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Article

Sensorless control of switched reluctance motors through artificial neural network with a fuzzy interface

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Abstract: Switched resistance motors, are becoming increasingly used in industrial and hybrid electric vehicle (HEV) applications. But improving SRM performance is still a crucial field for study, especially with regard to their inherent benefit of accurate rotor position estimate, which is closely related to operational effectiveness. Rotor position sensing has traditionally required the incorporation of specialized sensors, which has led to difficulties like increased costs, complicated alignment, limited size, and maintenance requirements. In order to overcome these constraints, this work promotes the creation of sensorless motor control schemes that make use of cutting edge Artificial intelligence methods such as fuzzy logic and Adaptive Neuro-Fuzzy Inference System (ANFIS).To provide robust control, the suggested sensorless control systems make use of inputs such bus voltage, rotor speeds, torque instructions, and SRM parameters. The effectiveness of these methods is thoroughly assessed by painstaking simulation experiments, confirming their capacity to attain accurate control and high-performance operation. To further illuminate the benefits of sensorless control implementations, this research also does a comparison analysis between the two suggested soft computing approaches and their sensor-based equivalents. In the end, this research advances the field of SRM technology, opening the door to more dependable, economical, and efficient motor control systems in a variety of industrial and automotive applications.

1. Introduction

SRM is one of the best highly variable speed motor drives that are available on the marketplace, and it has been gaining popularity most recently for several of reasons. First of all, it is cost-effective and has a straightforward design. Secondly, it doesn't need separate parts such as a rotor, magnet, or brushes. Additionally, it is frequently utilized across both domestic and commercial industries, including the aerospace sector and motor vehicles markets worldwide [1,2].

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1.1. Lliterature survey

Accurately estimating the rotor's position is essential to reaching the best performance from an SRM drive. Since the SRM drives are utilized in an increased number of industries, highly reliable rotor position detecting techniques are needed [3]. Typically, rotor angle information has been collected using several kinds of rotor position sensor methods [4, 5]. For efficient control of speed, torque, and other parameters, it is also necessary to synchronize the excitation of the SRM with the rotor's position [6]. Additionally, a specific mechanism is needed to determine the rotor's position for proper operation [7]. There have been reports of several encoder, resolver, and hall shaft position sensor kinds [5]. These separate sensors are quite complicated to estimate the position of rotor, and they contribute different types of encoders, resolvers and hall shaft position sensors reported to estimate the rotor position, these discrete position sensor is highly complex and increase the system's cost, which lowers system performance and reliability [5, 7, 8]. However, with the recent move to do away with direct rotor position sensors, indirect rotor position determination lowers costs, size, and other complexity issues and aids in the development of accurate, affordable, and dependable sensing tools [2].

A new technique is reported; the Sensorless schemes just make use of terminal parameters and does not require any additional hardware setup is presented [4], where a relationship is established between position of the rotor, current in each phase, and flux linkage, which leads to give the main idea to detect position of the rotor of SRM. A number of Sensorless control techniques and their corresponding merits and demerits taking the principle and operation into discussion are reported by Acarnley et al. [9]. Along with a few mathematical formulae, a variety of parameters, including current, flux, inductance, speed, torque, etc., are used to represent the SRM. Some of the values are derived from the measurement directly and others may have undermined [4], Estimating the position of the rotor of switching reluctance motor is made easier, nevertheless, by an intelligent method based on fuzzy control and other control techniques [4–6, 10]. Due to its capacity to handle unpredictable and uncontrollable inputs from the system signal, as well as circumstances in which the rules are invalid, SRM powers the rotor position estimate method proposed by certain authors utilizing the fuzzy logic idea [4, 11]. Rather of creating an intricate mathematical model, the primary benefit of fuzzy reporting is straightforward mathematical computation [12, 13]. Fuzzy logic approach may act as the best option in some circumstances when Sensorless SRM is operated in real-time [4]. The creation of fuzzy rules is dependent upon the operator's expertise and the data gathered from the experiment [4, 7].

Artificial neural networks (ANNs) are described by E. Mese et al. [6], wherein current and speed control are implemented through the ANN [6]. Levenberg-Marquardt algorithm implementation is reported for testing and training purposes, and it is noted that the performance of the SRM modeled design is enhanced by the use of ANNs and fuzzy analysis [7]. The fuzzy inference system with an adaptive network based on it (ANFIS) is developed and proposed [10, 14]. Flux linkage, Phase current and rotor position are three factors that are used in the estimation of rotor position. ANFIS [10] maps the parameters. A strategy dependent fuzzy neural network [6] is magnificent in the sensor-less sector, combining the advantages of ANN and fuzzy interference system (FIS) on a single platform, quick and easy. Be achieved in a single platform approach model by combining ANN and fuzzy inference system (FIS). This combined technique results in a simplified structure and reduced computational complexity, making it easier to implement online. It also accelerates the learning process to become fast and accurate. The ability to recognize linguistic information and data is highly evident in this combined technique, as fuzzy sets are its antecedents. It can also constrain noise input signals, demonstrating its robustness characteristics.

In this research, a Model Reference Adaptive System (MRAS) is used to offer a novel sensorless control method for a Switched Reluctance Motor (SRM).Phase inductance analysis based on finite elements is used to create a simpler nonlinear model. Over the whole operating range, a hybrid sensorless approach provides precise rotor position and speed predictions. Without the need for further sensors, location detection at stationary is made possible via a low-frequency ramp signal. High precision with estimating errors less than 1% up to 1500 rpm is confirmed by simulation and experimental data [15].

In order to improve robustness at medium and high speeds, this study presents a flux linkage-based sensorless control technique for switched reluctance motors (SRMs).Fourier expansion is used to model the rotor position as a function of flux linkage. DC bias and harmonics are successfully eliminated by an enhanced Orthogonal Signal Generation Estimator (OSGE) with a SOGI–Notch Filter. Accurate rotor angle estimate is ensured by a super linear Convergence (SLC) technique in Finite Control Set Model Predictive Control (FCS-MPC).Tests conducted on a six-phase 12-10 SRM show dependable and resilient performance [16].

In order to improve the design and control of switching reluctance motors (SRMs), this research investigates the modelling and prediction of their magnetization surfaces using neural network approaches. Using experimental data from a 7.5 kW SRM, it compares three methods: physics-informed neural networks (PINNs), radial basis function (RBF) networks, and traditional neural networks. The accuracy, computational effectiveness, and capacity to depict physical dynamics of each approach are assessed in the study. The magnetization surface may be roughly represented by classical and RBF networks, but the flux behaviour is not fully captured by them, according to the results. By incorporating physical rules into the learning process, physics-informed neural networks, on the other hand, attain the maximum accuracy and show great promise for improving SRM modelling and electric drive system [17].

In order to precisely predict rotor position and speed, this research suggests a sensorless control approach for a switching reluctance motor (SRM) drive that is based on artificial neural networks (ANNs). The ANN uses real-time magnetic data trained with the Levenberg–Marquardt backpropagation algorithm in a Simulink environment to overcome the challenge of traditional modelling caused by the nonlinear magnetic features of SRMs. For accurate fitting and trustworthy estimation, the network design is tuned for neuron count. Compared to traditional hysteresis controllers, an advance angle control approach is used in addition to sensorless control to minimize switching losses and regulate speed. The accuracy, effectiveness, and applicability of the suggested system for SRM drive control are confirmed by experimental validation conducted in both steady-state and transient scenarios [18].

1.2. Research Gap

Even though switched reluctance motors (SRMs) have drawn interest for use in industrial settings and in hybrid electric vehicles (HEVs), precise rotor position estimation remains a critical component of SRM performance. Although traditional sensor-based techniques offer accurate position data, they have a number of disadvantages, such as higher maintenance requirements, complicated mechanical alignment, restricted design flexibility, and higher costs.

Researchers have studied sensorless control methods utilizing a variety of estimating algorithms in order to address these issues. Many of these current approaches, however, continue to have issues with increasing computing load, susceptibility to parameter changes, and poor accuracy under dynamic operating situations. Furthermore, although artificial intelligence (AI) methods like fuzzy logic and neural networks have been used, there are still few thorough comparisons between various AI-based sensorless systems and their sensor-based equivalents.

Therefore, there exists a clear research gap in developing and evaluating robust, cost-effective, and computationally efficient sensorless control strategies for SRMs that can maintain accurate rotor position estimation under varying load and speed conditions. This study aims to fill this gap by implementing and comparing fuzzy logic and ANFIS-based sensorless control approaches to enhance SRM performance and reliability.

Implementation of AI-Based Sensorless Control Strategies: Elimination of the requirement for physical sensors by introducing strong artificial intelligence (AI) methods for sensorless rotor position estimation in SRMs, such as fuzzy logic and the Adaptive Neuro-Fuzzy Inference System (ANFIS).

1.3. Novelty and Contribution

Hybrid Neuro-Fuzzy Approach: This method suggests a hybrid fuzzy–neural model that combines neural networks' adaptive learning ability with fuzzy logic's interpretability, leading to better estimation accuracy and quicker convergence.

Reduction of Hardware Dependency: This eliminates the need for expensive and complicated position sensors like encoders or resolvers by achieving precise rotor position detection using only electrical terminal parameters (flux linkage, phase current, and bus voltage).

Simplified Model with Less Computational Complexity: The suggested ANFIS-based approach is appropriate for real-time applications because it has less mathematical and computational complexity than traditional estimation algorithms.

Robustness against Noise and Non-linearities: Shows that the hybrid AI-based estimate system is more capable than conventional sensor-based or model-driven methods of managing signal noise and nonlinear system behavior.

Thorough Comparative Evaluation: To distinctly demonstrate performance advantages, a comparative study is conducted between fuzzy logic and ANFIS-based control techniques, as well as with traditional sensor-based systems.

Enhanced System Reliability and Cost Efficiency: The suggested system increases reliability, compactness, and cost-effectiveness—all important aspects for industrial and automotive deployment—by doing away with mechanical sensors and improving estimation accuracy.

MATLAB/Simulink Implementation and Validation: Using MATLAB/Simulink simulations, the suggested control systems are implemented and validated, exhibiting excellent dynamic response and high accuracy in rotor angle estimation under various load and speed situations.

1.4. Paper Organization

The study is divided into five sections: in this Section 1 contain the introduction; next Section 2 describes the proposed SRM system; Section 3 presents the implementation of control approaches; Section 4 contains the results and analysis; and Section 5 contains the conclusions.

2. Proposed model of sensorless SRM

The Figure 1 shows the complete model of the suggested closed-loop Switched Reluctance Motor (SRM) drive system. This all-inclusive model is built by combining a number of discrete parts, each of which is modeled separately before being combined to create the system's ultimate representation. Each component of the SRM system drive is described in depth in the following sub-sections, each component of the system is modelled independently before being merged to create the final model. The subsections below provide a description of each part.

Switched Reluctance Motor (SRM): In the driving system, the SRM functions as the main actuator. Its model includes the motor's mechanical, magnetic, and electrical properties. These consist of variables including torque-speed characteristics, rotor position, magnetic flux coupling, winding resistance, and inductance. Precise control and optimization are made easier by the SRM model's realistic representation of the motor's behavior under various operating circumstances.

Power Electronics Converter: The power supply and the SRM are interfaced with by the power electronics converter. It usually consists of diodes set up in a certain topology (e.g., half-bridge, full-bridge) and switches (e.g., MOSFETs or IGBTs). Control signals, switching losses, voltage and current waveforms, and switching functions are all included in the converter model. This part is essential to regulating the motor's power flow and attaining the required performance.

Control System: By creating the proper control signals for the power electronics converter in response to data from sensors or estimators, the control system manages the functioning of the SRM drive system. It includes a range of control techniques, including Adaptive Neuro and Fuzzy Inference System (ANFIS), Fuzzy Logic Control, Model Predictive Control (MPC), and Proportional-Integral-Derivative (PID). Algorithms, feedback loops, reference signals, and tuning parameters are all part of the control system paradigm.

Sensors/Estimators: The control system receives output from sensors or estimators, which permits closed-loop operation and guarantees precise control of motor variables including torque, speed, and position. Hall-effect sensors, resolvers, encoders, and current sensors are frequently utilized in SRM systems. For sensorless operation, estimators like Kalman filters or Extended Kalman filters can also be used. These leverage voltage and current sensor readings to predict the location and speed of the rotor.

Power Supply and Energy Storage: While energy storage components like capacitors or batteries may be incorporated to minimize transitory changes in supply voltage or to provide energy buffering, the power supply supplies the electrical energy required to run the motor.

The complete model of the closed-loop SRM drive system shown in Figure 1 enables thorough analysis, modelling, and optimization by correctly representing the system's performance under various operating situations by combining multiple subsystems.

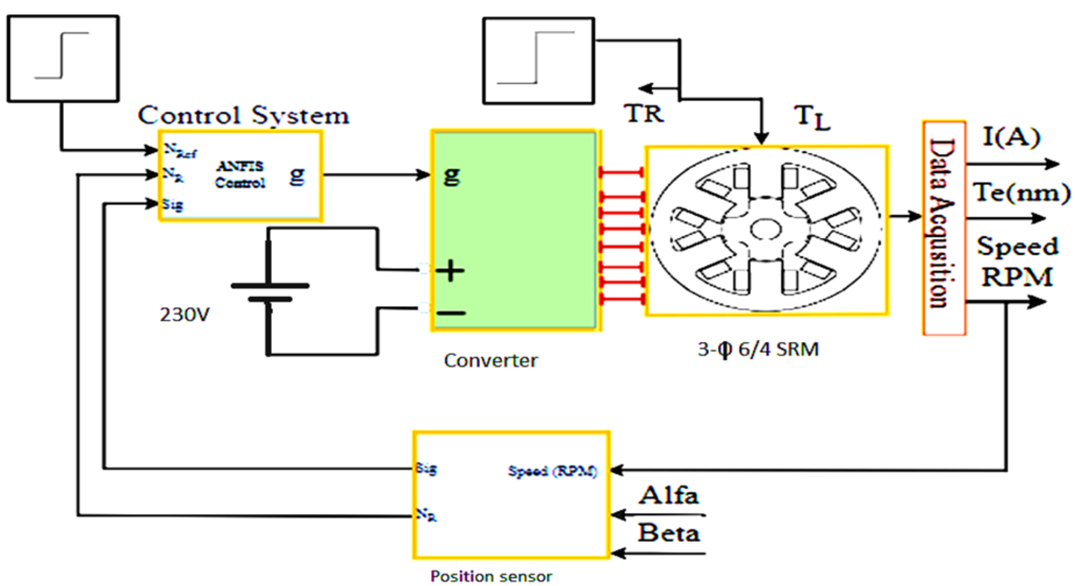

Figure 1. Complete model of the SRM drive proposed system.

3. Proposed control Technique

The neuro-fuzzy interference system controller is treated as an actuator that drives the SRM. The block diagram of control technique implementation is presented below in Figure 2. The error among the reference and actual speed is fed to PID controller, and the PID control signal is represented in discrete form as Gupta et al. [4]. By equate the actual speed and the desired speed, the feedback controller generates a controlled variable that has an impact on system performance [4].

$$u(k) = K_b e(k) + K_i T_s \sum_{i=1}^{n} e(k) + \frac{k_d}{T_s} \Delta e(k), \tag{1}$$

where,

$$\Delta e(k) = e(k) - e(k-1).$$

$u(k), e(k), T_s, k_p, k_i, k_d$ The hysteresis current controller for the voltage source inverter generates pulses as the operations of SRMs are based on the variation of flux linkage along the change of angular position of rotor. Phase voltage and phase current are used as input to the flux estimator and accordingly the flux linkage obtained [6]. The proposed ANFIS estimates the flux represents the control signal, error, sampling intervals, and gains.

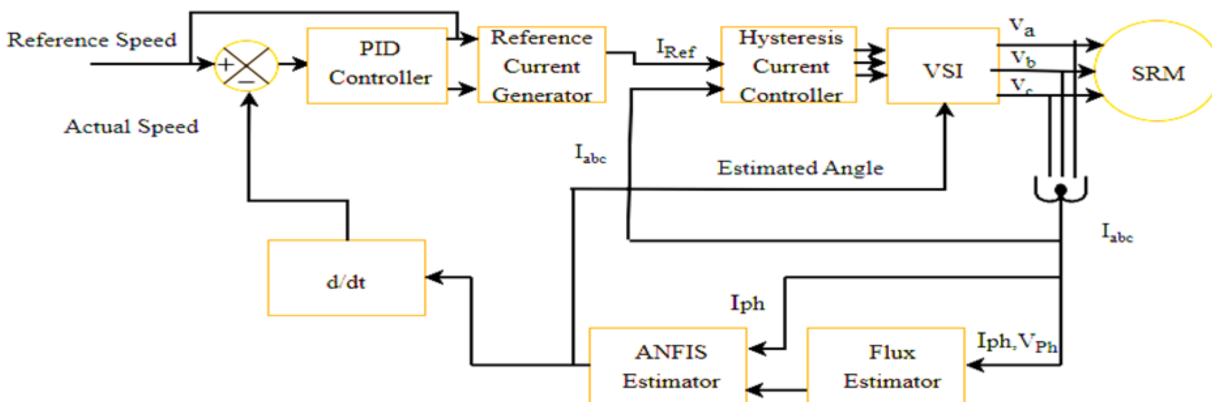

Figure 2. ANFIS Rotor Position Estimator.

3.1. SRM Modeling

The following equation controls the voltage across the SRM terminal at every instant due to its non-linear character:

$$v = ir + \frac{d\varphi}{dt}. \tag{2}$$

In the above Equation 1, i symbolizes the electric current flowing through the armature, r indicates the armature's resistance, φ indicates the armature's inductance, and v indicates the supply voltage. The electromechanical equation below determines the motor's performance:

$$\frac{d\omega}{dt} = \frac{(T_e - T_l)}{J}, \tag{3}$$

where T_e symbolizes the electrical torque, which can be written as,

$$T_e = \frac{d\omega}{d\theta}, \tag{4}$$

where ω symbolizes the frequency of supply and is written as,

$$\omega = \frac{d\theta}{dt}, \tag{5}$$

where θ indicates the rotor position, T_l shows the load torque, and J the moment of inertia.

3.2. Converter Modeling

The SRM and a voltage source inverter along hysteresis current control are interconnected. The below equation establishes whether or not it applies a positive or zero voltage to the angle of the rotor on the inverter output, contingent upon the positive and negative errors supplied to the hysteresis band:

$$\text{If } \theta \geq \theta_{on} \text{ and } \theta < \theta_{off},\ v_{out} = s * v, \tag{6}$$

$$\text{If } \theta \geq \theta_{off} \text{ and } \theta < \theta_{q},\ v_{out} = -v, \tag{7}$$

$$\text{If } \theta > \theta_{q},\ v_{out} = 0, \tag{8}$$

where s represents switching of hysteresis current control, θ_{on}, θ_{off} represent turn on and turn off phase excitation respectively.

The observation is made that when both angles occupy the rising profile area of the inductance, positive torque is created. These results in the rotor being driven forward and the same reasoning may be used for other phases. Similar patterns can be used to shift the rotor position ahead throughout the remaining stages. PV is supplied to the inverter's DC link in order to keep the voltage across the VSI constant.

3.3. FLC Modelling

To create a fuzzy estimate system, flux linkage and rotor current are used to generate fuzzy rules in the suggested SRM model. In order to create a fuzzy rule basis table, rotor position magnetization data must first be gathered and saved. With the help of this rule base, rotor position data may be retrieved from the specified input parameters. The fuzzy model uses these rule bases as inputs, and the qualitative values of the input variables are represented by linguistic variables like small, medium, and large.

The rotor position (output) is mapped in terms of angular values to flux linkage and current (inputs). Numerous academics have proposed this technique throughout the years [4,5], which converts ambiguous language descriptions into numerical representations. The degree of membership in the discourse universe is represented by a membership function that continually fluctuates from 0 to 1 for each fuzzy set. This feature permits partial membership, which means that real or crisp values can be regarded as members of fuzzy sets to different degrees, ranging from complete member (1) to non-member (0).

The fuzzifier, rule base, inference engine, and defuzzifier are the four primary parts of a fuzzy logic system (FLS) [5]. Figure 3 shows the entire fuzzy angle estimator system. The MATLAB/Simulink platform was used to design and simulate the model. Flux linkage was first estimated using fuzzy logic, and for increased flux estimation accuracy, a neuro-fuzzy system (ANFIS) was then used.

Figures 4 to 7, respectively, show the simulation results, which include fuzzy input and output membership functions, input–output mappings, and defuzzified values. The suggested fuzzy estimator has been precisely trained and works well for the intended SRM applications, as evidenced by the small deviation between the estimated and measured rotor angles.

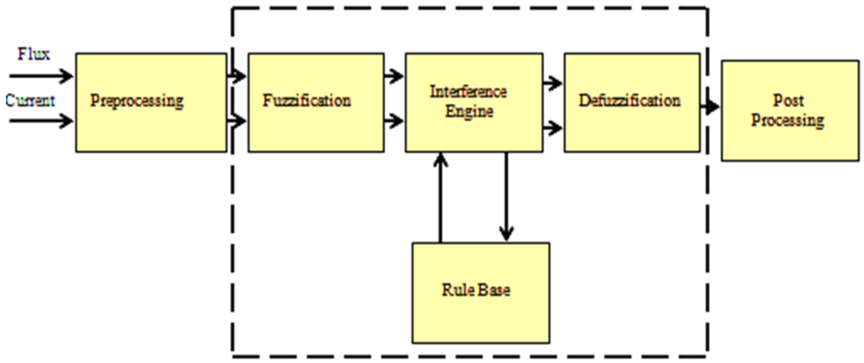

Figure 3. Block Diagram of Fuzzy control Angle Estimator.

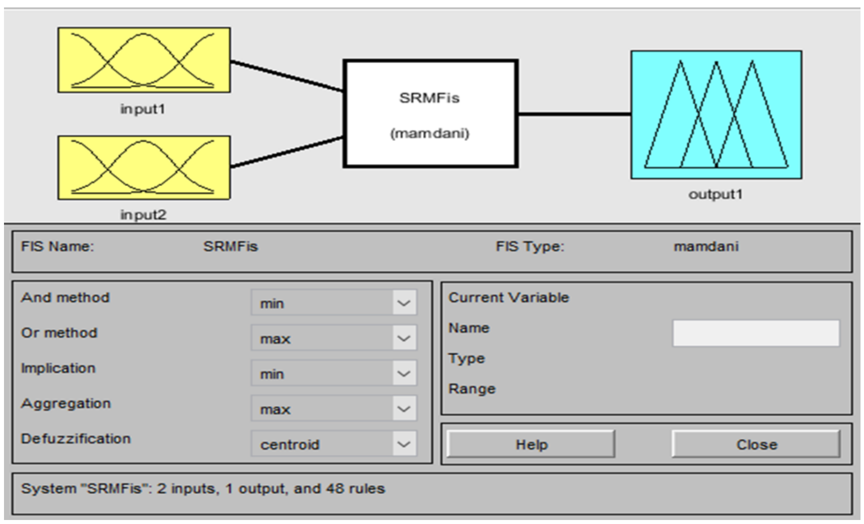

Figure 4. Fuzzy input and output.

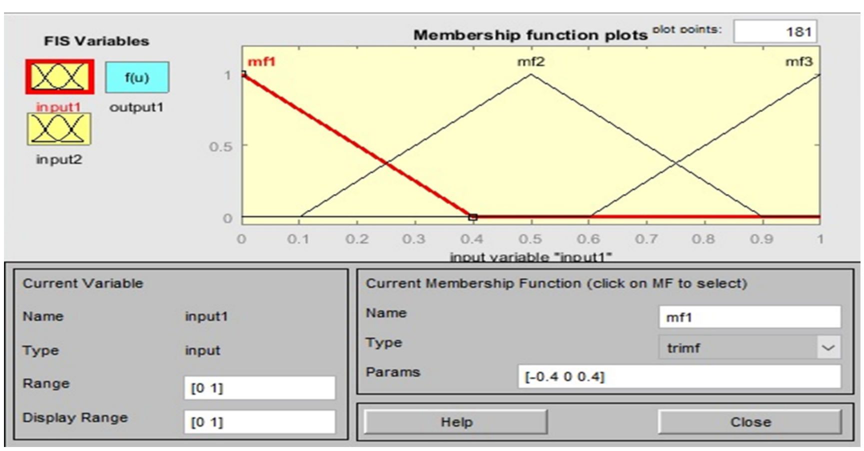

Figure 5. Membership function.

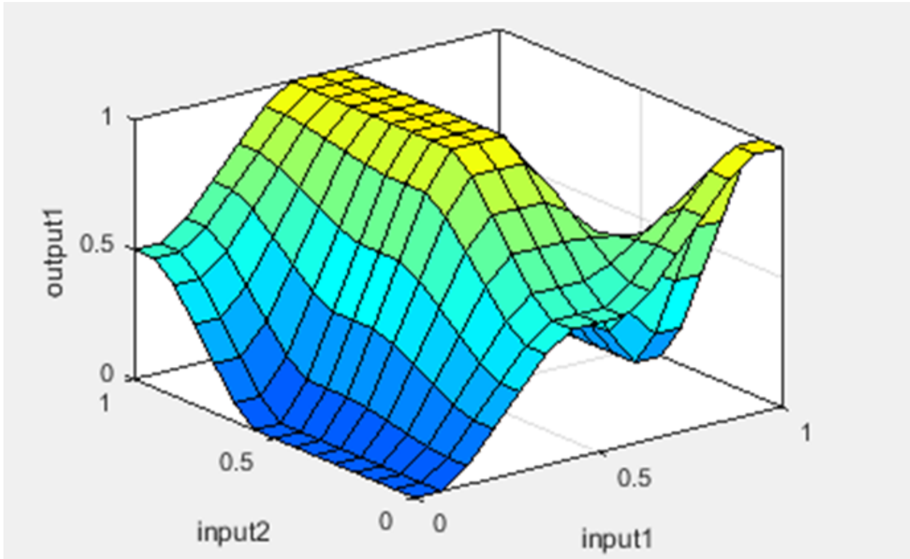

Figure 6. Membership function.

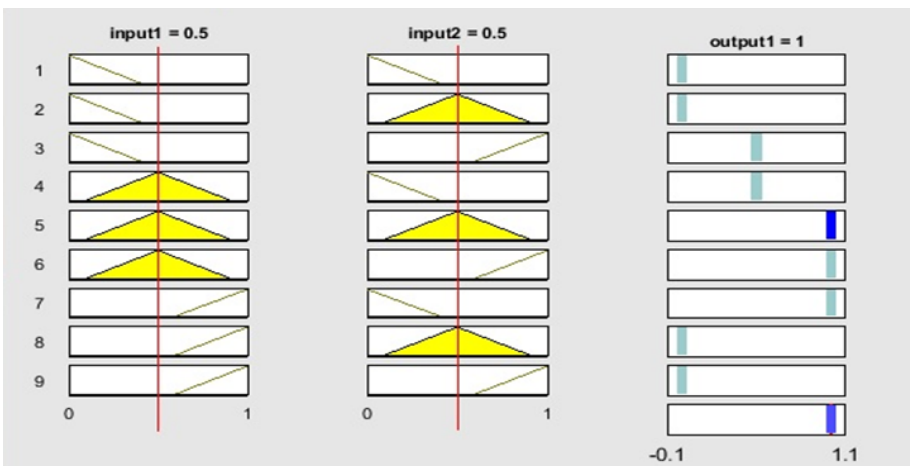

Figure 7. Value after defuzzification.

3.4. ANFIS Modeling

The ANFIS has been put into use [19]. It is a hybrid model that combines the efficiency and reduced error of both fuzzy and neural networks. To produce an output, the network needs to be trained with two inputs. Various layers are suggested for neural network training [7], and commands carry out the work. When training data is used to create a fuzzy interference system, parameters of membership function are modified using a variety of algorithms, including back-propagation algorithms and recursive least squares approaches combined with back-propagation [7, 10], among others the learning process accelerates when it is compared to the gradient technique alone, which becomes trapped in local minima [6]. There are one output (z) and two inputs (x & y) for fuzzy inference system under study. Two fuzzy if-then rules by Takagi and Sugeno [19] make up the rule base.

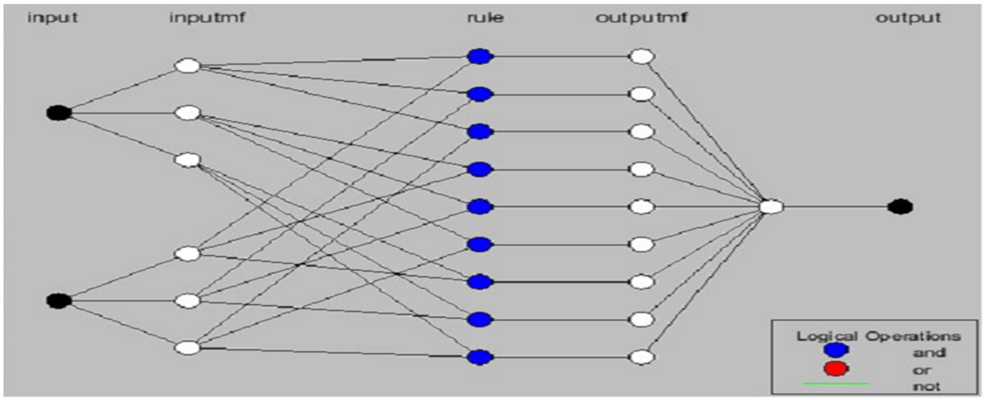

Figure 8. ANN Model of the proposed work.

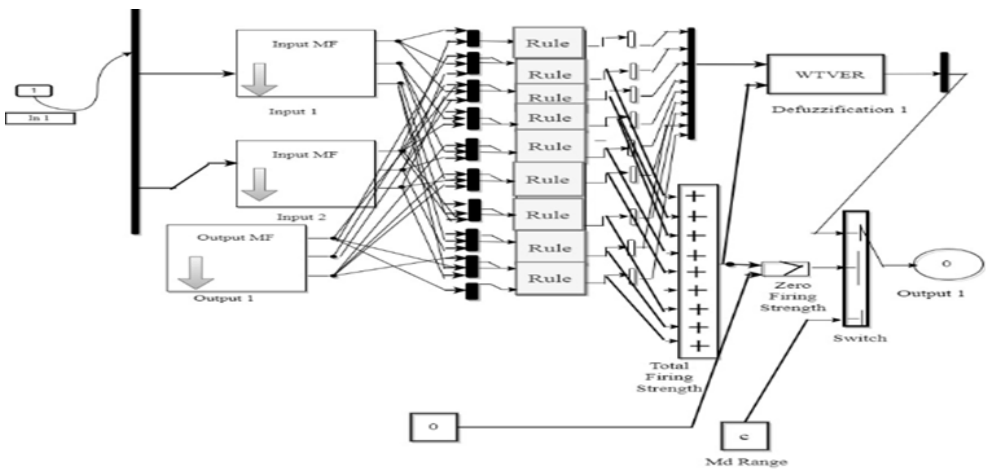

Figure 9. ANFIS Controller block diagram.

The control block diagram of ANFIS shown Figure 9, governed by the below rules [7, 10].

If x is A_1 & y is B_1, then f_1 can be express as,
$f_1 = p_1x + q_1y + r_1$, this is Rule1, similarly Rule2 can be framed as,
If x is A_2 & y is B_2, then f_2 can be expressed as,
$f_2 = p_2x + q_2y + r_2$, Rule 2.

The details of the node function in the layer is as follows. The neuron's output is computed as follows: the degree of input fulfills the linguistic label that is connected to the Rule node in Layer 1. This node computes the firing strength of the related rules.

$$\begin{aligned}
\alpha_1 &= L_1a_1 + L_2a_2 + L_3a_3, \\
\alpha_2 &= H_1a_1 + H_2a_2 + L_3a_3, \\
\alpha_3 &= H_1a_1 + H_2a_2 + H_3a_3.
\end{aligned} \tag{9}$$

After due normalization process in each node, the outputs in layer.3 are given as follows in Equation (10).

$$\beta_1 = \frac{\alpha_1}{\alpha_1 + \alpha_2 + \alpha_3},$$
$$\beta_2 = \frac{\alpha_2}{\alpha_1 + \alpha_2 + \alpha_3}, \tag{10}$$
$$\beta_3 = \frac{\alpha_3}{\alpha_1 + \alpha_2 + \alpha_3}.$$

The output of Layer 4 (the defuzzification layer) is obtained by multiplying the individual rule output by the normalization level. These outputs are represented in Equation (11).

$$\beta_1 Z_1 = \beta_1 VB^{-1}.\alpha_1,$$
$$\beta_2 Z_2 = \beta_2 VB^{-1}.\alpha_2, \tag{11}$$
$$\beta_3 Z_3 = \beta_3 VB^{-1}.\alpha_3.$$

Overall output of the system Z_0 in a single node is computed as,

$$Z_0 = \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3, \tag{12}$$

The input vectors are typically passed via the network layer by layer, as demonstrated by the aforementioned mathematical study of the ANFIS.

4. Results and Analysis

The given data is the simulation results of an SRM drive using several methods to determine the rotor position. Three examples are provided to demonstrate the efficacy of the created ANFIS.

Case-1 SRM with Sensor

First, as seen in Figure 10, SRM with a sensor that has distinct parameter features is seen from the simulated wave shape. When the phase current, torque, speed, and flux are displayed, it is clear that these parameters are not ideal for the optimal operation of the SRM.

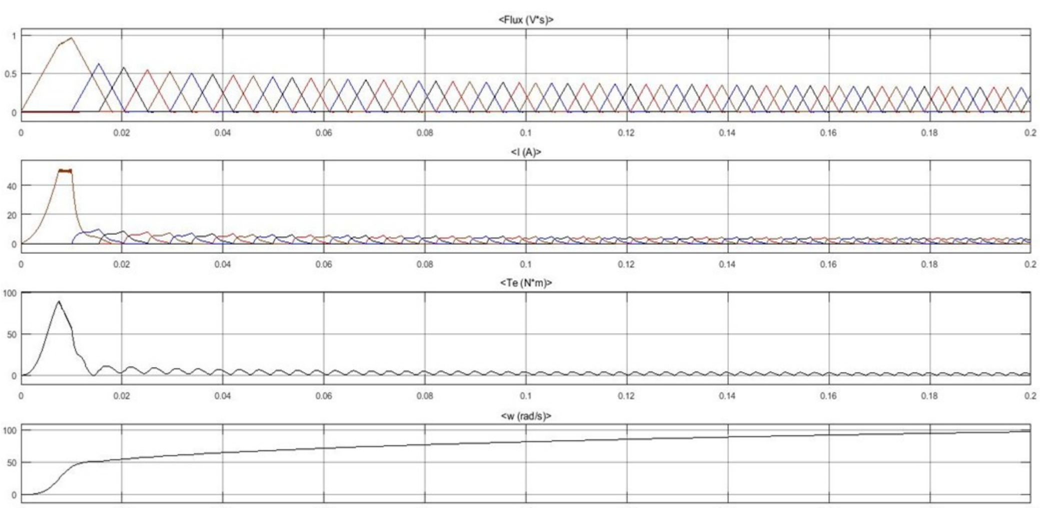

Figure 10. SRM with sensor.

Case-2 SRM with Sensor less with FLC

In order to thoroughly assess the efficacy of the Fuzzy Logic Control (FLC)-based method, the implementation process described in Section 3 is carried out. The final parameter features are then carefully examined and graphically shown in Figure 11 to allow for thorough comprehension and comparison.

When one looks closely at the simulated waveforms seen in Figure 11, one may see a pattern. It can be easily observed that the torque and speed characteristics are significantly improved by combining the sensorless method with Fuzzy Logic Control (FLC).

In particular, the torque and speed profiles produced by combining FLC with the sensorless approach show notable gains in a number of important areas. These enhancements include of increased stability in response to changing load circumstances, improved accuracy, and more seamless transitions between operational states. These improvements demonstrate the sensorless technique's strength and effectiveness when used with FLC to maximize system performance.

To sum up, the findings shown in Figure 11 highlight the significant advantages that come from combining the sensorless method with FLC, confirming its position as the method of choice for improving torque and speed characteristics in SRM systems.

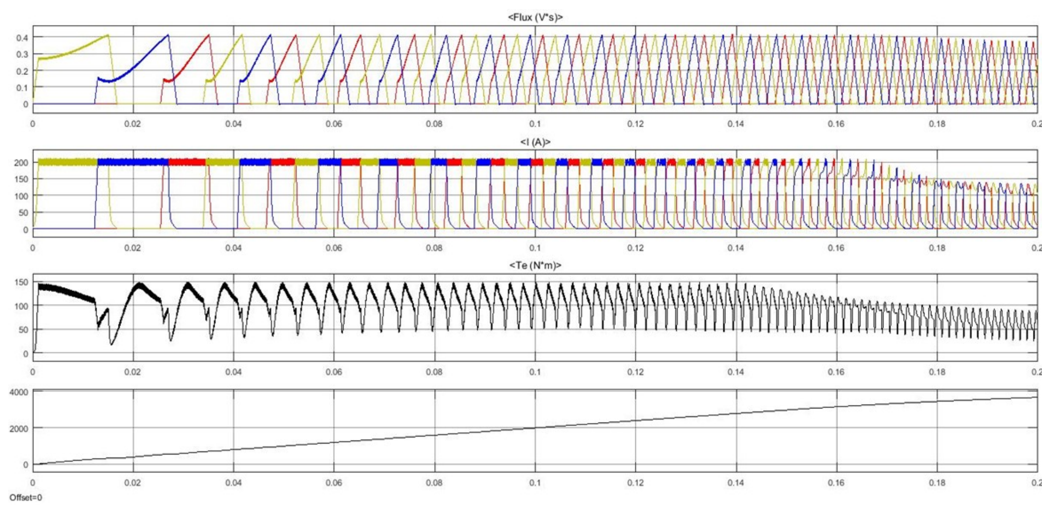

Figure 11. SRM with sensor less with fuzzy.

Case-3 SRM with Sensorless with ANFIS

In order to determine if the Fuzzy Logic Control (FLC)-based approach is effective, the implementation procedure outlined in Section 3 is carried out with great care. Following presentation and analysis of the resultant parameter characteristics, Figure 12 is used as a visual aid to highlight these conclusions.

When the simulated wave forms in Figure 12 are closely examined, a distinct and noteworthy tendency becomes apparent. It is clear that, in comparison to the FLC-based method, the sensorless strategy using Adaptive Neuro-Fuzzy Inference System (ANFIS) control produces significant improvements in torque and speed characteristics.

In particular, there is improved stability, smoother transitions, and more accurate control over the intended operational parameters in the torque and speed profiles produced by the sensorless ANFIS control. These enhancements demonstrate the sensorless system's greater effectiveness and performance ANFIS control strategy in comparison to the FLC-based method. All things considered, the outcomes shown in Figure 12 highlight the noteworthy benefits provided by the sensorless ANFIS control method, hence solidifying its standing as the method of choice for maximizing the effectiveness and performance of SRM systems.

Fuzzy logic and ANFIS–based controllers require significant processing power compared to conventional control schemes, ANFIS depends heavily on the quality and completeness of training data. Poorly chosen datasets or rule bases can lead to inaccurate rotor position estimation and unstable performance. Its performance mainly depends on Variations in temperature, magnetic saturation, or aging can degrade estimation accuracy. However, the complexity of the system raises as the inputs and hidden layers increases.

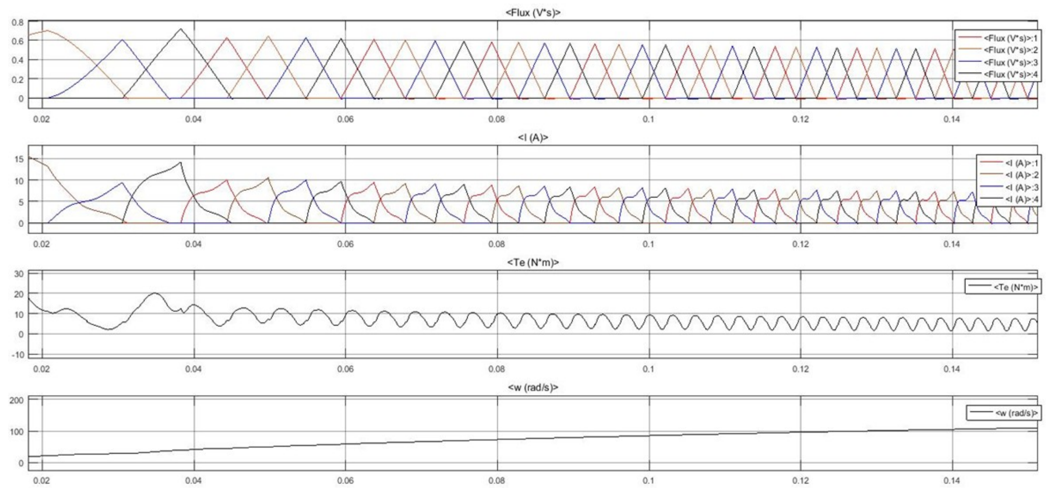

Figure 12. SRM with sensor less with fuzzy.

5. Conclusions

This research presents a detailed comparison of sensor-less and sensor-based switched reluctance motors (SRM), comparing their respective control systems. The results show that sensor-less SRM performs better in terms of torque and speed characteristics than its sensor-based equivalent. Additionally, the paper clarifies how different controller implementations affect sensor-less SRM's parameter characteristics. The study, of particular note, emphasizes the effectiveness of the Adaptive Neuro-Fuzzy Inference System over Fuzzy Logic Control. Fuzzy logic and Artificial Neural Network (ANN) approaches are used in ANFIS to provide a complete control solution. Performance is enhanced by this integration since it successfully combines the advantages of ANN and fuzzy logic techniques. As such, the use of ANFIS becomes the better option than FLC, adding to enhanced control precision and efficiency in the operation of sensor-less SRM systems.

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