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Original Article

Constraint-Aware Multi-Objective Reinforcement Learning Control for Energy-Efficient Low-Speed Induction Motor Systems

P. Chellammal[1], S. Rajeshwari[2], M. Kavitha[3], Priyanka. L[4], Prerna Dusi[5]

[1]*Department of Computer Science and Engineering, J.J College of Engineering and Technology College, Tiruchirappalli, Tamilnadu, India.*
[2]*Department of Computer Science and Engineering (Cyber Security), J.J College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India.*
[3]*Department of ECE, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamil Nadu, India.*
[4]*Department of Management studies, Easwari Engineering College, Ramapuram, Chennai, Tamil Nadu, India.*
[5]*Department of Computer Science & Information Technology, Kalinga University, Naya Raipur, Chhattisgarh, India.*

[3]*Corresponding Author: kavithaece@ieee.org*

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Abstract - *Low-speed operation of induction motors is a major problem because it induces more nonlinearity in the system, less electromagnetic torque, high inrush current, and poor dynamic operation with standard control methods. Conventional scalar V/f control in combination with PI regulators does not always allow stability and efficiency within this operating range, especially when the load varies.The paper proposes a multi-objective Reinforcement Learning (RL)-controlled control system to enhance the performance of low-speed induction motors. The framework integrates of dq-axis motor dynamic modelling, scalar V/f control, and a controller based on adaptive learning to optimize various performance goals; these are speed tracking accuracy, minimization of currents, as well as control effort. The control formulation has operational current and control-input limits, and the reinforcement learning reward function measures speed tracking error, stator current and control effort.A three-tier control architecture is created to integrate computational intelligence with physical actuation, including inverter-controlled motor control and real-time feedback of the speed and current sensors. Reinforcement learning agent is a dynamically updated control policy in the process of interaction with the system, which allows responding adaptively to disturbances and changes in loads.The framework is tested in closed-loop simulation environment and low-speed and disturbance conditions. The outcome shows that it has transient response improvements, such as less settling time and overshoot, as well as a large decrease in inrush and steady-state current. The proposed approach also demonstrates greater strength and stability when facing different working conditions. The general design is meant to enable future embedded running on DSP, FPGA or edge-AI.*

Keywords - *Induction motor, Reinforcement Learning (RL), Multi-Objective control, V/f control, Low-Speed operation, Energy efficiency, Adaptive control, Intelligent motor drives.*

1. Introduction

Induction motors have wide usage in the industrial and commercial sector because of its strength, inexpensive nature, dependability and minimum maintenance. They play a fundamental role in systems like manufacturing systems, transport, energy conversion systems and in process industries. Although they have advantages, they have a big challenge in establishing stable and efficient operation at low-speed conditions. Low speed results in poor performance, which may include oscillation, slow response to disturbances and high current consumption due to the loss of electromagnetic torque, the sensitivity to disturbances, and the incapacity to regulate the fluxes.The traditional approaches to scalar control, especially V/f control with PI controllers, are very popular, as they are easy and simple to implement. Nevertheless, such techniques have low performance in slow-speed areas, where nonlinear system dynamics and parameter changes are highly pronounced. PI controllers have a poor transient response and a higher steady-state error under changing operating conditions because they are not flexible due to their fixed gain structure. Moreover, start-up and transient currents with high inrush may cause thermal stress, inefficiency and shortened system life.

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To address these shortcomings, intelligent control methods like fuzzy logic and tuning methods are based on optimization. Fuzzy controllers can enhance the nonlinear handling behavior, and optimization methods like particle swarm optimization improve parameter optimization. Nevertheless, they are restricted by a set of preprogrammed rule structures or offline optimization and, as such, cannot adapt dynamically to real-time changes in system behavior.

Reinforcement Learning (RL) has become a strong paradigm of adaptive control of dynamical systems. RL makes systems more adaptive to uncertainty, nonlinearity and time-varying conditions, and also allows them to respond to uncertainty, nonlinearity, and time-varying conditions more efficiently than traditional controllers since they learn optimal control policies by interacting with the environment.

Applied to motor drives, RL gives the opportunity to keep adjusting control actions according to the system feedback, therefore enhancing performance and robustness without making any assumptions about the model. Although this is promising, reinforcement learning has not been used in induction motor control extensively, especially when running at low speeds, when control difficulties are most critical. Current literature usually dwells on the strategies of vector control or single-objective optimization, without considering the joint issues of tracking quality, energy savings and control requirements. In addition, the combination of learning-based control and practical drive architectures, as well as embedded implementation issues, is an unsolved field of research.

This paper suggests a multi-objective reinforcement learning-based control framework of low-speed induction motor systems in order to tackle these problems. In the presented approach, dynamic motor modelling, scalar V/f control, and adaptive learning are combined in a single model. Multi-objective formulation is implemented, and the error of speed tracking, stator current, and control effort are reduced together to provide equal performance in both dynamic and electrical sectors. Furthermore, a design that is aware of constraints is also taken into consideration in order to guarantee safe operation through limited overcurrent and control measures.

The suggested system is also designed based on the layer architecture, which isolates the policy computation, inverter actuation, and sensor feedback.

Such a design is not only more readable and modular, but it is also easy to implement in the future on embedded platforms (DSPs, FPGAs, edge-AI systems) or other platforms that have embedded hardware. The analysis of the framework is conducted on a multitude of simulation environment which recreates the realistic operating conditions, such as low-speed operation, variations in loads and disturbances.

The key contributions of the work can be summarised in the following way:

- Creation of a multi-objective reinforcement learning algorithm in low-speed, low-voltage induction motor control.
- Combination of RL and scalar V/f control to be used in an adaptive and efficient mode.
- Integration of constraint-based reward generation of safe and energy efficient performance.
- Architecture of a hardware-based control architecture to be embedded.
- Full assessment at low-speed, disturbance and load fluctuation conditions.

The rest of the paper is presented in the following way. Section 2 is a review of literature. In section 3, the system modelling and control methodology is presented. Section 4 outlines the arrangement of the simulation. Section 5 is on the results, and Section 6 is the conclusion of the paper.

2. Related Works

The traditional approach to low-speed control of induction motors is the use of scalar V/f-based strategies with PI controllers [1]. The two approaches are easy and work well in nominal conditions, but they are not stable and not effective at low speeds because of the restrictions in flux regulation and dynamic response [6]. These challenges have also been further emphasized in more advanced modelling and analysis of electrical machines, especially in low-speed regimes [16]. There is also a lot of research on classical drive control methodologies in the field of electrical drive systems, in which better control methods are required [18].

The use of nonlinear control has also been suggested using fuzzy logic controllers to improve the performance of the system [30]. Adaptive Neuro-Fuzzy systems also enhance the accuracy of control by integrating learning processes in fuzzy systems [8]. The use of intelligent control techniques such as neural network techniques has been shown to do better in motor drive systems [4]. The recent research has also discussed multi-physics optimization and advanced motor design techniques in order to enhance the performance and efficiency [3]. Also, control algorithms that are energy efficient have been studied in order to resolve the performance constraints in different load conditions [12]. Particle swarm optimization is an optimization-based technique that has been extensively applied in tuning the parameters of controllers to enhance response properties [9]. The performance trade-offs in control systems have also been used to determine the balance of weighting techniques using multi-objective optimization techniques such as NSGA-II [2]. Such optimization tools have been used in renewable integration and energy systems to maximise efficiency and stability of a system [14, 20].

In the optimisation-based system design, additional work has been carried out by extending it to multiport converters and integrated energy systems [10], bio-inspired optimization has also been used in sustainable system design [15]. Even though these are being made better, the methods are still rigid and cannot keep pace with the actual changes of the system in real-time. The latest developments in Artificial Intelligence have proposed learning-controlled approaches that can solve nonlinearity and uncertainty in systems [5]. Reinforcement learning has become one of the promising studies in adaptive control where systems can learn optimal policies after interacting with ever-changing environments [23]. Reinforcement learning-based control surveys indicate that it can be applied to operate autonomously and optimally in a system [11]. These capabilities have been extended to power electronics and energy system complex control problems with deep reinforcement learning [13]. Further studies have been devoted to the enhancement of policy learning methods to be used in continuous control applications [19].

Learning-based optimization and adaptive control schemes of energy systems and distributed infrastructures have also been studied recently [27, 28]. Such methodologies have been used with smart grids, IoT-based systems and edge intelligence frameworks to enhance efficiency and scalability [17, 26]. It is also possible to develop advanced control strategies that combine predictive control and model-based techniques to be used in the applications of power electronics [22]. Moreover, reinforcement learning and smart control methods have been used in new applications to smart charging infrastructure and energy management systems [24, 25]. In already existing studies, it has been confirmed that adaptive and data-driven control is gaining importance in intelligent electromechanical systems [24, 25].

Nonetheless, the literature so far is constrained in one of three aspects: either they are purely classical scalar or vector controllers without adaptive intelligence [1, 6], tuning is done using either fuzzy or optimization-based means without improving the policy on-the-fly [8, 9], or they use methods based on learning without expressly considering the low-speed operation, the existing constraints and multi-objective performance trade-offs [11, 13]. Specifically, the low-speed induction motor control is not actively researched in terms of the combined optimization of tracking, electrical stress, and robustness during dynamic loads [22, 27]. Thus, there is an obvious gap in research on a constraint-aware and multi-objective learning-based control structure that is capable of modifying control responses in real-time, maintaining safe motor operation and enhancing dynamic and electrical performance.

3. Methodology and System Modeling

3.1. Induction Motor Dynamic Model

The induction motor can be modelled in the dq reference frame by the following equations:

$$\frac{di_d}{dt} = \frac{1}{L_s}(v_d - R_s i_d + \omega L_s i_q)$$

$$\frac{di_q}{dt} = \frac{1}{L_s}\left(v_q - R_s i_q - \omega L_s i_d\right)$$

The dq-axis representation allows the expression of three-phase quantities in a two-axis rotating reference frame, which makes it easier to analyse the electromagnetic interactions in the motor. The formulation is an appropriate description of the interdependence between the stator currents and the rotor speed, especially when one needs to obtain insights into the transient behavior at low-speed conditions.

The electromagnetic torque has the following form:

$$T_e = \frac{3}{2} P \frac{L_m}{L_r}\left(i_d i_q\right)$$

This expression of torque is an expression of the interaction between flux-producing current flows and torque-producing current flows. This reliance on mutual inductance and rotor inductance points out the importance of mutual inductance on torque production, which is particularly severe in low-speed operation when flux regulation becomes particularly sensitive.

The mechanical equations can be given as:

$$J\frac{d\omega_m}{dt} = T_e - T_L - B\omega_m$$

The mechanical equation reflects the balance between the electromagnetic torque, load torque and the frictional losses. Inertia term controls the rate of change of rotor speed, whereas the damping coefficient takes into consideration the mechanical losses. The equation is used to analyse stability of systems and transient response when the load changes. These equations characterize the plant dynamics to which the proposed controller is to be applied. The dq-axis model that is applied to the current study serves not only to model the motor behaviour, but it also yields the state trajectories that are needed for control learning and performance appraisal. This allows the controller to react to electrical and mechanical changes in a similar way, especially when at low-speed transients when the coupling effect between current, torque, and rotor speed are predominant.

The entire control system incorporates motor model, controller and the feedback loop as in Figure 1. The architecture is of closed-loop design where the reinforcement learning controller creates control actions according to the system states, which are converted to voltage and frequency commands by V/f control block. These control commands are used in the inverter, which operates the motor. The feedback signals (speed and current) are continuously checked and utilized to revise the control policy to allow adaptive and real-

time optimization of the system. Figure 2 shows the equivalent circuit model used to model the circuit. This circuit is a physical interpretation of the motor parameters: the stator resistance, the rotor resistance, and the magnetizing inductance.

It is used as a parametric identification model and for validation of the dynamic equations. Current flow and voltage distribution can be examined as well using the equivalent circuit, and this is needed to assess the electrical performance and energy efficiency.

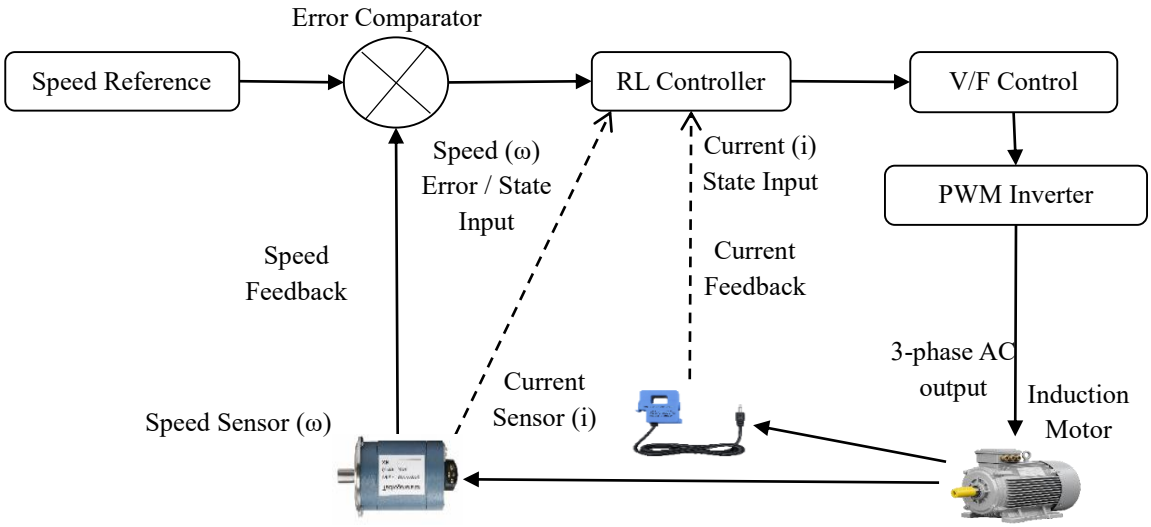

Fig. 1 Overall control architecture

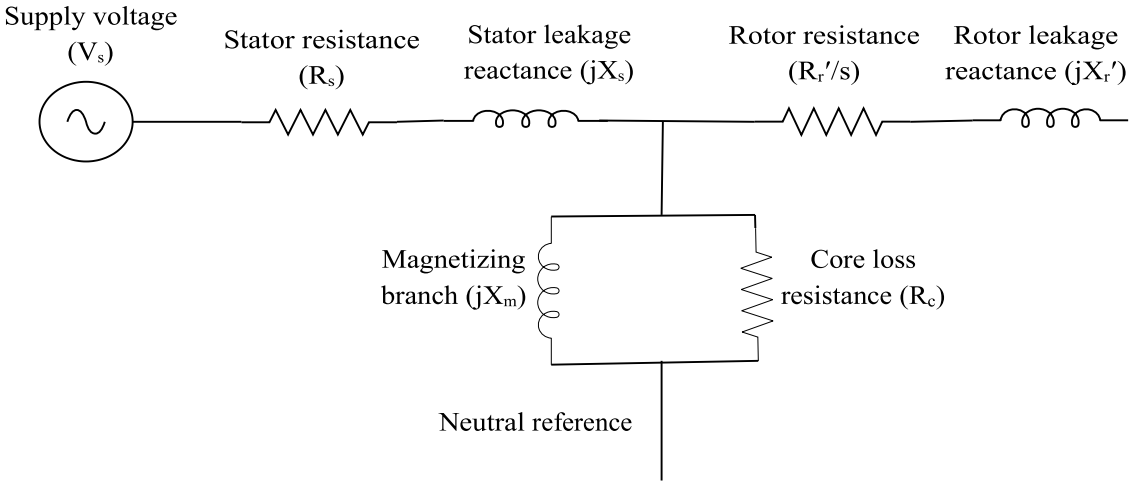

Fig. 2 Induction motor equivalent circuit

3.2. Multi-Objective Control Formulation

The control goal is developed into a multi-objective costing function that reflects the main performance needs of low-speed induction motor operation through tracking accuracy, current regulation, and control smoothness. The objective function can be defined as follows:

$$J = w_1 \int_0^T | e(t) | \, dt + w_2 \int_0^T i_s^2(t)\, dt + w_3 \int_0^T u^2(t)\, dt$$

Where, $e(t) = \omega^*(t) - \omega(t)$is the speed tracking error , $i_s(t)$is the stator current, $u(t)$represents the control input (voltage-frequency command), $w_1, w_2, w_3$are positive weighting coefficients.

This multi-objective formulation provides the ability to optimize dynamic and electrical performance criteria at the same time. The former reduces the tracking error to the lowest possible, which means that the speed is correctly regulated even in the low-speed regime where system nonlinearity is very visible. The second term penalizes excessive stator current, and so less energy is used, and copper and thermal stress to the motor are reduced. The third term constrains the control effort and encourages smoother actuation and eliminates sudden changes in voltage and frequency, which

can be detrimental to the stability of the system. The control formulation includes current and control limits to make sure that the control can be operated safely under realistic conditions. The following operational constraints are subject to the system:

$$i_s(t) \le i_{\max}, u_{\min} \le u(t) \le u_{\max}$$

The constraints are added to the learning framework as a penalty-based formulation, which is added to the objective function to punish constraint violations.

The adjusted cost can be modelled as:

$$J_c = J + \lambda \cdot \max(0, i_s(t) - i_{\max})^2$$

In which λ is a penalty factor that defines how strict the constraint enforcement will be. This formulation allows the controller to work within safe boundaries even though the controller is able to maximize performance goals, so there is a balance between efficiency and reliability. Weighting coefficients w_1, w_2, w_3 give the flexibility of giving priority to the various control objectives depending on the application needs. An example is that when w_1 is larger, the accuracy of tracking is emphasized, whereas as w_2 increases, the device is able to operate with less energy. This flexibility enables the given framework to be adapted to different industrial situations.

The reinforcement learning reward functionality is based on the concept of multi-objective formulation, which directs the controller to optimal decision-making by the continuous interaction with the system. The controller can obtain a global optimization by combining several performance measures into one objective as opposed to concentrating on one measure only. Section 3.1 dq-axis motor model gives the dynamics of the underlying system that are used to compute the cost function and produce state trajectories to learn. This integrated representation allows the controller to take into consideration the electrical as well as mechanical dynamics, which is especially important when operating at low speed where there is a strong interaction between current, torque and rotor speed.

3.3. Reinforcement Learning-based Controller

The reinforcement learning-based controller is designed to choose the voltage frequency adjustments based on the operating conditions of the induction motor.

The state vector is given as:

$$s_t = [e(t), \Delta e(t), \omega_m(t)]$$

where $e(t)$ is the speed tracking error, $\Delta e(t)$ is the change in error between successive sampling instants, and $\omega_m(t)$ is the measured rotor speed. These variables characterize the operating state at a particular moment and its dynamic change.

The reward functional is defined as:

$$R_t = -[\alpha|e(t)| + \beta i_s^2(t) + \gamma u^2(t)]$$

Where α,β and γ are weighting coefficients, $i_s(t)$ is the stator current, and u(t) represents the control input. Speed tracking error, current magnitude, and control effort are all included in the reward function as a single objective. The negative sign gives greater reward to those actions that are related to lower operating costs, which gives a platform on which to balance tracking performance and current demand.

Algorithm 1. Adaptive multi-objective learning control

1. Initialize the control policy.
2. Measure the motor speed and calculate the tracking error.
3. Construct the state vector.
4. Select a control action from the available actions.
5. Apply the selected adjustment through the V/f control module.
6. Observe the motor response and determine the next state.
7. Calculate the reward.
8. Update the action-value function and control policy.
9. Repeat the procedure at the next sampling instant.

The control framework assumes a limited number of variable voltage frequency changes. The action-value function is the anticipated cumulative reward in choosing a specific action in a specific state. The Q-learning update relation can be represented as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta \left[R_t + \gamma_d \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right]$$

Where η is the learning rate, γ_d is the discount factor, a t is the action chosen, and s_{t+1} is the next state.

To balance between exploration and exploitation in the learning process, an ϵ-greedy strategy can be used.

The controller is an iterative process where the motor condition is monitored, an action is chosen, and the observed reaction is assessed by means of the reward function. This

model characterizes the action-value learning principle, which is the basis of the proposed control framework without defining an untested neural-network implementation. The fact that it is formulated with multiple objectives enables the simultaneous consideration of the accuracy, stator current and control effort when estimating the control actions.

3.4. Hardware-Oriented System Integration

Figure 3 is the inverter that transforms the DC input into controlled AC output. It comprises switching elements like either IGBTs or MOSFETs configured in a three-phase bridge structure. Pulse-Width Modulation (PWM) is a method to produce both variable voltage and frequency signals using control inputs. The inverter is a very important part that converts the decisions made by the controller into an actual actuation in order to have the exact control of the speed and torque of the motor. Figure 4 presents the integrated system comprising the controller, inverter and motor. This topology brings to the foreplay the interplay between computational and physical units. The controller takes the feedback signals and compares them to convert them into control commands, whereas the inverter and motor act on the control commands. Sensors are used to give real-time measurements of current and speed that will ensure accurate feedback in updating the controls. The system supports real-time operation and has low latency, and hence it can be embedded by the industry applications.

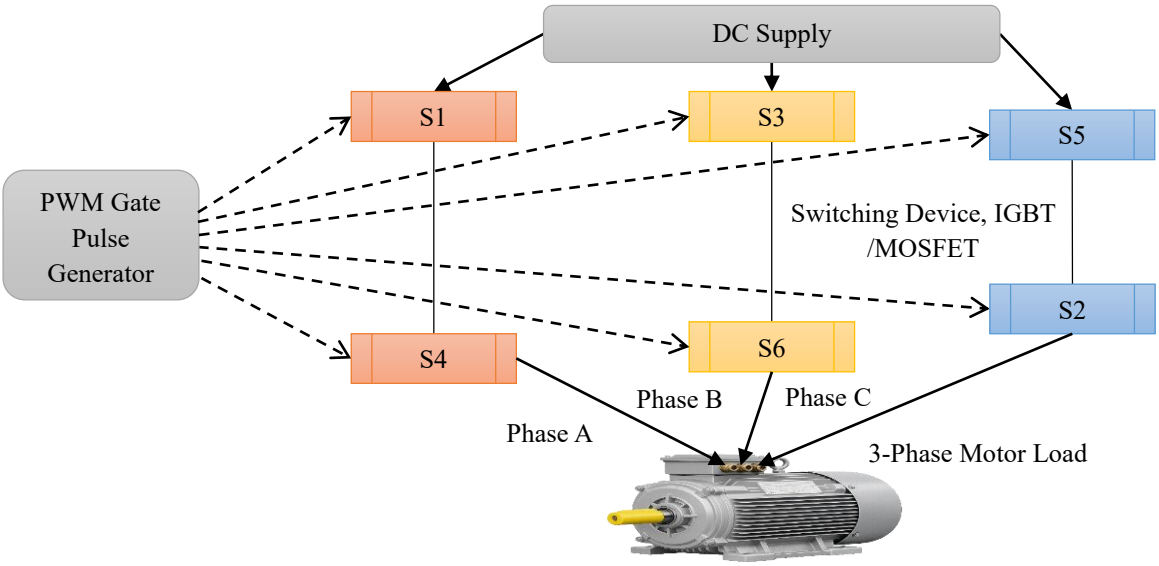

Fig. 3 Three-Phase PWM inverter circuit

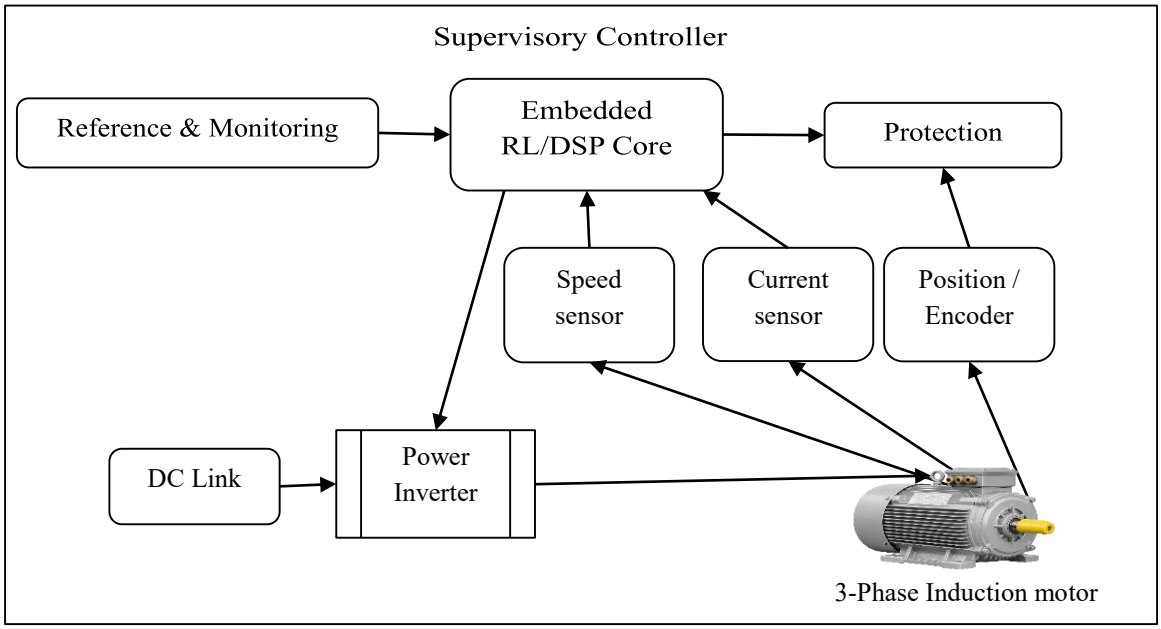

Fig. 4 Integrated motor drive system

Despite the fact that the current research is on development of controls and closed-loop analysis, the architecture of the system has been designed in a way that facilitates eventual embedded implementation. Especially, the decoupling of policy computation, inverter actuation, and sensor feedback in the proposed framework ensures that the proposed framework is compatible with controller implementation on a DSP, FPGA, or edge-AI platform to run real-time industrial motor drive applications.

4. Simulation Setup

The proposed control framework is tested with the closed-loop simulation model consisting of the induction motor, inverter, scalar V/f control module, and reinforcement learning-based controller. The simulation will use the electrical and mechanical dynamics of the motor to analyze the response of the motor during transient response, steady-state operation, and disturbance rejection in various operating conditions. The electrical characteristics of the motor given in Table 1 are used to parameterize the motor model. To compare the PI control strategy, the fuzzy control strategy, and proposed control strategy, the three-phase, 1.5 kW induction motor is taken into consideration. The simulation architecture isolates the computation of policy, actuation of inverter, and feedback provided by sensors, offering a modular architecture that can be extended to DSP, FPGA or embedded control platform in the future.

Table 1. Induction motor parameters

Parameter	Value
Rated Power	1.5 kW
Stator Resistance	1.2 Ω
Rotor Resistance	1.0 Ω
Inductance	0.15 H
Poles	4

The parameters of Table 1 determine the nature of electrical response, the production of torque and speed of the induction motor. The controller is fed with the reference speed and the measured rotor speed is the one that is used to establish the tracking error. The reinforcement learning-based controller uses the V/f control module to choose voltage-frequency adjustments, based on the observed motor state. These commands are then translated into three-phase voltage signals by the inverter, which are fed to the motor. The control process is modeled with the help of discrete sampling points.

The analysis takes into account the low-speed operation, load changes, and external disturbances. Special focus is on speeds less than 20 % of rated speed, where traditional control techniques can be characterized by lower tracking accuracy and sensitivity to load variation. The sudden change of load torque and reference speed is taken into consideration to investigate the stability of the proposed controller in light of the transient response and disturbance rejection.

The settling time, overshoot, steady-state error, Integral Absolute Error (IAE), and Integral Time-Weighted Absolute Error (ITAE) are used to compare the performance of the PI and fuzzy controllers and the proposed controller. The inrush current and RMS current are also used for the comparison. These signals can serve as a foundation to assess dynamical response and electrical performance. The comparisons reported pertain to the simulated responses; neither statistical repeatability nor independent reproducibility can be determined without the full simulation settings and repeated-run data.

Figure 5 demonstrates the closed-loop simulation model where the reinforcement learning agent, V/f module, inverter, induction motor model, evaluation of reward, and feedback mechanism interrelate with each other.

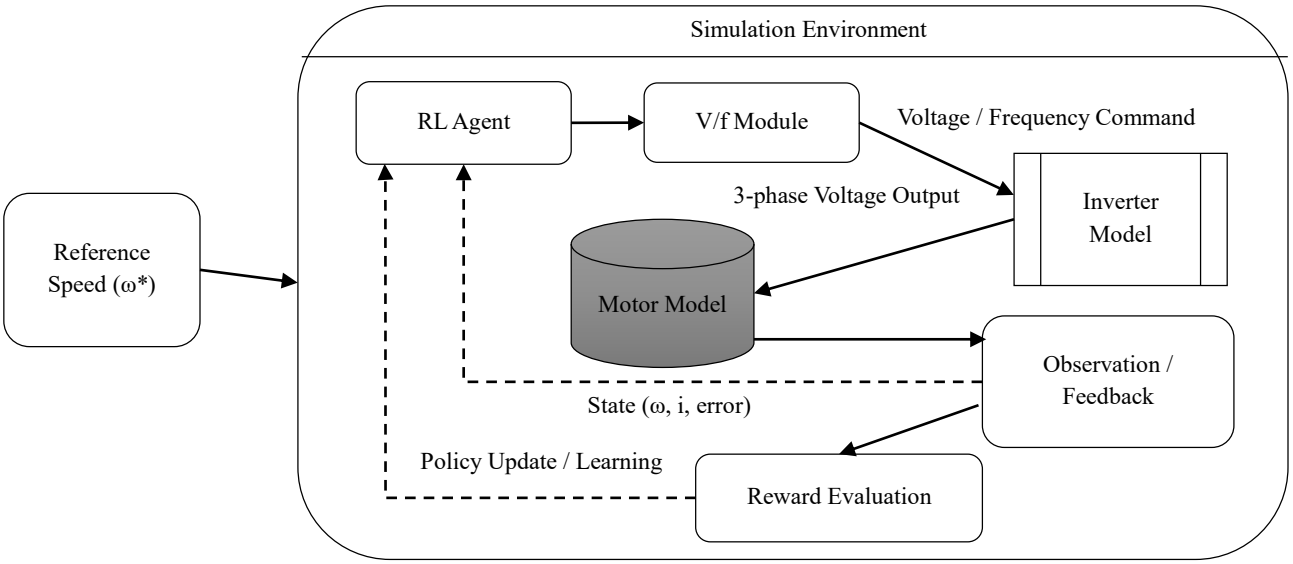

Fig. 5 Simulation framework block diagram

5. Results and Discussion

5.1. Dynamic Performance

The proposed method has faster settling time and lower overshoot, as demonstrated in Figure 6. Dynamic response of the system is considered under the same condition of operations of all three control strategies to ensure a fair comparison. The PI controller has a slow convergence with pronounced oscillations prior to reaching the steady state, especially at low-speed areas where the nonlinearity of the system is more evident. The fuzzy controller enhances the response, as it minimizes oscillations and increases the rate of convergence, but it still has a medium overshoot and a longer settling time than the proposed methodology. Contrastingly, the suggested adaptive learning-based controller exhibits a much better transient response in terms of rapid convergence, low overshoot, and steady-state stabilization. This has been enhanced by the fact that the controller can dynamically restructure control actions in response to real-time system feedback to be able to track the reference speed more accurately. The damping and stability of the system are also reflected by the decrease in oscillatory behaviour.

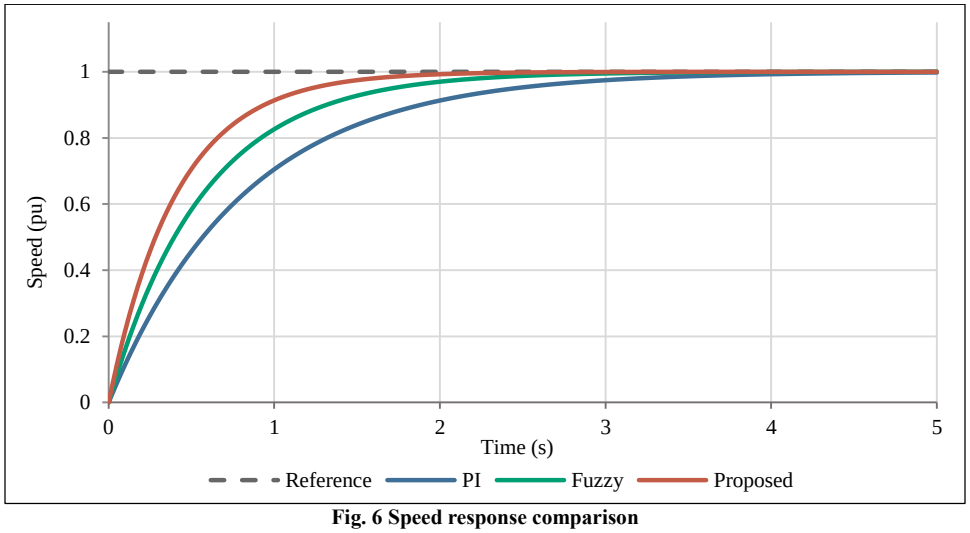

Fig. 6 Speed response comparison

Table 2. Performance comparison

Metric	PI	Fuzzy	Proposed
Settling Time (s)	3.5	2.8	2.1
Overshoot (%)	12	8	3
Steady Error	0.05	0.02	0.005

The proposed method has a settling time that is about 40 % lower than that of the PI controller and about 25 % lower than the fuzzy controller (see Table 2). The transient stability is greatly reduced and the chances of system stress during changes are minimized by the fact that the overshoot is greatly reduced. Moreover, steady-state error is minimized to almost zero levels, which proves great accuracy in tracking speed. The results of these experiments support the idea that the suggested control framework is effective in improving transient and steady states.

Table 3. Integral error performance metrics

Metric	PI	Fuzzy	Proposed
IAE	1.85	1.32	0.78
ITAE	4.60	3.10	1.95

In order to give a more detailed dynamic analysis, the Integral Absolute Error (IAE) and the Integral Time-Weighted Absolute Error (ITAE) were considered in all the control strategies. These measures are used to measure the cumulative tracking error as a function of time and focus on the transient and steady-state performance. The results of Table 3 show that the proposed controller offers much lower values of IAE and ITAE than PI and fuzzy controllers.The PI controller has the greatest error accumulation as it converges very slowly and oscillates, whereas the fuzzy controller has moderate improvement.

Conversely, the presented reinforcement learning-based controller shows the lowest error indices, which means that it has better trajectory tracking and quicker stabilization. The fact that ITAE decreased further supports that the given technique reduces the long-duration errors, resulting in higher quality of the entire control process within the whole range of responses.

5.2. Electrical Performance

Figure 7 compares the stator current response of PI, fuzzy and proposed reinforcement learning-based controllers. The PI controller has more inrush current during startup and can cause electrical and thermal stress. The fuzzy controller offers an intermediate decrease in start-up current, but there are still fluctuations. Comparatively, the proposed controller exhibits a smaller current peak and a smoother response, which indicates better current control when operating in transient mode. The proposed controller also has lower RMS current as

compared to the conventional controllers. This decrease implies that current regulation is better and there is a potential for lower resistive losses in similar operating conditions. The proposed controller minimizes the inrush current to 8 A, as shown in Table 4, whereas the PI controller minimizes inrush current to 12 A and the fuzzy controller minimizes inrush current to 10 A. These values are approximately 33.3% and 20% reductions, respectively. Equally, the RMS current drops to 4.8 A, equivalent to the 20% and 12.7% reductions over the PI controller and fuzzy controller, respectively. These findings indicate enhanced current regulation in both the startup and steady-state.

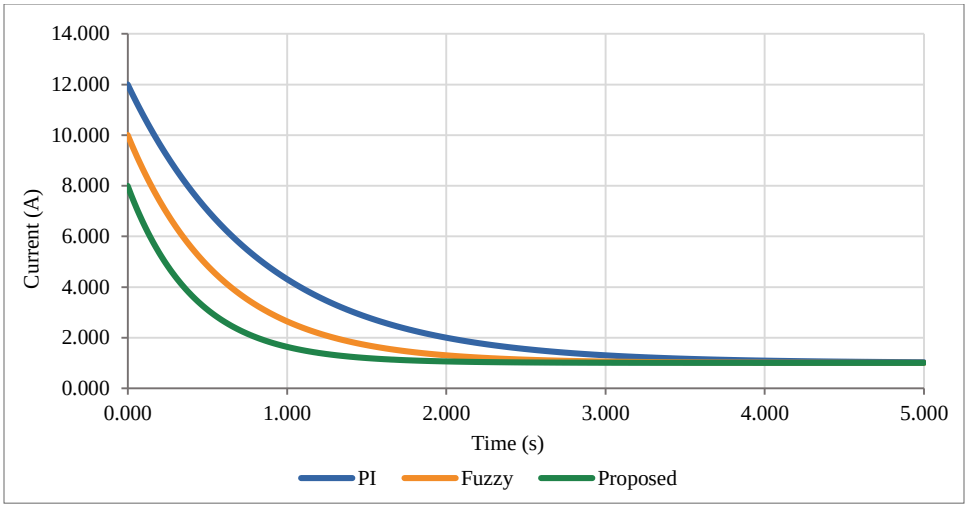

Fig. 7 Current profile

Table 4. Electrical metrics

Metric	PI	Fuzzy	Proposed
Inrush Current (A)	12	10	8
RMS Current (A)	6	5.5	4.8

The reduction in RMS current could help to reduce stator copper losses, since resistive losses are directly proportional to the square of the current under comparable operating conditions. Reduced inrush current can also help to minimize thermal stress on startup. Nonetheless, the supplied current measurements do not prove an increase in the overall motor efficiency. To measure energy savings, direct measurement of either input power, output power, or total energy losses would be necessary. Thus, the outcomes justify enhanced electrical operation and show that there are possible gains in energy-efficient low-speed operation of induction motors.

5.3. Robustness Analysis

At low speeds, the system is stable as indicated in Figure 8. Slow operation is intrinsically problematic because there is reduced electromagnetic torque as well as greater susceptibility to disruptions. At these conditions, the PI controller is unstable and experiences high oscillations renditions and is therefore inappropriate to be operated with a lot of reliability. The fuzzy controller enhances stability but continues to have moderate variations in circumstances of varying loads.The proposed control structure exhibits very strong performance since it can operate at a lower rate of under 10 percent of the rated value without its operation being affected. The controller is adaptive in nature and, therefore, capable of reacting to the disturbances and providing stable performance. The system reaches its stable state fast, and this implies that it can reject disturbances very well.

This fortification enhancement is mainly because of the adjustable policy update mechanism, which allows the controller to react to the variations in the operating conditions, without the need to adhere to the fixed tuning regulations.

In contrast to PI and fuzzy controllers, where the effectiveness of the controller is determined by the constituted goals of the gains or the definition of the membership, the proposed learning-based controller changes its decision policy based on observed system behaviour, thus maintaining stability with a wider scope of operating range.

Table 5. Robustness evaluation

Condition	PI	Fuzzy	Proposed
Low Speed Stability	Poor	Moderate	Stable
Load Disturbance	Unstable	Stable	Highly Stable

According to the results summarized in Table 5, the suggested approach is more robust than PI and fuzzy controllers. The stability in the low-speed and load disturbance conditions demonstrates the usefulness of the adaptive control strategy. The proposed controller alleviates instability in addition to being capable of quickly recovering after a disturbance hence, it can be used in a real-life setting in which the conditions under which it operates are dynamic and unpredictable.

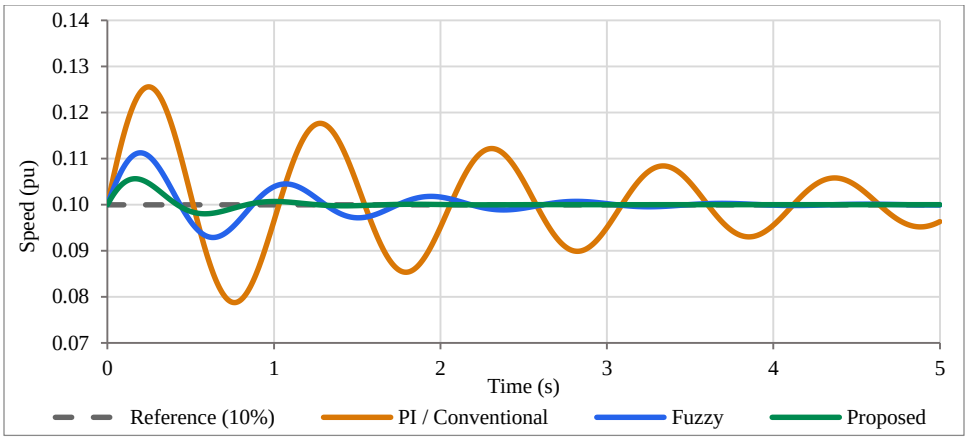

Fig. 8 Low-Speed stability

6. Conclusion

In this paper, a constraint-sensitive multi-objective reinforcement learning control of low-speed induction motors has been introduced. The suggested solution incorporates dynamic modelling of motor, adaptive learning-based control and multi-objective optimization to overcome the constraints of conventional PI and fuzzy controllers in low-speed operating regions. The framework will reach an efficient and balanced control strategy by minimizing tracking error, current consumption, and control effort simultaneously. The primary merit of the work is the combination of the multi-objective design of control and the reinforcement learning of its use in the case of low-speed induction motors with operation under constraints. This combination goes beyond the traditional tuning-based enhancements and creates an adaptive decision mechanism that has the ability to trade performance, efficiency, and robustness in one framework. Consequently, the research provides not only a methodological improvement of intelligent motor control but also a verifiable foundation for subsequent embedded implementation. This evidence shows that the given technique can contribute greatly to the dynamic performance, reaching shorter settling time, lowering overshoot and almost zero steady-state error. The proposed controller has lower inrush and RMS current than the PI and fuzzy controllers, which means that it can regulate the current better and resistive losses can be reduced. However, direct measurements of power and loss must be made to determine improvements in the overall motor efficiency. The robustness analysis also confirms stable operation at low speeds and under load disturbances, high adaptability and disturbance rejection ability.

This is because learning-based control together with constraint-aware design can make the system dynamically adapt to the changing operating conditions without compromising on safe and efficient operation. This renders the suggested framework applicable in contemporary smart motor drive systems that need high performance and dependability. Further efforts on the framework will mend towards real-time software-to-hardware implementation, embedded and FPGA-based platforms and further optimization of the learning strategy to enhance convergence and computational efficiency. There is also the introduction of advanced predictive and hybrid control methods, which can also develop the performance and scalability of the system to use in industries.

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