

DEVELOPMENT OF A HYBRID NEURO-FUZZY-PID CONTROLLER FOR INTELLIGENT SPEED CONTROL OF WOUND-ROTOR INDUCTION MOTORS

by

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ABSTRACT

This research discusses the advancements in intelligent speed controllers for wound-rotor induction motors, specifically highlighting the integration of neuro-fuzzy adaptation with traditional PID regulation. While fixed-gain PID controllers serve as effective baseline regulators, they often face challenges under varying motor parameters and load conditions. Experimental results demonstrate that the Neuro-Fuzzy-PID controller significantly outperforms both the Fuzzy-PID and traditional PID controllers. The Neuro-Fuzzy-PID achieves a rise time of 0.495 seconds, which is an improvement over the Fuzzy-PID's 0.525 seconds and the PID's 0.615 seconds. Additionally, the settling time for the Neuro-Fuzzy-PID is 0.705 seconds, better than the Fuzzy-PID's 0.720 seconds and the PID's notably longer 5.025 seconds. In terms of performance, the Neuro-Fuzzy-PID exhibits the lowest overshoot at 7.73%, compared to 8.96% for the Fuzzy-PID and a substantial 28.40% for the PID. The steady-state error for the Neuro-Fuzzy-PID is reduced to an impressive 0.074364 rad/s, outperforming the Fuzzy-PID at 0.199703 rad/s and the PID at 4.617537 rad/s. These findings indicate that the Neuro-Fuzzy-PID controller not only provides faster and more accurate speed tracking but also demonstrates superior transient performance. This represents a significant advancement in motor control strategies, highlighting the potential benefits of integrating neuro-fuzzy systems with conventional PID regulation.

Keywords: Induction Motor, Fuzzy Logic controller, PID, Artificial neural Network, Python, TensorFlow Kera's API.

I. INTRODUCTION

A wound-rotor induction motor (WRIM), often referred to as a slip-ring induction motor, stands out from squirrel-cage motors due to its rotor circuit's accessibility for external control. This characteristic pave the way for innovative speed regulation techniques outlined in the literature, such as external rotor resistances, phase-controlled rotor circuits, slip-energy recovery mechanisms, and rotor-side converters (Ponnu and Gomathy, 2016). While this

flexibility supports variable-speed applications, it also presents a challenging control design landscape. Factors such as actuator performance, rotor resistance, slip frequency, converter dynamics, and load torque all interact to affect speed response.

Intelligent control methods are transforming this landscape by leveraging nonlinear rules, learned models, and adaptive parameters. For instance, fuzzy logic effectively encodes control knowledge through easy-to-understand linguistic rules without relying on comprehensive plant models. On the other hand, neural networks excel at learning nonlinear relationships from operational data, although their training processes can be complex and hard to interpret. Neuro-fuzzy systems combine artificial neural networks (ANNs) with fuzzy inference's structured rule-based design, enhancing adaptability while maintaining interpretability (Pudari and Sabha, 2024; Nnamani et al., 2025). This synthesis permits a hybrid neuro-fuzzy-PID controller to fine-tune PID gains or generate corrective signals while ensuring the transparency and reliability of PID control. Wound-rotor induction motors (WRIMs) are particularly advantageous for high-torque and wide-speed applications because their rotor circuits are accessible through slip rings.

In configurations involving double inverters, these motors offer dual electrical ports and the capability to operate in both sub-synchronous and super-synchronous regions. This not only provides greater flexibility over torque, flux, and speed regulation (Nanda and Hari, 2023) but also complicates the control dynamics, as the system must effectively coordinate stator and rotor variables. It must maintain speed tracking amidst reference changes, load disturbances, parameter drift, and fluctuations between operating regions. While fixed-gain PI or PID controllers are effective due to their straightforward structure, addressing current error, accumulated error, and error trend through proportional, integral, and derivative terms, they often struggle when motor parameters, load torque, or operating speeds change. Conventional gains can lead to slow recovery, overshoot, steady-state error, or oscillatory behavior under variable conditions. As

a response to these challenges, recent studies on induction motors are shifting towards advanced techniques like fuzzy inference, neural networks, adaptive observers, and optimization algorithms to lessen the reliance of the speed loop on a single nominal model. For example, a study by Okeke and Okonkwo (2023) demonstrated that using speed error and its change as fuzzy inputs to adjust the PID command significantly improved performance—reducing rise time, settling time, and steady-state error compared to traditional PID setups.

The hybrid neuro-fuzzy-PID controller offers a compelling solution to these challenges by integrating three essential functions. The PID component delivers a clear error-correction strategy and integral action that effectively eliminates residual speed errors. The fuzzy component harnesses nonlinear knowledge through linguistic rules, adapting controller actions when the system deviates from nominal conditions. Meanwhile, the neural component learns complex relationships among speed errors, load responses, motor states, and optimal controller parameters. This structured division aligns seamlessly with cutting-edge research, where ANFIS or similar neuro-fuzzy configurations have been employed to enhance adaptive speed loops, estimate unmeasured variables, or replace traditional control elements. For instance, in their 2020 study, Fahassa et al. successfully substituted conventional direct torque control comparators and PI speed controllers with ANFIS-based components.

This innovation led to a significant reduction in ripple and an improved transient response when faced with various disturbances. Additionally, Açıkgöz (2020) found that an online-trained Type-2 fuzzy-neural controller outperformed both PI and Type-1 fuzzy-neural alternatives by delivering a faster and more stable dynamic response. The evidence is clear: adopting hybrid neuro-fuzzy-PID control systems can noticeably enhance motor control efficiency and reliability in dynamic environments.

II. LITERATURE SURVEY

The development of high-performance electrical drive control systems has advanced significantly. This section synthesizes recent research on the dynamics of Wound-Rotor Induction Motors (WRIM), the constraints of classical control methods, Fuzzy Logic Controllers (FLC), Artificial Neural Networks (ANN), and modern Hybrid Neuro-Fuzzy-PID (HNF-PID) control paradigms. Proportional-Integral-Derivative (PID) control

remains the standard in industrial drive applications (Kalyani and Ray, 2021).

Load variation is a critical aspect for evaluating the proposed WRIM controller, underscoring the necessity for advanced control methods. For instance, Hasan and Ahmed (2023) conducted a scalar-control study using ANFIS combined with an optimization technique to effectively adjust the reference amplitude and PWM modulation index. They tested two load torques, 10 and 20 N·m, at speeds from 1000 to 2000 rpm. The hybrid approach reported remarkable enhancements over traditional PI control, achieving about a 90% reduction in overshoot and a 94% decrease in settling time. While this study serves as a valuable benchmark, it is essential to recognize that it employs scalar control with an induction-motor model instead of a WRIM; therefore, its numerical advancements should be viewed as design benchmarks rather than direct performance predictions. In line with this approach, a recent study on induction motors applied similar evaluative logic, examining no-load, constant-load, and varying-load conditions alongside parameter variations.

The findings showed that the Fuzzy-PID controller considerably improved rise time, settling time, and steady-state error compared to traditional PID and fuzzy controllers, even amidst changes in stator resistance (Benjamin et al., 2025). Though this evidence does not directly pertain to WRIMs, it reaffirms the importance of incorporating parameter perturbations into the evaluation framework, moving beyond mere nominal tracking. The literature reflects an evolution from fixed-gain to adaptive intelligent control strategies. Açıkgöz (2020) compared an online-trained Type-2 fuzzy-neural controller with PI and Type-1 fuzzy-neural controls for vector-controlled induction motors. The Type-2 controller demonstrated notable improvements in dynamic response, settling behavior, overshoot, and recovery performance, thanks to its capability to handle parameter changes and disturbances. Concurrently, Fahassa et al. (2020) introduced an ANFIS-based DTC architecture equipped with a dual observer for sensorless operation, reporting significant reductions in electromagnetic, flux, and current ripple, coupled with enhanced rise and settling times. Further advancements in adaptive control were highlighted by Fakhruddin et al. (2021), who integrated PID speed control with ANFIS for the indirect vector control of a 2-hp three-phase induction motor, leveraging particle swarm optimization (PSO) to refine the ANFIS dataset. Their simulations

showcased significant performance improvements across reference speeds, with the fastest rise time achieving performance that was 1.5 times quicker and effectively eliminating undershoot and steady-state oscillation. This is particularly relevant for the proposed WRIM controller, illustrating an effective method for generating training data while using ANFIS as an adaptive enhancement to a PID speed loop. In exploring observer and sensorless-control literature, the benefits of adaptation become even clearer. Soni et al. (2022) integrated ANFIS into a model-reference adaptive system, comparing it against PI, PID, and fuzzy MRAS options using MATLAB/Simulink. A related study utilized an adaptive fuzzy-neural network to optimize the outer-loop PI controller online, providing improved speed-control accuracy, better disturbance rejection, and reduced reliance on speed sensors. Similarly, Umar et al. (2022) developed a fuzzy-adaptive PID speed controller for DTC, employing 49 rules to adjust PID gains dynamically based on variable loads and variations in speed, stator flux, and torque.

The 2023–2025 literature increasingly highlights the synergy between fuzzy logic and PID control as complementary rather than competing methodologies. In this context, Okeke and Okonkwo (2023) implemented a Mamdani fuzzy-PID controller that utilized speed error and error rate as inputs, achieving impressive simulation outcomes: a rise time of 0.8354 seconds, a settling time of 1.2240 seconds, and a steady-state error of just 0.1 rpm, compared to more traditional PID results. Although these results derive from a simulated induction motor model rather than a WRIM experiment, they provide strong support for the effectiveness of hybrid control strategies. Additionally, Ozoemena and Ashigwuike (2023) advanced the concept further by adopting a neuro-fuzzy architecture that replaced traditional PI elements in a DTC model with fuzzy-neural-network controllers. Their findings at 100 rpm demonstrated only 0.13% speed ripple, a clear advantage over switching-table DTC and SVM-DTC alternatives. This study holds particular

significance for WRIM applications, given the challenges of low-speed operation for sensorless and parameter-sensitive drives.

However, it is important to note that the findings pertain to general induction motor drives, rather than specifically addressing wound-rotor machines with controlled rotor-side variables. In conclusion, Aryam et al. (2024) innovatively combined ANFIS with a Flower Pollination Algorithm-optimized PI controller for a three-phase induction motor, further showcasing ANFIS's versatility in tackling nonlinearity within control systems. These ongoing advancements emphasize the potential for innovative control strategies as we refine the WRIM controller, paving the way for more robust and adaptive systems in this field. Through careful consideration of these findings, researchers and engineers can enhance performance and adaptability in future WRIM implementations.

III. MATERIALS AND METHODS

The Design was done by Python 3.13.5 with Jupyter Notebook. The design of the induction motor was based on the parameters shown in Table 2 and Table 3. The Python Libraries were installed and imported. The Methods employed in this design include:

- PID Control
- Fuzzy-Control
- Neuro-Fuzzy Control

In the PID control, the 3-phase wound rotor induction motor control has reference speed as 1780 rpm (186.4 rads^{-1}). The value of 186rad/s was utilized for a feed voltage of 460v and 60Hz a.c supply. The Proposed System Model of the Design is shown in Fig. 1. The Triangular membership function utilized about 50 rule-base using if-then-rules with the antecedents as error and change in error and the consequent as the change in rotor resistance using numpy and scikit-fuzzy as shown in Fig. 2 with the Fuzzy variables and seven Linguistic variables as described in Table 1.

Table 1: Description of Fuzzy variables control parameters

Linguistic Variables	Universe of Discourse	Fuzzy-variable	Description
Error	$-10 \text{ to } 10 \text{ rads}^{-1}$	NL NM NS ZE	Negative Low Negative Medium Negative Small Zero
Change in Error	$-10 \text{ to } 10 \text{ rads}^{-2}$	PS PM PL	Positive Small Positive Medium Positive Low

Change in Rotor Resistance	$-5 \text{ to } 5\Omega$		
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Table 2: Process Control gain Parameters for the Controllers

Control Gains	Type of Controllers		
	PID	Fuzzy-PID	Neuro-Fuzzy-PID
k_p	30	40	1.5
k_i	80	80	0.85
k_d	7.5	15	0.08

Table 3: Parameters of Wound Rotor Induction Motor

Motor Parameters	Values and units
Power, PW	50HP (37KW)
Voltage, V	460 V
Stator Resistance, Rs	99.61m Ω
Stator Inductance, Ls	0.867mH
Rotor Resistance, Rr	58.37m Ω
Rotor Inductance, Lr	0.867mH
Mutual Inductance, Lm	30.39mH
Moment of Inertia, J	0.40 kgm ²
Viscous Friction factor, B	0.02187 Nms
Number of Poles	2
Frequency, f	60 Hertz

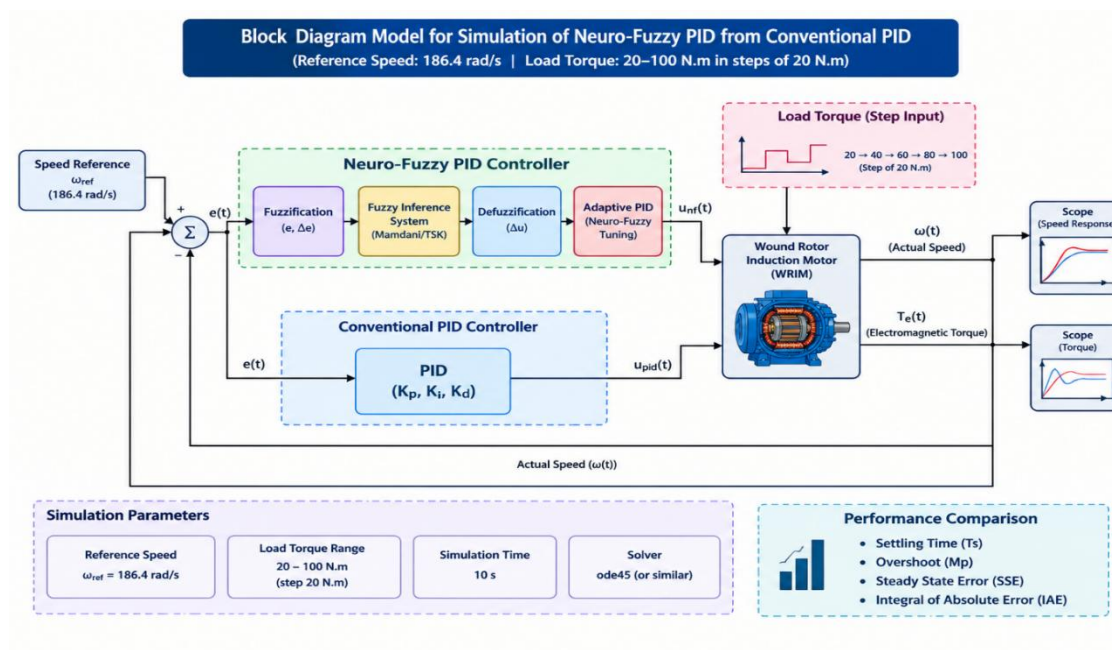


Fig. 1: Proposed System Model of Neuro-Fuzzy-PID Control

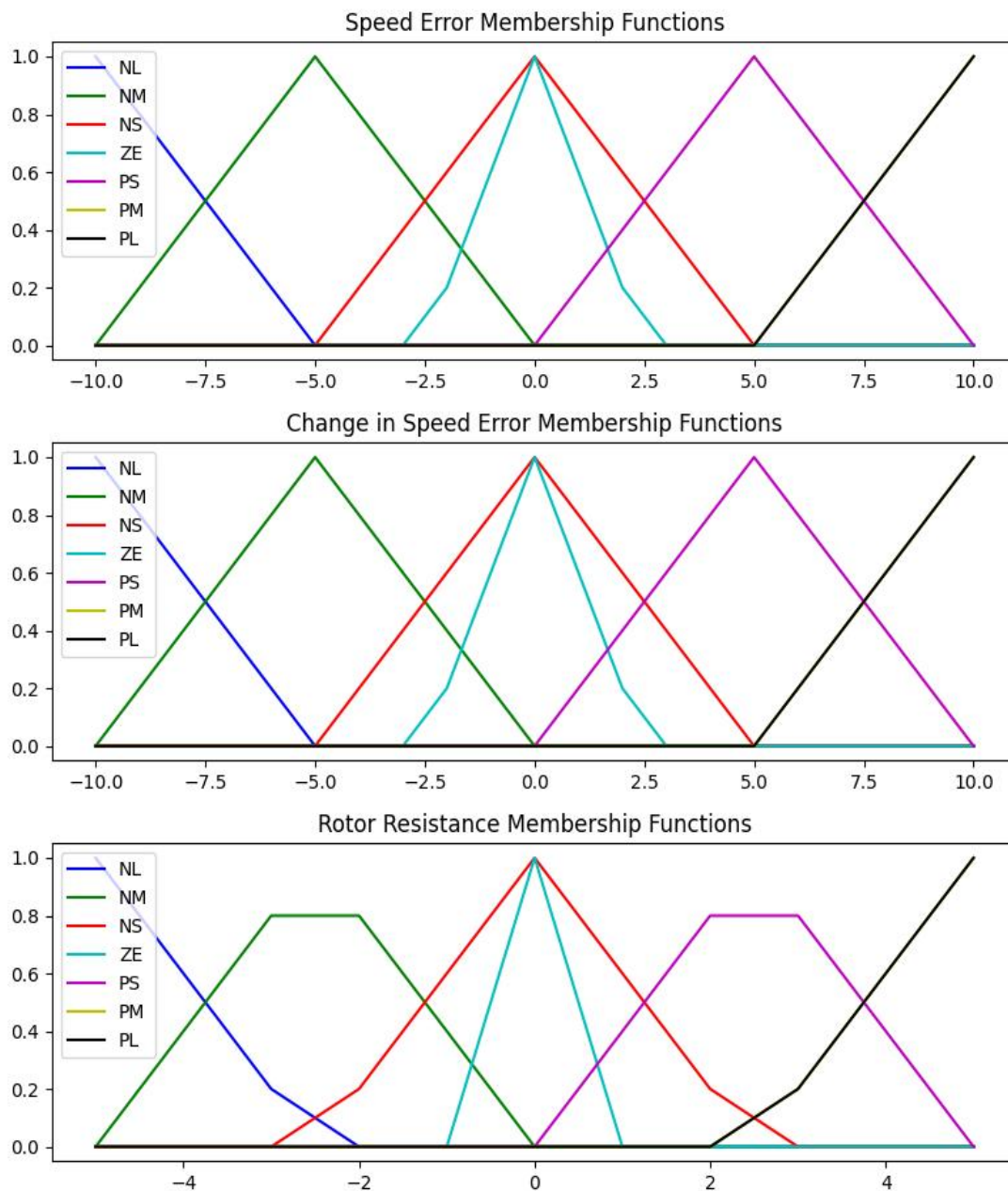


Fig.2: Fuzzy-Membership Functions for the antecedents and the consequents.

3.1 The Neuro-Fuzzy Control: This include the underlisted methods

3.1.1 Fuzzy controller

The system takes two inputs:

1. Error (e) = Desired speed - Actual speed
2. Change in error (de) = Rate at which the error is changing

These inputs produce a control signal (u).

For training the model, random values of error and change in error are generated.

The fuzzy controller then produces the corresponding control outputs, which serve as training examples for the neural network.

The training data is divided as follows: 20% for the training set, 40% for validation, and the remaining for testing. Approximately 1,000 random samples were tested.

The data is categorized into three groups: Training Data, Validation Data, and Testing Data.

3.1.2 Neural network

- A small neural network learns the relationship:

$$(e, d) \Rightarrow u \quad (1)$$

- It is trained for 50 epochs using convolutional neural network with TensorFlow Kera's API, having 2 inputs, ReLU activation with Two hidden layers and 10 neurons and 1 predicted linear output control signals. The Loss and Validation Loss are plotted in Fig. 7 to show the performance of the network.

3.1.3 Motor simulation

- The desired speed is set to 1780 RPM *i.e* 186.4 rads^{-1} .
- At every time step, the program calculates the speed error.
- The fuzzy controller and neural network both produce control signals.
- They are combined:

$$u_{control} = u_{fuzzy} + 0.5u_{neural} \quad (2)$$

IV. RESULTS AND DISCUSSIONS

As shown in Fig. 3, fig. 4 and Fig. 5, the performance of the wound rotor induction motor is depicted in Table 4. Also, Fig. 6 and Fig. 8 show the Neuro-Fuzzy architecture and the Neuro-Fuzzy speed control of the Wound rotor Induction Motor respectively.

The comparison of various control strategies highlights significant differences in their performance metrics. The traditional PID controller exhibits a rise time of 0.6150 seconds. In contrast, the Fuzzy-PID shows a slightly longer rise time of 0.6300 seconds, while the Neuro-Fuzzy-PID stands out with the best performance, achieving a rise time of just 0.4950 seconds. This showcases an impressive reduction of approximately 21.43% in rise time for the Neuro-Fuzzy-PID, indicating a faster response to changes in the reference input. When examining settling time, the traditional PID controller experiences a notable delay with a settling time of 5.0250 seconds.

The Fuzzy-PID improves this significantly to 0.7950 seconds, while the Neuro-Fuzzy-PID enhances performance even further, achieving a settling time of 0.7050 seconds. This results in an improvement of around 11.32% over the Fuzzy-PID, demonstrating the Neuro-Fuzzy-PID's ability to stabilize more rapidly in reaching the desired output.

In terms of overshoot, the traditional PID controller displays a substantial overshoot of 28.40%. The Fuzzy-PID manages to reduce this to 19.32%, but the Neuro-Fuzzy-PID substantially minimizes it further to only 7.73%. This represents a dramatic reduction of approximately 59.99% with the Neuro-Fuzzy-PID, indicating a smoother and less oscillatory response, which is crucial for preventing excessive deviations around the reference value.

Finally, the steady-state error illustrates the most significant improvement among the controllers. The traditional PID controller has an error of 4.617537 rad/s, which the Fuzzy-PID reduces to 1.595653 rad/s. In remarkable contrast, the Neuro-Fuzzy-PID achieves a minimal error of just 0.074364 rad/s, reflecting an outstanding reduction of approximately 95.34%. This demonstrates that the Neuro-Fuzzy-PID not only excels in transient response but also allows for precise tracking of the desired reference following initial disturbances.

Table 4: Wound Rotor Induction Motor Control Performances

Type of controllers	Control metrics			
	Rise Time (s)	Settling time (s)	% Overshoot (%)	Steady-state-Error (rad/s)
PID	0.6150	5.0250	28.40	4.617537
Fuzzy-PID	0.6300	0.7950	19.32	1.595653
Neuro-Fuzzy-PID	0.5250	0.7200	8.96	0.199703

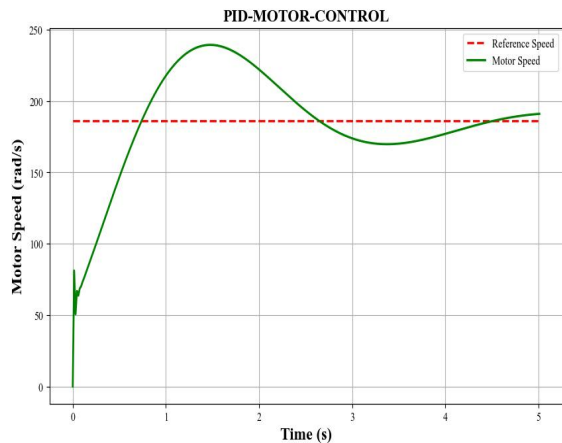


Fig 3: PID Speed Control of Wound-Rotor Induction Motor

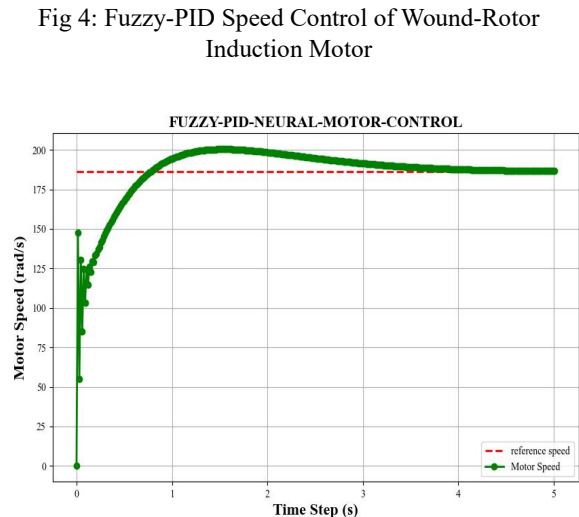


Fig 5: Neuro-Fuzzy-PID Speed Control of Wound-Rotor Induction Motor

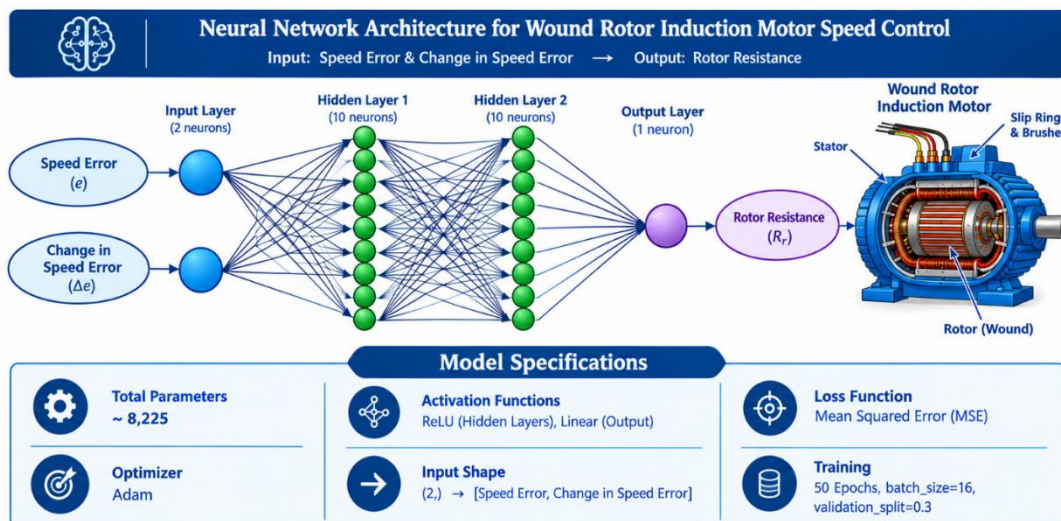
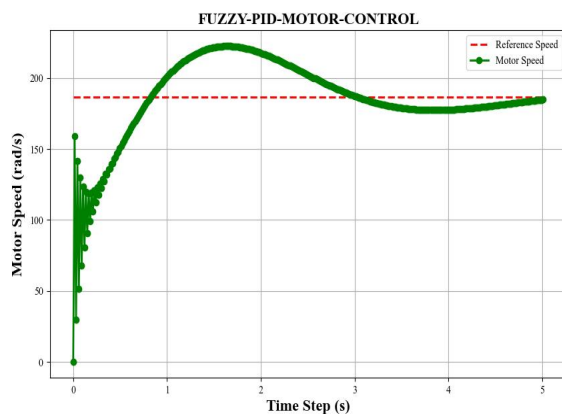


Fig. 6: Neural Network Architecture for Wound Rotor Induction Motor Speed Control

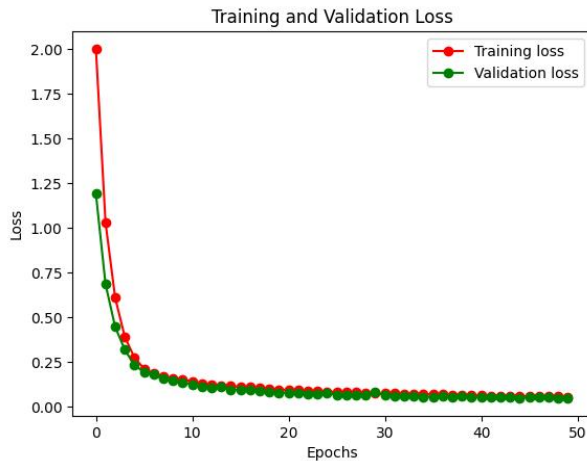


Fig. 7: Training versus Validation Loss of the induction Motor at 50 epochs

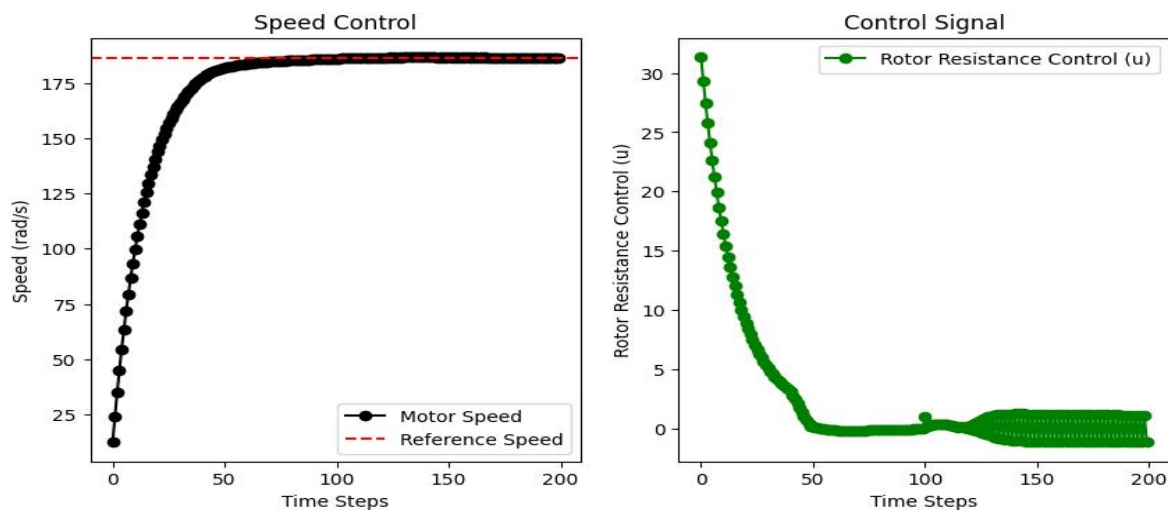


Fig. 8: Neuro-Fuzzy-PID Wound Rotor Induction Motor Speed Control

V. CONCLUSION

A hybrid neuro-fuzzy-PID controller is a technically justified approach for WRIM speed regulation because it combines PID's transparent error-correction structure with fuzzy nonlinear reasoning and neural adaptation. The literature provides direct WRIM evidence for adaptive fuzzy-neuro control and coordinated fuzzy/PID control, while related induction-motor studies provide evidence for self-tuned neuro-fuzzy-PID gains and improved disturbance response.

The particularly large reduction in steady-state error and overshoot suggests that incorporating the neuro-fuzzy mechanism enables the controller to adapt its control action more effectively to the system's nonlinearities and operating conditions. Thus, while the Fuzzy-PID provides acceptable transient control, the Neuro-Fuzzy-PID offers better speed tracking, improved stability, and higher overall control accuracy.

In conclusion, the Neuro-Fuzzy-PID has a fastest rise time, shortest settling time, substantially lowest

overshoot, and dramatically smallest steady-state error thereby having better-performing controller

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