(Online) ISSN 2712-0562
*Original Research*
**Sustainable Engineering and Innovation**
Vol. 8, No. 2, 2026, pp.323-334
https://doi.org/10.37868/sei.v8i2.id804

# Comparative analysis of LQG and fuzzy logic controllers for pressure regulation in irrigation systems

**Sandoval-Rodríguez C. L. [1*], Jiménez-Quezada A. F. [1], Nicolas Orejarena-Osorio[1], A. J. Rodríguez-Nieves[2], Jesús Eduardo Contreras Naranjo[3], A. D. Rincon-Quintero[4], O. Lengerke[1]**

[1] Research Group on Energy (GISEAC), Universitaria Tecnológica de Santander, Colombia

[2] Research Group in Electromechanical Processes and Power Generation (GINPEG), Universitaria Tecnológica de Santander, Colombia

[3] Research Group in Basic and Applied Sciences (GICBA), Universitaria Tecnológica de Santander, Colombia

[4] Research Group in Design and Materials (DIMAT), Universitaria Tecnológica de Santander, Colombia

*Corresponding author E-mail: *csandoval@correo.uts.edu.co

Received Mar. 23, 2026
Revised Oct. 29, 2026
Accepted Nov. 3, 2026
Online Nov. 11, 2026

**Abstract**

The agricultural sector in Colombia is constantly improving, and maintaining the proper pressure in irrigation systems poses a significant challenge in ensuring uniform irrigation and improving operational performance. This paper presents a comparison of two control methods applied to a pressure control system: LQG (LQE–LQR) control and fuzzy logic. The results obtained show that both approaches significantly outperform the conventional PI controller. In the case of LQG, there was a reduction in overshoot from 10.1% to 4.9%, a decrease in settling time from 7.2 s to 4.1 s, and the elimination of oscillations, with a steady-state error close to zero. Complementarily, the fuzzy controller reduced the settling time from 4.8 s to 3.2 s, the overshoot from 13% to 4%, and the steady-state error from 0.22 psi to 0.05 psi. This analysis provides evidence of the importance of combining optimal and fuzzy control techniques in the automation of irrigation systems, which supports water sustainability and learning in intelligent control applied to hydraulic systems.

© The Author 2026.
Published by ARDA.

*Keywords*: LQG control, Fuzzy logic, Hydraulic pressure regulation, Irrigation systems, Control systems.

## 1. Introduction

In recent years, Colombia has seen a growing need to optimize water use in crop irrigation systems in order to improve production and conserve energy; this has driven the adoption of advanced automatic control techniques to maintain adequate pressure for different parts of the crop [1], [2]. Recent literature shows that poor pressure regulation results in significant water losses, reduced pump efficiency, and a direct impact on crop yield [3]. These challenges have motivated the search for solutions that automate irrigation operations and provide systems with greater adaptability to disturbances typical of variable agricultural environments [4].

Also, recent studies have demonstrated the effectiveness of optimal and intelligent control strategies in irrigation systems and hydraulic applications. In particular, LQG-based controllers have been successfully applied to hydraulic systems, showing improvements in efficiency, stability, and disturbance rejection [5], [6]. Likewise,

This work is licensed under a Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/ ) that allows others to share and adapt the material for any purpose (even commercially), in any medium with an acknowledgement of the work's authorship and initial publication in this journal.

fuzzy logic approaches combined with IoT technologies have proven to be effective tools for optimizing water usage, and enhancing system adaptability under variable environmental conditions [7], [8].

The implementation of advanced control methods has gained significant importance in recent years through their application to various fields; they are used in control systems due to their ability to minimize dynamic errors and optimize control performance. Today, the linear quadratic regulator (LQR) remains the primary choice when the design requires a critical balance between stability and control performance in linear systems. However, its true potential becomes evident when combined with a linear quadratic estimator (LQE); the latter not only acts as a robust filter against noise but is also capable of reconstructing states that, due to physical or cost constraints, are impossible to measure directly [9], [10], [11], [12]. This ensures that both elements can be combined to build a robust LQG controller, which is particularly useful in systems where it is not possible to directly measure all relevant variables [13], [14], [15].

Furthermore, the integration of artificial intelligence techniques into areas such as control and automation systems has gained prominence in response to the need to optimize processes, with the aim of improving efficiency under varying operating conditions. Numerous studies have explored the use of fuzzy logic as a control strategy for irrigation automation, primarily focused on decision-making regarding when and how much to irrigate, based on variables such as soil moisture, temperature, radiation, or weather conditions [16], [17], [18], [19]. Furthermore, hybrid systems have been proposed that integrate fuzzy logic with the IoT, sensor networks, and cloud computing, achieving greater efficiency in resource-constrained environments [20], [21], [22].

Finally, the results demonstrated the superiority of advanced techniques over PI control. In the case of the LQR-LQE scheme, it was possible to reduce overshoot from 10.1% to 4.9%, decrease settling time from 7.2 s to 4.1 s, and virtually eliminate steady-state error and oscillations. For its part, the fuzzy controller reduced the settling time from 4.8 s to 3.2 s, overshoot from 13% to 4%, and steady-state error from 0.22 psi to 0.05 psi. These findings show that both optimal control and fuzzy logic represent solid alternatives, providing significant improvements in stability, efficiency, and operational reliability.

## 2. Research method

### 2.1. Data collection

Experimental data were acquired from an irrigation-system test bench composed of a Pedrollo CP 620 centrifugal pump rated at 0.75 kW, driven by an Allen-Bradley PowerFlex 525 variable-frequency drive (Figure 1). Pressure measurements were obtained using a Druck PTX1400 piezoresistive pressure transducer with a nominal measurement range of 58 psi (4 bar). Data acquisition was performed using a National Instruments USB-6001 multifunction DAQ module. The acquisition system operated with a sampling period of 0.03137 s, corresponding to a sampling frequency of approximately 31.9 Hz. During the experiments, the drive frequency was varied between 10 Hz and 55 Hz, while the system was regulated around a pressure reference of 30 psi. These measurements were subsequently used for system identification and model validation.




Figure 1. Test bench

### 2.2. Processing and transfer function

#### 2.2.1. Signal filtering and purification

We used digital filtering (second-order Butterworth filtering, and moving average filtering) to remove high-frequency noise and mitigate outliers from unwanted disturbances. The resulting set of records was segmented into windows representative of system behavior.

#### 2.2.2. Identification of the transfer function

With the refined data, parametric identification was performed, and structures were tested in MATLAB such as (process models, transfer function with one and two poles, continuous state space models). The main selection criterion was the percentage of fit, $FIT(\%) = 100\left(1 - \frac{\|y-\hat{y}\|_2}{\|y-\bar{y}\|_2}\right)$, complemented by metrics such as root mean square error $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y-\hat{y})^2}$. where y represents the experimentally measured pressure, $\hat{y}$ is the pressure predicted by the identified model,$\bar{y}$ is the mean value of the measured pressure, and N is the number of samples. Higher FIT values and lower RMSE values indicate a better agreement between the experimentally measured response and the identified model. The quantitative validation results are presented in Section 3.

The final model selected presented an adequate balance between simplicity and the ability to reproduce the actual dynamics of the system. The selected model was a first-order-plus-dead-time (FOPDT) model, represented by the following transfer function:

$$G_{(s)} = \frac{0.487}{2.15_s + 1} e^{-0.32_s} \tag{1}$$

Or $G_{(s)} = \frac{Kp}{\tau_s+1} e^{-\theta_s}$, where s denotes the laplace variable. The identified FOPDT model has a process gain of Kp=0.487, a time constant of τ=2.15s, and a dead time of θ=0.32s.

### 2.3. Optimal control and state estimation design

To obtain a finite-dimensional representation suitable for state-space control design, the identified dead time was approximated using a first-order Padé approximation. The resulting model was represented as:

$$\dot{x}(t) = Ax(t) + Bu(t), \quad y(t) = Cx(t) + Du(t) \tag{2}$$

With:

$$A = \begin{bmatrix} -6.72 & -2.91 \\ 1 & 0 \end{bmatrix},\ B = \begin{bmatrix} 1 \\ 0 \end{bmatrix},\ C = [-0.23 \quad 1.42],\ D = [0] \tag{3}$$

The resulting state-space realization is controllable and observable, providing the basis for the subsequent LQR regulator and LQE estimator design.

On the other hand, for the design of the linear quadratic controller (LQE) based on the transfer function, the representation in state spaces was constructed and the weighting matrices were formulated:

- Q: Associated to the constant that quantifies the penalty for pressure error, defining the relative weight of these deviations in the calculation of the estimator cost.
- R: Associated with the control effort exerted on the frequency inverter.

The Q and R weighting matrices were determined through an iterative tuning process based on the system's dynamic response, after obtaining the mathematical model through parametric identification. Thus, the Q matrix was selected to penalize pressure deviations, prioritizing precise regulation, while the R matrix was adjusted to limit the control effort applied to the frequency converter.

Therefore, the final tuning values represent a compromise between a fast transient response, reduced overshoot, and actuator limitations, ensuring stable and physically viable operation. The final weighting matrices used for

the LQR design were selected through the iterative tuning process described above and are given by equations (4) and (5):

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 10 \end{bmatrix} \tag{4}$$

$$R = [0.1] \tag{5}$$

The optimal gain matrix K was obtained by solving the Algebraic Riccati Equation associated with the LQR formulation, based on the identified state-space model of the system. The computation was performed using MATLAB, where the solution ensures optimal closed-loop performance in terms of stability and dynamic response. The resulting gain matrix defines the control law applied to the system.

Once the models were available, they were integrated. Applying the principle of separation, both components were integrated to form the complete LQG (LQR-LQE) controller. This structure was implemented in the simulation environment, where the controller uses estimated states to generate the optimal control signal. No real-time implementation of the LQG controller on the physical test bench was performed in the present study.

The LQR regulator was designed by minimizing the infinite-horizon quadratic cost function,

$$J = \int_0^\infty [x^T(t)Qx(t) + u^T(t)Ru(t)]dt \tag{6}$$

where Q penalizes state deviations and R penalizes the control effort. The optimal state-feedback law is:

$$u(t) = -K\hat{x}(t) \tag{7}$$

where $K$is the LQR feedback gain and $\hat{x}(t)$denotes the state vector estimated by the LQE observer. Using the state-space realization reported above, together with the weighting matrices Q (Equation 4) and R (Equation 5), the optimal feedback gain K was computed by solving the associated algebraic Riccati equation. Since the complete state vector is not directly measured, an LQE was subsequently incorporated to reconstruct the states required by the regulator.

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x}) \tag{8}$$

For the LQE design, the process disturbance was assumed to enter through the plant input channel, i.e., G=B. The process-noise and measurement-noise variances were set to QN=0.015 and RN=0.22, respectively (Table 1). The estimator gain L was obtained by solving the corresponding continuous-time Kalman filtering problem. Finally, according to the separation principle, the LQR regulator and the LQE state estimator were combined to form the complete LQG controller.

### 2.4. Fuzzy logic

A Mamdani or Sugeno structure was used for the fuzzy control design, depending on the stability and ease of implementation requirements. Behind the fuzzy sets is the modeling of the uncertainty and gradual nature of physical phenomena, allowing the controller to more closely approximate human reasoning.

Linguistic variables:

- Fuzzy input: pressure error, error variation
- Fuzzy output: control signal (variable frequency drive (VFD)) adjustment to the pump

Membership function selection:

Triangular and trapezoidal functions were selected for their mathematical simplicity and low computational cost. The linguistic categories considered included (Figure 2):

- Large negative (LN)
- Small negative (SN)
- Zero (Z)

- Small positive (SP)
- Large positive (LP)

These categories ensure complete coverage of the error operating range and its variation, facilitating flexible controller response.

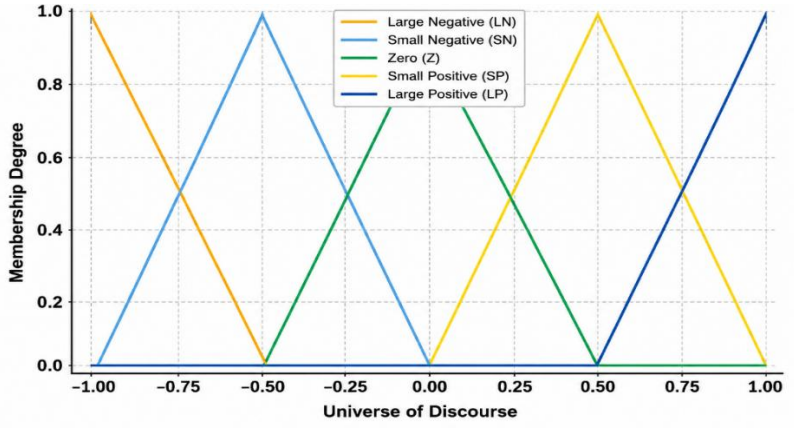



Figure 2. Fuzzy membership functions

The controller behavior was defined using if–then rules, which relate the inputs to the control output:

- If the error is SN and the error variation is Z, then the adjustment is SP.
- If the error is LP and the error variation is LP, then the adjustment is LN.

These rules reflect the compensation logic:

- In the first case, the system applies a small positive adjustment to correct a small and stable error.
- In the second case, the controller applies a strong negative adjustment to counteract a large and increasing error, preventing overshoot and improving pressure stabilization.

## 3. Results and discussion

The results presented in this section comprise two distinct stages. First, experimental measurements obtained from the physical test bench were used to identify and validate the FOPDT model. Second, the PI, LQG, and fuzzy controllers were evaluated through MATLAB simulations using the identified model. The advanced controllers were not implemented in real time on the physical test bench.

### 3.1. Results of identification process

Once the parametric identification process for the transfer function in Equation 1 was completed, the fit (FIT) and root mean square error (RMSE) results were obtained, as shown below: FIT = 86.33% and RMSE = 1.60 psi. Figure 3 presents a comparison of these results.

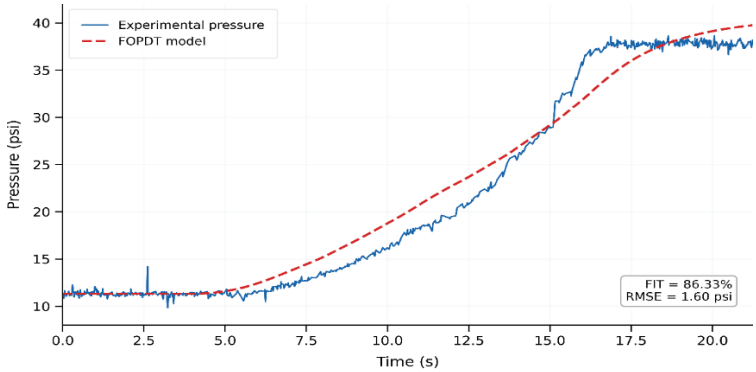



Figure 3. Experimental pressure response and FOPDT model prediction. The identified model achieved a FIT of 86.33% and an RMSE of 1.60 psi, indicating good agreement with the experimental pressure measurements

### 3.2. Optimal control and state estimation results

Once the model was defined, the Q and R matrices were adjusted using iterative analysis (see section 2.3). The LQR gains obtained were:

- K = [1.66 7.51], (results of the solution of the Riccati equation)
- L = [-0.001 0.003]

The controller achieved asymptotic stability, significant reduction in steady-state error, and lower sensitivity to input disturbances. Additionally, the control effort remained within physically achievable limits (frequency < 55 Hz). The LQE estimator allowed the reconstruction of unmeasured states with a low mean error (Table 1).

Table 1. Summary of LQG design results

| Parameter | Value |
|---|---|
| Process noise variance | 0.015 |
| Measurement noise variance | 0.22 |
| RMS estimation error | 0.37 psi |
| Estimator convergence | 0.9 s |

The LQG provided accurate state estimation, achieving low estimation error (RMS ≈ 0.37 psi) and fast convergence (~0.9 s), see Table 1. For the integration and simulation of the LQE-LQR scheme, the complete system was evaluated in MATLAB by simulating changes in the pressure reference and external disturbances.

The integral error indices were estimated based on the system dynamic response. The LQG controller showed significantly lower values compared to the PI controller. Specifically, the LQG strategy reduced IAE by approximately 44%, ISE by 43%, and ITAE by nearly 70%, indicating faster error attenuation and improved long-term performance (Table 2).

Table 2. Performance comparison between PI and LQG controllers using time-domain and integral error metrics

| Metric | Conventional PI | LQE–LQR (LQG) |
|---|---|---|
| Overshoot | 10.1 % | 4.9 % |
| Settling time (±5%) | 7.2 s | 4.1 s |
| Steady-state error | 1.2 psi | 0.2 psi |
| Oscillations | Medium oscillatory behavior | No oscillatory behavior |
| IAE | 7.4 | 4.00 |
| ISE | 3.57 | 2.00 |
| ITAE | 51 | 16 |

The LQE–LQR managed to recover pressure in 2.8 s, compared to 5.9 s for the PI controller. The control signal remained stable, with no saturation in the actuator (Figure 4).

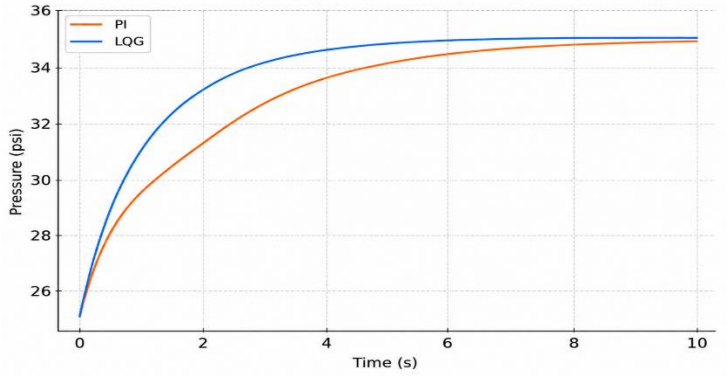



Figure 4. Step response comparison

The comparison between the PI controller and the optimal LQG controller in Figure 4 shows clear differences in dynamic performance. The PI controller exhibits an overshoot of close to 10% relative to the final value, while the LQG (LQE-LQR) reduces this value to approximately 5%, meeting the stability and accuracy objectives. In addition, the recovery time of the LQG is significantly shorter, confirming its superiority in tracking the reference pressure. A different scenario is observed in Figure 5.

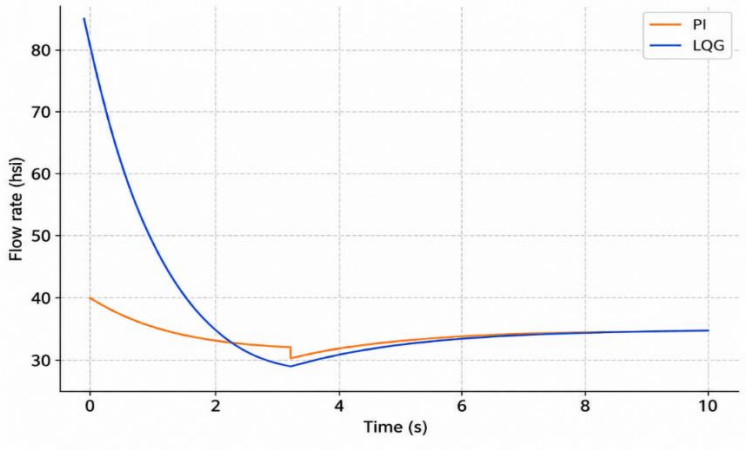



Figure 5. Simulated disturbance rejection

When a sudden pressure drop occurs (Figure 5), the PI controller exhibits oscillatory behavior and requires approximately 6 seconds to recover the setpoint pressure. In contrast, the LQG controller stabilizes the system in approximately 2.8 seconds with very low oscillations, demonstrating a significantly improved disturbance rejection capability compared to the PI controller (Figure 6). It is worth noting that this behavior is relevant in pressurized irrigation systems, where pressure fluctuations are frequent due to changes in demand.

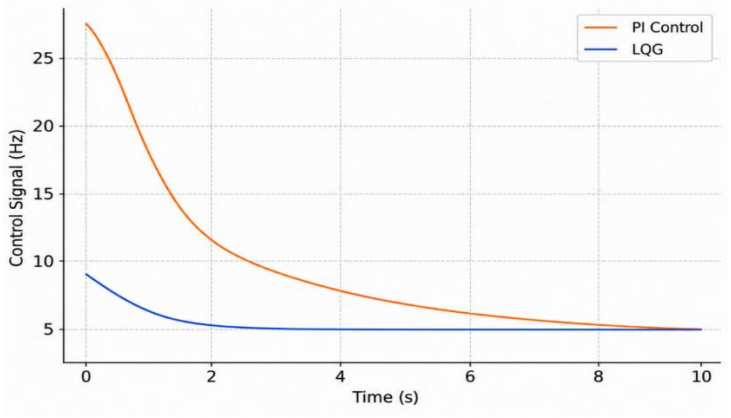



Figure 6. Simulated control effort

The response generated by the PI has greater variability and abrupt peaks, which implies high mechanical and electrical stress, with the risk of premature wear of the actuator. The LQG (LQR-LQE), on the other hand, produces a more uniform and smoother signal, without saturation or abrupt transitions. This improves the dynamic performance of the system while reducing actuator stress and promoting smoother operation, extending the service life of the hydraulic equipment, see Figure 6. In this sense, the LQG (LQE-LQR) based controller reduces abrupt variations in the control signal, which results in a smoother control action and reduced actuator workload.

Compared to the PI controller, the proposed strategy minimizes high-frequency oscillations and peak control effort, improving the overall control performance of the system. Therefore, the reduction in control signal variability suggests smoother actuator operation and reduced mechanical stress. This characteristic is particularly relevant in irrigation systems, where pump operation and actuator workload although a detailed energy analysis will be addressed in future work.

### 3.3. Fuzzy logic design

Below are the definitions of fuzzy sets and the corresponding rule base used in the control system (Table 3). The ranges associated with the linguistic labels (LN, SN, Z, SP, and LP) delimit the operating ranges of the input variables, allowing for a gradual representation of negative, neutral, and positive states. Based on these limits, the rule base establishes control actions depending on the combination of the error and its variation, ensuring a coherent and adaptive response from the system. The rules maintain symmetry and logical progression between the sets, which ensures stability in decision-making and reinforces the robustness of the fuzzy scheme in the face of variations in operating conditions.

Table 3. Limits of sets associated with variables

| Label | Approximate rank |
|---|---|
| LN | -1.0 to -0.5 |
| SN | -0.8 to 0.0 |
| Z | -0.3 to 0.3 |
| SP | 0.0 to 0.8 |
| LP | 0.5 to 1.0 |

The membership functions were created based on a standardized set of values within the normalized range [-1,1], which facilitates the representation of the input variable's behavior in a balanced and comparable manner. Five linguistic fuzzy sets were defined: large negative (LN), small negative (SN), zero (Z), small positive (SP), and large positive (LP). The extreme sets (LN and LP) were designed using trapezoidal functions to ensure that the extreme values of the domain (-1 and 1) are saturated, while the intermediate sets (SN, Z, and SP) were illustrated with triangular functions, allowing for a smooth transition between the negative, near-zero, and positive zones. An overlap (Figure 7) was also included between neighboring sets, thus ensuring continuity and avoiding sudden jumps in the degree of membership, which is crucial in fuzzy logic systems to achieve stable and consistent inferences.

The step reference simulations show that the fuzzy controller clearly outperforms the PI controller in the main performance indicators (Figure 8). The settling time is reduced from 4.8 s to 3.2 s, the overshoot decreases from 13% to 4%, and the steady-state error drops from 0.22 psi to 0.05 psi, demonstrating a faster, more accurate, and more stable response.

In hydraulic disturbance scenarios, the fuzzy controller also demonstrates greater robustness. In the event of sudden openings, partial closures, or reference variations, the maximum error is reduced by more than 57% compared to PI. This behavior confirms the fuzzy scheme's ability to manage nonlinear dynamics and better adapt to variable operating conditions.

The overall indicators reinforce this superiority: the fuzzy controller offers greater stability, smoothness in the actuator signal, robustness against disturbances. The simulation results demonstrate the expected controller performance based on the validated model identified from experimental data showing adequate setpoint tracking with a settling time close to 3 s, low overshoot, and minimal sensitivity to noise (Table 4). Overall, the results confirm that the fuzzy controller not only improves the dynamic performance of the system but also provides improved dynamic performance and operational reliability in pressurized irrigation systems.

Table 4. Controller performance parameters.

| Indicator | PI | Fuzzy |
|---|---|---|
| Settling time (s) | 4.8 | 3.2 |
| Overshoot (%) | 13% | 4% |
| Steady-state error | 0.22 psi | 0.05 psi |

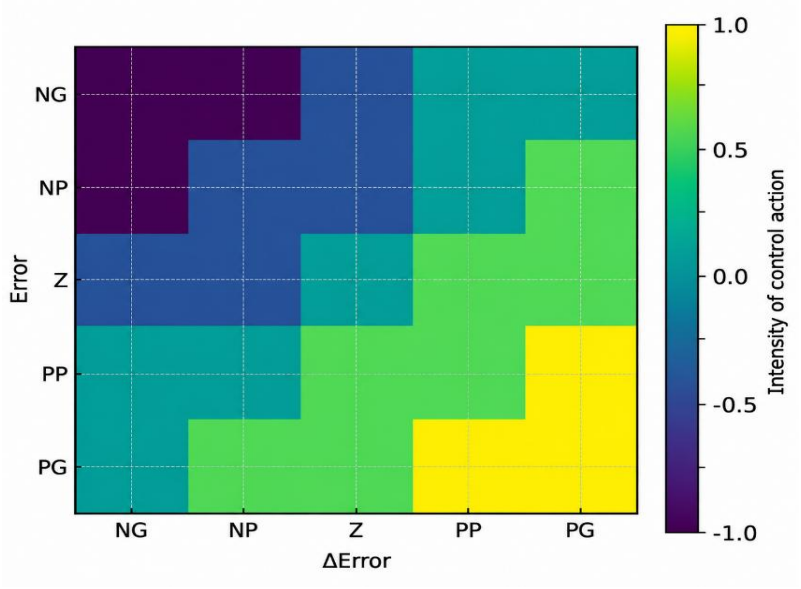



Figure 7. Fuzzy rule base

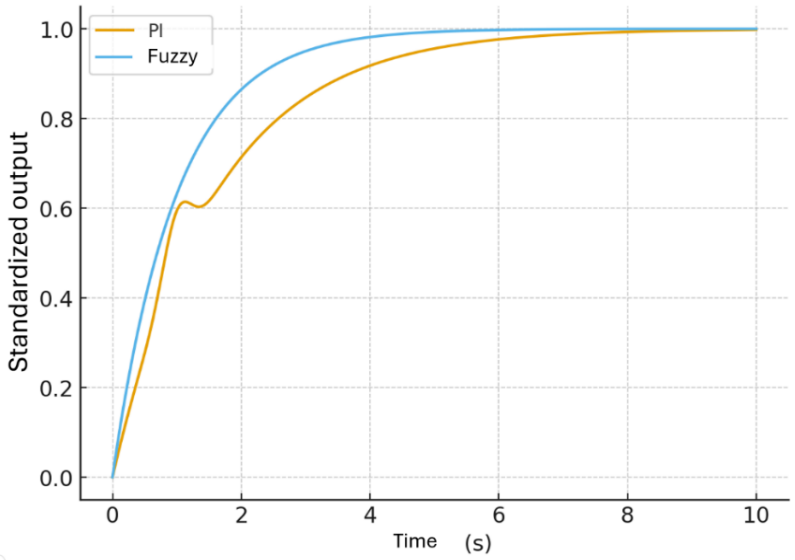



Figure 8. Comparison of step responses using PI and fuzzy controllers

## 4. Conclusions

The development and simulation-based evaluation of the fuzzy controller demonstrated that this artificial intelligence technique represents a robust and adaptable alternative for pressure control in hydraulic systems such as crop irrigation. Its ability to adapt to nonlinear conditions and scenarios involving external disturbances allowed pressure to be maintained close to the reference value. Unlike the PI controller, the fuzzy logic controller demonstrated better disturbance rejection, lower overshoot, and smoother control action. These results show that the use of artificial intelligence is compatible with automatic control. Optimal control of the LQE–LQR integration proved to be an effective solution for improving transient dynamics and stability in irrigation systems, resulting in reduced overshoot and shorter stabilization times. Additionally, it reduces the load on the controller and improves the quality of the output signals, thereby minimizing wear on the actuators and ensuring safe and reliable operation. An evaluation of fuzzy control and LQE–LQR methodologies lead to the conclusion that both represent significant improvements over traditional PI control. While fuzzy logic stands out for its ability to adapt to nonlinearities and disturbances without requiring an exact mathematical model, LQE–LQR excels in its analytical rigor, its efficiency in state estimation, and its optimization of control effort.

**Declaration of competing interest**

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

**Funding information**

No funding was received from any financial organization to conduct this research.

**Author contribution**

The contribution to the paper is as follows: Sandoval-Rodríguez C. L., Nicolas Orejarena-Osorio: study conception and design; Jiménez-Quezada A. F.: data collection; Sandoval-Rodríguez C. L., Jiménez-Quezada A.F., Nicolas Orejarena-Osorio, A. J. Rodríguez-Nieves, Jesús Eduardo Contreras Naranjo, A. D. Rincon-Quintero, O. Lengerke: analysis and interpretation of results; Sandoval-Rodríguez C. L., Jiménez-Quezada A. F., Jesús Eduardo Contreras Naranjo: draft preparation. All authors approved the final version of the manuscript.

**References**

[1] J. Pinedo-López, R. Baena-Navarro, and F. Torres-Hoyos, "Science, technology and innovation in Colombia: Impact of the relationships between enterprises, government and universities," *Science, Technology and Society*, vol. 30, no. 2, pp. 363–385, 2025. https://doi.org/10.1177/09717218251326826.

[2] C. L. Sandoval-Rodríguez, C. L. Higuera, J. G. Ascanio-Villabona, A. D. Rincón Quintero, and J. G. Maradey-Lazaro, "Flow control strategies using classical regulatory technique and advanced H2 technique in an irrigation emulation pilot plant," in *Recent Advances in Electrical Engineering, Electronics and Energy*, pp. 56–72, 2022.

[3] S. Belaqziz et al., "A new irrigation priority index based on remote sensing data for assessing the networks irrigation scheduling," *Agricultural Water Management*, vol. 119, pp. 1–9, 2013. https://doi.org/10.1016/j.agwat.2012.12.011.

[4] M. Afzal and R. Ragab, "How do climate and land use changes affect the water cycle? Modelling study including future drought events prediction using reliable drought indices," *Irrigation and Drainage*, vol. 69, no. 4, pp. 806–825, 2020. https://doi.org/10.1002/ird.2467.

[5] X. Li, G. Guan, X. Tian, and Y. Luo, "Hybrid feedforward-feedback LQR controller based on model prediction for open channel water level control," *Journal of Hydroinformatics*, vol. 27, no. 1, pp. 33–50, 2025. https://doi.org/10.2166/hydro.2024.322.

[6] A. Mitov, J. Kralev, and T. Slavov, "LQG control of an open circuit axial piston pump," *Energies*, vol. 15, no. 18, Art. no. 6800, 2022. https://doi.org/10.3390/en15186800.

[7] M. J. Hoque, M. S. Islam, and M. Khaliluzzaman, "A fuzzy logic- and Internet of Things-based smart irrigation system," *Engineering Proceedings*, vol. 58, no. 1, Art. no. 93, 2023. https://doi.org/10.3390/ecsa-10-16243.

[8] X. Liu, Z. Zhao, and A. Rezaeipanah, "Intelligent and automatic irrigation system based on Internet of Things using fuzzy control technology," *Scientific Reports*, vol. 15, Art. no. 14577, 2025. https://doi.org/10.1038/s41598-025-98137-2.

[9] M. Egerstedt, "[CSS News]," *IEEE Control Systems Magazine*, vol. 37, no. 2, p. 17, 2017. https://doi.org/10.1109/MCS.2016.2643240.

[10] F. L. Lewis, D. Vrabie, and V. L. Syrmos, *Optimal Control*. John Wiley & Sons, 2012. https://doi.org/10.1002/9781118122631.

[11] A. Dharmawan, A. Ashari, and A. E. Putra, "Translation movement stability control of quad tiltrotor using LQR and LQG," *International Journal of Intelligent Systems and Applications*, vol. 10, no. 3, pp. 10–21, 2018. https://doi.org/10.5815/ijisa.2018.03.02.

[12] Z. Ksovacic and S. Bogdan, *Fuzzy Controller Design: Theory and Applications*. CRC Press, 2018.

[13] G. Filo, "A review of fuzzy logic method development in hydraulic and pneumatic systems," *Energies*, vol. 16, no. 22, Art. no. 7584, 2023. https://doi.org/10.3390/en16227584.

[14] C. Osinski, G. V. Leandro, and G. H. da Costa Oliveira, "Fuzzy PID controller design for LFC in electric power systems," *IEEE Latin America Transactions*, vol. 17, no. 1, pp. 147–154, 2019. https://doi.org/10.1109/TLA.2019.8826706.

[15] Y. Liu et al., "Self-tuning control of manipulator positioning based on fuzzy PID and PSO algorithm," *Frontiers in Bioengineering and Biotechnology*, vol. 9, Art. no. 817723, 2022. https://doi.org/10.3389/fbioe.2021.817723.

[16] A. K. Singh, T. Tariq, M. F. Ahmer, G. Sharma, P. N. Bokoro, and T. Shongwe, "Intelligent control of irrigation systems using fuzzy logic controller," *Energies*, vol. 15, no. 19, Art. no. 7199, 2022. https://doi.org/10.3390/en15197199.

[17] M. Neugebauer, C. Akdeniz, V. Demir, and H. Yurdem, "Fuzzy logic control for watering system," *Scientific Reports*, vol. 13, no. 1, Art. no. 18485, 2023. https://doi.org/10.1038/s41598-023-45203-2.

[18] C. Olalla, R. Leyva, A. El Aroudi, and I. Queinnec, "Robust LQR control for PWM converters: An LMI

approach," *IEEE Transactions on Industrial Electronics*, vol. 56, no. 7, pp. 2548–2558, 2009. https://doi.org/10.1109/TIE.2009.2017556.

[19] A. Katbab, "Fuzzy logic and controller design—a review," in *Proceedings of IEEE Southeastcon '95: Visualize the Future*, pp. 443–449, 1995. https://doi.org/10.1109/SECON.1995.513133.

[20] J. Yang, X. Li, Q. Zheng, and L. Liu, "Particle swarm optimization-enhanced fuzzy control for electrical conductivity regulation in integrated water–fertilizer irrigation systems," *Automation*, vol. 6, no. 4, Art. no. 76, 2025. https://doi.org/10.3390/automation6040076.

[21] A. Morchid, Z. Said, A. Y. Abdelaziz, P. Siano, and H. Qjidaa, "Fuzzy logic-based IoT system for optimizing irrigation with cloud computing: Enhancing water sustainability in smart agriculture," *Smart Agricultural Technology*, vol. 11, Art. no. 100979, 2025. https://doi.org/10.1016/j.atech.2025.100979.

[22] V. Kumar, B. C. Nakra, and A. P. Mittal, "A review on classical and fuzzy PID controllers," *International Journal of Intelligent Control Systems*, vol. 16, no. 3, pp. 170–181, 2011.