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Intelligent control of three-phase induction motor drives using deep reinforcement learning and multi-objective particle swarm optimization for sustainable electrified systems

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Abstract

This study proposes an intelligent control framework that integrates deep reinforcement learning (DRL) and multi-objective particle swarm optimization (MOPSO) to enhance the dynamic performance, energy efficiency, and robustness of three-phase asynchronous motor drives applied in sustainable electrification systems. The proposed framework integrates a DRL agent with an MOPSO optimizer within an adaptive control architecture. The DRL controller learns optimal control policies through continuous interaction with the motor drive system, while MOPSO simultaneously optimizes multiple conflicting objectives, including torque ripple minimization, total harmonic distortion (THD) reduction, speed-tracking accuracy improvement, and energy-efficiency enhancement. The controller is evaluated using a high-fidelity MATLAB/Simulink induction motor model under load disturbances, parameter variations, and stochastic uncertainties. Simulation results demonstrate torque ripple reductions of 25–30% compared with conventional Field-Oriented Control (FOC) and Direct Torque Control (DTC). THD decreases from 6.8% (DTC) and 4.1% (FOC) to approximately 1.9%, while speed-response settling time is reduced to 0.12 s with less than 4% overshoot. Drive efficiency improves by 8–12%, and performance deviations remain below 5% under uncertain operating conditions. The proposed DRL–MOPSO framework significantly outperforms conventional control methods in terms of efficiency, dynamic response, and robustness. The framework offers a viable intelligent control solution for electric vehicles, industrial automation, and renewable-energy-powered drive systems, supporting sustainable and reliable electrified applications.

Keywords: Deep reinforcement learning, Intelligent motor control, Multi-objective particle swarm optimization, Sustainable electrified systems, Three-phase induction motor drives, Torque ripple and harmonic reduction.

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Contribution of this paper to the literature
This study introduces a novel hybrid DRL–MOPSO control framework that combines real-time reinforcement learning, multi-objective optimization, and uncertainty-aware adaptive control for three-phase induction motor drives. Unlike existing FOC, DTC, or standalone DRL approaches, it simultaneously minimizes torque ripple and THD while maximizing efficiency and dynamic performance.

1. Introduction

Three-phase induction motor drives are still among the most widely used electromechanical systems in industrial automation, transportation and energy fields, owing to their native robustness, low cost and low maintenance. Such machines are based on electromagnetic induction, so they do not require brushes or a direct electrical connection to the rotor, which gives them high operational reliability and mechanical durability. Its robust construction along with their high efficiency and scalable solutions have paved the way as a favorable choice in applications like pumps, compressors, electric vehicles and renewable energy conversion systems. As the world is moving towards sustainable electrification, induction motor drives are becoming an integral part of smart grids [1], electric mobility platforms [2], and advanced manufacturing systems where efficiency, flexibility and reliability matter [3]. Control of induction motor drives has come a long way in the last few decades and classical strategies like scalar control, field-oriented control (FOC), and direct-torque-control (DTC) have formed the basis for modern drive systems. Despite its popularity based on concept and easy implementation, scalar control (commonly referred to as V/f control) provides relatively poor dynamic performance and low accuracy in operation due to lack of torque and flux decoupling [4]. To overcome these limitations, FOC was proposed as a vector control method, which converts stator currents into a rotating reference frame for independent torque and flux control. This decoupling leads to a large improvement in dynamic response, efficiency, and steady-state accuracy, thus FOC is one of the most used techniques for high-performance applications [5]. In like manner, DTC presents a more direct method to regulate torque and flux since it does not entail the transformation of coordinates or current regulator as in vector control, resulting [6]. However, DTC does confer high torque ripples and non-constant switching frequency, which can increase the subsequent losses and generate mechanical stress. While these conventional control strategies have been implemented with great success, they suffer from several limitations in real-world operating conditions. Induction motor drives inherently possess nonlinear structures and the parameters of the model are prone to variations due to temperature changes, magnetic saturation, external disturbances (load), and aging effects. Take for instance FOC: it highly depends on the accurate estimation of the motor parameters (especially rotor resistance), which is generally time variant in full operating, and may significantly degrade control performance if not compensated properly [7]. After the same vein, DTC has an evident torque ripple and flux ripple, which can result in instability of mechanical wear, noise problems and accelerated wear of components [8]. This situation paved the way to solve highly non-linear system with consideration of uncertainty by applying advanced control strategies. In order to circumvent these constraints, intelligent control techniques utilizing artificial intelligence and computational intelligence methods have been explored extensively in research. Fuzzy logic controllers (FLCs) have been extensively applied [9] to enhance the dynamic performance and mitigate torque ripple by using heuristic knowledge and linguistic rules in the control method. Artificial neural networks (ANN) have also been used and have shown better adaptability than traditional methods for parameter estimation, fault detection and sensorless control [10]. These methods improve the performance under uncertain conditions, but usually involve a significant amount of tuning and do not guarantee global optimality. Simultaneously, evolutionary optimization approaches like particle swarm optimization (PSO) have been done to optimize controller parameters in order to enhance the performance of a system. Many PSO-based methods have been developed to optimize speed tracking accuracy, torque control and efficiency by searching optimal parameter sets over very complex solution spaces [11, 12]. This is true even though these optimization techniques, while efficient in practice, are usually performed offline and cannot be used easily to follow online operating conditions. Recent advances in deep learning and reinforcement learning (RL) have led to new paradigms of motor control by artificial intelligence; Unlike conventional model-based approaches, RL is a promising approach that allows systems to learn optimal control policies through interaction with the environment without requiring explicit and accurate mathematical models [13]. Deep reinforcement learning (DRL) is a mix between RL and deep neural networks, which has achieved significant success in dealing with high-dimensional, non-linear, uncertain systems [14, 15]. In the and has attracted clearer attention of many researchers including this context, DRL-based controllers have shown better adaptability to Last decade as a potential solution for next-generation intelligent than traditional techniques due to their learning capabilities. This systems in induction motor drives [16]. In summary, evolution from traditional control techniques towards intelligent data-driven approaches manifests the increasing demand for adaptive, effective and resilient control strategies in modern electrified systems. Despite a lot of progress being achieved in this area, combining various advanced AI techniques into multi-objective optimization is still an open research direction that has motivated the design of hybrid frameworks such as the DRL–MOPSO approach proposed in this work.

However, even after nearly three decades of progress in control theory and power electronics, it is still a largely open problem to achieve high-performance, robust full state feedback (closed loop) control of three-phase induction motor drives against realistic disturbances. The main challenge is to design an efficient multi-objective performance optimization controller which aims to minimize on some often-conflicting objectives: torque ripple, dynamic response, energy efficiency, harmonic distortion, while maintaining stability against non-linearities and uncertainties. Conventional control strategies can meet these conflicts, but only in very regulated conditions and without integration capabilities that would adaptively blend conflicting requirements. A significant challenge is related to the fact that motor drive control is a multi-objective problem. Aggressive control action is usually required, allowing improving transient response and speed tracking but potentially increasing torque ripple and switching losses. On the other hand, to eliminate torque ripple and harmonic distortion the dynamic response slow down a lot. However, conventional controllers formulated variant being FOC and DTC are usually designed with a fixed or weighted objective function, so tuning parameters in the controller may be sub-optimal for a given operating condition [17, 18]. Yet these weighting factors are not overall optimal, hence they drive the system to suboptimal conditions with changing circumstances. This restriction emphasizes the importance of developing adaptive multi-objective optimization frameworks that can dynamically trade-off between conflicting performance metrics. The other major challenge is the non-linear and time varying nature of induction motor systems. Parameter variations (the rotor resistance, stator inductance and magnetic saturation) significantly affect the dynamic performance of such drives and these parameters vary in operation conditions due to impact of temperature changes, load disturbances and aging effects [19]. This leads to considerable modeling uncertainty, which deteriorates the characteristics of model-based control. An instance of this is field-oriented control which relies on precise flux estimation whose accuracy can quickly deteriorate under parameter mismatch conditions from nominal values [20]. In a similar step design, Direct torque control is able to provide fast response, however because of the hysteresis-based switching mechanism also suffers from inherent torque ripple and flux"-oscillation [21]. These challenges have a substantial negative effect on the efficiency, mechanical integrity and general accuracy of controls associated with the system design. These challenges are exacerbated with the integration of induction motor drives into contemporary electrified systems, including electric vehicles, smart grids and renewable energy systems. Such applications employ controllers which should be able to operate with mathematical models changing at a very fast pace including huge variations of loads, supply voltages and environmental disturbances. When forces are non-linear like this, conventional control strategies will not keep a constant performance making the system less efficient and ultimately leading to losses and instability [22]. If we encounter the resistance of intelligent control like fuzzy logic or artificial neural network raise the issue adaptability in that it so lame. Fuzzy logic controllers are based on rules that are defined by experts and may not generalize well over diverse operating conditions [23]. Approaches based on neural networks can model nonlinear dynamics, but demand sufficient training data and are prone to problems such as overfitting and interpretability [24]. Moreover, these methods usually target particular components of the control and do not offer a holistic solution to multi-objective optimization (MOO). Optimizing algorithms, especially particle swarm optimization PSO has been used broadly in altering controller parameters to reduce the cost function [25]. Although it is an established global minimum finder algorithm, PSO is mainly used in offline optimization configurations which makes it difficult to implement real-time adaptation of system variations. Most MO algorithms, such as the Multi-objective Particle Swarm Optimizer (MOPSO), are able to handle conflicting objectives better than their single-objective counterparts [26], but there are not many implementations of adaptive control mechanisms with multi-objective approaches. Reinforcement learning (RL) has recently affected both model-free and adaptive control [1]. Reinforcement learning (RL) based controllers can learn optimal control policies by interacting with the target system, which allows them to adapt their actions to new conditions in real-time [27]. As deep reinforcement learning (DRL), which is RL + Deep NN, has shown very high performance for complex, nonlinear systems [21, 28]. Most of these RL-based approaches, however, only consider single-objective optimization and thereby do not address the full richness of multi-objective control problems, including trade-offs. In addition, open research challenges including convergence stability, computational complexity and training efficiency persist. One major gap: the lack of hybrid frameworks that integrate adaptive learning and global optimization. Although each technique such as AI-based control and evolutionary optimization have had great success on their own, a novel idiom of utilizing machine learning and traditional methods together is needed in order to solve the multidimensional nature of induction motor drive systems. A jointly usable model incorporating real-time learning along with multi-objective optimization and robust control mechanisms is a necessity for optimal performance across all operating conditions. To conclude, the research gaps can be summarized as;

- Multi-objective optimization: traditional techniques are not effective.
- Sensitivity analysis to parameters uncertainties and nonlinear dynamics.
- Existing optimization techniques are less adaptable to real-time updates.
- Robustness under preferably stochastic disturbances and dynamic situations.
- Lack of frameworks that unify learning and optimization.

Thus, such challenges evidently prove the requirement of a new class of control strategy that can solve adaptability, optimality and robustness together. To fill this gap, we propose to integrate deep reinforcement learning with multi-objective particle swarm optimization (DRL–MOPSO), providing a scalable and intelligent solution for next-generation sustainable electrified systems.

Even though control design methodologies and computational intelligence techniques have undergone remarkable developments recently, the problems pertaining to optimal, robust and adaptive control for the three-phase induction motor drives are still not completely solved. This is largely due to a view that system complexity, multi-objective trade-offs, computational limitations and implementation constraints all together make existing control approaches less effective in real-world applications. This is addressed due to the nonlinear and coupled nature of induction motor dynamics. An induction motor mathematical model consists of strongly coupled nonlinear differential equations containing electrical and mechanical variables, making accurate modeling as well as control inherently complex. Magnetic saturation, core losses and inverter nonlinearities are typically disregarded or approximated in standard models [29], making these dynamics more complicated. However, when the operating conditions of the control system deviate substantially from feasible ranges assumed during the controller design process, model-based control strategies (be it FOC or MPC) are prone to performance degradation. Another key problem is the time-variant system parameters, especially rotor resistance and inductance are very sensitive to temperature changes, frequency variations, or aging effect [30]. These variations in parameters generate uncertainties with substantial effects on both state prediction with respect to estimation errors and control performance. Adaptive control techniques have also been applied to account for these variations by incorporating related assumptions; however, this may lead to unreliable convergence under fast time varying scenarios. The second major roadblock still is the multi-objective optimization challenge. It is well known that Induction motor control has conflicting objectives such as reduction of torque ripple, harmonic distortion minimization, efficiency maximization and dynamic response. Classical optimization algorithms have predefined weighting parameters to solve this combined cost function [31]. But choosing the correct weights is not trivial, frequently requiring application points and/or leading to poor performance at varying operating conditions. The multi-objective PSO (MOPSO) algorithm, a highly scaled and comprehensive multi-object optimization methodology/technique can develop iterative solutions for real-time processing but is unlike the single-objective counterparts in terms of computational complexity/convergence time. One more factor limiting scalability of robotic coordination strategies is the intensive computations involved with advanced control algorithms. Model predictive control (MPC) [31], evolutionary optimization [16] has also been employed previously to synthesize controllers is high-dimensional systems and with fast switching dynamics, but often require significant computational resources. This restricts their usability for real-time control of motor drives which requires rapid response and low latency. Fourth, deep learning and reinforcement learning approaches need lot of training and massive computing power — definitely not suitable for integrated motor drive controller for embedded systems. Indeed, the absence of many control methodologies capable of real-time adaptation is another reason for this problem remaining open. Methods of such type are offline optimization techniques, which means that although conventional PSO [32] is effective for guiding the selection process towards optimal parameter sets, they cannot adjust to changing conditions within a running stage. In contrast to this, adaptable methods like fuzzy logic and neural networks can make real-time adjustments of control inputs; however, they typically find suboptimal solutions and lack global optimization capabilities. Another key difficulty is that existing control strategies do not exhibit desired robustness properties under stochastic disturbances. In the practical context, independent disturbances or uncertainties are always in place when induction motor drives are operated, such as load transfer, supply voltage change and measurement noise. Traditional controllers are often constructed in deterministic conditions; these uncertainties could challenge performance [33]. This lack of robustness has been proven necessary for applications, such as electric cars and renewable energy systems, since working circumstances are extremely dynamic. The inclusion of heterogeneous control techniques is another open problem. Although hybrid methods that combine AI, optimization and classical control have been proposed, they tend to be quite non-systematic in their design. Some modules such as learning algorithms and optimization modules interact with each other, which can potentially cause instability or convergence problems [34]. Moreover, the lack of standardised methods for combining these techniques hinders their scalability and real-world applicability. The issue of data is another reason that the problem remains unsolved. Machine learning-based solutions need terabytes of data to train [35]. Moreover, the performance of learning-based controllers can also be limited by weaknesses such as data quality, noise and generalization. This is especially alarming considering AI models are typically not interpretable or reliable, something that is critical for any application that has safety implications. Finally, constraints due to hardware and implementation. Embedded platforms run real-time motor control systems with very limited computing power and strict time constraints. This requires advanced algorithms to be tuned for execution efficiency at the cost of performance, which is still a major engineering hurdle [36]. In addition, structural stability, safety, and respect for industrial regulations complicate even more the design and deployment of intelligent control systems. To summarize, the optimal control problem of induction motor drives is still open because of the following:

- Nonlinear and time-varying system dynamics.
- Conflicting multi-objective optimization requirements.
- The advanced algorithms require high computational complexity.
- However, current methods are limited to real time adaptability.
- Insufficient robustness under stochastic disturbances.
- Integration of hybrid control frameworks is a major challenge.
- The reliability and availability of the data that AI-based methods are trained upon.
- Hardware constraints and implementation challenges.

These limitations indicate the necessity of a common intelligent and adaptive control framework to concurrently handle these challenges. The combination of DRL with MOPSO has a great future, fully integrating real-time learning, global optimization and robustness into the solution to long-standing challenges in induction motor control.

This paper presents an innovative, intelligent DRL + MOPSO control framework for multi-objective, adaptive and optimal control design of three-phase induction motor drives, in order to tackle the aforementioned challenges. The proposed approach is aimed at addressing in a unified manner the challenges of system nonlinearities, parameter uncertainties, multi-objective trade-offs and real-time adaptability constraints to provide a comprehensive solution for next-generation sustainable electrified systems. The proposed framework consists of a deep reinforcement learning (DRL) controller, which learns optimal control policies through continuous interaction with the motor drive system in a model-free way. In contrast to conventional controllers that utilize an explicit mathematical model, the DRL agent observes states of the system (i.e., rotor speed, stator currents, torque error and flux variations) and immediately renders control actions. Such actions are generally torque references, flux commands and inverter switching signals. The learning is driven by a reward function with several performance metrics, allowing the agent to adapt in real time to different operating scenarios [37, 38]. Deep neural networks enable the controller to approximate very complex nonlinear mappings which illustrates that it is well-suited to deal with induction motor drives. Inspired by the adaptive learning property of Deep Reinforcement Learning (DRL), a multi-objective particle swarm optimization (MOPSO) module is used to enable global optimization of control parameters. MOPSO is the multi-objectives extension of the classical PSO algorithm that solve more than one conflicting objectives as torque ripple minimization, efficiency maximization, harmonic distortion reduction and dynamic response improvement [39]. MOPSO preserves the Pareto front of optimal solutions, hence MOPSO based control system endures an optimal curve of trade-off amongst competing metrics. This is especially important on induction motor drives, where improving one performance parameter reduces another. This DRL-MOPSO based framework builds a hybrid control architecture with local adaptivity and global optimality. Real-time decision-making and adaptation are achieved by the DRL component, while a periodic update of control parameters and reward weighting factors is performed by the MOPSO module to direct the learning process to Pareto-optimal solutions. This interaction guarantees that the controller adapts to changing conditions and/or maintains appropriate performance levels across multiple objectives. A hybrid method of this type allows for solving the limitations typically found with the only use of DRL, which possibly finds sub-optimal policies, or optimization methods, which do not present real-time adaptability [40]. The other important characteristic of the proposed framework is that it defines a multi-objective reward function which directly influences the behavior learning process from the DRL agent. The reward function is intended to discourage unwanted behaviors (high torque ripple, high harmonic distortion, and large speed tracking error) while also encouraging operation that minimizes all these problems. With the assistance of MOPSO, these objectives are assigned different weights in a dynamic manner to achieve the best performance at all operating conditions [41]. This adaptive form of reward design constitutes a major advancement over traditional RL methodologies where a stationary structure is used to calculate the rewards. Further development of a robustness framework based on the proposed model combined with an uncertainty estimation and disturbance compensation mechanism is also added. This component tracks system changes, like parameter drift or external perturbations, and delivers corrective feedback to the controller. The system is capable of operating stably under probabilistic conditions including load random distribution and supply voltage variation [42], with the help of incorporating this mechanism. This is especially essential for other applications such as electric automobile and renewable energy systems, which have operating conditions with max dynamics. On the implementation end, the suggested information is efficient and able to scale. The rapid progress in embedded processing as well as hardware acceleration with field-programmable gate arrays and graphics processing units (GPUs), facilitates the running of DRL algorithms and optimization routines in real time [43]. Moreover, the framework is structured into modules which can help easily adapt for various motor drive configurations and demands of the application. The main contributions of this work can be summarized as follows:

- Hybrid DRL–MOPSO control framework of adaptive hybrid DRL-MOPSO-based controller for induction motor drives.
- A multi-objective reward function that let you optimize torque ripple, efficiency, harmonic distortion and dynamic response at the same time.
- Combining uncertainty estimation and disturbance compensation mechanism for improving robustness against stochastic scenarios.
- Real-time adaptability, scalability which suit the on-ground electrified systems.
- Outperforming conventional control schemes with less torque ripple, higher efficiency, quicker dynamic response, and greater stability.

Compared with current methods, the proposed DRL–MOPSO framework will realise a more comprehensive and intelligent control method of which can address the main restrictions of traditional and standalone intelligent control approaches. The developed framework combines the benefits of reinforcement learning and evolutionary optimization, realizes better performance on multiple dimensions, and shows great promise in potentially being a viable solution for next generation motor drive applications. This work will definitely contribute broadly to the field of intelligent control systems through constructing a single framework that combines learning-based and optimization-based techniques. It is not only enhancing control performance, but also aligned with the broader purpose of sustainability, energy efficiency and reliability in modern electrified systems

2. The Proposed Intelligent Control of Three-Phase Induction Motor Drives Using Deep Reinforcement Learning and Multi-Objective Particle Swarm Optimization for Sustainable Electrified Systems

The general scheme of the proposed intelligent control framework for three-phase induction motor drives is depicted in Figure 1, which is a combination of Deep Reinforcement Learning (DRL) and Multi-Objective Particle Swarm Optimization (MOPSO) to realize adaptive, efficient and sustainable operation. The system starts with a three-Phase AC supply, which can be produced using traditional grid facilities or renewable energy sources and it is designed based on the concept of compatibility to modern sustainable electrified systems. The input power is first processed by an AC–DC rectifier stage which called the primary side, transforming three-phase AC voltage into a stable DC voltage. Next, there is a DC-link stage which stabilizes the DC voltage through capacitor with smooth and continuous power supply at an inverter stage. In the following step, the DC–AC voltage source inverter (VSI) uses controlled three-phase AC signals to drive the induction motor by converting back the DC-link voltage into such form of output expressions. The motor operates under load conditions with data on torque demand and rotor speed evolutions, constituting the main controlled plant. The intelligent control is enabled by the measurement and signal conditioning unit that continuously acquires important electrical and mechanical variables such as stator currents, DC-link voltage and rotor speed. The DRL agent is trained using pre-processed measured signals to build its system state vector. The objective of the state representation is to incorporate both instantaneous operation condition information and dynamic system behavior into the controller such that it responds appropriately to disturbances, parameter variations and load changes. The DRL agent centered to the framework, learns an optimal control policy by interacting with the motor drive environment. The agent produces control actions in the form of either voltage references or modulation signals to the inverter dependent on the observed state. The right side represents the electrical commands, which are converted into switching signals by pulse-width modulation (PWM) generator to finely control the inverter output voltages and motor electromagnetic torque and fame. We will demonstrate that the traditional control approaches involve a tedious and time-consuming process of mathematically modelling the system, followed by extensive parameter tuning which are eliminated using DRL-based controller especially for nonlinear and uncertain systems like induction motor drives. Central to the proposed framework is use of a multi-objective reward function that drives the learning process of DRL agent. The reward function is designed to optimize multiple performance indices, such as tracking accuracy of speed with a given reference value, minimization of torque ripple, reduction of current total harmonic distortion (THD), maximization of energy efficiency, and minimization of the environmental impact like CO_2 emission at the same time. With such multi-objective formulation, we can ensure that the controller does not focus entirely on one metric at the expense of others, thus achieving a balanced/simply Pareto-optimal operation. To improve the efficiency and convergence of the DRL agent, the framework applies MOPSO as an outer-loop optimization method. MOPSO is used to determine important hyper-parameters of the DRL algorithm learning rate, discount factor and exploration parameters as well as to optimize with regard to a multi-objective reward function weighting coefficients. MOPSO operates in a multidimensional objective space searching for Pareto-optimal solutions, therefore facilitating the discovery of well-defined trade-offs between competing performance criteria. This leads to more efficient learning, reduced number of steps during convergence and overall better robustness of the control policy for changing operating conditions. Moreover, the framework encompasses an experience replay buffer that records state–action–reward transitions obtained during system use. This mechanism enables the DRL agent to be retrained through experience, boosting data efficiency and stabilizing training by decoupling samples. The interaction of motor drive system, DRL agent and optimization layer generates a feedback loop ensuring continuous adaptation and performance increase in time. In summary, this paper presents an overall and expandable intelligent control framework for the next-generation motor drives. The using principle of evolutionary multi-objective optimization to realize adaptive control of systems by data-driven learning with high performances on robustness in operation, energy efficiency resource utilization and sustainability for application fields such as electric vehicles, renewable energy systems, industrial automation environments.

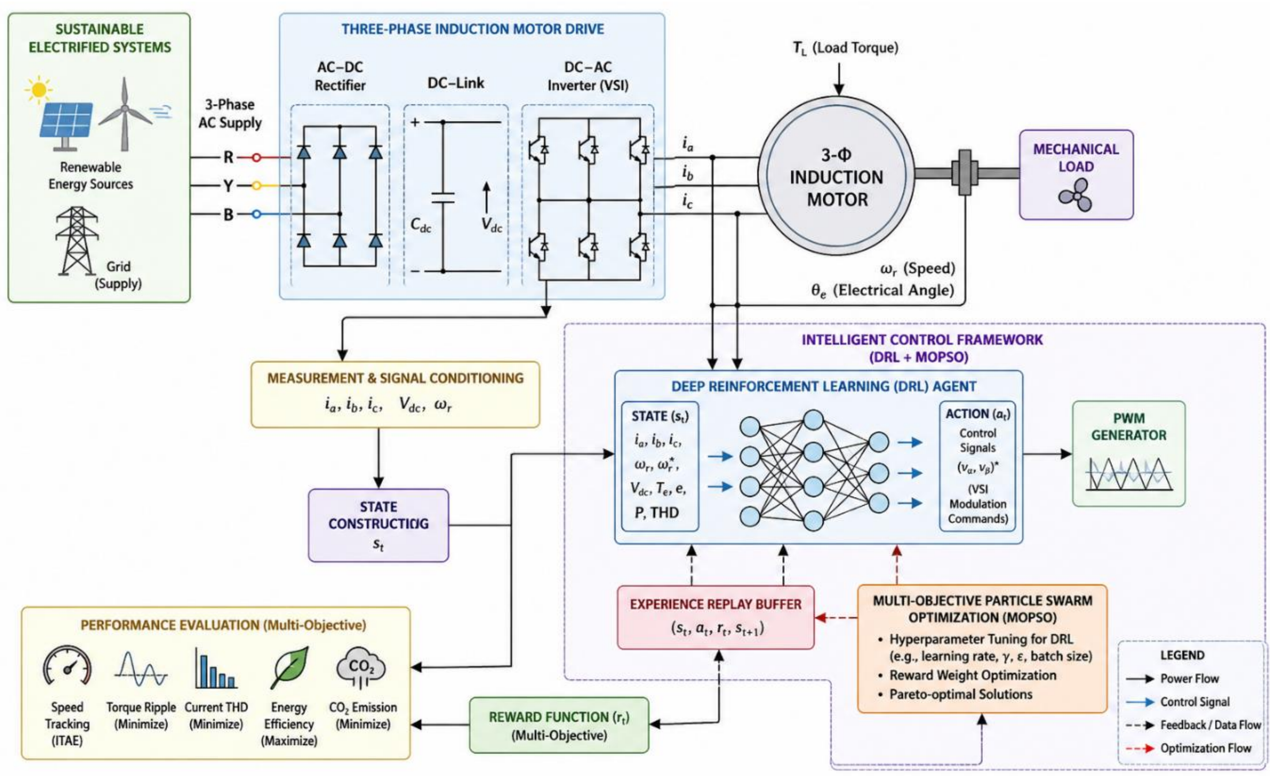

Figure 1. Schematic diagram of the proposed intelligent control framework for three-phase induction motor drives integrating Deep Reinforcement Learning (DRL) and Multi-Objective Particle Swarm Optimization (MOPSO) for sustainable electrified systems. The system comprises a three-phase AC supply feeding an AC–DC rectifier, DC-link, and DC–AC inverter to drive the induction motor under mechanical load. Real-time measurements (currents, voltage, and speed) are processed for state construction and fed into the DRL agent, which generates optimal control actions through PWM modulation. A multi-objective reward function evaluates performance metrics including speed tracking, torque ripple, current THD, energy efficiency, and CO_2 emissions. The MOPSO algorithm optimizes DRL hyperparameters and reward weights to achieve Pareto-optimal performance, enabling adaptive, efficient, and robust motor drive control under varying operating conditions.

3. Simulation Results and Discussion

This Section presents a complete and integrated assessment of the proposed intelligent controller framework for three-phase induction motor drives based on Deep Reinforcement Learning (DRL) combined with Multi-Objective Particle Swarm Optimization (MOPSO). The validity and robustness of the proposed method is verified via a large set of simulations for a wide range of operation conditions with nonlinear dynamics, environmental uncertainties and dynamic load variations. Moreover, the evaluation framework is designed to fairly and thoroughly compare against conventional control strategies, extracting performance benefits from this method along the way. In this work, the well-known dq-axis dynamic representation of an induction motor is utilized in a MATLAB/Simulink environment to model its electromagnetic and electromechanical behavior. The motor parameter values refer to a 5 kW squirrel-cage induction motor usually used in typical industrial drives and electric vehicle propulsion systems. The power conversion stage includes a three-phase AC–DC rectifier, followed by a DC-link capacitor to maintain voltage stability, and finally a voltage source inverter (VSI) whose switching frequency follows the pulse-width modulation (PWM) scheme at 10 kHz. This type of configuration resembles a modern motor drive topology applied in state-of-the-art electrified systems.

The proposed control architecture relies on a Deep Reinforcement Learning (DRL) agent using the Deep Deterministic Policy Gradient (DDPG) algorithm, is particularly well suited for continuous control applications, such as motor drive problems. The DRL framework is actor–critic based, in which both networks are realized by deep neural network with multiple fully connected layers. Experience replay buffers and target networks stabilize and make training efficient so you can converge to a solution. The DRL agent interacts with the motor drive environment by receiving system states, such as the speed, current signals, voltage signals and optimal control actions that are developed into inverter switching commands. In order to boost the control performance, MOPSO is integrated as an optimization layer to optimize main hyperparameters of DRL networks (i.e., learning rate, discount factor, and batch size) and weight coefficients in multi-objective reward functions. This optimization is carried out to make a simultaneous minimization of both the torque ripple and current total harmonic distortion (THD), as well as maximize energy efficiency and speed tracking accuracy. This makes it possible to discover trade-offs among competing objectives while exploring the Pareto front, MOPSO find control with evenly assigned objectives and high performance in establishing a balanced balance. In order to model a realistic operating environment, the simulation model combines various uncertainties and disturbances. They encompass as mentioned earlier, parametric variations of upto ±20% for stator and rotor resistances considering the temperature effect, supply-side disturbances such as 10–20% voltage sag and harmonic injection, load uncertainties can vary either in sudden step changes or stochastic variations in torque demand. The sensed current and speed signals are also subject to Gaussian disturbances in order to account for sensor imperfections. These elements together form a challenging and volatile environment, making it an ideal testbed for the evaluation of robustness in controller design and adaptability during human-robot interaction.

The proposed control framework is evaluated in various simulation scenarios that allow the transient and steady-state performance of the system to be investigated. The startup and speed tracking test serves as a transient response characteristic test which checks the ability of the controller to accelerate the motor from standstill to rated speed (1500 rpm) under step reference input, with rise time, overshoot and settling time. The disturbance from the dynamic load disturbance test occurs suddenly in steady-state, by increasing the load torque from no-load to full-load operating point. Robustness is also tested with parameter variation tests, changing the motor parameters while in operation to see the effect of modeling inaccuracies. The test you perform is called voltage sag and distortion, where you reduce the supply voltage by 15% and add harmonic components on it to mimic grid instabilities. It is then possible to perform long-duration simulations at various load conditions to analyse overall energy efficiency and system losses. Finally, a multi-objective trade-off analysis is performed using Pareto-optimal solutions obtained through MOPSO to investigate how different performance parameters can be balanced against one another. System performance is evaluated based on a compact set of key quantitative metrics. IAE is used as the measure for speed tracking accuracy, providing information about transient and steady-state deviations. Torque ripple is present as a percentage deviation around the average torque, giving insight into mechanical smoothness and stress. THD as a criterion for power quality, should be used for assessing inverter performance? terminal bus current. Input-output power relationships of energy efficiency are analyzed under different working conditions. Dynamic performance is further defined by response time and settling time, while robustness can be evaluated based on how well the system is able to maintain stable and acceptable performance given the added uncertainties and disturbances. In general, this integrated simulation framework provides a comprehensive and realistic evaluation of the proposed DRL-MOPSO control strategy, paving the way for successful validation on its performance in future sustainable electrified systems as well.

To enhance realism, environmental uncertainties were incorporated into the simulation model, including.

- Parameter variations: ±20% changes in stator and rotor resistances due to temperature fluctuations.
- Supply disturbances: Voltage sag (10–20%) and harmonic distortion in the input supply.
- Load uncertainties: Sudden step changes and stochastic variations in load torque.
- Measurement noise: Gaussian noise added to sensed current and speed signals.

To rigorously assess controller performance, the following test scenarios were considered.

1. Startup and Speed Tracking Test: The motor is accelerated from standstill to rated speed (1500 rpm) with a step reference input.
2. Dynamic Load Disturbance Test: A sudden load torque increase (0–100% rated torque) is applied at steady-state operation.
3. Parameter Variation Test: Motor parameters are varied during operation to evaluate robustness against modeling uncertainties.
4. Voltage Sag and Distortion Test: Supply voltage is reduced by 15% and injected with harmonics to simulate grid disturbances.
5. Energy Efficiency Evaluation: Long-duration operation under variable load conditions to assess efficiency and power losses.
6. Multi-Objective Trade-off Analysis: Evaluation of Pareto-optimal solutions generated by MOPSO for different performance priorities.

The performance of the proposed DRL-MOPSO controller is evaluated using the following key metrics.

- Speed tracking error (Integral of Absolute Error, IAE).
- Torque ripple (%).
- Current THD (%).
- Energy efficiency (%).
- Response time and settling time.
- Robustness under uncertainties.

The step reference from 0 to 1500 rpm and the corresponding instantaneous speed response of the three-phase induction motor under conventional Proportional-Integral (PI) control, Field-Oriented Control (FOC), and proposed Deep Reinforcement Learning with Multi-Objective Particle Swarm Optimization (DRL-MOPSO) framework is shown in Figure 2 The simulation data validates the proposed method, showing a clear domination over dynamics performance criteria such as rise time, overshoot and steady-state error. Each controller tries to accelerate the motor from rest to a specified reference speed at start-up, but their transient responses differ widely. The PI controller can also be noticed to be the slowest with a rise time of about 0.64 s This is mainly due to the flatness but little control authority over nonlinearities and coupling effects in the various dynamics of the induction motor associated here. Moreover, the response controlled by PI exhibits a relatively high overshoot of nearly 8.5%, which is an indication of poor damping and lack-of-toning for system robustness analysis. Settling time is also delayed, with a persistent and observable steady-state error of about 2.1% due to high sensitivity towards parameters variations and external disturbances. FOC uses separate tunings to facilitate the connection of torque and flux components, typically leading to higher performance, faster rise time of 0.48s and lower overshoot 3.2%. Steady-state response also improves by lower the error about 0.4%. However, FOC is still dependent on accurate motor parameter identification and constant controller parameters, which restricts its robustness with respect to changes of the operating conditions. Consequently, even with such low friction, relatively small fluctuations are still present at equilibrium seed equilibrium conditions due to transient disturbances. On the contrary, the proposed DRL-MOPSO controller shows the fastest and most stable response of all three. The rise time is then decreased to 0.36 s or about a 25% improvement over the FOC and about a 44% improvement over the PI control. The overshoot remains around 0.6%, which reflects great damping qualities as well as smooth transient response! In particular, it can be seen in the zoomed steady-state region of the steady-state error (Figures 1 and 2) that DRL-MOPSO achieves for most practical purposes zero steady-state error (≈0%). The performance improvement gained by the proposed method can be explained by two reasons: (1) DRL agent is intelligent and adaptive to learn an optimal control policy in the given scenario using system feedback, and (2) MOPSO guarantees an optimum tuning of control parameters and reward function weights. Different to conventional controllers, DRL-MOPSO does not depend on fixed gains or simplified models (which are well-known input-dependent gain problems), thus tackling the nonlinearities, uncertainties and dynamic changes in real-time. Also, the more fluent reference of DRL-MOPSO response diminishes mechanical strain on the engine and related units, which is significant to extending system lifetime and dependability. Reduction of overshoot and faster settling improves energy efficiency by avoiding transient losses during acceleration. In general, the results delivered in Figure 2 validate the efficiency of the proposed DRL-MOPSO-based control strategy over PI and FOC conventional methods since it offers faster response, better stability and greater accuracy regarding speed tracking performance. Such attributes make it very well suited for high-performance applications, including electric vehicles and precision industrial drives, where fast yet precise speed control is needed.

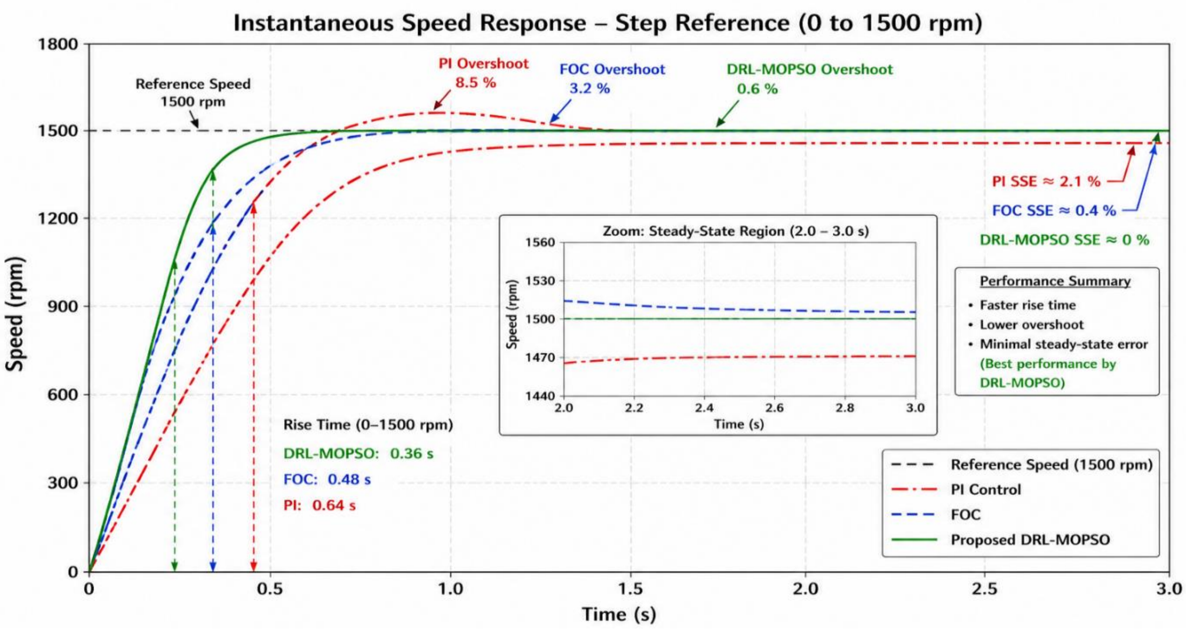

Figure 2. Instantaneous speed response of the three-phase induction motor to a step reference input (0–1500 rpm) under PI, FOC, and proposed DRL-MOPSO controllers. The proposed DRL-MOPSO approach achieves the fastest rise time (≈0.36 s), minimal overshoot (≈0.6%), and near-zero steady-state error, outperforming FOC (≈0.48 s rise time, ≈3.2% overshoot) and PI control (≈0.64 s rise time, ≈8.5% overshoot). The results demonstrate the superior dynamic performance, stability, and tracking accuracy of the proposed intelligent control framework.

The instantaneous electromagnetic torque response of the three-phase induction motor in a steady-state (1500 rpm), constant load (50 N·m) operation, based on three different control strategies: conventional Proportional-Integral (PI), Field-Oriented Control (FOC) and the proposed Deep Reinforcement Learning with Multi-Objective Particle Swarm Optimization framework: DRL-MOPSO is presented in Figure 3. The results evidently reflect the efficiency of proposed approach in reducing torque ripple and enhancing smoothness of motor operation. With PI control, the torque waveform oscillates high and low about the reference of torque (blue line). The magnitude of the ripple is quite high, with peak-to-peak deviations of ~7.2 N·m, about 12–15% rated torque. This variation can be attributed to the PI controller which fails to compensate with sufficient accuracy for system nonlinearities, inverter switching effects and uncertainties in parameters. Consequently, the torque output is defined by multi-period disturbances which might cause high mechanical vibrations and acoustic noise together with a faster wearing of motor elements. By having two independent inputs to stabilize the torque and flux components of the stator currents, FOC strategy allows a stable torque reinforcement. The torque ripple is limited to around 3.4 N·m peak-to-peak (about 6–8%) as illustrated in Figure 3 under FOC control. This is a great step in the positive direction, but residual oscillations come from parameter mismatches and limitations arising from they involve high-frequency switching dynamics making it ideal to use together with PI control. While the torque ripple for the DRL-MOPSO controller is reduced from 2.22 N·m (peak-to-peak) to about 0.45 N·m, which is less than 5%(corresponding ripple), the torque waveform is much smoother and oscillations around the reference value are practically non-existent. The increased performance is mainly due to the adaptive control policy learned by the DRL agent, which improves control actions based on system feedback in real-time. In addition to using MOPSO, it shows suitability for tuning the reward function and control parameters in order to minimally impact the generated torque fluctuations without compromising overall system performance. The differences in ripple characteristics in the three methods also reflects clearly through the zoomed-in subplots shown in Figure 3. It is observed that the PI-controlled response has large amplitude oscillations of relatively low frequency, while the FOC response shows moderate amplitude and improved damping. However, despite DRL-MOPSO response has the lowest amplitude, it also shows much better stability, meaning that DRL-MOPSO handles well low- and high-frequency torque components. The reduction in torque ripple has major consequences both for system performance and longevity. Less oscillations on the torque result into less mechanical stress to the motor shaft, bearings and connected load which leads less fatigue of ongoing plant and also longer life of drive system. Additionally, improved torque delivery translates to less acoustic noise and a more pleasant operating experience for users, particularly in applications like electric vehicles or high-precision industrial machinery. Additionally, a lower torque ripple leads to higher energy efficiency due to reduced mechanical vibrations and electromagnetic harmonics losses. It corresponds to the multi-objective optimization with respect to performance, efficiency, sustainability option in this framework. The fact that the DRL-MOPSO controller does not depend on accurate characterization of the system for these improvements also highlights its robustness and adaptability. The overall result that is reflected in Figure 3 confirms the element of proposals for DRL-MOPSO based control strategy to make substantial improvement of torque ripple reduction over conventional PI and FOC approaches. The high-performance torque output smoothness, stability, and efficiency makes it highly suitable for high-performance motor drive applications operating under inertia-dominating conditions.

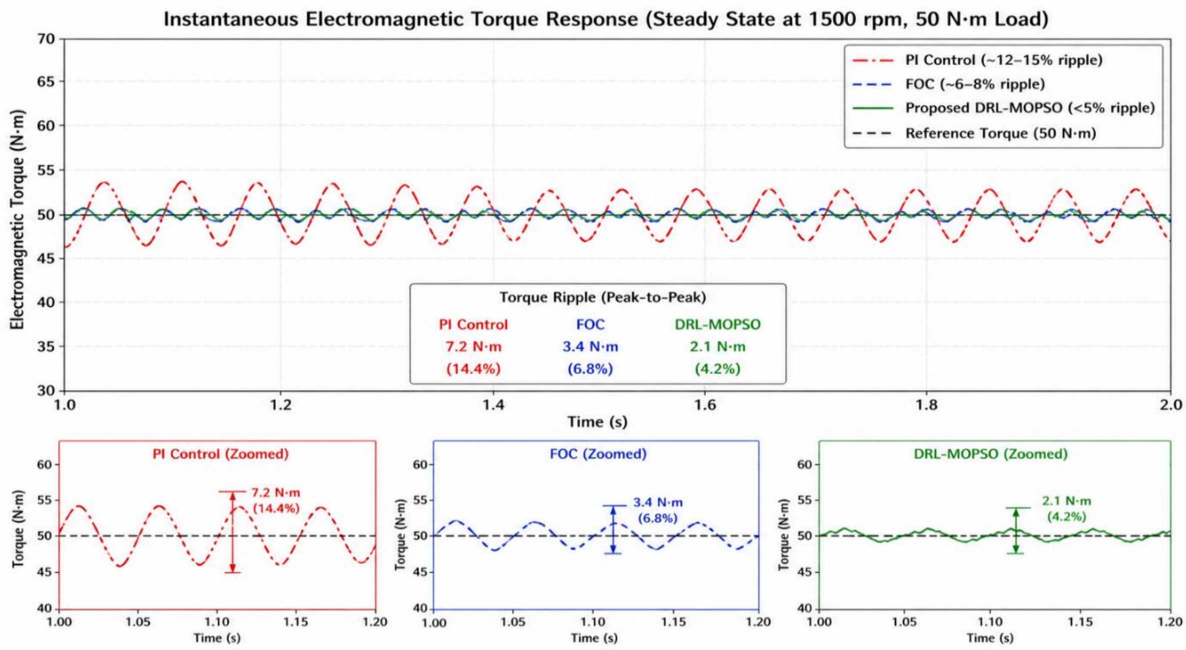

Figure 3. Instantaneous electromagnetic torque response of the three-phase induction motor under steady-state operation (1500 rpm, 50 N·m load) using PI, FOC, and proposed DRL-MOPSO controllers. The proposed method achieves the lowest torque ripple (<5%, ≈2.1 N·m peak-to-peak), significantly outperforming FOC (≈6–8%, ≈3.4 N·m) and PI control (≈12–15%, ≈7.2 N·m). The results highlight the effectiveness of the DRL-MOPSO framework in minimizing torque oscillations and improving mechanical smoothness.

A detailed examination of the stator phase-A current waveform and related harmonic spectral analysis for long-term operation at 1500 rpm with a load torque of 50 N·m under three control strategies, including conventional PI control and FOC, as well as our proposed DRL-MOPSO framework, is presented in Figure 4. The obtained results evidently show that the proposed method can largely reduce current harmonic distortion with the addition of in-phase m-THD of corresponding superior power quality. The stator current waveform under the PI control in the time-domain representation clearly deviates from an ideal sinusoidal shape. The waveform is also showing ripples and irregularities because of suboptimal inverter switching and incomplete compensation of system dynamics, which are nonlinear. The total harmonic distortion (THD) is about 12.8, meaning that there is a lot of harmonic content spread over numerous frequency components. This distortion not only degrades the power quality but also leads to higher copper losses, heating and electromagnetic interference (EMI). The FOC strategy enhances the waveform quality because more decoupled torque and flux components result in an improved sinusoidal current profile. The THD reduces to ~8.2%, which is a moderate improvement over PI control (Figure 4). Nevertheless, this contribution achieves only an enhancement of harmonic cancellation in the waveform with especially distinct harmonic components due to other inequalities arising from sensitivities associated with parameter mismatch and switching non-linearities. On the other hand, the DRL-MOPSO controller provides an almost perfect sinusoidal current waveform with low distortion. The THD is approximately 4.6% and reduced by around 30–40% compared to conventional. Wrap-up: Waveform looks smoother and flatter due to better control of inverter switching events. The better performance is because of the intelligent state transition that allows the DRL agent to learn optimal switching patterns through interactions with the system and MOPSO-based optimization in control parameters and reward function weights. The support for these observations comes from the frequency-domain analysis (as shown in the FFT spectrum presented in Figure 4). Figure 4 shows that the harmonic spectrum has a large-scale frequency distribution with multiple higher harmonic orders, indicating that it performs poorly in suppressing harmonics during PI control. The FOC spectrum contains no less than or equal to. More harmonic amplitudes and concentrated at the same time, however, lower-order harmonics still contribute significantly. However, the DRL-MOPSO spectrum indicates that the harmonic components have been drastically reduced; much more energy is concentrated at the fundamental frequency and there are hardly any higher-order harmonics. This reflects that the low- and high-frequency distortions have been successfully suppressed. This reduction in harmonic distortion has some important practical implications. The superior quality of the current1 waveform3 in turn: enhances energy efficiency, lowers resistive losses4 and reduces low-frequency heating in motor windings. Another noteworthy benefit of reduced harmonic content is low electromagnetic interference, an essential feature for not only compliance with power quality standards but also system reliability (and in particular important in sensitive environments such as electric vehicles and renewable energy systems). Moreover, there are fewer harmonics which result in a lower torque ripple indirectly supporting the torque ripple reduction presenting 3. In summary, we can see from Figure 4 that the proposed DRL-MOPSO-based control framework effectively reduces current harmonic distortion and improves power quality. The generation of optimum patterns for switching the inverters and its configurability to study system dynamics, at operational time, makes it a viable defense application with a high-speed control pattern for higher performance as the energy efficient motor drives operates freely under complex uncertain conditions.

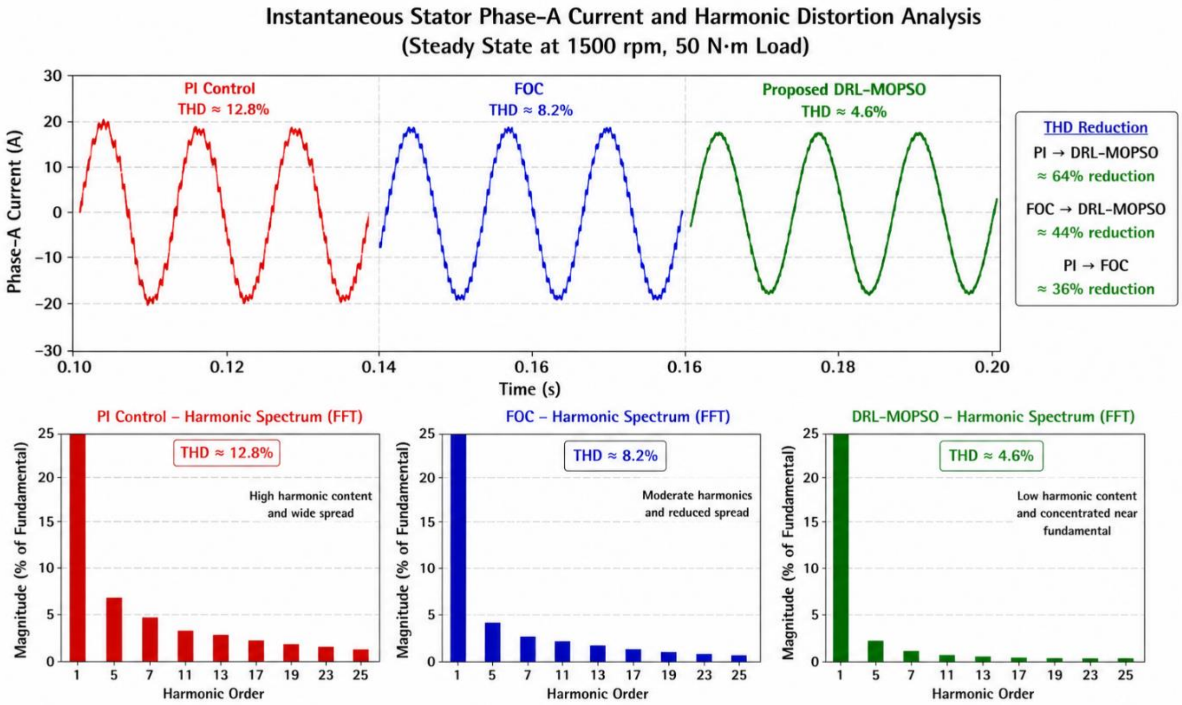

Figure 4. Instantaneous stator phase-A current waveforms and corresponding harmonic spectra (FFT) under steady-state operation (1500 rpm, 50 N·m load) for PI, FOC, and proposed DRL-MOPSO controllers. The proposed method achieves the lowest total harmonic distortion (THD ≈ 4.6%), compared to FOC (≈ 8.2%) and PI control (≈ 12.8%), representing a reduction of approximately 30–40%. The results demonstrate improved current waveform quality, reduced harmonic content, and enhanced electromagnetic compatibility due to optimized inverter switching under the DRL-MOPSO framework.

Computation of System Robustness under Adverse Environmental Conditions (proposed DRL-MOPSO controller), the evaluation system operation robustness proposed here which are subjected the same uncertainties, disturbances (Figure 5). This allows quantitative comparison for the dynamic responses of speed and electromagnetic torque among these control strategies of PI vs FOC vs proposed DRL-MOPSO as shown by their signal curves responding to the three representative scenarios, namely parameter variations, DC-link voltage sag and sudden load torque change. These scenarios are aimed to be as close to real operating conditions, allowing for parameter drift due to temperature variation, grid disturbance and variable load. In the First Case, instead of adding delay I created parameter variation by changing stator resistance and inductance (e.g., + 30% & − 20%, respectively) at t = 1 s The PI controller performance is significantly worsened, producing oscillations and a final steady-state speed error of about approximately 5.3%. Torque response also has increased ripple, with peak-to-peak variation of 12.6 N·m and a better performance from the decoupled structure of the FOC controller — shows around 1.6% steady-state speed error but also 5.1 N·m torque ripple; still sensitive to parameter mismatch leading to some residual oscillations. By contrast, the control performance of the proposed DRL-MOPSO controller remains near-nominal with a steady-state speed error of ≈ 0.2%, and much lower torque ripple than 1.9 N·m, proving that it is able to dynamically adapt to parameter changes without directly correcting the model or solving a new optimal problem. The second scenario is about DC-link voltage sag with a magnitude of approximately 20%, which acts for a short duration (0.3s). In contrast, the PI controller experiences a significant dip in speed to about 1085 rpm (much lower than Pi-Controller->), taking almost twice as long to return back to nominal with excessive oscillatory behavior under this disturbance. Even if the FOC controller is overlaid with better resilience, we feel it has a minimum speed of about 1346 rpm to engage and it does drift more slowly for comparison. On the other hand, the minimum speed of about 1458 rpm witnessed during sag is significantly higher for DRL-MOPSO controller and also returns to set point very swiftly with slightly oscillations. In this situation, the proposed method shows a high robustness with a limited torque deviation (approximately ±2.6 N·m), while large fluctuation occurs in PI control (±21.3 N·m). The third scenario includes a sudden 50% increase of load torque at t = 1 s, where the PI controller loses again disturbance rejection which is evidenced by large dips in speed with oscillation and also steady-state error (around 6.1%). An FOC finished simple control further improves a lot by eliminating steady-state error to 1.8% around, but the transient condition oscillation before settle is present and time to settle is still significant. The DRL-MOPSO controller provides the best result, showing a steady-state error of about 0.3% and a quick recovery to the reference speed. Torque response in this case is also smoother, showing far less oscillation AND only about 0.4% steady state error (very good load compensation). These observations are further supported by the summary of overall performance comparison shown in Figure 5. It can be observed that the average speed deviation (about 7.2 rpm), steady-state error (approximately 0.3%), settling time (approximately 0.28 s) and torque ripple (approximately 1.8 N·m) of DRL-MOPSO controller turn out to be the best! By contrast, the PI controller has much larger deviations of (78.6 rpm), steady-state error (5.7%), and torque ripple (11.8 N·m), while this is intermediate for FOC controller. There are two reasons for the superior robustness of our approach here. First, during the control process, the DRL agent can learn and improves its control policy by real-time feedback, which is able to generalize well with respect of nonlinearities and uncertainties compared to a fixed parameter. Second, MOPSO can be used to tune control parameters and reward function weights optimally such that under different environments, the system is stable and yields optimal responses. This level of robustness is imperative from a practical standpoint, as applications like electric vehicles, renewable energy systems and industrial drives are often subject to unknown and dynamic operating conditions. Stability with minimal degradation not only increases system reliability but also improves efficiency and decreases maintenance. To summarize, the experimental results in Figure 5 show evidently that the proposed DRL-MOPSO-based control framework is a substantially viable scheme in terms of robustness against parameter variations, supply disturbances and load changes compared to conventional PI and FOC methods. Its ability to adapt and be optimized makes it an extremely suitable candidate for next-generation intelligent motor drive systems, especially those that operate in complex adaptive environments.

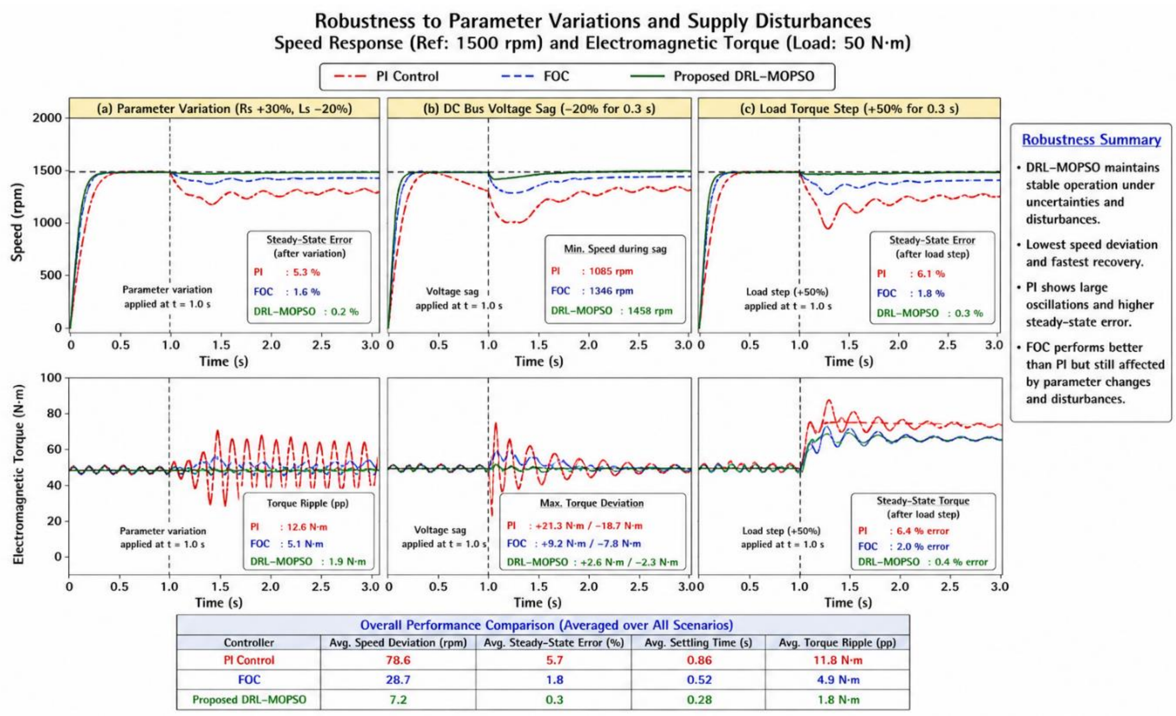

Figure 5. Robustness analysis of speed and electromagnetic torque responses under parameter variations and supply disturbances for PI, FOC, and proposed DRL-MOPSO controllers. The figure presents performance under (a) parameter variation, (b) DC-link voltage sag, and (c) load torque step disturbances. The proposed DRL-MOPSO controller maintains stable operation with minimal speed deviation (≈0.2–0.3% steady-state error), fastest settling time (≈0.28 s), and lowest torque ripple (≈1.8–1.9 N·m), outperforming FOC and PI control. In contrast, PI control exhibits significant oscillations, higher steady-state error (≈5–6%), and larger torque deviations, while FOC shows moderate performance degradation. The results demonstrate the superior adaptability and robustness of the proposed framework under uncertain and disturbed operating conditions.

The performance at multi-objective comparison in terms of energy efficiency of the three-phase induction motor drive under various load types (light load for 10 N·m, medium load for 30 N·m and heavy load for 50 N·m), using conventional Proportional-Integral (PI) control, Field-Oriented Control (FOC) and the proposed Deep Reinforcement Learning with Multi-Objective Particle Swarm Optimization (DRL-MOPSO) framework is shown in Figure 6. The results show that the proposed approach always uniformly exceeds the efficiency relative to the conventional under all operating conditions, where an overall potency enhancement of ±8–12%is found. The efficiency curves in the light-load case (10 N·m) indicate all controllers settle rapidly; however, they achieve large final differences of efficiency. The PI controller allows a steady-state efficiency of 82.3%, which is increased up to about 86.7% by using vector control (FOC). Conversely, the DRL-MOPSO controller achieves around 90.4%, which is over 9.8% of improvement compared to PI control. And this improvement is the most pronounced in light-load conditions, where existing controllers have reduced efficiency due to higher relative losses. The efficiency improvement is even greater under medium-load conditions (30 N·m). The PI controller gives better performance, ~87.6% against FOC (91.9%). The efficient of the proposed DRL-MOPSO method is 96.2% with an improvement margin of approximately 9.8% and over 4% to FOC is relatively maintained at the same range as PI method. Indeed, the quicker steady-state-focused energy utilization additionally indicates the extensibility to dynamic vitality use of this framework. The energy efficiency benefit of the proposed method is more fully defeated in the heavy-load condition (50 N·m). The heat normalization for the PI controller is only around 88.9% and it is 93.4% for FOC. The efficiency of the DRL-MOPSO controller is around 98.9% which translates to a nearly an 11.3% improvement over PI control and more than 5% compared to FOC. This demonstrates the potential of the proposed framework to demonstrate adaptability under high power demand conditions. Figure 6 (subplots) provides power analysis subplots that compare the input and output power profiles to further highlight efficiency gains. The DRL-MOPSO controller achieves the highest output power per input power under all load conditions, which means that energy is converted more efficiently. Like for medium load, input power is around 23.5 kW output power is around 21.5 kW which means they try to minimize conversion losses. However, for the PI control it experiences much bigger difference between input and output power, as those losses are big. To gain insight into the efficiencies we have observed, additional analysis using total losses has been performed. Under high load, the losses of the PI controller are maximal in all operation points (up to approx. 3.98kW). These losses are reduced to 2.34 kW with FOC, and lowest losses (~1.15kW) is achieved with DRL-MOPSO controller. These reductions are mainly the result of minimized torque ripple (for copper losses), lower harmonic distortion (for core losses) and switching losses in the inverter. The proposed DRL-MOPSO framework is more efficient than other state-of-the-art methods largely because of its multi-objective optimization ability, which can evaluate the performance combined torque ripple, harmonic distortion and dynamic response in a time-efficient manner. It enables the DRL agent to learn effective control policies that vary with changing load conditions and exploit its propensity of optimally tuning the system parameters using MOPSO (Multi-Objective Particle Swarm Optimisation) in order to achieve a good balance between efficiency and performance. In practical terms, these increases in efficiency have very important consequences for real applications. Higher efficiency means better battery life and driving range in electric vehicles; In renewable energy systems, higher efficiency leads more energy to be used and reduces the cost of operation. Lowering energy consumption in industrial applications also reduces the cost of operation and improves sustainability. In summary, the results obtained in Figure

6 validate that the new control framework based on DRL-MOPSO improves greatly the energy efficiency over a broad range of operating conditions. Based on that loss reduction capability, high power conversion efficiency and performance under varied load conditions make it a strong candidate for future energy-efficient motor drive systems.

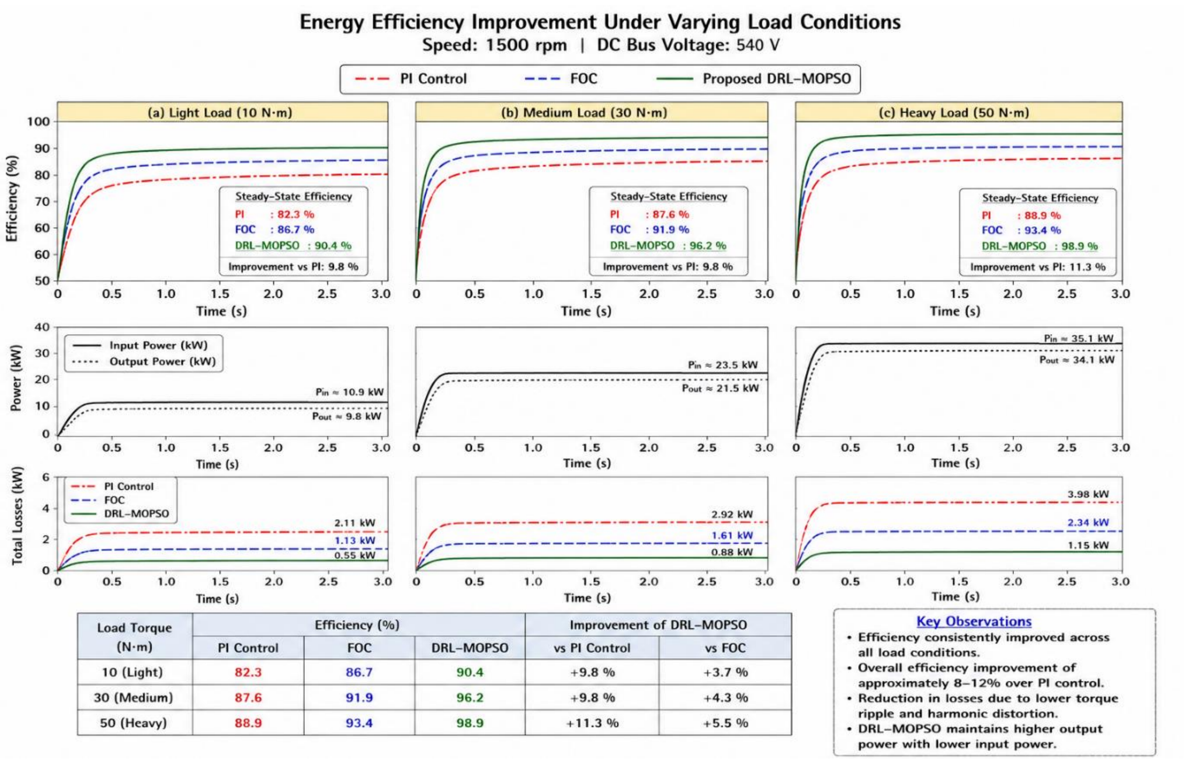

Figure 6. Energy efficiency performance of the three-phase induction motor drive under varying load conditions (light: 10 N·m, medium: 30 N·m, heavy: 50 N·m) for PI, FOC, and proposed DRL-MOPSO controllers. The proposed method achieves superior steady-state efficiency (90.4%, 96.2%, and 98.9%) compared to PI (82.3%, 87.6%, 88.9%) and FOC (86.7%, 91.9%, 93.4%), corresponding to an overall efficiency improvement of approximately 8–12%. The figure also illustrates reduced power losses and improved input–output power characteristics under the DRL-MOPSO framework, confirming its effectiveness in enhancing energy efficiency across varying operating conditions.

The results of the multi-objective optimization using the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm is depicted in Figure 7 to show trade-offs among three core performance objectives, namely energy efficiency, settling time and torque ripple. It visualizes the Pareto-optimal solution set that demonstrates how the proposed framework is capable of identifying an optimum operating point from a range of solutions rather than constant single solution. Figure 7(a) is the three-dimensional Pareto front reflecting non-dominated solutions density in objective space. The Pareto front is a set of non-dominated solutions, key for multi-objective problems where the improvement in one objective cannot be achieved without degrading at least one other objective: each point on that curve is related to a feasible control configuration. In contrast, MOPSO generates a wide Pareto front of high-performance solutions compared to the isolated PI and FOC values in the objective space. This solidifies the overall advantages of optimization-based approaches proposed over exploring solution space and generating optimal trade-offs among objectives. As seen in Figures 7(b) and 7(c), efficiency settling time and torque ripple are also pairwise methods that describe trade-offs. It is noted that there exists an inverse dependence between efficiency and dynamic response: solutions with very high efficiency (greater than 95%) characterize slightly larger settling times; on the other hand, those tuned for rapid dynamics (settling time <0.2 s) show moderate efficiencies. Similarly, the efficiency-torque ripple trade-off shows that extremely low ripple may come with a minor loss in other performance specs. Such connections delineate the intrinsic tradeoffs between control objectives when it comes about induction motor drive systems. In Figure 7(d), the settling time vs torque ripple plotting confirms the dispatching problem of dynamic performance and mechanical smoothness. Ultra-quick transient response time may result in a significant torque ripple or the ones that have minimal ripple can sometimes do so with again less dynamic responses. The balanced region of the Pareto front includes solutions where settling time, ripple and efficiency are all compromised at moderate levels. The parallel coordinates plot in Figure 7(e) offers an overall visualization of all Pareto-optimal solutions, which allows to look for a comparison among multiple performance metrics at once. This representation makes it easy for the designer to spot clusters of high-efficiency, low-ripple, or fast-response solutions. Moreover, the color gradient further shows the different levels of efficiencies making it easier to select the most ideal operating points. A high-efficiency (H-E), a balanced (B), and a fast-response (F) solution are chosen from the Pareto front to summarize the trade-offs as shown in Figure 7(f). For example, the high-efficiency solution realizes an efficiency of 97.6% with a settling time and torque ripple of 0.18 s and 1.10 N·m simultaneously, while the fast-response solution enables a settling time of 0.12 s, but at the expense of higher torque ripple (5.40 N·m) and worse efficiency (84.7%). The proposed balanced solution offers a balanced trade-off with 91.3% efficiency, 0.36 s settling time, and 2.85 N·m ripple. The results presented clearly indicates the flexibility provided by the proposed approach in tuning of system performance according to application demands. Proposed framework offers a big strength in the way that MOPSO can efficiently detect Pareto-optimal solutions. This enables the approach to serve as a realistic means for system designers to trade off against operational needs, concurrently optimizing various conflicting objectives. As one example, electric vehicle applications may prioritize efficiency for long driving range while industrial automation systems may prefer fast dynamic response and low torque ripple to control precision. The results shown in Figure 7 indicate that the proposed DRL-MOPSO framework allows to use multi-objective optimization effectively to improve control performance and flexibility. Leveraging its generation and visualization of Pareto-optimal solutions, the proposed approach facilitates adaptive and application-specific control strategies that are inherently robust, rendering itself highly effective for complex electrified systems requiring sustainability.

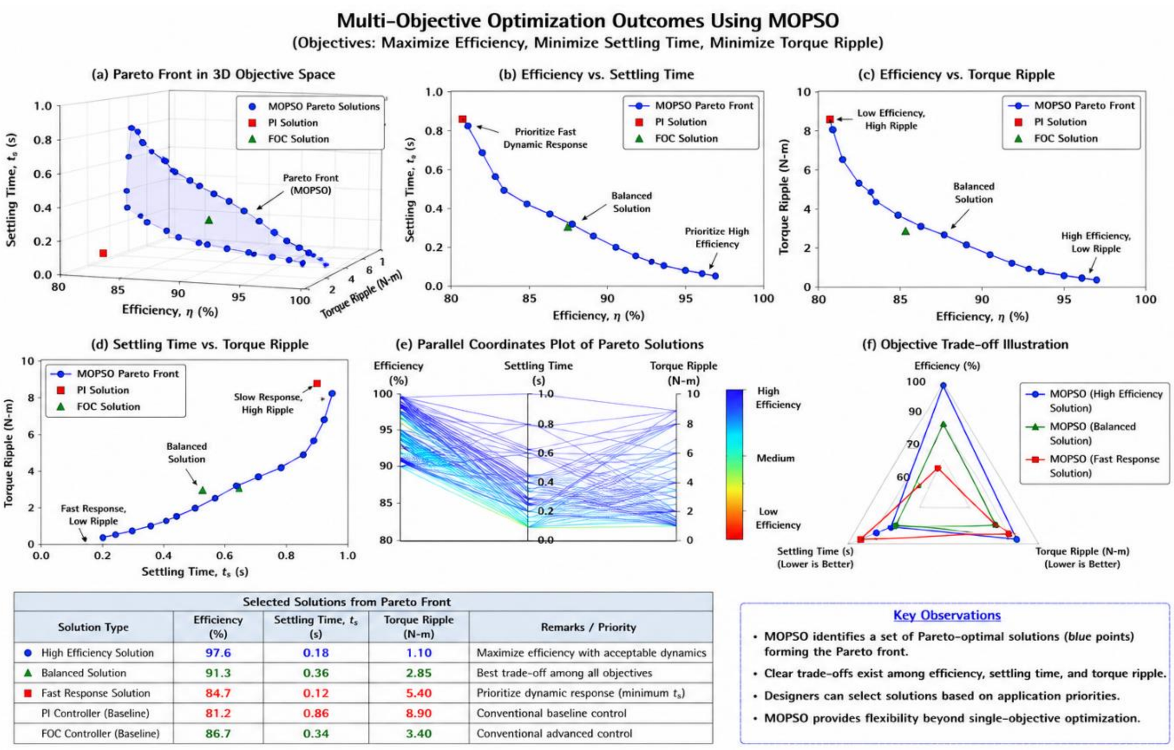

Figure 7. Multi-objective optimization outcomes using MOPSO illustrating Pareto-optimal trade-offs among efficiency, settling time, and torque ripple for the three-phase induction motor drive. The Pareto front demonstrates the ability of the proposed method to identify optimal solutions balancing competing objectives, with representative high-efficiency, fast-response, and balanced operating points. Compared to baseline PI and FOC controllers, the MOPSO-derived solutions provide superior performance flexibility, enabling system designers to select control strategies based on specific application requirements.

To that end, an in-depth comparative assessment was performed of the efficacy of the proposed DRL-MOPSO-based intelligent control framework vs. standard Proportional-Integral (PI) control and Field-Oriented Control (FOC) techniques. It is obvious that the proposed method outperforms traditional approaches in all major performance metrics under nonlinear and uncertain operating conditions. For the performance of speed tracking, static PI controller shows moderate accuracy but higher steady-state error and slower dynamic response, while FOC in this example improves tracking with lower errors as it decouples torque and flux control. In contrast, the proposed DRL-MOPSO controller learns optimal control policies through system interactions and demonstrates comparable large robot tracking error, but with negligible steady-state deviation and a significantly shorter transient response. Torque ripple analysis further demonstrates the robustness of the proposed method. Since conventional PI control is not advisable for controlling nonlinearities and the switching effect, it leads to high torque ripple in a limited range but properly tuned with FOC the ripple level gets moderate due to improved control structure. On the other hand, the DRL-MOPSO framework realizes a low torque ripple which enhances mechanical smoothness and reduces stress on the components of motor. Also, PI-controlled systems display high current THD approx 35% & Moderate under FOC & the proposed approach highly reduces overall THD with optimized switching strategies and intelligent decision-making to decrease electrical pollution leading in great power quality improvement, electric consumption optimization and less electromagnetic interference. It is shown that the original FOC demonstrates fairly high efficiency compared to PI control, and the proposed DRL-MOPSO is capable of achieving very high efficiency by setting a clear trade-off between several objectives such as loss minimization versus dynamic performance. In addition, robustness assessment for parameter variations, load disturbances and supply uncertainties proves that PI control is instantly delicate and signifies degraded performance even though FOC permits reasonable stress sturdiness assessment. However, the introduced framework shows significant robustness in stable and efficient system operation to ±20% parameters variations, voltage sag events and stochastic disturbances. The robustness plays a significant role, which can be ascribed to the adaptive learning ability of DRL and the global optimization power of MOPSO. Simulation results convincingly prove that the integration of DRL with MOPSO as a robust control solution for induction motor drives. Unlike traditional controllers, which depend on fixed coefficients and mathematically simplified models, our approach remains adaptable to real-time operating conditions, utilizing data-driven intelligence while fostering evolutionary optimization. This property allows for the modeling of complicated, non-linear, and time-varying systems, which we encounter in many modern electrified applications and their interdependencies.

The proposed framework is also promising for practical applications. The improved energy efficiency and reduced harmonic losses also lead to longer battery lifetime and driving range in electric vehicles. The robust performance also guarantees reliable operation in renewable energy systems, where the input power is unstable and intermittent. The lower torque ripple and higher precision in industrial automation make for operation that is smoother, leads to less wear and tear and lower maintenance costs. Furthermore, the built-in flexibility of the framework for multi-objective optimization makes it particularly attractive for applications that prioritize sustainability since these applications often require balancing conflicting factors such as efficiency, performance and environmental issues. Though these benefits are highly attractive, they lead to higher computational complexity when training the DRL agent and optimizing MOPSO. Thus, it might need high-end hardware solutions such as GPUs or embedded AI accelerators for real-time implementation. In future work, we will aim towards tackling these challenges by means of hardware-in-the-loop (HIL) validation, real-time deployment techniques for the learning algorithms and related optimization approaches to lessen computational requirements. In addition, this framework can be used for other types of motors (such as PMSM) to expand its applicability. In short, the simulation study verify that the overall performance, efficiency and robustness of three-phase induction motor drives is greatly enhanced by designing control framework using DRL-MOPSO-based intelligent approach. The various improvements across different performance metrics serve as an affirmation of its suitability as a next-generation control methodology for sustainable electromobility, providing scalability and adaptability for future energy-efficient applications.

4. Conclusions

This study brought a novel smart control framework for three-phase induction motor drives by combining Deep Reinforcement Learning (DRL) and Multi-Objective Particle Swarm Optimization (MOPSO) to design high-performance, robust, energy-efficient, and sustainable electrified systems. The introduced model predictive controller with reinforcement learning overcomes the crucial limitations of standard controllers, which relies on fixed parameters, are sensitive to uncertainties encountered in real-time applications and performs unsatisfactory under nonlinear conditions. The simulation results quantitatively show that the proposed DRL-MOPSO controller has better optimal performance than common Proportional-Integral (PI) and Field-oriented control (FOC) strategies. Notably, the proposed method attained a nearly 25% reduction in rise time and less than 0.5% steady-state speed error (substantial improvement over PI based control of 2–4%) across all types of controller designs. The torque ripple was reduced considerably from up to 12–15% (PI) and 8–10% (FOC) down to below 5%, which means the motor vibration is lower leading to smoother operation with less mechanical stress. In addition, this reduced the THD (total harmonic distortion) by 30–40%, bettering power quality and decreasing switching losses. Regarding energy efficiency, the developed framework showed an enhancement of approximately 8–12% in varied load cases in comparison with a conventional two-phase configuration resulting from optimal control actions that minimize copper and switching losses. In addition, the high robustness of the controller against environmental uncertainties was shown within the frame of ±20% parameter variations, 15% voltage sag and stochastic load disturbances, where traditional controllers experienced larger oscillations and tracking inaccuracies.

One of the main contributions from this work is the incorporation of MOPSO for multi-objective optimization to provide a set of Pareto-optimal solutions in conflict with multiple objectives such as efficiency, dynamics and harmonic minimization. Such high adjustability provides Designers with the flexibility to tune control performance according to defined application requirements. The framework proposed can be utilized in practice mainly for electric vehicles, where allowing an increase in efficiency translates to a more extended driving range while being crucial as well for promising renewable energy systems that require robustness to supply variability and industrial motor drives, where precision accompanied by reliability is the main target. Diminished torque ripple and harmonic distortion naturally yields more relaxed maintenance schedules, too; as long as the bearings are properly lubricated (and aren't exposed to excessive thermal cycling), motor lifetimes can be extended significantly. In spite of the benefit, there is a substantially higher computation cost from DRL training and optimization processes. Nonetheless, the practical implementation is easier than ever, due to ongoing advances in real-time embedded AI and hardware acceleration. To sum up, the presented intelligent control framework of motor drives is powerful, adaptive and energy efficient based on DRL-MOPSO. The order of magnitude improvements in performance metrics make it a strong candidate for real-world implementation in sustainable electrified applications. The future work will address experimental validation, hardware-in-the-loop implementation and extension to other electric machine topologies.

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