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# Performance Comparison of Fuzzy-PID and MPC for Cascade Water Tank Control Systems

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## ABSTRACT

Level and flow control systems are widely used in industrial processes, where poor control performance may cause process instability, energy inefficiency, and reduced product quality. This study aims to design and compare the performance of Model Predictive Control and Fuzzy-PID in a cascade level-flow control system based on models obtained through system identification. An experimental simulation approach was conducted, including system identification, process modeling, controller design, and performance evaluation. Black-box modeling was performed using bump test data processed in the MATLAB System Identification Toolbox, producing level and flow models with average fit estimations of 87.54% and 85.19%, respectively. The identified models were used to develop both controllers. MPC was designed with a prediction horizon of 40, a control horizon of 3, and a sampling time of 0.01 s, while Fuzzy-PID employed a fuzzy inference system to tune PID parameters based on error and change of error. Simulation results show that both controllers achieved the desired setpoint. However, MPC provided superior performance with no overshoot, a settling time of approximately 8 s, and a steady-state error of 0.0001. In contrast, Fuzzy-PID produced 24% overshoot, a settling time of 28 s, and oscillatory responses under disturbances. These results indicate that MPC is more effective and reliable for cascade level-flow control applications in industrial systems.

## INTRODUCTION

Level and flow control in tank systems is one of the most important issues in process control engineering, particularly in chemical industries, power plants, and water treatment facilities (Dewi et al. 2023). These systems often exhibit nonlinear dynamics, response delays, and strong interactions between process variables, making it difficult to maintain system stability and ensure that the controlled variables accurately follow the desired setpoint (Prabowo et al. 2022; Wati, Santoso, and Laksono 2024). Therefore, effective control strategies are required to improve system performance and enhance disturbance rejection (Li 2023; Li, Lu, and Zhang 2022). One of the most widely adopted approaches is cascade control, which consists of a primary and a secondary control loop. In this configuration, the primary loop regulates the liquid level, while the secondary loop controls the flow rate. By compensating disturbances in the inner loop before they propagate to the outer loop, cascade control provides faster response and better stability than conventional single-loop control (Hamdani et al. 2022).

The Proportional–Integral–Derivative (PID) controller remains the most commonly used control method in industrial applications because of its simple structure, ease of implementation, and satisfactory performance in a wide range of processes (Aristoni et al. 2024). However, conventional PID controllers often exhibit limited performance when applied to nonlinear systems with complex dynamics and process disturbances, resulting in excessive overshoot, longer settling times, and reduced robustness (Akkoç 2025; Saad, Alshara, and Mustafa 2023). To overcome these limitations, several intelligent control approaches have been developed. Among them, the Fuzzy-PID controller combines the adaptability of fuzzy logic with the effectiveness of PID control, enabling automatic adjustment of controller parameters according to process conditions. Previous studies have demonstrated that Fuzzy-PID can improve system stability while reducing overshoot and steady-state error in nonlinear control systems (Akkoç 2025; Hamdani et al. 2022; Maniha et al. 2023; Saad et al. 2023).

Another advanced control strategy that has gained increasing attention is Model Predictive Control (MPC). Unlike conventional controllers, MPC utilizes a mathematical model of the process to predict future system behavior over a specified prediction horizon and determines the optimal control action by solving an optimization problem while considering process constraints. Owing to its predictive capability, MPC is particularly suitable for multivariable systems, processes with time delays, and systems operating under varying conditions (Achirei et al. 2023; Amine et al. 2024). Previous research has shown that MPC outperforms conventional controllers, including PI, IMC-PI, and Fractional-Order PI controllers, by providing better stability and lower control error indices in cascade tank control

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applications (Bhawesh, Kumar, and Singh 2021).

Although previous studies have demonstrated the effectiveness of cascade control, Fuzzy-PID, and MPC in improving tank level control performance, most investigations have evaluated these control strategies independently. Comparative studies between Fuzzy-PID and MPC under the same cascade control configuration remain limited, particularly for multivariable systems in which the primary loop controls the liquid level and the secondary loop regulates the flow rate. Consequently, a comprehensive evaluation of the relative performance of these intelligent control strategies under identical operating conditions is still lacking.

Therefore, this study aims to compare the performance of Fuzzy-PID and Model Predictive Control implemented in a cascade water tank control system. In the proposed configuration, the secondary flow loop is regulated using a conventional PID controller, while the primary level loop employs either a Fuzzy-PID or an MPC controller. A mathematical model of the plant is developed using the System Identification Toolbox based on experimental input–output data. The two control strategies are implemented and evaluated in MATLAB/Simulink using transient and steady-state performance indices, including rise time, settling time, overshoot, steady-state error, and integral error criteria. The findings of this study are expected to provide useful insights into the selection of an appropriate intelligent control strategy for cascade level–flow control systems in industrial applications.

## LITERATURE REVIEW

Water tank level and flow control systems are widely used in industrial processes such as water treatment, chemical manufacturing, and energy systems. These processes often exhibit nonlinear behavior, process delays, and disturbances that degrade control performance. To overcome these challenges, cascade control architectures have been extensively adopted because they improve disturbance rejection by combining an inner flow control loop with an outer level control loop.

Bhawesh et al. (2021) implemented Model Predictive Control (MPC) for a cascade tank system using MATLAB/Simulink and compared its performance with conventional PI, IMC-PI, and fractional-order PI controllers. Their results demonstrated that MPC achieved lower values of IAE, ISE, ITAE, ITSE, and RMSE, indicating superior tracking accuracy and disturbance rejection compared with conventional control methods. Similarly, Andersen et al. (2022) conducted an experimental comparison of PID, Linear Model Predictive Control (LMPC), and Nonlinear Model Predictive Control (NMPC) on a quadruple-tank system. The study found that both MPC approaches outperformed PID in setpoint tracking and overall control performance, while the performance difference between LMPC and NMPC remained relatively small under normal operating conditions.

Research by Kakani et al. (2024) compared PI and PID controllers for coupled tank level and flow control. The findings showed that PID produced faster rise time and better tracking accuracy than PI. However, the controller exhibited higher sensitivity to measurement noise, suggesting that more adaptive control strategies are required for nonlinear processes.

Recent advances have also highlighted the effectiveness of fuzzy-based controllers. Sunarya et al. (2025) developed a Feedforward–Feedback Fuzzy-PID controller for PLC- and IoT-based water level control. Their hybrid approach reduced steady-state error to approximately 0.67%, eliminated overshoot, and shortened disturbance recovery time to about three seconds, demonstrating the benefits of combining fuzzy logic with conventional PID control.

Another study by Ibrahim et al. (2025) integrated MPC with an Adaptive Neuro-Fuzzy Inference System (ANFIS) observer for a four-tank process. The proposed method improved state estimation accuracy, enhanced disturbance rejection, and maintained control performance while satisfying pump flow constraints, illustrating the potential of MPC for multivariable tank systems.

Kuscu and Ozyalcin (2025) investigated the performance of PID and Fuzzy Logic Control in a two-input, two-output mixing tank system. The simulation results indicated that fuzzy control handled nonlinear process characteristics more effectively without requiring a highly accurate mathematical model, whereas PID remained suitable for relatively stable operating conditions.

More recently, Ulhaq et al. (2026) compared PID, Fuzzy-PID, and MPC for reservoir water level regulation. Their simulation results showed that MPC achieved faster settling time and lower steady-state error than both PID and Fuzzy-PID, although its computational complexity was higher. The study further confirmed the advantages of predictive control in dynamic water level regulation systems

## METHOD

This study employed experimental and simulation methods to design and evaluate a cascade control system for tank level and flow rate. The research stages consisted of system identification, process modeling, controller design, simulation, and evaluation of the system response to setpoint changes and disturbances. System identification was performed using a bump test with the MATLAB System Identification Toolbox to obtain mathematical models for the level and flow loops. The identified models were then used to design the cascade control structure, with the level as the primary loop and flow rate as the secondary loop. Two control strategies were implemented in the primary loop, namely Fuzzy-PID and Model Predictive Control (MPC), while a PID controller was applied to the secondary flow loop.

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Plant modeling refers to the research in (Dewi et al. 2023) and was performed using the black-box method through a bump test. The test was conducted three times for each level and flow rate process by applying changes to the servo valve opening in each trial. The acquired Process Variable (PV) and Manipulated Variable (MV) data were then processed using the System Identification Toolbox in MATLAB to obtain the transfer function models that represent the system dynamics.Based on the identification results, the level process model is represented as a first-order system, while the flow rate process model is also represented as a first-order system. The model with the highest fit estimation value was selected as the plant model for the controller design. The obtained transfer functions are:

$$G_L(s) = \frac{0.46003}{0.21903s + 1} \tag{1}$$

$$G_F(s) = \frac{0.16665}{0.2237s + 1} \tag{2}$$

Where $G_L(s)$ and $G_F(s)$ are the transfer functions for the level plant and flow plant, respectively. These models were subsequently used as the foundation for the design and evaluation of the Fuzzy-PID and MPC controllers.

The Fuzzy-PID controller was developed using a Mamdani-type Fuzzy Inference System (FIS) in the MATLAB Fuzzy Logic Toolbox. The FIS consisted of two inputs, namely error and change of error, and three outputs representing the PID parameters: proportional gain ($K_p$), integral gain ($K_i$), and derivative gain ($K_d$), as shown in Figure 1. The inference process employed minimum (min) and maximum (max) operators, with centroid defuzzification to produce smooth and stable outputs for adaptive PID tuning.

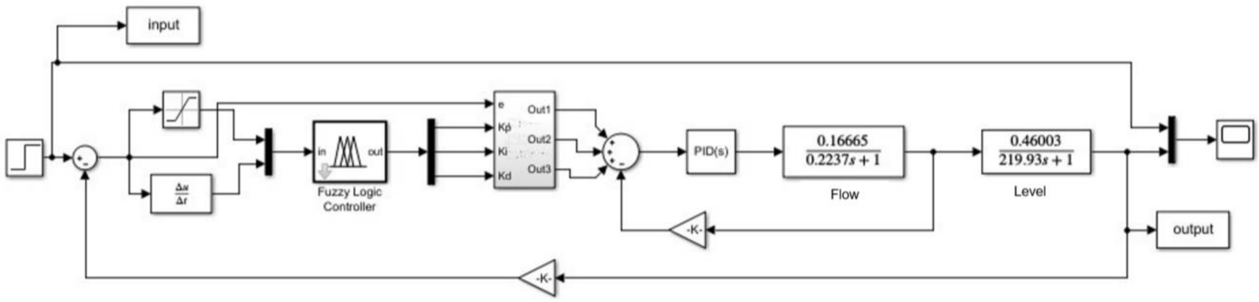
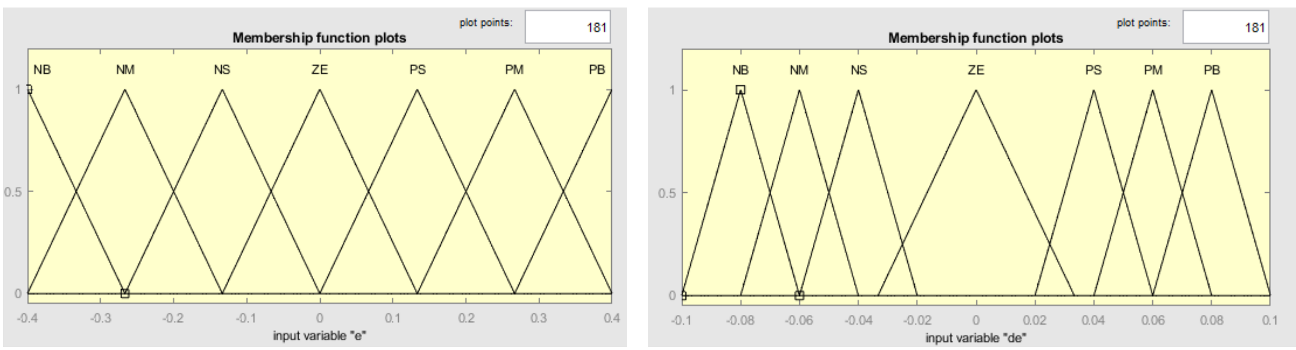



Figure 1. Simulink Model of the Fuzzy-PID-Based Cascade Control System

The error input ranged from −0.4 to 0.4, while the change of error ranged from −0.1 to 0.1, as shown in Figure 2. Both inputs used seven triangular membership functions: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM), and Positive Big (PB). The seven fuzzy sets provided a detailed representation of system conditions and enabled smoother control actions in response to error variations.

The output variables, $K_p$, $K_i$, and $K_d$, were each represented by three membership functions: Negative (N), Zero (Z), and Positive (P), as shown in Figure 3. The Negative and Positive membership functions were trapezoidal, while the Zero function was triangular. The ranges were of $K_p$, $K_i$, and $K_d$ set to 0–5, 0–0.05, and 0–0.1, respectively. After the inference process, the fuzzy outputs were converted into crisp values using the centroid defuzzification method. The resulting $K_p$, $K_i$, and $K_d$ values were used as adaptive PID parameters in the primary loop, allowing the controller to adjust to changes in system conditions and improve response speed, reduce overshoot, and enhance system stability compared with a fixed-parameter PID controller.




(a) (b)

Figure 2. Graphical Representation of the Membership Functions for the Input Variables: (a) Error Input Variable and (b) Change of Error Input Variable.

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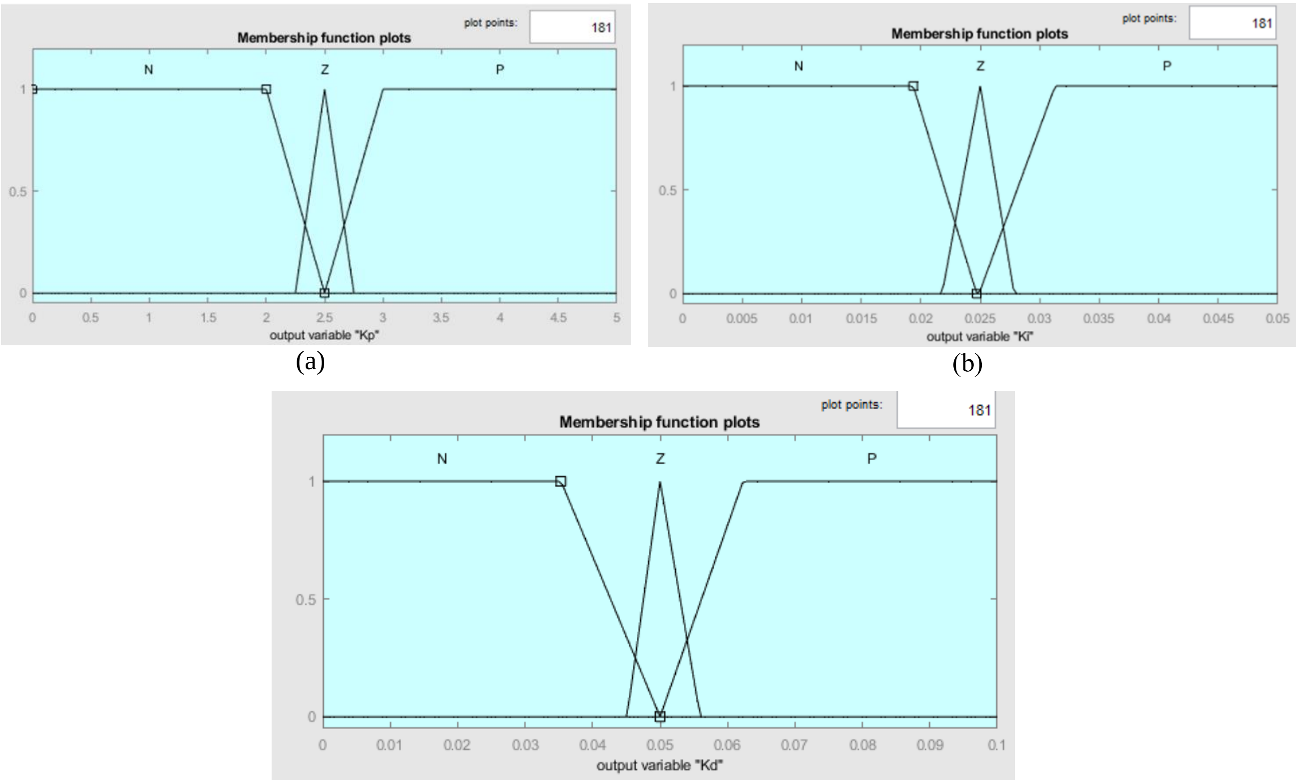


(a) (b)

(c)

Figure 3. Graphical Representation of the Membership Functions for the Output Variables: (a) Kp, (b) Ki, and (c) Kd.

The fuzzy rule base was developed based on the observed system response under input changes and disturbances until the desired operating condition was achieved. The rules were used to adaptively determine the PID controller parameters according to the current error and change of error. Three fuzzy rule bases were designed to tune the proportional gain (Kp), integral gain (Ki), and derivative gain (Kd), as presented in Table 1, Table 2, and Table 3, respectively. Table 1 presents the fuzzy rule base for Kp, which determines the proportional gain based on the combination of the error and change of error. Table 2 presents the fuzzy rule base for Ki, which adjusts the integral gain to reduce the steady-state error and improve the tracking performance. Meanwhile, Table 3 presents the fuzzy rule base for Kd, which determines the derivative gain to improve damping and reduce oscillations caused by rapid changes in the error. The three rule bases work together to provide adaptive tuning of the PID parameters according to the current system condition. Thus, the Fuzzy-PID controller can respond to changes in the process more effectively while maintaining the controlled variable close to the desired setpoint.

Table 1. Fuzzy Rule Base for Kp

| **e** | **de** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **NB** | **NM** | **NS** | **ZE** | **PS** | **PM** | **PB** |
| **NB** | P | Z | N | N | N | Z | P |
| **NM** | P | P | P | N | Z | P | P |
| **NS** | P | P | Z | N | Z | P | P |
| **ZE** | P | P | P | Z | P | P | P |
| **PS** | P | P | Z | N | Z | P | P |
| **PM** | P | P | Z | N | Z | P | P |
| **PB** | P | Z | N | N | P | Z | P |

Table 2 Fuzzy Rule Base for Ki

| **e** | **de** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **NB** | **NM** | **NS** | **ZE** | **PS** | **PM** | **PB** |
| **NB** | P | Z | N | N | N | Z | P |
| **NM** | P | Z | Z | N | Z | Z | P |
| **NS** | P | P | Z | N | Z | P | P |

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| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **ZE** | P | P | P | Z | P | P | P |
| **PS** | P | P | Z | N | Z | P | P |
| **PM** | P | Z | Z | N | Z | Z | P |
| **PB** | P | Z | N | N | P | Z | P |

Table 3 Fuzzy Rule Base for Kd

| **e** | **de** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **NB** | **NM** | **NS** | **ZE** | **PS** | **PM** | **PB** |
| **NB** | N | P | P | N | P | P | N |
| **NM** | N | Z | P | P | P | Z | N |
| **NS** | N | N | Z | P | Z | N | N |
| **ZE** | N | N | N | Z | N | N | N |
| **PS** | N | N | Z | P | Z | N | N |
| **PM** | N | Z | P | P | P | Z | N |
| **PB** | N | P | P | P | N | P | N |

The Model Predictive Control (MPC) controller was designed using the MATLAB MPC Toolbox based on the process model obtained from system identification, as shown in Fig. 4. The controller was configured with a prediction horizon of 40, a control horizon of 3, and a sampling time of 0.01 s. These parameters were selected to achieve optimal control performance, enabling the system to track setpoint changes rapidly while maintaining system stability. Through prediction and optimization at each sampling interval, MPC generated control signals that minimized the error between the system output and the desired reference. Its performance was subsequently evaluated based on the system response to setpoint changes in the tank level and flow control process.

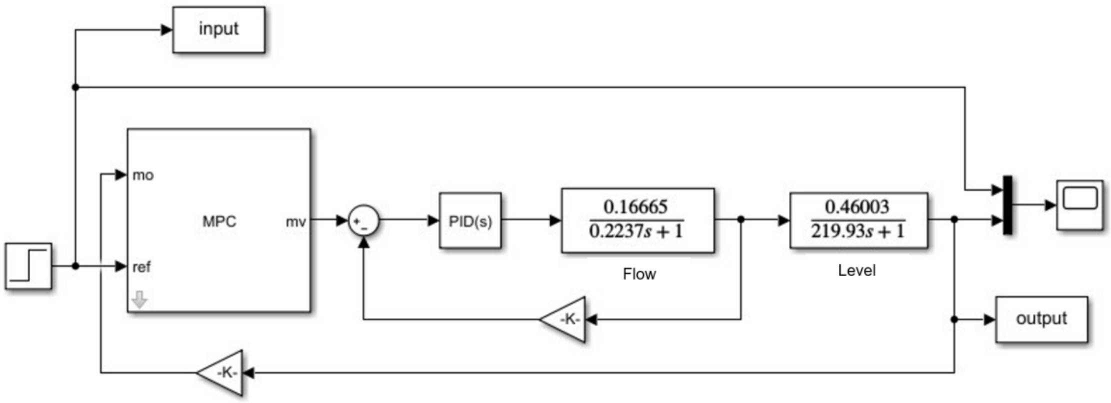


Figure 4. Simulink Model of the MPC-Based Cascade Control System

## RESULT

This section presents the results of system identification, controller design, and performance evaluation of the cascade level-flow control system using Fuzzy-PID and Model Predictive Control (MPC). The controllers were evaluated based on their dynamic responses to setpoint changes and disturbance conditions to assess the effectiveness of each control strategy.

Figure 5 presents the comparison of the cascade control system responses using Fuzzy-PID and Model Predictive Control (MPC) under a setpoint change to 2.8 m. Both controllers successfully regulated the water level to reach the desired reference, indicating that each control strategy was capable of maintaining closed-loop stability. However, their transient characteristics differed significantly.

The Fuzzy-PID controller was able to drive the system toward the 2.8 m setpoint, reaching the reference at approximately 28 s. During the transient phase, the controller produced a relatively aggressive control action, resulting in a 24% overshoot before the output gradually converged toward the steady-state condition. After the peak response, slight oscillations were observed before the water level stabilized at the target value. Although the steady-state error remained negligible, the relatively large overshoot and oscillatory behavior indicate that the online tuning mechanism of the Fuzzy-PID controller generated a faster but less damped response during the initial adjustment period.

In contrast, the MPC controller exhibited a smoother and more controlled transient response. The system output increased rapidly from the initial condition toward the 2.8 m setpoint without producing overshoot or noticeable oscillations. The response reached the steady-state condition within a shorter settling time while maintaining a negligible steady-state error. This behavior reflects the predictive capability of MPC, which optimizes future control

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actions over the prediction horizon while considering the system dynamics, thereby preventing excessive control effort and maintaining a well-damped response.

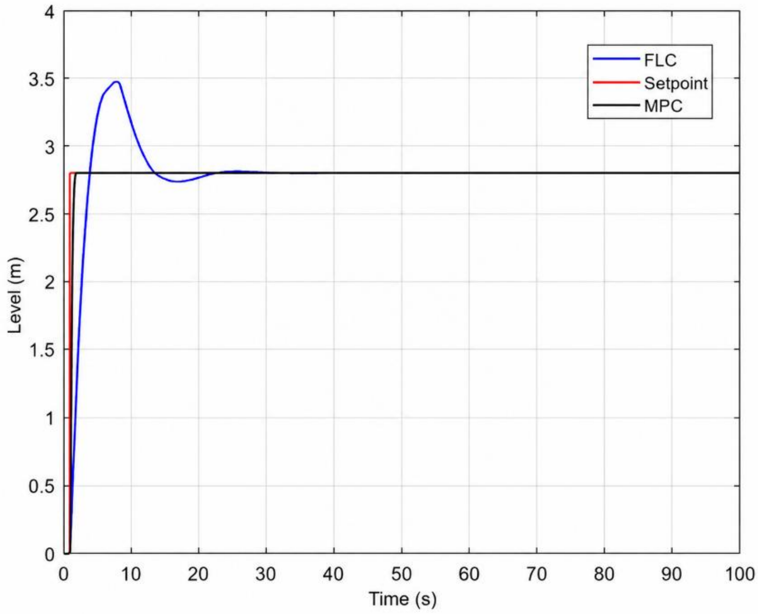


Figure 5. Comparison of Cascade Control System Responses Using Two Control Methods

The comparison demonstrates that MPC provided superior setpoint-tracking performance compared with Fuzzy-PID. While both controllers achieved the desired reference value, the Fuzzy-PID response was characterized by higher overshoot and residual oscillations, whereas MPC maintained a smoother trajectory throughout the transient process. These observations are supported by the quantitative performance indices presented in Table 4. The Fuzzy-PID controller produced an overshoot of 24% and a settling time of 28 s, while the MPC achieved a faster settling time of 8 s without overshoot. In terms of steady-state accuracy, Fuzzy-PID resulted in a steady-state error of 0.012, whereas MPC reduced the error to 0.0001. Furthermore, the rise time of MPC was 1.51 s, which was faster than the 3.42 s obtained by Fuzzy-PID. Overall, the results in Table 4 indicate that MPC provided faster response, lower steady-state error, zero overshoot, and better transient performance than Fuzzy-PID. These results demonstrate that MPC offered improved setpoint tracking and greater closed-loop stability for the tested control system.

Table 4. Comparison of Cascade Control System Responses Using Fuzzy-PID and MPC

| Parameter | Fuzzy logic controller | Sliding mode control |
|---|---|---|
| **Overshoot (%)** | 24 | - |
| **Settling time (s)** | 28 s | 8 |
| **Error steady state** | 0,012 | 0,0001 |
| **Rise time (s)** | 3,42 | 1,51 |

A disturbance test was subsequently conducted by introducing random disturbance to simulate pressure fluctuations affecting the flow rate. The test aimed to evaluate the controller's ability to maintain system stability and minimize deviations from the setpoint. As shown in Fig. 6, the disturbance caused oscillations and ripple in the Fuzzy-PID control response. Although the system was still able to maintain the output around the setpoint, the observed variations indicate that the Fuzzy-PID controller remained sensitive to pressure fluctuations and had limited disturbance rejection capability. In contrast, as shown in Fig. 7, the MPC response remained relatively smooth and stable under the same disturbance condition. The MPC was able to compensate for the disturbance more effectively, maintaining the process variable closer to the setpoint with smaller fluctuations. These results indicate that MPC provides better disturbance rejection and robustness compared with Fuzzy-PID for the tested flow control system.

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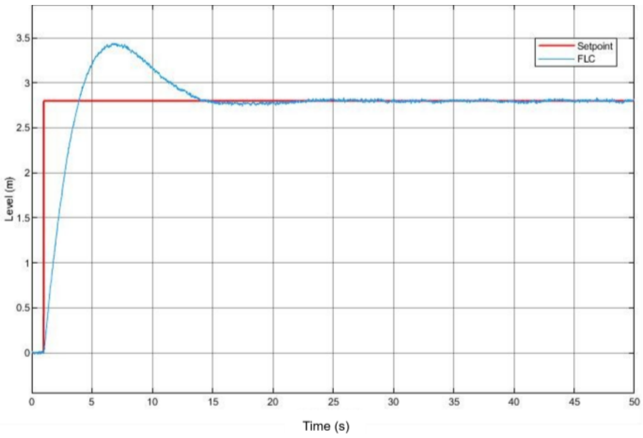


Figure 6. Fuzzy-PID Control Response Under Disturbance

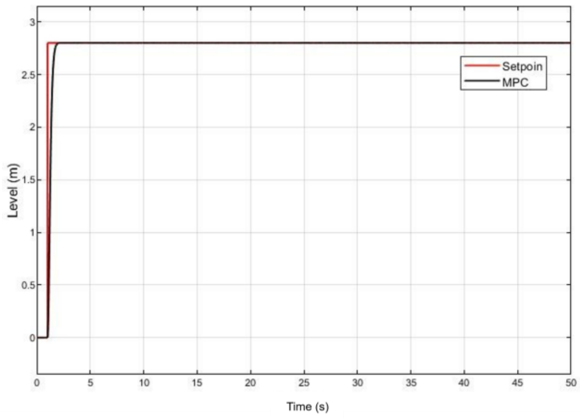


Figure 7. MPC Control Response Under Disturbance

## DISCUSSION

The experimental results demonstrate that both Fuzzy-PID and Model Predictive Control (MPC) successfully regulated the tank level toward the 2.8 m setpoint within the cascade control architecture. Although both controllers achieved the desired reference with negligible steady-state error, their transient responses exhibited clear differences. The Fuzzy-PID controller produced a relatively fast initial response but generated a 24% overshoot followed by slight oscillations before reaching the steady-state condition. This behavior suggests that the online adjustment of the PID parameters through fuzzy logic produced a relatively aggressive control action during the transient phase, enabling rapid setpoint tracking at the expense of reduced damping. Such behavior is commonly observed in adaptive fuzzy-based controllers when the tuning rules prioritize response speed over overshoot suppression.

In contrast, MPC produced a smoother and better-damped response. The system reached the desired setpoint without significant overshoot and settled more quickly while maintaining a near-zero steady-state error. This performance can be attributed to the predictive optimization mechanism of MPC, which determines the control action by minimizing a cost function over the prediction horizon while accounting for the identified process dynamics. As a result, unnecessary control effort is reduced, allowing the controller to achieve a more gradual transition toward the reference without introducing oscillatory behavior. These findings indicate that incorporating a predictive model into the outer loop of the cascade controller improves transient performance compared with rule-based adaptive tuning.

The superiority of MPC became more evident during the disturbance test. When random disturbances were applied to represent process fluctuations, the Fuzzy-PID response exhibited increased oscillations and ripple, whereas MPC maintained a smoother output with smaller response deviations. This result indicates that MPC provided better disturbance rejection under the tested operating conditions because the predictive algorithm continuously updated future control actions based on the current process state. Consequently, the controller compensated for disturbances before they propagated into larger output fluctuations, contributing to improved overall system stability.

The obtained results are consistent with previous studies reporting the advantages of both approaches. Fuzzy-PID controllers have been shown to improve adaptability and reduce the need for manual retuning compared with conventional PID controllers, particularly in nonlinear liquid-level systems. However, several studies have also reported that fuzzy-based tuning may still produce overshoot depending on the selected membership functions and rule base. Conversely, previous research on MPC for coupled-tank and liquid-level control systems has consistently demonstrated superior performance in minimizing overshoot, reducing settling time, and improving disturbance rejection through predictive optimization. Therefore, the present findings reinforce the conclusion that MPC offers more robust dynamic performance for cascade tank-level control while confirming that Fuzzy-PID remains an effective alternative when adaptive tuning with lower computational complexity is preferred.

Despite these promising results, several limitations should be acknowledged. First, the evaluation was conducted under simulation-based conditions using an identified process model, meaning that practical implementation issues such as sensor noise, actuator nonlinearities, valve hysteresis, and communication delays were not fully represented. Second, the controller parameters, including the MPC prediction horizon and the fuzzy membership functions, were selected for the investigated operating conditions and may require retuning for different process characteristics. Finally, the disturbance scenarios were limited to random signal disturbances and did not include more complex industrial operating conditions such as varying inflow rates, actuator saturation, or multiple simultaneous disturbances. Future work should therefore validate the proposed controllers on a real experimental cascade tank system and investigate adaptive or hybrid MPC–Fuzzy approaches under broader operating conditions to further improve robustness and practical applicability.

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## CONCLUSION

Based on the system identification, controller design, and experimental evaluation of the cascade level-flow control system, this study demonstrates that both Fuzzy-PID and Model Predictive Control (MPC) are capable of regulating the tank level toward the 2.8 m setpoint, although they exhibit different performance characteristics. The Fuzzy-PID controller provides a relatively fast response but produces a 24% overshoot and slight oscillations before reaching steady state, whereas MPC generates a smoother and more stable response with negligible overshoot and near-zero steady-state error. Under random disturbance conditions, MPC also demonstrates better disturbance rejection capability than Fuzzy-PID. These findings indicate that MPC is more suitable for level-flow control applications requiring high stability and accuracy, while Fuzzy-PID remains applicable to systems with less demanding control requirements. The main limitation of this study is that the evaluation was conducted under specific operating conditions and model-based scenarios, so a wider range of disturbances and process conditions has not yet been fully investigated. Future studies should focus on real-time implementation of both controllers on hardware, evaluation under various load and disturbance conditions, and further controller parameter optimization to improve transient performance and overall system efficiency.

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