

Neural Direct Torque Control of Permanent Magnet Synchronous Motor Based on Fuzzy Logic Stator Resistance Estimator Fed by a Photovoltaic Generator

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Abstract

This paper investigates the neural control of a permanent magnet synchronous Motor (PMSM) utilizing direct torque control (DTC) techniques, powered by a photovoltaic generator. The study emphasizes the effectiveness of DTC in regulating motor torque and flux while integrating Perturb and Observe (P&O) control for optimizing energy extraction from the photovoltaic generator. The proposed DTC-ANN framework incorporates two Artificial Neural Network (ANN) controllers. The first controller replaces the traditional switch table, providing the voltage vector. The second ANN controller replaces the conventional PI controller and operates on a feedforward back mechanism. Additionally, a Fuzzy Logic Stator Resistance Estimator is employed to accurately estimate stator resistance, compensating for variations caused by temperature changes and load fluctuations. Simulation results illustrate the performance improvements achieved through this novel approach, underscoring its applicability in renewable energy systems and advanced motor control applications.

Keywords: Permanent Magnet Synchronous Motor (PMSM), Direct Torque Control (DTC), Photovoltaic (PV), Artificial Neural Networks (ANN).

1. Introduction

The increasing demand for efficient and sustainable energy solutions has spurred significant advancements in the field of electric motor control, particularly in the integration of renewable energy sources. Permanent Magnet Synchronous Motors (PMSMs) have emerged as a prominent choice due to their high efficiency, compact design, and excellent torque characteristics. As the world shifts towards greener energy solutions, the application of PMSMs powered by photovoltaic (PV) systems presents a promising avenue for reducing reliance on fossil fuels [1].

The development and implementation of a neural control strategy for PMSMs, utilizing Direct Torque Control (DTC) methods to enhance performance and responsiveness, has gained considerable attention. DTC is recognized for its capability to provide precise torque and flux control, which is crucial for the effective operation of PMSMs [2]. However, traditional control strategies often face challenges in dynamic environments, particularly under varying operational

conditions such as changes in temperature and illumination.

We explore the integration of Artificial Neural Networks (ANN) into the control strategy to address these challenges. ANNs are capable of learning from data and adapting to complex patterns, making them an ideal complement to DTC methods. This research aims to model the PMSM and its characteristics, analyze the performance of the PV generator, and evaluate the effectiveness of the proposed neural control approach [3].

This study contributes to the advancement of renewable energy technologies and their application in electric motor systems by investigating the interplay between PMSM, DTC, and PV systems. The findings from this research can potentially enhance the reliability and efficiency of PMSMs, paving the way for the broader adoption of sustainable energy solutions in various industrial and commercial applications.

2. General Structure of DTC

Direct Torque Control (DTC) is a robust method for controlling the torque and flux of Permanent Magnet Synchronous Motors (PMSMs). Developed in the late 1980s, the use of flux and torque estimation characterizes this approach. DTC provides fast dynamic response and precise control, making it particularly suitable for applications requiring high performance [4].

In Direct Torque Control (DTC), the stator flux $\hat{\phi}_s$ is estimated using the components $\hat{\phi}_{s\alpha}$ and $\hat{\phi}_{s\beta}$, which represent the flux in the α and β axes. These components are obtained through integration of the voltage equations:

$$\hat{\phi}_{s\alpha} = \int_0^t (v_{s\alpha} - R_s i_{s\alpha}) dt \quad (1)$$

$$\hat{\phi}_{s\beta} = \int_0^t (v_{s\beta} - R_s i_{s\beta}) dt \quad (2)$$

The magnitude of the stator flux vector $\hat{\phi}_s$ is then given by:

$$\hat{\phi}_s = \sqrt{\hat{\phi}_{s\alpha}^2 + \hat{\phi}_{s\beta}^2} \quad (3)$$

The sector in which the vector $\hat{\phi}_s$ is located is determined from the components $\hat{\phi}_{s\alpha}$ and $\hat{\phi}_{s\beta}$. The angle θ_s between the frame (α, β) and the vector $\hat{\phi}_s$ is equal to:

$$\theta_s = \arctan \left(\frac{\hat{\phi}_{s\beta}}{\hat{\phi}_{s\alpha}} \right) \quad (4)$$

The electromagnetic torque can be estimated from flux estimation and current measurement using the expression:

$$\hat{T}_{em} = p \left(\hat{\phi}_{s\alpha} \hat{i}_{s\beta} - \hat{\phi}_{s\beta} \hat{i}_{s\alpha} \right) \quad (5)$$

where:

P is the number of pole pairs, $\hat{i}_{s\beta}$ and $\hat{i}_{s\alpha}$ are the stator currents in the α and β reference frame.

3. Proposed DTC-ANN

The proposed DTC-ANN includes two ANN controllers. The first controller replaces the switching table to provide the voltage vector. This controller takes the stator flux error, torque error, and sector number N (figure. 2) as inputs. This ANN uses feed-forward backpropagation with two hidden layers, each containing a group of neurons. The output layer contains three neurons, which provide the voltage vector. The proposed ANN switching table is shown in figure. 1.

The second ANN controller (figure. 3) replaces the traditional PI controller and operates using feed-forward backpropagation. The propagation process involves two hidden layers, each containing five neurons. The ANN input represents the difference between the measured speed ω_m and the reference speed ω_{ref} , while the output corresponds to the reference torque $C_{e,ref}$ [5].

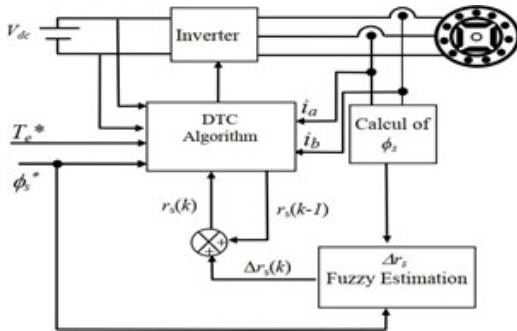


Figure 1: Diagram of DTC control applied for PMSM with a fuzzy rsestimator.

4. Fuzzy Estimator of Stator Resistance

The unknown stator resistance r_s may vary because of incorrect machine parameters, load changes, or temperature variations, leading to errors in stator flux magnitude estimation and voltage vector selection.

A fuzzy-logic controller is proposed to compensate for these variations. This estimator can identify fluctuations in r_s by using the error between the reference and estimated stator flux [6, 7].

The normalized error between the reference and estimated stator flux is defined as:

$$e(k) = \phi_s^*(k) - \phi_s(k) \quad (6)$$

and the normalized change in flux error is:

$$\Delta e(k) = e(k) - e(k-1) \quad (7)$$

These two variables are used as inputs to the fuzzy r_s estimator, as shown in figure. 4.

Figure 5 shows the DTC control applied to PMSM with a fuzzy r_s estimator, which uses the centroid defuzzification algorithm to calculate the fuzzy output variable. The updated stator resistance is then directly used in the DTC estimation algorithm.

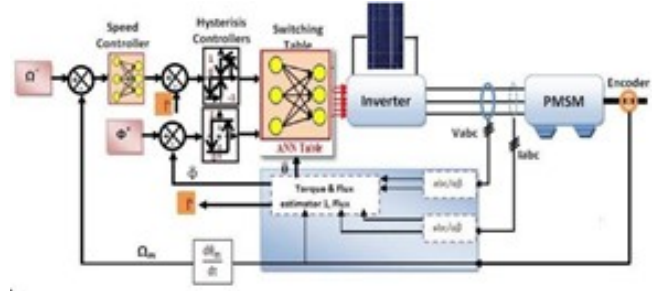


Figure 2: DTC-ANN scheme.

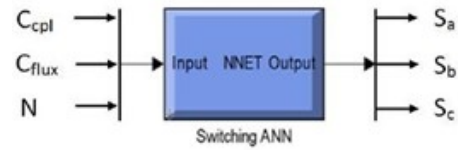


Figure 3: Neural network switching table.

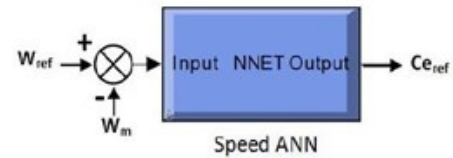
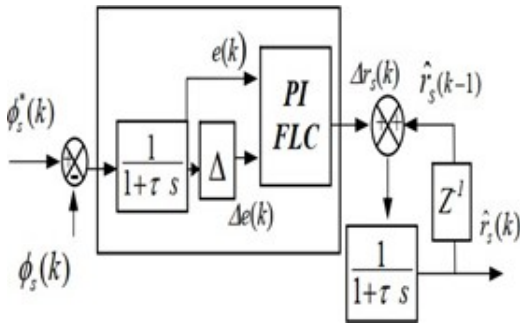
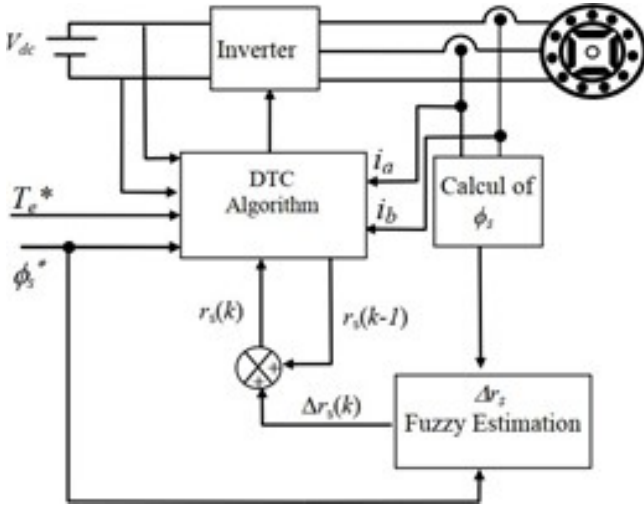


Figure 4: Neural network speed controller.

5. Proposed Maximum Power Point Tracking of the Photovoltaic Generator

The electrical power produced by a photovoltaic panel strongly depends on solar irradiance and temperature. cell temperature. Both variables influence the system behavior, exhibiting daily and seasonal fluctuations. For these reasons, the photovoltaic panel can only deliver maximum power at a particular voltage and a well-defined current.

The method known as Maximum Power Point Tracking (MPPT) relies on an algorithm that searches for the maximum power point on the photovoltaic panel power curve. Unlike fixed voltage control, tracking is not based on a pre-determined reference value; instead, it continuously searches for the operating point corresponding to maximum power on the current-voltage characteristic. MPPT plays a crucial role


 Figure 5: Block diagram of fuzzy-logic r_s estimator.

 Figure 6: Diagram DTC control applied to PMSM with fuzzy r_s estimator.

in maximizing system efficiency while minimizing energy losses and operational costs.

Several MPPT algorithms have been proposed in the literature. The most widely used methods include fuzzy logic-based algorithms, Perturb and Observe (P&O), and Incremental Conductance.

In this article, our study focuses on the Perturb and Observe (P&O) control strategy. The principle of this method is presented in the following section.

The Perturb and Observe (P&O) method [8] is a widely adopted approach in MPPT research due to its simplicity and reliance on measuring the photovoltaic panel voltage V_{pv} and current I_{pv} . This method can track the maximum power point under varying irradiation and temperature conditions.

As its name suggests, the P&O method operates by perturbing the photovoltaic voltage V_{pv} and observing the resulting effect on the PV output power. Figure 7 illustrates the P&O algorithm.

During each cycle, V_{pv} and I_{pv} are measured to calculate the instantaneous power:

$$P_{pv}(k) = V_{pv}(k) I_{pv}(k) \quad (8)$$

This value is then compared with the previous cycle power:

$$P_{pv}(k-1) \quad (9)$$

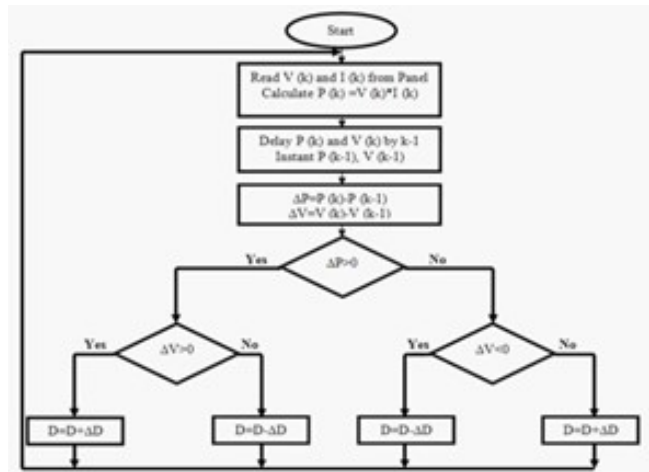


Figure 7: Flowchart of the Perturb and Observe (P&O) MPPT algorithm.

If the output power increases, V_{pv} is adjusted in the same direction as the previous perturbation. Otherwise, if the output power decreases, V_{pv} is adjusted in the opposite direction.

Thus, the operating voltage is continuously perturbed during each MPPT cycle. When the maximum power point is reached, V_{pv} oscillates around the optimal MPP voltage.

This oscillation introduces power losses that increase with the perturbation step size. A large perturbation step provides faster response under sudden operating condition changes but increases steady-state oscillations around the MPPT [9].

6. Simulation Results

MATLAB/Simulink simulations were carried out to evaluate the performance of the proposed Direct Torque Control (DTC) architecture applied to a Permanent Magnet Synchronous Motor (PMSM) supplied by a three-phase voltage inverter.

In the first step, a classical DTC strategy including a PI speed controller was implemented for comparison purposes.

Next, the proposed DTC-ANN model was developed, incorporating two Artificial Neural Network (ANN) controllers. The first ANN controller replaces the conventional switching table, while the second ANN controller replaces the traditional PI speed controller.

The simulation results compare the conventional DTC and the proposed DTC-ANN control under a load torque of $C_r = 5 \text{ N.m}$ applied at $t = 0.1 \text{ s}$, with a reference speed of $\omega_{ref} = 100 \text{ rad/s}$.

The obtained results are presented in figures. 11–17.

Figure 8 illustrates the convergence behavior of the Artificial Neural Network (ANN) output toward the predefined target value during training.

At the beginning of the training process, an error is observed between the ANN output and the target value, reflecting the initial learning stage. As the training iterations progress, the ANN output gradually converges toward the target value, indicating that the network effectively learns from the input data and adjusts its parameters to minimize the error.

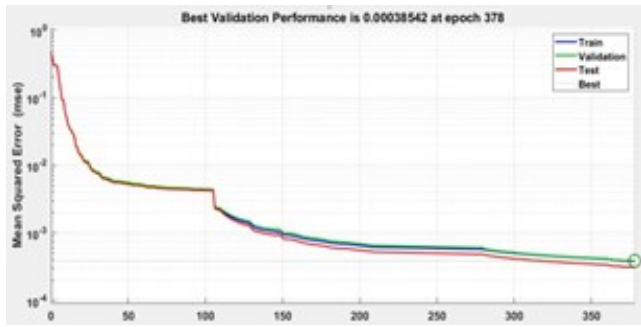


Figure 8: Convergence of the ANN output toward its target.

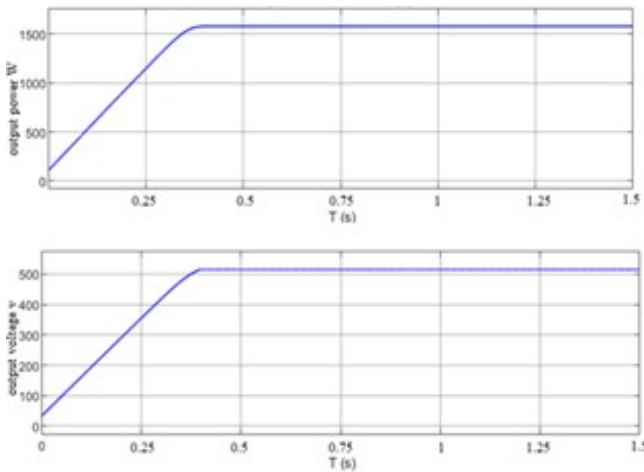


Figure 9: Output power and voltage using the Perturb and Observe (P&O) method.

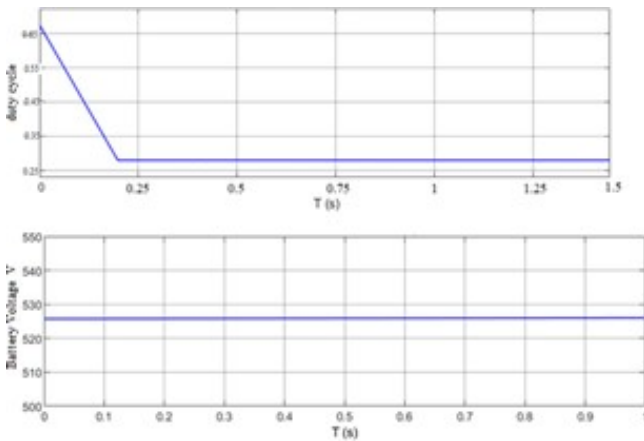


Figure 10: Duty cycle and battery voltage using the Perturb and Observe (P&O) method.

Figures 11 and 12 illustrate the rotation speed response of the PMSM using classical DTC and ANN-based DTC control strategies. The ANN controller demonstrates a faster and more accurate response to reference speed changes, reducing overshoot and settling time.

The speed profile remains stabilized at the reference speed even after the application of the load torque, indicating improved robustness and precision compared with the conventional DTC approach.

Figures 14 and 15 show the electromagnetic torque responses. The ANN controller provides faster torque ad-

justment under load disturbances, resulting in improved dynamic performance and better disturbance rejection.

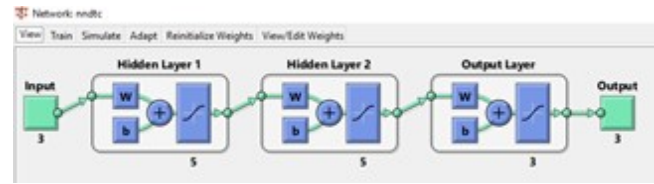


Figure 11: The network architecture of the controller

Figures 8–10 demonstrate the effectiveness of the Perturb and Observe (P&O) algorithm for optimizing the photovoltaic system output power and battery voltage.

These figures illustrate the relationship between output power, voltage, and the power curve around the maximum power point. The P&O algorithm continuously adjusts the operating point to track the optimal power point, ensuring efficient energy extraction and improved energy management.

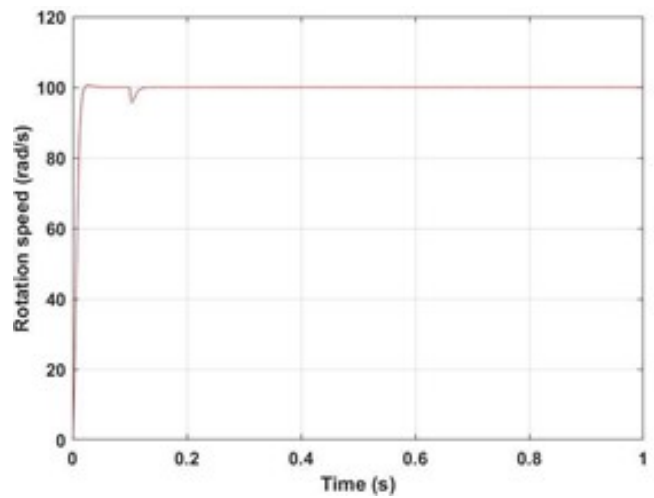


Figure 12: Rotation speed using classical DTC.

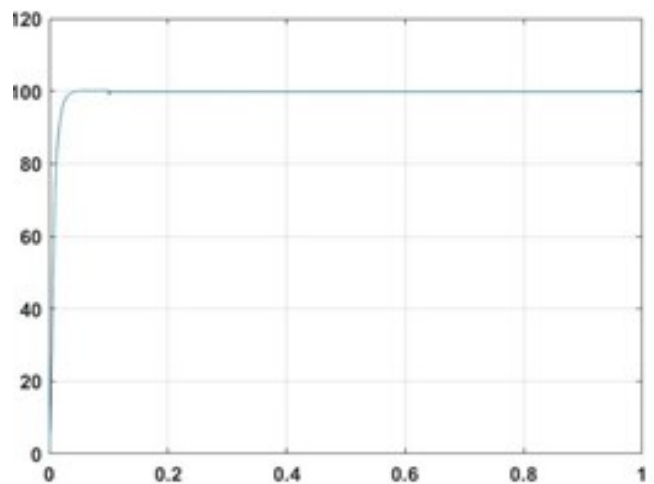


Figure 13: Rotation speed using ANN-based DTC.

The simulation results shown in Figure 13 confirm that the proposed stator resistance estimation algorithm accurately tracks the real stator resistance with minimal estimation error.

This improvement is significant for enhancing DTC performance and increasing the operational efficiency of Permanent Magnet Synchronous Motors (PMSMs).

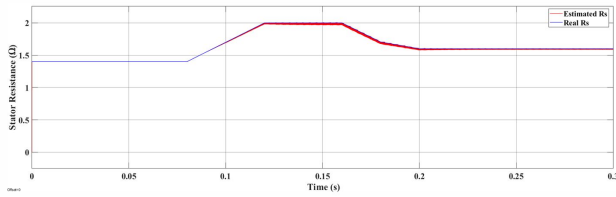


Figure 14: Estimated and real stator resistance.

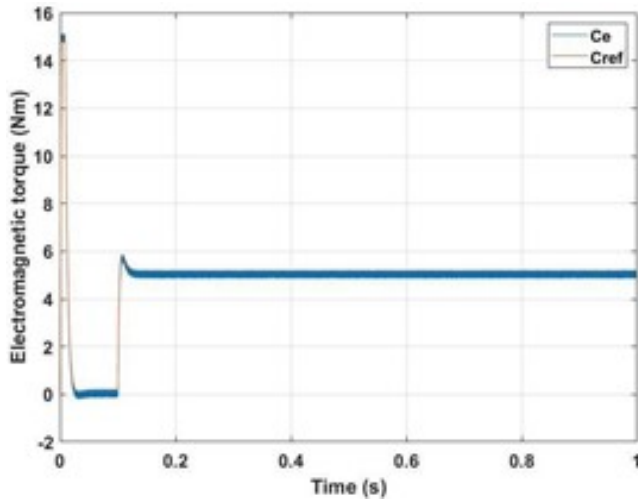


Figure 15: Electromagnetic torque using classical DTC.

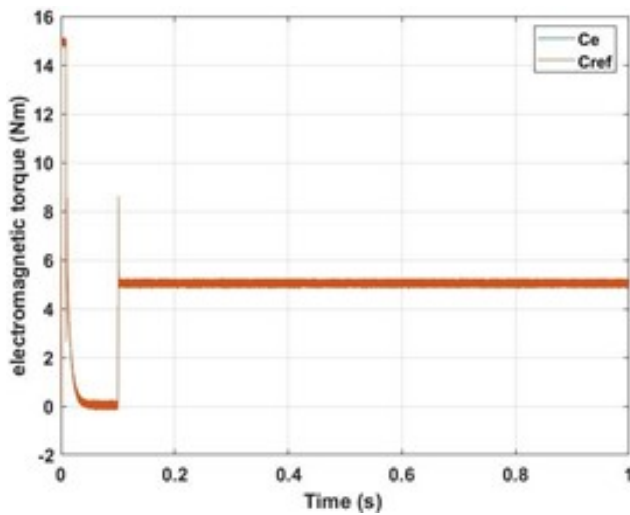


Figure 16: Electromagnetic torque using ANN controller.

7. Conclusions

This study demonstrates the effectiveness of Artificial Neural Network (ANN) controllers integrated into Direct Torque Control (DTC) of Permanent Magnet Synchronous Motors (PMSMs) supplied by photovoltaic generators.

The proposed ANN-based controller exhibited significantly improved dynamic performance in terms of response

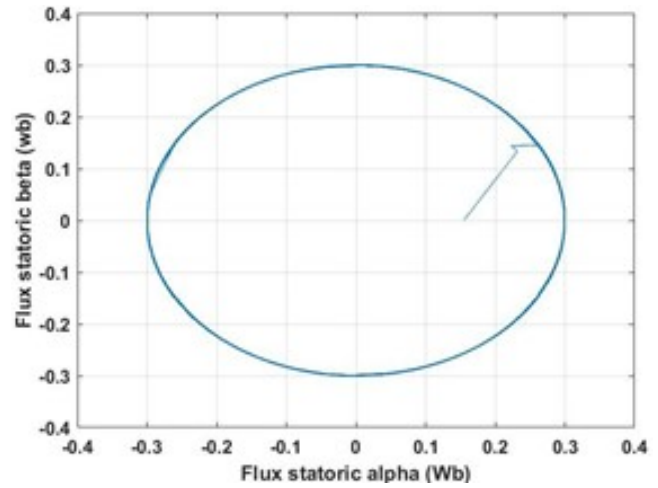


Figure 17: Stator flux using classical DTC.

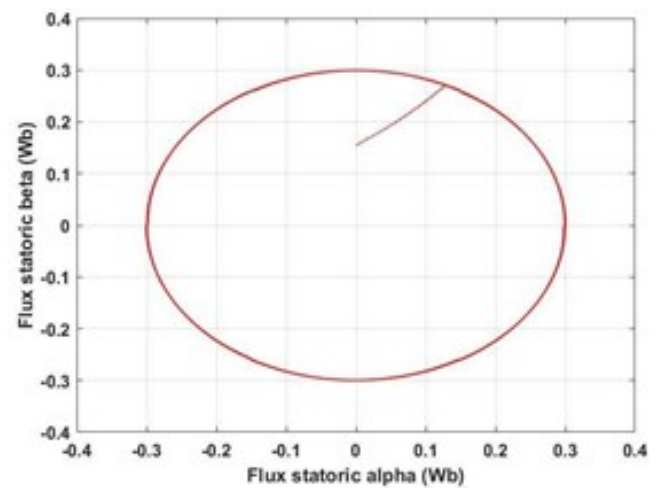


Figure 18: Stator flux using ANN controller.

time, tracking accuracy, and robustness under speed and load variations.

The simulation results showed faster adjustments of electromagnetic torque and stator flux, resulting in a more responsive and stable control system compared with the classical DTC approach.

The integration of ANN controllers into DTC frameworks not only enhances PMSM performance but also contributes to the development of more efficient and reliable control strategies for renewable energy applications.

Future work may focus on investigating the scalability of the proposed approach and its implementation in larger and more complex motor drive systems, further highlighting the importance of intelligent control techniques in modern electrical engineering applications.

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Table 1: Machine Parameters

Parameter	Value
Stator resistance R_s	1.3 Ω
Rotor resistance R_r	0.91 Ω
Stator inductance L_s	0.191 H
Rotor inductance L_r	0.18 H
Mutual inductance L_m	0.18 H
Number of pole pairs p	2
Moment of inertia J	0.009 kg.m ²
Viscous friction coefficient f	0.030

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