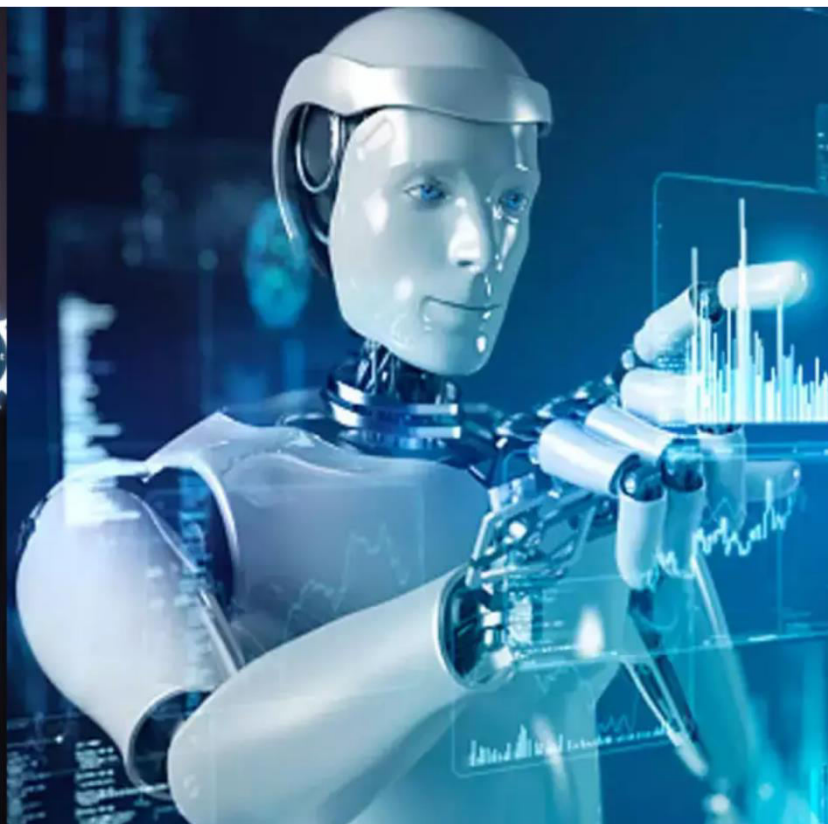




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An Integrated Power Converter-Based BLDC Motor using ANFIS Controller

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ABSTRACT: This study investigates the performance enhancement of a brushless DC motor integrated with a power converter using an ANFIS controller. ANFIS, which stands for Adaptive Neuro-Fuzzy Inference System, is a hybrid intelligent system combining the benefits of fuzzy logic and neural networks to provide an optimized control approach for various applications. The integrated system is expected to achieve improved efficiency, reliability, and accuracy compared to traditional control methods. The experimental setup involves implementing the ANFIS controller to regulate the motor speed and torque, and evaluating the performance metrics such as rise time, settling time, overshoot, and steady-state error. The results of the study could provide insights into the feasibility and effectiveness of using ANFIS-based control for a power converter-based brushless DC motor.

KEYWORDS: BLDCM, DC bus voltage boost, field-oriented control (FOC), integrated power converter, Anfis controller

I. INTRODUCTION

The development of power semiconductors, digital integrated circuits, and high-energy permanent magnet materials has led to the emergence of brushless DC (BLDC) motors. BLDC motors are the best option for any application that needs an electric motor but has limited weight and space. A BLDC motor can reach high speeds, has an excellent dissipation characteristic, and has a high power-to-mass ratio [1].

A Brushless DC (BLDC) motor is widely used in applications requiring high efficiency, precise speed control, and low maintenance due to the absence of brushes and a mechanical commutator.[4] However, BLDC motors exhibit nonlinear behaviour and parameter variations under different operating conditions, making conventional control techniques such as Proportional-Integral-Derivative (PID) or traditional fuzzy logic controllers (FLC) less effective in dynamically changing environments. To address these challenges, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has emerged as a robust and intelligent control strategy that combines the strengths of artificial neural networks (ANNs) and fuzzy logic systems. ANFIS utilizes the learning capability of neural networks to adaptively tune fuzzy membership functions and inference rules, enabling the system to handle uncertainties and nonlinearities effectively. In the context of BLDC motor control, ANFIS takes inputs such as speed error and change in error, processes them through a fuzzy inference system, and generates an optimized control signal to adjust the motor's pulse-width modulation (PWM) inverter, ensuring optimal speed and torque regulation. Through training with appropriate datasets, ANFIS dynamically adjusts its internal parameters, thereby improving system stability, minimizing overshoot, reducing steady-state error, and enhancing transient response. This hybrid control approach not only improves the overall performance of BLDC motors but also provides robustness against external disturbances, making it perfect for use in robotics, renewable energy systems, and electric automobiles.

II. LITERATURE REVIEW

Proportional Fuzzy Under load-varying conditions, an integral-based speed controller for brushless DC motors shows a more oscillatory speed response. Fuzzy logic-based current and speed controller simulation results for BLDC motor driving were shown, and they resulted in a more oscillatory speed response. The topic of fuzzy logic controller for BLDC permanent magnet motor drive was covered. The results of the simulation and experiment showed that the speed response created overshoot and undershoot during load disturbance. A comparison of hybrid fuzzy logic PID controllers and classical PID controllers has been provided.[6] The findings demonstrated that fuzzy logic controllers perform better than PID controllers; however, the speed response recorded during load fluctuations showed both overshoot and undershoot.

For BLDC motor drives, an adaptive fuzzy logic speed controller was constructed using a modified model reference. This controller requires a reference plant model to train the fuzzy logic controller, and the response is more erratic. Two fuzzy proportional derivative and fuzzy integral controller structures have been described in the adaptive fuzzy logic speed controller for brushless DC motor drive. This controller does not apply to other plant models, and it is adjusted based on the error signal received. For the BLDC motor drive, three different controller types have been proposed: adaptive sliding mode controller, non-adaptive fuzzy controller, and adaptive fuzzy-based controller.

Recently, the combination of neural networks with fuzzy systems has gained popularity in engineering domains. The Adaptive Neuro-Fuzzy Inference System is one such structure that was covered in. To identify BLDC motors using the Non-linear Auto-Regressive Moving Average with exogenous input (NARMAX) method,[8] an intelligent agent-based Adaptive Neuro-Fuzzy Inference method (ANFIS) was created. It was shown how ANFIS predicted the back electromagnetism force for sensorless brushless DC motor control. Adjust the deadbeat. Particle Swarm using ANFIS has created a speed controller for BLDC motors that is based on proportional integrals. This controller's drawback is that it was only effective under specific operating circumstances. When operational conditions changed, the controller's response altered suddenly. The system also showed higher rise and settling times, greater overshoot, and a higher chance of entering an unstable condition. The speed controller was designed using a hybrid technique. The controller combines a traditional integral controller with a proportional derivative controller based on neuro-fuzzy. More noise was produced in the control system by the neuro-fuzzy controller, and overshoot and settling time were affected by the integral gain tuning. For brushless DC motors, an ANFIS-based controller was devised; nevertheless, the speed response showed a bigger steady-state error, a high rising time, and a high settling time. An emotional learning algorithm-based ANFIS controller was introduced.

According to the literature review, the design of artificial intelligence-based controllers has received more attention in the field of BLDC motor speed control than regulating the system's performance. It appears that the performance of the BLDC controller under simultaneous step load and step speed changes under all potential circumstances has never been covered in the literature. Given this, the following are the goals of the suggested work that is being described in this paper:

- (a) To offer a comprehensive and effective method for creating an ANFIS-based controller.
- (b) To take into consideration step load and step speed changes simultaneously in every scenario, and then use an ANFIS controller to achieve system dynamic reactions under various load and speed situations.
- (c) To contrast the outcomes of the ANFIS controller with those of the proportional integral controller, fuzzy-tuned PID controller, and fuzzy variable structure controller that have already been published. Additionally, to evaluate the suggested controller's dynamic performance using the previously mentioned control technique.

In this paper, the Fuzzy Inference System (FIS) constructs the initial input–output membership functions and 49 rules for the proposed ANFIS-based BLDC speed controller [3]. The modified According to the suggested methodology, reference signals—that is, error, error rate of change, and control signal from a fuzzy-tuned PID controller—are used offline to update the ANFIS parameters. The suggested Adaptive Neuro-Fuzzy System (ANFIS) controller was designed using the ANFIS toolbox in the MATLAB environment, and it was incorporated into the Simulink toolbox to do

simulation studies. The suggested ANFIS controller's performance is examined and contrasted with that of the fuzzy-tuned PID controller, fuzzy variable structure controller, and classical proportional-integral controller.

III. INTEGRATED CONVERTER

The suggested converter integrates the BBD converter with the TVSI's one-phase bridge leg using a three-switch leg. The three-switch leg may link the battery source and the A-phase winding simultaneously with only one extra power switch. The suggested architecture can save 50% on power switches and drive circuits in the DC-DC system when compared to the conventional two-stage topology, illustrated in Fig. 1. Through terminals N and M, respectively, the three-switch leg can interface with the ac load (BLDCM drive) and dc source (battery).[5] Any two of the three power switches should be switched on, and the third should be turned off, to prevent terminal floating, bus voltage, and shoot-through. Three switching states are thus possible. Each power switch has current traversing it, and the terminal voltages of M and N can be found. As shown in Fig. 2, $V_{bat-L-T4-T^*}$ can build an equivalent BBD cell to interface with the battery source if T1 and T7 are considered a common switch T^* . Similarly, T1-T# can be thought of as an equivalent A-phase bridge arm of the TVSI if T7 and T4 are seen as a single common switch $T\#$. The BBD cell and the TVSI can therefore be operated independently if the three-switch leg is in one of the three switching states [2].

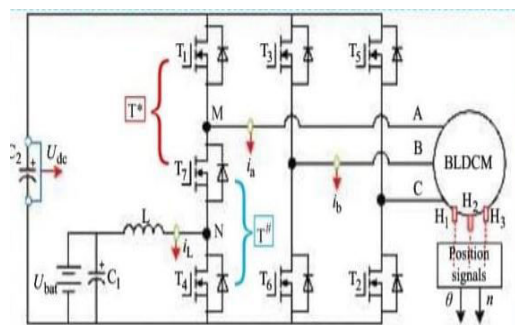


Fig. 1 Integrated converter circuit of BLDC Motor

IV. EXISTING CONTROLLER

To ensure reliable functioning of the integrated converter-based BLDCM drive, the voltage of the DC bus boosting control and BLDCM driving control should be decoupled with the aforementioned Pulse width modulation (PWM) modulation scheme. To implement the modulation scheme, the boost duty ratio D and the BLDCM control reference $C_{tra}-C_{trc}$ are generated by a FOC algorithm. The overall control algorithm consists of the following three parts. (1) BBD control part: As can be seen in the converter topology, T4 and T^* will construct the equivalent BBD converter bridge arm. To control the DC bus voltage, a control configuration with an outer voltage loop plus an inner current loop is selected to produce the modulation reference D . In the perspective of the modulation rule, as presented in (1), the power signals that drive the gate switch T4 can be generated. (2) TVSI control part: In the integrated topology, the T1- $T\#$, T3-T6, and T5-T2 will construct the equivalent TVSI for BLDC drive control. In this article, a traditional $i_d = 0$ -based FOC algorithm, the space vector pulse width modulation (SVPWM) technology is created for BLDCM driving control. The direct- and quadrature-axis currents (i_d and i_q) are calculated from the measured two-phase current through Clark and Park transformations. To ensure reliable rotor speed closed-loop control, an outer rotor speed loop with a proportional-integral (PI) regulator is added to generate the current reference i_q^* for tracking. The i_d and i_q are regulated with PI controllers for generating the direct- and quadrature-axis voltages (u_d and u_q). Then, through the inverse Park transformation, the u_α and u_β may be acquired to perform the SVPWM control. According to the SVPWM algorithm, the three control references $C_{tra}-C_{trc}$ can be obtained. According to the modulation logic, as presented in (1) and (3), the gate-driving signals for T1, T3-T6, and T5-T2 can be obtained.

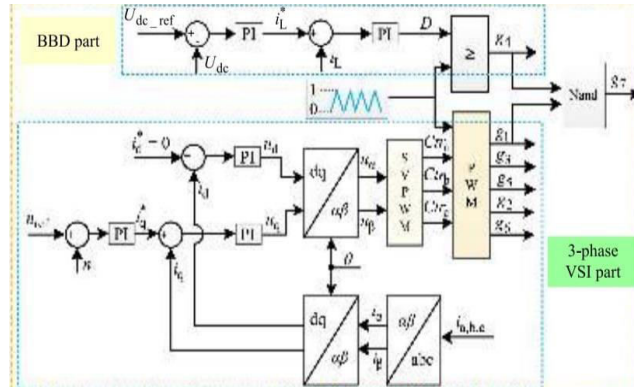


Fig. 2 PI Controller circuit

V. ANFIS CONTROLLER

Through the possible exception of the neural network block, the general ANFIS control structure has the same elements as the FIS. The network's structure consists of a collection of units (and connections) grouped into five interconnected network layers, or layers 1 through 5. The four key components of the suggested ANFIS controller structure are the knowledge base, neural network, defuzzification, and fuzzification. Triangular or bell-shaped membership functions and input variables (membership functions) make up Layer 1.

The membership layer, which is Layer 2, verifies the weights of each membership function. It represents the fuzzy sets of the corresponding input variables by acting as membership functions after receiving the input values from the first layer. The preceding layer provides input to Layer 3, sometimes known as the rule layer. Every node (neuron) in this layer carries out the fuzzy rules' pre-condition matching. Each rule's activation level is determined by this layer, and the quantity of layers corresponds to the quantity of fuzzy rules. The weights that will be normalized are determined by each node in this layer. The output values derived from the inference of rules are provided by Layer 4, also known as the defuzzification layer [10].

Layer 5 is known as the output layer since it converts the fuzzy classification results into a precise value by adding up all of the inputs from Layer 4 [3]. Takagi–Sugeno (T–S) type systems are used to model ANFIS, and they need to have the following characteristics: The system must be of the first or zero-order T-S type. It should use weighted average defuzzification to provide a single output. Every output membership function needs to be of the same kind and either constant or linear. Different rules cannot share the same output membership function, hence there must be no rule sharing. There must be an equal number of output membership functions and rules. Different rules cannot share the same output membership function, hence there must be no rule sharing. There must be an equal number of output membership functions and rules. Each must have the same weight rule. Using the backpropagation algorithm and least-square estimation, the ANFIS structure is automatically adjusted. The ANFIS approach's adaptability allows it to be applied to a variety of control applications. In the part that follows, the aforementioned technique is used to construct the ANFIS controller, which controls the BLDC motor's speed.

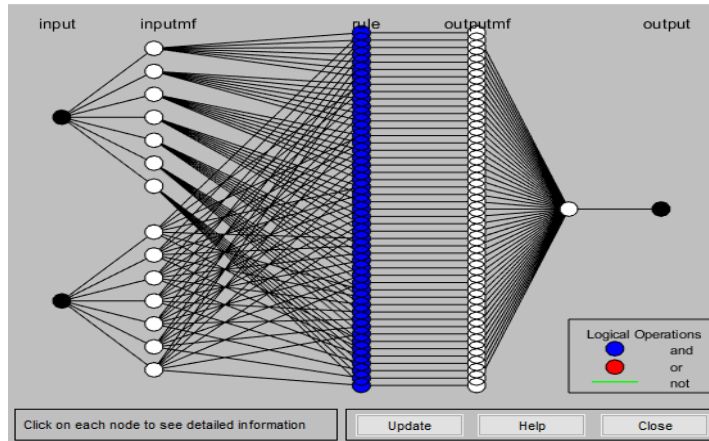


Fig-3 ANFIS Model Structure

A hybrid intelligence system called the Neuro-Fuzzy In (ANFIS) learns and adapts to complicated control systems by fusing the advantages of artificial neural networks and fuzzy logic. A Sugeno-type fuzzy inference system (FIS) serves as the foundation for an ANFIS controller and consists of five distinct layers, each of which plays a distinct role during training and inference [7]. Layer 1: Fuzzification Layer (Input Layer) This layer creates fuzzy values by passing the variables that provide input through membership functions (MFs). Each input is assigned a given extent of membership to a certain fuzzy set. Usually, bell-shaped, triangular, or Gaussian membership functions are employed. This layer's outputs are the fuzzy membership values, which have the following mathematical representation:

$$L_{1,j} = \mu A_j(e) \quad \text{for } j = 1, 2, \dots, q$$

$$L_{1,j} = \mu B_j(\Delta e) \quad \text{for } j = 1, 2, \dots, q$$

Where x and y are input variables and μA_i and μB_j indicate the membership functions associated with the fuzzy sets.

Layer 2: Fuzzy Rule Evaluation (Rule Layer): The firing strength (weight) of each fuzzy rule is determined by this layer using the fuzzy AND (or product) operation between the membership values. The outcome of each fuzzy rule represented by a node in this layer is the product of the corresponding membership degrees:

$$L_{2,i} = W_i = \begin{bmatrix} W_1 & \dots & W_q \\ \vdots & \ddots & \vdots \\ W_{q^2-(q-1)} & \dots & W_{q^2} \end{bmatrix} = \begin{bmatrix} \mu A_1 \times \mu B_1 & \dots & \mu A_1 \times \mu B_q \\ \vdots & \ddots & \vdots \\ \mu A_q \times \mu B_1 & \dots & \mu A_q \times \mu B_q \end{bmatrix}$$

Where w_i is the rule i 's firing strength. In essence, this layer maps the input space to the rule space.

Layer 3: A Layer of Normalization. This layer normalizes the firing strengths by calculating the proportion of the strength of each rule to the sum of the strength of all the rules. Because of this normalization, the sum of all the standardized firing strengths will equal one:

$$L_{3,j} = \bar{W}_i = \frac{W_i}{\sum_{i=1}^{q^2} W_i}$$

Where n is the quantity of rules in total. By standardizing the weights, each rule's contribution is guaranteed to be proportionate to its strength.

Defuzzification at Layer Four (Further Layer) Each rule's weighted output is calculated by this layer using a linear function of the inputs. The rule output for a Sugeno model of the first order is provided by:

$$L_{4,i} = \overline{W_i} f_i = \overline{W_i} (P_i e + R_i \Delta e + s_i)$$

The resulting attributes that are refined throughout the training process are pi, qi, and ri [9].

Layer 5: The Summation Layer, or Output Layer. To obtain the overall system output, the last layer adds up every single one of the weighted outputs from the preceding layer. The result is calculated as follows:

$$L_{5,1} = \sum_i \overline{W_i} f_i = \frac{\sum_i W_i f_i}{\sum_i W_i}$$

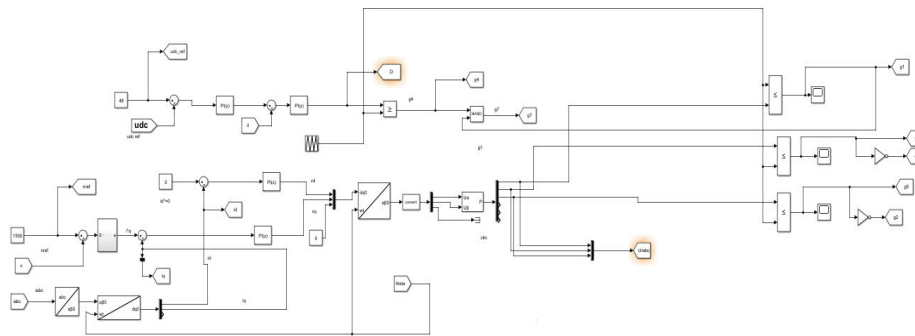


Fig (4). Simulation model ANFIS CONTROLLER

VI. RESULTS

The evaluations were conducted on a rated 60 W BLDCM driving system to verify the reliability of the integrated power converter and its control schemes. Table I lists the integrated power converter's parameters, and Fig. 12 illustrates the entire testbed. Discrete MOSFET power switches are employed in the integrated power converter, which is powered by a 12 V/20AH lead-acid battery in the test system.

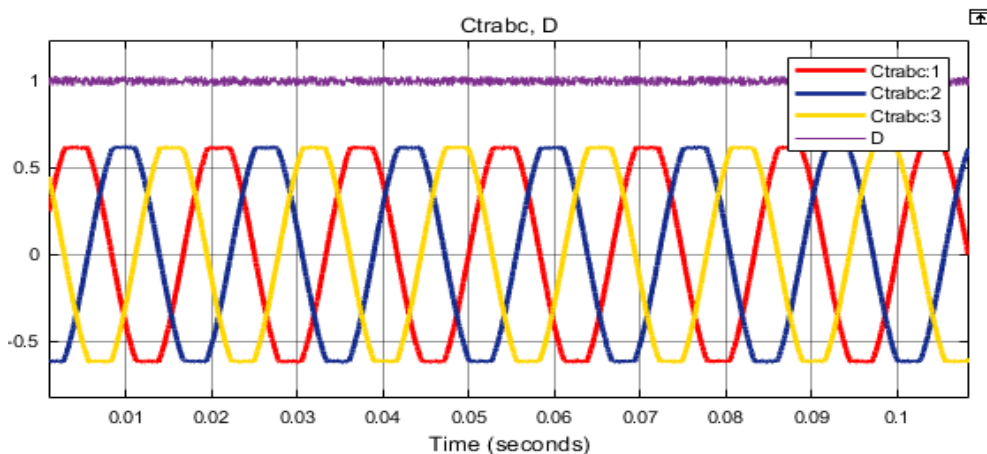


Fig. 5(a) Modulation waves of the integrated converter under different DC bus voltages and rotor speeds. (a) Udc = 48 V V=1500r/min

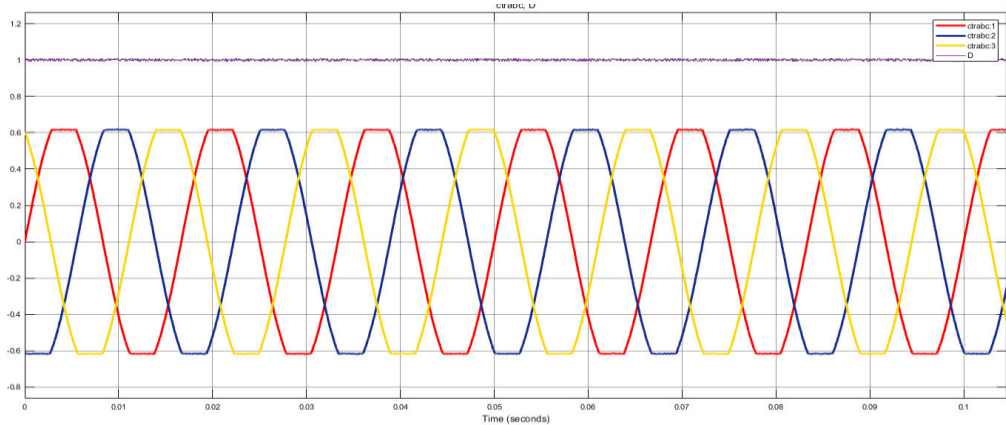


Fig. 5(b). Modulation waves of the integrated converter under different DC bus voltages and rotor speeds
(b) $U_{dc} = 48 \text{ V}$; 2500 r/min

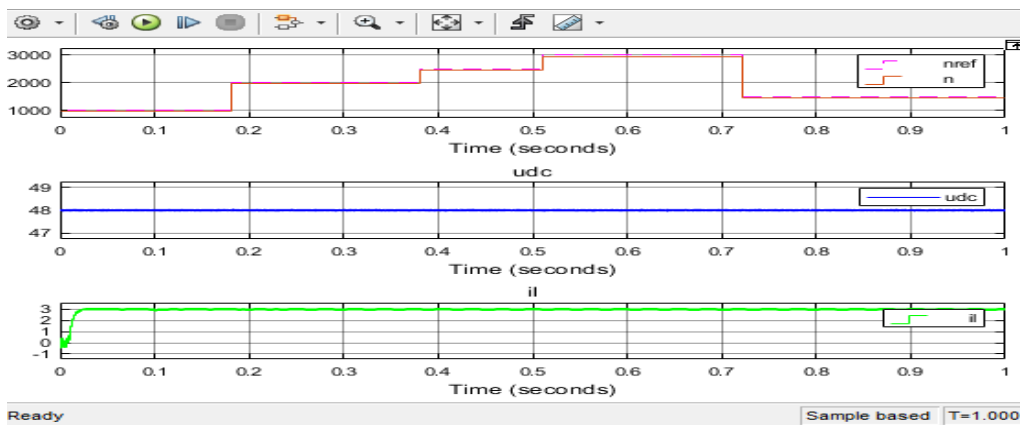


Fig. (a) Speed tracking performance under different speed references and DC bus voltages.
(a) $U_{dc} = 48 \text{ V}$

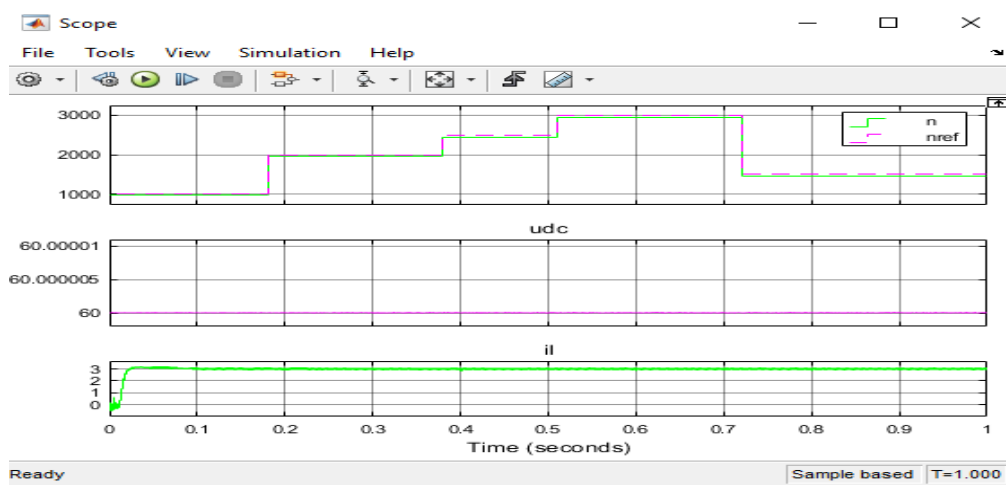


Fig. (b) Speed tracking performance under different speed references and DC bus voltages.
(b) $U_{dc} = 60 \text{ V}$

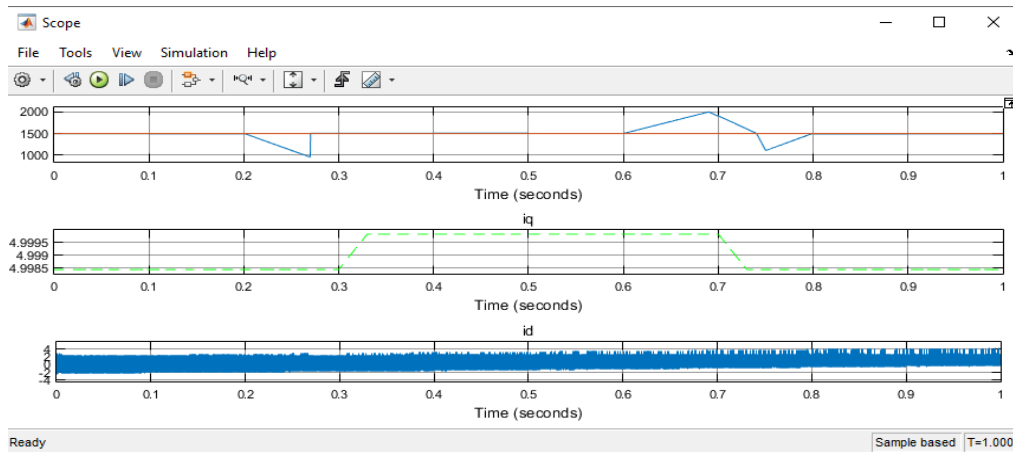


Fig. (7) i_d and i_q waveforms during load mutations at different DC bus voltages. (a) $U_{dc} = 48v$

VII. CONCLUSION

The process of a DC motor without brushes performs with an integrated power converter, can be enhanced by using an ANFIS controller, according to the information that is currently available. The ANFIS controller combines fuzzy algorithms and neural network algorithms, which leads to improved accuracy, efficiency, and smoother operation. The power converter's integration lowers overall complexity and costs while further streamlining the control system. However, some variables, including the particular motor and controller being used, the operating environment, and the needs of the application, would affect the system's actual performance. The effectiveness of this strategy in real-world applications in terms of accuracy, efficiency, and scalability would require more investigation and testing. Ongoing developments in AI and NLP technologies will be essential in resolving current constraints and enhancing the chatbot's functionalities.

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