by Aziz *et al.* [7] and Blaschke [8], two Hall effect sensors are used in the air gap for determining rotor flux. The drawback of the direct field-oriented control (DFOC) method is that it gives poor dynamic performance when the resistance value of the stator and rotor increases. Ease of use, low sensitivity to parameter variations, rapid torque response, and simple implementation has made DTC a better choice than FOC. Moreover DTC approach doesn't require the coordinate transformation or the current regulators [5]. This control technique, which was introduced by Takahashi and Noguchi in Japan in the mid of 1980's, operates solely in a stationary frame (co-ordinates fixed to the stator) in contrast to FOC [9]. Also it eliminates the need for any modulation, such as pulse width modulation (PWM), by producing the inverter's gating signals directly through the look-up switching table [10]. In DTC selection of inverter switching sector for the regulation of flux and torque is a very crucial part as a slight difference in the vector during the voltage sector selection process may cause a substantial phase shift mistake in the command torque and cause ripples in torque and current [11]-[13]. When variable frequency operations are applied by hysteresis comparators, conventional DTC has drawbacks such as decreased robustness due to variations in stator and rotor resistances. These elements shorten the machine's lifespan by raising the harmonics in the system, producing audible noises, and causing mechanical vibrations [14]. By integrating optimization and machine learning techniques discussed in [15], the drawbacks of conventional DTC techniques have been overcome, and thereby motor efficiency could be improved. Use of these universal approximation methods through various controllers' non-linearities of motors also have been addressed in [16]. Study in [17] used a model reference adaptive system (MRAS), which could improve the performance of the control scheme by giving faster speed response and high robustness against external load disturbance and reference speed variation. A research article [18] presents a model reference adaptive system based on the active power (P-MRAS) which can estimate stator resistance where the model is insensitive to parameter variations. Here a new structure of 12-sector DTC in combination with P-MRAS estimator and a back stepping speed controller is proposed to improve the direct torque control (DTC) strategy. Mahfoud *et al.* [19] have used genetic algorithm (GA) based DTC approach for optimizing K_p, K_I, and K_D parameters and have presented a comparison of different objective functions with respect to speed overshoot and rejection time, fluxes, and torque ripples and current total harmonic distortion (THD). Control technique like direct torque fuzzy control (DTFC), direct torque neuro control (DTNC), and direct torque neuro-fuzzy control (DTNFC) has improved the efficiency of the conventional technique and helped the system to perform better. Hysteresis comparators and truth tables have been replaced in DTNFC by fuzzy logic and ANN. The torque and flux can be navigated towards their references over a predetermined amount of time because of the voltage vector created by ANFIS, which combines artificial neural network (ANN) and fuzzy logic. Using neural networks and fuzzy logic techniques, DTC drives' PI speed controller is upgraded in [20]-[22].

In this research article, the authors have discussed different conventional controllers along with various machine learning techniques implemented in them for the performance enhancement of IM drive system. All the techniques discussed here has some advantages and also some drawbacks and limitations. To mitigate issues like high torque and flux ripples, reduced control accuracy at low speed, and difficulty in optimal tuning, machine learning techniques have started been implemented in DTC of IM to make the motor performance better. ANN technique can model complex and nonlinear motor dynamics and also has the capability of learning control strategies from training data. Once the system is trained ANN makes the signal generation faster. The accuracy of the stator flux location, which can be determined using the ANN technique, is crucial for sector verification in the DTC scheme. The quality of reducing the dependency on identifying accurate motor parameters makes ANN a better choice for controlling a non-linear system. Modern industry's requirement for intelligent motor drives has been met with techniques like ANN, as it made the system sensor less and self-tuned.

A study in [23] explains how fine-tuning the conventional PI speed controller with artificial intelligence can improve the upgraded DTC IM drive's performance. Aziz *et al.* [7] discussed about the use of the ANN technique in various industrial applications, and the results obtained from those studies proves the ability of the ANN technique in giving better results towards solving engineering problems than conventional techniques. In this study, the performance of traditional DTC is enhanced through the application of the ANN technique.

The result in [24] achieved an improvement of 85% in response time, reduction of speed overshoot, and 50% reduction in torque ripples by using the ANN technique in a doubly fed IM. Djeriri *et al.* [25] an ANN-based DTC controller is used for a doubly fed induction generator in selecting switching volatge vectors. Here 'tansig' and 'purelin' functions are used for hidden and output layers, respectively. Aissa *et al.* [26], a neural switching table along with a fuzzy logic controller is used for broken bar fault diagnosis of IM. Here, also'tansig' and 'purelin' functions are used as hidden and output layers, respectively.

In this research an ANN-based DTC model with sigmoid hidden neurons and tansig output neurons is developed for the enhancement of the IM's transient performance under varied dynamic situations. The Simulink model is first run with the trained ANN controller and then the system responses are checked with various ANN activation functions like Sigmoid, hyperbolic tangent, rectified linear unit (ReLU), leaky ReLU, softmax. After running the simulation model it is observed that with sigmoid, ReLU, and Leaky ReLU functions, the speed response of the motor going beyond the rated speed, and with the Softmax function, the motor is running at below rated speed. During this process it has been observed that the model is giving better response with the 'hyperbolic tangent' function compared to the inbuilt function. Therefore, in this work the motor responses are verified and compared for the conventional systems with the proposed ANN model with the new function. The structure of this research article is organized as: i) Section 2 explains the system in general; ii) Section 3 explains ANN structure and its algorithm; iii) Section 4 presents the methodology of proposed HTAF-ANN technique for DTC of IM; iv) Section 5 presents results and discussions; and v) This research article is concluded in section 6 which is followed by further research perspective in future.

2. SYSTEM OVERVIEW

2.1. Conventional DTC of IM

In this system, the values of reference flux and speed are compared with the actual values. In the conventional technique, the speed error through the PI controller generates torque. The flux and torque error signal, after being controlled by a hysteresis controller, is used to produce a regulated switching signal so that the inverter can function. The correct vector is determined from the lookup database based on the torque error, flux vector angle, and flux error. After the selected vector is sent to the inverter, the converter output powers the motor [27]. The mathematical equations mainly used for designing DTC of 3-phase IM with respect to the stator reference frames are listed here as (1) and (2).

$$\psi_{ds} = \int (V_{ds} - R_s i_{ds}) dt \tag{1}$$

$$\psi_{qs} = \int (V_{qs} - R_s i_{qs}) dt \tag{2}$$

Where, ψ_{ds}, ψ_{qs} represents stator d and q axes flux linkages and V_{ds}, V_{qs}, i_{ds}, i_{qs} represents the stator d and q axes voltage and current components receptively. Finally the electromagnetic torque of 3-phase IM can be expressed as (3).

$$T_e = \frac{3}{2}\frac{P}{2}(\psi_{ds} i_{qs} - \psi_{qs} i_{ds}) \tag{3}$$

Where, P is the total no of poles in the IM. Conventional DTC technique requires proper tuning of PI controller to achieve expected output from the motor. Various tuning methods are discussed in [28] among which 'trial and error' method is the most popular approach that decides gain parameters of the controller using (4).

$$u(t) = K_p e(t) + K_i \int_0^t e(t) dt \tag{4}$$

Where, u(t) represents controlled output. K_p stands for proportional gain. K_i is the integral gain. e(t) stands for error signal and can be represented as the subtractive value of reference input and the process variable. But this method gives sluggish and improper response. Therefore optimization and machine learning techniques started getting implemented to overcome the shortcomings of PI controller. In this article DTC model of IM is trained with a proposed ANN model to get better performance of the machine drive system.

2.2. Proposed DTC with HTAF-ANN controller

A model that emulates the structure and operation of actual neural networks found in animal brains is called a neural network (NN). It is basically a connection of artificial neurons. A non-linear function called activation function is used to determine the output of each neuron. Weight defines the connection from one neuron to another which determines the strength and direction of the influence one neuron has on another. In an ANN, output is determined by a series of mathematical operations [29]. Figure 1 represents the block diagram of DTC of 3-phase IM with proposed ANN controller. One neural network is suggested in this paper to maximize the performance of the PI controller. Here, the speed error is estimated using a neural network and to generate the electromagnetic torque. This neural network is associated with one input which is taken by comparing actual with reference speed of the motor and one output. It is a feed forward, two-layer network with 10 neurons in hidden layer. Here Levenberg Marquardt algorithm is used and the weights and bias values are updated according to this technique. After the training process is over if the output doesn't meet the exact requirement then the training process is repeated. A neural network's tendency is to approximate the output for new input data because of which they are used in intelligent system analysis [30].

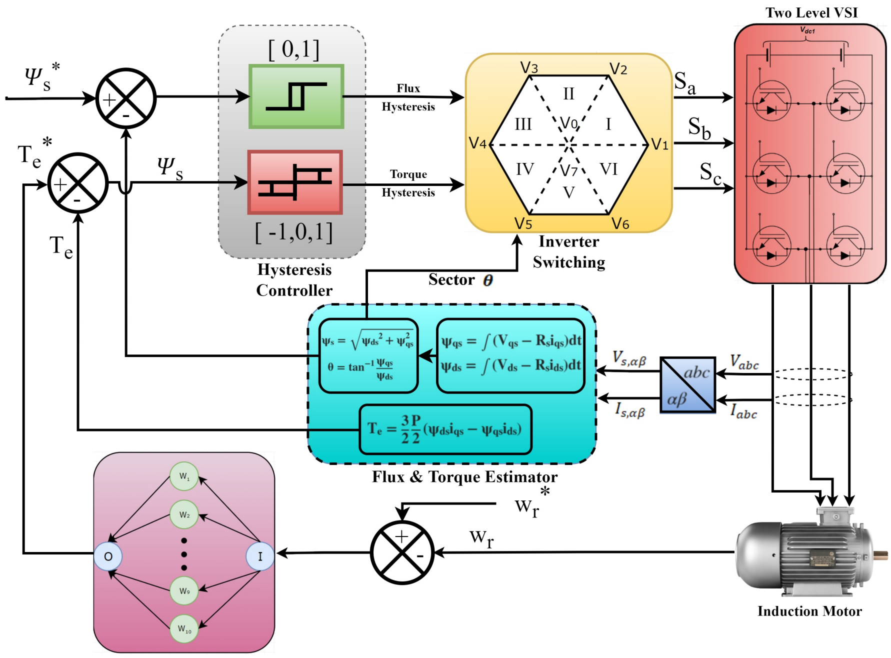


Figure 1. Block diagram of DTC of 3-phase IM with proposed ANN controller

3. ANN STRUCTURE AND ITS ALGORITHM

3.1. Training data generation

ANN technique can minimize the effort in evaluating appropriate K_p K_i values in conventional PI controller. An elaborate training process for ANN controller is discussed in [31]. In this work to replace PI controller an ANN is used to predict motor's reference torque T_e^* taking speed error as input. Input matrix for the ANN controller is as:

$$\mathbf{X} = \begin{bmatrix} e_\omega & \dot{e_\omega} & \omega_r & T_L \end{bmatrix}$$

Where, speed error e_ω is the difference between the motor's actual speed and its rated speed, $\dot{e_\omega}$ is the rate of change of speed error and T_L is the load torque. Here the output is as:

$$\mathbf{Y} = \begin{bmatrix} T_e^* \end{bmatrix}$$

T_e^* is the optimal torque.

Figure 2 shows the architecture of ANN. It has to predict the optimal torque by learning the mapping of speed error to the reference torque. Training data is generated using a conventional PI controller ensuring proper tuning of K_p and K_i. Simulation is run with variable speed reference and with step changes in load torque T_L. Input and output variables are saved in workspace in exporting the data to MATLAB. Once the data is collected ANN is trained using MATLAB's NN Toolbox. Ultimately, a MATLAB function block is developed and used in place of PI controller. At last simulation is run with ANN controller block and the motor response is analyzed.

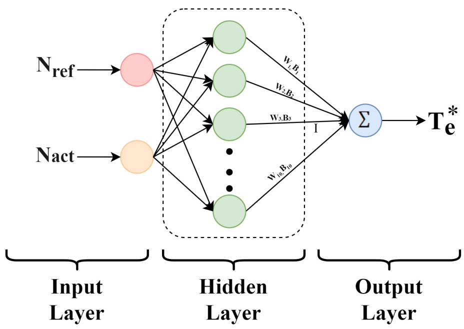


Figure 2. Architecture of ANN

3.2. Training of the network

In MATLAB/Simulink the process followed by a neural network to solve DTC of IM model can be explained as follows: In MATLAB neural network simulation generates a function as 'myNeuralNetworkFunction' which takes an $N \times 1$ matrix as input and gives an $N \times 1$ matrix as output using the trained network. This function is represented by the MATLAB neural network as in (5).

$$functiony_1 = myNeuralNetworkFunction(X_1) \tag{5}$$

Where the input function is x_1 and output function is y_1.

Prior to data being fed into the neural network, this stage involves scaling the input data using normalization parameters. The equation used in this step is as (6).

$$X_p1 = (x_1 - x_{offset}).gain + y_{min} \tag{6}$$

Where, x_{offset} is the offset value subtracted from the input data, gain is the factor by which input data is multiplied, y_{min} is the minimum value after scaling. In this step first and second layer parameters are defined which includes weights and biases for both the layers as $IW1\_1$ & $b1$ and $LW2\_1$ & $b2$ respectively. Computation of hidden layer is done for both the layers using (7) and (8) for layer 1 and layer 2 respectively.

$$a1 = tansig(W_1X_p1 + b_1) \tag{7}$$

$$a2 = LW2\_1.a1 + b_2 \tag{8}$$

In this step output normalization parameters are defined to get the output data back to its original range. Equation followed in this step is as (9).

$$y_1 = (a_2 - y_{min})/gain + x_{offset} \tag{9}$$

Where, y_{min} is the minimum value after scaling, gain is the factor by which output data is divided, x_{offset} is the offset value added to the output data. In this step simulation process starts where input data x_1 is transposed and normalized using mapminmax_apply function. The output of the first layer is calculated using 'tansig_apply' function having an expression of (10).

$$\begin{cases} functiona = tansig\_apply(n, \sim) \\ \qquad a = \dfrac{2}{1 + e^{-2n}} - 1 \end{cases} \tag{10}$$

Then the output in the second layer is computed and the same is denormalized using 'mapminmax_reverse' function and the final output is then denormalized to match the original data scale. In the proposed method the gain factor of (6) is changed and the output is computed using hyperbolic tangent function, expressed as (11).

$$\begin{cases} functiona = tanh\_apply(n, \sim) \\ \qquad a = \dfrac{e^{\alpha n} - e^{-\alpha n}}{e^{\alpha n} + e^{-\alpha n}} \end{cases} \tag{11}$$

α is a parameter here which scales the input.

MSE is a loss function in ANN that is used to evaluate the network's performance. It is calculated by comparison between actual target values and the network's predicted results. MSE can be expressed by (12).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\{y_{act,i} - y_{pred,i}\}^2 \tag{12}$$

Where, N is no. of data points, $y_{act,i}$ and $y_{pred,i}$ are the actual target value and predicted output from the network for $i-th$ data point respectively. The weight update expression, found in (13), is used to modify the weight of each neuron in order to lower the cost function and MSE values. To update rule using gradient descent following is an expression for the weight w_{ij} that joins neurons i in the first layer to neurons j in the subsequent layer, as (13).

$$w_{ij}(t+1) = w_{ij}(t) - \eta\frac{\partial MSE(t)}{\partial w_{ij}(t)} \tag{13}$$

Where, t is the iteration, w_{ij} is the weight, η is the learning rate, $\frac{\partial MSE(t)}{\partial w_{ij}(t)}$ is the gradient of the MSE with respect to the weight w_{ij}. In a NN, an activation function is a mathematical function that is applied to a neuron's (or node's) output to cause the model to become non-linear.

4. METHODOLOGY OF PROPOSED HTAF-ANN TECHNIQUE FOR DTC OF IM

As discussed in introduction section a neural network may have various activation functions which can be chosen basis the problem statement. In this research after verifying motor responses with all the functions it is found that hyperbolic tanget is giving the best results for this problem statement. So inbuilt function is replaced here by the proposed function. The expression for this hyperbolic tangent function is given in (11). Simulation results shows that this proposed ANN algorithm has given significant improvement in motor responses compared to conventional PI controller and ANN controller.

Figure 3 shows the flowchart of proposed ANN control technique for DTC of 3-ph IM. The simulation steps followed for improving the technique is explained here in the chart. Simulation results obtained from the model following these steps have given a significance improvement in the motor performance and the results are listed in section 5.

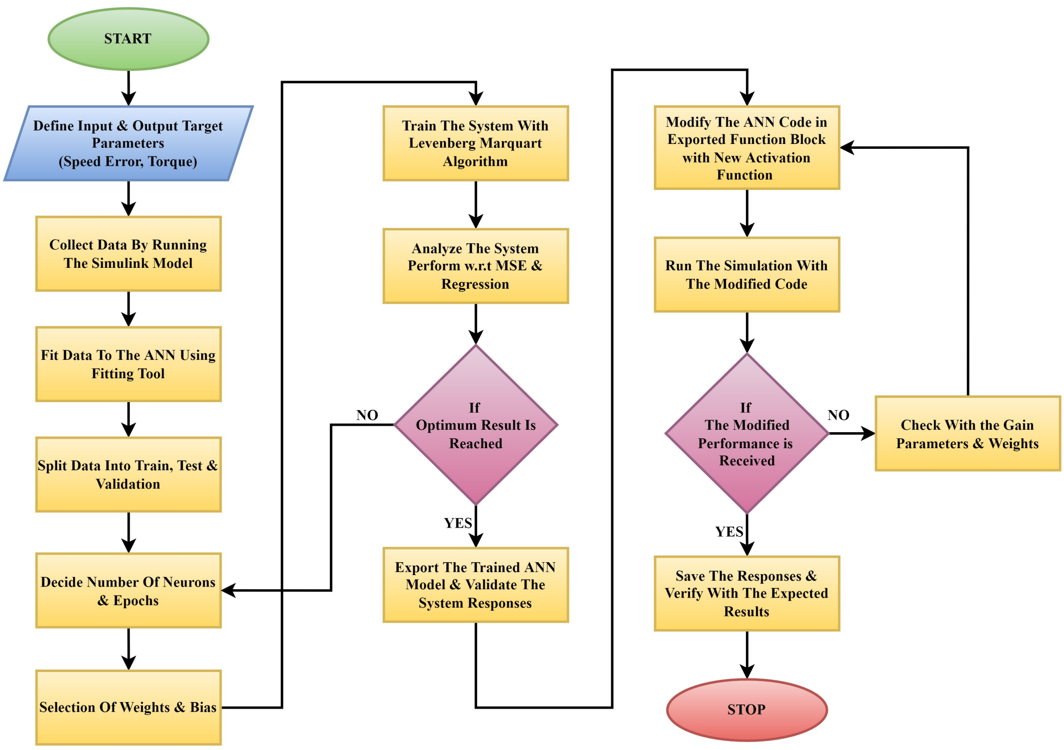


Figure 3. Flowchart of proposed ANN technique

5. RESULTS AND DISCUSSIONS

Simulink model of DTC of 3-phase IM is developed in MATLAB platform here. Since the main target of this research is to control the speed and torque parameters of the motor, hence the trained ANN controller takes place of the PI controller when it has been tuned. Here, the DTC analysis is conducted using a 750 VA IM. Table 1 contains a list of the motor parameters. The rated speed of the motor is 145.56 rad/sec. The flowchart in Figure 3 discusses the research process that is incorporated here. In this article first the responses obtained during the ANN training is discussed and then the motor responses for three different dynamic cases are discussed. Motor parameters like t_s, t_r, t_p, %Mp, speed and torque ripples are analyzed and compared here for the proposed technique with the conventional one. Also experimental results with speed and torque variation has been included here.

5.1. Performance analysis of ANN controller

Figure 4(a) shows the operation of gradient training for induction motor speed at an epoch of 1000. It can be seen in the figure that the range of mean gradient variation is 10^0 to 10^5. Figure 4(b) shows each test point's validation check. Here, it is evident that every sample passed the test over the course of 1000 epochs. Figure 4(c) displays the mean squared error performance across 1000 epochs. At epoch 1000, the optimal training performance is 0.0020364.

The estimated and actual data regression analysis is shown in Figure 5(a). It shows that for R = 0.99931, 0.99927, and 0.99914 the training, validation and testing is close to the trajectory. Finally with R = 0.99928 validates the complete model by exactly meeting the trajectory path. The error histogram is shown in Figure 5(b). Here, the ANN model's entire error range is distinguished into 20 bins. Total error in this research ranges from -6.155 (left side bin) to 2.446 (right side bin).

Table 1. Specifications of the IM

Motor parameters	value	unit
Nominal power	750	VA
Frequency	50	Hz
Stator resistance	8.6	Ohm
Stator inductance	0.045	Henry
Rotor resistance	6.26	Ohm
Rotor inductance	0.045	Henry
Mutual inductance	0.709	Henry
Pole pairs	2	-
Inertia	0.0002	kg.m-2

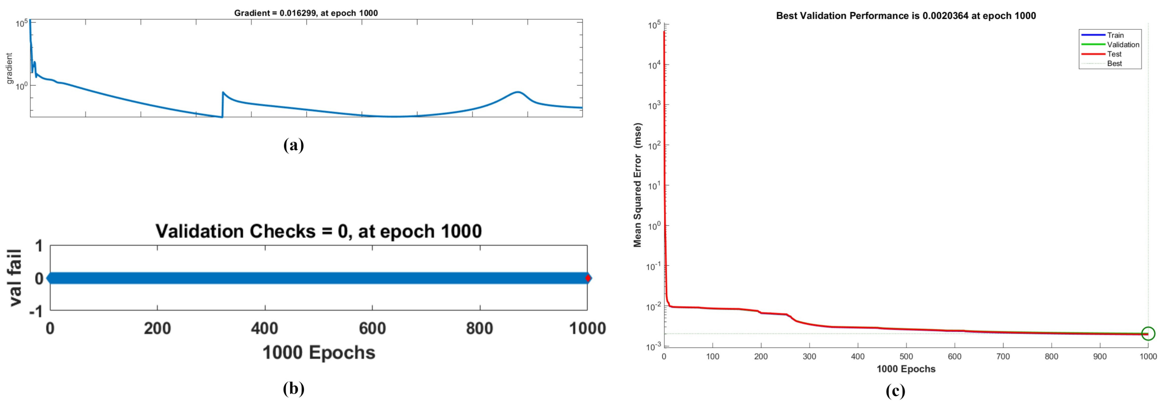
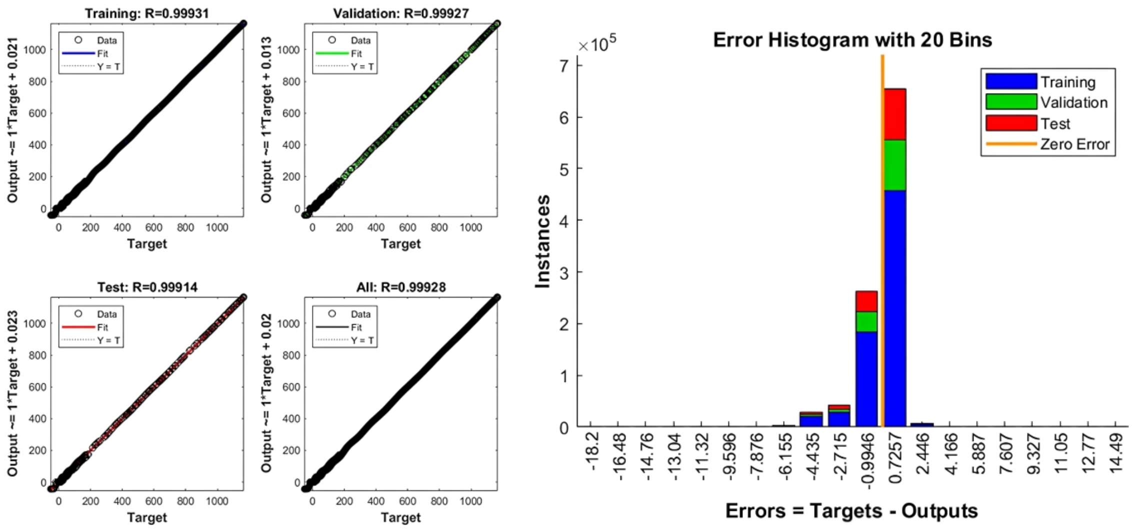


Figure 4. ANN training pattern analysis: (a) gradient training, (b) validation check, and (c) mean square error performance across training, testing and validation

5.2. Assessment of the simulation results

The implemented model of ANN based DTC of IM using MATLAB/Simulink is shown in Figure 6. At first DTC algorithm for IM is developed in MATLAB using Simulink blocks. Here flux and torque estimation blocks are designed using the measured values of stator voltages and currents. To get the inverter switching pulses switching table logic is developed and finally the signal is sent to the IM. In this research first conventional DTC of IM using a PI controller is modeled and later the ANN technique is incorporated to replace the PI controller for improving the performance of the system. The system is further modified by implementing the proposed technique and the obtained results are compared with the conventional technique responses. Here the performance analysis is done for various speed and load conditions of the motor using MATLAB/Simulink.



(a) (b)

Figure 5. Results of the regression analysis: (a) regression analysis for ANN and (b) histogram for regression analysis

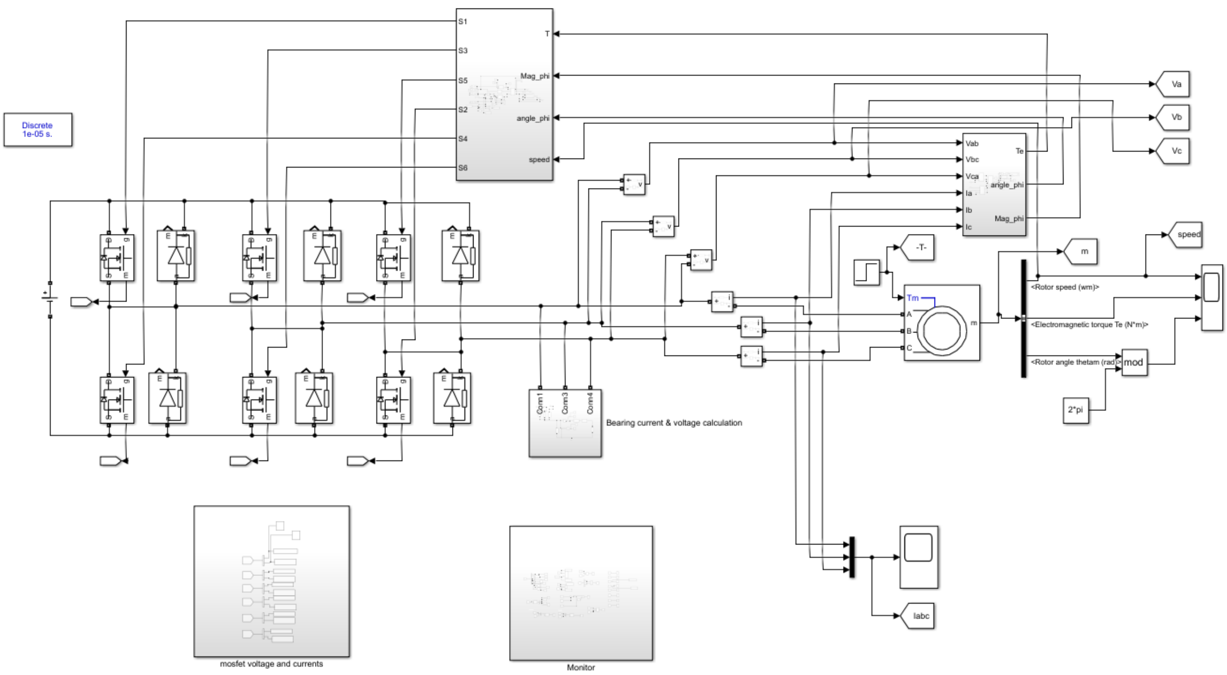


Figure 6. Simulink model of ANN based DTC

5.2.1. Speed analysis

This section discusses the results of the MATLAB simulation and evaluates the different motor parameters based on the responses. In this instance, the entire analysis is divided into three cases, as follows:

– Case 1: Investigation of motor response during starting at rated speed under no load condition:

In this particular case, the motor is running at its rated speed of 145.56 rad/sec with no load. At first the PI controller is tuned with suitable K_p and K_i values and the DTC model of IM is run at rated speed. Then with the data collected in workspace ANN is built and the model is run with the trained ANN controller and finally the model is run with proposed ANN controller and the responses are collected and compared.

Motor transient responses at rated speed (145.56 rad/sec) under no-load with various controllers are shown in Figures 7(a), 7(b), and 7(c), and a list of every parameter that was examined from these waveforms is provided in Table 2. It is evident from the values of every parameter given in Table 2 that the proposed controller performs significantly better than the traditional PI and ANN for case 1.

– Case 2: Examination of motor response and parameters with variable speed command under no load condition with PI, ANN and proposed controller:

Figures 8(a), 8(b), and 8(c) shows the speed responses of DTC of IM model with all three controllers at 25% (36.39 rad/sec), 50% (72.78 rad/sec), 75% (109.17 rad/sec), and 100% (145.56 rad/sec) of rated speed. The motor parameters for all these four speed commands are listed in Tables 3, 4, and 5 respectively. From the values tabulated here it is evident that the proposed controller is making the motor perform better compared to the other two controllers. Here all the responses are meticulously examined to ensure the better performance of the motor.

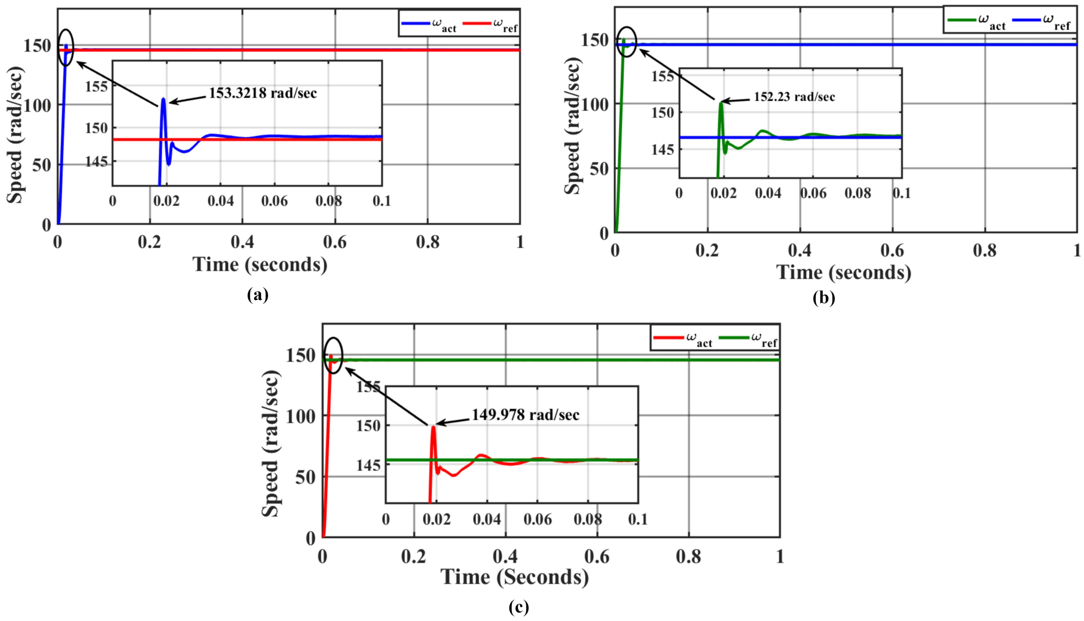


Figure 7. Speed responses at rated speed under no-load with (a) PI controller, (b) ANN controller, and (c) proposed ANN controller

Table 2. Motor parameters with different controllers under no load and at rated speed

Parameters	PI	Conventional ANN	Improved ANN	Improvement w.r.t PI (%)	Improvement w.r.t conventional ANN (%)
%Mp	5.33	4.58	3.04	42.96	33.62
t_r (sec)	0.0112	0.0102	0.01	10.71	1.96
t_p (sec)	0.019	0.018	0.0168	11.58	6.67
t_s (sec)	0.08	0.07	0.03	62.5	57.14
Speed ripple (rad/sec)	0.081	0.07	0.062	23.46	11.43

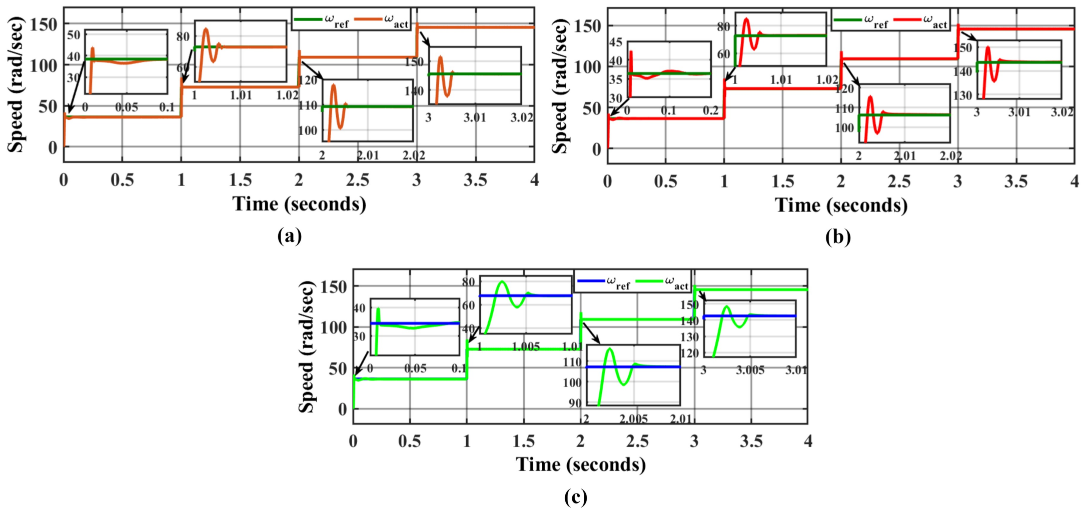


Figure 8. Speed responses with variable speed commands under no-load with (a) PI controller, (b) ANN controller, and (c) proposed ANN controller

Table 3. Motor parameters with PI controller under no load and at variable speed

Parameters	25% of rated speed (36.39 rad/sec)	50% of rated speed (72.78 rad/sec)	75% of rated speed (109.17 rad/sec)	100% of rated speed (145.56 rad/sec)
%Mp	18.16	17.10	8.21	4.36
t_r (sec)	0.003	0.0013	0.0011	0.0014
t_p (sec)	0.0087	4.0025	8.0025	8.0025
t_s (sec)	0.2	4.007	8.0055	8.0055
Speed ripple (rad/sec)	0.02	0.045	0.039	0.039

Table 4. Motor parameters with ANN controller under no load and at variable speed

Parameters	25% of rated speed (36.39 rad/sec)	50% of rated speed (72.78 rad/sec)	75% of rated speed (109.17 rad/sec)	100% of rated speed (145.56 rad/sec)
%Mp	15.14	14.32	6.256	3.05
t_r (sec)	0.0028	0.0013	0.0011	0.0014
t_p (sec)	0.0085	4.0025	8.0025	12.0025
t_s (sec)	0.015	4.007	8.0055	12.007
Speed ripple (rad/sec)	0.019	0.045	0.039	0.039

Table 5. Motor parameters with proposed ANN controller under no load and at variable speed

Parameters	25% of rated speed (36.39 rad/sec)	50% of rated speed (72.78 rad/sec)	75% of rated speed (109.17 rad/sec)	100% of rated speed (145.56 rad/sec)
%Mp	9.92	8.54	4.42	2.02
t_r (sec)	0.002	0.0012	0.00129	0.001
t_p (sec)	0.008	4.002	8.0023	12.0025
t_s (sec)	0.008	4.006	8.0052	12.005
Speed ripple (rad/sec)	0.019	0.046	0.039	0.062

– Case 3: Evaluation of motor response at rated speed with variable load conditions

In this case the motor behaviour is examined for sudden change in load torque. At first, the motor operates at its rated speed of 145.56 rad/sec without any load, and then motor is suddenly exposed to a 5.15 N-m load. The performance of the motor is observed here precisely as this case conditions determines the robustness of the motor and ensures the effectiveness of the system in managing dynamic load changes. The performance of the motor under different load conditions with different controllers are shown in Figures 9(a), 9(b), and 9(c). The various motor parameters related to speed response under no load condition is given already in Table 2 and same for full load is listed in Table 6.

5.2.2. Torque analysis

Here the torque analysis for the motor is done at rated speed (145.56 rad/sec) and rated load torque (5.15 N-m). At first the motor is run with no load at rated speed and then keeping the speed constant sudden load is applied. The motor's performance under these conditions using all of the ways that were taken into consideration is depicted in Figure 10. Value of torque ripple with PI controller at no-load is 0.27 N-m and at full load is 1.14 N-m. With ANN controller the ripple value is found as 0.2 N-m at no-load and 0.25 N-m at full load. The same with the proposed controller is found as 0.126 N-m at no-load and 0.11 N-m at full load which proves the effectiveness of the system performance with the proposed controller.

Table 6. Motor parameters comparison with PI, conventional ANN, and proposed ANN controllers

Parameters	PI	Conventional ANN	Proposed ANN	Improvement w.r.t PI (%)	Improvement w.r.t conventional ANN (%)
Speed dip (%)	14.81	12.06	10.69	27.82	11.36
t_s (sec)	0.03	0.028	0.0275	8.33	1.79

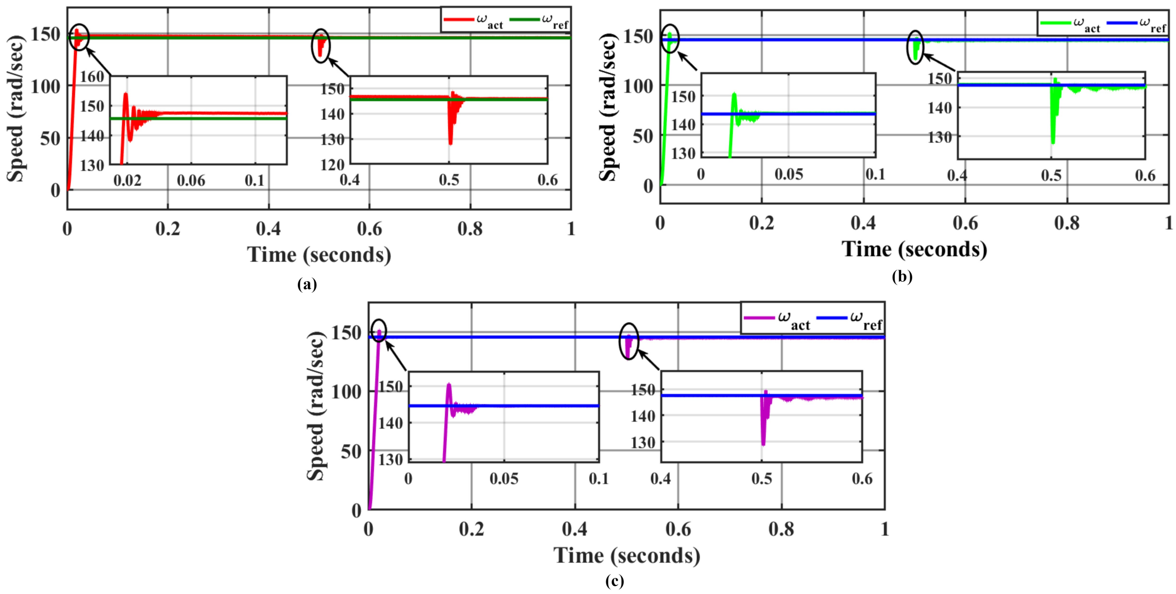


Figure 9. Speed responses at different load conditions with (a) PI, (b) ANN, and (c) proposed ANN controller

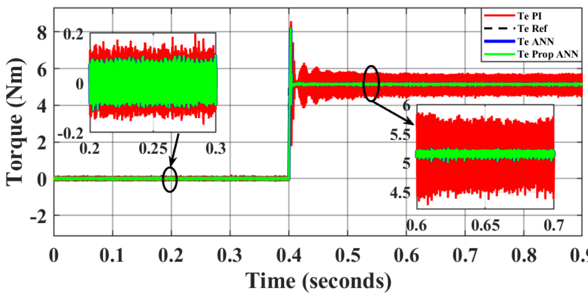


Figure 10. Torque responses at rated speed under variable load with PI controller, ANN controller and proposed ANN controller

5.3. Experimental results

This section includes the discussion on hardware setup for the validation of simulation results. At first the control logic is modeled using MATLAB/Simulink. Then interfacing with dSPACE is done by converting the Simulink model to a real-time implementation using rti1202 library of dSPACE. Analog input signals of simulation (current signals) are converted to digital output pulses for the inverter. Current and voltage sensors are connected to the IM and the outputs from the sensors are fed to the dSPACE analog input channels. dSPACE generates the switching pulses for the inverter which is fed to the gate driver inputs. The model is compiled here using the dSPACE rti1202 library, which automatically creates C code and sends it to the dSPACE target processor. The hardware prototype used to verify the suggested controller is displayed in Figure 11. In order to verify the suggested controller using DTC of IM drive prototype two types of dynamic scenario is configured here. One with the variation of speed and another with step torque change. In first case the torque is kept constant at 0.5 N-m and speed is varied from 72.78 rad/sec to 145.56 rad/sec. In the second case torque is varied from 0.5 N-m to 3 N-m keeping speed constant at 145.56 rad/sec. Results of both the cases are shown in Figures 12(a) and 12(b).

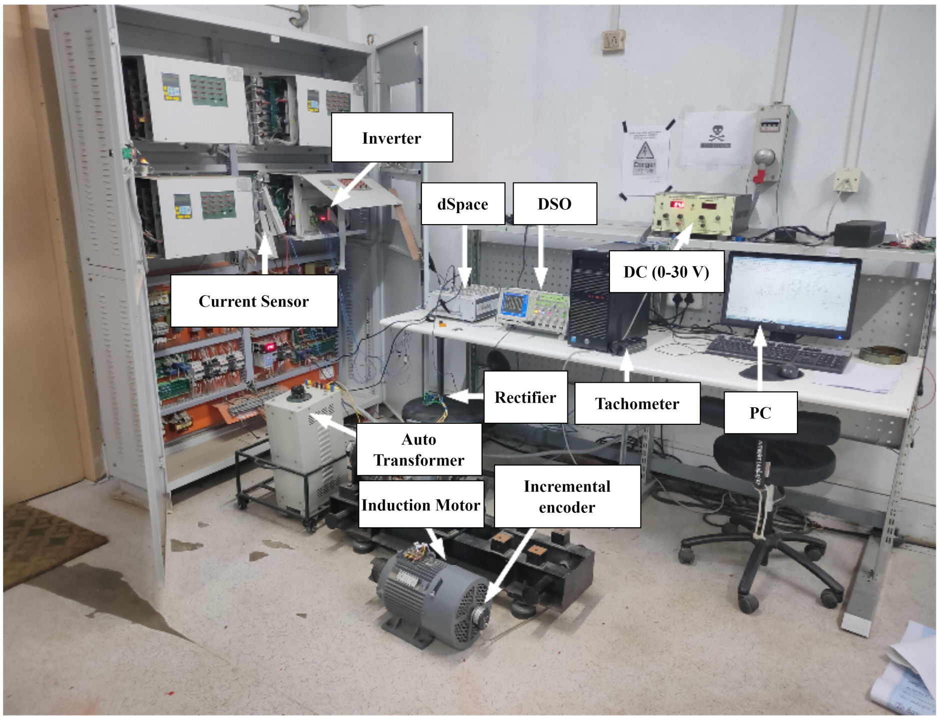
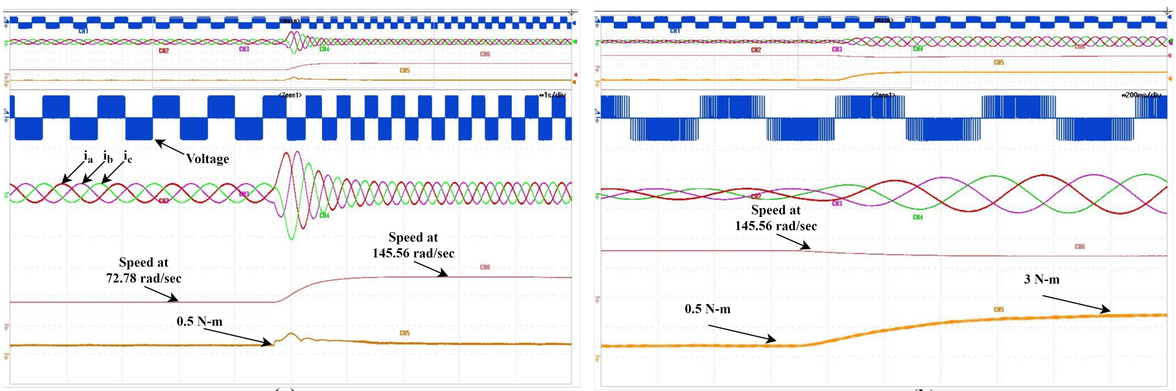


Figure 11. Experimental setup of HTAF-ANN based DTC controlled IM



(a) (b)

Figure 12. Performance of the motor under different conditions: (a) speed variation curve and (b) torque variation curve

6. CONCLUSION

This study employs an HTAF-ANN-based DTC technique for IM to adjust the torque and speed of the system during transients. The PI controller is replaced here with an ANN to enhance the system's functionality. This ANN controller is later replaced with the HTAF-ANN controller for further improvement of the responses. Results of experiments and simulations using MATLAB prove the efficiency of the chosen controller over PI and conventional ANN. It is observed here that the proposed technique can manage rapid changes in motor behavior during start-up, with variable speed and load conditions. Result analysis shows the substantial reduction in various parameters like %Mp, t_r, t_p, t_s, and torque ripple with the proposed technique compared to the conventional PI and ANN technique. For future development of the HTAF-ANN-based DTC technique, THD analysis can be done to improve the IM drive system's performance.

FUNDING INFORMATION

No specific grant from a public, private, or nonprofit funding organization was obtained for this research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest.

DATA AVAILABILITY

This published article contains all of the data created or examined during this investigation.

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