Comparative Study of PID, MPC, Fuzzy and FOPID Control for Conical Tank System

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Abstract— **Nonlinear process systems such as conical tanks exhibit varying cross-sectional area, making liquid-level control highly challenging with conventional control methods. This work presents an intelligent control framework for a nonlinear conical tank by integrating classical, model-based, and reinforcement learning control strategies. The system is experimentally tested using PID, Model Predictive Control (MPC), Fuzzy Logic, and Fractional-Order PID (FOPID) to establish baseline performance. A nonlinear mathematical model of the conical tank is developed, and open-loop tests are carried out to validate the process dynamics. To address the limitations of conventional methods in handling nonlinearity and varying inflow conditions, advanced reinforcement learning controllers—Soft Actor Critic (SAC), Twin Delayed Deep Deterministic Policy Gradient (TD3), and Deep Deterministic Policy Gradient (DDPG)—are implemented. These algorithms learn optimal control actions through continuous interaction with the environment, eliminating the need for manual tuning. Experimental analysis demonstrates that reinforcement learning controllers achieve faster settling time, lower error, improved disturbance rejection, and superior adaptability compared to traditional controllers. The results highlight the potential of RL-based controllers as robust, self-learning solutions for nonlinear industrial level-control applications.**

Keywords— Conical Tank, Nonlinear System, PID Control; MPC, Fuzzy Logic, FOPID, Reinforcement Learning, SAC, TD3, DDPG, Process Control, Level Control.

I. INTRODUCTION

Liquid-level regulation plays a vital role in various industrial processes, including chemical plants, food processing, wastewater treatment, and thermal systems. Among different process configurations, conical tanks are widely used due to their compact design and ability to handle variable flow operations. However, the nonlinear geometry of a conical tank causes the cross-sectional area to change with height, resulting in nonlinear and time-varying dynamics. This makes precise control difficult using traditional linear controllers.

Conventional control strategies such as PID, MPC, and Fuzzy Logic have been applied to conical tanks in previous studies, but their performance is often limited when dealing with abrupt disturbances, model uncertainties, and dynamically changing operating conditions. Fractional-Order PID (FOPID) controllers have been proposed as an enhancement, but they still require extensive parameter tuning and lack adaptability.

With recent advancements in artificial intelligence, Reinforcement Learning (RL) has emerged as a powerful tool for real-time control of nonlinear systems. RL algorithms learn optimal control behavior by interacting with the environment, making them suitable for systems with nonlinear, stochastic, or poorly modelled dynamics. Algorithms such as SAC, TD3, and DDPG offer continuous-control capability, stable learning, and improved robustness.

This journal presents an experimental approach to controlling a nonlinear conical tank using both classical and intelligent controllers. A complete comparison is performed to evaluate the improvement offered by RL-based strategies. The results show that reinforcement learning controllers significantly enhance accuracy, settling time, and adaptability, thereby demonstrating their applicability in modern industrial process control.

II. LITERATURE REVIEW

The level control of conical tanks has been widely studied due to their inherent nonlinear characteristics and industrial relevance in chemical, wastewater, and food processing applications. Several conventional, intelligent, and advanced control strategies have been proposed in literature. This section summarizes the most significant contributions and identifies the research gaps addressed in the present work.

Ravi et al. (2012) implemented *Dynamic Matrix Control (DMC)* on an interacting conical tank system and demonstrated improved servo and regulatory performance compared to classical controllers. However, the method exhibited a strong dependency on accurate system modeling, thereby limiting its applicability for highly nonlinear tanks where model mismatch is inevitable. This highlights the need for controllers that do not rely heavily on precise mathematical models.

Vavilala (2020) proposed a *Fractional Order Internal Model Controller (FOIMC)* for nonlinear conical tanks and reported enhanced tracking accuracy. Despite its improved performance, the tuning of fractional-order parameters was found to be complex, reducing its usefulness for real-time industrial deployment. Similarly, Kumar (2023) employed an *IMC-based PID strategy*, achieving reduced error indices but poor robustness under disturbance conditions. These studies collectively reaffirm that model-based controllers deliver good performance but struggle with nonlinearities and uncertainty.

Montaluisa et al. (2024) developed a *Model Predictive Control (MPC)* scheme for conical tanks, reporting effective setpoint tracking under nominal conditions. Nevertheless, the controller lacked adaptability under varying operating environments, underscoring the limitations of MPC when confronted with unmodeled dynamics or disturbances.

Omran et al. (2018) applied an *Artificial Neural Network (ANN) controller* to handle nonlinear level dynamics. The controller performed well within the trained operating range but required a large dataset for training and lacked adaptability to unseen conditions. This limitation draws attention to the need for controllers capable of autonomous learning without explicit offline training.

Urrea et al. (2021) compared *PID, gain-scheduled PID, fuzzy control, and IMC techniques* for an inverted conical tank. While fuzzy control demonstrated robustness to moderate disturbances, it failed under large variations and suffered from rule-dependence. The sensitivity of rule-based systems to process variations strengthens the motivation for adaptive learning-based control.

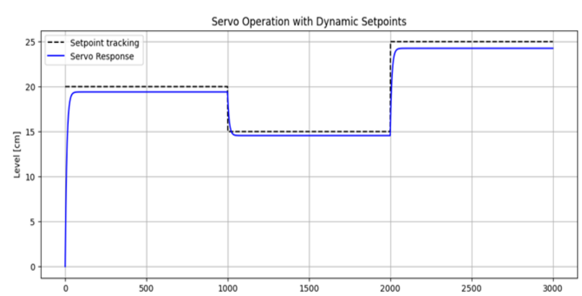
Ramanathan et al. (2018) and Noel (2014) explored *reinforcement learning (RL)-based controllers* for liquid level systems and reported better adaptability and robustness. However, existing RL implementations did not consider system identification techniques or hybrid modeling, leaving room for improved integration of RL with nonlinear process models.

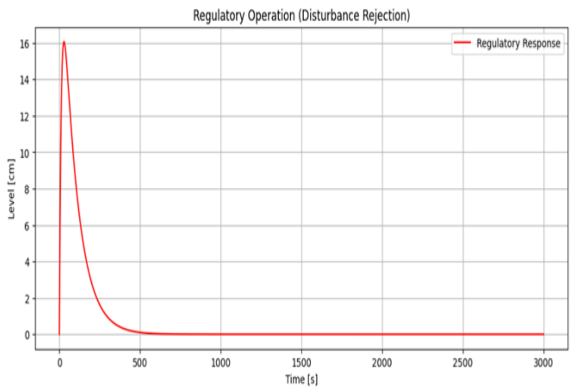
III. METHODOLOGY

3.1 *PID CONTROLLER*

The PID controller is a classical feedback control method that maintains the desired tank level by minimizing the error between the set point and the measured level. It uses three control actions — Proportional for present error correction, Integral for eliminating steady-state error, and Derivative for predicting future changes to reduce overshoot. In the conical tank system, the PID controller adjusts the inlet flow to keep the level constant. Although it provides a simple and effective control action, its performance decreases under nonlinear conditions, requiring frequent manual retuning.

Equation The continuous-time PID control law is:
$u(t) = Kp \cdot e(t) + (Kp / Ti) \cdot \int e(t)\, dt + Kp \cdot Td \cdot (de(t)/dt)$





3.2 MPC CONTROLLER

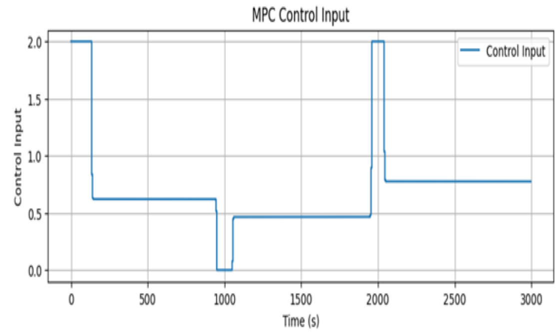
The Model Predictive Controller (MPC) is an advanced control strategy that predicts the future behavior of the system using a mathematical model and computes the optimal control action by minimizing a cost function. It adjusts the inlet flow of the conical tank to maintain the desired level while considering system constraints. MPC provides accurate and stable control, but its performance depends on an accurate process model and involves high computational effort, making it less suitable for highly nonlinear systems.

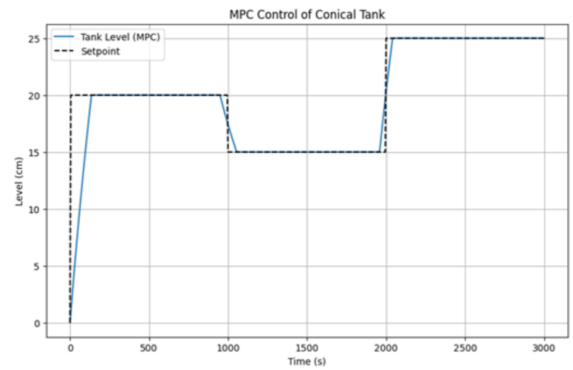
Prediction Model
For a nonlinear tank:
$h(k+1) = f(h(k), u(k))$
Linearized form used in MPC:
$x(k+1) = A\,x(k) + B\,u(k)$

Cost Function
$J = \Sigma(i = 1 \text{ to } Np)\ [\ y(k+i) - r(k+i)\ ]^2 \ + \Sigma(i = 1 \text{ to } Nu)\ [\ \lambda \cdot (\Delta u(k+i-1))^2\ ]$
Where:
Np = prediction horizon
Nu = control horizon
λ = input weight
Δu = change in control input

Constraint Handling
$u\_min \le u(k) \le u\_max$
$\Delta u\_min \le \Delta u(k) \le \Delta u\_max$

Optimization Step
The optimal control action is:
$u^*(k) = \arg\min(J)$ with respect to u





3.3 FUZZY LOGIC CONTROLLER

The Fuzzy Logic Controller (FLC) is a knowledge-based control technique that uses if–then rules to mimic human decision-making. Instead of requiring a precise mathematical model, it works with linguistic variables such as “low,” “medium,” and “high” to handle uncertainty and nonlinearity effectively. In the conical tank system, the FLC adjusts the inlet flow based on the error and rate of change of error using fuzzy rules. It provides smooth and robust control, but its performance depends on the design of membership functions and rule base, which require expert knowledge.

Structure
1. Fuzzification
   Convert inputs e(t)e(t)e(t) and Δe(t)\Delta e(t)Δe(t) into fuzzy sets.
2. Rule Base
   Set of IF–THEN rules.
3. Inference Engine
   Applies fuzzy reasoning (typically Mamdani inference).
4. Defuzzification
   Converts fuzzy output to numerical control signal u(t)u(t)u(t).

Equation (General Form)

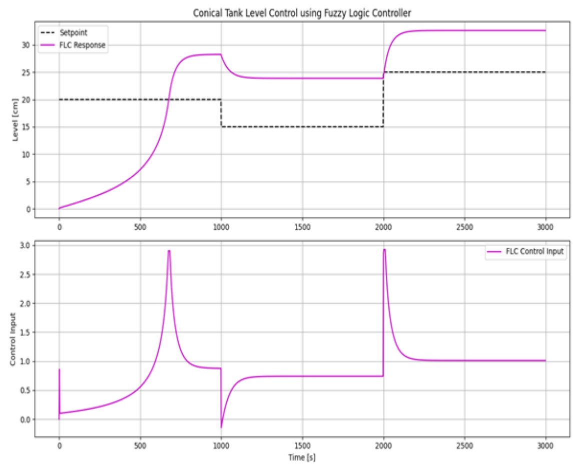
The FLC output is computed as:

$u(t) = \text{Defuzzify}\ \{ \sum \mu_i \cdot R_i(e, \Delta e) \}$

Where:

μ_i = firing strength of rule i

R_i = output of rule



3.4 FRACTIONAL ORDER PID CONTROLLER

The Fractional Order PID (FOPID) controller is an advanced version of the conventional PID controller where the integral and derivative orders are fractional (non-integer) rather than fixed at 1. This adds two extra tuning parameters that provide greater flexibility in shaping the system response. In the conical tank system, the FOPID controller improves performance by offering better robustness, faster response, and reduced steady-state error compared to the standard PID controller. However, it is complex to tune and requires accurate system modeling, which limits its adaptability for highly nonlinear systems.

Control Law

$u(t) = Kp \cdot e(t) + Ki \cdot D^{(-\lambda)}[e(t)] + Kd \cdot D^{(\mu)}[e(t)]$

Where:

Kp = proportional gain

Ki = integral gain

Kd = derivative gain

λ = fractional order of integration

μ = fractional order of differentiation

$D^{(-\lambda)}$ = fractional integral operator

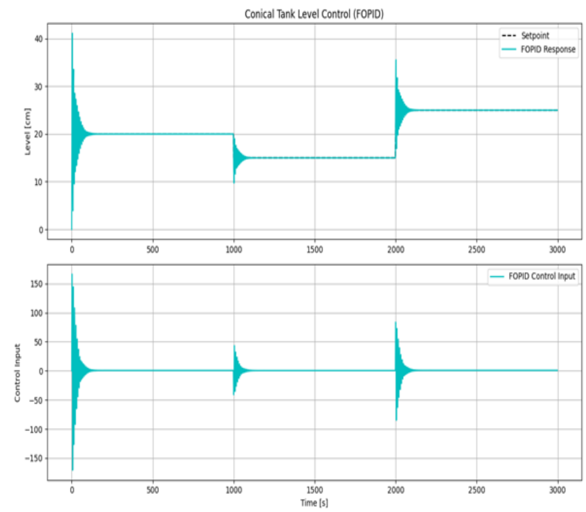
$D^{(\mu)}$ = fractional derivative operator

Parameter Set

FOPID has five tuning parameters:

$\{ Kp, Ki, Kd, \lambda, \mu \}$

Compared to only three for PID, giving significantly improved design freedom.



Controller	ISE	IAE	ITAE
PID	2937.716	543.359	392024.520
MPC	3585.492	291.553	72592.072
FLC	317505.978	28727.807	36681995.115
FOPID	5740.204	767.933	542436.574

IV. CONCLUSION

A comparative study of four classical controllers applied to a nonlinear conical tank system was presented. Experimental results show that FOPID performs best among classical methods, offering strong robustness, low overshoot, and fast settling. Fuzzy control provides smooth but slower responses, while MPC offers prediction-based control but lacks adaptability. PID remains simple and fast but handles nonlinearity poorly. The insights gained here form the foundation for implementing reinforcement learning controllers, which can dynamically adapt to the nonlinear behavior of the tank.

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