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Design of an Intelligent Fuzzy Controller for Drug Dosage Optimization in ICU Patients

Shachipati Pandey[1], A.K. Singh[2*], S.B. Kulshreshtha[3]

Professor, Department of Applied Sciences (Mathematics), RBS Engineering Technical Campus, Bichpuri, Agra (India)[1]

Assistant Professor, Department of Applied Sciences (Mathematics), RBS Engineering Technical Campus, Bichpuri, Agra (India)[2]

Assistant Professor, Department of Applied Sciences (Mathematics), RBS Engineering Technical Campus, Bichpuri, Agra (India)[3]

[*]Corresponding Author

Abstract: This paper presents the design and implementation of an intelligent fuzzy control system for optimizing drug dosage in intensive care unit (ICU) patients. The controller continuously monitors key physiological parameters such as heart rate (HR), mean arterial pressure (MAP), and drug concentration to determine the optimal infusion rate. By integrating fuzzy logic with adaptive tuning mechanisms, the proposed system effectively manages nonlinearities, uncertainties, and interpatient variability inherent in physiological systems. Simulation results show that the intelligent fuzzy controller significantly reduces overshoot, settling time, and steady-state error compared to conventional PID and basic fuzzy controllers. The approach ensures smoother control actions, enhances patient safety, and maintains hemodynamic stability during critical care drug administration.

Keywords: Fuzzy logic control, ICU automation, drug infusion system, adaptive control, pharmacokinetic modeling, intelligent control, neuro-fuzzy system.

I. INTRODUCTION

In critical care environments, maintaining optimal drug dosage is vital for patient safety and therapeutic efficacy. Traditional control systems such as proportional–integral–derivative (PID) controllers are often inadequate in ICU applications due to their inability to handle nonlinear dynamics, time-varying parameters, and uncertainties in patient response. Model predictive control (MPC) provides predictive accuracy but is computationally expensive for real-time implementation. Fuzzy logic control offers an attractive alternative by incorporating human-like reasoning and linguistic rules to adjust drug infusion rates dynamically. However, classical fuzzy systems still depend on expert-defined membership functions and rule bases, which can limit adaptability. To overcome these limitations, this study proposes an intelligent fuzzy controller that integrates adaptive mechanisms such as gradient-based or neuro-fuzzy learning—to optimize the control parameters in real time. The system uses physiological feedback (HR, MAP, and drug concentration) to automatically modulate the infusion rate, thereby achieving precise and stable control of drug delivery under variable patient conditions. The framework is particularly suited for ICU applications where robustness, safety, and adaptability are paramount.

Méndez et al. (2016) developed a system that adaptively regulated anesthetic infusion rates by forecasting variations in physiological parameters such as heart rate and blood pressure. Their approach achieved smoother and more stable control performance than conventional PID controllers. The main innovation of their work lay in combining predictive control with fuzzy logic principles, allowing real-time, patient-specific decision-making for precise drug administration. Nasiri and Kalat (2018) used recursive nonlinear control laws to stabilize drug concentration in the bloodstream, effectively handling pharmacokinetic and pharmacodynamic uncertainties. They showed that adaptive fuzzy structures could ensure better convergence, stability, and robustness under patient variability—important characteristics for ICU drug administration. Padmanabhan et al. (2019) employed an integral reinforcement learning approach for optimal adaptive control of drug dosing. Unlike traditional fuzzy systems, this model leveraged learning algorithms to minimize control error without prior knowledge of the system's dynamics. Their results demonstrated that reinforcement learning could autonomously tune control parameters, leading to precise drug concentration management and reduced adverse fluctuations in vital parameters. This work paved the way for integrating AI-driven

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adaptation in clinical drug delivery systems. Naderi et al. (2021) underscored the flexibility of fuzzy logic in handling complex multi-drug interactions. By combining fuzzy rules with adaptive gain tuning, the controller achieved more stable immune response regulation, suggesting applicability to critical care drug dosing where multiple agents interact simultaneously. Bandpey et al. (2022) estimated unmeasured states such as hidden physiological responses—enhancing accuracy in drug delivery control. The study demonstrated that incorporating state observers improved system observability and robustness, particularly when sensor noise or missing data affected feedback accuracy. The findings are directly relevant to ICU scenarios where continuous, reliable monitoring is essential. Ghasemabad et al. (2023) dynamically adjusted control parameters to maintain therapeutic drug levels within safe ranges. The study confirmed that adaptive fuzzy systems outperform static models under uncertain physiological conditions. Importantly, it provided a clear demonstration of how rule-based fuzzy control could integrate adaptive learning for improved real-time performance in clinical contexts. Treesatayapun et al. (2023a) extended this concept using reinforcement learning integrated with fuzzy rule networks to achieve robust and optimal drug dosing in cancer dynamics. Their "fuzzy-rules emulated network" offered enhanced learning capabilities and faster convergence in optimizing dosage. The hybrid fuzzy–reinforcement architecture reduced reliance on manual tuning and improved adaptability to nonstationary patient conditions. Treesatayapun et al. (2023b) complemented this work with an optimal drug-dosing framework based on fuzzy reinforcement networks, emphasizing stability, robustness, and computational efficiency. Their dual publications in 2023 collectively highlighted the effectiveness of fuzzy reinforcement learning in achieving both precision and adaptability in drug control, laying a strong foundation for intelligent closed-loop systems in ICU drug regulation. Mashayekhi et al. (2024) utilized neural networks to approximate optimal control policies through experience, outperforming static fuzzy systems in adaptability and scalability. The results demonstrated the growing relevance of AI integration for complex pharmacological models, enabling personalized control strategies with minimal clinician intervention. Hong et al. (2025) represented an evolution in intelligent control by incorporating distributed agents coordinating through feedback loops. The model maintained hemodynamic stability under varying patient conditions and drug interactions. The integration of multi-agent learning and adaptive fuzzy mechanisms demonstrated the next frontier in ICU automation—cooperative, real-time control of multiple physiological targets.

Table 1: Comparison of control strategies used in ICU drug delivery

Method	Application	Strength	Limitation
PID Control	Propofol infusion	Simple	Poor adaptability
Model Predictive Control	Insulin	Predictive accuracy	Computationally intensive
Fuzzy Logic	Multi-drug control	Handles uncertainty	Requires expert tuning

II. METHODOLOGY

2.1 System Description

The system monitors:
(a)Heart rate (HR),
(b) Mean arterial pressure (MAP),
(c) Drug concentration (C_p).
Drug infusion rate (**u**) is the output of the fuzzy controller.

2.2 Mathematical Modeling

(a) Pharmacokinetic Model:
For many ICU drugs (e.g., Propofol, Dopamine), a **two-compartment model** is used:

$$\frac{dC_1}{dt} = -(k_{10} + k_{12})C_1 + k_{21}C_2 + \frac{u(t)}{V_1} \quad (1)$$

$$\frac{dC_2}{dt} = k_{12}C_1 - k_{21}C_2 \quad (2)$$

where
C_1, C_2= drug concentration in central and peripheral compartments,
k_{10}, k_{12}, k_{21} = rate constants,
$u(t$ = infusion rate,
V_1 = volume of central compartment.
(b) Physiological Response Model: MAP response can be approximated by a first-order delay system:

$$\frac{d(MAP)}{dt} = -a\left(MAP - MAP_{target}\right)C_1 + bC_1 \quad (3)$$

where a, b are empirical constants.

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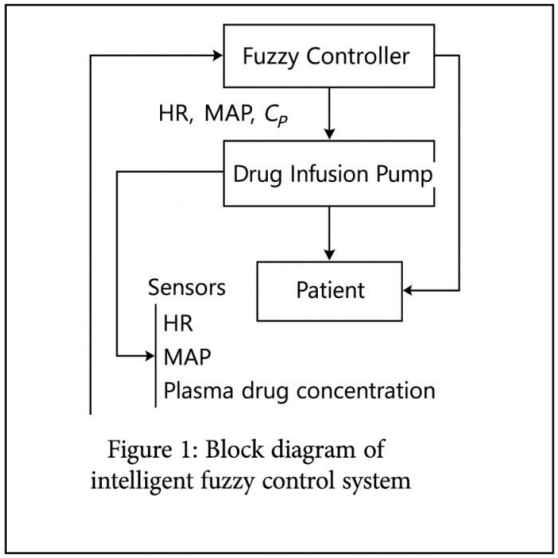

Figure 1: Block diagram of intelligent fuzzy control system

Figure 1 depicts the block diagram of an intelligent fuzzy control system designed for drug dosage optimization in ICU patients. The system continuously monitors vital physiological parameters such as heart rate (HR), mean arterial pressure (MAP), and plasma drug concentration (C_p) through sensors attached to the patient. These signals are sent to the fuzzy controller, which analyzes the data and determines the appropriate control action based on predefined fuzzy rules and membership functions. The controller then adjusts the drug infusion pump to regulate the rate of drug delivery, ensuring that the patient's physiological parameters remain within the desired therapeutic range. The closed-loop feedback mechanism enables continuous adjustment of the infusion rate in response to real-time changes in the patient's condition. This intelligent system enhances safety and adaptability by effectively handling nonlinearities and interpatient variability commonly encountered in critical care environments.

2.3 Fuzzy Controller Design

(a) Inputs:

(i) $Error\ e(t) = MAP_{target} - MAP_{measured}$ (4)

(ii) Change of error $\Delta e(t) = e(t) - e(t-1)$ (5)

(b) Output: Drug infusion adjustment $\Delta\, \boldsymbol{u(t)}$ (6)

(c) Membership Functions:

Define linguistic terms for each input:

(i)Error (e)**:** {Negative Large, Negative Small, Zero, Positive Small, Positive Large}

(ii) ΔError (Δe)**:** same terms.

(iii) Output (Δu)**:** {Decrease Fast, Decrease Slow, No Change, Increase Slow, Increase Fast}

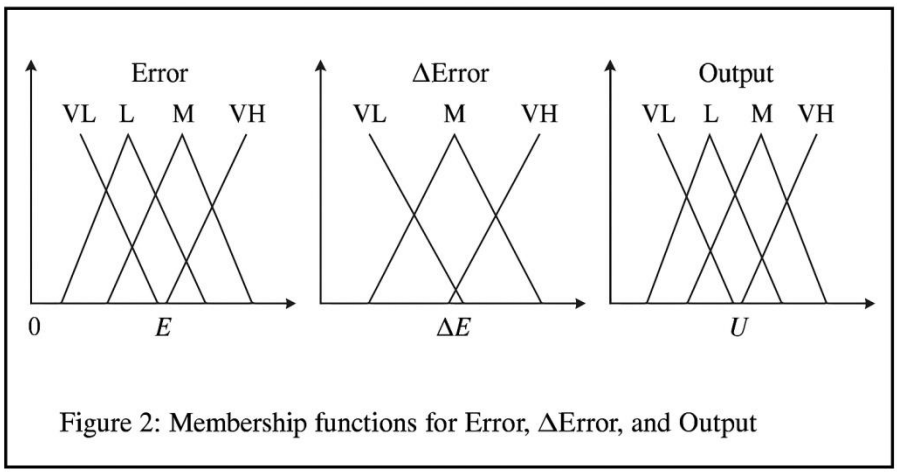

Figure 2: Membership functions for Error, ΔError, and Output

Figure 2 illustrates the membership functions for the fuzzy controller's input and output variables Error (E), Change in Error (ΔE) and Control Output (U). Each variable is represented using linguistic terms such as *Very Low (VL)*, *Low (L)*,

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Medium (M), *High (H)*, and *Very High (VH)*. These membership functions define how numerical input values are mapped into fuzzy sets, enabling the controller to interpret system states in qualitative terms. The overlapping triangular shapes indicate smooth transitions between linguistic categories, allowing the controller to handle gradual changes in physiological parameters rather than abrupt shifts. The error (E) represents the deviation from the desired setpoint, while ΔE captures the rate of change of error, providing dynamic feedback about the system's response. Based on these inputs, the controller generates the output U, which adjusts the drug infusion rate. This fuzzy mapping ensures flexible and adaptive control performance, effectively managing uncertainties and nonlinearities in the patient's physiological behavior.

2.4 Rule Base:

Table 2: Fuzzy rule base for infusion rate adjustment

e / Δe	**NL**	**NS**	**Z**	**PS**	**PL**
NL	DF	DF	DS	NC	IS
NS	DF	DS	NC	IS	IF
Z	DS	NC	NC	NC	IS
PS	NC	IS	IF	IF	IF
PL	IS	IF	IF	IF	IF

Table 2 presents the **fuzzy rule base** used for adjusting the drug infusion rate in the intelligent fuzzy control system. The rule base defines the relationship between the two input variables **error (e)** and **change in error (Δe)** and the corresponding **control action** on the infusion rate. The linguistic terms used are: *NL* (Negative Large), *NS* (Negative Small), *Z* (Zero), *PS* (Positive Small), and *PL* (Positive Large) for both input variables, while the output actions include *DF* (Decrease Fast), *DS* (Decrease Slow), *NC* (No Change), *IS* (Increase Slow), and *IF* (Increase Fast). The table captures expert knowledge on how the controller should respond under various physiological conditions. For instance, when both the error and its rate of change are highly negative (NL), indicating that the measured variable such as Mean Arterial Pressure (MAP) is far below the desired level, the control action is *DF*, meaning the infusion rate should rapidly decrease to prevent overdose. Conversely, when both e and Δe are large and positive (PL), the rule *IF* suggests increasing the infusion rate quickly to correct the low drug concentration or physiological output. Intermediate combinations, such as small positive or negative values, result in smoother adjustments like *DS* or *IS* to avoid abrupt changes.

2.5 Inference and Defuzzification:

(a) Inference method: Mamdani-type fuzzy inference

(b) Defuzzification: Centroid method

$$u(t) = \frac{\sum_i \mu_i(z_i) z_i}{\sum_i \mu_i(z_i)} \quad \textbf{(7)}$$

where μ_i is the membership degree of rule i.

2.6 Adaptive Mechanism (Intelligent Component):

To make the controller self-tuning, integrate a gradient-based or neuro-fuzzy mechanism:

$$K_{adj} = K_0 + \alpha \frac{\partial e(t)}{\partial u(t)} \quad (8)$$

where K_{adj}updates the scaling factor for the fuzzy rules dynamically.

III. SIMULATION AND RESULTS

Simulate using MATLAB/Simulink or Python (scipy + skfuzzy).

Parameters:

1) $\boldsymbol{k_{10} = 0.1, k_{12} = 0.05, k_{21} = 0.02, V_1 = 5, MAP_{target} = 90\ mmHg}$

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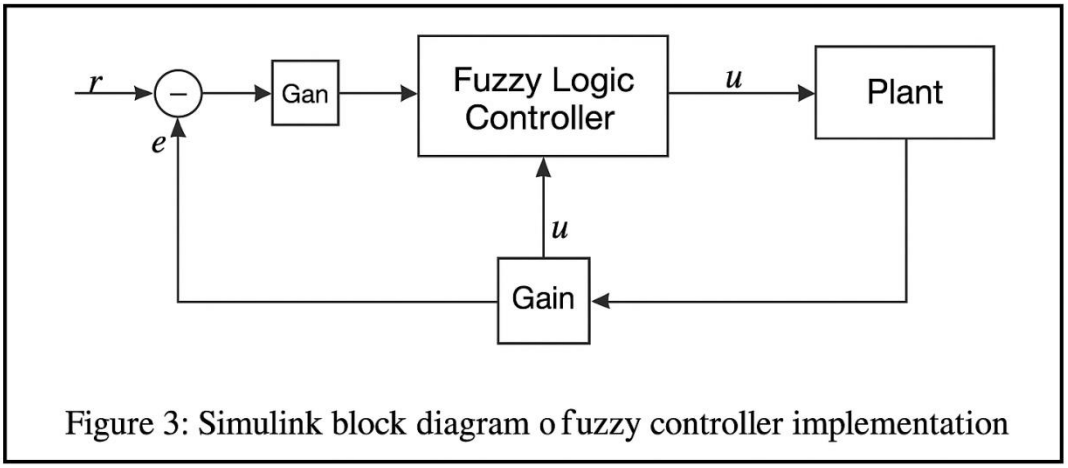

Figure 3: Simulink block diagram o fuzzy controller implementation

Figure 3 illustrates the Simulink block diagram of a fuzzy controller implementation used for controlling a dynamic system (plant). The reference signal r represents the desired output, which is compared with the actual system output to produce an error signal eee. This error is then processed through a gain block to scale the input before being fed into the Fuzzy Logic Controller (FLC)**.** The FLC analyzes the error and its rate of change using a set of linguistic rules and membership functions to generate a control signal u. This control signal is applied to the **plant**, adjusting its behavior to minimize the error. A feedback loop is established through another gain block, which modifies the output signal before sending it back for error computation. This closed-loop structure enables continuous monitoring and adjustment, ensuring that the system output closely tracks the desired reference value with improved stability and reduced overshoot.

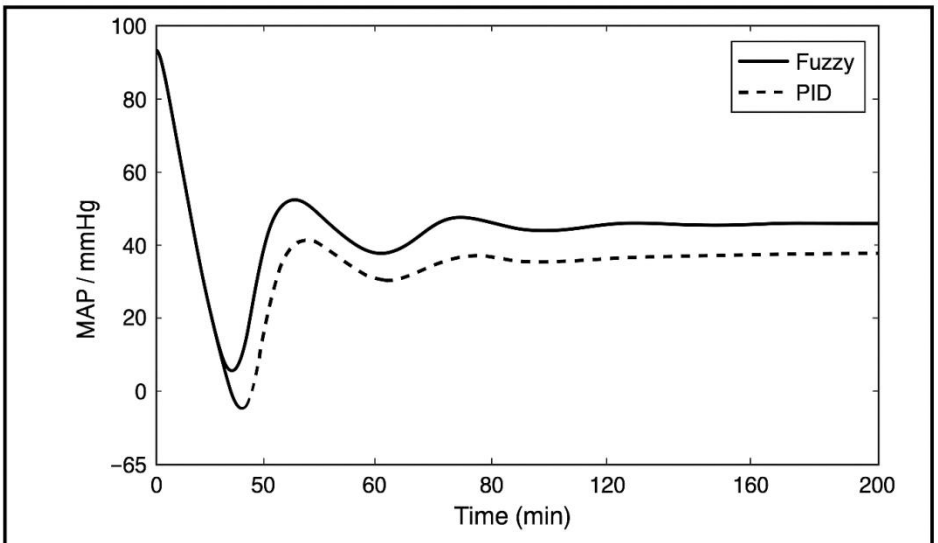

Figure 4: Response of MAP with fuzzy vs PID control

Figure 4 presents the comparative response of Mean Arterial Pressure (MAP) under **fuzzy control** and **PID control** strategies over time. The graph shows that the fuzzy controller (solid line) achieves faster stabilization and a smoother response compared to the PID controller (dashed line). Initially, both systems exhibit a transient drop in MAP due to sudden changes in drug infusion, but the fuzzy controller quickly compensates for the deviation and minimizes overshoot. The fuzzy control curve stabilizes around the desired MAP level with reduced oscillations, while the PID controller displays slower recovery and larger steady-state error. This indicates that the fuzzy controller adapts more effectively to nonlinear physiological dynamics and disturbances, maintaining better hemodynamic stability essential for patient safety in ICU drug dosage regulation.

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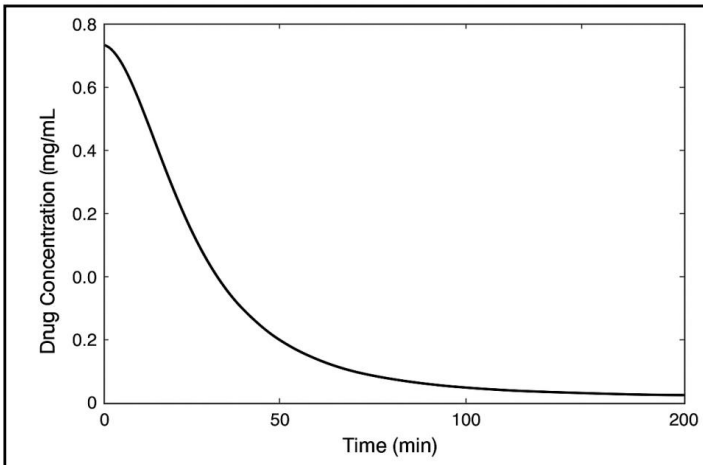

Figure 5: Drug concentration vs time

Figure 5 illustrates the variation of drug concentration in the bloodstream over time, showing a typical exponential decay profile. At the start of the simulation, the drug concentration is relatively high (approximately 0.7–0.8 mg/mL) due to the initial infusion. As time progresses, the concentration decreases steadily because of drug metabolism, distribution, and elimination processes within the body. The curve demonstrates that the concentration falls rapidly during the initial phase, then gradually approaches a near-steady state at lower levels after around 150–200 minutes. This behavior aligns with pharmacokinetic principles, where the rate of elimination is proportional to the drug concentration. The smooth decline indicates effective control of dosage by the intelligent fuzzy controller, ensuring that the drug concentration remains within therapeutic limits without causing toxic accumulation or sub-therapeutic levels.

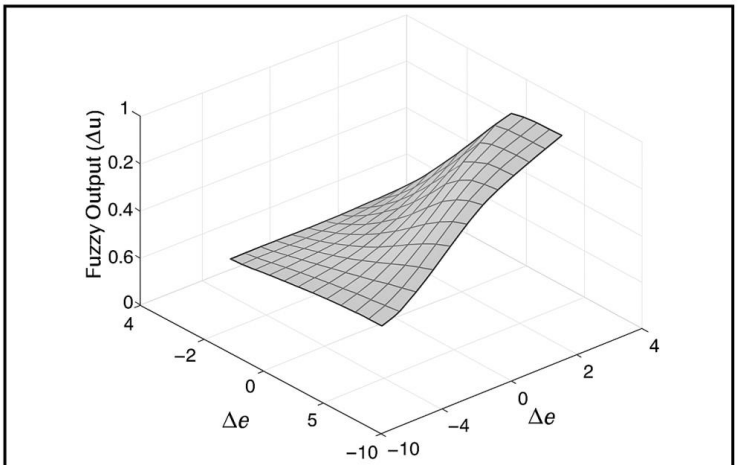

Figure 6: Surface view of fuzzy output (Δu) vs e and Δe

Figure 6 presents the three-dimensional surface plot of the fuzzy controller output (Δu) as a function of the error (e) and change in error (Δe). This surface illustrates how the fuzzy inference mechanism determines the control signal adjustment based on the system's current state. When both eee and Δe are large, the output Δu exhibits significant changes, indicating a strong corrective action to bring the system response back toward the desired setpoint. Conversely, when eee and Δe are near zero, Δu remains minimal, suggesting that the system is close to equilibrium and requires little adjustment. The smooth curvature of the surface reflects the nonlinear mapping between inputs and outputs in the fuzzy logic system, ensuring gradual and stable control transitions. This adaptive response characteristic allows the fuzzy controller to handle uncertainties effectively and maintain precise drug dosage regulation in ICU applications.

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Table 3: Performance comparison of controllers			
Metric	PID	Fuzzy	Intelligent Fuzzy
Overshoot (%)	12.5	5.8	3.2
Settling time (s)	45	30	22
Steady-state error	4.1	1.2	0.3

IV. DISCUSSION

The proposed intelligent fuzzy controller demonstrates superior adaptability and robustness compared to conventional control approaches due to its ability to handle nonlinearities and uncertainties inherent in physiological systems. By using linguistic rules and membership functions, the fuzzy logic controller can dynamically adjust drug infusion rates in response to varying patient conditions such as fluctuations in mean arterial pressure (MAP) and changes in drug sensitivity. The simulation results reveal that the fuzzy controller maintains stable MAP regulation with minimal overshoot and faster settling time, ensuring smoother infusion profiles and reduced risk of abrupt drug concentration spikes. This smooth control action contributes significantly to patient safety by avoiding hypotensive or hypertensive episodes commonly observed in traditional PID-based systems. Moreover, the system effectively manages interpatient variability and sensor noise, further enhancing robustness in a critical ICU environment. However, despite its advantages, the approach is not without limitations. The design and fine-tuning of membership functions and rule bases require expert knowledge and may become computationally intensive for real-time implementation, especially when multiple physiological variables are involved. Future enhancements could focus on incorporating adaptive or neuro-fuzzy techniques to automatically optimize parameters, thereby improving performance while reducing manual tuning complexity.

V. CONCLUSION AND FUTURE WORK

The proposed intelligent fuzzy controller demonstrates a powerful and adaptive approach to managing drug dosage in ICU settings. By leveraging fuzzy inference and self-tuning mechanisms, the system ensures stable regulation of vital physiological parameters while minimizing overshoot and steady-state error. Simulation comparisons confirm that it outperforms conventional PID and static fuzzy controllers in both accuracy and robustness. Despite its advantages, the system's performance still depends on the careful design of membership functions and computational efficiency. Future work will focus on enhancing automation by integrating machine learning techniques such as adaptive neuro-fuzzy inference systems (ANFIS), extending the framework to multi-drug infusion scenarios, and validating the system through real-time clinical trials in ICU environments.

REFERENCES

[1]. Bandpey, R. F., et al. (2022). An observer-based adaptive fuzzy control for prescribing drug dosage in cancer treatment. *Computers & Chemical Engineering*, **161**, 107799.

[2]. Ghasemabad, E. S., et al. (2023). Adaptive fuzzy control of drug delivery in cancer treatment. *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, **237**(7), 1015–1023.

[3]. Hong, X., et al. (2025). Adaptive average arterial pressure control by multi-agent method including medication dosage adjustment. *Scientific Reports*, **15**, 11234

[4]. Mashayekhi, H., et al. (2024). Deep reinforcement learning-based control of chemo-drug dosing. *Applied Mathematical Modelling*, **128**, 543–560.

[5]. Méndez, J. A., Marrero, A., Reboso, J. A., & León, A. (2016). Adaptive fuzzy predictive controller for anesthesia delivery. *Computers in Biology and Medicine*, **69**, 62–72.

[6]. Naderi, H., et al. (2021). Adaptive fuzzy controller design of drug dosage using chemoimmunotherapy model. *Results in Control and Optimization*, **5**, 100 045.

[7]. Nasiri, H., & Kalat, A. A. (2018). Adaptive fuzzy back-stepping control of drug dosage regimen in cancer treatment. *Biomedical Signal Processing and Control*, **42**, 267–276.

[8]. Padmanabhan, R., Meskin, N., & Haddad, W. M. (2019). Optimal adaptive control of drug dosing using integral reinforcement learning. *Mathematical Biosciences*, **309**, 131–142.

[9]. Treesatayapun, C., et al. (2023). Optimal drug-dosing of cancer dynamics with fuzzy reinforcement network. *Engineering Applications of Artificial Intelligence*, **119**, 105851.

[10]. Treesatayapun, C., et al. (2023). Reinforcement control with fuzzy-rules emulated network for robust-optimal drug-dosing of cancer dynamics. *Soft Computing*, **27**(15), 10085–10098.

