Genetic Algorithm-Optimized LQR for Enhanced Stability in Self-Balancing Wheelchair Systems

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***Abstract*—Balancing systems, exemplified by electric wheelchairs, require accurate and effective functioning to maintain equilibrium across many situations. This research looks at how well a standard linear quadratic regulator (LQR) and its genetic algorithm (GA)-optimized version keep an electric wheelchair stable when it stands on its own. The aim of the optimization was to improve energy economy, robustness, and responsiveness through the refinement of control settings. Simulations were performed under two scenarios: stabilizing the system from a tilt and recovering from an external force. Both controllers stabilized the system; however, the GA-optimized LQR demonstrated considerable improvements in control efficiency, decreased stabilization time, and enhanced response fluidity. It exhibited improved resilience to external disturbances, as indicated by a decrease in oscillations and an increase in fluid displacement recovery. These enhancements highlight the LQR's versatility, resilience, and appropriateness for real-world applications, including Segways, balancing robots, and patient wheelchairs. This study highlights the ability of evolutionary algorithms to enhance the effectiveness of traditional control systems in dynamic and unpredictable settings.**

***Keywords*—Self-Balancing Wheelchair, Linear Quadratic Regulator (LQR), Genetic Algorithm (GA), Dynamic Stability, System Optimization**

I. Introduction

Control systems are essential to contemporary engineering, greatly enhancing the development and operation of dynamic systems. The formulation of advanced control techniques relies on mathematical models grounded on classical mechanics, encompassing Newtonian and Lagrangian principles. Models regulate these systems. Proportional-Integral-Derivative (PID), LQR, and fuzzy logic systems are some of the most commonly utilized controllers. Each has exhibited efficacy in tackling certain technical issues, highlighting unique benefits and limitations. [1]-[3].

In linear systems, the PID controller stands out for its simplicity and effectiveness. Still, the fact that it depends on fixed parameters and can't easily adapt to changes in the environment or nonlinear dynamics may make it less useful in situations with a lot of variation. On the other hand, the LQR works well in changing systems by using state-space methods to make control actions more effective. Its efficacy in stabilizing tasks like inverted pendulums and self-balancing devices serves as evidence. [4]-[6]. While LQR exhibits exceptional accuracy and energy efficiency, it struggles to address uncertainties and dynamic fluctuations due to its reliance on predetermined parameters.

Fuzzy logic controllers, particularly Type-1 and Interval Type-2 systems, effectively manage nonlinearities and uncertainties by emulating human thinking. Type-1 fuzzy systems, although computationally efficient, may face challenges in dynamic and noisy environments. Interval Type-2 fuzzy systems address this problem by incorporating a Footprint of Uncertainty (FOU), hence enhancing resilience and stability during disruptions. However, studies [7] and [8] have shown that interval-type-2 fuzzy systems may be hard to use in real time because they require more computing power.

The LQR employs an optimal control approach grounded in state-space representation, aiming to minimize energy consumption and system errors. Its precision and reliable control mechanisms have rendered it highly effective in applications such as self-balancing devices, including wheelchairs, robots, and drones. The LQR achieves optimal performance by solving the Riccati equation under standard conditions. However, its reliance on established parameters limits its adaptability in contexts marked by dynamic uncertainty or external disruptions. Proposed enhancements to LQR include fuzzy-immune-regulated adaptive methodologies and the use of neural networks. The design aims to improve resilience and flexibility in handling complex dynamics and nonlinearities [9]-[11].

Researchers have looked into hybrid approaches that combine old-fashioned control systems with newer optimization methods, such as genetic algorithms (GA), teaching–learning-based optimization (TLBO), and metaheuristic methods. These optimization algorithms change controller parameters, like the Q and R matrices in LQR or PID controller gains, on the fly to improve performance measures like overshoot, settling time, and how well the controller handles disturbances from the outside. For instance, TLBO and quantum particle swarm optimization (QPSO) have been shown to be good at adjusting control parameters for complicated systems like ball-and-beam setups, which makes control more stable and accurate. Similarly, GA-based optimization improves the adaptability and responsiveness of control systems by accommodating environmental changes. Using these ideas, hybrid approaches make classical controllers more adaptable and resilient, which makes them perfect for real-life situations with nonlinear or changing systems [12]-[15].

The goal of this study is to test and improve the LQR and its genetic algorithm (GA)-enhanced version (LQR-GA) for wheelchairs that can balance themselves. These wheelchairs, vital assistive devices, require precise control and stability, especially in dynamic scenarios such as sudden external disturbances and uneven surfaces. MATLAB simulations are utilized to assess critical performance metrics, including percentage overshoot, rise time, settling time, and displacement, in both hardware-limited and regulated settings. This study exclusively examines the LQR framework and its enhancement using GA optimization. This study differs from others that examine various hybrid methodologies, including the integration of fuzzy logic with optimization techniques for the control of robotic and dynamic systems. This study shows how flexible and strong the LQR-GA is by giving an in-depth look at its features and importance in real-life situations, especially in assistive and self-balancing technologies [16]-[20].

This work meticulously analyzes the distinctions between LQR and its GA-optimized variant. It demonstrates how hybrid optimization methodologies can enhance system performance, particularly regarding stability, adaptability, and efficiency. The findings highlight the practical use of these methods in assistive technology, such as self-balancing wheelchairs, where stability in dynamic environments is crucial. Researchers have found that combining gravitational search algorithms [21], fuzzy-tuned LQR [22], and advanced multi-objective optimization [23] is a good way to combine old-fashioned control methods with newer optimization methods. Particle swarm optimization [24] and hybrid genetic algorithms [25] are used in control systems, which shows that they can make them more resilient and flexible. This study's results indicate that optimization tactics are crucial for enhancing traditional control methods and increasing the reliability and utility of self-balancing technologies [26]-[29].

This study aims to develop and evaluate a self-balancing control system for wheelchairs. It will concentrate on employing an enhanced LQR optimized through a GA. The research employs MATLAB simulations to examine critical performance metrics, including percentage overshoot, rise time, settling time, and displacement, under both controlled conditions and hardware constraints. This paper carefully examines the GA-optimized LQR, focusing on how it could improve stability, adaptability, and efficiency in real-life assistive technology applications, especially in environments that are changing or are uncertain.

II. METHOD

A. Balance System Design for Electric Wheelchairs

This work employs a structural model from prior research [29] to determine the balance mechanism for the electric wheelchair. The core model was modified to include certain aspects and variables essential for the study's objectives. The balance system employs the inverted pendulum principle, a well-established technique in control system design that guarantees stability and accuracy in dynamic settings.

Prior study underscored the efficacy of the LQR in attaining system stability, improving performance, and minimizing energy usage. Thus, the LQR was selected as the principal control strategy. The LQR design was refined using a GA to improve its robustness and adaptability, as GA is a potent metaheuristic tool recognized for refining parameters in intricate dynamic systems.

A comprehensive simulation-based evaluation was performed to examine the proposed system's performance in both optimal and realistic conditions. Critical performance metrics, including overshoot, settling time, rising time, and control input efficiency, were meticulously assessed to determine the effectiveness of the GA-optimized LQR.

The subsequent sections outline the study's results, highlighting the improvements achieved through optimization, and examine the system's potential applications in real-world scenarios, emphasizing its stability, efficiency, and adaptability.

B. Dynamic Model of Self-Balancing Wheelchairs

Eight DC motors power the dynamic variant of the two-wheeled self-balancing wheelchair, which offers a wide range of capabilities and a three-degree-of-freedom arrangement. The four primary motors propel the rear axles, which aid in navigation and forward movement. Two auxiliary motors elevate the front casters, simplifying the process of transitioning between operational modes. The two remaining actuators regulate the robotic arm's position, thereby enhancing control and ensuring stability. Table 1 details the physical parameters implemented in the simulation.

The act of transitioning from a seated to a standing position involves the transition from a quadrupedal configuration to a bipedal equilibrium mode. The prosthetic limb retracts during this transition, causing the wheelchair's center of gravity (COG) to shift toward the rear wheels. This procedure initiates the equilibrium mechanism. Fig. 1 (b) to Fig. 1 (e) illustrate the wheelchair's motion progression and show the four phases of COG adjustment.

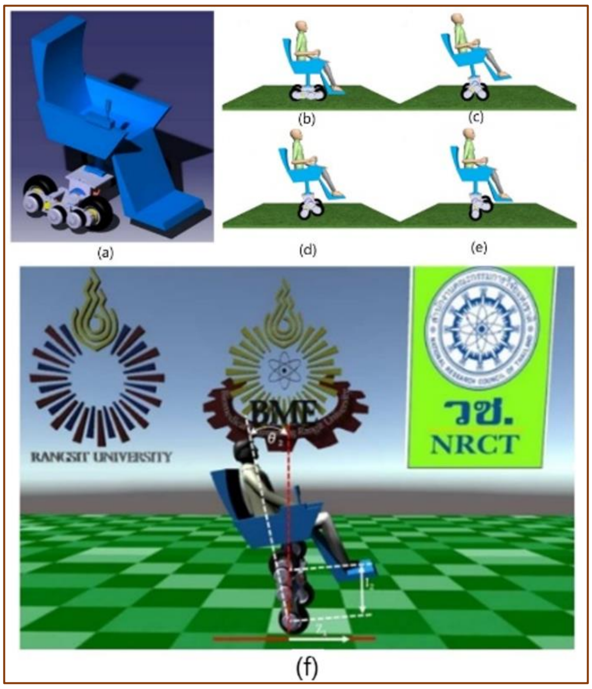

Fig. 1. The structure of the wheelchair system

The wheelchair's dynamics are defined as a single-link inverted pendulum in its vertical two-wheeled configuration.

The Euler-Lagrange equation is employed to construct this non-linear dynamic model, which guarantees precise simulation results by presuming that there is no wheel-ground slippage. The Appendix provides a detailed explanation of the specific parameters, while Fig. 1 (f) illustrates the mathematical model of the system. This dynamic model enables the design and improvement of the control system, ensuring its stability and efficacy in a wide range of operational scenarios.

Table 1. Physical parameters for simulation results

Detail	Parameter	Value	Unit
Wheel Mass	M_w	3.2000	kg
Vehicle Mass	M_p	36.1760	kg
Wheel Radius	r	0.1450	m
Height of COG	l	0.4025	m
Wheel Moment of Inertia	I_w	0.0250	
Vehicle Moment of Inertia	I_p	1.7363	
Gravity	g	9.8067	m/s^2
Motor Torque Constant	Km	2.64	Nm/A
Back EMF Constant	Ke	0.58	V_s/rad
Terminal Resistance	R	0.91	Ohm

Fig. 1 (f) illustrates the system's mechanics, where Link 1 denotes the rear wheels and Link 2 includes the front wheels and payload. The Lagrangian function approach is utilized to represent the system's dynamic behavior, using established frameworks from previous studies [26], [27], [29].

A state-space representation articulates the system dynamics.

$$\begin{bmatrix} \dot{z} \\ \ddot{z} \\ \dot{\theta} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & \mathrm{E} & \mathrm{T} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \Upsilon & \Phi & 0 \end{bmatrix} \begin{bmatrix} z \\ \dot{z} \\ \theta \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} 0 \\ \mathrm{K} \\ 0 \\ \Lambda \end{bmatrix} V_a \tag{1}$$

$$\mathrm{E} = \frac{2k_m k_e\left(M_p l r - I_p - M_p l^2\right)}{R r^2 \alpha} \tag{2}$$

$$\mathrm{T} = \frac{\left(M_p^2 g l^2\right)}{\alpha} \tag{3}$$

$$\Upsilon = \frac{2k_m k_e\left(r\beta - M_p l\right)}{R r^2 \alpha} \tag{4}$$

$$\Phi = \frac{\left(M_p g l \beta\right)}{\alpha} \tag{5}$$

$$\mathrm{K} = \frac{2k_m\left(I_p + M_p l^2 - M_p l r\right)}{R r \alpha} \tag{6}$$

$$\Lambda = \frac{2k_m\left(M_p l - r\beta\right)}{R r \alpha} \tag{7}$$

$$\alpha = \left(I_p\beta + 2M_p l^2\left(M_w + \frac{I_w}{r^2}\right)\right) \tag{8}$$

$$\beta = \left(2M_w + \frac{2I_w}{r^2} + M_p\right) \tag{9}$$

The parameters (E, T, Υ, and Φ) characterize the system's angular and linear accelerations, whereas K and Λ specify the influence of the control input. This mathematical framework effectively simulates and analyzes the dynamic behavior of the wheelchair in balancing scenarios, facilitating the subsequent design and optimization of the control system.

C. Linear Quadratic Regulator (LQR)

The LQR is a contemporary control technique that enhances system performance by minimizing a quadratic performance metric. A cost function evaluates the performance by balancing system stability and energy efficiency. The LQR mathematical framework depicts the system dynamics as a state-space model.

$$\dot{x}(t) = Ax(t) + \mathrm{B}u(t) \tag{10}$$

Let A denote the system dynamics matrix, B represent the control input matrix, $x(t)$ signify the state vector, and $u(t)$ indicate the control input vector.

The following cost function evaluates the effectiveness of the LQR system

$$J = \int_0^\infty \left(x^T(t)Qx(t) + u^T(t)Ru(t)\right) dt \tag{11}$$

Where Q represents the state weighting matrix, which penalizes deviations from the target state, and R denotes the control weighting matrix, which penalizes control effort, The optimal control law minimizes this cost and is expressed as

$$u(t) = -Kx(t) \tag{12}$$

Where K, the feedback gain matrix, is derived from the Algebraic Riccati Equation

$$K = R^{-1}B^T P \tag{13}$$

P represents the solution to the Algebraic Riccati Equation (ARE)

$$\mathrm{A}^T\mathrm{P} + \mathrm{PA} - \mathrm{PBR}^{-1}\mathrm{B}^T\mathrm{P} + \mathrm{Q} = 0 \tag{14}$$

The dynamics of the self-balancing wheelchair system provide the state-space matrices and parameters for this investigation.

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -6.779 & 16.06 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & -9.939 & 49.58 & 0 \end{bmatrix} \tag{15}$$

$$B = \begin{bmatrix} 0 \\ 1.695 \\ 0 \\ 2.485 \end{bmatrix} \tag{16}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{17}$$

$$D = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{18}$$

The simulation uses the following standard $Q_{default}$ and $R_{default}$ matrices

$$Q_{default} = \begin{bmatrix} 150 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 150 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{19}$$

$$R_{default} = 1 \tag{20}$$

The resultant feedback gain matrix, $K_{default}$ is

$$K_{default} = [-12.25 \quad -14.89 \quad 93.58 \quad 16.23] \tag{21}$$

Fig. 2 presents the design of the LQR Controller Framework for a self-balancing system. The technology employs feedback control to stabilize the robot. The inputs comprise the specified setpoint, denoting the intended angle or location, together with the state variables (θ, $\dot{\theta}$, z, and $\dot{z}$), which signify the tilt angle, angular velocity, position, and velocity of the cart, respectively.

The controller utilizes these inputs in conjunction with the state-space model to compute control actions. The gain matrix (K) comprises gains (K_1, K_2, K_3, K_4) assigned to the state variables to determine the control force. This control force ensures that the system remains in balance and advances toward the desired setpoint.

Fig. 2 demonstrates the utilization of feedback from output states to mitigate faults and maintain system stability. This closed-loop control system demonstrates that the LQR controller can proficiently regulate many variables and attain optimal dynamic performance.

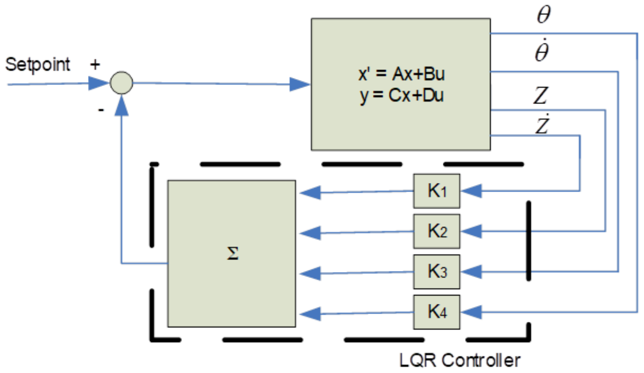

Fig. 2. LQR controller framework

D. Linear Quadratic Regulator Optimization

The LQR Optimization process emphasizes designing an LQR system using a GA to determine optimal gain values. This optimization framework is particularly applied for controlling a self-balancing electric cart. The methodology is illustrated through block diagrams in Fig. 3, which highlights the integration of the LQR controller with an optimization framework, and Fig. 4, which demonstrates the operational flow of the GA algorithm. These figures illustrate how optimization methods are applied to fine-tune the Q and R matrices of the LQR system.

The GA evaluates the eigenvalues of the closed-loop system matrix to ensure stability and optimal performance. By iteratively adjusting the weights in the Q and R matrices, the algorithm minimizes oscillations, improves settling time, and enhances system responsiveness. The following sections provide a detailed explanation of the GA optimization process and its integration into the LQR system.

As depicted in Fig. 3, the LQR controller integrates optimization frameworks to enhance system performance. The process begins with a reference signal (setpoint), representing the desired state of the system. The feedback loop compares the actual state with the reference and adjusts the control signal using the optimized gain matrix. This integration ensures stability and precision in the self-balancing robot's motion.

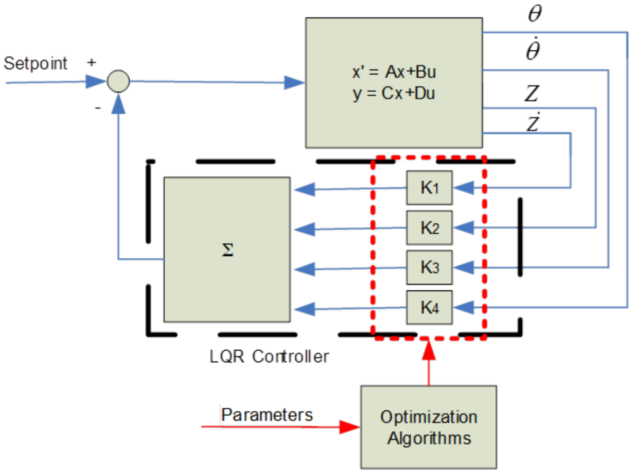

Fig. 3. LQR controller with parameter optimization framework

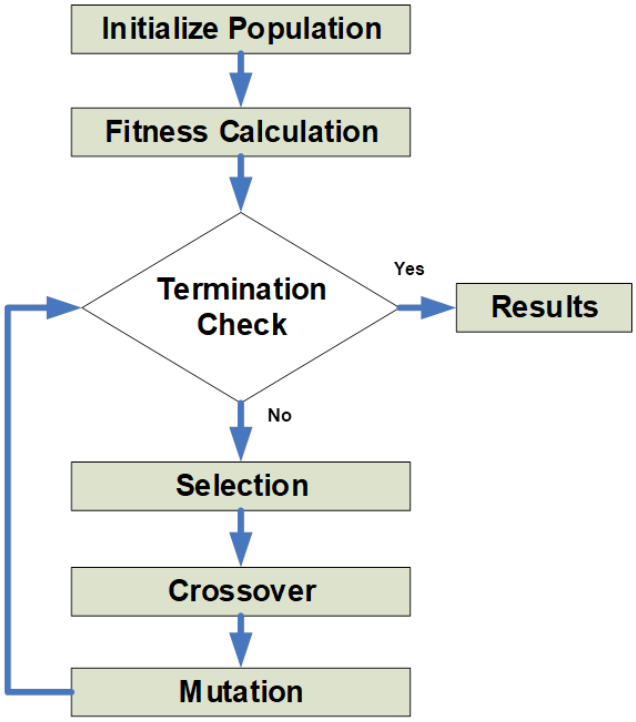

Fig. 4. Genetic algorithm (GA) workflow for parameter optimization

In Fig. 4, the GA workflow is illustrated, starting from population initialization, fitness evaluation, and iterative improvement through selection, crossover, and mutation. The process continues until termination criteria, such as achieving the target fitness or reaching a maximum number of generations, are met. The result is a fine-tuned LQR controller optimized for performance. Fig. 4 shows how the conventional LQR controller can be optimized to make the LQR controller work better. This controller already does a good job, but it could do even better with some fine-tuning. This study utilized a GA to enhance the Q and R matrices, consequently optimizing system performance by reducing the LQR cost function. The primary objective of GA optimization is to enhance system performance by reducing critical parameters, including overshoot, settling time, and control effort. The fitness function evaluates the eigenvalues of the closed-loop system and imposes penalties on solutions that yield suboptimal performance or instability. The GA ensures the system's improved stability and efficiency by systematically optimizing controller parameters.

$$Fitness = \sum Real\big(\lambda(A - BK)\big)^2 \tag{22}$$

The genetic algorithm commences by initializing a population of prospective solutions for the Q and R matrices. The eigenvalues of the closed-loop system matrix serve as the basis for a fitness function that assesses the solutions. Selection, crossover, and mutation accomplish iterative enhancement, optimizing the population until a termination requirement is satisfied. The matrices have been optimized

The Algebraic Riccati Equation (ARE) was employed with selected Q and R values to obtain the best feedback gain matrix K. The established parameter boundaries guided the execution of the optimization method.

$$Q_{Bounds} = [9.99 \quad 9.95 \quad 0.01] \text{ to } [9.995 \quad 9.955 \quad 0.011] \tag{23}$$

$$R_{Bounds} = 0.01 \ to \ 0.011 \tag{24}$$

The optimization technique yielded the subsequent optimal Q_{opt} and R_{opt} matrices

$$Q_{opt} = \begin{bmatrix} 9.99 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 9.95 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{25}$$

$$R_{opt} = 0.011 \tag{26}$$

The optimal feedback gain matrix (K_{opt}) is

$$K_{opt} = [-30.14 \quad -29.27 \quad 176.66 \quad 33.56] \tag{27}$$

This procedure illustrates how the genetic algorithm proficiently adjusts the Q and R matrices, yielding an improved linear quadratic regulator controller. The revised controller demonstrates improved stability and performance, minimizing oscillations and enhancing response in the self-balancing robot.

III. Results and Discussion

The efficacy of the electric wheelchair stability apparatus was assessed in two separate contexts. The initial test sought to stabilize the system from a tilt angle of 5 degrees, evaluating its capacity to revert the angular position and displacement to their equilibrium states. The second test assessed the system's resistance to significant disturbances by measuring its ability to recover from an external impulse force of 100 N. In multiple scenarios, both assessments examined the system's ability to maintain stability and restore balance. The results compare the effectiveness of the traditional LQR with the enhanced LQR that GA developed.

A. System Response to Initial Tilt Angle

The performance of the electric wheelchair balance system was assessed at an initial tilt angle of 5 degrees to evaluate its capability to stabilize by returning the angular position and displacement to their equilibrium states of 0 degrees and 0 meters, respectively. Fig. 5, Fig. 6, Fig. 7 and Table 2 and Table 3 illustrate the reactions of angular displacement, angular velocity, displacement, velocity, and control force.

Fig. 5 and Table 2 demonstrate that both the standard and augmented LQR controllers effectively stabilized the system. The modified LQR attained expedited stability with much less angular overshoot relative to the standard LQR. These tiny enhancements, albeit not significant, demonstrate the advantages of optimization in improving system responsiveness to minor perturbations. The improved LQR demonstrated an angular displacement overshoot of -2.145 degrees, somewhat above the -1.835 degrees of the default LQR; nevertheless, it attained a more rapid steady state of 1.864 seconds, in contrast to 2.008 seconds for the default controller.

Fig. 6 and Table 3 depict the displacement and velocity responses. The optimized LQR exhibited a more seamless recovery with slightly less peak displacement and variations in velocity. The modified controller attained a peak overshoot of -0.114 meters for displacement, marginally superior to the -0.130 meters seen with the default LQR. The optimized controller decreased the Integral of Absolute Error (IAE) for displacement to 0.097 m and the Root Mean Square Error (RMSE) to 0.039 m, in contrast to 0.116 m and 0.045 m for the default controller.

Fig. 7 illustrates the control forces and angular displacement responses. The modified LQR produced control forces that were significantly smoother and less variable than those of the default controller, indicating modestly enhanced efficiency. Although the differences were modest, the improved controller exhibited slight superiority in diminishing oscillations and enhancing overall stability.

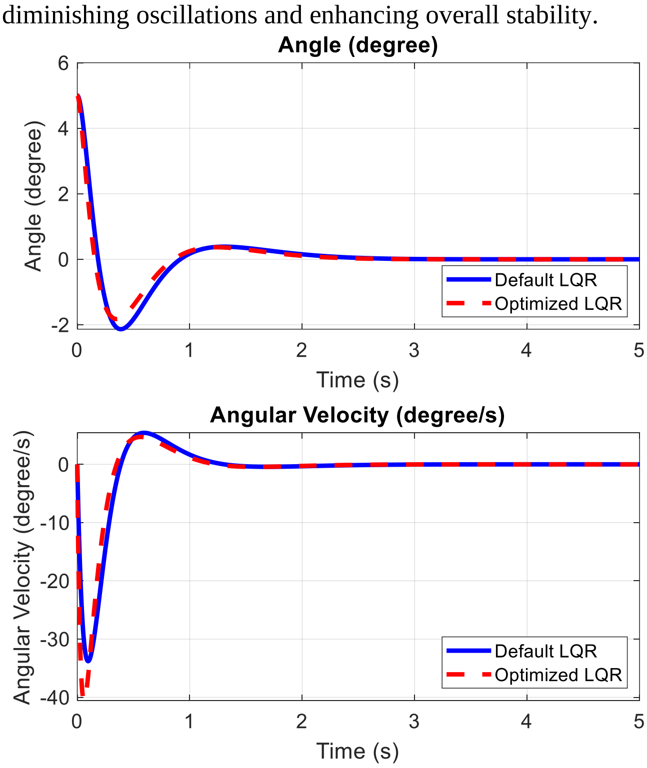

Fig. 5. System responses of angular displacement and angular velocity for default and optimized LQR controllers

In conclusion, although the modified LQR controller showed marginal enhancements in settling time, overshoot, and control effort, both controllers effectively stabilized under the first tilt disturbance. These results highlight the incremental benefits of genetic algorithm optimization in enhancing control dynamics.

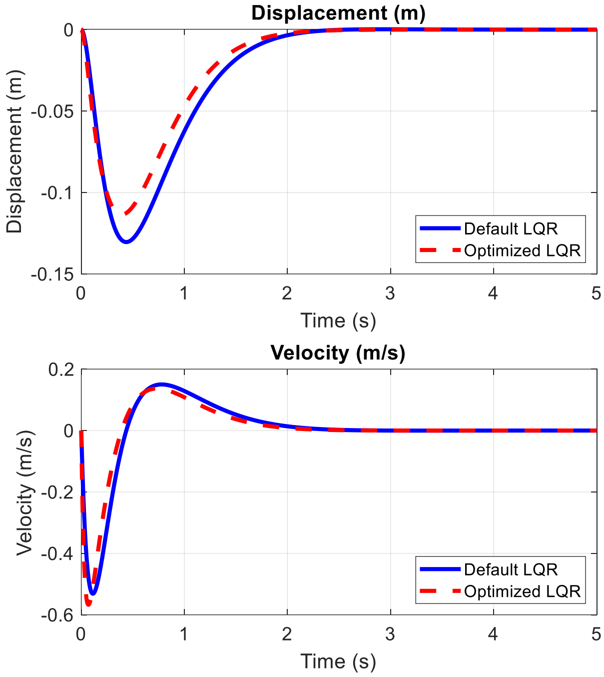

Fig. 6. System responses of displacement and velocity for default and optimized LQR controllers

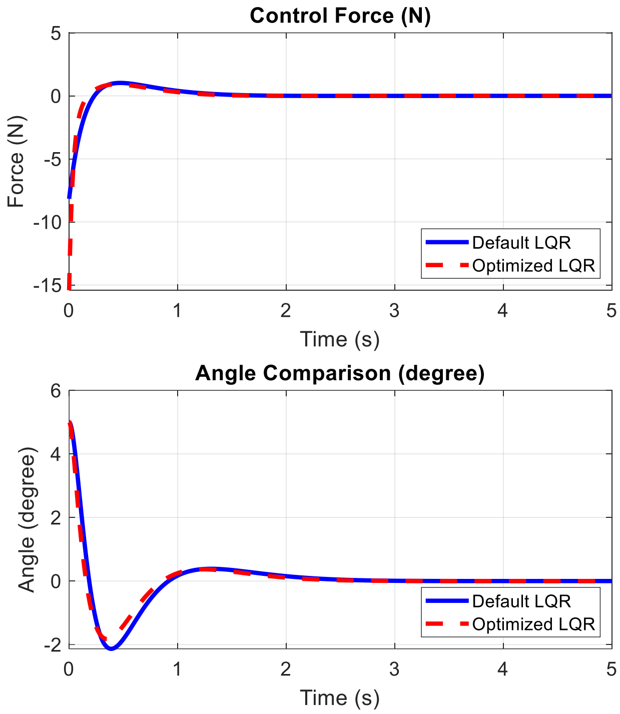

Fig. 7. Comparison of control force and angular displacement under default and optimized LQR controllers

Table 2. Performance metrics angle for initial angle 5 degree

Type	RiseTime (s)	OS (degree)	SteadyState (s)	IAE (degree)	RMSE (degree)
Default LQR	0.175	-1.835	2.008	1.733	0.820
Optimized LQR	0.146	-2.145	1.864	1.445	0.709

Table 3. Performance metrics displacement for initial angle 5 degree

Type	SteadyState (s)	OS (m)	IAE (m)	RMSE (m)
Default LQR	1.47	-0.130	0.116	0.045
Optimized LQR	1.33	-0.114	0.097	0.039

B. System Response to External Force

This section evaluates the balancing robot system's performance under an external impulse force of 100 N, using two LQR controller configurations: the traditional LQR with static parameters and the optimized LQR enhanced by a GA. The analysis investigates angular displacement, displacement profiles, and control forces to assess the system's ability to recover balance and maintain stability.

The results for angular displacement, shown in Fig. 8, show that the standard and enhanced LQR controllers perform very differently. The conventional LQR had an angular overshoot of 4.5 degrees and required 1.85 seconds for stabilization. The adjusted LQR reduced the angular overshoot to 2.6 degrees and attained a stabilization time of 0.844 seconds. The results show that the GA-based optimization method works to improve the system's response to angular disturbances by reducing oscillations and speeding up stability.

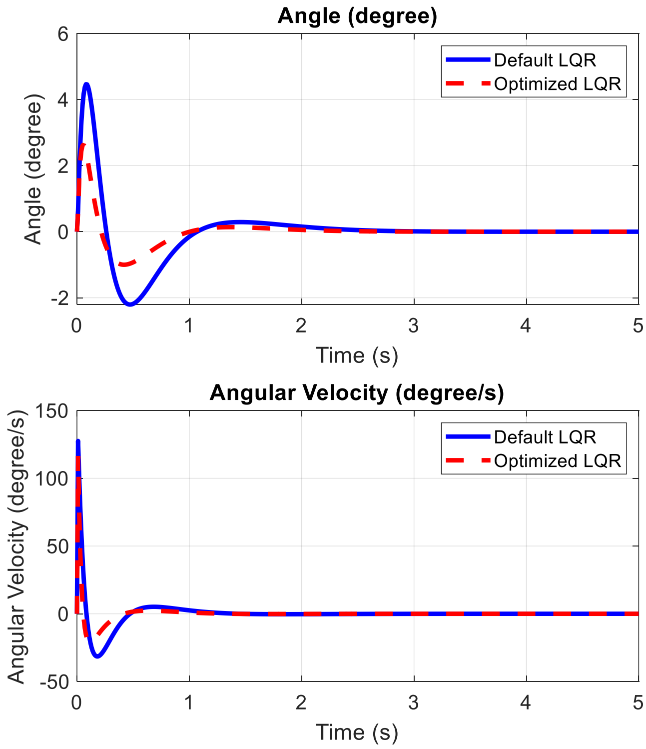

Fig. 8. System response in angular displacement and angular velocity under external force

Fig. 9 illustrates the displacement and velocity trajectories for both controllers. The typical LQR demonstrated a displacement overshoot of -0.010 meters and achieved stabilization in 1.506 seconds. The redesigned LQR concurrently reduced the displacement overshoot to -0.004 meters and shortened the stabilization time to 1.067 seconds. These modifications illustrate the controller's augmented ability to reduce oscillations and facilitate smoother recovery from external inputs. The velocity response exhibited reduced fluctuations, hence underscoring the improved efficacy of the modified LQR.

Fig. 10 illustrates the control force analysis, which shows that the standard LQR required greater and more oscillatory control forces to maintain balance, indicating inefficiency in energy utilization. In contrast, the optimized LQR utilized fewer and more gradual control forces, thereby improving system stability and energy efficiency. The attributes of the optimized LQR render it more appropriate for practical applications, especially in situations requiring reliable performance and reduced energy consumption.

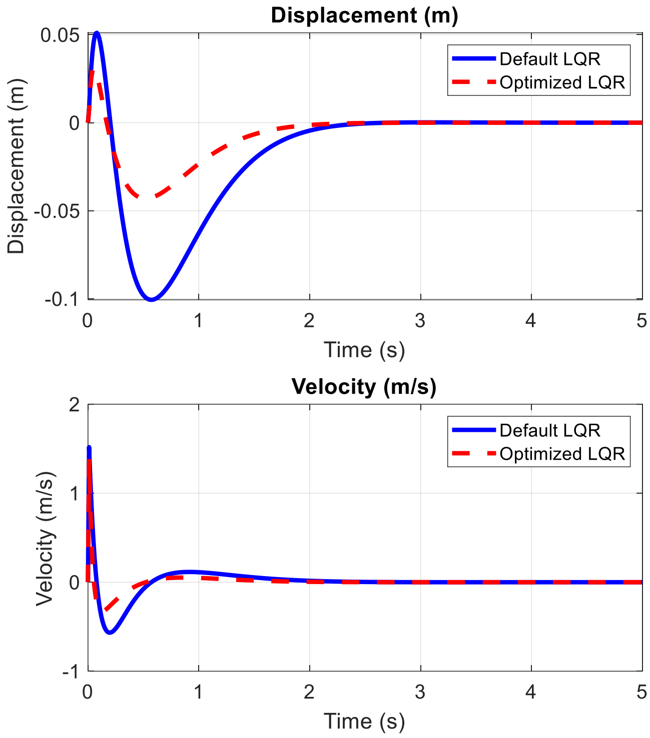

Fig. 9. System response in displacement and velocity under external force

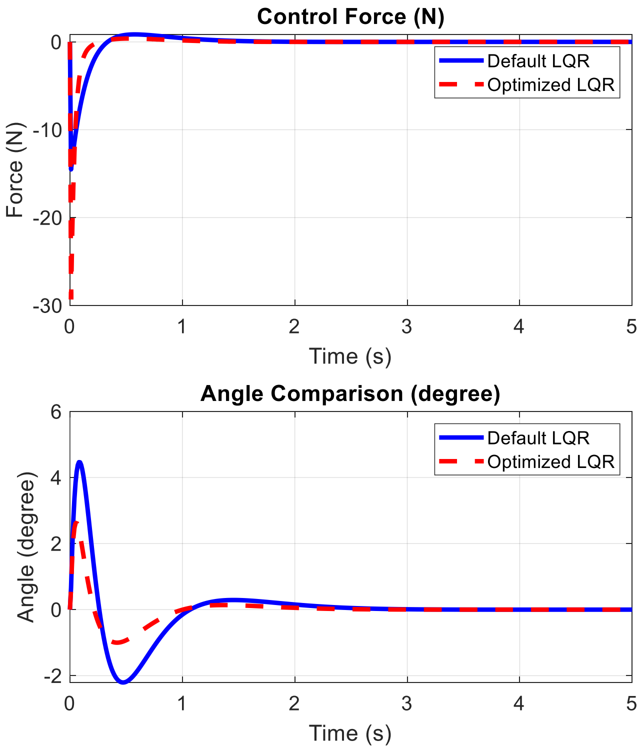

Fig. 10. Control force and angular displacement response under external force

Table 4 and Table 5 provide a quantitative comparison of the primary performance characteristics for angular and linear displacement, respectively. The improved LQR demonstrated a significant reduction in both integral absolute error (IAE) and root mean square error (RMSE), indicating superior system management. The optimized LQR reduced IAE and RMSE for angular displacement by 55.2% and 57%, respectively, compared to the default LQR. Similarly, for linear displacement, the modified LQR achieved a 60% improvement in overshoot and a 29.14% reduction in stabilization time.

Table 4. Performance metrics angle for initial force 100 N

Type	SteadyState (s)	OS (degree)	IAE (degree)	RMSE (degree)
Default LQR	1.85	0.45	0.192	0.100
Optimized LQR	0.844	0.26	0.086	0.043

Table 5. Performance metrics displacement for initial force 100 N

Type	SteadyState (s)	OS (m)	IAE (m)	RMSE (m)
Default LQR	1.506	-0.010	0.010	0.004
Optimized LQR	1.067	-0.004	0.004	0.002

In summary, the optimized LQR exhibited distinct benefits compared to the default configuration regarding angular stabilization, displacement control, and energy efficiency. These findings highlight the need of incorporating genetic algorithm optimization into conventional control methods, enhancing their reliability and efficacy for intricate robotic systems in dynamic real-world environments.

C. Comparative Analysis of System Performance in Both Test Scenarios

The comparative study of the system's performance in the two test situations underscores the advantages and drawbacks of both the default and enhanced LQR controllers. The findings indicate that although both controllers can stabilize the system under diverse situations, the improved LQR provides considerable benefits, particularly in the face of more severe disturbances.

In the initial test, with a tilt angle of 5 degrees, both controllers demonstrated effective stability skills. The modified LQR demonstrated minor enhancements, decreasing the settling time by almost 7% (from 2.008 seconds to 1.864 seconds) and somewhat reducing the angular overshoot. These improvements, however modest, demonstrate that the improved controller can deliver smoother and marginally quicker responses. Nevertheless, the discrepancies were negligible, indicating that the standard LQR is adequate for addressing minor perturbations.

The second test, which incorporated an external impulse force of 100 N, demonstrated more significant disparities among the controllers. The modified LQR exhibited enhanced resilience, diminishing the angular overshoot by approximately 42% (from 0.45 degrees to 0.26 degrees) and reducing the settling time by almost 54% (from 1.85 seconds to 0.844 seconds). Furthermore, it attained a more seamless velocity recovery and necessitated less control effort, thereby improving the energy economy. The standard LQR, on the other hand, had problems with high oscillations, long settling times, and more variability in control forces, which meant it wasn't effective at dealing with big outside disturbances.

These findings highlight the practical significance of the improved LQR in real-world scenarios when systems encounter unforeseen and considerable disturbances. A decrease in settling time and overshoot improves the system's responsiveness and stability, essential for applications such as self-balancing wheelchairs navigating uneven terrain or encountering abrupt external stimuli. Enhanced energy efficiency leads to extended operational durations and less wear on mechanical components.

Although the standard LQR controller works well in controlled or moderate conditions, the comparison analysis shows that the optimized LQR has better features, making it better for situations that are changing or are challenging to control. The incorporation of genetic algorithm-based optimization enhances the controller settings, yielding a system that is more robust, efficient, and dependable. This shows how modern optimization methods can greatly improve traditional control methods, making it easier to create solutions for complex robotic systems that are more adaptable and resilient.

IV. Conclusion

An electric wheelchair balancing system was tested in two situations: stabilization from a 5-degree tilt angle and recovery from a 100 N external impulse force. The study looked at both the default and genetic algorithm (GA)-optimized linear quadratic regulators (LQRs). Both controllers effectively stabilized the system; however, the enhanced LQR demonstrated measurable improvements. In the original scenario, the optimized LQR achieved somewhat faster stabilization and reduced control effort, albeit the differences were negligible. In the second case, the improved LQR showed better robustness by having less angular and displacement overshoot, faster settling times, and a more even distribution of control force. These results show how important evolutionary algorithms are for finding the best linear-quadratic regulator parameters to make systems more stable and energy-efficient, especially in environments that change quickly. In the future, researchers may investigate the application of this optimization method in systems with numerous degrees of freedom and hardware validation. This would enhance its utility in practical scenarios.

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