Journal of Power Electronics and Drives
Volume 9, Issue 1, January-April 2024

Intelligent Control Strategies (AI/ML-Based) for Electric Drives

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ABSTRACT

Electric drives are widely used in electric vehicles, robotics, industries, and renewable energy systems. Conventional control methods like PI, PID, vector control, and direct torque control are effective but they suffer from parameter sensitivity, nonlinearity issues, and performance degradation under uncertainties. In recent years, Artificial Intelligence (AI) and Machine Learning (ML) techniques are increasingly applied for improving the performance of electric drive control. Intelligent controllers such as fuzzy logic, artificial neural networks, genetic algorithms, reinforcement learning, and deep learning provide adaptive, self-learning, and robust control under varying operating conditions. This paper presents a detailed review of AI/ML-based intelligent control strategies used in electric drives, highlighting their principles, advantages, limitations, and real-time implementation challenges. Comparative analysis with conventional controllers is also discussed. The study aims to provide a comprehensive understanding for researchers working on next generation smart drives.

***KEYWORDS:** Electric drives, Intelligent control, Artificial Neural Network, Fuzzy logic, Reinforcement learning, Sensorless control, AI in drives*

INTRODUCTION

Electric drives plays an important role in modern automation, electric vehicles (EVs), industrial motors, and renewable energy systems. Traditionally, drives are controlled using linear controllers such as PI or PID with field oriented control (FOC) and direct torque control (DTC). However, electric machines like induction motors (IM), permanent magnet synchronous motors (PMSM), and brushless DC motors (BLDC) are nonlinear systems and affected by temperature, load variation, parameter change and disturbances.

Because of these nonlinearities, classical controllers fails to give optimal performance at all operating conditions. Intelligent control based on AI/ML techniques are introduced to overcome this problem. These techniques do not require exact mathematical model and can learn from data and experience.
This paper reviews different AI and ML based control methods applied in electric drives.

2. NEED FOR INTELLIGENT CONTROL IN ELECTRIC DRIVES

Electric drives operate in highly dynamic and nonlinear environments. Although conventional controllers such as PI, PID, Field Oriented Control (FOC), and Direct Torque Control (DTC) are widely used in industry, their performance strongly depends on accurate motor parameters and fixed tuning. In practical conditions, these assumptions are rarely valid. Variations in temperature, load, magnetic characteristics, and sensor reliability degrade the performance of classical controllers. This motivates the adoption of intelligent control strategies based on AI and ML, which can learn, adapt, and self-tune in real time.

The major reasons demanding intelligent control in drives are discussed below.

2.1 Motor Parameter Variation Due to Temperature

Motor parameters such as stator resistance RsR_sRs, rotor resistance RrR_rRr, inductances, and flux linkage change significantly with temperature rise during operation. For example:

- Stator resistance of an induction motor may increase by 30–50% after prolonged heating.
- Magnet flux in PMSM reduces with temperature, affecting back EMF and torque

production.

Conventional PI/FOC controllers are tuned based on nominal parameters. When parameters drift, the controller produces steady-state error, poor torque response, and oscillations.

Intelligent controllers like ANN and adaptive fuzzy systems can estimate parameters online and adjust control gains automatically, maintaining performance even when temperature changes.

2.2 Load Torque Disturbances and Sudden Load Changes

Industrial drives and EV traction motors frequently face unpredictable load disturbances:

- Sudden change in mechanical load in conveyors or pumps
- Road slope variations in EVs
- Variable payload in robotics

Classical controllers respond slowly to such disturbances because they rely on fixed gains and linear assumptions.

AI-based controllers learn the system behavior and predict disturbance patterns. Reinforcement learning and neuro-fuzzy controllers can quickly compensate torque variations and maintain constant speed with minimal overshoot.

2.3 Magnetic Saturation and System Nonlinearity

Electric machines are inherently nonlinear due to:

- Magnetic saturation of iron core
- Cross-coupling between d–q axes
- Hysteresis and core losses
- Dead-time and inverter nonlinearity

PI/PID controllers are designed for linear models and cannot effectively handle these nonlinear effects, especially at low speeds or high load.

Fuzzy logic and neural networks do not require linear mathematical models. They can approximate nonlinear mappings between input and output, providing better control in saturated and nonlinear regions.

2.4 Sensor Noise, Offset, and Failures

Speed sensors, current sensors, and position encoders are prone to:

- Electrical noise
- Drift and offset
- Mechanical wear and misalignment
- Complete failure in harsh environments

Conventional controllers depend heavily on accurate sensor feedback. Any noise leads to oscillations and inaccurate control.

AI/ML techniques can filter noisy signals, estimate states from partial measurements, and even operate in sensorless mode using learned patterns from voltage and current signals.

2.5 Requirement of Fast Dynamic Response in Electric Vehicles

In EV applications, drives must respond very fast to:

- Acceleration and deceleration commands
- Regenerative braking
- Traction control on slippery roads

Conventional PI-based speed loops have limited bandwidth and may cause delay in torque production.

Reinforcement learning and ANN controllers can predict the required torque instantly from driving conditions, providing faster and smoother dynamic response suitable for EV traction systems.

2.6 Complexity of Sensorless Control

Sensorless control techniques estimate rotor position and speed from electrical signals. However, estimation becomes difficult at:

- Low speed and standstill
- Parameter variation

- Noisy measurements

Model-based observers require precise parameters and complex calculations.

Deep learning and ANN estimators can learn the relationship between voltage/current waveforms and rotor position without relying strictly on mathematical models, improving low-speed sensorless performance.

2.7 Automatic Tuning and Self-Learning Capability

One of the biggest drawbacks of conventional controllers is manual tuning of gains. For different motors and operating conditions, retuning is required.

Genetic algorithms, adaptive neuro-fuzzy systems, and RL can automatically tune controller parameters during operation, reducing human intervention and commissioning time.

3. CLASSIFICATION OF AI/ML TECHNIQUES FOR ELECTRIC DRIVES

Artificial Intelligence (AI) and Machine Learning (ML) techniques applied in electric drives can be broadly classified based on their learning mechanism, decision-making ability, and application purpose. Unlike conventional controllers that depend on fixed mathematical models, these techniques learn from data, rules, optimization, or interaction with the environment. Each technique has unique strengths and is suitable for specific control tasks such as speed control, torque estimation, parameter identification, sensorless operation, and fault diagnosis.

The major AI/ML techniques used in electric drives are discussed below.

3.1 Rule-Based Intelligent Techniques

These techniques rely on human knowledge, linguistic rules, and reasoning rather than numerical models.

Fuzzy Logic Control (FLC):

- Uses IF–THEN rules based on expert knowledge.
- Does not require exact motor model.
- Suitable for speed control, torque ripple minimization, and disturbance rejection.
- Widely used as a replacement for PI controller in FOC and DTC.

Characteristics:

- Handles nonlinearity effectively
- Easy to implement
- Rule design can be complex for large systems

3.2 Learning-Based Techniques

These methods learn the input–output relationship from data through training.

Artificial Neural Network (ANN):

- Mimics biological neurons.
- Learns mapping between voltage/current signals and motor states.
- Used for speed estimation, torque estimation, and parameter identification.

Deep Learning (DL):

- Multi-layer ANN (CNN, LSTM).
- Extracts features automatically from large datasets.
- Used in sensorless control, fault detection, and predictive maintenance.

Characteristics:

- Requires training data
- High accuracy after training
- Computationally intensive

3.3 Optimization-Based Techniques

These techniques are used to find optimal controller parameters or operating points.

Genetic Algorithm (GA):

- Inspired by natural evolution.
- Used to tune PI/PID and fuzzy controller gains.
- Finds global optimum solution.

Particle Swarm Optimization (PSO):

- Based on swarm behavior of birds/fish.
- Faster convergence compared to GA.
- Used for controller tuning and efficiency optimization.

Characteristics:

- Offline or online tuning possible
- Improves dynamic response
- Requires objective function definition

3.4 Experience-Based Learning Techniques

These techniques learn by interacting with the environment using reward and penalty.

Reinforcement Learning (RL):

- Learns optimal control action through trial and error.
- No need of exact model.
- Suitable for adaptive speed control and EV traction control.

Characteristics:

- Self-learning capability
- Large training time
- Requires exploration of states

3.5 Hybrid Intelligent Techniques

Combination of two or more AI techniques to utilize advantages of each.

Neuro-Fuzzy (ANFIS):

- Combines learning ability of ANN and reasoning of FLC.
- Used in nonlinear PMSM and IM control.

GA-Fuzzy / GA-ANN:

GA used to optimize fuzzy rules or ANN weights.

Characteristics:

- High robustness
- Better performance than single technique
- Increased complexity

Table 1: AI/ML techniques in electric drives

Technique	Principle	Application in Drives
Fuzzy Logic Control (FLC)	Rule-based reasoning	Speed and torque control
Artificial Neural Network (ANN)	Learning from data	Parameter estimation, control
Genetic Algorithm (GA)	Optimization	Controller tuning
Reinforcement Learning (RL)	Trial and error learning	Adaptive drive control
Deep Learning (DL)	Multi-layer neural nets	Fault detection, sensorless control
Neuro-Fuzzy	Hybrid approach	Robust drive control

4. FUZZY LOGIC CONTROL (FLC) FOR ELECTRIC DRIVES

Fuzzy Logic Control (FLC) is one of the earliest and most successful intelligent control techniques applied to electric drives. Unlike conventional controllers that depend on accurate mathematical models and fixed parameters, FLC works on **linguistic rules** and **human reasoning**. This makes it highly suitable for electric machines, which are nonlinear, time-varying, and affected by uncertainties such as parameter drift, load variation, and magnetic saturation.

FLC does not require precise knowledge of motor equations. Instead, it uses expert knowledge in the form of IF–THEN rules to control the drive system.

4.1 Basic Structure of Fuzzy Logic Controller

A typical FLC used in motor drives consists of four main blocks:

1. **Fuzzification**

Converts crisp inputs (such as speed error and change in error) into fuzzy linguistic variables like *Negative Large (NL)*, *Zero (ZE)*, *Positive Small (PS)*, etc.

2. **Rule Base**

Contains a set of IF–THEN rules derived from expert knowledge. Example:

IF speed error is Positive Large AND change in error is Positive Small THEN control output is Medium.

3. **Inference Engine**

Processes the rules and determines the fuzzy output based on input conditions.

4. **Defuzzification**

   Converts fuzzy output back into a crisp control signal (e.g., voltage reference or current reference).

4.2 Why FLC is Suitable for Electric Drives

Electric drives exhibit:

- Nonlinear magnetic characteristics
- Parameter variations with temperature
- Sudden load disturbances
- Coupling between electrical and mechanical dynamics

Designing an exact mathematical model to cover all these effects is difficult. FLC bypasses this need by using qualitative knowledge of system behavior.

4.3 Applications of FLC in Different Drives

4.3.1 Speed Control of Induction Motor (IM)

In IM drives, rotor resistance variation and load disturbance affect speed regulation. Replacing the PI speed controller in FOC with FLC results in:

- Faster settling time
- Reduced overshoot
- Better disturbance rejection
- Smooth low-speed operation

4.3.2 Speed and Torque Control of PMSM

PMSM performance depends on accurate flux and torque control. FLC can directly regulate torque-producing current without exact parameter knowledge, improving:

- Dynamic torque response
- Robustness to magnet flux variation
- Stability at low speeds

4.3.3 Torque Ripple Minimization in BLDC Motor

BLDC motors suffer from torque ripple due to commutation. FLC can adjust current reference dynamically during commutation intervals, resulting in:

- Reduced torque pulsations
- Smooth operation
- Less vibration and noise

ARTIFICIAL NEURAL NETWORK (ANN) BASED CONTROL

ANN mimics human brain and learns from input-output data.

Uses in drives:

- Speed estimator in sensorless drives
- Online parameter estimation
- Torque and flux estimation
- Replacement of PI in DTC

ANN provides fast response but requires training data.

GENETIC ALGORITHM FOR CONTROLLER OPTIMIZATION

GA is used to tune parameters of PI/PID or fuzzy controllers.

Benefits:

- Finds global optimum
- Automatic tuning
- Improves dynamic performance

REINFORCEMENT LEARNING (RL) IN DRIVE CONTROL

RL is modern technique where controller learns optimal action by reward and penalty.

Used for:

- Adaptive speed control
- Energy efficient drive operation
- EV traction control

RL does not need model but training time is large.

DEEP LEARNING FOR SENSORLESS AND FAULT DIAGNOSIS

Deep learning methods like CNN and LSTM are used for:

- Rotor position estimation
- Fault detection in stator winding
- Bearing fault diagnosis
- Predictive maintenance

NEURO-FUZZY CONTROLLERS

Combination of ANN and FLC provides better adaptability and reasoning.

Used in:

- High performance PMSM drives
- Nonlinear drive control

COMPARISON WITH CONVENTIONAL CONTROLLERS

Table 2: Comparison of controllers

Feature	PI/PID	AI/ML Controllers
Need accurate model	Yes	No
Adaptability	Low	High
Handling nonlinearity	Poor	Good
Computational cost	Low	High
Performance under disturbance	Moderate	Excellent

APPLICATIONS IN DIFFERENT MOTORS

Table 3: Motor-wise AI applications

Motor Type	AI Application
Induction Motor	ANN speed estimator, FLC speed control
PMSM	Neuro-fuzzy torque control
BLDC	GA tuned controller

Motor Type	AI Application
SRM	RL based torque control

IMPLEMENTATION CHALLENGES

- Requirement of high processing power (DSP/FPGA)
- Training data requirement
- Real-time execution difficulty
- Stability analysis complexity

FUTURE TRENDS

- Edge AI in EV drives
- Online learning controllers
- Digital twin with AI
- AI-based predictive maintenance

CONCLUSION

AI and ML based intelligent control strategies significantly improves performance of electric drives compared to conventional methods. They provide robustness, adaptability, and better handling of nonlinearities. However, computational complexity and real-time implementation are challenges. With advancement in processors and AI algorithms, intelligent drives will become common in EVs and industries.

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