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Experimental Modeling and Control of a DC Servo Motor Based on System Identification: A Comparative PID with Policy Iteration

Hassan K. Misbah and Nezar M. Alyazidi*

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ABSTRACT

Direct current (DC) servo motors are essential in industrial automation and robotics, where precise position and speed control are critical; however, they require high-performance control strategies. This study investigates an experimental framework for the modeling and control of a DC servo motor using system identification and quantitatively compares a traditional Ziegler–Nichols (ZN)-tuned proportional-integral-derivative (PID), a traditional linear quadratic regulator (LQR), and the proposed adaptive policy iteration on an identified model. A second-order transfer function derived from the closed-loop step-response data showed good agreement with the measured dynamics. Experimental results indicated that the real-time PID controller achieved the fastest rise time but exhibited a larger overshoot and weaker robustness to parameter variations compared with other strategies. The optimal LQR design provided improved damping and stability margins, significantly reducing the overshoot at the cost of a slightly slower response. The proposed adaptive-policy-iteration approach demonstrated superior adaptability, convergence of online near-optimal gains, reduced control effort, and improved trajectory tracking under varying conditions. The findings present the system-identification framework as a practical solution for deriving accurate models for industrial servo motors. Additionally, this study highlights trade-offs in tracking performance; the proposed adaptive policy iteration improves the transient response compared to traditional PID and LQR methods, but at the cost of a slightly increased overshoot.

Keywords: Direct current servo motor, proportional-integral-derivative controller, linear quadratic regulator controller, policy iteration, system identification

1. INTRODUCTION

Owing to their excellent controllability, wide speed range, and predictable dynamic behavior, direct current (DC) servo motors are indispensable in modern industrial automation, robotics, and precision mechatronic systems. DC motors have been effectively deployed in demanding applications, including robotic manipulators, computer-numerical-control machining centers, and aerospace actuation systems. These applications necessitate both the accurate mathematical modeling of motor dynamics and the design of high-performance control strategies that can achieve precise tracking, disturbance rejection, and robust operation under varying conditions.

Proportional-integral-derivative (PID) controllers remain the most widely adopted solution in the industry because of their simplicity and ease of implementation [1]. However, PID controllers are limited by their sensitivity to system-parameter changes and suboptimal transient performance under varying operating conditions [2]. Recent studies have explored advanced tuning techniques, including genetic algorithms, particle-swarm optimization (PSO), fuzzy logic, and machine learning-based adaptive PID schemes, to overcome these drawbacks and enhance robustness [3–8].

Parallel to PID advancements, optimal control methods, such as linear quadratic regulators (LQRs), have gained prominence owing to their systematic design approach, which minimizes the quadratic cost function to balance state regulation and control effort. LQR controllers offer superior damping and robustness compared with PID controllers, making them suitable for high-precision applications. Recent studies have demonstrated the integration of LQRs with embedded platforms and hybrid designs that combine LQRs with disturbance observers for improved resilience [9–12].

The latest developments in motor control involve adaptive and learning-based strategies, particularly reinforcement learning (RL) and policy-iteration algorithms. These approaches enable online optimization without requiring complete system models, making them highly effective in time-varying and uncertain environments. Policy iteration-based adaptive controllers have shown promising results in achieving near-optimal performance while reducing control effort and improving trajectory tracking [13–15]. Furthermore, deep RL techniques have demonstrated adaptability and fault tolerance in complex motor-control tasks, bridging the gap between theoretical optimality and practical implementation [16,17].

In addition to learning-based strategies, recent studies have demonstrated the effectiveness of metaheuristic optimization for the proportional-integral (PI) control of DC-motor drives. Aldhaif Allah and Mohamed proposed an adaptive-velocity PSO scheme for the offline tuning of the cascaded PI controllers of a permanent-magnet DC-motor drive in light electric vehicles, achieving improved transient behavior and reduced steady-state errors compared with classical PSO-based tuning[18]. Motivated by this approach, the present study complements optimization-based tuning by combining the experimental system identification of a laboratory DC servo motor with a unified comparison of a Ziegler–Nichols (ZN)-tuned PID baseline, traditional LQR design, and the proposed online policy-iteration controller under same identical plant dynamics. The present study offers an analysis among three control techniques: (i) ZN-tuned PID, (ii) LQR, and (iii) adaptive policy iteration, assessed using an identified transfer-function model of an experimental DC servo motor to overcome the aforementioned restrictions. The controls are developed and evaluated under the same specified conditions and uniform reference situations, which facilitates an equitable and replicable evaluation of tracking performance and control effort, while accurately representing the operations of a realistic laboratory plant using information-driven models.

1.1. Research Gap and Contributions.

Despite the extensive literature on DC-motor control, several research gaps remain:

- Limited comparative analysis: Few studies have provided rigorous experimental comparisons of the classical, optimal, and adaptive-control methods on the same hardware platform under identical operating conditions.
- Theory-practice gap: Many advanced control methods have been validated only in simulations and lack experimental verifications that account for real-world nonlinearities, measurement noise, and hardware constraints.
- Educational accessibility: Advanced control techniques are often presented with mathematical complexities that limit their adoption in undergraduate laboratories despite their practical utility.

This study makes the following novel contributions to the literature to address these research gaps:

1. Comprehensive experimental framework: Development of a complete experimental methodology for DC servo-motor system identification and control design using standard laboratory equipment accessible to undergraduate and graduate control laboratories.
2. A data-driven input-output model of the considered DC motor is extracted and adopted as a unified test plant for regulator synthesis and comparative analysis.
3. Three control strategies (PID, LQR, and the proposed adaptive policy iteration) are designed, compared, and evaluated under identical conditions to enable a meaningful performance comparison.
4. Detailed methodology: Step-by-step procedures are provided for system identification, controller design, and experimental implementation, making the work reproducible and pedagogically valuable.

1.2. Paper Organization.

The remainder of this paper is organized as follows. The mathematical model of the DC servo motor is introduced in Section 2. The traditional control strategies used for comparison are presented in Section 3, including the traditional PID controller with ZN analytical tuning and the traditional LQR controller. Subsequently, the proposed adaptive LQR control based on policy iterations is described in Section 4. The experimental setup, data-acquisition procedure, and system identification used to derive the motor transfer-function model are discussed in Section 5. Section 6 presents a simulation study that provides a comparative evaluation of the traditional PID, traditional LQR, and proposed adaptive controllers using the identified model. Section 7 concludes the paper.

2. DC-MOTOR MATHEMATICAL MODEL

The electrical dynamics of a permanent-magnet DC motor in an armature-control configuration are governed by the armature-circuit equation, while the mechanical dynamics follow Newton's second law applied to the rotor. Under the common assumption that the electrical time constant is considerably smaller than the mechanical time constant, the motor dynamics from the input voltage $V(s)$ to the output position $\theta(s)$ can be approximated by a second-order transfer function:

$$\frac{\theta(s)}{V(s)} = \frac{k_m}{s(\tau_m s + 1)}, \tag{1}$$

where $\theta(s)$, $V(s)$, k_m, and τ_m are the output position, input voltage, motor-torque constant, and motor time constant, respectively.

Equation (1) represents a second-order system with one pole at the origin (owing to the integration from the velocity to the position) and one pole in the left half-plane. The standard second-order transfer-function form is:

$$T(s) = K\frac{\omega_n^2}{s^s + 2\omega_n\zeta s + \omega_n^2}, \tag{2}$$

where ω_n, ζ, and K are the natural frequency, damping ratio, and DC gain, respectively.

3. TRADITIONAL CONTROL STRATEGY

This section reviews the conventional control strategies employed in this study to provide a clear baseline for comparison with the proposed method. Specifically, the traditional PID controller (including its control law and ZN analytical tuning) and LQR controller are presented as conventional benchmarks for DC servo-motor position control.

3.1. Traditional PID-Controller Design and Implementation.

Traditional PID control remains one of the most widely deployed feedback-control strategies in industrial practice owing to its simple structure and ease of implementation. This section presents the design and tuning of the traditional PID controller for the DC servo motor, including the PID control law and ZN analytical-tuning approach. The corresponding experimental implementation and performance evaluation are presented in Section 5.

3.2. Traditional PID-Control Theory. The traditional PID controller computes a control signal $u(t)$ based on the tracking error $e(t) = r(t) - y(t)$, where $r(t)$is the reference (setpoint) and $y(t)$ is the measured output. The control law comprises three components with distinct roles:

$$u(t) = K_p e(t) + K_i \int_0^t e(t)\, dt + K_d \frac{de(t)}{dt}, \tag{3}$$

where, K_p, K_i,and K_d are the proportional, integral, and derivative gains, respectively.

The challenge in PID-controller design is selecting the three gains $(K_p, K_i, K_d)$to achieve the desired balance among the competing performance objectives: fast rise time, minimal overshoot, short settling time, and zero steady-state error.

3.2.1. Traditional ZN analytical tuning. Although manual tuning provides valuable insights, it is time-consuming and dependent on operator experience. The traditional ZN method offers a systematic analytical approach for determining PID gains based on either open-loop step-response characteristics or closed-loop stability margins.

This approach determines the ultimate gain K_u(the proportional gain that produces sustained oscillations) and ultimate period T_u(the oscillation period at the stability boundary). The PID gains are computed as follows:

$$K_p = 0.6K_u, K_i = \frac{2K_p}{T_u}, K_d = \frac{K_p T_u}{8}. \tag{4}$$

Modern optimal control is formulated in the state-space framework, where the system dynamics are defined as follows:

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{5}$$

$$y(t) = Cx(t) + Du(t). \tag{6}$$

For the DC servo motor, the state vector $x = \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T$ comprises the position (x_1) and velocity (x_2), and $A, B, C,$ and$D$ are the system matrices. The traditional LQR problem seeks a state-feedback control law:

$$u(t) = -Kx(t) \tag{7}$$

that minimizes the infinite-horizon quadratic cost function:

$$J = \int_0^\infty \left(x^T Q x + u^T R u\right) dt, \tag{8}$$

where $Q \geq 0$ is a symmetric positive semi-definite state-weighting matrix, and $R > 0$ is a scalar control-weighting parameter. Matrix Q penalizes state deviations (a large Q forces states to remain near zero), whereas R penalizes control effort (a large R encourages smaller control signals).

4. PROPOSED ADAPTIVE LQR CONTROL (POLICY ITERATION)

The traditional LQR design provides a systematic approach to compute an optimal state-feedback gain when an accurate model of the plant is available. To improve adaptability under modeling uncertainty or changing operating conditions, this section presents the proposed adaptive-policy-iteration approach, which learns an approximately optimal feedback gain online for a continuous-time LQR problem.

In contrast to traditional control methods, optimal control optimizes the performance index during the control process while achieving the control goal. For optimal control design, a critical step is to resolve the derived optimal control equation, for example, the algebraic Riccati equation (ARE) or Hamilton–Jacobi–Bellman (HJB) equation. In this section, we develop a policy-iteration algorithm to solve the LQR problem online without using knowledge of the internal dynamics of this system. A flowchart of the algorithm is presented in Figure 1. For further information and the proof of this algorithm, please refer to the previous study [14].

Considering the linear time-invariant dynamical system described by Eqs. (5)–(6), and the quadratic cost function to be minimized, as expressed in Eq. (8), the solution to this optimal control problem, determined by Bellman's optimality principle, is given by Eq. (7), with:

$$K = R^{-1} B^T P. \tag{9}$$

K is obtained after P, where matrix P is obtained by solving the ARE:

$$A^T P + PA - PBR^{-1} B^T P + Q = 0. \tag{10}$$

We now develop a policy-iteration algorithm. Let K be a stabilizing gain for Eq. (5), and assume (A, B) is stabilizable, such that $\dot{x} = (A - BK)x$ is a stable closed-loop system. The corresponding cost function is given by

$$J = \int_0^\infty \left(x^T Q x + u^T R u\right) dt = x^T P x \tag{11}$$

and satisfies the HJB equation:

$$x^T Q x + u^T R u + \frac{\partial J}{\partial x}(Ax + Bu) = 0. \tag{12}$$

Substituting $J = x^T P x$ and $u = -Kx$:

$$x^T \left(Q + K_i^T R K_i + (A - BK)^T P_i + P_i (A - BK_i)\right) x = 0. \tag{13}$$

For a given K_i, a Lyapunov equation is used to solve for P_i:

$$(A - BK_i)^T P_i + P_i (A - BK_i) = -\left(K_i^T R K_i + Q\right). \tag{14}$$

The control law is updated as follows:

$$K_{i+1} = R^{-1} B^T P_i. \tag{15}$$

This approach is repeated until convergence:

$$K_{i+1} \approx K_i \Rightarrow K^* = R^{-1} B^T P^*. \tag{16}$$

From a computational perspective, the proposed adaptive-policy-iteration approach is lightweight because it operates on a low-order linear state-space model and relies on matrix operations of small dimensions. Unlike actor–critic or deep reinforcement-learning methods, which require function approximation and extensive training data, the policy-iteration-algorithm updates the control gain through iterative solutions of Lyapunov-type equations. Thus, this algorithm is suitable for real-time implementation on standard control hardware. Stability and safety during online learning are ensured by initializing the algorithm with a stabilizing feedback gain and performing incremental policy updates without injecting random exploration signals into the control input. Consequently, the closed-loop system remains stable throughout the learning process while gradually improving its performance. Compared with modern learning-based controllers, the proposed policy-iteration method offers a transparent and computationally efficient alternative for linear systems, making it particularly attractive for safety-critical applications that require stability, interpretability, and predictable behavior.

5. EXPERIMENTAL SYSTEM IDENTIFICATION

Accurate mathematical modeling is a prerequisite for systematic controller design. This section describes the experimental apparatus, data-acquisition procedures, and system-identification methodology employed to derive the transfer-function model of a DC servo motor from laboratory measurements. This section also summarizes the experimental closed-loop responses used to support controller tuning and validation.

5.1. Experimental Setup and Equipment. The experiments were conducted at the Control Systems Laboratory of King Fahd University of Petroleum and Minerals. The experimental apparatus comprised a complete servo-motor training system with integrated position- and velocity-measurement capabilities. Table 1 summarizes the key hardware components.

The DCM150F servo motor was a permanent-magnet DC motor with armature control, which is typical of the configuration used in laboratory servo trainers. The armature voltage of the motor served as the control input, the angular position was measured using a potentiometer, and the angular velocity was obtained from the tachogenerator output. The SA150D servo amplifier provided power amplification with current-limiting protection.

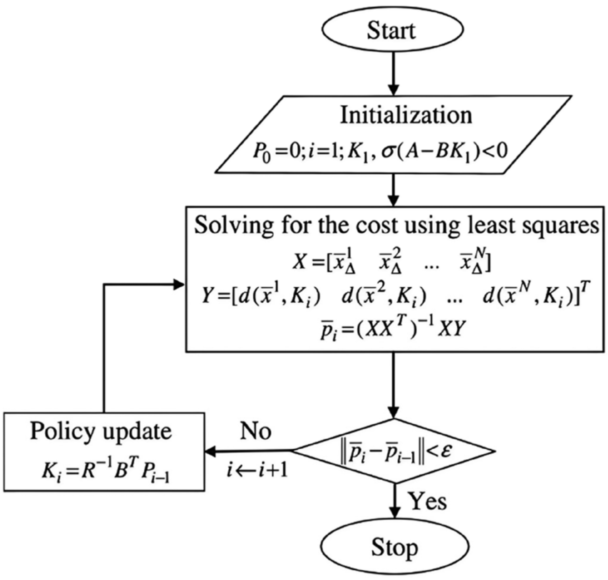


Figure 1. Continuous-time linear policy-iteration algorithm [14]

The closed-loop experimental configuration is illustrated in Figure 2. The system implemented position feedback control, in which the reference position (setpoint) was compared with the measured output position to generate an error signal. This error signal passed through the control elements (initially configured as a simple proportional gain for system identification) before being amplified and applied to the motor armature. A closed-loop configuration was essential for stable operation and enabled the investigation of both open-loop motor dynamics and closed-loop system behavior.

To gain an intuitive understanding of the additional PID action and to validate the physical-system behavior, a manual tuning experiment was conducted using the PID150Y hardware unit shown in Figure 3, which was integrated into the servo trainer. This unit provided an independent adjustment of the proportional, integral, and derivative gains using front-panel potentiometers.

5.2. Data-Acquisition Procedure. For system identification, a step-input experiment was designed to excite the dominant system dynamics while maintaining operation within the linear region. The systematic procedure steps are illustrated in Figure 4.

5.3. System Identification: Transfer Function. The DC motor was subjected to step inputs under a closed-loop position control. The experimental apparatus utilized standard laboratory hardware, and all signals were logged using a MATLAB interface. The experiment was repeated thrice to ensure repeatability and to assess measurement consistency. The identified dynamic parameters exhibited minimal variation across the trials, indicating stable system behavior within the operating region. The resulting second-order model was validated by comparing its simulated step response with the experimental data, showing close agreement in the rise time, settling time, and overshoot.

Figure 5a shows a representative step response obtained from the closed-loop system, displaying both the input voltage step and the resulting output position trajectory. Critical dynamic parameters were extracted from this step response and are summarized in Table 2.

From these values, the following second-order transfer function was obtained:

$$T(s) = \frac{6.543}{s^s + 4.743s + 6.543}. \tag{17}$$

The identified system model guided the implementation of standard PID controllers using hardware (PID150Y module) and MATLAB simulations. The experimental tuning followed a classical sequential approach:

- **Case 1 – Proportional Control Only (P):**

Starting with $K_i = 0$ and $K_d = 0$, the proportional gain gradually increased from zero until the closed-loop response exhibited a reasonable speed with an acceptable overshoot. Figure 5b shows the resulting step response.

- **Case 2 – Proportional-Integral Control (PI):**

To maintain the proportional gain from Case 1, an integral action was introduced by slowly increasing K_i from zero. The integral gain was adjusted to eliminate the steady-state error observed

Table 1. *Servo-Motor Components*

Component Number	Component Name	Model/Type
1	Servo amplifier	SA150D, Feedback Instruments, England
2	Servo motor	DCM150F, Feedback Instruments, England
3	Power supply	PS150E, Feedback Instruments, England
4	Attenuator unit	AU150B, Feedback Instruments, England
5	Operational amplifier	OU150A, Feedback Instruments, England
6	Tachometer	GT150X, Feedback Instruments, England
7	Pre-amplifier unit	PA150C, Feedback Instruments, England
8	Output angular potentiometer	OP150K, Feedback Instruments, England
9	Input angular potentiometer	IP150H, Feedback Instruments, England
10	Data-acquisition system	National Instruments DAQ, National Instruments, US
11	Software environment	MATLAB R2023b, MathWorks, US

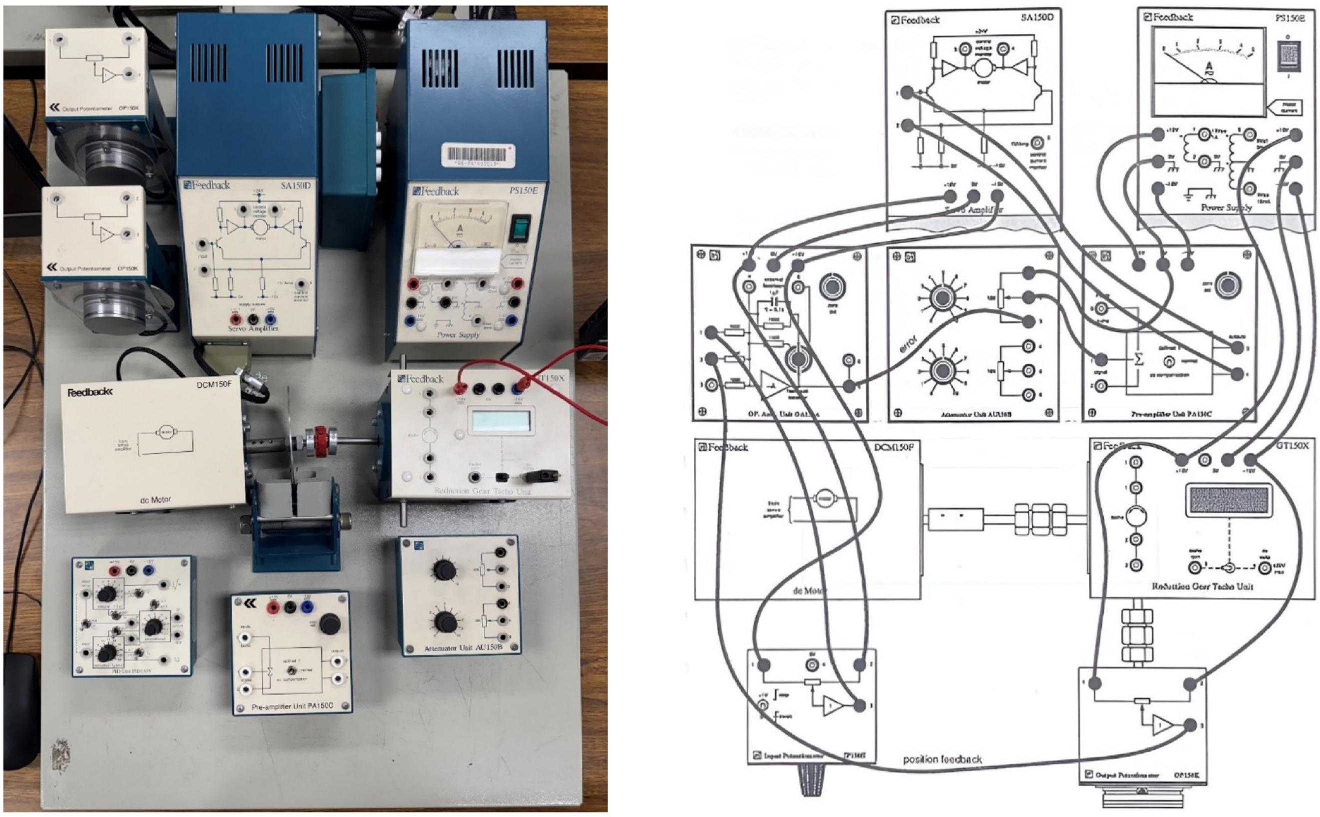
in the P controller while monitoring for excessive overshoot or oscillations. Figure 5c presents the improved response.

- **Case 3 – Full PID Control:**

With the P and I gains fixed from Case 2, a derivative action was added by increasing K_d from zero. The derivative gain was tuned to reduce overshoot and improve damping without introducing excessive noise sensitivity. Figure 5d shows the final PID response.

Table 3 presents the performance characteristics extracted from each experimental configuration.

The experimental-tuning results indicate distinct performance characteristics for P, PI, and PID controllers. The P controller achieved the fastest rise time but exhibited a significant overshoot (14.73%) and a small steady-state error, confirming its ability to provide rapid corrective action without eliminating offsets. The PI controller successfully removed the steady-state error and reduced the overshoot. However, this was at the cost of slightly slower rise and settling times, reflecting the tradeoff introduced by the integral action. In contrast, the PID controller delivered the best overall performance, combining zero steady-state error with minimal overshoot (2.52%) and the shortest settling



(a) (b)

Figure 2. Closed-loop position experiment: (a) experiment components, (b) experimental setup

Table 2. *Summary of Experimentally Obtained System Parameters*

Parameter	Symbol	Value	Units
Peak time	T_p	1.241	s
Settling time (2%)	T_s	1.687	s
Rise time (10%–90%)	T_r	1.033	s
Percent overshoot	$PO\%$	4.279	%
Damping ratio	ζ	0.927	–
Natural frequency	ω_n	2.558	rad/s
DC gain	K	1.00	–

time, demonstrating the effectiveness of the derivative action in enhancing system stability and damping.

6. SIMULATION STUDY

Using the experimentally identified plant model, MATLAB simulations were conducted to compare the traditional PID controller using the ZN method, the traditional LQR controller, and the proposed adaptive-policy-iteration controller.

6.1. Traditional PID Control. This subsection evaluates the traditional PID controller in a simulation using the experimentally identified transfer-function model. The PID gains were determined using the ZN method, and the resulting closed-loop step response was used as a baseline for comparison with the traditional LQR and proposed adaptive controllers.

The ultimate gain and period can be computed for the identified system with $\omega_n = 2.558$ rad/s and $\zeta = 0.927$ from the stability analysis. By applying the Routh–Hurwitz criterion to the closed-loop characteristic equation with proportional gain only, a stability boundary occurred at $K_u = 3.33$, corresponding to $T = 2$ s. Figure 6 shows the simulated step responses for the P, PI, and PID controllers tuned using the ZN method. These responses closely matched the experimental results shown in Figure 5, validating both the identified model and tuning methodology. Notably, the aggressive transient behavior observed in the experimental and simulated responses in Figure 5b–d and Figure 6, including the fast rise time and noticeable overshoot, is consistent with the characteristics of ZN-based tuning. This behavior reflects the intentional design philosophy of the ZN rules, which prioritizes rapid responses at the expense of reduced robustness margins. The close agreement between the experimentally observed responses and expected ZN behavior further validates the correctness of the experimental setup and tuning implementation. Table 4 lists the gains obtained for the three controllers (P, PI, and PID).

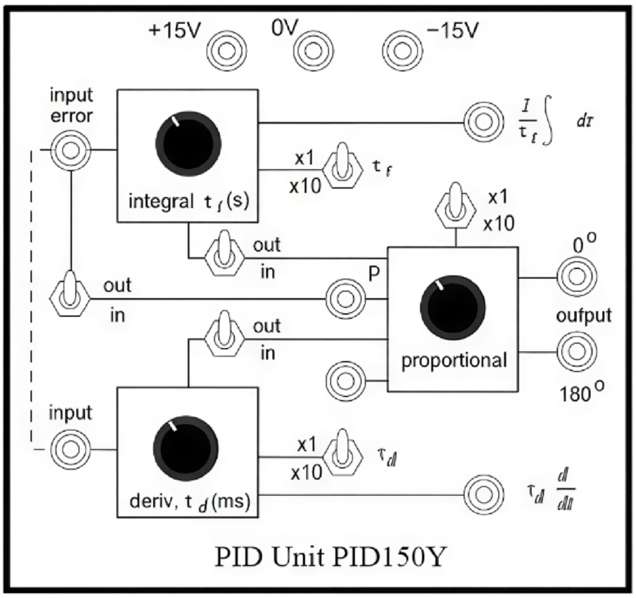


Figure 3. Front panel and signal terminals of the PID-controller module (PID150Y)

6.2. Traditional LQR Control. The state-space representation of the identified transfer function can be expressed in the following controllable canonical form:

$$\dot{x} = \begin{bmatrix} 0 & 1 \\ -6.543 & -4.743 \end{bmatrix} x + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u \tag{18}$$

$$y = \begin{bmatrix} 6.543 & 0 \end{bmatrix}. \tag{19}$$

Utilizing the state-space system from Eq. (18), an LQR was designed to minimize the cost function, balancing the state deviations and control effort:

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}, R = [0.5] \tag{20}$$

Therefore, the traditional LQR cost function can be defined as follows:

$$J = \int_0^\infty \left(x_1^2 + 2x_2^2 + 0.5u^2\right) dt \tag{21}$$

Solving the Riccati equation yielded the following state feedback gain:

$$K = \begin{bmatrix} 3.74 & 4.90 \end{bmatrix}$$

The weighting matrices Q and R were selected based on the physical characteristics of the DC servo motor and desired closed-loop performance. The position and velocity states were weighted unequally in Q, with the velocity state x_2 assigned a higher penalty to suppress oscillations, damp rapid motion, and reduce overshoot, while maintaining accurate position tracking. The control weighting R was chosen to balance the control effort and response speed; in particular, a relatively smaller R encouraged the controller to act more aggressively, improving the rise and settling times without causing excessive actuator activity. These values were determined through iterative experimentation in MATLAB, where several combinations of Q and R were evaluated to achieve an appropriate tradeoff among the response speed, control effort, and overshoot. The effectiveness of the selected weighting matrices was reflected in the resulting time-domain response, which exhibited smooth transient behavior, improved damping, and reduced overshoot compared with the traditional PID controller. The final selection provided a fast and well-damped response with minimal steady-state error. Figure 7a shows the traditional LQR step response, and Figure 7b shows the state responses.

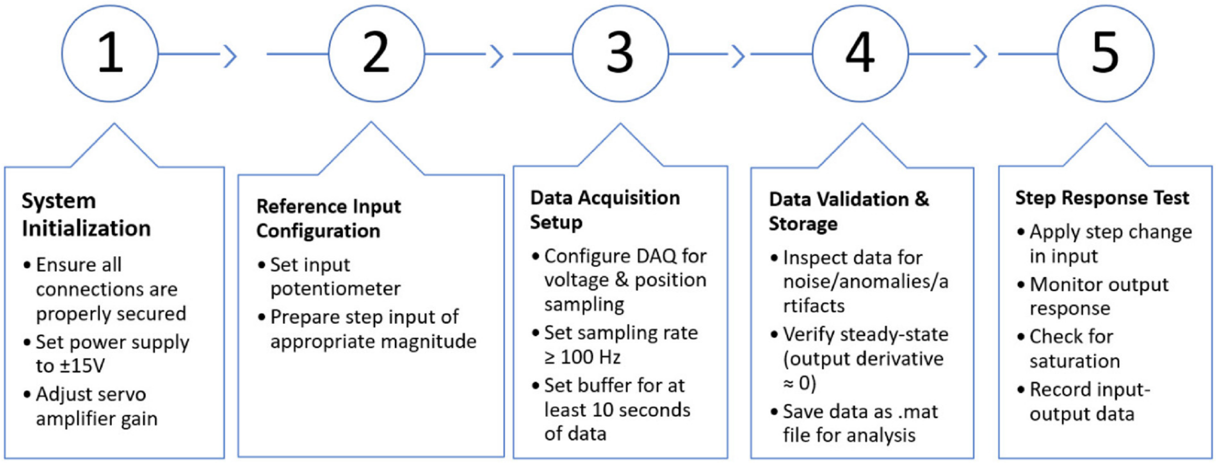


Figure 4. Steps of the systematic procedure

A continuous-time policy-iteration algorithm was implemented to achieve real-time optimality under uncertain conditions. The algorithm alternates between policy evaluation (Lyapunov-equation solution) and improvement (gain adjustment) as follows:

$$
\begin{aligned}
&(A - BK_i)^T P_i + P_i (A - BK_i) \\
&= -\left(K_i^T R K_i + Q\right) \\
&K_{i+1} = R^{-1} B^T P_i.
\end{aligned}
\tag{22}
$$

The iterative update trajectory, cost-matrix convergence, and closed-loop pole migration are shown in Figure 8a-d. The proposed adaptive controller not only achieved LQR-level performance but also displayed a rapid adjustment capability for changing motor parameters.

Figure 9 and Table 5 provide a direct simulation-based comparison of the three control strategies: the traditional PID controller tuned using the ZN method, the traditional LQR controller, and the proposed adaptive controller. The traditional PID

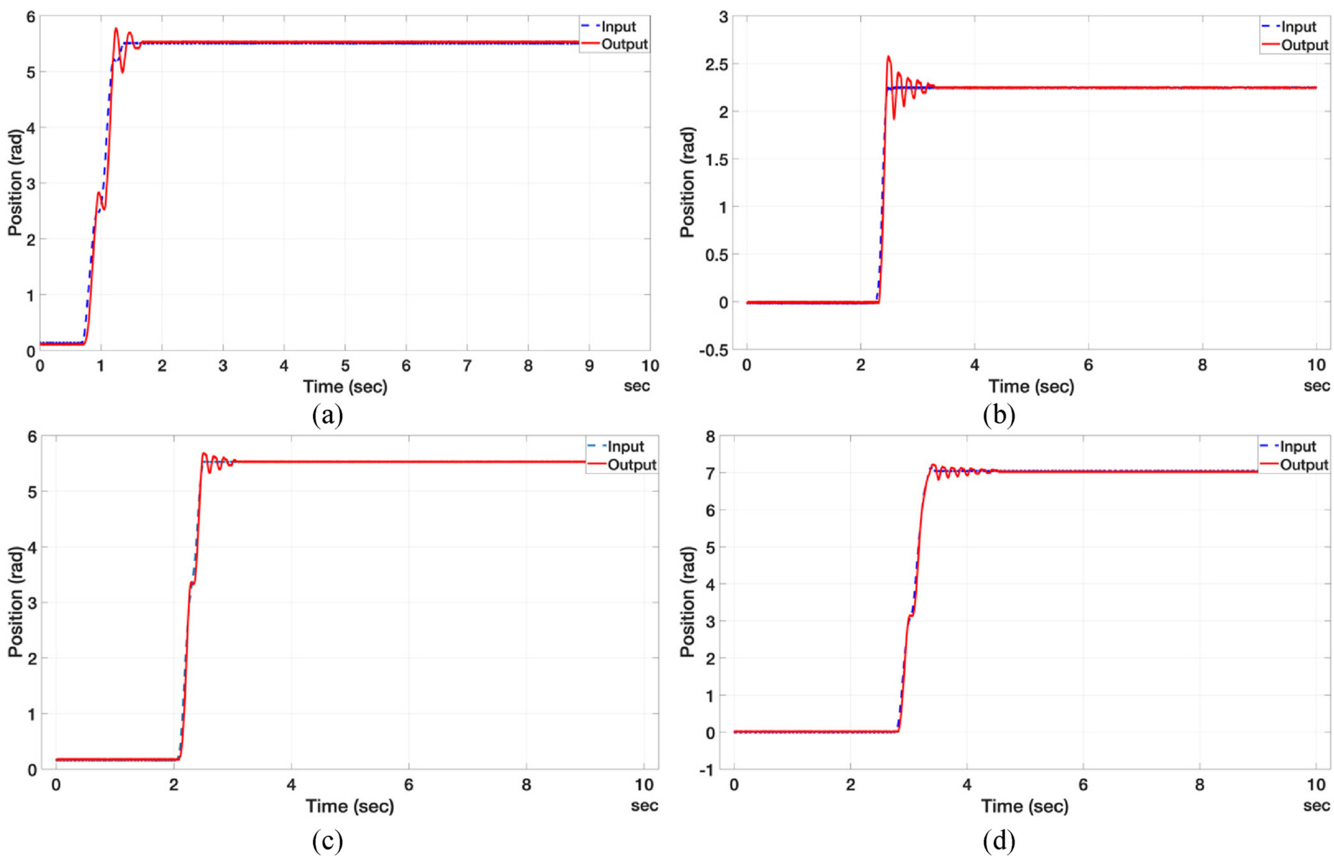


Figure 5. Experimental results with traditional PID controller: (a) step input response, (b) response with P controller, (c) response with PI controller, and (d) response with PID controller

Table 3. *Summary of Experimental PID-Tuning Performance*

Controller	Rise Time (s)	Settling Time (s)	Overshoot (%)	S.S. Error
P	0.132	1.016	14.7336	0.01227
PI	0.141	1.086	2.951	0
PID	0.133	0.985	2.5178	0

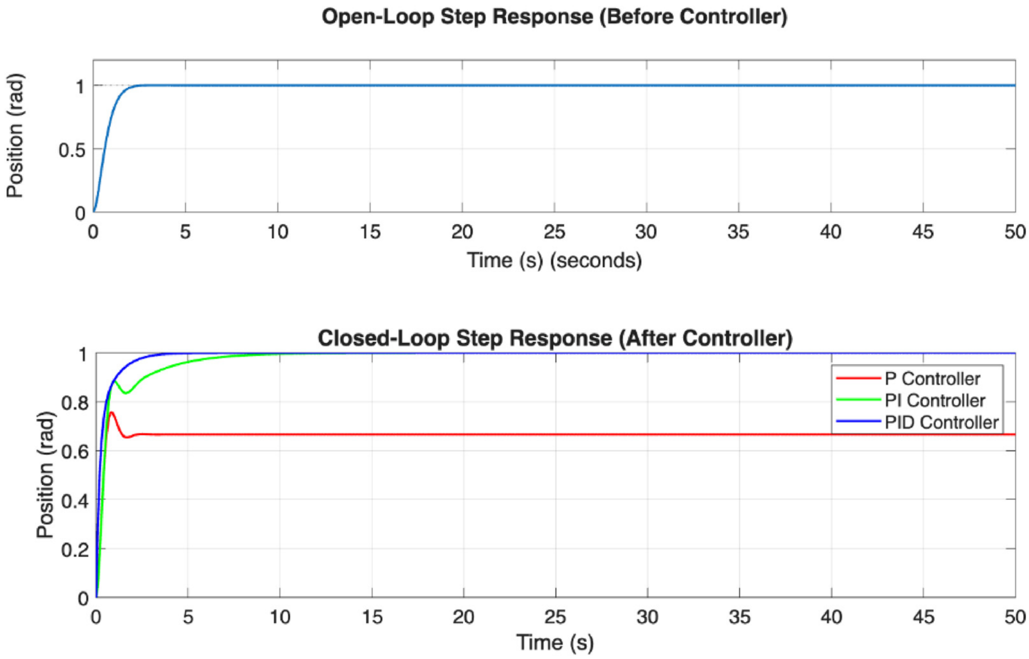
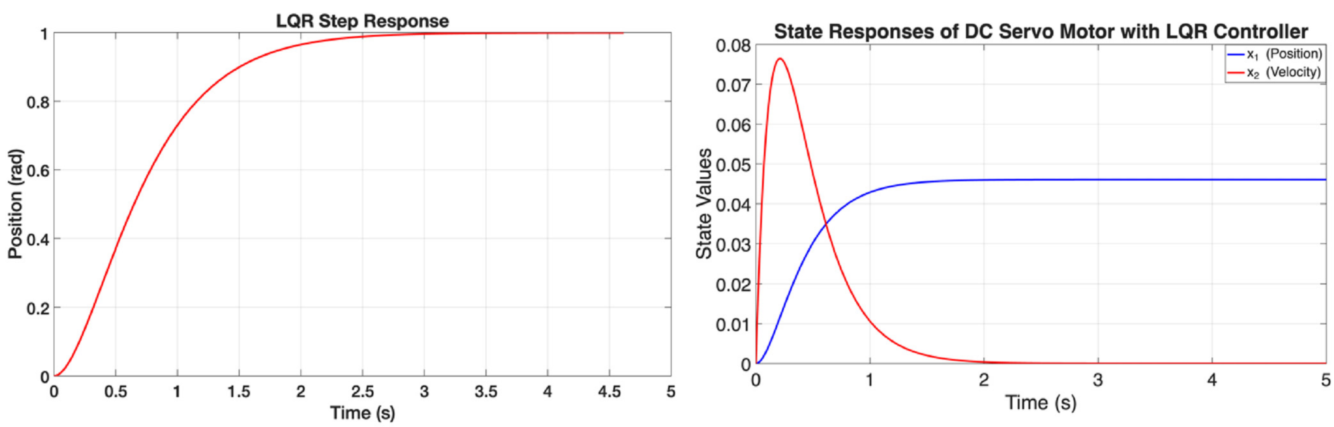


Figure 6. PID tuning with ZN method

Table 4. *ZN PID Gain Values*

Controller / Gain	K_P	K_I	K_D
Case 1 (P)	2	-	-
Case 2 (PI)	1.8	1.08	-
Case 3 (PID)	2.4	2.4	0.6

ZN controller achieved a faster rise time (1.0519 s) than the traditional LQR controller (1.2984 s); however, it required a longer settling time (2.5455 s versus 2.2548 s), reflecting the typical tradeoff between the faster initial response and damping. In contrast, the proposed adaptive controller provided the best overall transient performance, yielding the shortest rise time (1.0271 s) and settling time (1.7066 s). Compared with the traditional LQR, the proposed adaptive controller improved the rise and settling times by approximately 20.9% and 24.3%, respectively, and by approximately 2.36% and 33.0%, compared with the traditional PID ZN controller. All three controllers achieved approximately zero steady-state error, and the overshoot remained negligible (PID and LQR showed ~0% overshoot, whereas the proposed



(a) (b)

Figure 7. Simulation under traditional LQR: (a) step response with LQR, (b) state responses under LQR

Table 5. *Performance Comparison between the Traditional PID ZN, Traditional LQR, and Proposed Adaptive LQR*

Controller	Rise Time (S)	Settling Time (S)	Overshoot (%)	S.S. Error
Traditional PID ZN	1.0519	2.5455	<0.01	0
Traditional LQR	1.2984	2.2548	0	0
Proposed Adaptive	1.0271	1.7066	0.0429	0

adaptive controller exhibited a very small overshoot of approximately 0.0429%). Overall, the results confirm that the proposed adaptive strategy improved convergence speed while maintaining good damping and steady-state accuracy relative to both traditional baseline controllers.

7. CONCLUSION

This study presents a comprehensive experimental framework for DC servo-motor modeling and control using traditional PID, traditional LQR, and the proposed adaptive-policy-iteration strategy. A second-order transfer function was accurately identified from closed-loop experiments, providing a reliable basis for controller design. Comparative evaluation using the experimentally identified model revealed that PID control offers simplicity and a fast response but can be sensitive to parameter variations, whereas LQRs achieve systematic optimality and superior damping at the cost of a slower rise time. The proposed adaptive-policy-iteration approach demonstrated the most advanced capabilities, including online gain updating and improved transient responses, making it highly suitable for time-varying systems. Overall, the results confirmed that the controller selection should align with application-specific requirements: PID for quick implementation, LQR for robust optimal performance, and adaptive methods for dynamic environments. While the proposed framework provides a comprehensive comparative evaluation, the study is limited to a single DC servo motor platform and primarily linear model-based analysis under nominal operating conditions. These limitations motivate further investigation into real-time adaptive implementation, disturbance-aware control design, and extension to nonlinear or higher-order modeling frameworks. Future work will further investigate these directions, including disturbance rejection, constraint-aware control,

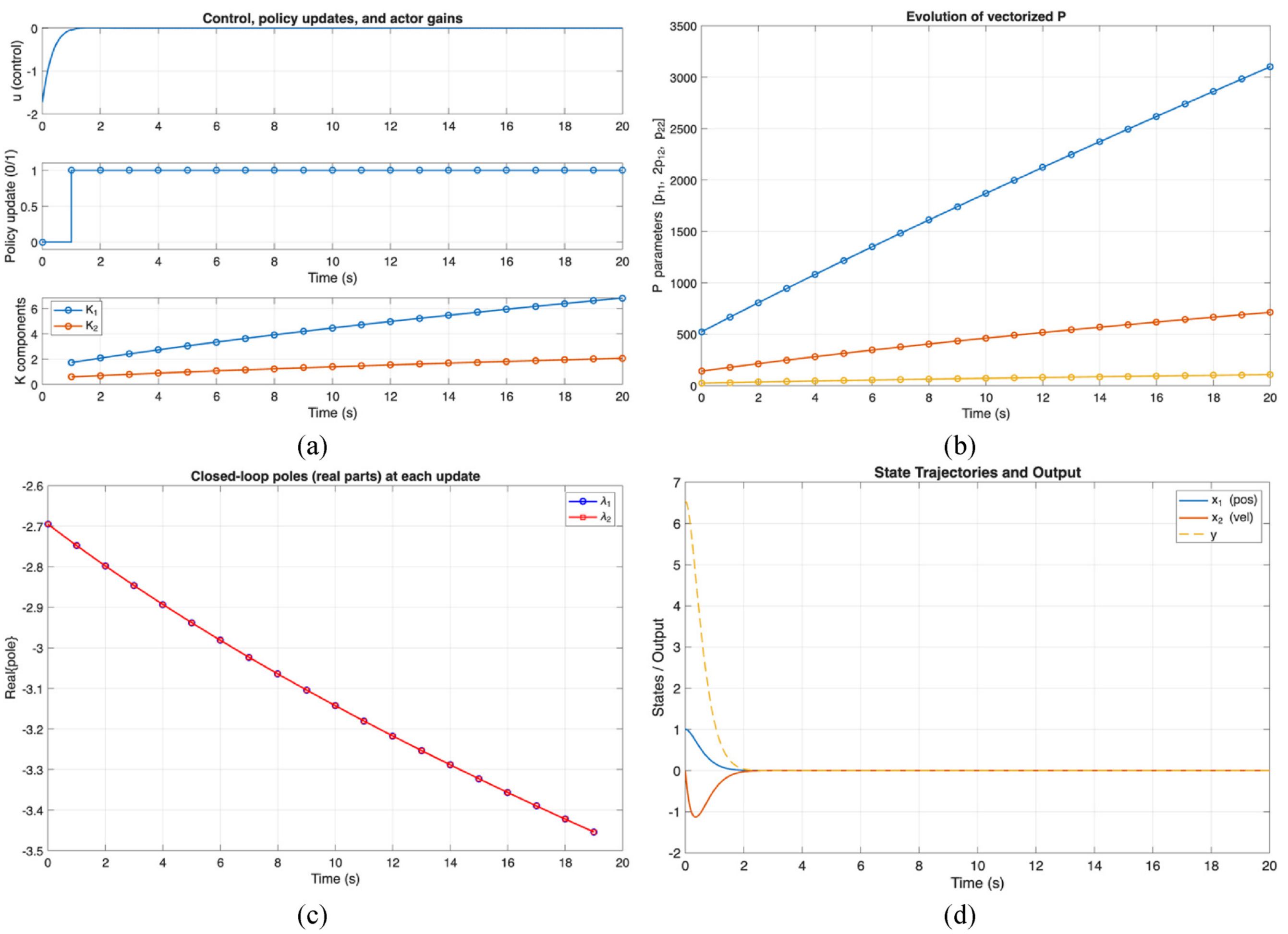


Figure 8. Proposed adaptive online LQR control: (a) control, policy updates, and actor gains, (b) evaluation of vectorized P, (c) closed loop (real parts) at each update, and (d) state trajectories and output

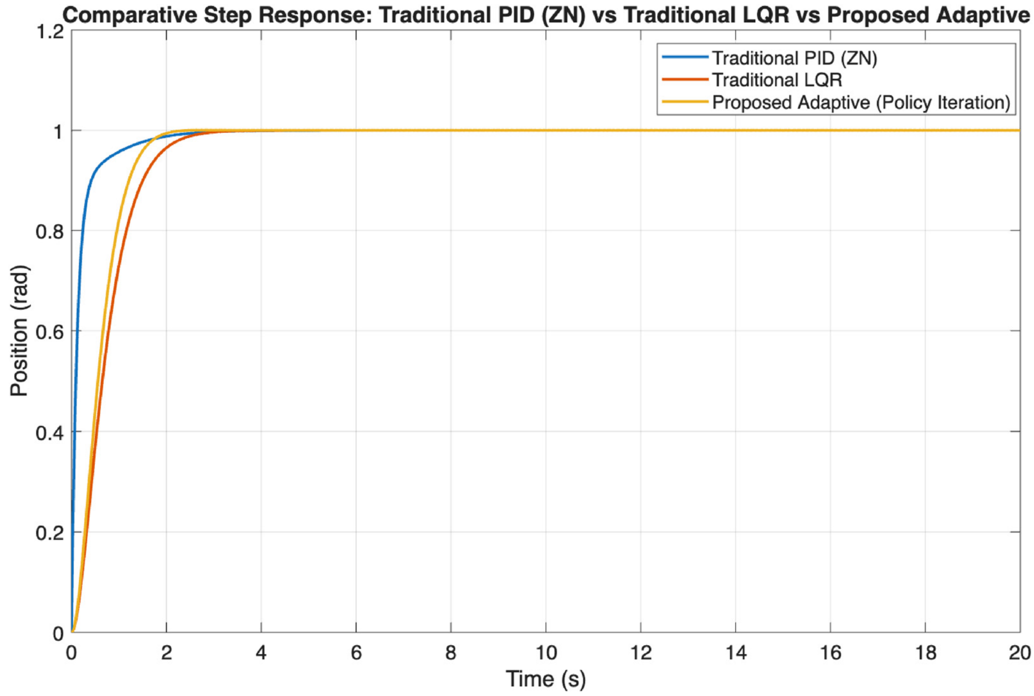


Figure 9. Comparison of all controllers: traditional PID controller tuned using ZN method, traditional LQR controller, and proposed adaptive LQR controller

and integration of reinforcement learning techniques to enhance adaptability and industrial applicability.

AFFILIATIONS AND AUTHOR DETAILS

Undergraduate Author

Hassan K. Misbah – *Department of Control and Instrumentation Engineering, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia*; 0009-0002-1714-9197
Email: s202031840@kfupm.edu.sa

Corresponding Author

Nezar M. Alyazidi – *Research Mentor, Associate Professor, Department of Control and Instrumentation Engineering, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia*; 0000-0001-8977-9302
Email: nalyazidi@kfupm.edu.sa

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