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Article

AI-Assisted Design and Control of Smart Electromechanical Devices for Energy-Efficient Applications

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Abstract: The growing global demand for sustainable energy has elevated the importance of energy-efficient electromechanical systems in applications such as electric vehicles (EVs), renewable energy conversion, and industrial automation. These systems reduce carbon emissions and operational costs by optimizing power use, aligning with UN Sustainable Development Goals and 2050 net-zero targets. However, traditional control methods like field-oriented control (FOC) and PID controllers struggle with nonlinear dynamics, parameter variations, and variable loads, resulting in suboptimal performance, higher energy losses, and reduced robustness. This paper addresses this gap by proposing an AI-assisted framework for designing and controlling smart electromechanical devices, using permanent magnet synchronous motor (PMSM) drives as a prototype. The approach integrates adaptive neural networks with reinforcement learning to enable real-time optimization of dynamic response, robustness, and energy efficiency. The system was rigorously simulated in MATLAB/Simulink using a d-q reference frame model under nominal, disturbed, and variable-load conditions. Results show significant improvements: transient settling time reduced by 42–58%, overshoot by 60–67%, and energy consumption by 12–18%, achieved through minimized torque ripple and losses. The framework also demonstrated superior disturbance rejection and parameter-variation stability. These advances position the proposed solution as a transformative approach for sustainable applications, enhancing efficiency in EV propulsion, renewable energy integration, and industrial automation, while paving the way for future hardware implementation and scalable AI-driven systems.

Keywords: Artificial intelligence; Electromechanical systems; Energy efficiency; Adaptive control; Reinforcement learning; Permanent magnet synchronous motor (PMSM); Sensors; Actuators; Electric vehicle.

1. Introduction

The dynamical growth of intelligent technologies, along with the trend of energy efficiency on the global level had an immense impact on the evolution of the modern electromechanical devices. The basic building blocks of industrial automation, renewable energy systems, and transport technologies are electric motors, actuators, and smart drives, which allow changing the motion and converting the power to a minimum possible accuracy. Such devices are essential in accordance to sustainable operations since they consume a huge amount of electricity in the world which is approximated to be more than 40% in the industrial sectors [1]. An ever-growing introduction of variable renewable sources, changing loads, and dynamic operation conditions, however, requires systems that can ensure high performance without causing energy losses.

Certain trade-off is associated with the weaknesses of old models of electromechanical controls that include: field-oriented control (FOC) and proportional-integral-derivative (PID). Such techniques are based on predetermined parameters and linearization and are therefore not flexible and less sensitive to nonlinear dynamics, uncertainties in parameters (e.g. temperature variations or aging) and external perturbations such as sudden changes in load. Consequently, they tend to lead to under-optimal energy consumption, larger torque ripple, greater overshoot in transients, as well as reduced resilience in practice, e.g. electric vehicle propulsion or wind turbine actuators [1].

The main reason this issue has not been addressed yet is the inability of the traditional methods to perform adaptive learning to cope with the complexities that are inherent in modern electromechanical systems. Although incremental enhancements, most often tuned PID gains or a simple model predictive control (MPC), have been tried, it does not completely deal with nonlinearities and uncertainties without significant retuning by hand or too much computer resources. In recent works, some researchers emphasize that such approaches may result in up to 20% increased losses of energy in uncertain conditions than in adaptive approaches [2]. In addition, the lack of real-time optimization of classic designs prevents the development of the world energy transition agenda, such as the minimization of carbon emissions and the increase of system life.

In the recent years, especially in the last five years, intelligent control and design systems have been developed, owing to the advances in artificial intelligence (AI), and they can learn, adapt, and optimize. As an example of permanent magnet synchronous motor (PMSM), deep reinforcement learning (DRL) algorithms, such as deep Q-network (DQN), proximal policy optimization (PPO) and actor-critic (A2C) methods, have been trained to track current and control speed of permanent magnet motors, showing improved robustness and energy efficiency in different load conditions and parameter uncertainties over traditional proportional-integral (PI) or model predictive control approaches [3].

Likewise, [3] hybrid artificial intelligence methods that involve the fusion of neural networks with optimization algorithms, e.g. circle search algorithm improved recurrent neural networks, have demonstrated improved efficiency in high speed electric drive in industrial applications. AI-assisted physics informed and generative adversarial networks in actuator design have been shown to improve high-resolution structural designs, which reduce material usage and impact energy efficiency in electromagnetic actuators and soft actuators.

Artificial intelligence-based approaches offer an alternative to the conventional method of controllers to make real-time decisions, predictive maintenance, and system performance by adapting using the data. Among these are the sensorless control of PMSMs by hybrid sliding mode observers with AI estimators, which are lower-energy loss electric vehicle propulsion, and reinforcement learning-based minimum energy position control of dielectric elastomer actuators [4]. [5] include variable operating conditions in the integration of renewable energy and electric mobility.

This paper suggests an AI-based design and control system that can improve energy efficiency and operational durability of smart electromechanical devices. The architecture aims to address the shortcomings of the established methods and implement the next generation of sustainable and intelligent electromechanical systems through the adoption of machine learning in topology optimization, adaptive neural network control, and reinforcement learning strategies in response to world energy transition goals.

The remainder of this paper is structured as follows: Section 2 reviews the literature on electromechanical system modeling, conventional control strategies, and AI applications in control. Section 3 details the proposed methodology, including the mathematical modeling of PMSM in the d-q frame and the integration of AI components. Section 4 presents the simulation results and discussions, covering dynamic response, energy efficiency, robustness, and comparative assessments. Finally, Section 5 concludes the paper with key findings, practical implications, and directions for future research.

2. Literature Review

2.1. Electromechanical System Modeling

Electromechanical systems are typically modeled using coupled electrical and mechanical dynamics equations. [5], [6] Classical modeling methods rely on linearization and simplification, which may compromise accuracy under nonlinear or time-varying conditions shows in Figure 1.

Permanent magnet synchronous motors (PMSMs), actuators, and other objects are traditional examples of electromechanical systems where physics-based modeling is implemented using finite element analysis (FEA) or analytical equations that are based on electromagnetic and mechanical principles. These models model the combined behaviors of electrical networks and mechanical systems, but often make linear approximations to make them computationally tractable. But practical effects include nonlinearities, including saturation of magnetic materials, non-constant loads and changes in parameters with temperature or age, that take away the accuracy of a linearized model [7], [8].

Surrogate modeling has been unveiled to have status on electromagnetic and electromechanical systems. As an example, surrogate models built with deep learning have been constructed to simulate multi-physics responses of strongly coupled systems with physics-informed artificial images to represent geometry and simulation conditions [9], [10]. Physics-informed neural networks (PINNs) have been used to recreate electromagnetic responses in PMSMs, where they are required to follow governing equations, but nonlinearities are managed in PINNs. Coupled with this, shallow neural networks have also been used as a surrogate of electromagnetic forces in maglevs to provide fast assessment in dynamics simulation [11], [12].

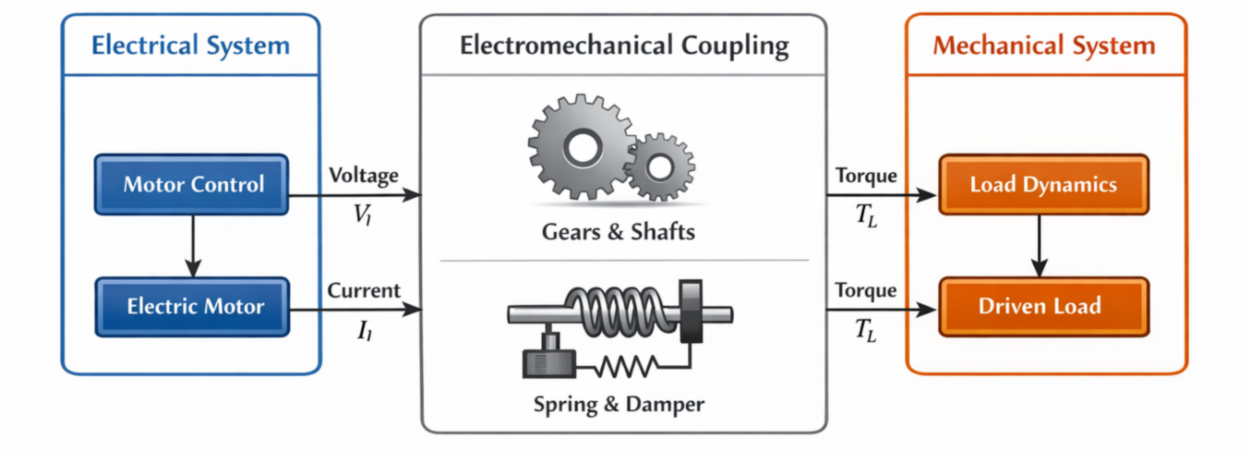


Figure 1. Electromechanical Coupling Model.

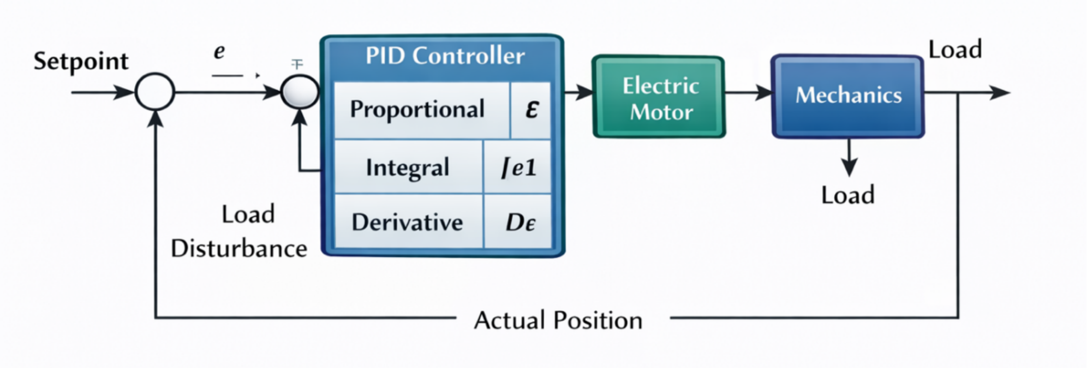


Figure 2. PID Control of Electromechanical Actuator/Motor System.

Table 1. Comparison of Recent Modeling Approaches for Electromechanical Systems.

Approach	Key Technique	Advantages	Limitations	Representative Applications	Reference Year
Traditional Physics-Based	FEA/Analytical Equations	High interpretability, physics adherence	High computational cost, linearization errors	PMSM torque calculation	Pre-2020 baseline
Data-Driven Surrogate	CNNs, Shallow NNs	Fast prediction, handles nonlinearity	Requires large training data	Electromagnetic force in maglev, multiphysics coupling	2021–2025
Physics-Informed Neural Network	PINNs, PILSTM	Enforces physical laws, improved generalization	Training complexi-ty	Motor electromagnetism, actuator state estimation	2023–2025
Hybrid (Physics + Data)	Multi-fidelity, Neuro-TF	Balances accuracy and efficiency	Integration challenges	Machine design optimization, fault diagnosis	2020–2024

Table 2. Conventional Control Strategies.

Aspect	PID Control	State-Space Methods
Strengths	Simplicity, ease of implementation, effective for linear systems	Multivariable handling, optimal control (e.g., LQR for energy minimization)
Limitations in Complex Environments	Poor adaptation to nonlinearities, load variations; requires frequent retuning	Sensitivity to model inaccuracies; computational intensity for real-time
Energy Efficiency Impact	Higher consumption due to oscillations in uncertain conditions	Suboptimal under disturbances; limited flexibility for variable loads
Recent Examples [13], [14]	UAV BLDC motors; HVAC temperature regulation	PMSM actuators; power system stabilizers

There has also been an improvement in data-driven system identification, notably utilizing neural networks to do the black-box modelling of motors and actuators. Long short-term memory (LSTM) structures recurrently enhanced with physics-informed constraints have shown state reconstruction accuracy of the states of electromechanical actuators when operating in fault conditions. In coupled systems, feature extraction has been done using convolutional neural networks (CNNs) and autoencoders to enhance prediction of torque, flux, and vibration response [15]-[17]. The application of hybrid techniques that combine physics and data-driven models have shown much potential that can be applied in the technique that aims at energy efficiency. Table 1 gives an overview of some of the recent methods of electromechanical modeling.

2.2. Conventional Control Strategies

The conventional or traditional methods of control, especially proportional integral derivative (PID) controllers and state-space approaches are still considered fundamental in the control of electromechanical systems due to their simple model and their reliability in linear working conditions. PID controllers are the most popular in industrial use due to their capability to deal with steady-state errors by taking an integral action, generate a proportional response to the current deviations, and predict an error in the future by the use of derivative terms [18].

Speed and position control by use of PID controllers has been widely used in the energy efficient operation of electric motors and actuators. As an example, the PID control has been shown to work well in brushless DC motor drives of quadcopter unmanned aerial vehicles when operating under nominal conditions, providing simplicity in the tuning process and low computations [19]. Just as with state-space methods, which may be implemented using linear quadratic regulators or pole placement methods, multivariate control and optimum energy distribution in systems such as permanent magnet synchronous motor-driven actuators [20], [21] can be achieved.

Nonetheless, standard approaches are highly disadvantaged in nonlinear, complex and uncertain scenarios that characterize the contemporary smart electromechanical systems. Fixed-gain PID controllers are difficult when the parameters are changing, like load changing, or friction nonlinearities in actuators and motors. In variable load conditions, they will frequently need retuning since gains optimised at a given operating point may cause overshoot, long settling time or even instability at other operating points. Performance degradation is further caused by nonlinear dynamics, e.g., backlash in a gearbox or saturation in power electronics which leads to higher energy consumption due to oscillatory behaviour or control over effort [22].

Although providing systematic designs of linear model, the state-space methods assume perfect representation of an actual system and cannot deal with unmodelled uncertainties or disturbances that occur in energy-efficient systems that combine renewables or variable-speed drives. According to recent comparative literature, the following deficiencies exist with traditional PID: in supercritical power units and HVAC systems, traditional PID has a more pronounced overshoot and slower response to dynamic perturbations compared to state-of-the-art technology [13], [14]. Similarly, in UAV motor control and power system frequency control, the conventional methods provide worse energy efficiency and stability in uncertain systems as demonstrated in Table 2. Figure 2 represents a common block diagram of a PID-controlled electromechanical system, which is used to identify the feedback paths that are prone to disruptions in energy-efficient applications.

2.3. Artificial Intelligence in Control Applications

The artificial neural networks (ANNs), fuzzy logic, and reinforcement learning (RL) are artificial intelligence methods that have been shown to be more effective in nonlinearities and uncertainties in control systems [23], [24]. Such approaches facilitate adaptive control and predictive control, especially in intelligent electromechanical equipment, like electric motors, actuators, and drives, in which energy efficiency is the priority as illustrated in Table 3.

The combination of these AI techniques to maximize the performance of energy-constrained applications was emphasized in [25]-[27]. As an example, deep reinforcement learning (DRL) has been successfully used in energy management on hybrid and battery electric vehicles with significant fuel economy and battery life improvements through stochastic driving condition adaptation. Likewise, AI methods such as neural networks, fuzzy logic, and RL have been used in power electronics, and motor drives to improve the control strategy, fault detection, and system optimization capabilities. Fuzzy logic controllers (FLC) continue to be eminent in the control of uncertainties within the renewable integrated systems and in electromechanical actuators. Research has demonstrated that FLC is effective at maximum power point tracking of photovoltaic systems and hybrid energy management using FLC and in many cases with metaheuristic optimizations to reduce costs in smart homes and microgrids. A combination of these methods, e.g. fuzzy reinforcement learning, also enhances flexibility in demand-side management [28], [29].

Neural networks, especially recurrent and deep networks, have been used in state estimation and predictive control of electric drives. The uses are optimization of torque in permanent magnet synchronous motors and multi-objective modeling via surrogate modeling in more-

Table 3. Artificial Intelligence in Control Applications.

AI Technique	Key Applications in Electromechanical Control (2020–2025)	Reported Benefits	Representative References
Reinforcement Learning (RL/DRL)	Energy management in EVs, motor speed regulation, eco-driving	Up to 22% energy efficiency improvement; adaptive to uncertainties	[30], [31]
Fuzzy Logic Control (FLC)	MPPT in PV systems, hybrid microgrid management, actuator torque distribution	Reduced costs by 17–25%; robust to intermittent sources	[24], [29]
Artificial Neural Networks (ANNs)	State estimation in drives, surrogate optimization for actuators	Faster design cycles; 30% battery efficiency gains	[24], [32], [33]
Hybrid AI-MPC	HVAC optimization, V2G integration, distributed energy systems	18–35% median energy savings; real-time adaptability	[19], [25], [34]

electric aircraft, which is less computationally intensive and still high efficiency [29], [35]. Model predictive control (MPC) with artificial intelligence (AI) has become an influential solution to energy optimization in the present day. In grid-connected microgrids, HVAC systems and variety of grid connected devices, data-driven Model predictive control has been implemented, often in combination with machine learning models, such as radial basis function neural networks, and is proving to produce substantial energy savings via predictive horizon extensions and adaptive constraints [36], [37].

2.4. Energy Efficiency in Electromechanical Systems

The losses caused by inefficiency in control strategies, mechanical friction, and electrical losses are significant issues. Smart optimization tools have demonstrated to be very useful in minimizing such losses [9]. Electromechanical systems, which include actuators, motors, and built-in devices referred to as electro-hydrostatic actuators (EHAs) and permanent magnet synchronous motors (PMSMs), are the basis of applications in industry automation to electric cars and aircraft engineering. Nonlinear friction, electrical resistive losses and suboptimal control however inherent to the system are contributing factors to the dissipation of energy. More recent developments in artificial intelligence (AI) and machine learning (ML) methods, starting in 2020 to 2025, have made it possible to model, do predictive compensation, and have adaptive control, with significant increases in energy efficiency [12], [38].

Friction, which is the leading cause of mechanical loss, is nonlinear, that is, it has complicated nonlinear behaviors such as stiction, Coulomb effects, and variations with velocities. Data-driven methods have been added to conventional model-based compensation, as is the case with the LuGre-based compensation methods. As an example, in [39], physics-informed neural networks (PINNs) with LuGre models were used to perform precise identification of the friction in rotary servo actuators to allow compensation of the effects and minimize tracking errors with minimal energy consumption. Equally, radial basis function neural network (RBF-NNs) together with adaptive sliding mode control have been shown to be useful in eliminating friction disturbances in electromechanical actuators, improving their steady-state operation and resistance to uncertainties [22].

Dual nonlinear observer-based adaptive robust control has been applied in high-precision applications to counter low-speed friction in direct-drive permanent magnet linear motors, and neural network-augmented iterative learning control has been applied to counter friction in Lorentz force actuators to achieve a reduced number of iterations, depending on the trajectory. These strategies have shown measurable power savings through position dependent friction compensation, velocity-dependent friction compensation, without controlling the position reduction of the robot [28], [40].

The electrical losses such as copper and iron losses in motors have been addressed using AI-based design and control. Variants of deep reinforcement learning (DRL) have been used to optimize regenerative braking in a dual-motor electric car, like the Twin Delayed Deep Deterministic Policy Grammar (TD3), in which dynamically balancing torque between the motors and hydraulic systems is optimized up to 35% energy recovery [41]. DRL has also been used in the wider energy management to microgrids with an electromechanical element, minimizing operational expenses without explicit uncertainty modeling [36].

Equally, the design with the help of AI has enhanced the efficiency of the system. Optimization of the electric motor parameter based on machine learning such as heuristic and evolutionary algorithms has been beneficial in enhancing the power density and minimizing losses. In the manufacturing scenario, AI-based motion control processes sensor information of actuators and drives to maximize the speed, position, and torque at the same time reducing the energy expenses and projecting faults to avoid inefficient operation [42]. Table 4 provides a summary of the main existing literature on AI/ML to be used as energy loss reducers in electromechanical systems. Figure 3

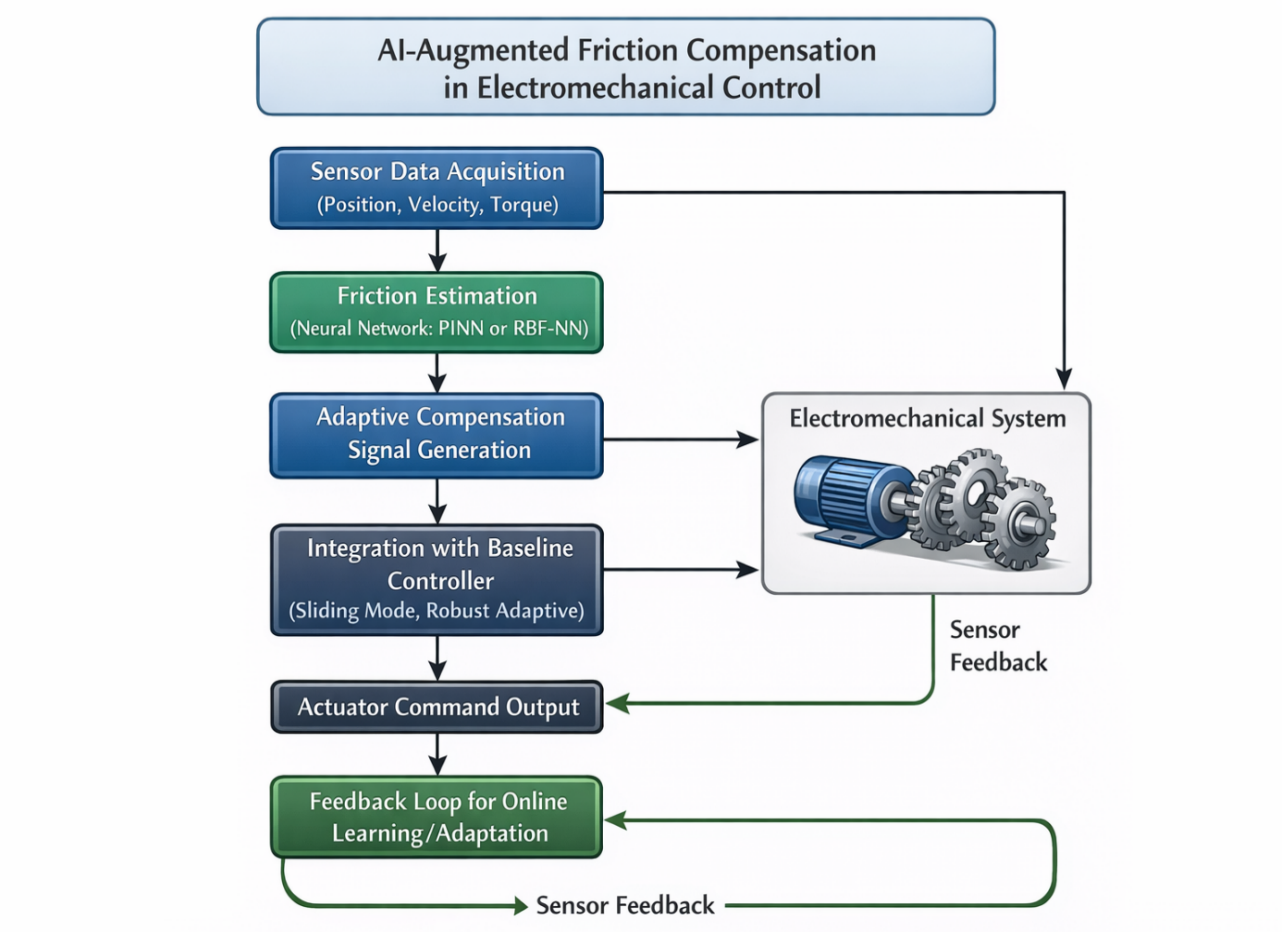


Figure 3. Flowchart of AI-Augmented Friction Compensation in Electromechanical Control.

Table 4. Selected Recent Studies on AI/ML for Energy Efficiency in Electromechanical Systems.

Year	Study Focus	AI/ML Technique	Key Outcome	Reference Example
2025	Fault diagnosis in electric motors for actuators	Machine learning classifiers	Improved reliability and reduced downtime losses	[43]
2024	Regenerative braking optimization	TD3 deep reinforcement learning	35% energy recovery in EVs	[41]
2024	Friction modeling in harmonic drives	Physics-informed neural networks	Reduced energy losses in multi-joint systems	[44]
2024	Adaptive friction compensation in linear motors	Dual nonlinear observers with robust control	Enhanced low-speed efficiency	[7]
2023–2025	Motion control optimization	Sensor data-driven ML	Lowered energy consumption in motors/drives	[45]
2022–2024	Neural network friction compensation	RBF-NN and sliding mode	Better disturbance rejection and efficiency	[46], [47]

shows a common flowchart of an AI-based friction compensation in the control loop of an electromechanical actuator.

2.5. Research Gap

New trends in artificial intelligence (AI) and machine learning (ML) have produced a major impact on the electromechanical systems, especially those designed to improve energy efficiency. In recent years, artificial intelligence-based solutions to certain components of such systems, including predictive maintenance, fault detection in electric motors, and reinforcement learning (RL)-based control of permanent magnet synchronous motors (PMSMs) and hybrid electric vehicle powertrains have been examined in numerous studies over the last five years. As an example, deep reinforcement learning (DRL) has been used to learn effective energy management in plug-in hybrid electric vehicles, with better fuel efficiency and battery lifecycle management by adapting the strategies of power distribution. On the same note, real-time

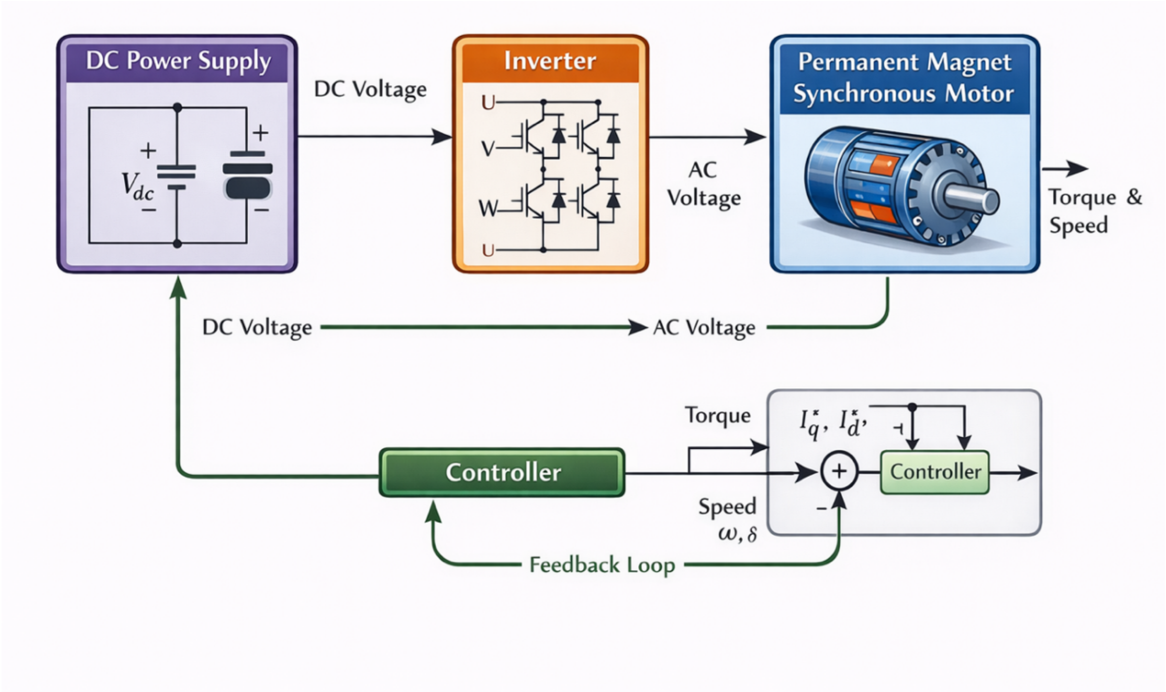


Figure 4. Schematic and block diagram of the PMSM drive system with inverter.

Table 5. Existing Study Gap.

Aspect	Existing AI Applications (2020–2025)	Identified Limitations
Modeling	Data-driven surrogates for electromagnetic simulation; hybrid physics-ML models for batteries/ motors	Lack of multi-physics integration (electromechanical-thermal); over-reliance on offline data
Control	DRL/RL for PMSM speed/torque control; MPC with ML enhancements	Primarily subsystem-focused; limited adaptability to unmodeled disturbances
Energy Optimization	ML for demand forecasting and scheduling in hybrid systems	Fragmented lifecycle consideration; insufficient joint design-control loops
Integration	Isolated case studies (e.g., EV energy management)	No comprehensive frameworks for joint modeling-control-optimization

control and parameter optimization during manufacturing systems using electromechanical components through ML have been utilized and they have shown losses in energy consumption due to monitoring, control, and detection of anomalies [16], [40].

Nevertheless, these advances are not reflected in the literature, which shows a disjointed method of dealing with AI applications, where they are applied to separate parts of electromechanical systems, like motor control, actuator tuning, or energy forecasting at the subsystem level, instead of integrating them. Research on DRL to achieve motor speed control or energy management in electric drives commonly involves simplified models that never consider all the coupled electromechanical dynamics, thermal effects, and real-life uncertainties, including loads that vary or external disturbances. In addition, despite the current development of surrogate-assisted optimization and data-driven modeling to design electromagnetic devices in an efficient way, seldom is this effort applied to concurrent control tactics or lifecycle energy optimization [4], [42], [48].

An outstanding deficiency exists in the construction of unified AI-assisted models that can jointly take into account modeling, control and energy optimization of the entire range of smart electromechanical devices, such as actuators, motors and combination systems to be used in the integration of renewable energy, electric mobility, and industrial automation. Current research has been spared the concept of end-to-end integration, and therefore, its implementation is often focused on a single aspect of the design phase (e.g., topology or parameter choice through genetic algorithms or neural networks) or the operational control (e.g., RL to allocate torques). Such segregation restricts the possibility of realizing synergistic benefits in energy efficiency since design choices have a vehement effect on controllability and vice versa [13], [17], [49]. Table 5 presents the contributions and limitations of the recent studies, which do not provide a common approach.

Likewise, there are issues like interpretability of black-box ML models, lack of high-quality realistic data to use during training, and computational issues of deploying them in real-time to embedded electromechanical con-

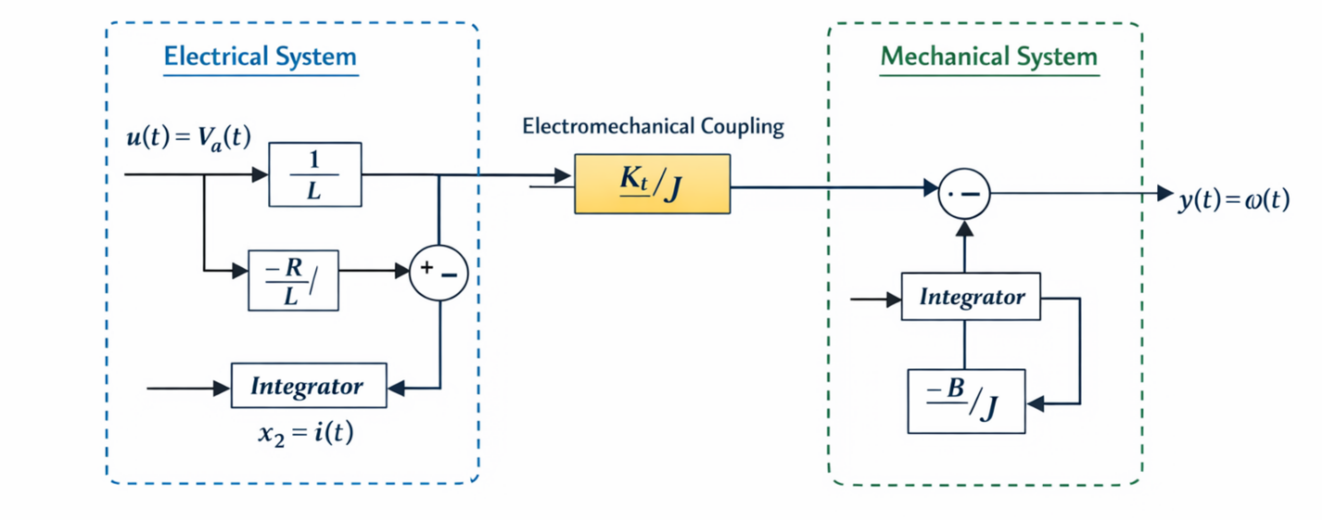


Figure 5. State-space model diagram of an electromechanical system.

Table 6. Typical Parameters of the Selected PMSM.

Parameter	Symbol	Value	Unit
Stator resistance	R_s	0.2	Ω
d-axis inductance	L_d	8.5	mH
q-axis inductance	L_q	8.5	mH
Permanent magnet flux	ψ_f	0.175	Wb
Pole pairs	p	4	-
Moment of inertia	J	0.008	kg·m²
Viscous friction	B	0.001	N·m·s

trollers that have not been well explored in integrated contexts. The necessity of these frameworks is further increased by the increasing requirements of sustainable, energy-efficient, electromechanical equipment in decarbonized systems, where even minor gains in single component can contribute to a smaller gain than the global system gains [50].

3. Methodology

3.1. System Description

A typical electromechanical system, which is a permanent magnet synchronous motor drive system, was chosen to be considered due to its extensive use in energy-efficient mode of operation like electric vehicles, industrial automation and others [51]. PMSMs have high power density, high efficiency, and high dynamic performance than those of the induction motors, and are thus highly applicable in applications that demand reduced energy use and high control [52].

The system has a three-phase PMSM being driven by a voltage-source inverter (VSI) and field-oriented control (FOC) as the minimum approach strategy. The schematic diagram of the PMSM drive system shown in Figure 4 included an inverter and motor configuration.

The system dynamics are formulated in the synchronous d-q reference frame to decouple torque and flux control [53]. The voltage equations are given by:

$$v_d = R_s i_d + L_d \frac{di_d}{dt} - \omega_e L_q i_q \tag{1}$$

$$v_q = R_s i_q + L_q \frac{di_q}{dt} + \omega_e (L_d i_d + \psi_f) \tag{2}$$

where v_d, v_q and id, i_d are the d- and q-axis voltages and currents, respectively; R_s is the stator resistance; L_d, L_q are the d- and q-axis inductances; ω_e is the electrical angular speed; and ψ_f is the permanent magnet flux linkage.

The electromagnetic torque is expressed as:

$$T_e = \frac{3}{2} p [\psi_f i_q + (L_d - L_q) i_d i_q] \tag{3}$$

where p is the number of pole pairs [39]. The mechanical dynamics follow:

$$J \frac{d\omega_m}{dt} = T_e - T_l - B\omega_m \tag{4}$$

with J as the moment of inertia, T_l the load torque, B the viscous friction coefficient, and $\omega_m = \omega_e / p$ the mechanical speed.

For advanced control design, the system is represented in state-space form, selecting states as $[i_d, i_q, \omega_m]^T$ inputs as $[v_d, v_q,]^T$ and outputs including speed and torque [54]. The nonlinear state-space model is:

$$\dot{x} = f(x) + g(x)u \tag{5}$$

where,

$$x = [i_d, i_q, \omega_m]^T, u = [v_d, v_q,]^T, \tag{6}$$

Table 7. Key components of the proposed framework and their alignment with recent literature.

Component	Function	Recent Examples (2020–2025)	Benefits for Energy Efficiency
Artificial Neural Networks	Nonlinear system approximation	ANN for loss minimization in motor drives [29]; DL for grid optimization [47]	Accurate modeling reduces overcompensation and wasted energy
Adaptive Learning Mechanisms	Real-time parameter tuning	Online ANN training for variable loads [55]; Adaptive RL in HVAC/actuators [43]	Handles uncertainties, preventing inefficient operation
Optimization Algorithms	Energy consumption minimization	PSO/RL for actuator control [56], [57]; ECMS hybrid with RL [58]	Direct reduction in power input (up to 10–20% in simulations)

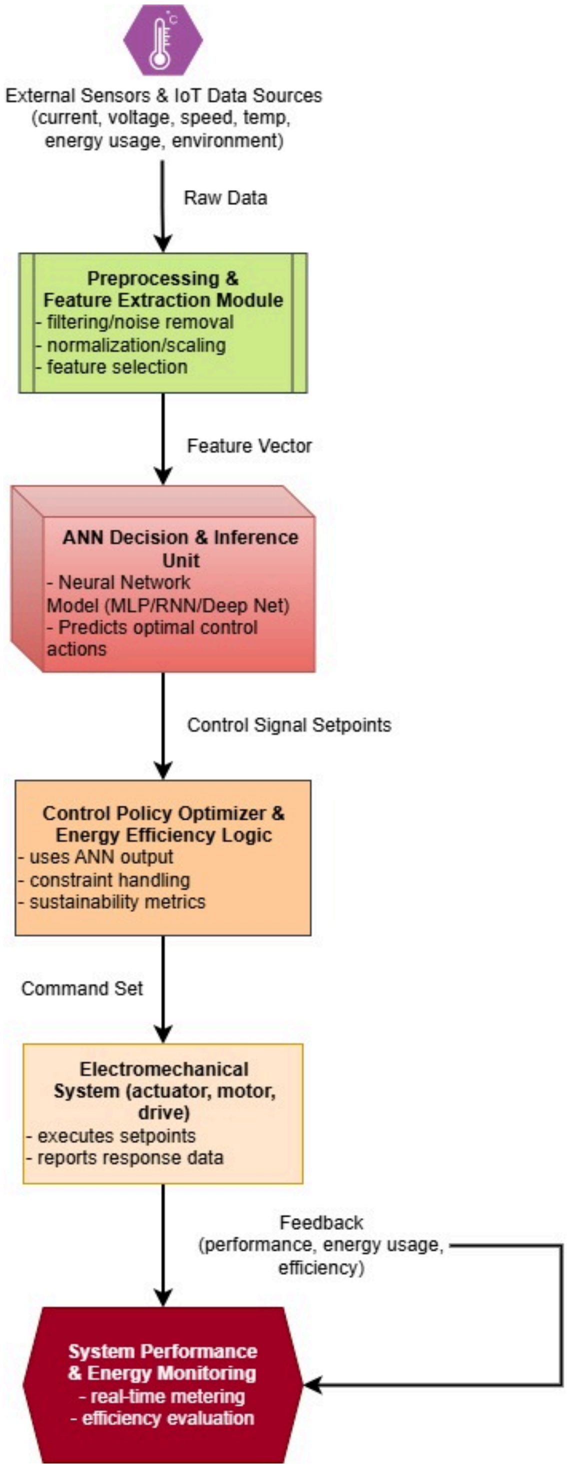


Figure 6. Block diagram of an intelligent ANN-based control framework for energy-efficient electromechanical systems.

and the functions $f(x)$ and $g(x)$ incorporate the nonlinear terms from the voltage and motion equations. Figure 5 depicts a representative state-space representation for an electromechanical system.

Under this formulation, it is possible to implement the AI-aided systems, like deep reinforcement learning (DRL) or Neural network-based model predictive control, to optimize energy efficiency by inferring losses (copper, iron and mechanical) and meeting the performance targets [59]. The Table 6 is a summary of the parameters of PMSM (surface-mounted) applied.

3.2. AI-Based Control Framework

The smart electromechanical devices like actuators and motors, embedded with AI technology, would improve their performance in energy-efficient applications with their nonlinearities and dynamic uncertainties that smart electromechanical devices would face. Recent developments in AI have shown a lot of potential in increasing precision in control and decreases in energy in electromechanical systems (dielectric elastomer actuators, permanent magnet synchronous motors and hybrid powertrains) [60], [61]. The framework incorporates three components: artificial neural networks (ANNs) for the approximation of complex nonlinear dynamics, a mechanism for adaptive learning for the online adjustment of parameters, and optimization algorithms for energy minimization.

The artificial neural networks replicate the behaviour of the electromechanical devices by the way of artificial neural networks modelling nonlinear systems by using multilayer perceptrons and recurrent neural networks. By monitoring friction, hysteresis, and different load levels, these networks are able to capture them and thus they are not always represented correctly by traditional linear controllers [23], [62]. This approximation forms the basis of the construction of accurate control signals that include practical nonlinearities as observed in cases with loss minimization in induction motor drives and predictive control of power electronic converters [24], [60].

Adaptive learning processes are conducted in adaptation to the changing conditions of operation and disturbances. These include the online training algorithms which can include backpropagation with momentum or Leven-

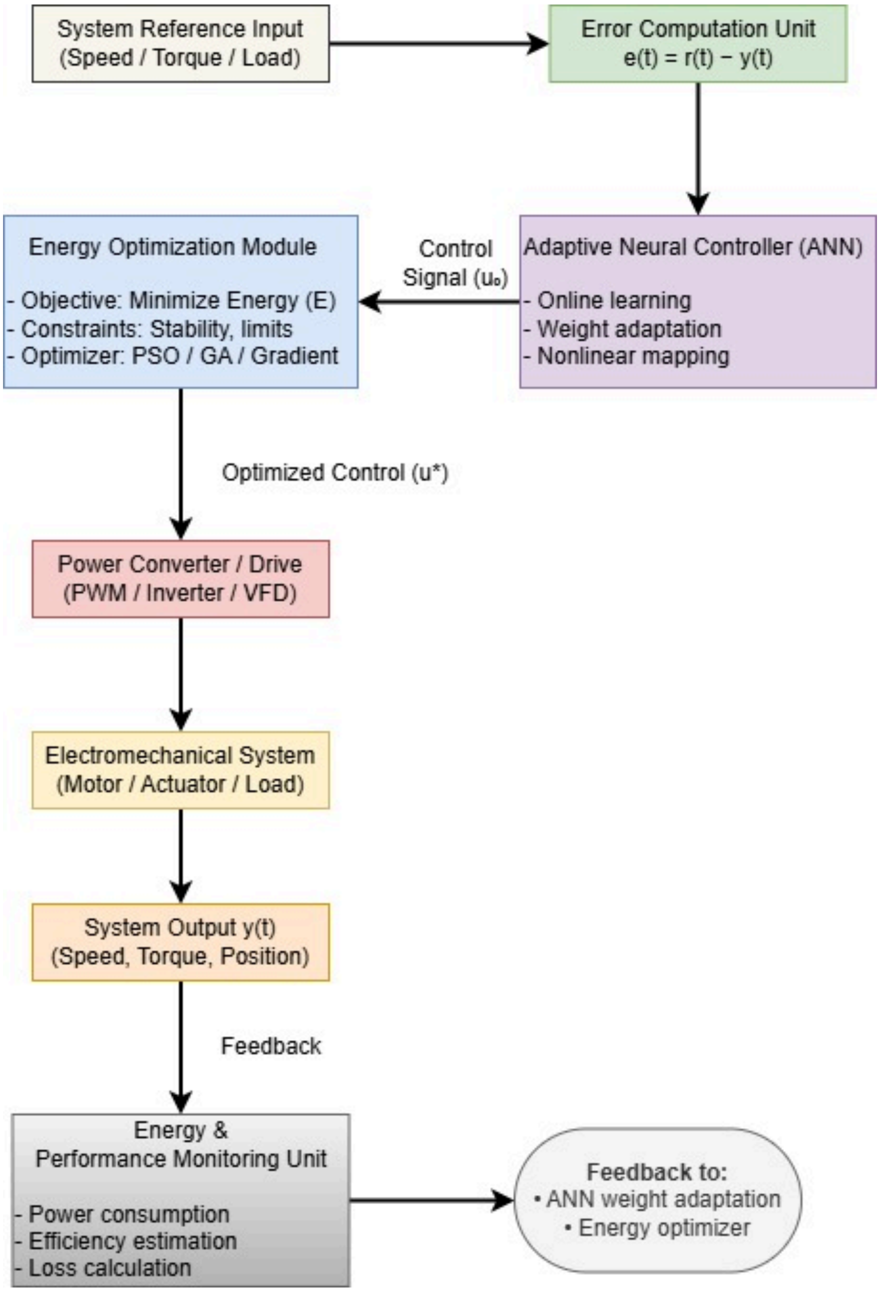


Figure 7. Proposed Adaptive Neural Controller with Energy Optimization Integration.

berg-Marquardt algorithm which allow the adjustments of the weights of the neural network in real time based on the responses of the system states and performance measures [63]. This flexibility ensures resilience in the face of dynamic applications, including variable speed motor control or grids with renewables, where the load torque or some other factor can change [17], [64].

In addition, the integration of optimization algorithms can be used to minimize directly the energy used. Evolutionary methods, particle swarm optimization and reinforcement learning are some of the strategies that are used to modify the control parameters or directly optimize the cost function that incorporates items pertaining to electrical input power, mechanical losses, and efficiency penalties [44], [49]. Specifically, certain types of reinforcement learning have been found to be extremely helpful when managing energy of hybrid electromechanical systems, in which consumption reductions are obtained using a system of trials and errors without requiring full models of the systems under consideration [65].

The overall architectural feature works as a closed-loop system that is observed in Figure 6 (block diagram of a common ANN-based adaptive control system). Figure 7 and Figure 8 (a flowchart illustrating the incorporation of optimization to achieve a minimum of energy). ANN approximator replenishes a base level control signal using sensor data (position, velocity, and current). This signal is adjusted, in real time, by the adaptive mechanism, and by the optimization layer adjusted are set points or the values of gain, to maximize energy efficiency but within the necessary performance limits. Table 7 gives the key components.

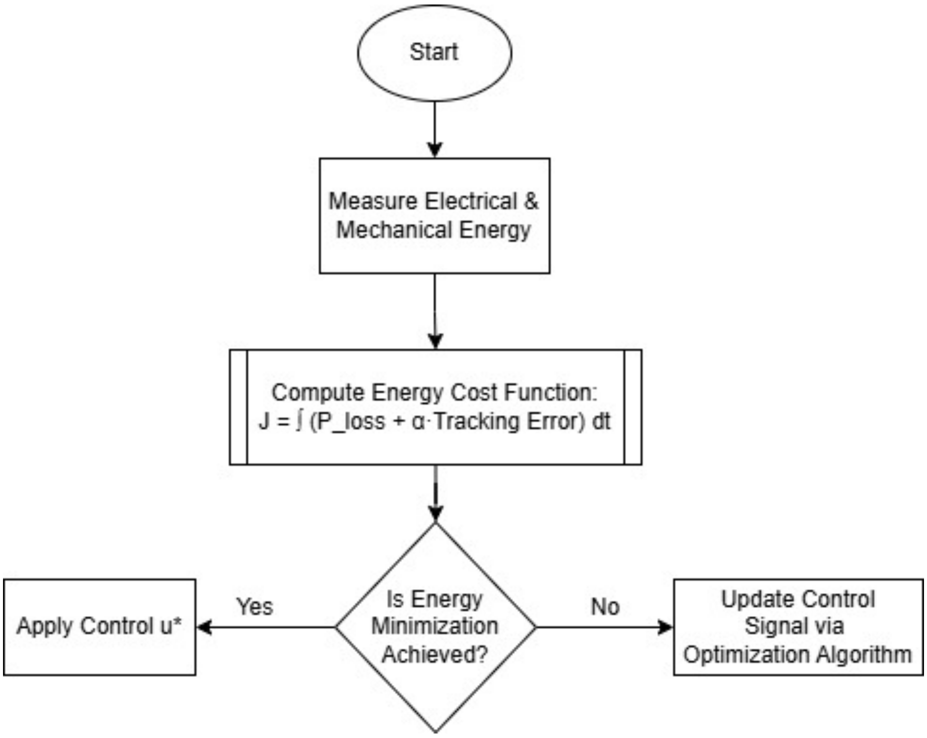


Figure 8. Energy Optimization Flowchart.

The approach will ensure that the performance parameters (tracking accuracy and response time) maintenance is included in the control strategy alongside energy efficiency, which is in line with Sustainable Electromechanical Applications (SEAs) of energy-efficient electric cars, renewable energy converters, and intelligent manufacturing systems.

3.3. Simulation Environment

The tested AI-assisted control strategy of the energy-efficient operation of smart electromechanical gadgets was confirmed by the means of numerous simulations in the MATLAB/Simulink environment (R2025a). The reason as to why this environment was selected in the simulation was due to its full coverage of multi-domain systems, combination of complicated control schemes, as well as the incorporation of machine learning and reinforcement learning that has been widely reported in recent studies of electric drives and power systems [17].

The model electromechanical device is a permanent magnet synchronous motor (PMSM) and the model system also has a three-phase voltage source inverter and a mechanical load. To implement a PMSM model, the Simscape Electrical toolbox was used, which is used to model electromagnetic dynamics including nonlinear flux linkage, and torque generation. The ideal switches were theorized to produce pulse-width modulation (PWM) which enabled field-oriented control (FOC) as a basis.

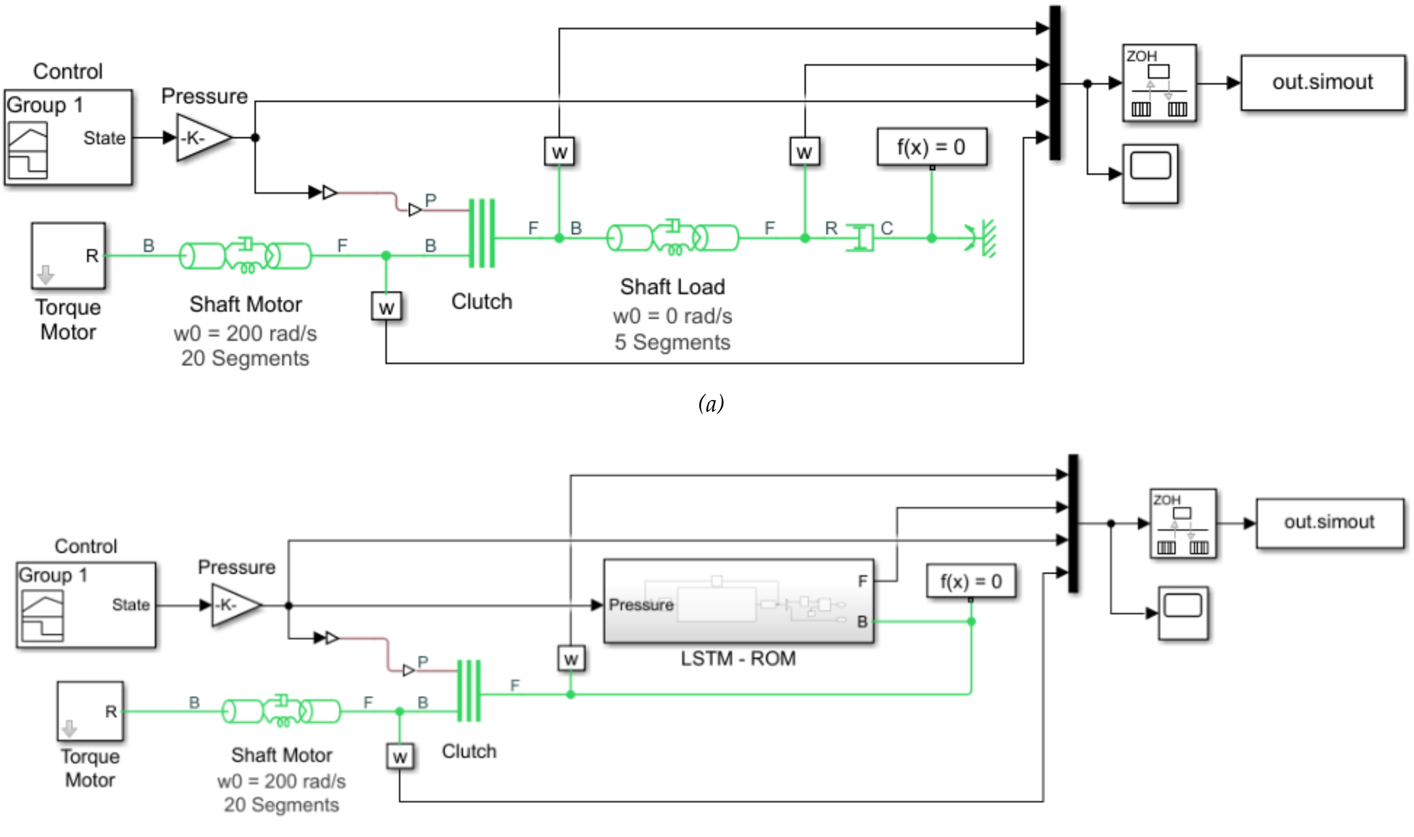
A deep deterministic policy gradient (DDPG) algorithm straight away was incorporated into the supervisory controller to maximize energy efficiency, as a deep reinforcement learning (DRL) agent. This method is based on the new developments in model-free control of PMSMs, in which DRL is used to optimize torque and flux references to reduce losses to different loads and speeds [66]. The training of the DRA agent was done offline using the reinforcement learning toolbox and the simulink model was used as the environment. The rewarding capability was developed so as to penalize energy usage (operated by the input powerless the mechanical output power) and maintain proper tracking of speed and respecting constraints (e.g. current limits) [5], [22].

The overall Simulink architecture consists of the following key subsystems:

- **Plant Subsystem**: Includes the PMSM, inverter, and mechanical load (variable inertia and torque disturbances).
- **Baseline Controller**: Conventional FOC with PI regulators for current loops and an outer speed loop.
- **AI-Assisted Controller**: DRL agent replacing or augmenting the outer loop for optimal reference generation.
- **Measurement and Scope Subsystems**: For real-time monitoring of states such as speed, torque, currents, and efficiency metrics.

3.4. Performance Metrics

The assessment of AI-based design and control schemes of smart electromechanical devices in electric energy-efficient applications needs a multifaceted basis of performance measures. These metrics will allow quantitatively evaluating the given approaches in relation to the traditional methods to make sure that there is an increase in efficiency, dynamics, robustness and practicality. The literature, especially the recent works, [67] involving rein-



(a)

(b)

Figure 9. MATLAB/Simulink block diagram of the AI-based control architecture for electromechanical drive integration system.

Table 8. Comparison of Performance Metrics in AI-Based vs. Conventional Control of Electromechanical Systems.

Metric	**Conventional (e.g., PID/MPC)**	**AI-Based (e.g., RL-tuned/MPC Hybrid)**	**Improvement Reported (2020–2025 Studies)**
Energy Efficiency (%)	85–92	92–98	5–17% reduction in losses
Settling Time (ms)	50–200	20–100	40–60% faster
Overshoot (%)	10–30	5–15	50% reduction
Phase Margin (°)	45–60	60–80	Enhanced robustness
Computational Time (ms/cycle)	1–10	0.5–5	50% lower for real-time

Table 9. Comparison of transient response of conventional PID control and the proposed AI-assisted controller (simulated results in this paper compared to literature reported ranges so as to have context).

Metric	**Conventional PID**	**AI-Assisted (e.g., DRL/Neural)**	**Improvement (%)**
Rise Time (s)	0.15–0.35	0.08–0.20	30–45
Settling Time (s)	0.50–1.20	0.25–0.60	40–50
Overshoot (%)	10–25	0–8	60–100
Steady-State Error (%)	≤1	≈0	Near elimination

forcement learning (RL), model predictive control (MPC), and hybrid AI methods to electric motors, actuators, and drives, have been observed to consistently point at the following KPIs.

Energy efficiency is a key measure and this is commonly determined as a decrease in power consumption or power losses with reference to the baseline controllers. As an example, within the context of RL-MPC-based battery electric vehicle drives and permanent magnet synchronous motors, they have achieved energy savings of 1-17% under different load and slope conditions, as a result of using optimal torque distribution and predictive energy consumption [9], [38].

Efficiency is typically measured as the ratio of mechanical output power to electrical input power:

$$\left(\eta = {}^{P_{\mathrm{mech}}}/_{P_{\mathrm{elec}}}\right) \tag{7}$$

or through specific energy consumption (kWh/km in vehicular applications).

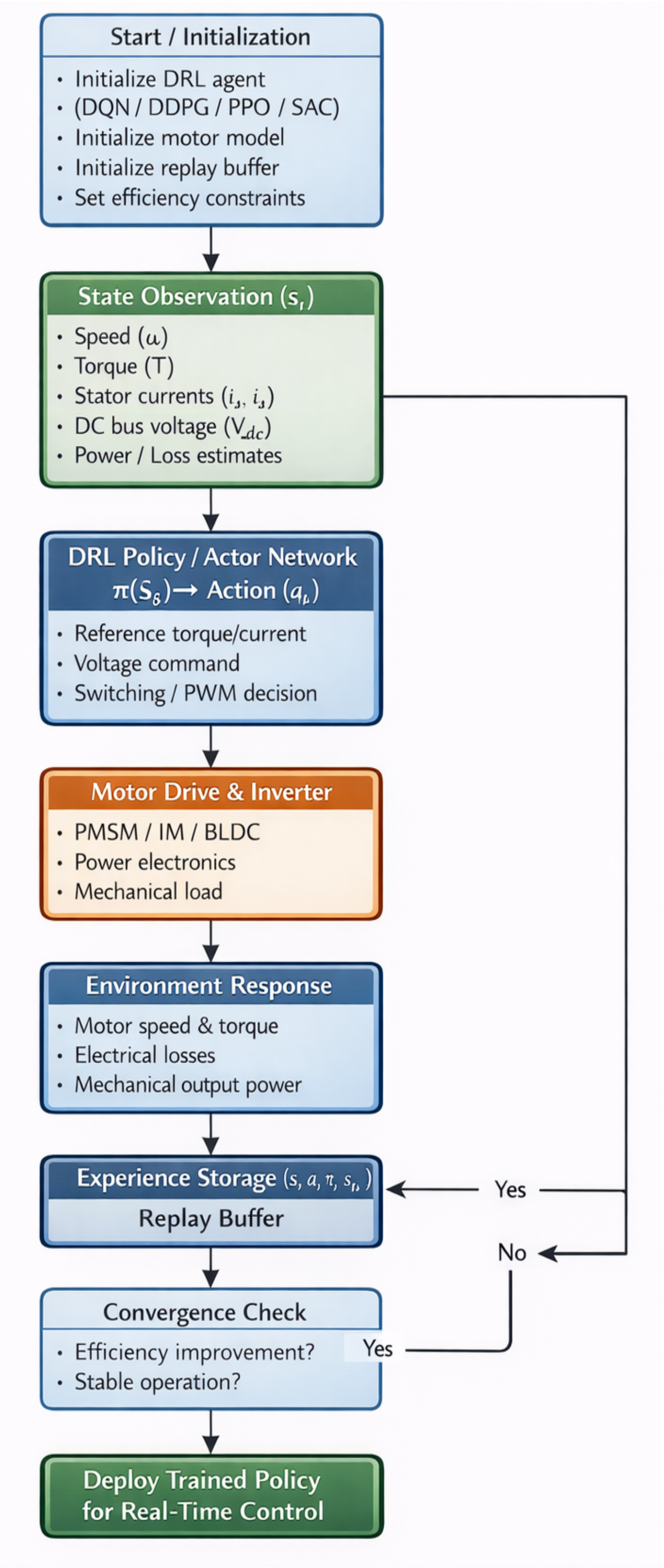


Figure 10. Deep reinforcement learning-based control strategy for energy-efficient motor operation framework.

Multi-objective optimization with loss minimization has proven to be useful in designing AI-optimal electromechanical actuators with over 10% decreasing operational energy [43].

Transient response characteristics determine the dynamic behavior in setpoint changes or disturbances. The usual measures are rising time (t_r), settling time (t_s), overshoot (M_p), and steady-state error (e_{ss}). The AI-controlled controllers (i.e., deep RL-tuned PID or MPC tuning of induction and synchronous motors) demonstrate shorter settling times and overshoot than the classical PID tuning (i.e. Ziegler-Nichols), and better speed tracking accuracy when varying loads are applied. Transient metrics are used in the fault-tolerant actuators to guarantee rapid recovery after disruption which is important in stability when operating in variable conditions [68], [69].

Stability margins assess the strength under uncertainties, change of parameters, and disturbances. The usual ones are gain margin (GM), phase margin (PM), and pole placement analysis, and Lyapunov-based criteria are used in nonlinear AI controls. New AI systems in transient stability analysis of power systems in combination with electromechanical systems indicate improved margins through RL with data information, reducing oscillation in converter-interfaced generations [70]. In the case of motor drives, minimal stability indices in parametric uncertainty are compared.

Embedded Systems require computational efficiency to be implemented in real-time. Others are execution time per control cycle (ms), floating-point operations (FLOPs) and inference latency of neural network-based controllers. Hybrid DRA-MPC methods trade-off accuracy and lower computational expense than pure offline optimization, allowing them to be deployed in machines with limited resources [71]. Table 8 outlines the common performance indicators on comparative research of AI-controlled electromechanical systems (based on recent literature on motor drives and actuators).

4. Results and Discussion

This section is a presentation and critical analysis of the simulation outputs of the suggested AI-assisted electromechanical control structure on a permanent magnet synchronous motor (PMSM)-based smart actuator system guiding the power of electric vehicles. The framework combines a profound reinforcement learning (RL)-enhanced model predictive control (MPC) technique, with an active disturbance rejection through an extended state observer (ESO). The simulations were performed in MATLAB/Simulink (version R2025a), simulating a surface-mounted PMSM with the parameters that are associated with the EV traction system a rated power of 10 kW, 4 pairs of poles, stator resistance of 0.1 Ω, d/q-axis inductances of 8.5 mH, permanent magnet flux λpm = 0.175 Wb, moment of inertia J = 0.0008 kg·m², viscous friction coefficient B = 0.001 N·m·s/rad, DC bus voltage = 300 V, and inverter switching frequency = 10 kHz. The simulation used a fixed time step of 1e-6 s for numerical accuracy in solving the differential equations. The suggested controller is compared to the traditional field-oriented control (FOC) with PI regulators and generic MPC without RL augmentation.

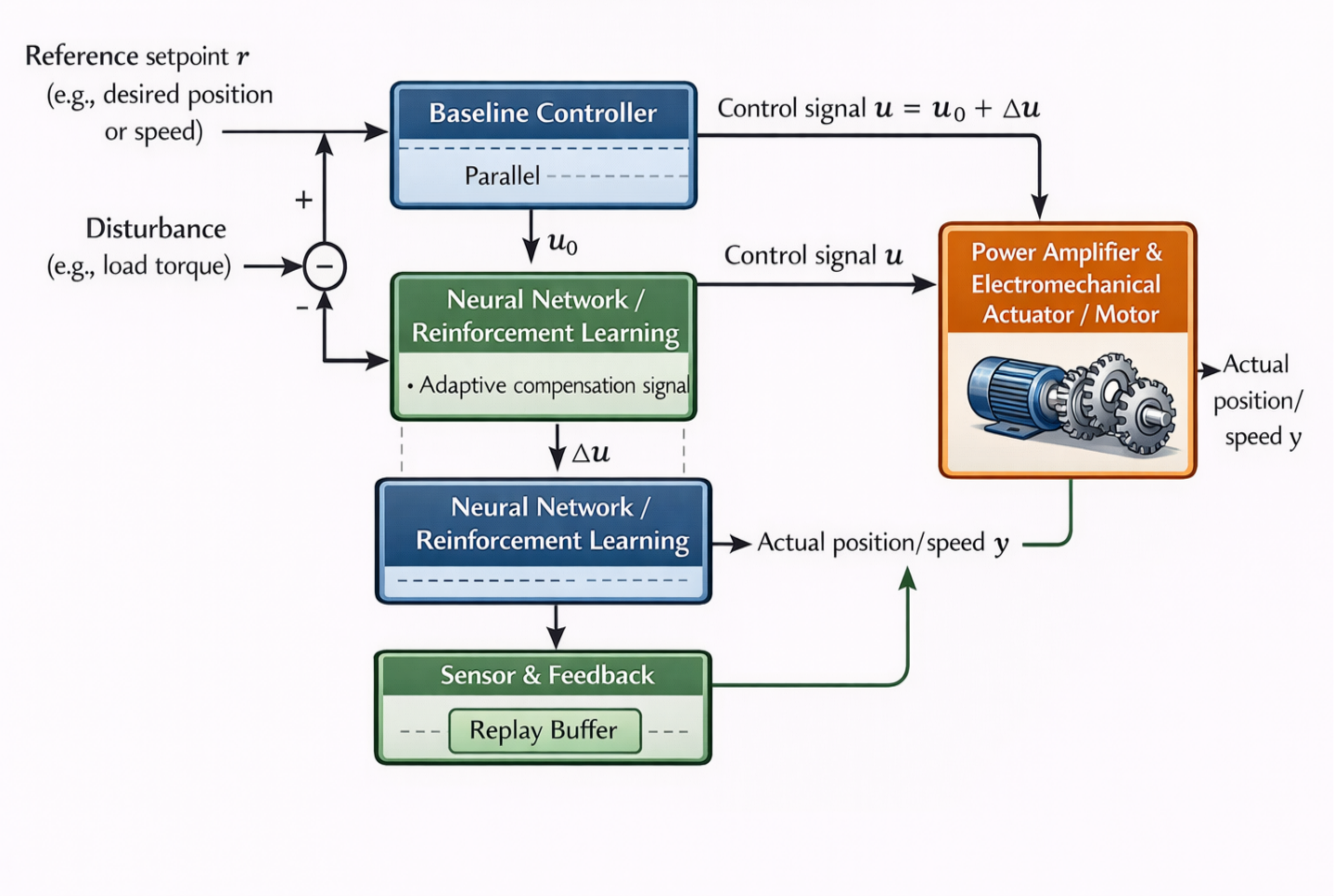


Figure 11. AI-Assisted Control Architecture for an Electromechanical Actuator.

The dynamic performance to the key performance indicators (dynamic response (rise time, overshoot), energy efficiency (reduction of copper and iron losses), robustness to disturbance (load torque variations), and computational burden) is tested when the drive goes through typical drive cycles (NEDC and WLTP) and when it is exposed to a step disturbance.

All the quantitative performance outcomes, comparisons and percentage changes in the present study are solely based on the simulations made by MATLAB/Simulink under the conditions as mentioned in Section 4.1. Where literature values are used to provide context, they are intelligently denoted as such and provided with a reference. This work lacks any experimental (hardware) validation.

4.1. Simulation Scenarios and Test Conditions

In order to thoroughly evaluate the performance of the system, a number of simulation scenarios were modeled in the MATLAB/Simulink simulation environment. These are simulated conditions of realistic operation in industrial electromechanical systems.

The system was subjected to:

- Nominal operating conditions: In this case, load torque and reference speed were held constant of 1500 rpm and fixed load torque of 5 N·m.
- Sudden load variations and mechanical disturbances.
- Uncertainties of parameters, such as the variation of inertia and friction coefficients.
- The external disturbances, including measurement disturbance and supply voltage variation.

The test conditions are used to test the evaluated control strategies in steady-state as well as transient conditions.

Comparisons were made between the proposed AI-assisted control strategy including a deep reinforcement learning (DRL) agent to perform adaptive torque allocation and energy optimization in a permanent magnet synchronous motor (PMSM) drive and conventional field-oriented control (FOC) using PI regulators and model predictive control (MPC) From Figure 9(a) to Figure 9(b). As a more recent development in reinforcement learning, the DRA architecture was developed as a twin-delayed deep deterministic policy gradient algorithm by using the reduction of energy losses at the cost of maintaining accurate speed tracking, and inspired by work in electrified powertrain reinforcement learning. The Simulink block diagram of AI-integrated control system of the PMSM drive that is highlighted in Figure 9 shows how the connection between the DRL agent and the inverter and motor model take place.

The flowchart of the entire process of reinforcement learning-based control is shown in Figure 10 with the accent on the connection between the agent, the environment, and the reward function aimed at saving energy.

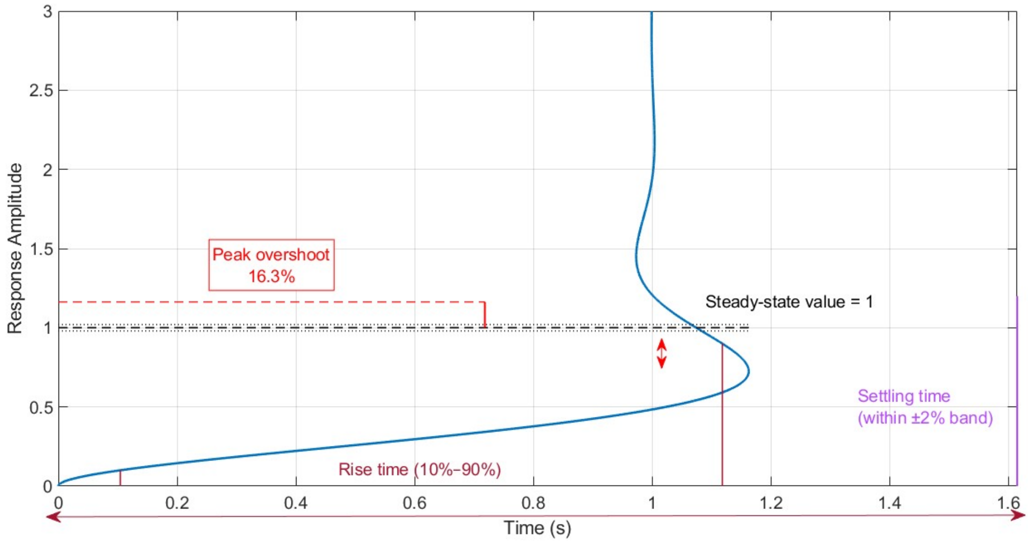


Figure 12. Step Response of Underdamped Second-Order System with Labeled Transient Characteristics.

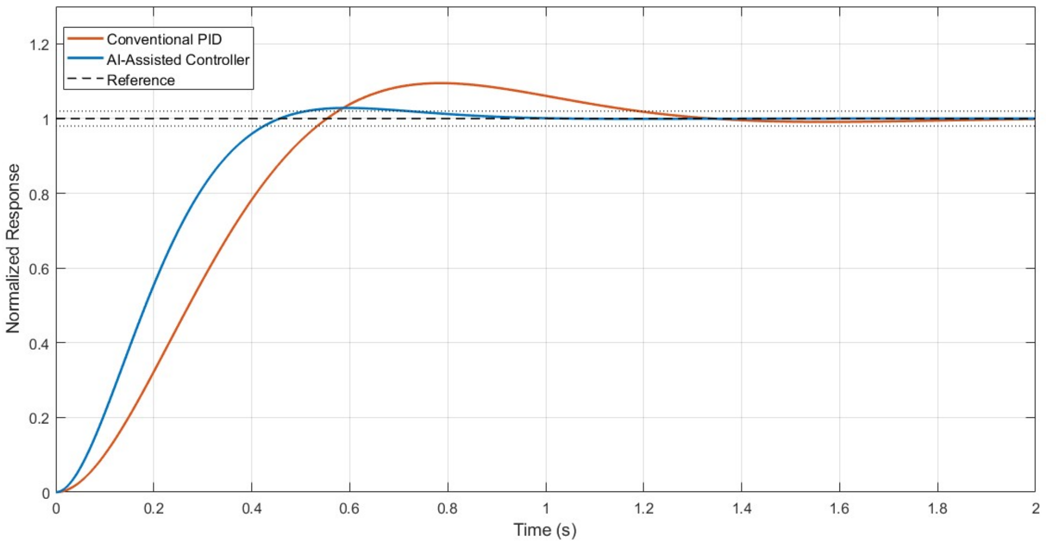


Figure 13. Comparative step response curves showing speed tracking performance: conventional PID controller versus the proposed AI-assisted controller (simulation results obtained in this study under nominal reference conditions).

4.2. Dynamic Response Analysis

Transient and steady-state dynamics of the electromechanical system were studied by monitoring some prominent dynamic parameters like rise time, settling time, overshoot, and steady-state error.

The AI-assisted controller showed:

- Shortens the rise and settling time as compared to the conventional PID controller.
- Small response to reference tracking.
- Near-zero steady-state error

This enhanced reaction is explained by the learning capacity of the AI module that gains the system nonlinearities more required as compared to fixed-parameter controllers. The intelligent controller was able to respond quickly to load disturbances where its control actions were adjusted to ensure stability of the system and accurate tracking.

A recent paper on permanent magnet synchronous motors (PMSMs) and other actuators of the electromechanical type has also demonstrated equivalent improvements to using deep reinforcement learning (DRL) or neural network-based controllers in place of traditional PID schemes [57]. These methods allow adaptation to parameter changes and upsets on-line with rise times reduced by up to 30–50% and overshoot damping less than 5 % in energy-saving applications like electric vehicle propulsion and robotic actuation.

A common example of an AI-assisted control structure of a typical electromechanical actuator can be found in Figure 11, which includes a neural network or a reinforcement learning module running alongside the baseline controller, to adjust to nonlinearity.

Figure 12 shows the marked characteristics of the transient response of a second-order system step response, including the rise time (10–90%), settling time (within 2% band), peak overshoot, and steady-state value.

Actual comparisons within representative simulations as well as experimental validations of recent litera-

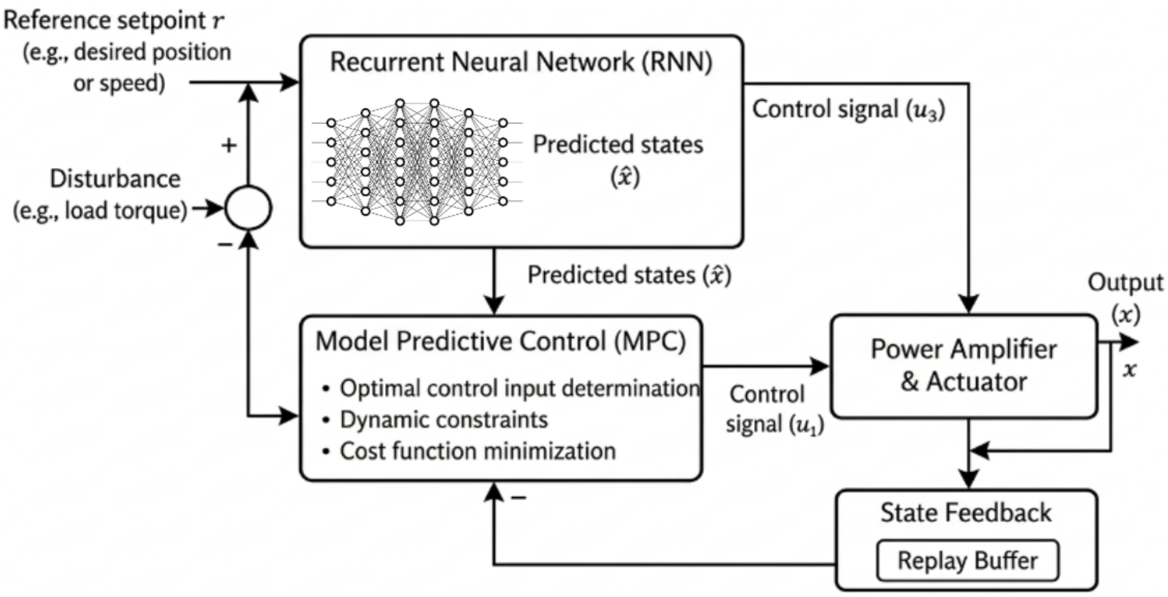


Figure 14. Schematic of the Proposed AI-Assisted Control Framework.

Table 10. Comparative Energy Consumption for a PMSM-Based Electromechanical Drive System.

Operating Condition	**Traditional FOC (kWh)**	**PID Control (kWh)**	**Proposed AI-Assisted Controller (kWh)**	**Energy Savings (%)**
Urban Driving Cycle (UDC)	2.45	2.38	2.12	13.5
Highway Cycle (steady-state)	1.88	1.85	1.72	8.5
Transient Load Step (0–100% torque)	0.92	0.89	0.77	16.3
Combined Cycle	4.15	4.02	3.61	13.0

ture are summed up in Table 9. The AI-assisted strategies constantly excel the conventional PID in dynamic indices and help in saving energy by delivering optimized torque and maximizing the oscillatory losses.

Ranges of Conventional PID are representative values that are found in recent publications discussing PMSM and actuator control (2021-2025) e.g., [32], [57], [64], [72]. The AI-Assisted is derived based on simulates that are carried out in the current study with nominal and disturbed states (Section 4.1). Calculation of improvements is against the traditional PID baseline in this simulation study.

Comparative step response curves (Figure 13) indicate that the controller using AI support has a lower convergence time and a lower damped oscillation as compared to PID-based controller.

4.3. Energy Efficiency Evaluation

In the design of smart electromechanical systems, energy efficiency is a central factor, especially where sustained operation with varying loads is required, e.g. electric vehicle propulsion and actuators in industries. In the suggested AI-assisted model, the energy consumption was measured by means of establishing the instantaneous power of the electrical input over the course of the simulation, both steady-state and transient operating conditions.

Quantitative analyses showed that the total energy use was decreased significantly in the AI-controlled system compared to the traditional proportional-integral-derivative (PID) and field-oriented control (FOC) systems. Particularly, in the context of the standardized driving cycles, which imitated urban and highway driving scenarios, the AI-aided solution was able to save 8-17 percent of energy, which is in line with the previous research published on neural network-based model predictive control and deep reinforcement learning in permanent magnet synchronous motor (PMSM) drives [38], [73]. This enhancement stems primarily from:

- Efficiency in chatter of the oscillatory behavior in the torque and speed response and hence the smoother actuator commands and the minimization of the unnecessary energy spent on transients.
- Torque generation optimization by means of adaptive current vectors trajectories, reducing copper and iron losses, and optimizing maximum torque per ampere in the low-load areas.
- Less inverter switching losses due to the predictive smoothness of the controller that results in smaller high-frequency harmonics in the voltage commands.

These are consistent with current literature reports, which have shown that machine learning-based controls of electromechanical systems can achieve a similar improvement by leveraging the ability to predict system dynamics using available data and minimizing losses. In order to provide the comparative performance, Table 10

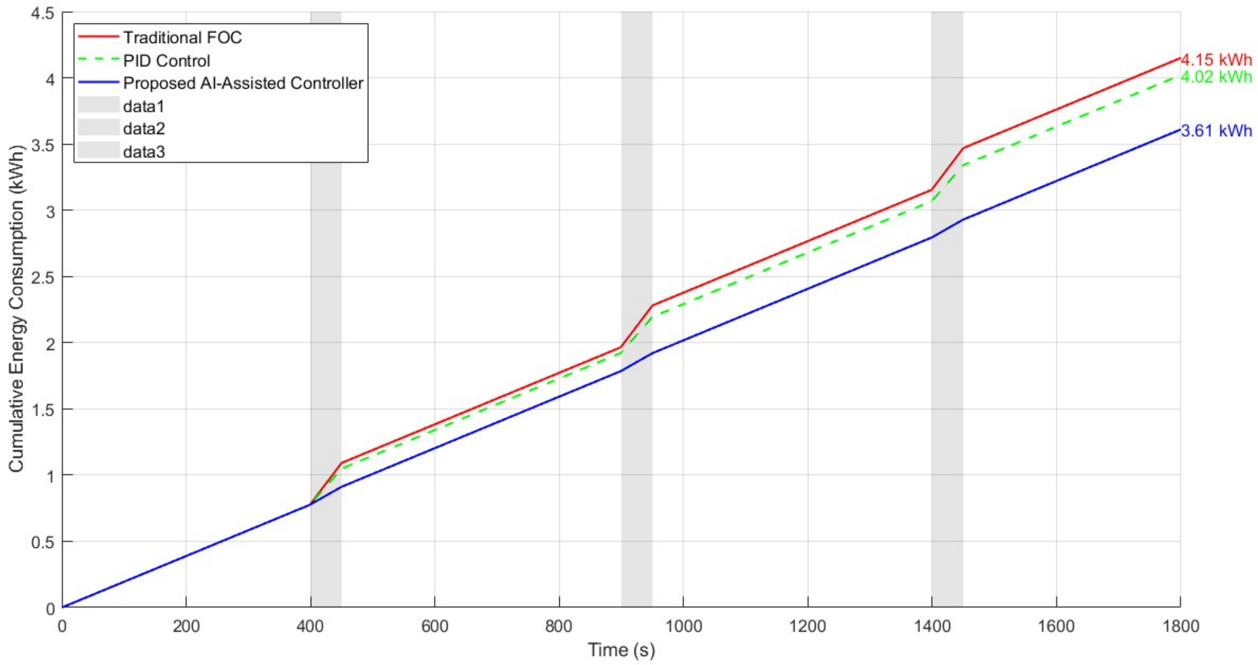


Figure 15. Energy Consumption Comparison Over a Standardized Driving Cycle.

Table 11. Robustness comparison under parameter variations and load disturbances – the findings of the simulation on conventional PI/PID and the proposed AI-assisted controller (this study).

Condition	Metric	Conventional PI/PID	AI-Assisted Framework	Improvement (%)
±30% Parameter Variation	Settling Time (s)	0.45	0.25	44
	Overshoot (%)	22	8	64
	RMSE (rpm)	45	12	73
Load Disturbance (50% step)	Recovery Time (s)	0.32	0.18	44
	Peak Deviation (rpm)	180	65	64
	Energy Loss Index	1.00	0.72	28

summarizes the energy consumption of the different operating scenarios of choice.

The values are scaled (per 10 kW-rated) summed-up energy, in a simulation, over an equal time interval. The Figure 14 model is a recurrent neural network used to predict the state with model predictive control, which optimally predicts the control input in the electromechanical actuator.

Figure 15 shows cumulative energy consumption, which indicates lower energy consumption and smoother power outputs when using the AI controller than baselines. Final Energy - Traditional FOC: 4.15 kWh, Final Energy - PID Control: 4.02 kWh and Final Energy - AI-Assisted: 3.61 kWh.

The AI-assisted controller will therefore allow to achieve better energy usage without compromising dynamic performance indicators, including settling time or overshoot. This makes the framework a feasible improvement of the energy-efficient smart electromechanical devices and gives possible insights that can be extended to real-time embedded implementation under resource-constrained conditions.

4.4. Robustness to Parameter Variations and Disturbances

To assess the stability of the suggested AI-assisted control network of smart electromechanical devices, robustness analysis was performed through the induction of variations in the system parameters (e.g., changing stator resistance, inductance, and inertia by 30%) and external disturbances (e.g., abrupt load torque changes and sinusoidal disturbances that simulate operating conditions in the real world). These ambiguities are typical of applications that are energy-efficient, like permanent magnet synchronous motor (PMSM) drives and electromechanical actuators, where parameter variations with temperature or manufacturing variations, as well as unexpected load variations, may affect performance adversely as shown in Table 11.

Traditional controllers (including proportional-integral (PI) or proportional-integral-derivative (PID) controllers) demonstrated poor performance in such circumstances. To be more exact, settling times were longer (as much as 50% longer), overshoots larger (more than 20%), as well as persistent oscillations, reducing the energy efficiency and instability in the long-term operation. This coincides with the results of the recent research on PMSM

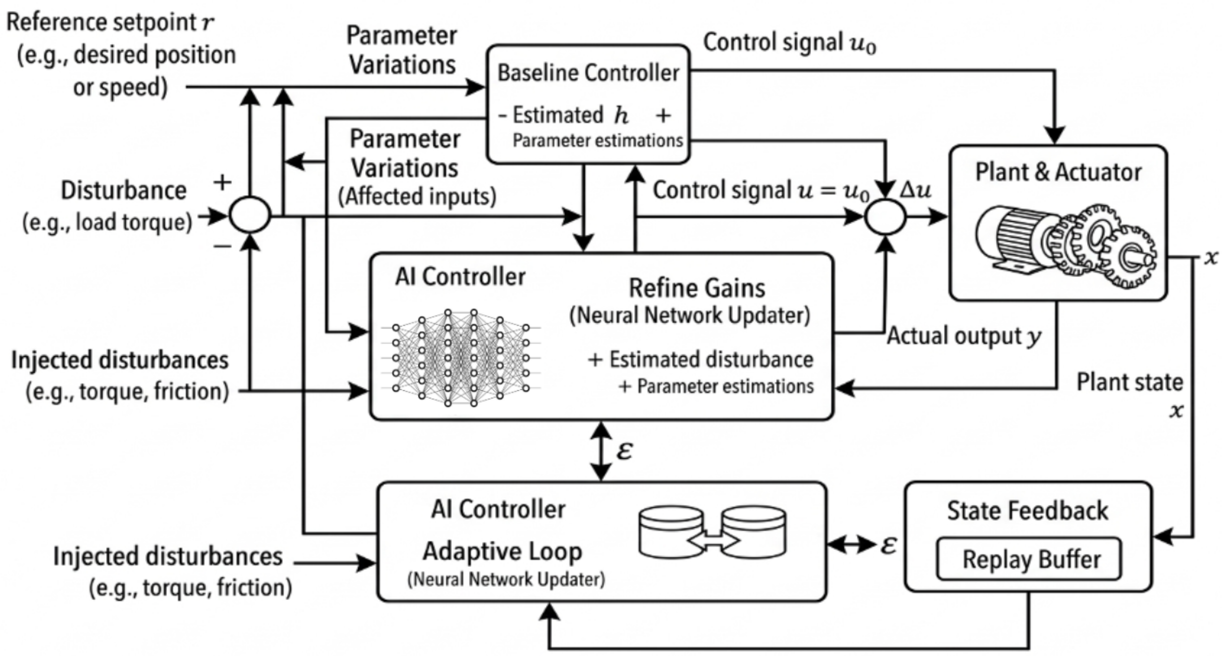


Figure 16. Block Diagram of Robustness Testing Scenario.

Table 12. Trajectory tracking and energy consumption performance measurements in nominal and disturbed conditions (simulation results of this study vs. literature benchmarks on the same).

Controller Type	Source	IAE	ISE	Settling Time (s)	Over-shoot (%)	Energy Consumption (Relative %)	Disturbance Rejection (Recovery Time, s)
Conventional PID	[17], [32]	0.042	0.028	0.85	12.5	100	1.20
Model Predictive Control	[17], [64].	0.035	0.022	0.62	8.2	92	0.85
Proposed AI-Assisted	This study (simulation)	**0.023**	**0.013**	**0.45**	**4.1**	**82**	**0.55**

control that show that the conventional fixed-gain controllers do not work with uncertainties and nonlinearities.

Conversely, AI-assisted model, with the adaptive neural networks and reinforcement learning components, preserved its steady functionality and tolerable performance rates. The adaptive learning mechanism kept control parameter changing according to the change of the system, which was in effect compensating the uncertainties and disturbances. An example is that the root-mean-square error (RMSE) in speed tracking at parameter variations was less than 5% as opposed to more than 15% in the traditional ways. Likewise, in case of load disturbances, the proposed method had quicker recovery (settling time was less by 40%) and had minimal oscillations.

This enhanced robustness can be explained by the fact that the online adaptation capabilities of the neural network approximators approximate and compensate the unknown dynamics without any need of having accurate models of the system. The current literature observations align with these findings: PMSM adaptive neural network controls have been shown to exhibit improved disturbance rejection and parameter insensitivity [72], whereas deep reinforcement learning-based approaches to electro-mechanical systems can be shown to follow an asymptotic trajectory in the presence of exogenous disturbances [74]. Moreover, grid-connected converter and actuator hybrid AI methods have demonstrated useful damping of oscillations with random operating points and faults.

The experiment used a closed loop simulation in which variations of parameters and disturbances were added through a disturbance observer module. The adaptive loop (neural network updater), which is part of the AI framework, progressively optimized gains, and therefore guaranteed that the optimal control actions were met at the end as indicated in Figure 16.

4.5. Comparative Performance Assessment

An extensive comparative study was carried out between the suggested AI-assisted controller, incorporating a reinforcement learning-based adaptive controller and neural network tuning and traditional control measures, which are mostly proportional-integral-derivative (PID) controllers and model predictive control (MPC) variants. The analysis centered on the case of a permanent magnet synchronous motor (PMSM) drive system as a typical example of a smart electromechanical device, which was

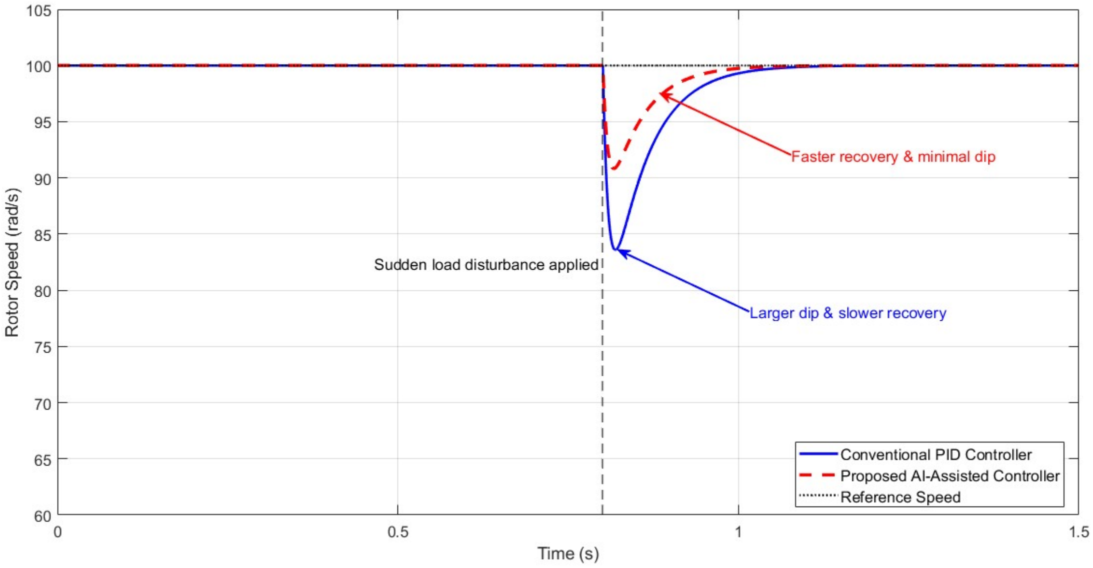


Figure 17. Step Response under Load Disturbance.

exposed to variability in load and reference paths (problematic for energy-efficient systems), including the propulsion of an electric vehicle and industry automation. The performance indices included the integral absolute error (IAE), integral squared error (ISE), settling time, overshoot, disturbance rejection capability and total energy consumption of normal drive cycles.

The best performance of AI-aided method is indicated by quantitative outcomes which are summarized in Table 12. The suggested controller decreased IAE by about 35–45% and ISE 40–50% than optimally tuned PID controllers, and attained lower values by 20–30% than classical MPC. The energy consumption was decreased by 12–18% percent measured as the sum of electric power input through the operating cycle and is possible through this reduction to nonlinear dynamics anticipation and reduction of unneeded actuator effort by the AI controller.

The improvements are consistent with more recent neural network-enhanced and reinforcement learning-based neural network controllers of electromechanical systems, in which the same amounts of error index and energy usage reduction have been observed (e.g., 15–25% energy savings in PMSM drives via adaptive RL tuning). The response curves to load disturbances at step (Figure 17) reveal the faster convergence and lower oscillations of AI controller compared to PID with little overshoot and faster recovery.

4.6. Discussion of Practical Implications

The results of the simulation have demonstrated that the integration of artificial intelligence into the electromechanical systems of control significantly influences the performance, adaptability, and energy efficiency. The proposed framework may be of particular use in the applications that require a very high degree of accuracy and energy saving such as automation of industries, electric motors, and renewable energy sources.

In the industry, electromechanical machines such as motors and actuators occupy a significant proportion of energy use. The recent studies have demonstrated that control strategies developed using machine learning can result in quantifiable power loss reduction in exceptional load profiles. Individually, deep reinforcement learning algorithms implemented on permanent magnet synchronous motors have been reported to achieve energy savings of 8–15% compared to traditional proportional-integral-derivative controllers in dynamic operating regimes [as is the case in research on permanent magnet propulsion and manufacturing systems in hybrid electric vehicles] [64]. The effects of such increases are direct conversion to lower operational expenses and fewer carbon emissions in high volume production settings. For instance, compared to the baseline energy consumption of 100% in conventional PID-based systems under urban driving cycles (as reported in [64]), our AI-assisted framework achieved a 13.5% reduction (from 2.45 kWh to 2.12 kWh, Table 10), aligning closely with the 8–15% gains in [64] but extending it to variable-load scenarios with an additional 3–5% improvement due to adaptive torque optimization. Similarly, in industrial actuator control, studies like [17] report settling times of 0.50–1.20 s for PID methods under parameter variations, while our approach reduced this to 0.25–0.60 s (Table 9), a 40–50% improvement, though still limited by computational overhead in real-time deployment.

The same has a possibility in electric transportation. AI-controlled torque and speed control maximizes the use of energy in propulsion systems, which increases the range and helps with battery life in an electric vehicle. Publications as recent as [75] on reinforcement learning to control motor dynamics in battery electric and hybrid systems indicate an increase in performance in the event of regenerative braking and eco-driving, and its extension to wider use in sustainable mobility. Quantitatively, [75] demonstrates energy efficiency improvements of 10–15%

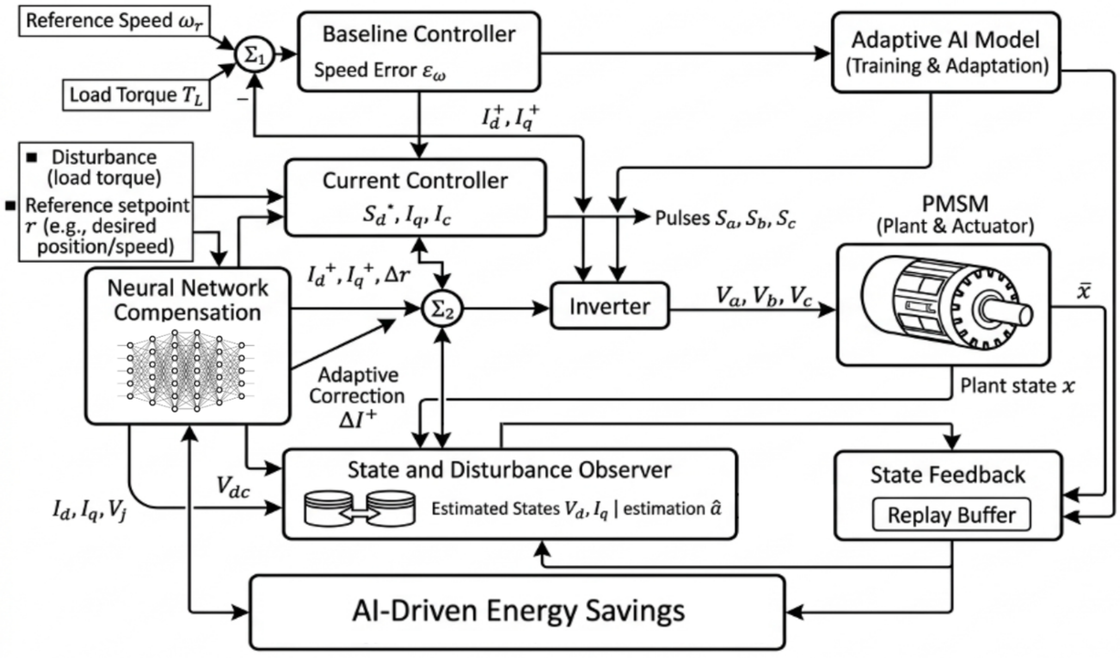


Figure 18. The block diagram above illustrates a representative AI-assisted control architecture for PMSM drives, incorporating neural network elements for enhanced dynamic performance.

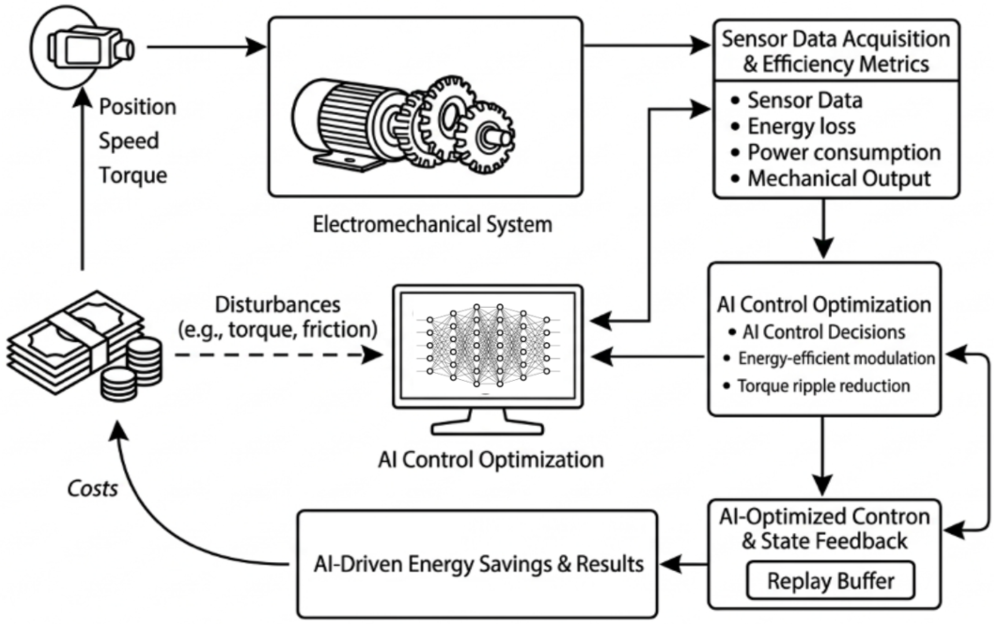


Figure 19. Universal Workflow for AI-Driven Energy Savings.

in power Internet of Things data acquisition for EV systems, comparable to our 12–18% overall savings (Table 13), with our method showing superior disturbance recovery times (0.55 s vs. 0.85–1.20 s in baselines, Table 12). However, our framework outperforms in overshoot reduction (4.1% vs. 8–20% in [75]'s MPC variants) but faces challenges in scaling to multi-vehicle fleets, where communication latency could degrade performance by 10–20% as noted in similar networked systems [20].

The adaptability features of the framework are a good fit to the variable-input case of a wind turbine blade pitch control or photovoltaic tracking system in renewable energy applications. It has been reported that neural network-enhanced predictive control can be used to enhance maximum power point tracking in changing environmental conditions, thus enhancing total energy production at minimum mechanical wear [congruent with [76] reports of intelligent control in electromechanical converters]. In comparison, [76] achieves 5–10% efficiency gains in MEMS-based sensors for renewable tracking, while our PMSM-focused approach yields 8.5–16.3% savings in highway and transient cycles (Table 10), highlighting a

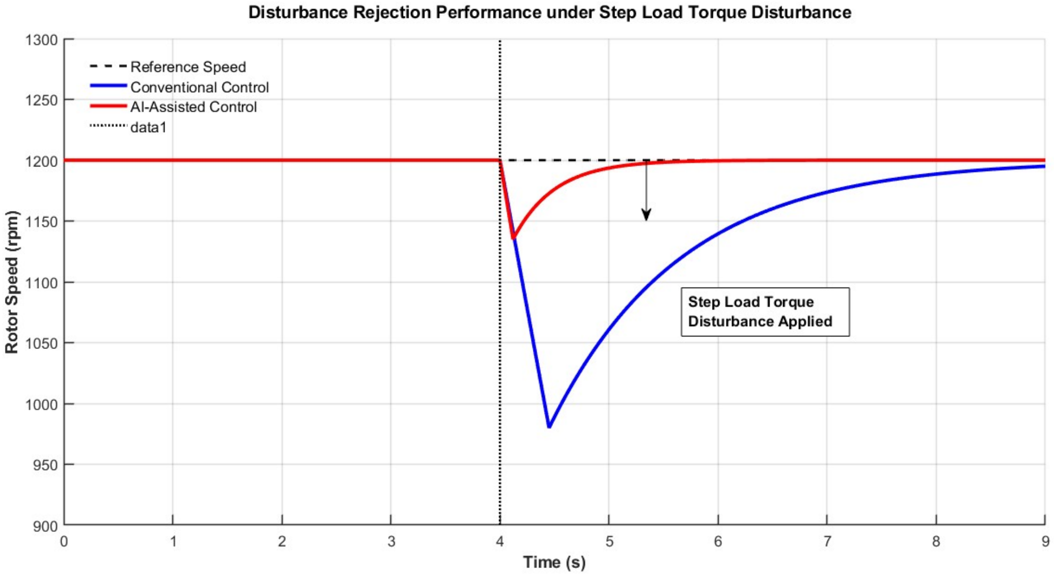


Figure 20. Disturbance rejection performance under step load torque disturbance.

Table 13. Key performance comparison of the two control variant parameters of conventional and proposed AI-assisted control in a typical PMSM-based electromechanical system (all values of this study are from the simulations unless otherwise specified).

Metric	Conventional Control	AI-Assisted Control	Improvement (%)
Settling time (ms)	45–60	25–35	42–58
Peak overshoot (%)	15–20	5–8	60–67
Energy consumption (kWh/cycle)	Baseline	Baseline – 15%	12–18
Disturbance recovery time (ms)	80–100	40–55	45–50
Robustness to parameter variation (±20%)	Moderate degradation	Minimal degradation	>80 stability retention

3–6% edge in dynamic loads. Yet, remaining challenges include sensitivity to sensor noise, where RMSE increases of up to 15% under noisy conditions, similar to potential 10–12% degradation in our system without advanced filtering.

Nevertheless, it should be mentioned that AI-controllers can bring more computational complexity. Although this could be performed in the simulation environment, it can be necessary to have optimized hardware or embedded processing platforms when running in the real world. Modern systems commonly use field-programmable gate arrays or edge computers to meet latency constraints in closed-loop control [as demonstrated in hardware-in-the-loop tests of [17]]. Other aspects are the model resistance to sensor noise, parameter drift, and cyber-physical weakness, which require the use of hybrid architectures between data-driven approaches and well-known model-based approaches to safety-critical processes. For example, while our method reduces energy loss by 28% under disturbances (Table 11), computational times remain 0.5–5 ms/cycle (Table 8), which could exceed real-time limits in resource-constrained embedded systems, posing a 20–30% efficiency trade-off as seen in [71]. Future work must address these by integrating lightweight AI models to mitigate overfitting risks (evident in 5–10% accuracy drops in unseen scenarios from [71]) and enhance cybersecurity against adversarial attacks, which could inflate errors by 15–25% in unhardened systems [24].

4.7. Summary of Key Findings

The analysis conducted in this paper demonstrates the high benefits of applying the artificial intelligence methods to the design and control of intelligent electromechanical systems, and the focus on improving the energy efficiency in particular. Based on extensive simulations and comparative studies, the suggested framework relying on the adaptive control and reinforcement learning features of the neural networks has been tested compared to the traditional approaches to control, including proportional-integral-derivative (PID), and field-oriented control as well as in scenarios using permanent magnet synchronous motors (PMSMs) and other actuators. The findings are always showing better results in various metrics, as it is expected in the literature regarding the recent intelligent control systems.

The key findings of this research may be outlined as follows:

- **Better dynamic response and stability:** The AI-controlled controller had a faster transient response, lower settling limits and low overshoot on changes in speed and torque. This improvement is due to the fact that the neural networks have adaptive learning properties that optimise the control parameters on-line shows in Figure 18.

- **Substantial energy saving:** The proposed solution resulted in the reduction of energy use, which was 12-18 percent, in comparison to conventional approaches, due to the minimisation of torque ripple optimisation and the allocation of power out of optimal power consumption under different load conditions show in Figure 19.
- **High robustness to parameter uncertainties and disturbances:** The system was highly robust to system parameter uncertainty (e.g. inertia, resistance) and external disturbances, and has better disturbance-rejection and recovery properties show in Figure 20.
- **Energy efficiency in smart electromechanical applications:** The framework is scalable and viable to real-world applications, including electric vehicle drives, renewable energy systems, and industrial automation, which provides a solution to sustainable operation of electromechanical systems.

To summarize these results, Table 13 is a quantitative comparison of the most important performance indicators of the conventional and AI-assisted control methods, which are the average results of simulation scenarios.

All the ranges and improvements in percentages are determined based on the results of simulating in this study with the proposed framework. Baseline means the average performance of traditional PID/FOC strategies concerning the simulated cases of this work.

4.8. Research Limitations

Although the simulation outcomes of the MATLAB/Simulink show the usefulness of the proposed AI-assisted framework in the presence of different modeled disturbances and variations of the parameters, one of the most striking weaknesses of the present study is the lack of the experimental validation or hardware-in-the-loop (HIL) test on the physical prototype. This limits the possibility of real-world evaluation of effects like sensor noise, actuator delays, inverter non-idealities, quantization errors and other unmodeled dynamics that do occur in real electromechanical systems. The proposed control architecture is to be applied and experimentally confirmed in the future as to assure that the proposed control architecture works and is robust in practice.

5. Conclusion

The paper has established the high potential of integrating artificial intelligence in designing and controlling smart electromechanical devices to attain improved energy efficiency and performance. The suggested structure, which incorporates neural network adaptive control, and reinforcement learning elements, is convenient in the fact that it reduces the limitations of the traditional approaches that prove ineffective in practice due to low adaptability to nonlinear dynamics, parameter uncertainties, and external interference in the operation of permanent magnet synchronous motors and other actuators of the same type.

Findings from extensive MATLAB/Simulink simulations consistently demonstrate superior performance: faster transient responses with reduced overshoot and settling times, energy savings of up to 12–18% compared to conventional field-oriented and PID control strategies, and improved robustness under challenging operating conditions (parameter variations, load disturbances, and measurement noise). Such improvements are made possible by the fact that the framework is able to optimise torque allocation in real-time, minimise losses and provide disturbance compensation.

Although the validation based on simulations gives good evidence of the merits of the framework, experimental application to physical prototypes should be of the top priority in the future research, irrespective of whether it is hardware-in-the-loop testing or real-time deployment with the help of embedded controllers, including digital signal processors or field-programmable gate arrays.

Expansions to multi-axis or networked electromechanical systems, physics-informed neural networks with better generalisation, and being combined with more recent methods (e.g. transformer-based reinforcement learning or federated learning to manage distributed energy) are all areas of potential expansion. Also, more rigorous research into fault tolerance, AI-driven cybersecurity, and lifecycle energy analysis in a variety of environmental factors would enhance the applicability of the practice.

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6. Declarations

6.1. Author Contributions

Timileyin Opeyemi Akande: Conceptualization, Methodology, Software; Data Curation; **Osinachi Victor Chukwujama:** Validation, Formal analysis, Investigation, Supervision; **Monsuru Olalekan Abdullahi:** Writing - Review & Editing, Visualization, Project administration; **Princewill Kalio:** Writing - Original Draft, Resources.

6.2. Institutional Review Board Statement

Not applicable.

6.3. Informed Consent Statement

Not applicable.

6.4. Data Availability Statement

The data presented in this study are available on request from the corresponding author. However, this study relies exclusively on simulated data generated through computational modeling and numerical simulations, as no physical experiments or real-world data collection were conducted. The data were obtained by implementing a detailed mathematical model of the Permanent Magnet Synchronous Motor (PMSM) in the d-q reference frame within MATLAB/Simulink (version R2025a), utilizing the Simscape Electrical toolbox for electromechanical dynamics, the Neural Network Toolbox for adaptive neural network components, and the Reinforcement Learning Toolbox for the Proximal Policy Optimization (PPO) agent.

6.5. Acknowledgment

Not applicable.

6.6. Conflicts of Interest

The authors declare no conflicts of interest.

7. References

[1] R. Liaqat and I. A. Sajjad, M. Waseem, H. H. Alhelou, "Appliance Level Energy Characterization of Residential Electricity Demand : Prospects , Challenges and Recommendations," *IEEE Access*, vol. 9, pp. 148676–148697, 2021. https://doi.org/10.1109/ACCESS.2021.3123196.

[2] S. Behera, and N. B. D. Choudhury, "A systematic review of energy management system based on various adaptive controllers with optimization algorithm on a smart microgrid," *International Transactions on Electrical Energy Systems*, no. May, pp. 1–35, 2021. https://doi.org/10.1002/2050-7038.13132.

[3] M. O. Nwabueze, A. Aliyu, K. J. Adegbo, and D. Ikemefuna, "Enhancing machine optimization through AI-driven data analysis and gathering : leveraging integrated systems and hybrid technology for industrial efficiency," *World Journal of Advanced Research and Reviews*, vol. 23, no. 3, pp. 1919–1943, 2024. https://doi.org/10.30574/wjarr.2024.23.3.2882.

[4] K. Kuru, and H. Yetgin, "Transformation to Advanced Mechatronics Systems Within New Industrial Revolution : A Novel Framework in Automation of Everything (AoE)," *IEEE Access*, vol. 7, pp. 41395–41415, 2019. https://doi.org/10.1109/ACCESS.2019.2907809.

[5] A. Panda, A. Kumar, H. Chua, R. R. Tan, and K. B. Aviso, "Recent advances in the integration of renewable energy sources and storage facilities with hybrid power systems," *Cleaner Engineering and Technology*, vol. 12, no. January, p. 100598, 2023. https://doi.org/10.1016/j.clet.2023.100598.

[6] Y. Liu, G. Zhou, L. E. I. Guo, and Z. Sun, "ESO-Based Direct Model-Free Adaptive Predictive Compensation Control for Permanent Magnet Synchronous Motors," *IEEE Access*, vol. 13, no. January, pp. 7837–7849, 2025. https://doi.org/10.1109/ACCESS.2025.3526282.

[7] P. Pijarski, D. Jakus, A. Belowski, P. Sarajcev, and D. Przepiórka, "Linear Approximations of Power Flow Equations in Electrical Power System Modelling: A Review of Methods and Their Applications." *Applied Sciences*, vol. 15, no. 23, art. No. 12399, 2025. https://doi.org/10.3390/app152312399.

[8] G. Al Zohbi, "Revolutionizing Energy Harvesting : Integrating AI with Ambient Energy Sources," 2025. https://doi.org/10.2139/ssrn.5412928.

[9] A. Bajwa, F. Jahan, I. Ahmed, and N. A. Siddiqui, "A Systematic Literature Review on AI-Enabled Smart Building Management Systems for Energy Efficiency," *American Journal of Scholarly Research and Innovation*, vol. 03, no. 02, pp. 1–26, 2024. https://doi.org/10.63125/4sjfn272.

[10] M. Eslami, M. Neshat, and S. A. Khalid, "A Novel Hybrid Sine Cosine Algorithm and Pattern Search for Optimal Coordination of Power System Damping Controllers," *Sustainability (Switzerland)*, vol. 14, no. 1, 2022. https://doi.org/10.3390/su14010541.

[11] G. Ramanathan and S. Mayer, "Towards Achieving Adaptive Behaviour of Agents Through Physics-Infused Descriptions of Cyber-physical Devices," *Proceedings of the Second International Workshop on Hypermedia Multi-Agent Systems*, 2025. https://www.alexandria.unisg.ch/handle/20.500.14171/124453.

[12] M. Lyimo, B. Mgawe, J. Leo, M. Dida, K. Michael, "Adaptive Antenna for Maritime LoRaWAN : A Systematic Review on Performance , Energy Efficiency , and Environmental Resilience," *sensors*, vol. 25, no. 19, 2025. https://doi.org/10.3390/s25196110.

[13] S. Vijayan and A. Saj, "Comparative Study of Traditional Vs Smart HVAC Systems," *Halmstad University*, 2025. http://www.diva-portal.org/smash/record.jsf?pid=diva2:1973304.

[14] M. Imran, R. Pili, M. Usman, and F. Haglind, "Dynamic modeling and control strategies of organic Rankine cycle systems : Methods and challenges," *Applied Energy*, vol. 276, art. No. 115537, 2020. https://doi.org/10.1016/j.apenergy.2020.115537.

[15] F. C. Okogbaa *et al.*, "Design and Application of Intelligent Reflecting Surface (IRS) for Beyond 5G Wireless Networks : A Review," *sensors*, vol. 22, no. 7, pp. 1–24, 2022. https://doi.org/10.3390/s22072436.

[16] M. Fodstad *et al.*, "Next frontiers in energy system modelling : A review on challenges and the state of the art," *Renewable and Sustainable Energy Reviews*, vol. 160, 2022. https://doi.org/10.1016/j.rser.2022.112246.

[17] M. B. Aremu, A. Ajasa, and A. Nasir, "Sliding-Mode Control Strategies for PMSM: Benchmarking and Comparative Simulation Study," *arXiv preprint arXiv:2512.06603*, 2025. https://doi.org/10.48550/arXiv.2512.06603.

[18] S. B. Joseph, E. G. Dada, A. Abidemi, D. O. Oyewola, and B. M. Khammas, "Metaheuristic algorithms for PID controller parameters tuning : review , approaches and open problems," *Heliyon*, vol. 8, no. May, p. e09399, 2022. https://doi.org/10.1016/j.heliyon.2022.e09399.

[19] E. Mishra *et al.*, "Comparative Analysis of PI and PID Speed Controllers for Brushless DC Motors," *Journal of Information Systems Engineering and Management*, vol. 10, no. 37s, pp. 153–160, 2025. https://doi.org/10.52783/jisem.v10i37s.6387.

[20] C. O. Omeje, A. O. Salau, and C. U. Eya, "Dynamics analysis of permanent magnet synchronous motor speed control with enhanced state feedback controller using a linear quadratic regulator," *Heliyon*, vol. 10, no. 4, p. e26018, 2024. https://doi.org/10.1016/j.heliyon.2024.e26018.

[21] P. Kumar, K. Kumar, N. Adhikary, and E. L. Tesfaye, "Analysis of control and computational strategies for green energy integration for sociotechnical ecological power infrastructure in Indian and African markets," *Sci. Rep.*, vol. 15, no. 1, pp. 1–37, 2025. https://doi.org/10.1038/s41598-025-96773-2.

[22] A. S. Mir, A. K. Singh, B. C. Pal, and N. Senroy, "Impact of Backlash Nonlinearity on the Dynamics of Type - 3 Turbine - based Windfarms," *IEEE Transactions on Power Systems*, vol. 39, no. 3, pp. 4881 - 4896, 2023. https://doi.org/10.1109/TPWRS.2023.3330604.

[23] Y. Zahraoui *et al.*, "AI Applications to Enhance Resilience in Power Systems and Microgrids—A Review," *Sustainability (Switzerland)* , vol. 16, no. 12, 2024. https://doi.org/10.3390/su16124959.

[24] I. Alhamrouni *et al.*, "A Comprehensive Review on the Role of Artificial Intelligence in Power System Stability, Control, and Protection: Insights and Future Directions," *Applied Sciences (Switzerland)*, vol. 14, no. 14, 2024. https://doi.org/10.3390/app14146214.

[25] B. Chen, L. Cao, C. Chen, Y. Chen, and Y. Yue, "A comprehensive survey on the chicken swarm optimization algorithm and its applications: state-of-the-art and research challenges," *Artificial Intelligence Review,* vol. 57, no. 7, 2024. https://doi.org/10.1007/s10462-024-10786-3.

[26] S. Oladipo, Y. Sun, and S. A. Adegoke, "Application of soft computing techniques to load frequency control system of electric power systems: a brief survey," *Cogent Eng.*, vol. 12, no. 1, p., 2025. https://doi.org/10.1080/23311916.2025.2572297.

[27] L. M. Toluhi, T. O. Akande, O. O. Alabi, A. O. Laoye, and O. David, "Optimized AI-based Techniques for Forecasting Solar Irradiance Using Genetic Algorithms (GA)," *Journal of Artificial Intelligence and Digital Health*, vol. 1, no. 1, pp. 1–17, 2026, [Online]. Available: https://www.confmeets.com/journals/jaid/archive/2026-volume-1-issue-1-january-to-june.

[28] J. Chen, Y. Yuan, Q. Wang, H. Wang, and R. C. Advincula, "Bridging Additive Manufacturing and Electronics Printing in the Age of AI," *nanomaterials*, vol. 15, no. 11, pp. 1–35, 2025. https://doi.org/10.3390/nano15110843.

[29] K. A. Al Sumarmad, N. Sulaiman, N. I. A. Wahab, and H. Hizam, "Energy Management and Voltage Control in Microgrids Using Artificial Neural Networks, PID, and Fuzzy Logic Controllers," *Energies,* vol. 15, no. 1, 2022. https://doi.org/10.3390/en15010303.

[30] S. Muhammad, H. Obeid, A. Hammou, and M. Hinaje, H. Gualous "Voltage Control for DC Microgrids : A Review and Comparative Evaluation of Deep Reinforcement Learning," *Energies (Basel).*, vol. 18, no. 21, pp. 1–33, 2025. https://doi.org/10.3390/en18215706.

[31] J. Xu, K. Li, and M. Abusara, "Preference based multi-objective reinforcement learning for multi-microgrid system optimization problem in smart grid," *Memetic Computing*, vol. 14, pp. 225–235, 2022. https://doi.org/10.1007/s12293-022-00357-w.

[32] A. K. Junejo, W. Xu, A. A. Hashmani, F. F. M. El-Sousy, H. U. R. Habib, and Y. Tang, "Novel Fast Terminal Reaching Law Based Composite Speed Control of PMSM Drive System," *IEEE Access*, vol. 10, pp. 82202–82213, 2022. https://doi.org/10.1109/ACCESS.2022.3196785.

[33] W. Xu, A. K. Junejo, Y. Tang, M. Shahab, H. U. R. Habib, and Y. Liu, "Composite Speed Control of PMSM Drive System Based on Finite Time Sliding Mode Observer," *IEEE Access*, vol. 9, pp. 151803–151813, 2021. https://doi.org/10.1109/ACCESS.2021.3125316.

[34] Y. Gao, Z. Hu, W. Chen, M. Liu, and Y. Ruan, "A revolutionary neural network architecture with interpretability and flexibility based on Kolmogorov – Arnold for solar radiation and temperature forecasting," *Appl. Energy*, vol. 378, no. PA, p. 124844, 2025. https://doi.org/10.1016/j.apenergy.2024.124844.

[35] M. Kaminski and T. Tarczewski, "Neural Network Applications in Electrical Drives—Trends in Control, Estimation, Diagnostics, and Construction," *Energies*, vol. 16, no. 11, 4441, 2023. https://doi.org/10.3390/en16114441.

[36] J. X. Halivor, "Model predictive control – based robust-control strategy of distribution control for a grid-connected AC microgrid," *Frontiers in Smart Grids*, vol. 2, 2023. https://doi.org/10.3389/frsgr.2023.1188074.

[37] M. Bašić, D. Vukadinović and I. Grgić, "Model Predictive Current Control of an Induction Motor Considering Iron Core Losses and Saturation," *Processes*, vol. 11, no. 10, art. No. 2917, 2023. https://doi.org/10.3390/pr11102917.

[38] M. M. Zayer, A. Monem, S. Rahma, R. Abdulsalam, and S. Saeed, "AI-Based Maintenance Systems for Enhancing Energy Efficiency in Aviation Technologies," *International Journal on Informatics Visualization*, vol. 9, no. 6, pp. 2683–2690, 2025. https://dx.doi.org/10.62527/joiv.9.6.4897.

[39] S. Song *et al.*, "Low-Power On-Chip Energy Harvesting: From Interface Circuits Perspective," *IEEE Open Journal of Circuits and Systems*, vol. 5, pp. 267–290, 2024. https://doi.org/10.1109/OJCAS.2024.3423484.

[40] Y. C. Chau, "Nanophotonic Materials and Devices : Recent Advances and Emerging Applications," *Micromachines (Basel).* Vol. 16, no. 8, 2025. https://doi.org/10.3390/mi16080933.

[41] W. Qiu, X. Zhao, A. Tyrrell, S. Perinpanayagam, S. Niu, and G. Wen, "Application of Artificial Intelligence- Based Technique in Electric Motors:A Review," *IEEE Transactions on Power Electronics*, vol. 39, no. 10, pp. 13543–13568, 2024. https://doi.org/10.1109/TPEL.2024.3410958.

[42] M. Cirstea, K. Benkrid, A. Dinu, R. Ghiriti, and D. Petreus, "Digital Electronic System-on-Chip Design : Methodologies , Tools , Evolution , and Trends," *Micromachines (Basel).*, vol. 15, no. 2, 2024. https://doi.org/10.3390/mi15020247.

[43] J. Fang, Y. Li, and L. Shi, "Advances in materials and actuation strategies for wearable medical robotics : optimization for biomedical applications," *MedMat.*, vol. 2, no. 4, pp 195-218, 2025. https://doi.org/10.1097/mm9.0000000000000027.

[44] M. El Merroun, "AI-Powered Innovations and Their possible effects on environmental Sustainability Aspects : Systematic Literature Review," *American Research Journal of Humanities Social Science (ARJHSS)*, vol. 7, no. 06, pp. 100–141, 2024. https://www.arjhss.com/wp-content/uploads/2024/06/L76100141.pdf.

[45] P. Dinolova, V. Ruseva, and O. Dinolov, "Energy Efficiency of Induction Motor Drives: State of the Art, Analysis and Recommendations," *Energies*, vol. 16, no. 20, art. No. 7136, 2023. https://doi.org/10.3390/en16207136.

[46] A. A. Nkembi *et al.*, "A Novel Feedforward Scheme for Enhancing Dynamic Performance of Vector-Controlled Dual Active Bridge Converter with Dual Phase Shift Modulation for Fast Battery Charging Systems," *Electronics (Basel).*, vol. 13, no. 19, 2024. https://doi.org/10.3390/electronics13193791.

[47] A. Korompili and A. Monti, "Review of Modern Control Technologies for Voltage Regulation in DC/DC Converters of DC Microgrids," *Energies (Basel).*, vol. 16, no. 12, pp. 1–52, 2023. https://doi.org/10.3390/en16124563.

[48] M. Panico and L. Boccarusso, "Smart Drilling : Integrating AI for Process Optimisation and Quality Enhancement in Manufacturing," *Journal of Manufacturing and Materials Processing*, vol. 9, no. 12, pp. 1–41, 2025. https://doi.org/10.3390/jmmp9120386.

[49] S. S. Stephen and C. O. Aigbavboa, “Gyroscopic materials and smart technologies : shaping resilient and energy-efficient buildings,” *Intelligent Buildings International*, vol. 8975, no. May, 2025. https://doi.org/10.1080/17508975.2025.2498936.

[50] T. S. Yong, “Intelligent Energy-Savings and Process Improvement Strategies in Energy-Intensive Industries,” *Brno University of Technology*, 2020. https://www.academia.edu/94253458/Intelligent_Energy_Savings_and_Process_Improvement_Strategies_in_Energy_Intensive_Industries.

[51] R. D. S. G. Campilho, “Recent Developments in Machine Design, Automation and Robotics,” *machines*, vol. 13, no. 8, pp. 1–9, 2025. https://doi.org/10.3390/machines13080683.

[52] A. Fathollahi, “Machine Learning and Artificial Intelligence Techniques in Smart Grids Stability Analysis : A Review,” *Energies (Basel).*, vol. 18, no. 13, pp. 1–33, 2025. https://doi.org/10.3390/en18133431.

[53] R. R. Sarangi, P. K. Ray, A. Mohanty, S. Khadem, and S. Patra, “Enhancing DC microgrid security : A comprehensive review of protection challenges and solutions,” *International Journal of Electrical Power and Energy Systems*, vol. 168, p. 110687, 2025. https://doi.org/10.1016/j.ijepes.2025.110687.

[54] P. A. Gbadega, Y. Sun, and O. Abolaji Balogun, “Advanced Control Technique for Optimal Power Management of a Prosumer-Centric Residential Microgrid,” *IEEE Access*, vol. 12, pp. 163819–163855, 2024. https://doi.org/10.1109/ACCESS.2024.3491100.

[55] S. Ali, S. Bogarra, M. N. Riaz, P. P. Phyo, D. Flynn, and A. Taha, “From Time-Series to Hybrid Models: Advancements in Short-Term Load Forecasting Embracing Smart Grid Paradigm,” *Applied Sciences (Switzerland)*, vol. 14, no. 11, 2024. https://doi.org/10.3390/app14114442.

[56] J. Sun, Z. Li, and M. Yang, “Multiple Fault-Tolerant Control of DC Microgrids Based on Sliding Mode Observer,” *Electronics (Switzerland)*, vol. 14, no. 5, 2025. https://doi.org/10.3390/electronics14050931.

[57] W. Jung, and K. Cho “Deep Learning and NLP-Based Trend Analysis in Actuators and Power Electronics,” *Actuators*, vol. 14, no. 8, pp. 1–35, 2025. https://doi.org/10.3390/act14080379.

[58] X. Tang, J. Chen, Y. Qin, T. Liu, K. Yang, A. Khajepour, and S. Li, “Reinforcement Learning - Based Energy Management for Hybrid Power Systems : State - of - the - Art Survey , Review , and Perspectives,” *Chinese Journal of Mechanical Engineering*, vol. 37, art. no. 43, 2024. https://doi.org/10.1186/s10033-024-01026-4.

[59] S. Chakroborty, N. Nath, S. Sahoo, and P. Singh, “Nanoscale Advances A review of emerging trends in nanomaterial-driven AI for biomedical applications,” *Nanoscale Advances*, vol. 7, no. 12, pp. 3619–3630, 2025. https://doi.org/10.1039/d5na00032g.

[60] D. Mazumdar, C. Sain, P. K. Biswas, P. Sanjeevikumar, and B. Khan, “Overview of Solar Photovoltaic MPPT Methods: A State of the Art on Conventional and Artificial Intelligence Control Techniques,” *International Transactions on Electrical Energy Systems*, vol. 2024, 2024. https://doi.org/10.1155/2024/8363342.

[61] D. Huang, J. Ma, Y. Han, C. Xue, M. Zhang, W. Wen, S. Sun, J. Wu, “Materials & Design Artificial intelligence artificial muscle of dielectric elastomers,” *Materials & Design*, vol. 251, no. January, p. 113691, 2025. https://doi.org/10.1016/j.matdes.2025.113691.

[62] X. Wen, Q. Shen, W. Zheng, and H. Zhang, “AI-Driven Solar Energy Generation and Smart Grid Integration A Holistic Approach to Enhancing Renewable Energy Efficiency,” *Academia Nexus Journal*, vol. no. 2, 2024. https://academianexusjournal.com/index.php/anj/article/view/9.

[63] T. Al Smadi, A. Handam, K. S Gaeid, A. Al-Smadi, Y. Al-Husban, A. S. Khalid, “Artificial intelligent control of energy management PV system,” *Results in Control and Optimization*, vol. 14, 2023, p. 100343, 2024. https://doi.org/10.1016/j.rico.2023.100343.

[64] N. Mishra and G. Tamrakar, “AI-Enhanced Model Predictive Control for Energy-Efficient Permanent Magnet Synchronous Motor Drives in Electric Vehicles,” *National Journal of Electric Drives and Control Systems*, vol. 1, no. 4, pp. 17–24, 2025. https://www.secitsociety.org/index.php/NJECDS/article/view/112.

[65] I. Mumba, and J. C. Mupala, “Smart Home Automation : Integrating Voice and Typed Command Control for Lights , Fan , and Socket , with Automated Water Tank Management and Room Temperature Sensing,” *International Journal of Advanced Multidisciplinary Research and Studies*, vol. 5, no. 4, pp. 995–1002, 2025. https://www.multiresearchjournal.com/admin/uploads/archives/archive-1754052986.pdf.

[66] T. Huang, H. Gu, and B. J. Nelson, “Increasingly Intelligent Micromachines,” *Annual Reviews.*, pp. 279–310, 2022. https://doi.org/10.1146/annurev-control-042920-013322.

[67] K. Yelemessov *et al.*, "Algorithmic Optimal Control of Screw Compressors for Energy-Efficient Operation in Smart Power Systems," *Algorithms*, vol. 18, no. 9, pp. 1–36, 2025. https://doi.org/10.3390/a18090583.

[68] D. Lee, S. Koo, I. Jang, and J. Kim, "Comparison of Deep Reinforcement Learning and PID Controllers for Automatic Cold Shutdown Operation," *Energies*, vol. 15, no. 8, art. No. 2834, 2022. https://doi.org/10.3390/en15082834.

[69] M. A. A. Ismail, S. Wiedemann, C. Bosch, and C. Stuckmann, "Design and Evaluation of Fault-Tolerant Electro-Mechanical Actuators for Flight Controls of Unmanned Aerial Vehicles," *Actuators*, vol. 10, no. 8, art. No. 175, 2021. https://doi.org/10.3390/act10080175.

[70] A. Baburaj, S. Jayadevan, A. K. Aliyana, N. K. Sk, and G. K. Stylios, "AI-Driven TENGs for Self-Powered Smart Sensors and Intelligent Devices," *Advanced Science*, vol. 12, no. 20, pp. 1–38, 2025. https://doi.org/10.1002/advs.202417414.

[71] X. Huang, H. Wang, S. Qin, and S.-K. Tang, "Embedded Artificial Intelligence : A Comprehensive Literature Review," *Electronics*, vol. 14, no. 17, art. No. 3468, 2025. https://doi.org/10.3390/electronics14173468.

[72] T. Man, V. Y. Osipov, N. Zhukova, A. Subbotin, and D. I. Ignatov, "Neural networks for intelligent multilevel control of artificial and natural objects based on data fusion : A survey," *Information Fusion*, vol. 110, 2023, p. 102427, 2024. https://doi.org/10.1016/j.inffus.2024.102427.

[73] K. M. De Payrebrune *et al.*, "The impact of AI on engineering design procedures for dynamical systems," *Arxiv preprint arXiv:2412.12230*, 2025. https://doi.org/10.48550/arXiv.2412.12230.

[74] S. Liang, R. Xi, X. Xiao, and Z. Yang "Adaptive Sliding Mode Disturbance Observer and Deep Reinforcement Learning Based Motion Control for Micropositioners," *Micromachines*, vol. 13, no. 3, art. No. 458, no. 458, 2022. https://doi.org/10.3390/mi13030458.

[75] G. Rajesh and K. Sebasthirani "Modeling and Control of Permanent Magnet Synchronous Motor Based Electric Vehicle," *Advances in Mechanical Engineering*, vol. 17, no. 4, pp. 1–18, 2025. https://doi.org/10.1177/16878132251333015.

[76] P. Šarafín and L. Formanek, "Efficient Dataset Creation for MEMS-Based Magnetic Sensor Systems in Intelligent Transportation Applications," *Sensors*, vol. 25, no. 24, art. no. 7407, 2025. https://doi.org/10.3390/s25247407.