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Fuzzy Insulin Dosing Policy Design for Type 1 Diabetes Under Different Pump Constraints: An LMI Approach

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Abstract

This paper presents an insulin dosing policy for individuals with Type 1 Diabetes (T1D), utilizing Linear Matrix Inequality (LMI) techniques in combination with the TakagiSugeno (TS) fuzzy approximator. The primary goal is to regulate blood glucose levels by employing robust control strategies for the nonlinear dynamics of the glucose-insulin system, which are described using the Bergman Minimal Model. The proposed approach systematically incorporates insulin pump constraints, such as maximum insulin delivery rates, to ensure practical applicability in real-world scenarios. Simulation results demonstrate that the proposed controller maintains blood glucose levels within a safe range for over 84% of the time, with average glucose levels reduced to as low as 95mg/dL under the least restrictive input constraints. Furthermore, the controller effectively mitigates meal-induced disturbances while minimizing hypoglycemia risks, demonstrating its robustness under varying parameter uncertainties. This research highlights the potential of the proposed method for use in closed-loop insulin delivery systems, offering a promising solution for personalized and adaptive diabetes management.

Keywords: LMI; Takagi-Sugeno Fuzzy; Blood Glucose Control; Type 1 Diabetes; Robust Control.

1. Introduction

Type 1 Diabetes (T1D) is a chronic disease marked by the loss of insulin secretion, necessitating external insulin regulation to maintain healthy blood glucose levels [1]. This insulin deficiency leads to elevated blood sugar [2], which over time can result in long-term complications such as cardiovascular disease, nerve damage, kidney failure, and vision loss [3,4]. Consequently, individuals with T1D rely on insulin injections to mitigate high blood sugar levels.

Defining the required insulin dose for each patient can be challenging, as an excessive dosage may lead to hypoglycemia [5]. Hypoglycemia, characterized by dangerously low blood sugar levels, can cause symptoms such as dizziness, confusion, seizures, and in severe cases, loss of consciousness or death [5]. Therefore, blood glucose regulation becomes a control problem aimed at minimizing blood glucose excursions while avoiding hypoglycemia, ensuring that blood sugar levels remain within a safe range for patients [6].

Control engineers have been developing dosing strategies to control blood glucose levels, leveraging various control techniques to maintain glucose within a safe range. Early methods, such as

Proportional-Integral-Derivative (PID) controllers, aimed to adjust insulin doses based on blood sugar deviations [7,8,9]. More advanced approaches include Model Predictive Control (MPC), which predicts future glucose trends based on current and past data [10,11,12], and sliding mode controllers, designed to handle uncertainties in insulin-glucose dynamics [13,14]. Additionally, adaptive receding horizon control strategies have been introduced to optimize basal insulin dosing [15]. These methods form the foundation for closed-loop control systems in diabetes management.

Recent advancements in TS fuzzy controllers for diabetes management have demonstrated their utility in handling the nonlinearities of the glucose-insulin system. For instance, Nath et al. [16] developed TS fuzzy logic controllers to regulate blood glucose levels under meal disturbances, while Dehghani et al. [17] employed adaptive fuzzy control for insulin delivery. Farahmand et al. [18] expanded upon these methods with LMIbased robust control approaches, optimizing H_∞ performance criteria. However, most of these studies do not systematically account for input saturation.

The novelty of the proposed approach lies in its systematic incorporation of insulin pump constraints and varying levels of input saturation into the controller design. By developing four distinct configurations, this study offers a flexible framework that can adapt to different patient needs and device limitations. Moreover, the robustness of the controller was evaluated under various parameter uncertainties, demonstrating its applicability across a wide range of physiological conditions.

The goal of this paper is to first develop TS fuzzy model approximations for the nonlinear blood glucose dynamics in individuals with T1D. Then, these fuzzy models will be leveraged to design a robust controller using Linear Matrix Inequalities (LMI) with H_∞ performance criteria. The design will systematically account for insulin rate constraints, ensuring that the controller performs effectively under varying levels of input saturation. The controller design includes four variations with different degrees of input saturation, and their performance will be evaluated under different disturbance scenarios.

2. Methods

This section outlines the modeling and control techniques employed in this paper. First, we introduce the Bergman Minimal Model to describe the glucose-insulin dynamics for individuals with T1D. Then, the TS fuzzy system is presented to handle the nonlinearity in the glucose regulation dynamics.

Next, the design of a LMI-based controller is detailed, with a focus on ensuring system stability and robustness. Finally, the simulation setup is described, including meal disturbance modeling and control signal constraints.

2-1. Bergman Minimal Model

The Bergman Minimal Model is used to describe the glucose-insulin dynamics in T1D patients [19]. It uses three state variables: glucose concentration $G(t)$, insulin concentration $I(t)$, and insulin action in the remote compartment $X(t)$. The governing equations are:

$$\dot{G}(t) = -P_1 G(t) - X(t)(G(t) + G_b) + d(t) \quad (1)$$

$$\dot{I}(t) = -n(I(t) + I_b) + \frac{u(t)}{V_1} \quad (2)$$

$$\dot{X}(t) = -P_2 X(t) + P_3 I(t) \quad (3)$$

where $d(t)$ represents meal disturbances, $u(t)$ is the insulin infusion rate, and P_1, P_2, and P_3 are system parameters. The parameter values are presented in Table 1.

Table 1. Parameters of the bergman minimal model

Parameter	Description	Value
$P1$	Glucose decay rate	0min^{-1}
$P2$	Insulin action decay rate	0.025min^{-1}
$P3$	Insulin sensitivity	$5.0 \times 10^{-5}\text{min}^{-2}$
G_b	Basal glucose concentration	4.5mmol/L
I_b	Basal insulin concentration	15mU/L
$V1$	Insulin distribution volume	12L
n	Insulin decay rate	0.1min^{-1}

2-2. Takagi-Sugeno Fuzzy System

To handle the nonlinearity in the system, the TS fuzzy approach is employed [20]. This method approximates the nonlinear system by partitioning the state space into regions, with each region described by a linear subsystem. These linear subsystems are represented as fuzzy IF-THEN rules, and the overall behavior of the system is captured through a weighted combination of these rules.

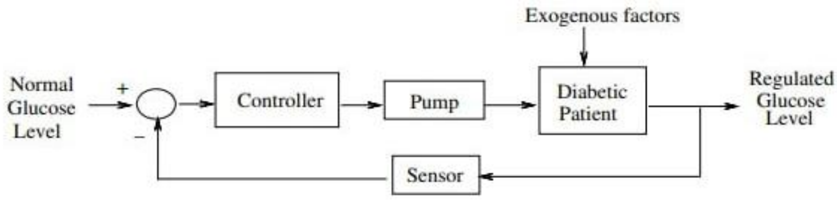

Fig. 1. Block diagram of the proposed controller

The local linear approximations of a nonlinear system within each fuzzy rule can be described using fuzzy IF-THEN statements as follows:

IF $z_1(t)$ *is* M_{i1} *AND* $z_p(t)$ is M_{ip}, THEN:

$$\dot{x}(t) = A_i x(t) + B_i u(t) + E_i v(t) \tag{4}$$

$$y(t) = C_i x(t) \tag{5}$$

The membership functions M_{ij} are designed to partition the input space into overlapping regions. For example, glucose levels $G(t)$ were divided into low, normal, and high ranges, with triangular-shaped membership functions to account for smooth transitions.

The Sector Nonlinearity Approach (SNA) [21] was used to approximate nonlinear interactions between glucose and insulin in each region. This resulted in two rules, each corresponding to one region of the state space, where the dynamics could be locally linearized:

$$\dot{x}(t) = \sum_{i=1}^{2} h_i(z(t))\big(A_i x(t) + B_i u(t) + E_i v(t)\big),$$

where $h_i(z(t))$ are the normalized membership functions that blend the outputs of the linear subsystems.

2-3. LMI-Based Controller Design Procedure

The controller is designed using LMI methods to ensure stability and robustness [22]. By solving a set of LMIs, feedback gains for each linear subsystem are computed, ensuring that the closed-loop system meets the desired H_∞ performance criteria [23]. The controller is also constrained to respect input saturation limits, which are important for real-world applications involving insulin infusion pumps [24]. The block diagram of the proposed controller, illustrating the integration of the Takagi-Sugeno fuzzy approximator, the LMI-based controller, and the insulin pump constraints, is shown in Fig. 1.

The system integrates glucose measurement, the Takagi-Sugeno fuzzy approximator, LMI-based control, and insulin delivery while respecting pump constraints.

2-3-1. Bounded Real Lemma

The bounded real lemma provides a sufficient condition for H_∞ stability [23]. For the TS fuzzy system to be H_∞ stable, there must exist a positive definite matrix P such that the following LMI holds for each local linear system:

$$\begin{bmatrix} A_i^T P + P A_i + C_i^T C_i & P B_i & P E_i \\ B_i^T P & -\gamma_i^2 I & 0 \\ E_i^T P & 0 & -I \end{bmatrix} < 0,$$

where A_i, B_i, and E_i are the system matrices, P is a positive definite matrix, and γ is the H_∞ performance bound. This condition ensures that the closed-loop system is robust against disturbances.

2-3-2. Control Signal Constraints

The control signal is constrained to ensure that the insulin infusion rate $u(t)$ remains within allowable bounds [22]. The constraint $\|u_i\|_2 \leq \mu_i$ is satisfied for $t \geq 0$ if the following LMIs hold:

$$\begin{bmatrix} 1 & x(0)^T \\ x(0) & x_i^{-1} \end{bmatrix} \geq 0$$

$$\begin{bmatrix} x_i & M_i^T \\ M_i & \mu_i^2 I \end{bmatrix} \geq 0,$$

where $X_i = P_i^{-1}$ and $M_i = K_i P_i^{-1}$. These LMIs ensure that the control signal respects input saturation limits, maintaining the system's stability while preventing excessive insulin doses.

2-4. Control System Stability Analysis

The following Lyapunov function is selected to analyze the stability of the system [25]:

$$V(t) = \sum_{j=1}^{r} h_j v_j(t) = \sum_{j=1}^{r} h_j x_j^T P_j x_j$$

where $P_j > 0$. The derivative of the Lyapunov function is:

$$\begin{aligned} \dot{V}(t) &= \sum_{j=1}^{r} h_j \dot{V}_j \\ &= \sum_{j=1}^{r} h_j\big(\dot{x}_j^T P_j x_j + x_j^T P_j \dot{x}_j\big) \\ &= \sum_{j=1}^{r} h_j \Big(\big(A_j x_j + B_j K_j x_j\big)^T P_j x_j \\ &\qquad + x_j^T P_j\big(A_j x_j + B_j K_j x_j\big)\Big) \\ &= \sum_{j=1}^{r} h_j\big(x_j^T\big(A_j^T P_j + K_j^T B_j^T P_j\big)x_j \\ &\qquad + x_j^T P_j\big(A_j x_j + P_j B_j K_j\big)x_j\big) \end{aligned}$$

Considering $A_i + B_i K_i$ from the system dynamics, we ensure that:

$$A^T P_j + K_j^T B^T P_j + P_j A_j + P_j B_j K_j < 0$$

and since $\sum_{j=1}^{r} h_j = 1$, the following condition holds:

$$\sum_{j=1}^{r} h_j x_j^T \left(A^T P_j + K_j^T B^T P_j + P_j A_j + P_j B_j K_j\right) x_j < 0$$

Thus, $V(t) > 0$, and by the Lyapunov theorem, the system is asymptotically stable.

To minimize the effects of disturbances on the output signal, we consider the H_∞ norm of y with respect to v as:

$$||T_{yv}||_\infty = \frac{||y||_2}{||w||_2} < \gamma_i$$

Therefore, a sufficient condition for H_∞ performance is:

$$\dot{V} + y^T y - \gamma_i^2 < 0$$

2-5. Simulation Setup

In the simulation, the exponential function $v = \alpha e^{-\beta t}$ is used to model the glucose disturbances caused by meals. In this context, α represents the magnitude of the disturbance, corresponding to different meal sizes, and β is the decay rate that dictates how quickly the meal's effect diminishes. A larger α results in a bigger glucose disturbance, while β controls the rate at which glucose levels return to baseline after the meal.

In this simulation, meal events are modeled as disturbances to the glucose level at specific times of the day. These events mimic typical eating patterns such as breakfast, lunch, dinner, and snacks. The meals are defined by their timing, magnitude (multiplier), and decay rate (β) as follows:

- Breakfast: 8:00 AM, $\alpha = 20$, $\beta = 0.05$
- Lunch: 12:00 PM, $\alpha = 30$, $\beta = 0.07$
- Dinner: 6:00 PM, $\alpha = 20$, $\beta = 0.06$
- Morning Snack: 10:00 AM, $\alpha = 10$, $\beta = 0.1$
- Afternoon Snack: 3:00 PM, $\alpha = 15$, $\beta = 0.12$

3. Results

3-1. Fuzzy Approximation of the Bergman Model

To derive the TS fuzzy approximation of the Bergman system, we consider $u^* = -nI_b + \frac{u}{V_1}$ and the upper and lower bounds of $(G + G_b)$ as specified in the model. By applying the Sector Nonlinearity Approach (SNA) to the nonlinear terms [21], the two-rule TS fuzzy representation of the minimal Bergman model is formulated as:

$$\dot{x}(t) = \sum_{i=1}^{2} h_i(z(t))\left(A_i x(t) + B_i u(t) + E_i v(t)\right)$$

where $x = [G,I,X]^T$ is the state vector and:

$$A_1 = \begin{bmatrix} P_1 & 0 & -a_1 \\ 0 & n & 0 \\ 0 & P_3 & -P_2 \end{bmatrix} \quad B_1 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad E_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} P_1 & 0 & -a_2 \\ 0 & n & 0 \\ 0 & P_3 & -P_2 \end{bmatrix} \quad B_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad E_2 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

with $a_1 = 60$mg/dL and $a_2 = 120$mg/dL.

The membership functions are defined as:

$$h_1 = \frac{120 - (G + G_b)}{120 - 60}, \qquad h_2 = 1 - h_1$$

This TS fuzzy model represents a piecewise approximation of the nonlinear Bergman system. The fuzzy rule base was designed to approximate the nonlinear glucose-insulin dynamics while considering critical operating ranges for glucose. The membership functions were selected to ensure smooth transitions between linear models, focusing on key regions near physiological thresholds, such as hypoglycemia (< 60mg/dL) and hyperglycemia (> 120mg/dL).

3-2. Controller Gains for Various Values of μ

The calculated controller gains k_1 and k_2 for different controllers, corresponding to various values of μ, are presented below.

- Controller 1 ($\mu = 0.05$):

$$k_1 = \begin{bmatrix} 0.0789 & -0.0174 & -140.4310 \end{bmatrix}$$
$$k_2 = \begin{bmatrix} 0.0884 & -0.0315 & -271.1489 \end{bmatrix},$$

- Controller 2 ($\mu = 0.25$):

$$k_1 = \begin{bmatrix} 0.4793 & -0.0613 & -597.8929 \end{bmatrix},$$
$$k_2 = 1.0 \times 10^3 \begin{bmatrix} 0.0005 & -0.0001 & -1.0288 \end{bmatrix}$$

- Controller 3 ($\mu = 0.5$):

$$k_1 = 1.0 \times 10^3 \begin{bmatrix} 0.0010 & -0.0001 & -1.0288 \end{bmatrix}$$
$$k_2 = 1.0 \times 10^3 \begin{bmatrix} 0.0010 & -0.0001 & -1.7333 \end{bmatrix},$$

- Controller 4 ($\mu = 1$):

$$k_1 = 1.0 \times 10^3 \begin{bmatrix} 0.0020 & -0.0001 & -1.7333 \end{bmatrix}$$
$$k_2 = 1.0 \times 10^3 \begin{bmatrix} 0.0020 & -0.0002 & -2.8836 \end{bmatrix},$$

4. Simulation Results

This section details the simulation results for the proposed LMI-based TS fuzzy controller. The simulations were conducted over a 24-hour period, with meal disturbances introduced at predefined times to mimic typical eating patterns. The following plots illustrate the plasma glucose concentration, meal glucose disturbances, and insulin control signals for each of the four controllers (Controller 1, Controller 2, Controller

3, and Controller 4) under different meal disturbance scenarios (Fig. 2).

Table 2. Time in range (tir) and average glucose levels for each controller

Controller	TIR (%)	Average Glucose (mg/dL)
Controller 1	61.49	176.54
Controller 2	84.32	122.57
Controller 3	76.13	109.45
Controller 4	63.22	94.96

In the first subplot, the plasma glucose concentration is shown for each controller over time. The second subplot presents the meal glucose disturbances corresponding to the scheduled meal events. The final subplot illustrates the insulin infusion rates for each controller as a function of time. The results indicate that the proposed control strategy successfully regulates the glucose levels, keeping them within safe bounds despite the meal disturbances.

The simulation results demonstrate the effectiveness of the proposed LMI-based TS fuzzy controller in maintaining blood glucose levels within a safe range despite meal disturbances. Key performance metrics, including Time in Range (TIR) and average glucose levels for each controller, are summarized in Table 2. These results highlight the trade-offs between controllers, with Controller 2 achieving the highest TIR of 84.32% and Controller 4 maintaining the lowest average glucose level of 94.96mg/dL. The metrics emphasize the impact of input saturation constraints on glycemic control performance.

4-1. Robustness of the Controller to Varying Parameters

The robustness of the controller 3 to varying Parameters was assessed by varying the insulin sensitivity parameter (P_3) by ±50% in 20% intervals. The resulting glucose profiles and insulin control efforts were analyzed to evaluate how well the controller manages the system under different parameter conditions.

Fig. 3 shows the plasma glucose concentrations and insulin control signals over time for different values of P_3. Despite the variations in P_3, the controller effectively maintains blood glucose levels within a safe range, while adapting the insulin infusion rates accordingly. This robustness is crucial, as physiological parameters can vary significantly among individuals and over time.

Table 3 presents the mean glucose levels, coefficient of variation (CV) of the average glucose, mean Time in Range (TIR), and CV of TIR for the different values of P_3. These metrics help illustrate the performance and stability of the controller under varying insulin dynamics.

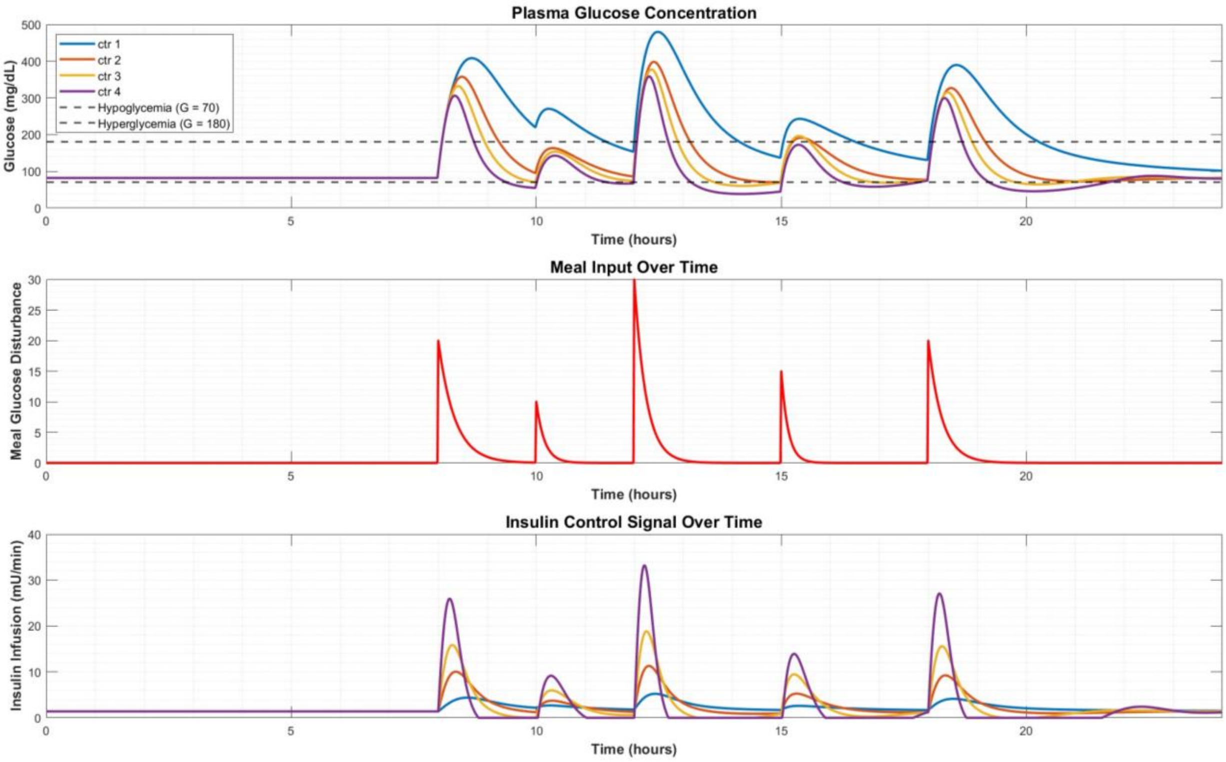

Fig. 2. Plasma glucose concentration, meal input, and insulin control signal over time

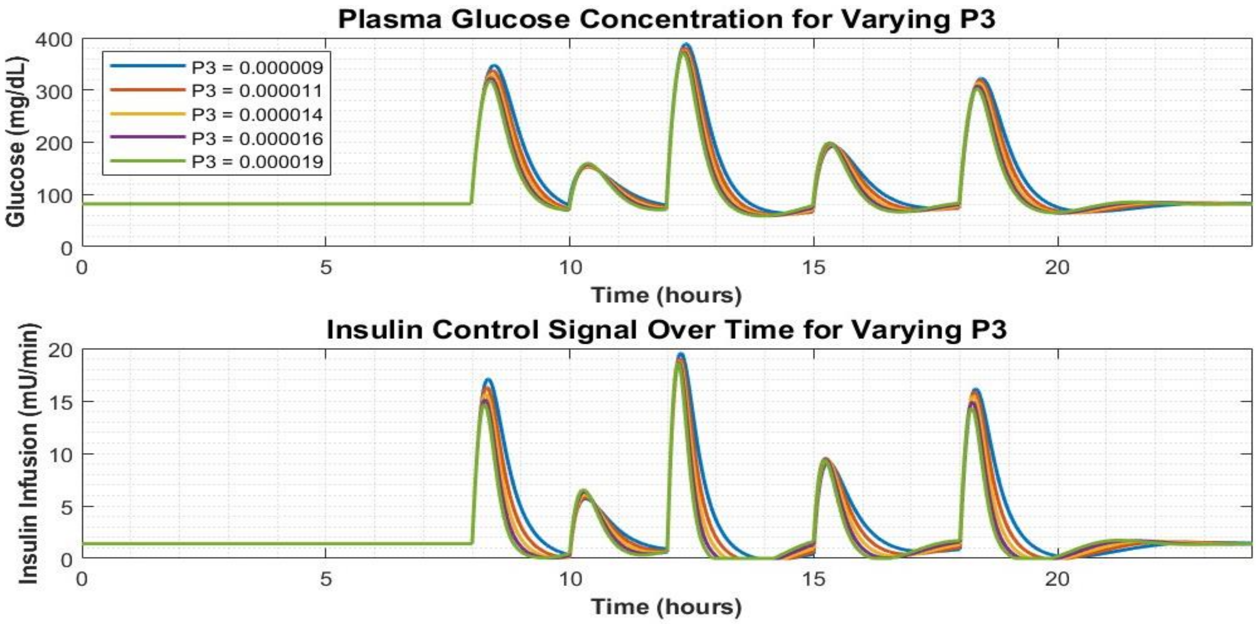

Fig. 3. Plasma glucose concentration and insulin control signal over time for different values of p_3

The relatively small variations in mean glucose levels and TIR across different P_3 values, as reported in Table 3, indicate that the controller is resilient to parameter uncertainties. The coefficient of variation values show consistent control performance, highlighting the robustness and adaptability of the proposed control strategy.

Table 3. Robustness analysis results for varying p_3

Metric	Value
Mean Average Glucose (mg/dL)	109.27
Coefficient of Variation of Average Glucose	0.0391
Mean Time in Range (%)	77.20
Coefficient of Variation of TIR	0.0122

5. Discussion

The simulation results demonstrate the effectiveness of the LMI-based TS fuzzy controller in maintaining blood glucose levels within a safe range, despite meal disturbances. The fuzzy approximations successfully address the nonlinearities in the glucose-insulin dynamics.

As presented in the results section, with less restrictive input constraints, more insulin is injected. However, this increased insulin delivery raises the risk of hypoglycemia. These findings suggest that input saturation is not only a constraint for satisfying actuator limitations but also a parameter that determines the aggressiveness of the controller. This parameter could be adapted to better suit individual patient needs and preferences, potentially allowing for a more personalized approach to insulin therapy in diabetes management.

The proposed approach has the potential to enhance realworld diabetes management in several ways. By incorporating insulin pump constraints and systematically addressing input saturation levels, the controller design ensures that insulin delivery remains both effective and safe under varying conditions. This adaptability is critical for personalizing therapy, as patients with T1D have diverse physiological responses to insulin and meal disturbances.

Moreover, the robustness of the proposed controller to parameter uncertainties, demonstrated in simulations, suggests that it could accommodate patient-specific variability, such as changes in insulin sensitivity or meal timing. This makes the approach particularly suited for closed-loop systems, where real-time adjustments are necessary to maintain glycemic control.

In real-world applications, the ability to adjust the controller's aggressiveness based on individual patient needs and preferences could lead to more personalized and patientcentric diabetes management. Additionally, the systematic handling of device constraints ensures that the proposed methodology aligns with the practical limitations of existing insulin pump technology, facilitating smoother integration into commercial closed-loop systems. These advancements have the potential to reduce the burden on patients and healthcare providers, improving both clinical outcomes and quality of life for individuals with T1D.

One limitation of this study is that the same model used to develop the controller is also used in the simulation platform. Testing the controller on a different simulation platform or with real-world data could provide further insights into its robustness and practical applicability. There have been significant advancements in the development of simulation platforms for testing insulin dosing strategies, such as the UVA/Padova Type 1 Diabetes Simulator and the UVa Virtual Lab (UVLab) [26,27,28]. These platforms could offer more realistic environments to evaluate the performance of the proposed controller in various clinical scenarios.

Future research could explore the integration of probabilistic frameworks to enhance the robustness of the decision-making process under the inherent uncertainty of physiological and environmental conditions [29]. In addition, learning-based sequential modeling strategies could significantly enhance the controller's capacity to adapt to real-time changes in patient behavior and physiological responses [30,31]. Techniques such as physics-informed neural networks (PINNs) and transformer-based architectures have shown promise in dynamically capturing complex relationships in time-series data [32,33]. Applying these methodologies to diabetes management could enable the controller to adjust to sudden changes, such as unexpected meal intakes or physical activity, in real time.

Another promising direction is the development of explainable AI (XAI) approaches tailored for healthcare applications [33]. Explainable frameworks could provide clinicians with insights into the controller's decision-making process, fostering trust and enabling personalized treatment adjustments. Moreover, incorporating pathologist-guided learning into the control design could improve interpretability and clinical applicability.

6. Conclusion

This paper presents an LMI-based controller for regulating blood glucose levels in individuals with T1D, using TakagiSugeno fuzzy approximations to handle system nonlinearities. The simulation results showed that the controller is capable of effectively managing glucose levels under varying meal disturbances. Future work could focus on evaluating the performance of the controller on different simulation platforms or real-world clinical data to verify its robustness in practical scenarios.

References

[1] Atkinson, M. A., Eisenbarth, G. S., & Michels, A. W. (2014). Type 1 diabetes. *The lancet*, *383*(9911), 69-82.

[2] National Institute of Diabetes and Digestive and Kidney Diseases. (n.d.). *Type 1 diabetes*. National Institutes of Health. Retrieved October 11, 2024, from https://www.niddk.nih.gov/health-information/diabetes/overview/what-is-diabetes/type-1-diabetes

[3] Nathan, D. M. (2005). Long-term complications of diabetes mellitus. *New England journal of medicine*, *323*(25), 2609-2619.

[4] American Diabetes Association. (2021). *Complications of diabetes*. Retrieved October 11, 2024, from https://www.diabetes.org/diabetes/complications

[5] Cryer, P. E. (1994). Hypoglycemia: the limiting factor in the management of IDDM. *Diabetes*, *43*(11), 1378-1389.

[6] Kovatchev, B., Tamborlane, W. V., Cefalu, W. T., & Cobelli, C. (2016). The artificial pancreas in 2016: a digital treatment ecosystem for diabetes. *Diabetes Care*, *39*(7), 1123.

[7] Steil, G. M., Panteleon, A. E., & Rebrin, K. (2004). Closed-loop insulin delivery—the path to physiological glucose control. *Advanced drug delivery reviews*, *56*(2), 125-144.

[8] Paiva, H. M., Keller, W. S., & da Cunha, L. G. R. (2020). Blood-glucose regulation using fractional-order PID control. *Journal of Control, Automation and Electrical Systems*, *31*(1), 1-9..

[9] Rosales, N., De Battista, H., & Garelli, F. (2022). Hypoglycemia prevention: PID-type controller adaptation for glucose rate limiting in Artificial Pancreas System. *Biomedical Signal Processing and Control*, *71*, 103106.

[10] Hovorka, R., Canonico, V., Chassin, L. J., Haueter, U., Massi-Benedetti, M., Federici, M. O., ... & Wilinska, M. E. (2004). Nonlinear model predictive control of glucose concentration in subjects with type 1 diabetes. *Physiological measurement*, *25*(4), 905-920.

[11] Kang, S. L., Hwang, Y. N., Kwon, J. Y., & Kim, S. M. (2022). Effectiveness and safety of a model predictive control (MPC) algorithm for an artificial pancreas system in outpatients with type 1 diabetes (T1D): systematic review and meta-analysis. *Diabetology & metabolic syndrome*, *14*(1), 187.

[12] Aiello, E. M., Jaloli, M., & Cescon, M. (2024). Model Predictive Control (MPC) of an artificial pancreas with data-driven learning of multi-step-ahead blood glucose predictors. *Control Engineering Practice*, *144*, 105810.

[13] Lee, H., Buckingham, B. A., Wilson, D. M., & Bequette, B. W. (2009). A closed-loop artificial pancreas using model predictive control and a sliding meal size estimator. *diabetes science and technology* 3(5), 1082-1090.

[14] Ebrahimi, N., Ozgoli, S., & Ramezani, A. (2020). Model free sliding mode controller for blood glucose control: Towards artificial pancreas without need to mathematical model of the system. *Computer Methods and Programs in Biomedicine*,

195, 105663.

[15] El Fathi, A., Ganji, M., Boiroux, D., Bengtsson, H., & Breton, M. D. (2023, August). Intermittent Control for Safe Long-Acting Insulin Intensification for Type 2 Diabetes: In-Silico Experiments. In *2023 IEEE Conference on Control Technology and Applications (CCTA)* (pp. 534-539). IEEE.

[16] Nath, A., Dey, R., & Balas, V. E. (2018). Closed loop blood glucose regulation of type 1 diabetic patient using Takagi-Sugeno fuzzy logic control. In *Soft Computing Applications: Proceedings of the 7th International Workshop Soft Computing Applications (SOFA 2016), Volume 2 7* (pp. 286-296). Springer International Publishing..

[17] Farahmand, B., Dehghani, M., & Vafamand, N. (2019). Fuzzy model-based controller for blood glucose control in type 1 diabetes: An LMI approach. *Biomedical Signal Processing and Control*, *54*, 101627.

[18] Farahmand, B., Dehghani, M., & Vafamand, N. (2019). Fuzzy model-based controller for blood glucose control in type 1 diabetes: An LMI approach. *Biomedical Signal Processing and Control*, *54*, 101627..

[19] Bergman, R. N. (2006). Minimal model: perspective from 2005. *Hormone research*, *64*(Suppl. 3), 8-15..

[20] Mehran, K. (2008). Takagi-sugeno fuzzy modeling for process control. *Industrial Automation, Robotics and Artificial Intelligence (EEE8005)*, *262*, 1-31..

[21] Sala, A., & Arino, C. (2009). Polynomial fuzzy models for nonlinear control: A Taylor series approach. *IEEE Transactions on Fuzzy Systems*, *17*(6), 1284-1295.

[22] Scherer, C., & Weiland, S. (2000). Linear matrix inequalities in control. *Lecture Notes, Dutch Institute for Systems and Control, Delft, The Netherlands*, *3*(2).

[23] Wang, H. S., Yung, C. F., & Chang, F. R. (1998). Bounded real lemma and $H\infty$ control for descriptor systems. *IEE Proceedings-Control Theory and Applications*, *145*(3), 316-322.

[24] Fushimi, E., Rosales, N., De Battista, H., & Garelli, F. (2017, September). Constraints on the insulin infusion for artificial pancreas clinical trials. In *2017 XVII Workshop on Information Processing and Control (RPIC)* (pp. 1-6). IEEE.

[25] Khalil, H. K. (2009). Lyapunov stability. *Control systems, robotics and automation*, *12*, 115.

[26] Man, C. D., Micheletto, F., Lv, D., Breton, M., Kovatchev, B., & Cobelli, C. (2014). The UVA/PADOVA type 1 diabetes simulator: new features. *Journal of diabetes science and technology*, *8*(1), 26-34.

[27] GANJIARJENAKI, M., FABRIS, C., EL FATHI, A. N. A. S., LV, D., KOVATCHEV, B., & BRETON, M. D. (2024). 75-OR: In-Silico Replay of Insulin Degludec and Liraglutide Clinical Trial Data in Subjects with Type 2 Diabetes. *Diabetes*, *73*(Supplement_1).

[28] Ganji, M., Fathi, A. E., Fabris, C., Lv, D., Kovatchev, B., & Breton, M. (2024). Distribution-Based Sub-Population Selection (DSPS): A Method for in-Silico Reproduction of Clinical Trials Outcomes. *arXiv preprint arXiv:2409.00232*.

[29] Mehrnia, M., Kholmovski, E., Katsaggelos, A., Kim, D., Passman, R., & Elbaz, M. S. (2024). Novel Self-Calibrated Threshold-Free Probabilistic Fibrosis Signature Technique for 3D Late Gadolinium Enhancement MRI. *IEEE Transactions on Biomedical Engineering*.

[30] Hadizadeh Moghaddam, A., Nayebi Kerdabadi, M., Liu, M., & Yao, Z. (2024, October). Contrastive learning on medical intents for sequential prescription recommendation. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management* (pp. 748-757).

[31] Naderi, F., Perez-Raya, I., Yadav, S., Kalajahi, A. P., Mamun, Z. B., & D'Souza, R. M. (2024). Towards chemical source tracking and characterization using physics-informed neural networks. *Atmospheric Environment*, *334*, 120679.

[32] Tezerjani, M. D., Carrillo, D., Qu, D., Dhakal, S., Mirzaeinia, A., & Yang, Q. (2024). Real-time Motion Planning for autonomous vehicles in dynamic environments. *arXiv preprint arXiv:2406.02916*.

[33] Ferrero, A., Ghelichkhan, E., Manoochehri, H., Ho, M. M., Albertson, D. J., Brintz, B. J., ... & Knudsen, B. S. (2024). HistoEM: A Pathologist-Guided and Explainable Workflow Using Histogram Embedding for Gland Classification. *Modern Pathology*, *37*(4), 100447.

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