International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I10P115

Volume 74 Issue 10, 213-224, October 2026
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Original Article

Genetic Algorithm-Optimized LQR Control Strategy for Boosting Ethanol Production and Minimizing Control Effort

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Received: 18 April 2026 Revised: 13 August 2026 Accepted: 26 August 2026 Published: 27 October 2026

Abstract - *This paper presents a novel control strategy for the dynamic optimization of ethanol fermentation using a Linear Quadratic Regulator (LQR) whose gains are tuned via Genetic Algorithm (GA). The fermentation process, characterized by nonlinear and time-varying dynamics, demands advanced control strategies for optimal performance to maximize the production of ethanol and to minimize its environmental impact. A procedure for controlling the bioreactor's temperature is created because it is a crucial component of an effective process. Multiple evaluations conducted using genuine computational simulations are provided to confirm the efficacy of controlling techniques. A GA is employed to optimize the LQR's cost function matrices Q and R, aiming to minimize a composite performance index based on tracking error and control energy. The fitness function evaluates each candidate based on performance of various criteria such as Integration of Absolute Errors (IAE), Integral Time Squared Error (ITSE), Integral Time Absolute Error (ITAE), and Integration of Square Errors (ISE). The simulation results demonstrate that the GA-optimized LQR outperforms conventionally tuned controllers in terms of ethanol yield, disturbance rejection, and system stability. This approach shows promise for scalable implementation in industrial biochemical process control.*

Keywords - *Ethanol production, Fermentation, Genetic Algorithm, LQR, Optimal control.*

1. Introduction

Procedures must be developed at each of the atomic and business levels in order to efficiently create innovative goods utilizing the intricate makeup of biomass. After a proposal has shown viability in a modest context, certain techniques are needed to rank the many process possibilities in an expansive context and aid in forecasting the results, allowing the best option to be chosen. Procedure simulation programs and diagrams are two techniques that aid in designing the process, such as figuring out the procedure, apparatus demands and implementation demands of a certain procedure. [1, 2].

A processing system can be constructed, developed, or rebuilt employing such kinds of techniques. This may be aided by a variety of tools. The first popular application is Super Pro Designer (SPD), a computerized package for simulating procedures at an industrial level. The program's specialty is techno-economic computations. In a variety of business sectors, including pharmaceuticals, biotech, specialized chemical substances, nourishment, and minerals, SPD is the most popular simulator [2]. Maintaining optimal conditions such as substrate concentration, temperature, and pH is essential for maximizing yield and productivity. Traditional PID control methods often fall short due to the nonlinear and time-varying nature of the process. Linear Quadratic Regulator (LQR) controllers offer an optimal approach to feedback control design, but their performance is highly sensitive to the choice of weighting matrices Q and R [3-6]. Manual tuning of these parameters is both time-consuming and suboptimal. To address these issues Genetic Algorithm (GA) was proposed to automatically optimize the LQR parameters for improved performance in ethanol fermentation control [7-9].

2. Background

The invention of various forms of renewable energy (like hydropower, solar power, fusion components, wind, geothermal power, and biomass) for energy production has attracted a lot of attention in recent years, whereas traditional fossil fuel energy supplies (such as fossil fuels) are very limited [10]. Alongside the advancement of methane gases and producing biogas methods [11], these days, fermentation is used to produce ethanol with a particular focus [12]. Bioethanol is seen as a substitute for fossil fuels and may be made from a variety of ingredients in addition to biomass transformation. Additionally, ethanol is thought to represent

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the least polluting liquid fuel because it is less harmful, rapidly recyclable, and emits fewer pollutants into the air than fossil fuels [13]. The bioprocess equations' ambiguous kinetic variables and production factors make it difficult to create effective control plans for those processes [14-18]. Ethanol, which may be produced from resources that are renewable, like lignocellulosic waste, is one of the most promising biofuels (Ward and Singh, 2002) [19].

The largest national ethanol fuel industries in the world exist in Brazil (Jennifer Eaglin, 2024) [20], where almost fifty percent of all cars can use hundred percent ethanol fuels and gasoline sold contains at least twenty percent ethanol. The model used in this paper was developed by Kumar [21] to explain oscillations observed during the continuous production of ethanol using cultures of Saccharomyces cerevisiae. In [22], a fractional order model was proposed for a bioreactor system, considering a fractional differential equation for 'Biomass' and an integer-order differential equation for the 'substrate' dynamics.

A developed computational model was used to numerically evaluate the gas and heat output from bioreactors [23]. An advanced control of ethanol fermentation remains an active research topic, like Ethanol production optimization using intelligent optimization methods based on Machine learning [24]. Reinforcement advanced temperature control of continuous ethanol fermentation bioreactor [25], Optimal linear feedback control applied to the temperature control of a bioreactor [26].

3. Scientific Model of Bioreactor

A system investigated in this paper is presented in [27-29], which defines vigorous performance of 6 states that include the percentages of yeast (C_y), methanol (C_e), glucose (C_g), oxygen that is soluble (C_{Ox}), the temperature of the reactor (T_{re}), and jackets temperature (T_{ja}), which expressed by the following equations.

$$\frac{dC_y}{dt} = \mu_y C_y * \frac{C_g}{(K_g+C_g)} * e^{\frac{-K_e}{C_e}} - \left(\frac{F_e}{V}\right) * C_y \quad (1)$$

$$\frac{dC_e}{dt} = \mu_e\, C_y * \frac{C_g}{(K_{g1}+C_g)} * e^{\frac{-K_{e1}}{C_e}} - \left(\frac{F_e}{V}\right) * C_e \quad (2)$$

$$\frac{dC_g}{dt} = -\left(\frac{1}{R_{gy}}\right)\mu_y\, C_y * \frac{C_g}{(K_g+C_g)} * e^{\frac{-K_e}{C_e}} - \left(\frac{1}{R_{ge}}\right) * \mu_e\, C_y * \frac{C_g}{(K_{g1}+C_g)} * e^{\frac{-K_{e1}}{C_e}} - \left(\frac{F_i}{V}\right) * C_{g,in} - \left(\frac{F_e}{V}\right) * C_g \quad (3)$$

$$\frac{dC_{ox}}{dt} = K_{1a} * (C^*_{ox} - C_{ox}) - \mu_{ox} * \left(\frac{1}{Y_{ox}}\right) * C_y \left(\frac{C_{ox}}{K_{ox}-C_{ox}}\right) \quad (4)$$

$$\frac{dT_{re}}{dt} = \frac{F_i}{V} * (T_{in} + 273) - \left(\frac{F_e}{V}\right) * (T_{re} + 273) - \mu_{ox} * \left(\frac{1}{Y_{ox}}\right) * C_y \left(\frac{C_{ox}}{K_{ox}-C_{ox}}\right) * \left(\frac{\Delta H_{re}}{(32 * P_{re} * C_{heat,re})}\right) - \left(\frac{K_T\, A_T\, (T_{re}-T_{ja})}{V * P_{re} * C_{heat,re}}\right) \quad (5)$$

$$\frac{dT_{ja}}{dt} = \frac{F_{ja}}{V_j} * \left(T_{in,ja} - T_{ja}\right) + \left(\frac{K_T\, A_T\, (T_{re}-T_{ja})}{V_j * P_{ja} * C_{heat,re}}\right) \quad (6)$$

A comprehensive explanation of the prototype, variables values and nominal situations are defined in [30, 31]. Mass transfer ratio (k_1a), particular rate of growth (μ_y), and equations needed to compute the neutral quantity of oxygen (C^*_{ox}), whose value is an index of temperature and the strength of ionization, are also included. Presenting vector representing system state $\boldsymbol{x}$ = [C_y, C_e, C_g, C_{Ox}, T_{re}, T_{ja}], output measured vector $\boldsymbol{y}$, and the inputs $\boldsymbol{u}$ = [F_{in}, F_{ja}], functioning of entire structure may be concisely expressed in matrices form as depicted in Figure 1 [32]:

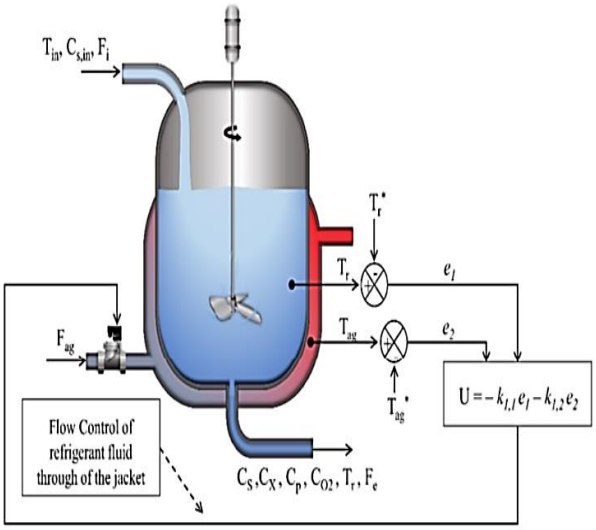

Fig. 1 A diagrammatic illustration of a bioreactor with internal temperature regulation

$$\frac{dx}{dt} = (x, u) \quad (7)$$

$$y = h(x) \quad (8)$$

When h(x) is a vector connecting states and measured outcomes, while (x,u) is a system vector field that connects states, perfect bioreactor mixing conditions, constant reactor volume, and biological kinetic parameters vary within their nominal operating ranges.

The parameter values are selected from experimentally validated bioreactor models available in the literature and correspond to typical industrial ethanol fermentation operating conditions. The parameters mentioned in the above equations are listed in Table 1.

Table 1. Definitions of used parameters

Symbol	Description	Units (Typical)
A_T	Heat transfer area	m^2
$C_{heat,\ re}$	Specific heat of reactor fluid	J/kg·K
ΔH_{re}	Heat of respiration	J/mol
F_e	Flow rate out of the reactor	L/h
F_i	Inlet flow rates	L/h
F_{ja}	Flow rate of fluid through the jacket	L/h
K_{1a}	Oxygen transfer coefficient	1/h
K_e	Inhibition constant related to ethanol	g/L
K_{e1}	Inhibition constant for ethanol	g/L
K_g	Monod constant	g/L
K_{g1}	Substrate affinity constant for ethanol production	g/L
K_{ox}	Inhibition threshold or half-rate oxygen level	g/L
K_T	Overall heat transfer coefficient	W/m²·K
P_{ja}	Density of jacket fluid	kg/m³
P_{re}	Density of the reactor liquid	kg/m³
R_{ge}	Yield coefficient (glucose per biomass)	g/g
R_{gy}	Yield coefficient (glucose per ethanol)	g/g
T_{in}	Inlet temperature of jacket fluid	°C or K
T_{ja}	Jacket temperature	°C or K
T_{re}	Reactor temperature	°C or K
V	Reactor volume	L
V_j	Volume of jacket fluid	L
Y_{ox}	Biomass yield per oxygen	g biomass / g oxygen
μ_e	Specific ethanol production rate constant	1/h
μ_{ox}	Specific oxygen-limited growth rate of biomass	1/h
μ_y	Specific growth rate of biomass	1/h

4. Controller Design

4.1. Process Control

Process control programs benefited from computational frameworks that explain the operation of bioreactors, which helped make it possible to optimize the ethanol manufacturing process. Regarding the reactor's temperature management, a fractional order PID control was suggested in [33]. Nonlinear control systems were investigated in [34] to mitigate the impacts of the system's nonlinearities. For control of chemical reactors in [35], a cascade control was proposed. Optimal control design was used by [36] in the control of the reactor jacket temperature. A PI-fuzzy controller was designed by [37] to regulate the temperature inside a fermentation tank. In [38], a control system for the fermentation process was proposed, considering the use of an Adaptive Linear Neural Network (ADALINE) to control the process. A control system for a continuous bioreactor with an unknown reaction rate term subjected to input saturation is proposed in [39]. In [40, 41], a PID controller for integrating systems with time delay was suggested, utilizing numerous dominant pole placement strategies and a straightforward synthesizing method. A model of a nonlinear continuous stirred tank reactor was used for evaluating the suggested control.

A key issue that has to be managed in the bioreactor is the level of quality of the finished products. In case of disruptions, the controller's goal is to reach the targeted concentration as quickly as possible. By exploring several scenarios in relation to measured outcomes, the job was completed. Firstly, the resultant vector is $\boldsymbol{y}\ I\ = [(t\ ), T\ \text{ja}(t\ )]$, and only reactor and cooling agent temperature measurements are regarded as applicable. Because the analyzer needs a period of time to complete the measurement, the subsequent choice is ethanol concentration, which is provided with a period of delay, and the resultant vector is $\boldsymbol{y}\ I\ I\ = [(t\ -), T_{re}(t\ ), T_{ja}(t\ )]$. In the last scenario, temperature, the quantity of substrate, quantity of oxygen, and output vector are $\boldsymbol{y}\ I\ I\ I\ = [(t\ ), C_{ox}(t\ ), T_{re}(t\ ), T_{ja}(t\ )]$ can all be detected online. Based on a prior study and an examination of the existing detectors for biosystems, readings of the material being studied and oxygen dissolved in it were taken into consideration immediately and instantaneously.

4.2. Standard Linear Quadratic Regulator

By adding fractional derivatives to the reactor and jacket temperatures formulas, LQR control took into account the conventional linear control approach while introducing nonlinear behavior in the reactor-jacket exchange of heat. The goal of LQR control is to deliver a workable control framework, which lowers expenses for operation while delivering the required efficiency in operation. Additionally, as stated by [42], in reactor control tasks, the LQR control has shown itself to be effective. Investigators have focused a great deal of interest on modular models for heat exchange because they can better capture non-linearity and memory impacts of the system [17]. The transfer of heat is one of the many scientific and technological domains that have previously made utilization of fractional models [43].

This work advances our knowledge of the decreased ordering control framework by focusing solely on the formulas that depict the reactor and jacket fluctuations in temperature in the LQR control scheme. This approach enables effective system control regardless of whether derivatives with fractions are included in the reactor and jacket thermal calculations, and thus facilitates control in real-world applications. Avoiding potential singularity and initial circumstance assessment issues that arise in implementations

of Riemann-Liouville differentiated operators. Since the suggested control is not dependent on derivatives with fractional values, these issues are dealt with, and the entire system can be fully controlled. In automation and control platforms, the LQR algorithms are among the most popular and successful techniques. The fundamental challenge is to determine a route via states to control mechanisms that lower a linear system's quadratic function, which may or may not be time consistent. The goal of LQR is to regulate the system's state variables (like biomass concentration, substrate concentration, and product concentration) to achieve optimal performance in terms of ethanol yield, minimizing costs, or maximizing efficiency. A quadratic function takes the formula,

$$cf(x,u) = x^T Qx + u^T Ru \quad (9)$$

As $x \in Rn$ is the internal state of the system, and $u \in Rk$ is the control signal. u selected to denote activities to be steady through general collected works on control. In the objective function, Q must be symmetric positive semi-definite ($Q = Q^T$, $Q \geq 0$). To prevent limitless control energy, R must be rigorously positive and confident ($R = R^T$, $R > 0$). Figure 2 represents a Standard LQR Controlled Ethanol Bioreactor block diagram.

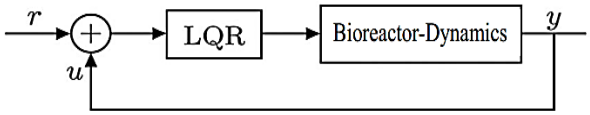

Fig. 2 Standard LQR controlled ethanol bioreactor

4.3. Genetic Algorithm Optimized Linear Quadratic Regulator

Linear Quadratic Regulator (LQR) is a well-established method in control theory for designing optimal feedback controllers. It minimizes a cost function that balances state error and control effort, making it suitable for dynamic systems where both precision and energy efficiency are important, such as bioreactors or fermentation processes. However, the effectiveness of LQR depends heavily on the choice of two tuning matrices:

- Q: penalizes deviation of the system states from their desired values
- R: penalizes the magnitude of the control inputs

Selecting these matrices manually is often trial-and-error-based, lacks rigor, and may lead to suboptimal performance, especially in nonlinear or time-varying systems. A Genetic Algorithm (GA) is a type of evolutionary optimization technique inspired by natural selection. It is particularly useful for solving problems where the solution space is large, nonlinear, or non-convex-conditions under which traditional tuning methods may fail. In the context of LQR, a GA can be used to automatically search for the optimal Q and R matrices that yield the best control performance according to a chosen metric, such as minimizing tracking error, energy consumption, or settling time.

How GA Optimizes LQR

1. Initialization: Random sets of Q and R matrices are encoded as chromosomes.
2. Evaluation: Each set is tested by simulating the control system and scoring performance using a fitness function (e.g., ITAE).
3. Selection: The best-performing candidates are selected.
4. Crossover & Mutation: Genetic operations are used to create new candidates.
5. Iteration: The process repeats until convergence on a high-performance solution.

This results in a controller that is: Automatically tuned, Robust to disturbances, and Well-suited for nonlinear or bio-inspired systems like ethanol fermentation, where traditional models may be insufficient. The GA parameters and hyperparameters are specified as follows: population size is 100, maximum generations are 200, selection method is tournament selection, crossover fraction is 0.8, mutation rate is 0.05, elite count is 5, and the termination criterion is reaching maximum generations or fitness convergence. The optimization variables consist of the diagonal entries of the Q and R matrices. Constraints require $Q \geq 0$ and $R > 0$ (positive definite), with lower and upper bounds set to \$0.001\$ and 1000, respectively. A fixed random seed (Seed = 2026) is utilized to guarantee strict reproducibility of the optimization results. GA-LQR is used in bioprocesses due to the following: Bioreactors often have nonlinear dynamics, parameter variability, and uncertainties due to biological fluctuations. Manual LQR tuning in such conditions is difficult and may not yield global optimum performance, and GA provides a systematic, data-driven approach to optimize control without requiring deep analytical insight into system dynamics. To address control stability under nonlinear plant dynamics, the nonlinear bioreactor model is linearized around the nominal operating trajectory (x_0, u_0) at each evaluation step within the GA framework. The continuous Algebraic Riccati Equation (ARE):

$$A^T P + PA - PB^{-1}B^T P + Q \quad (10)$$

is solved to calculate the unique positive-definite solution $P > 0$, deriving the optimal feedback gain matrix $K = R^{-1} B^T P$. Consequently, all closed-loop eigenvalues $\lambda (A - BK)$ strictly reside in the open left-half complex plane $Re(\lambda_i) < 0$ confirming local asymptotic stability. Extensive simulations under nonlinear plant dynamics and step disturbances further verify that closed-loop stability and robust performance are preserved, as illustrated in the GA-LQR optimization framework in Figure 3. The block diagram of the GA Optimized LQR Controlled Ethanol Bioreactor is shown in Figure 4.

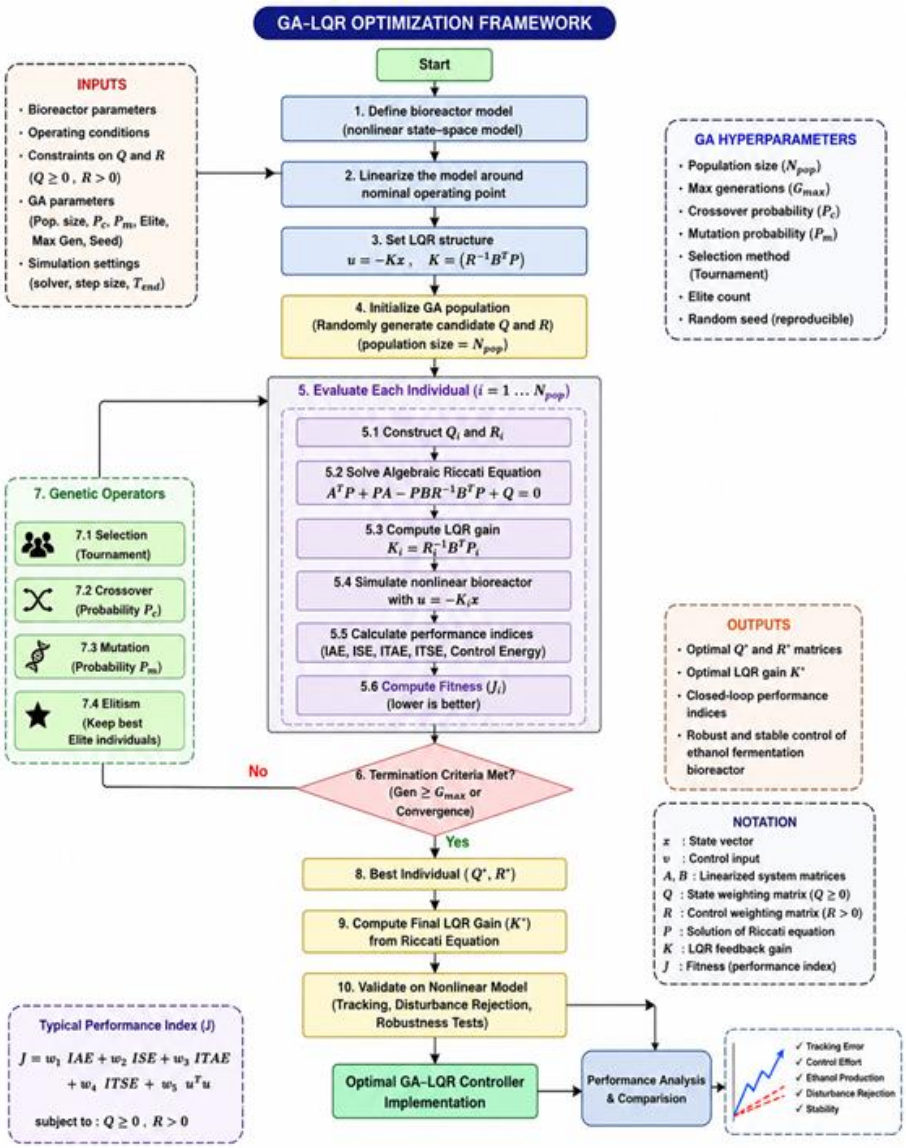

Fig. 3 GA optimized LQR framework

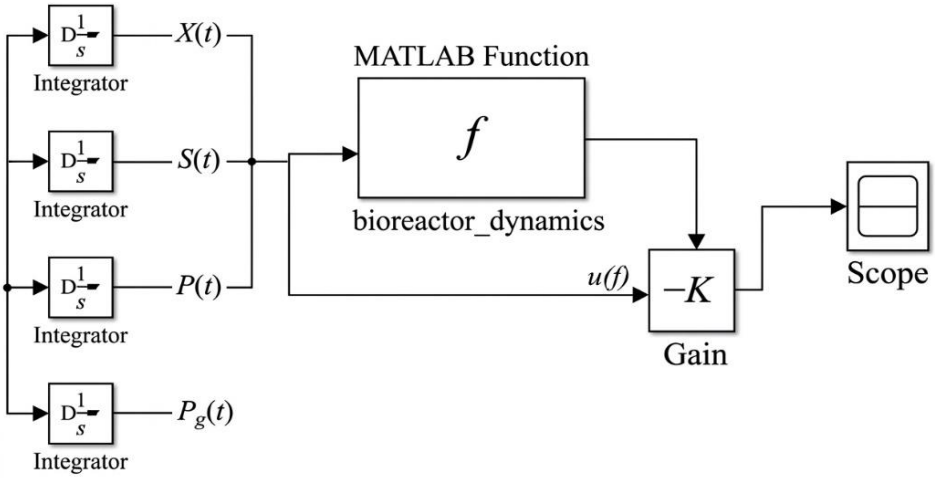

Fig. 4 GA optimized LQR controlled ethanol bioreactor

5. Results and Discussion

A plant system for Ethanol production based on a gas separator process has been designed to enhance ethanol recovery and energy efficiency by integrating fermentation and gas separation technologies into a single or continuous process line, as depicted by the process flow diagram shown in Figure 5.

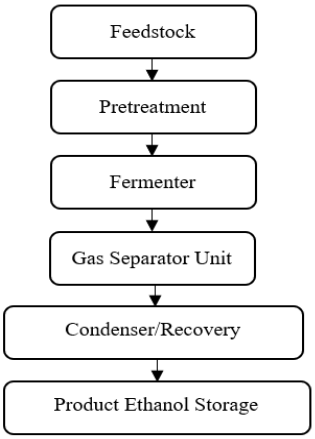

Fig. 5 Process flow diagram for ethanol production

MATLAB/Simulink platform used to model a bioreactor plant for Ethanol production and build a Linear Quadratic Regulator (LQR) for controlling the processes depicted in Figure 6. To evaluate the reliability of the controller in tracking the variations of the controlled variable of input temperature varied in step changes during system simulation. The numerical simulation methodology specified as MATLAB/Simulink was used for all simulations, the variable-step ODE45 solver was employed, Relative tolerance = 1×10-6, Absolute tolerance = 1×10-8, and simulation time = 500 hours.

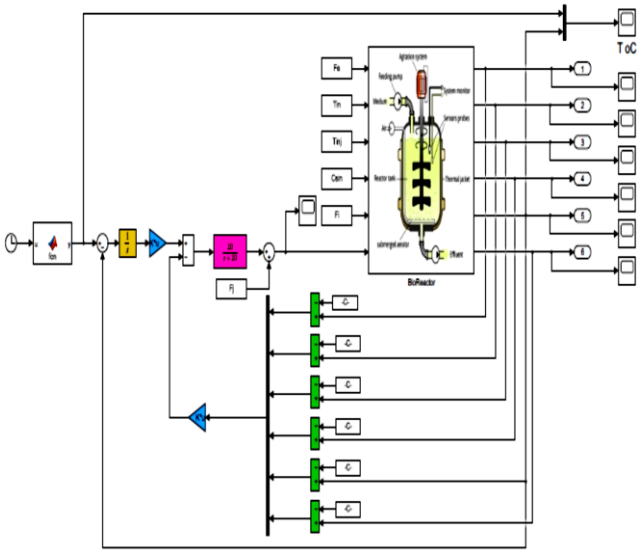

Fig. 6 Simulink model for ethanol production control

Two approaches of LQR were experimented in this simulation study: First, one is standard LQR, and the second one is GA tuned LQR, and a sample of the obtained results is presented in the following figures to evaluate and investigate the performance of each approach.

Figure 7 describes the performance of moderate manual tuned LQR Control, where balanced weights were applied for control action (Q) and control energy (R), leading to reasonable control action. Stronger control action is achieved when heaver weight is applied to the control action factor (Q) steered to a smaller system output error, but at the expense of control energy as presented in Figure 8.

Applying a heavier weight to control the energy factor (R) resulted in weaker action, producing a larger system output error with smaller control energy and Figure 9 describes that.

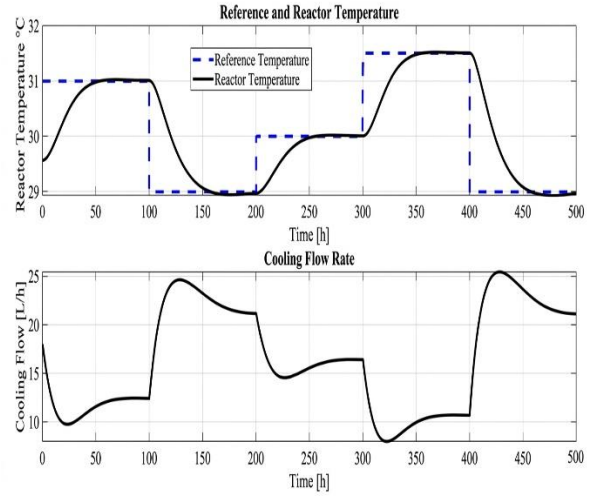

Fig. 7 Reactor performance for moderate manual tuned LQR control

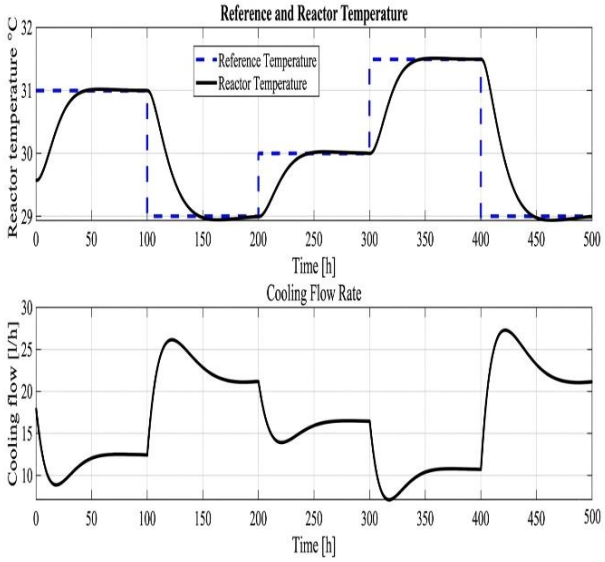

Fig. 8 Reactor performance for active manual tuned LQR control

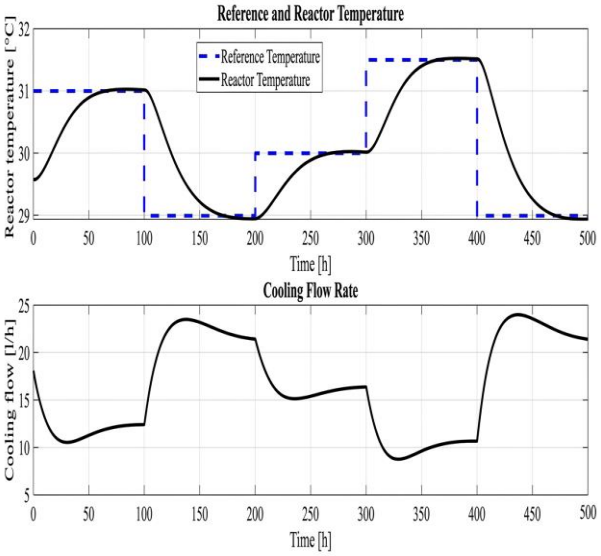

Fig. 9 Reactor performance for preserve manual tuned LQR control

Summary of Total Output Errors and Total Input Efforts are presented in Table 2. These data are for controlling types of Manual tuned LQR Moderate Control, Manual tuned LQR Active Control, and Manual tuned LQR Preserve Control.

Table 2. Summary of total output error and total control energy for manually tuned LQR

Item	Moderate Control	Active Control	Preserve Control
Total output error	47,884	39,953	57,329
Total Control Energy	2,0604,00	2,068,400	2,050,300

The performance of the proposed GA optimized LQR controller for four cost function criteria was examined, and a sample of the obtained results is documented.

Figure 10 defines the performance of the controller based on the criteria of Integral Time Absolute Error (ITAE), giving high system output error but small control energy.

Stronger control action achieved a smaller system output error but at the expense of higher control energy, as shown in Figure 11 with the criteria of Integration of Absolute Error (IAE) and with the criteria of Integral Time Squared Error (ITSE), as shown in Figure 12.

Figure 13 describes the performance of the controller when the cost function is based on the criteria of Integral Squared Error (ISE), which led to higher system output error but smaller control energy.

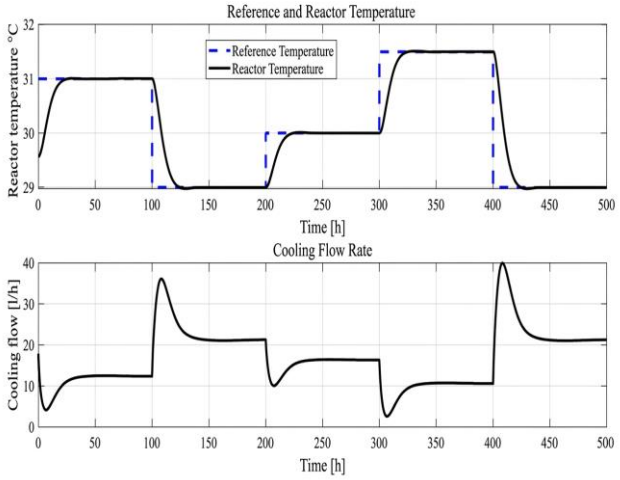

Fig. 10 Reactor performance for GA tuned LQR control based on ITAE cost function

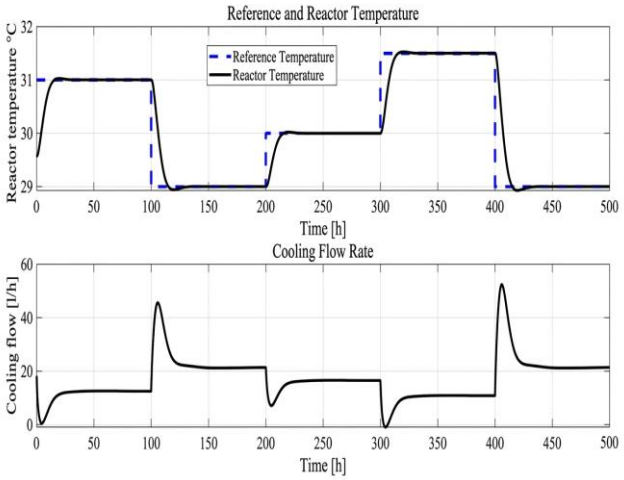

Fig. 11 Reactor performance for GA tuned LQR control based on IAE cost function

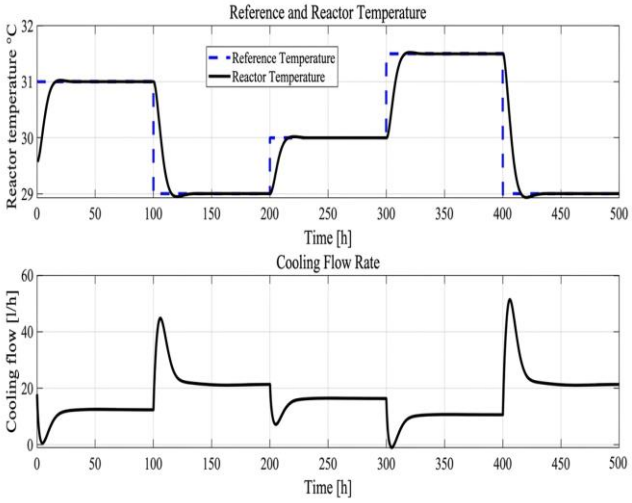

Fig. 12 Reactor performance for GA tuned LQR control based on ITSE cost function

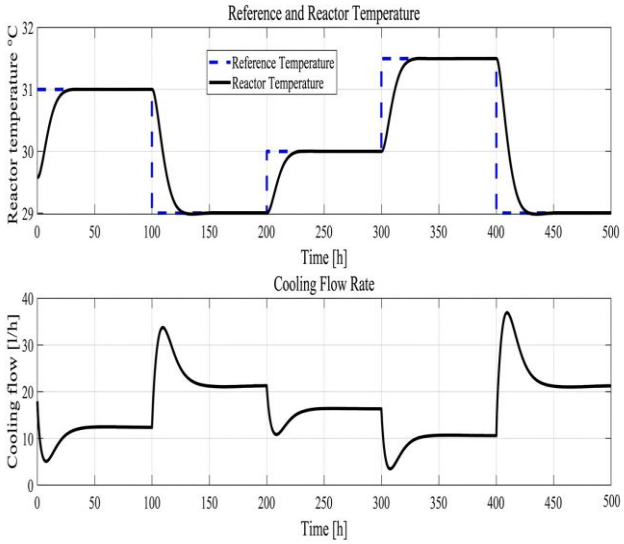

Fig. 13 Reactor performance for GA tuned LQR control based on ISE cost function

A summary of Total Output Error and Total Input Effort is presented in Table 3. These data are for controlling types of GA Optimized LQR/ Cost Function ITAE, GA Optimized LQR/ Cost Function IAE, GA Optimized LQR/ Cost Function ITSE, and GA Optimized LQR/ Cost Function ISE.

The following performance indices are statistically evaluated: ITAE, IAE, ITSE, ISE, Total output error, and Control energy. The results indicate that the proposed GA-LQR controller exhibits very small variations among optimization runs, demonstrating excellent robustness and repeatability.

Table 3. Summary of total output error and total control energy for GA optimized LQR

Performance Metric	ITAE	IAE	ITSE	ISE
Total output error	19,199± 185	14,004± 112	14,265± 128	21,519± 204
Total Control Energy	2,095,900 ±8500	2,115,800 ±9200	2,114,100 ±8800	2,090,800 ±7900

Summary of Total Output Error and Total Input Effort normalized on manually tuned LQR Moderate Control values as the base are presented in Table 4. These data are for controlling types of Manual tuned LQR Moderate Control, Manual tuned LQR Active Control, Manual tuned LQR Preserve Control, GA Optimized LQR/ Cost Function ITAE, GA Optimized LQR/ Cost Function IAE, GA Optimized LQR/ Cost Function ITSE, and GA Optimized LQR/ Cost Function ISE.

Table 4. Summary of total output error and total control energy

Controller	Normalized Total Output Error	Normalized Total Control Energy
Manual tuned LQR Moderate Control	1.000	1.000
Manual tuned LQR Active Control	0.834	1.0039
Manual tuned LQR Preserve Control	1.197	0.995
GA Optimized LQR/ Cost Function ITAE	0.401	1.017
GA Optimized LQR/ Cost Function IAE	0.292	1.027
GA Optimized LQR/ Cost Function ITSE	0.298	1.026
GA Optimized LQR/ Cost Function ISE	0.449	1.015

To test the system behavior for step response, a step input temperature was used with the different controllers mentioned previously. A sluggish system response resulted of using active manual tuned LQR Control as shown in Figure 14.

Figure 15 presents Ethanol and Yeast concentration versus time for active manual tuned LQR Control and Oxygen and Glucose concentration versus time for active manual tuned LQR Control, as described by Figure 16.

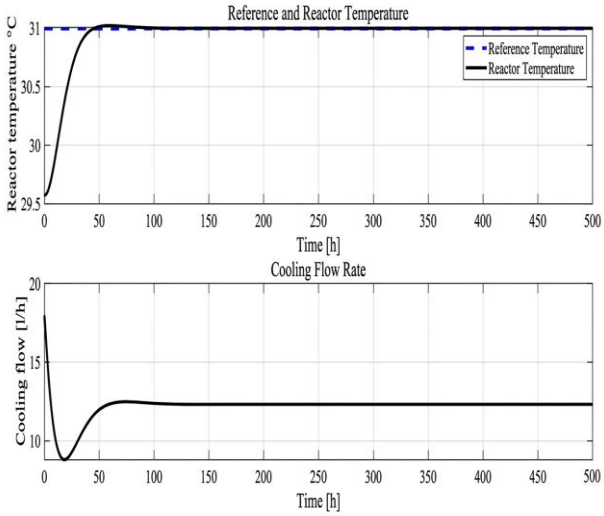

Fig. 14 Reactor step performance for active manual tuned LQR control

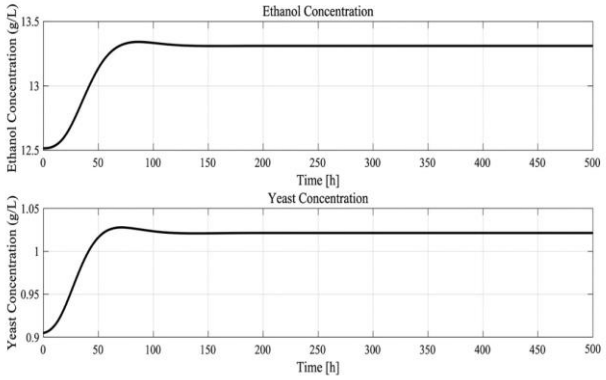

Fig. 15 Ethanol and yeast concentration versus time for active manual tuned LQR control

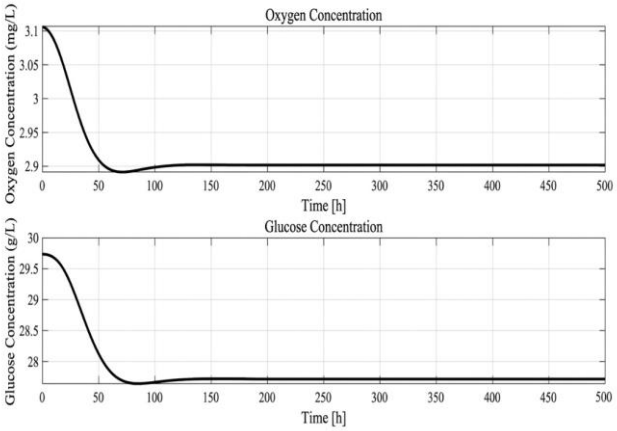

Fig. 16 Oxygen and glucose concentration versus time for active manually tuned LQR control

The system behavior for a step input temperature with GA tuned LQR Control based on ITSE cost function is depicted in Figure 17 providing faster response, lesser overshoot, and smaller steady state error. Figure 18 presents Ethanol and Yeast concentration versus time for GA tuned LQR Control based on ITSE cost function, and Oxygen and Glucose concentration versus time for GA tuned LQR Control based on ITSE cost function described by Figure 19.

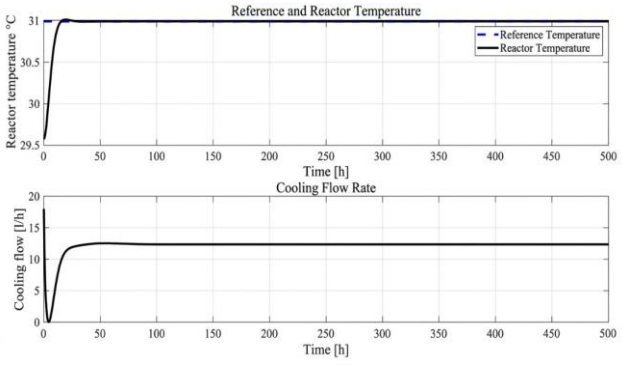

Fig. 17 Reactor step response for GA tuned LQR control based on ITSE cost function

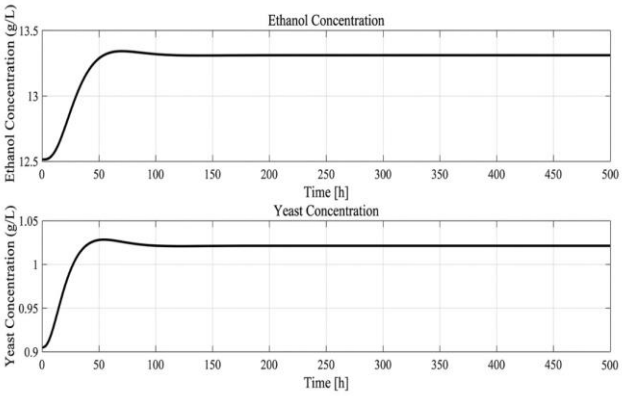

Fig. 18 Ethanol and yeast concentration versus time for GA tuned LQR control based on ITSE cost function

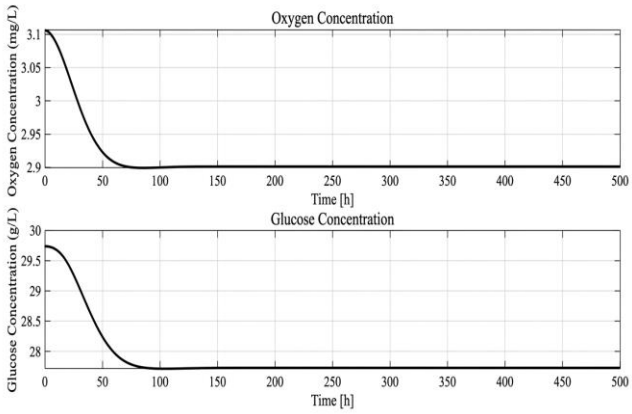

Fig. 19 Oxygen and glucose concentration versus time for GA tuned LQR control based on ITSE cost function

The comparison study has been investigated between manual tuned LQR and GA optimized tuned LQR, which offers: Automatic controller tuning, reduced output tracking error, Lower control effort, improved disturbance rejection, Easier implementation than MPC, and Lower computational burden than nonlinear optimal control methods.

Compared with advanced nonlinear controllers, GA-LQR provides an attractive trade-off between performance, implementation complexity, computational requirements, and scalability, as future direction further study to involve: Machine learning and robust bioreactor control. Summary of average Output Error, average cooling flow, average reactor temperature, average Ethanol concentration, Yeast concentration, Oxygen concentration, and Glucose concentration for Manual tuned LQR Active Control and GA Optimized LQR with Cost Function ITSE are tabulated in Table 5.

The superior performance of the proposed GA-LQR controller can be attributed to the following factors: Automated Optimization of LQR Parameters. Multi-Objective Optimization; the fitness functions simultaneously minimize:

tracking error, settling time, control effort, Steady-state error. Improved closed-loop dynamics, the GA-LQR controller reduced the average output error by approximately 54.8% while slightly improving ethanol production and reducing cooling flow requirements.

The optimized weighting matrices allow the controller to respond more efficiently to temperature disturbances and process variations. Although designed using a linearized model, the GA-LQR controller performs effectively on the nonlinear ethanol fermentation process because the optimization procedure explicitly accounts for closed-loop performance through nonlinear simulations.

Table 5. Summary comparison between standard LQR and GA optimized LQR

Item	Standard LQR	GA Optimized LQR
Average Reactor Temperature ^{o}C	30.9504	30.9803
Average System Output Error ^{o}C	0.0522	0.0236
Average cooling flow rate (L/hr)	12.1783	12.0782
Average Ethanol Concentration (g/L)	13.2537	13.2691
Average Yeast Concentration (g/L)	1.0151	1.0174
Average Oxygen Concentration (g/L)	2.9121	2.9081
Average Glucose Concentration (g/L)	27.8594	27.8201

6. Conclusion

Designing an LQR for a fermentation bioreactor is a systematic process involving modeling, linearization, and control design. The LQR approach can help achieve efficient ethanol production by optimizing the control of key state variables. The effectiveness of LQR depends heavily on the choice of two tuning matrices Q and R. Selecting these matrices manually is often trial-and-error-based, lacks rigor, and may lead to suboptimal performance. Simulations were conducted in MATLAB/Simulink a step change in substrate feed rate applied to evaluate controller performance.

The obtained results of using standard LQR with heavily weighted applied to Q produce strong action leading to smaller system output error, but at the expense of control energy. Weaker control action resulted from applying a heavy weight on R, producing a larger system output error and smaller control energy.

Balanced control action and control energy are achieved by applying balanced weights for Q and R. The GA-optimized LQR based on cost functions Integral Time Squared Error (ITSE), (IAE) attained the smallest system output error, while with cost functions Integral Time Absolute Error (ITAE), and (ISE), the system's output error is not as small as the previous cost functions. Over the entire GA optimized LQR compared to standard LQR shows: Faster convergence to set-point, Higher ethanol yield, Lower overshoot and settling time, and Reduced control effort compared to standard LQR.

The proposed GA-optimized LQR controller significantly enhances the control of ethanol fermentation processes. It automates the tuning of LQR parameters, enabling better tracking performance and disturbance rejection.

This hybrid AI-control strategy is scalable to other nonlinear biochemical processes and can serve as a basis for future real-time adaptive control systems.

Although the present work is simulation-based, future research will focus on: Laboratory-scale ethanol fermentation experiments, Hardware-in-the-loop implementation, Real-time control implementation, robust nonlinear observer design, Integration with machine learning-based predictive control, and Industrial-scale fermentation applications.

Conflicts of Interest

The author announces that there are no known competing financial interests or personal matters that may appear to influence the work mentioned in this letter.

Funding Statement

This research received no specific subsidies from financing agencies in public, commercial, or non-profit sectors.

Data and Code Availability Statement

The simulation datasets generated and the MATLAB/Simulink source code used during the current study are available from the corresponding author upon reasonable request.

Author Contribution

All authors contributed equally to the conception, modeling, simulation, and revision of the manuscript and approved the final version for submission.

Acknowledgment

The authors would like to express their sincere appreciation to the Department of Petroleum Systems Control Engineering at Tikrit University for the technical support provided during the course of this research. The authors also acknowledge the valuable discussions with colleagues and the support and encouragement from their families throughout this work.

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