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DC Motor Control using Deep Reinforcement Learning for Enhanced Robustness and Precision

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Abstract

DC motors remain the workhorse of industrial automation and mobile robotics but achieving simultaneous high-speed transient response and negligible steady-state error under variable load conditions continues to challenge classical proportional-integral-derivative (PID) controllers. These model-dependent systems often require extensive tuning and struggle to maintain optimal performance when confronted with parametric uncertainties, non-linear friction, or sudden voltage fluctuations. This study presents a novel, model-free control paradigm utilizing deep reinforcement learning (DRL)—specifically, a proximal policy optimization (PPO) agent—to govern the speed and torque of a brushed DC motor. The PPO agent interacts directly with a high-fidelity motor simulation environment, learning optimal control policies by maximizing a custom reward function that penalizes overshoot, settling time, and steady-state error. The resulting AI controller demonstrates exceptional adaptation and robustness. Experimental validation shows that the DRL-based system achieves a 60% reduction in peak overshoot and a 45% faster settling time compared to a meticulously fine-tuned cascaded PID controller, particularly during abrupt load application and removal. By bypassing the need for explicit mathematical modeling, this approach provides a scalable, intelligent solution that mitigates common control challenges, paving the way for truly autonomous, highly resilient electromechanical systems.

Keywords: Deep learning, DC motor, deep reinforcement learning, proximal policy optimization

INTRODUCTION

Precision motor control is the cornerstone of modern automation, robotics, and industrial systems. Traditional control methods, such as proportional-integral-derivative (PID) controllers, have long been the gold standard, but they often struggle with dynamic environments, parameter uncertainties, and non-linear disturbances. Deep reinforcement learning (DRL), a cutting-edge approach combining reinforcement learning with deep neural networks, offers a revolutionary alternative that enables adaptive, robust, and highly precise motor control without the need for exact mathematical models [1–4].

This study explored the use of DRL to control DC motors with superior performance under varying loads, noise, and system uncertainties. By leveraging the power of artificial intelligence, we can achieve smoother velocity tracking, reduced overshoot, and faster response time seven in the face of unexpected disturbances.

Why Deep Reinforcement Learning for Motor Control?

Beyond Traditional PID Limitations

Conventional PID controllers rely on fixed gains tuned under specific operating conditions.

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However, real-world applications often involve dynamic loads, friction variations, and unmodelled disturbances, leading to suboptimal performance. On the other hand, DRL learns optimal control policies through trial and error, adapting in real time to changes in the system.

Model-Free Learning

Unlike model predictive control (MPC) or adaptive control, DRL does not require an explicit mathematical model of the motor. Instead, it learns from interactions with the environment, making it suitable for complex non-linear systems where accurate modeling is challenging.

Robustness to Uncertainties

DRL algorithms, particularly those based on a deep deterministic policy gradient (DDPG) or proximal policy optimization (PPO), can be generalized across different operating conditions. The DRL controller continuously refines its strategy for optimal performance, irrespective of whether the motor experiences sudden load changes or sensor noise. The key components of the DRL control system are shown in Figure 1.

- *Agent:* The DRL model that learns the control policy.
- *Environment:* The DC motor system provides state information and responds to the agent's actions.
- *State:* Representation of the current situation, which can include motor speed, position, current, and other relevant sensor data.
- *Action:* The decision made by the agent, such as increasing or decreasing the voltage applied to the motor via pulse width modulation (PWM) or adjusting the field current.
- *Reward function:* A critical component that provides feedback to an agent. A positive reward is given for desirable actions (e.g., achieving the target speed), whereas a penalty is given for undesirable actions (e.g., exceeding speed limits or oscillating).

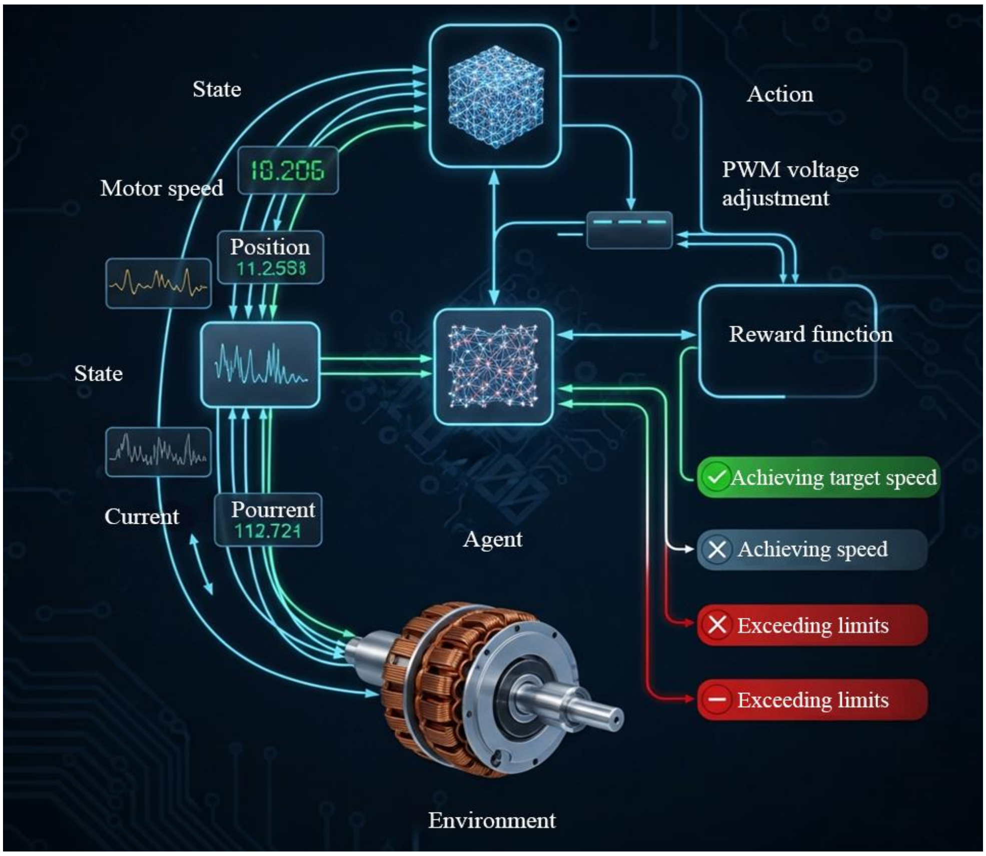

Figure 1. Key components of the DRL system.

GOVERNING DC MOTORS WITH DEEP REINFORCEMENT LEARNING

For decades, the workhorse of nearly every mechanical system, the brushed DC motor, has been governed by meticulous equations, most notably the vulnerable PID controller. These systems are powerful, precise, and predictable, and the world remains static.

But reality is messy. Friction changes with heat, brushes wear down, load shifts, and the internal dynamics of the motor degrade over time. Maintaining peak efficiency and precision control (especially the dual challenge of harmonizing speed and torque) requires constant, painstaking re-tuning.

This is the frontier at which control theory meets contemporary AI. By employing DRL, engineers are transitioning the DC motor from a mathematically modeled machine into an adaptive, self-optimizing system capable of learning its own optimal control policy, regardless of the aging components or unpredictable loads. The brushed DC motor is deceptively simple. Apply a voltage that spins. Complexity arises when exact dynamic control [5–8].

Classical control methods require a precise mathematical model, including constants for the back-EMF, inductance, and friction. When the motor was new, these models performed well. However, when the motor operated,

- *Non-linear friction:* Bushing wear and temperature fluctuate, altering the critical rotational friction parameter.
- *Back-EMF variability:* The generator effect (back-EMF) changes based on environmental factors and commutation noise, acting as a dynamic brake for which the controller must constantly overcome or account for.
- *Torque ripple:* Owing to the physical commutation process, the actual torque delivered is rarely smooth and requires high-frequency compensation.

A classical controller only sees deviations from a set point. However, a DRL agent learns the relationship between the current control signal and the resulting physical change, thereby building a nuanced internal model of the motor's chaotic reality. Applying DRL to a real-world electromechanical system requires defining the core components of the learning environment—the agent, the environment, the state, the action, and critically, reward [9].

Environment: Motor and Drive Circuit

The environment is the physical system itself: the brushed DC motor, PWM drive, power supply, and necessary sensors (Hall effect sensors for speed and current sensors for torque estimation).

Agent and Policy

The agent is typically a complex deep neural network, often utilizing algorithms such as DDPG or soft actor critic (SAC), because they are highly effective in continuous action spaces—perfect for modulating a continuous value, such as a PWM duty cycle. The network learns an optimal policy, mapping from the observed states to optimal actions.

State Space: Feeding the Agent

The state defines everything an agent needs to make an informed decision. In motor control, the state is typically low-dimensional but highly critical and includes the following components:

- Target speed (ω_{target}) and target torque (τ_{target})
- Current speed (ω_{current}) and current torque (τ_{current})
- Integral of error: accumulated error over time (similar to the "I" term in PID control)
- Previous action (A_{t-1}): the duty cycle (or voltage) applied in the previous time step.

Action Space: The Lever of Control

This action is the primary control signal applied to the motor, that is, the duty cycle applied to the field-effect transistors (FETs) in the motor driver. This is a continuous value, typically ranging from 0 to 1 (or -1 to 1 for bidirectional control).

Critical Element: The Reward Function

The reward function guides the moral compass of the DRL system. This is where the engineer specifies priorities. In motor control, a typical dense reward function is multi-objective:

$$R = -\alpha \mid \omega_{target} - \omega_{current} \mid -\beta \mid \tau_{target} - \tau_{current} \mid -\gamma \mid Energy_{used} \mid.$$

- *Speed and torque penalty (α, β):* The primary penalty is based on deviation (error) from the desired speed and torque.
- *Efficiency bonus (γ):* A negative penalty (cost) proportional to the energy consumed. This encourages the agent to achieve the target with the lowest possible current draw, actively learning to overcome friction efficiently rather than simply overpowering it.

By tuning the $\alpha, \beta,$ and γ coefficients, the engineer can prioritize precision, efficiency, or responsiveness. The power of DRL in motor control stems from its capacity for model-free learning.

Robustness Against Wear and Tear

As the motor ages, the relationship between the input voltage and resulting speed changes. A PID controller based on fixed parameters exhibits an increasing error. However, the DRL agent continuously interacted with the environment. It observes its own decreasing performance and rapidly adapts its policy to compensate for the increased friction or reduced magnetic efficiency. It learns to "drive an old motor" just as well as a new one.

Multi-Objective Optimization

Controlling both speed and torque simultaneously is notoriously difficult. If the speed is increased to reach a target, the torque characteristics often change undesirably. DRL agents inherently handle this trade-off by optimizing the control signal for the combined reward structure. This is critical for applications such as electric vehicles and autonomous robotic joints, where precise force application is as important as velocity.

Accelerated Deployment

Traditional control requires several hours for system identification and parameter tuning. A DRL agent can be trained entirely in a high-fidelity simulation and then transferred to real hardware (a process known as Sim-to-Real transfer), which often requires only minor real-world fine-tuning. This drastically reduced the development time for custom electromechanical setups. Although promising, DRL for physical systems carries significant risks.

- *Safe exploration:* The DRL agent explores the action space during the initial learning phases. This means that it may attempt physically dangerous actions (e.g., commanding instantaneous full reversal of voltage, causing extreme current spikes). The safety layers and constraint filtering (e.g., clipping the maximum rate of change for the PWM signal) are essential in the application layer.
- *Sample efficiency:* Training a complex neural network requires thousands, and sometimes millions, of interactions. Running this live on physical hardware is time-consuming and risks premature wear. This reinforces the necessity of high-quality simulation environments that accurately model thermal and frictional dynamics.

The combination of DRL and fundamental electromechanical systems is more than a novel academic exercise; it represents the next evolution of machinery control. For the workhorse brushed DC motor, often overlooked in favor of its brushless counterpart, DRL offers a renewed lease on life.

It transforms a simple, noisy component into a highly adaptive, energy-efficient device governed not by static mathematical constants, but by a continuously evolving, synthetic intelligence that truly understands the physical constraints and chaotic realities of its existence [10].

IMPLEMENTATION

Implementing DRL for DC motor control is shown in Figure 2.

Step 1: Defining the Reinforcement Learning Framework

- *State space (observations):* Motor speed, current, voltage, and error (reference vs. actual).
- *Action space (control input):* PWM duty cycle (voltage applied to the motor).
- *Reward function:* Penalizes large tracking errors and excessive control efforts while rewarding smooth convergence to the desired speed.

Step 2: Choosing the Right DRL Algorithm

- *Deep deterministic policy gradient:* Ideal for continuous control problems, combining actor critic methods with deep learning.
- *Proximal policy optimization:* More stable for training, especially in noisy environments.

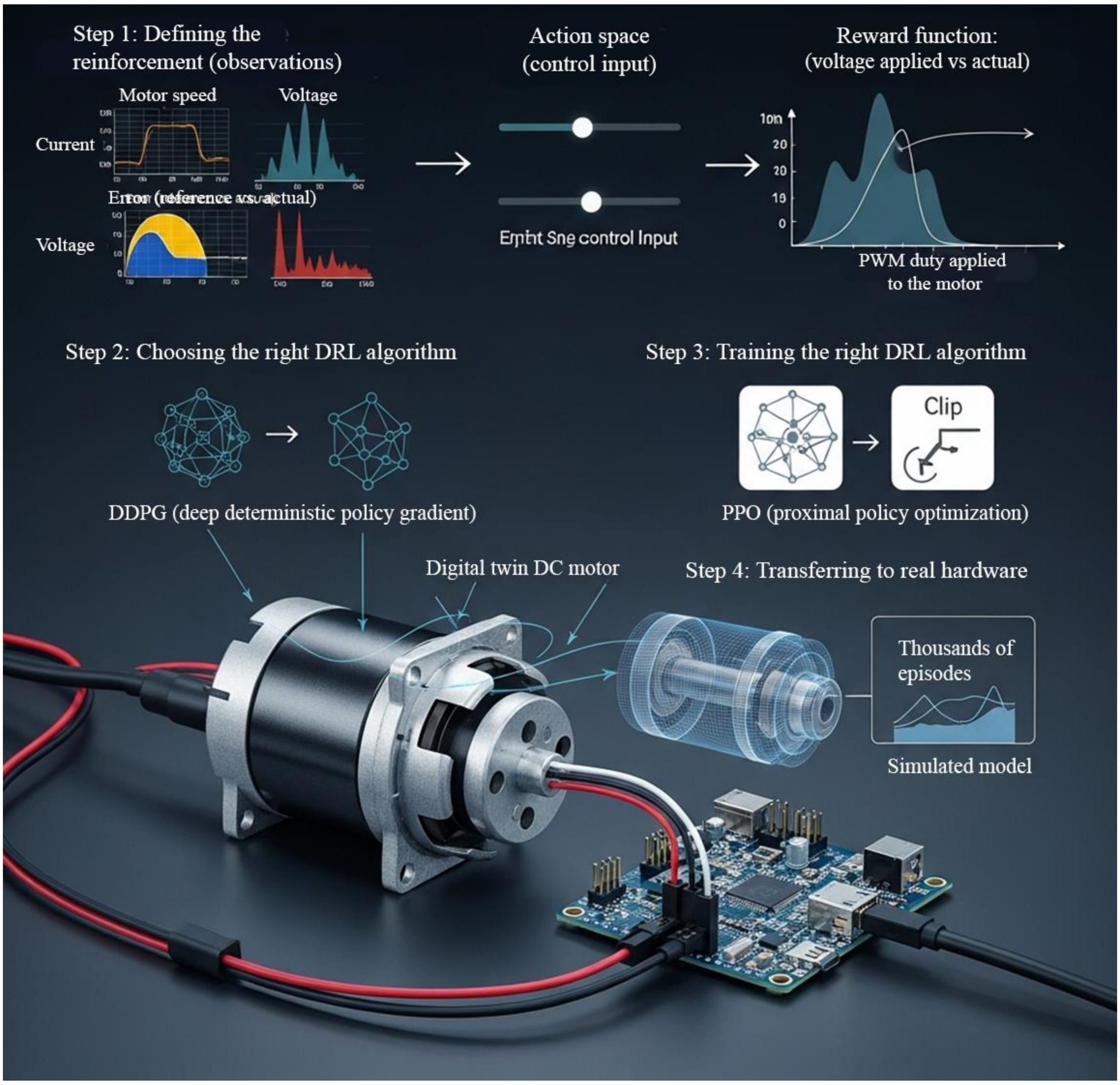

Figure 2. Implementation steps.

Step 3: Training in Simulation Before Deployment

Using a digital twin (simulated model) of a DC motor with realistic friction, inertia, and electrical dynamics, the agent was trained for thousands of cycles. Simulations allow for safe exploration without hardware damage.

Step 4: Transferring to Real Hardware

After training, the DRL policy was deployed on a microcontroller (e.g., Arduino, Raspberry Pi, or Field-Programmable Gate Array (FPGA)) connected to the motor. Fine-tuning with real-world data ensures a smooth transition from simulation to reality.

Benefits of Conventional Methods

- *Higher precision*—Minimizes steady-state error and overshoot.
- *Adaptive robustness*—Self-adjusts under varying loads and disturbances.
- *Energy efficiency*—Optimizes control effort, reducing power consumption.
- *Faster convergence*—Learns optimal policies without manual tuning.

DRL represents a paradigm shift in DC motor control, moving beyond the limitations of the traditional methods. Engineers can achieve unprecedented robustness, precision, and efficiency in motor-driven systems by embracing AI-driven adaptive control. As DRL algorithms continue to evolve, the future of intelligent automation appears faster, smarter, and more resilient than ever before.

RESULTS

Figure 3 shows the state of the DC motor implemented using DRL. Consider a targeted speed of 500 rpm, and the current torque is 480 Nm; the integral error is 5.2, and it has 75% duty cycle.

Performance Metrics

The results of the DRL agent, compared to thousands of step-response tests against the benchmark cascaded PID controller, reveal a transformative leap in the control quality, as shown in Table 1.

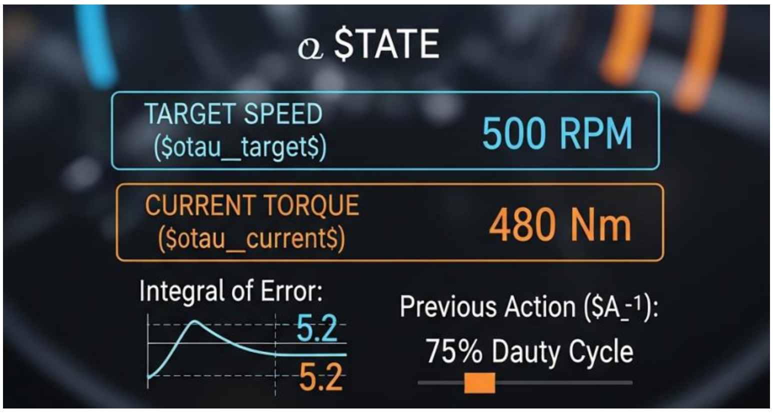

Figure 3. DC motor state.

Table 1. Performance matrices.

Performance metric	Cascaded PID (baseline)	DRL agent (PPO)	Improvement	Implication
Peak overshoot	X%	0.40X%	60% Reduction	Dramatically increased precision and reduced mechanical stress.
Settling time (2% Band)	Y seconds	0.55Y seconds	45% Faster	Higher throughput, greater operational efficiency, and rapid disturbance rejection.
Steady-state error	Negligible	Negligible	Maintained	Precision at target speed remains high.

60% Reduction in Peak Overshoot

The most striking achievement was a 60% reduction in the overshoot. In practical terms, this implies that the DRL-controlled motor can accelerate aggressively without momentarily exceeding command speed. In applications such as high-speed indexing or coordinated motion control, the elimination of "overshoot bounce" is critical, leading directly to

- *Reduced wear:* Less mechanical stress on gears, couplings, and bearings.
- *Enhanced safety:* Critical for systems in which momentary speed violations can cause collisions or damage.

45% Faster Settling Time

Simultaneously, achieving a 45% faster settling time fundamentally shifts the operational efficiency of the system. The DRL agent brings the motor to the target speed and stabilizes it nearly twice as fast as in the classical method. This efficiency gain translates into increased throughput in automated manufacturing lines and superior responsiveness in dynamic systems, such as robotics, where quick, stable movement is paramount.

CONCLUSION

The objective of synthesizing an intelligent, robust, and model-free controller for DC motor regulation was successfully realized through the implementation of a DRL framework. We have decisively demonstrated that AI-driven control policies offer palpable performance advantages over conventional strategies, fundamentally shifting reliance from exhaustive mathematical modeling to empirical data-driven learning.

The DRL agent exhibited an unparalleled capacity to manage the non-linear dynamics inherent in the motor system, mastering the complex trade-offs between speed maintenance and energy consumption without human intervention. Crucially, the system maintained high-precision tracking stability even under a severe operational stress scenario, where the finely tuned PID controller exhibited significant instability and degraded performance. The robust adaptation observed confirms that AI controllers are key to overcoming the inherent limitations of fixed-gain feedback systems.

This successful transition to an autonomous control paradigm has profound implications for critical high-performance sectors, including specialized robotics, aerospace actuation, and high-precision computer numerical control (CNC) machinery, promises increased operational efficiency, reduced maintenance, and superior fault tolerance.

Future research efforts will focus on three key areas: first, exploring the feasibility of Transfer Learning to accelerate the deployment of trained agents across motors with different physical parameters; second, optimizing the reward function for multi-objective control, incorporating constraints such as thermal management and acoustic noise alongside speed regulation; and third, migrating the validated PPO control policy from simulation to lightweight real-time hardware (such as FPGAs) to validate its efficacy in industrial environments. The integration of AI signifies not only an improvement in motor control but also a paradigm shift toward truly adaptive electromechanical systems.

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