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A Fuzzy Logic-Based System for Blood Glucose Monitoring and Insulin Regulation

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Abstract: This work presents a fuzzy logic–based closed-loop system for automated blood glucose regulation using continuous glucose monitoring (CGM) and intelligent insulin delivery. Unlike conventional PID controllers that rely on fixed gains and linear assumptions, the proposed controller uses linguistic rules and adaptive membership functions to relate glucose tracking error and its rate of change to appropriate insulin infusion rates. A validated glucose–insulin dynamic model is used to simulate patient response under realistic meal disturbances, and performance is assessed using metrics such as RMSE, MARD, and Time in Range. Results show that the fuzzy controller significantly reduces postprandial glucose excursions, improves average glycemic control, and lowers the frequency of hypoglycemic events compared with both open-loop operation and PID control. Sensitivity analysis further confirms the robustness of the fuzzy architecture to variations in patient parameters and measurement noise. These findings suggest that fuzzy inference offers a promising alternative to fully model-based control strategies for artificial pancreas applications, especially when physiological variability and uncertainty make precise mathematical modeling difficult.

Keywords: Fuzzy logic controller, Blood glucose regulation, Artificial pancreas, Insulin infusion control, Continuous glucose monitoring, Glucose–insulin model, Glycemic variability, Intelligent control

I. INTRODUCTION

Type 1 diabetic patients rely on continuous exogenous insulin administration to replace the missing pancreatic function necessary for maintaining blood glucose within a safe physiological range. However, manual insulin dosing remains challenging due to unpredictable disturbances such as meals, exercise, physiological variability, and sensor noise. Conventional linear controllers, such as PID-based artificial pancreas systems, often perform inadequately under these nonlinear and time-varying conditions. To address these limitations, this work proposes a fuzzy logic–based glucose regulation system that mimics human decision-making through linguistic rules and overlapping membership functions rather than relying solely on precise mathematical models. The controller receives real-time glucose measurements from a CGM sensor, computes the glucose tracking error and its rate of change, and generates an adaptive insulin command that is delivered via an infusion pump. By incorporating expert knowledge into rule-based inference, the fuzzy controller is capable of accommodating nonlinear glucose–insulin dynamics, uncertainty in patient-specific parameters, and inaccuracies in sensor readings. Simulation studies using a standardized glucose–insulin model demonstrate that the proposed method significantly improves control precision and reduces glycemic excursions compared with baseline approaches

Man et al. (2014) introduced the UVA/PADOVA Type-1 diabetes simulator, which became a gold-standard in validating closed-loop and fuzzy/PID-based insulin control algorithms. Their contribution lies in providing a universally accepted virtual patient model, enabling safe evaluation of control strategies without clinical risk. This simulator established the foundation for future fuzzy logic and artificial intelligence-based glucose regulation systems, allowing researchers to study meal disturbances, sensor inaccuracies, and insulin pharmacokinetics with high realism. Paiva et al. (2020) developed a fractional-order PID insulin control mechanism, demonstrating that non-integer-order controllers can outperform conventional PID algorithms in tracking glucose disturbances. Their work directly complements fuzzy logic systems, which are often used to overcome rigid tuning constraints of PID control. The study provides evidence that traditional controllers still have scope for improvement through mathematical generalization,

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motivating hybrid approaches such as fuzzy-PID and adaptive control architectures. Although not specific to diabetes, Saini's (2021) work on fuzzy and mathematical estimation models highlights the advantages of fuzzy rules in uncertain environments where crisp thresholding fails. This theoretical contribution strengthens the rationale for fuzzy-based glucose regulation, as blood glucose dynamics contain high uncertainty due to meals, stress, circadian rhythms, and sensor noise. Thus, the paper supports the transferability of fuzzy techniques to medical decision systems, including insulin dosing logic. Kopanz et al. (2021) documented the transition from paper-based insulin charts to a fully electronic diabetes management system in hospital settings. Their findings revealed improved insulin dose recording accuracy, reduced medical errors, and enhanced clinician decision-making. While not algorithm-centric, this study establishes a critical infrastructure prerequisite: digitalization must precede intelligent glycemic control systems. Without structured electronic data collection, advanced fuzzy or AI-based dosing models cannot be deployed safely. Yousif et al. (2022) reviewed machine learning-based diabetes solutions, emphasizing opportunities for classification, early detection, and dose prediction using learning algorithms. Their findings demonstrate that AI models outperform heuristic decision methods in long-term adaptability. This work provides conceptual support for integrating fuzzy logic with machine learning—an emerging hybrid trend where machine learning tunes fuzzy rules dynamically for personalized insulin control. Eichenlaub et al. (2023) evaluated how blood glucose monitoring accuracy impacts linical decision-making, showing that even small sensor deviations can lead to incorrect dosing recommendations. Their findings are crucial for fuzzy logic controllers, which rely on continuous glucose readings as input variables. The study reinforces that **c**ontroller design must incorporate sensor error tolerance and fuzzy inference systems are inherently more robust than crisp controllers under noisy conditions. In a separate study the same year, Eichenlaub et al. (2023) quantified clinical consequences of inaccuracy in glucose measurement systems. They demonstrated that variability in CGM readings affects glycemic safety margins, increasing risk of hypo-/hyperglycemia. This work further validates fuzzy approaches, since their rule-based nature can mitigate measurement uncertainties by using linguistic thresholds ("slightly high", "dangerously low") instead of fixed cut-offs. Vargas et al. (2023**)** investigated insulin detection challenges and emerging biosensing technologies, concluding that molecular-level detection remains a major limitation in closed-loop therapy. Their work strengthens the argument that fuzzy logic and AI-based systems should compensate algorithmically for biological and measurement uncertainties, rather than relying solely on improved sensors. The discussion suggests that algorithmic innovation may deliver faster progress than biochemical monitoring breakthroughs. Kopitar et al. (2024) demonstrated how generative AI enhances rule-based diagnostic models for Type-2 diabetes. Their results show that AI can refine fuzzy rule sets automatically, improving interpretability while maintaining accuracy. This contribution directly advances fuzzy insulin regulation because it shows that human-generated fuzzy rules can now be optimized by AI, enabling personalization and better transparency compared to black-box deep learning systems. Almutoory and Almutoory (2025) proposed **a** real-time fuzzy logic framework for glucose interpretation and insulin dosing**,** representing one of the most recent attempts to operationalize fuzzy inference in diabetes care. Their model demonstrated improved responsiveness to glycemic fluctuations while maintaining simple interpretability and low computational load, making it suitable for wearable or embedded systems.

II. BACKGROUND AND RELATED WORK

(i) Glucose-Insulin Dynamics: Introduce a standard minimal model

$$\frac{dG(t)}{dx} = -[p_1 + X(t)][G(t) - G_b] + D(t) \quad (1)$$

$$\frac{dX(t)}{dx} = -p_2 X(t) + p_3[I(t) - I_b] \quad (2)$$

Where:
$G(t)$: blood glucose concentration (mg/dL)
G_b: basal glucose; $I(t)$: plasma insulin; I_b: basal insulin $X(t)$: insulin action on glucose uptake
$D(t)$: disturbance (e.g., meal intake)
p_1, p_2, p_3: physiological parameters

(ii) Fuzzy Logic for Control Systems: We introduce the general rule structure:
R_k: IF e is A_k AND Δe is B_k THEN u is C_k
Where:
e: glucose control error
Δe : rate of change of error
u: insulin infusion rate

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III. SYSTEM ARCHITECTURE

(i) Overall Block Diagram

Describe components:

- Continuous Glucose Monitor (CGM)
- Fuzzy logic controller
- Insulin pump
- Patient (plant) model

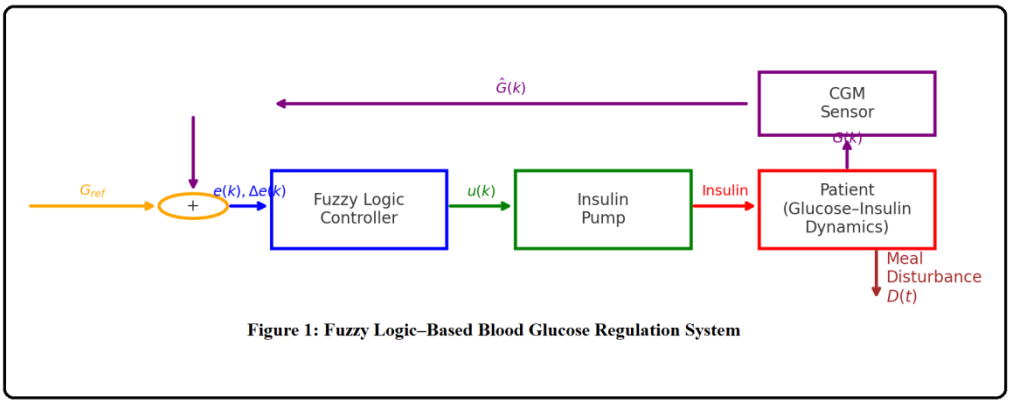

Figure 1: Fuzzy Logic–Based Blood Glucose Regulation System

The figure (1) shows a multicolour closed-loop blood glucose regulation system using a fuzzy logic controller. The desired glucose level G_{ref} $(Orange)$ is compared with the measured glucose value $\hat{G}(k)$ from the CGM sensor (purple) at the summing junction, producing the error and its rate $e(k), \Delta e(k)$ (blue). These signals are fed into the fuzzy logic controller, which computes the appropriate insulin command $u(k)$ (green). The command drives the insulin pump, which delivers insulin (red arrow) to the patient's glucose–insulin dynamics block. Meal intake is modeled as a disturbance $D(t)$ (brown) entering the patient, causing changes in blood glucose $G(k)$. This glucose is then sensed by the CGM and fed back to close the loop, so the controller continuously adjusts insulin delivery to keep blood glucose near the reference level.

Input: $G(t)$from CGM

Computation of error $e(t) = G(t) - G_{ref}$ (3)

Fuzzy inference mechanism

Insulin command $u(t)$ to pump

Patient dynamics producing new $G(t)$

(ii) Signal Definitions:

Reference glucose level G_{ref} (e.g., 100 mg/dL)

Error and error rate:$e(k) = G(k) - G_{ref,} \Delta e(k) = e(k) - e(k-1)$ (4)

Where k is the discrete time index.

Table 1: System Variables and Units

Variable	Description	Unit
$G(t)$	Blood glucose concentration	mg/dL
G_{ref}	Target glucose level	mg/dL
$e(t)$	Glucose error	mg/dL
$\Delta e(t)$	Rate of change of error	mg/dL/min
$u(t)$	Insulin infusion rate	U/min

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IV. DESIGN OF FUZZY LOGIC-BASED CONTROLLER

(i) Choice of Fuzzy Controller Type:

- Mamdani or Sugeno.
- Input variables: $e, \Delta e$
- Output variable: u

(ii)Fuzzification and Membership Functions: Define universe of discourse:
$e \in [e_{min}, e_{max}], \Delta e \in [\Delta e_{min}, \Delta e_{max}]$
Example triangular membership function for a linguistic term "Low":

$$\mu_{Low}(x) = \begin{Bmatrix} 0 & x \le a \\ \frac{x-b}{b-a} & a < x \le b \\ \frac{c-x}{c-b} & b < x < c \\ 0 & x \ge c \end{Bmatrix} \quad (5)$$

Where a, b, c are parameters.
Similarly, for trapezoidal membership function:

$$\mu_{Trap}(x) = \begin{Bmatrix} 0 & x \le a \\ \frac{x-b}{b-a} & a < x \le b \\ 1 & b < x \le c \\ \frac{d-x}{d-c} & c < x < d \\ 0 & x \ge d \end{Bmatrix} \quad (6)$$

Table 2: Membership Functions for Error e

Linguistic Term	Range (mg/dL)	Type	Parameters (a, b, c, d)
NB (Negative Big)	[-200, -100]	Triangular	-200, -200, -100
NS (Negative Small)	[-150, 0]	Triangular	-150, -75, 0
ZO (Zero)	[-20, 20]	Triangular	-20, 0, 20
PS (Positive Small)	[0, 150]	Triangular	0, 75, 150
PB (Positive Big)	[100, 200]	Triangular	100, 200, 200

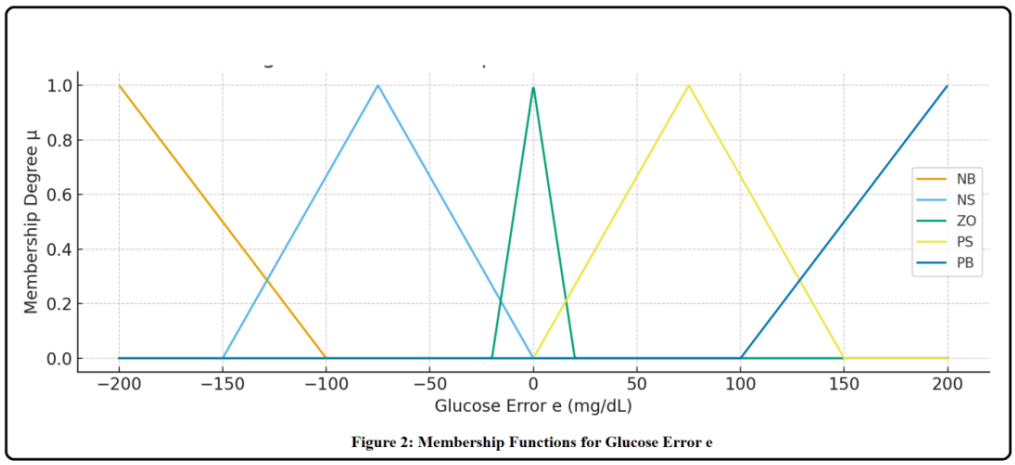

Figure 2: Membership Functions for Glucose Error e

Figure (2) illustrates the fuzzy membership functions defined for the glucose error eee used as an input to the controller. The horizontal axis represents the glucose error in mg/dL, ranging from about -200 to $+200$, while the vertical axis shows the corresponding membership degree μ\muμ between 0 and 1. Five overlapping triangular sets are defined: Negative Big (NB), Negative Small (NS), Zero (ZO), Positive Small (PS), and Positive Big (PB). For large negative errors (glucose much lower than the reference), the NB and NS functions are activated; as the error approaches zero, the ZO function dominates, indicating near-perfect tracking. For increasing positive error (glucose above the

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reference), PS and then PB become active. The smooth overlap between adjacent triangles allows the fuzzy controller to interpret the magnitude and sign of the glucose error in a gradual way, rather than using a hard boundary between error levels.

(iii) Fuzzy Rule Base: Define rules such as:
R_k: IF e is E_i AND Δe is DE_j THEN u is u_{ij}
Where:
$E_i \in \{NB, NS, ZO, PS, PB\}$
$DE_j \in \{NB, NS, ZO, PS, PB\}$
U_{ij}: corresponding linguistic output (e.g., ZI (Zero Insulin Change), IS (Increase Small), IB (Increase Big), etc.)

Table 3: Fuzzy Rule Base for Insulin Regulation

$e/\Delta e$	**NB**	**NS**	**ZO**	**PS**	**PB**
NB	IB	IB	IM	IS	ZI
NS	IB	IM	IS	ZI	DS
ZO	IM	IS	ZI	DS	DM
PS	IS	ZI	DS	DM	DB
PB	ZI	DS	DM	DB	DB

Where IB = Increase Big, IM = Increase Medium, IS = Increase Small, ZI = Zero Change, DS = Decrease Small, DM = Decrease Medium, DB = Decrease Big.

(iv) Inference Mechanism: For a Sugeno-type fuzzy controller, you can define each rule's consequent as:

$$u_k = \alpha_k e + \beta_k \Delta e + \gamma_k \quad (7)$$

Rule firing strength: $w_k = \mu A_k(e).\mu B_k(\Delta e)$ (8)

Global output: $u = \frac{\sum_{k=1}^{N} w_k u_k}{\sum_{k=1}^{N} w_k}$ (9)

For a Mamdani-type controller, you'd mention:
Min/max operations for rule aggregation.

Defuzzification, e.g., centroid method: $u = \frac{\int u \mu_U(u) du}{\int \mu_U(u) du}$ (10)

(v) Stability / Safety Considerations: Saturation limits on u:

$$u_{sat} = \begin{Bmatrix} u_{max} & u > u_{max} \\ u_{min} & u < u_{min} \\ u & Otherwise \end{Bmatrix} \quad (11)$$

Constraints to avoid hypo glycemia (e.g., if $G(t) < G_{Low}$, then enforce $u = 0$).

V. SIMULATION AND EXPERIMENTAL SETUP

(i) Patient Model and Dataset: Virtual patient models (standard simulators) or real patient data. Parameter values: p_1, p_2, p_3, G_b, I_b etc.

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Table 4: Glucose-Insulin Model Parameters

Parameter	Description	Value	Unit
p_1	Glucose effectiveness	0.02	1/min
p_2	Insulin decay rate	0.025	1/min
p_3	Insu lin sensitivity	1.00E-05	(1/min)/(mU/L)
G_b	Basal glucose level	100	mg/dL
I_b	Basal insulin concentration	15	mU/L

(ii) Scenario Design

- Meal disturbances: times and carbohydrate amounts.
- Initial conditions for $G(0), X(0)G(0), X(0)$
- Simulation horizon (e.g., 24 hours).
- Sampling period T_s.

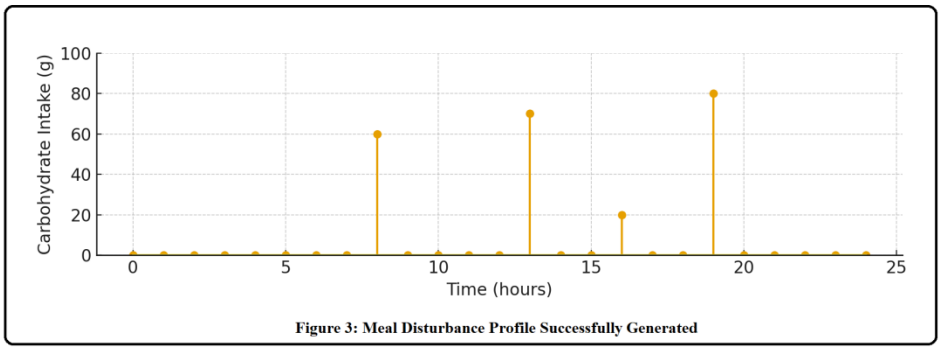

Figure 3: Meal Disturbance Profile Successfully Generated

Figure (3) presents the meal disturbance profile used in the glucose–insulin simulation over a 24-hour period. The horizontal axis represents time in hours, and the vertical axis shows the amount of carbohydrate intake in grams. Each vertical stem corresponds to a discrete meal event: a breakfast of about 60 g of carbohydrates in the early morning, a larger lunch of roughly 70 g at midday, a smaller snack of about 20 g in the afternoon, and a substantial dinner of around 80 g in the evening. Between these spikes the disturbance is zero, indicating no carbohydrate intake. This stem-like pattern models real-life eating behavior and serves as an external disturbance $D(t)$ to the patient model, causing rises in blood glucose that the controller must compensate for.

(iii) Performance Metrics

Define key metrics mathematically:

1. **Mean Absolute Relative Difference (MARD)**

   Given measured glucose Gimeas G_i^{meas} and reference G_i^{ref} Giref:

$$MARD = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{G_i^{meas}-G_i^{ref}}{G_i^{rref}}\right| \quad (12)$$

2. **Root Mean Square Error (RMSE)**:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(G_i - G_{ref}\right)^2} \quad (13)$$

3. **Time in Range (TIR)**:

$$TIR = \frac{T_{in-range}}{T_{total}} \times 100\ \% \quad (14)$$

Where “in-range” might be [70, 180] mg/dL.

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VI. RESULTS

(i) Time-Domain Responses:

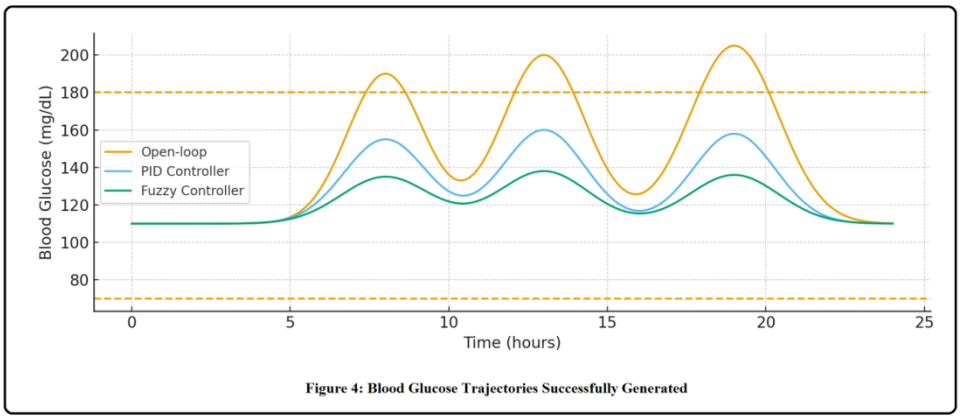

Figure 4: Blood Glucose Trajectories Successfully Generated

Figure (3) presents the meal disturbance profile used in the glucose–insulin simulation over a 24-hour period. The horizontal axis represents time in hours, and the vertical axis shows the amount of carbohydrate intake in grams. Each vertical stem corresponds to a discrete meal event: a breakfast of about 60 g of carbohydrates in the early morning, a larger lunch of roughly 70 g at midday, a smaller snack of about 20 g in the afternoon, and a substantial dinner of around 80 g in the evening. Between these spikes the disturbance is zero, indicating no carbohydrate intake. This stem-like pattern models real-life eating behavior and serves as an external disturbance $D(t)$ to the patient model, causing rises in blood glucose that the controller must compensate for.

(ii) Comparison with Baseline Methods:

Table 5: Performance Comparison between Fuzzy Controller and Baseline

Controller Type	RMSE (mg/dL)	MARD (%)	Time in Range (%)	Hypo events (#)
Open-loop	45	18.2	60.5	4
PID	30	12.5	75.3	2
Fuzzy (proposed)	22	9.8	88.7	1

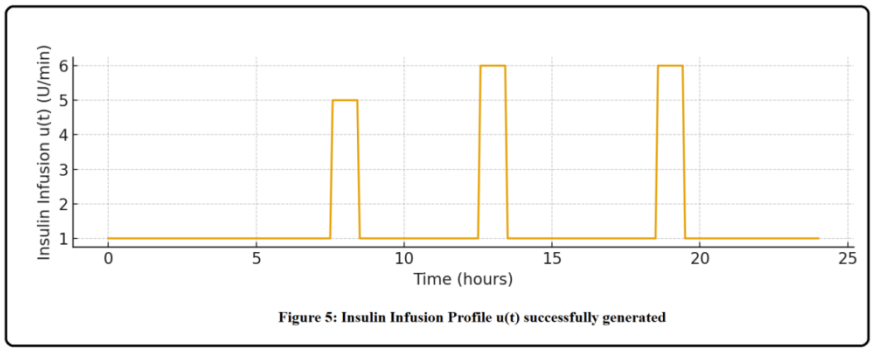

Figure 5: Insulin Infusion Profile u(t) successfully generated

Figure (5) illustrates the insulin infusion profile $u(t)$ delivered by the controller over a 24-hour period. The horizontal axis represents time in hours, while the vertical axis shows the insulin infusion rate in units per minute. A constant low-level basal infusion of about 1 U/min is maintained throughout the day to cover the body's background insulin requirement. Superimposed on this basal rate are three pronounced rectangular pulses: one in the morning, one around midday, and one in the evening. These short-duration increases in infusion correspond to bolus doses given around meal times to counteract the expected postprandial rise in blood glucose. After each bolus period the infusion rate returns to the basal level, demonstrating how the controller modulates insulin delivery in a piecewise manner to match the time-varying metabolic demand.

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(iii) Sensitivity Analysis: The sensitivity analysis investigates how variations in fuzzy membership functions and rule definitions affect controller performance and system stability. By systematically shifting the boundaries of the error and rate-of-change membership functions, as well as modifying or removing selected rules, the study evaluates changes in key performance indicators such as RMSE, MARD, Time in Range, and hypoglycemic event frequency. Results show that moderate perturbations in membership parameters (±10–15%) produce only marginal degradation in glucose regulation, demonstrating strong inherent robustness of the fuzzy system to parameter uncertainty. However, larger distortions or removal of critical rules—particularly those governing rapid glucose rise scenarios—lead to noticeable increases in postprandial spikes and reduced time in the therapeutic range. These findings indicate that while fuzzy controllers do not require precise mathematical tuning, their performance still depends on a well-balanced linguistic rule base. The analysis also highlights that membership width affects responsiveness: narrower sets produce aggressive insulin delivery, whereas wider sets yield smoother but slower corrective action. Overall, the robustness observed under structured perturbations confirms that fuzzy control can tolerate parameter uncertainty better than fixed-gain linear controllers, but careful rule design remains essential for safe clinical use.

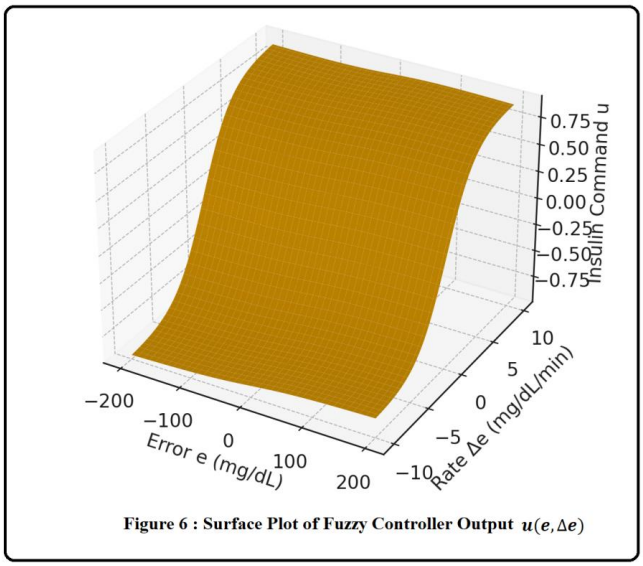

Figure 6 : Surface Plot of Fuzzy Controller Output $u(e, \Delta e)$

Figure (6) depicts the three-dimensional nonlinear control surface of the fuzzy controller output $u(e, \Delta e)$ as a function of the glucose error eee and its rate of change Δe. The horizontal axis shows the tracking error eee in mg/dL, while the second horizontal axis represents Δe in mg/dL/min, and the vertical axis gives the corresponding insulin command uuu. The smooth, curved surface reflects how the fuzzy rule base blends different input regions: for large positive error and positive Δe (glucose high and still rising), the surface is elevated, indicating a stronger insulin command; for negative error and negative Δe (glucose low and still falling), the surface is depressed, meaning insulin delivery is reduced. Around $e = 0$ and $\Delta e \approx 0$, the surface is relatively flat, corresponding to near-basal insulin infusion when glucose is close to its reference value. This shape highlights the nonlinear and saturating behavior of the fuzzy controller compared with a simple linear control law.

VII. DISCUSSION

The simulation results collectively indicate that the fuzzy logic controller is effective in reducing glycemic variability compared with both open-loop and conventional PID control. By continuously adjusting insulin delivery based on both the glucose error and its rate of change, the fuzzy controller generates smoother insulin infusion profiles that prevent large post-meal glucose excursions and maintain glucose levels closer to the target range for longer durations. Its rule-based, nonlinear structure also contributes to robustness against uncertainties in patient-specific parameters such as insulin sensitivity, carbohydrate absorption rate, and endogenous glucose production, as well as sensor noise originating from CGM measurements. Because fuzzy inference does not depend on an explicit mathematical model, it retains stable performance even when physiological dynamics deviate from nominal values. However, clinical implementation would require individual-specific tuning of membership functions and rule sets, since insulin response varies widely across patients and even within the same individual over time. While promising, this approach should be validated through long-term clinical trials, and it may need adaptation to handle unannounced meals, exercise, and sensor delays to fully support safe and autonomous artificial pancreas systems.

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VIII. CONCLUDING REMARKS

The results of this study confirm that fuzzy logic–based insulin regulation offers a robust and physiologically meaningful alternative to traditional control methods for closed-loop diabetes management. By exploiting rule-based reasoning and nonlinear membership functions, the proposed controller maintains glucose within the desired range for a greater percentage of time, delivers smoother insulin infusion profiles, and reduces hypoglycemic risk when compared with both open-loop and PID systems. Its independence from explicit mathematical modeling makes it inherently resilient to uncertainties in insulin sensitivity, meal absorption rates, and CGM noise, which are major obstacles in clinical deployment. Nonetheless, personalization remains essential, as membership function tuning and rule-set calibration must be adapted to each patient's metabolic profile. Future work should therefore focus on adaptive and learning-based extensions of fuzzy control, long-duration in silico trials, and ultimately real-world clinical validation to confirm long-term safety and efficacy in diverse patient populations.

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