ROBUST ARTIFICIAL PANCREAS SYSTEM

CONTROLER FOR TYPE - 1 DIABETES PATIENTS

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Table of Contents

[Table of Figures 1](#_Toc134891046)

[Acknowledgements 2](#_Toc134891047)

[Abstract 2](#_Toc134891048)

[Introduction 2](#_Toc134891049)

[Major Components 3](#_Toc134891050)

[Development Lifecycle 3](#_Toc134891051)

[Critical Analysis 3](#_Toc134891052)

[Conclusion 4](#_Toc134891053)

[Bibliography 4](#_Toc134891054)

[Appendices 4](#_Toc134891055)

# Table of Figures

Abstract

# 1. Introduction

Type 1 Diabetes (T1D) is a chronic condition that affects millions of people worldwide, disrupting their ability to produce insulin - a hormone responsible for regulating blood sugar levels. The absence of insulin impairs the body's ability to process glucose properly, leading to high blood sugar levels, which can cause serious health complications[[1]](#_Centers_for_Disease). Although the history of diabetes dates back to ancient civilizations, the modern era has seen significant milestones, with experimental medicine playing a crucial role in the evolution of diabetes management.

At present, managing type 1 diabetes involves a combination of insulin therapy, diet, and regular physical activity. However, these treatment methods come with significant daily challenges, requiring individuals to keep their blood glucose levels within an optimal range to avoid detrimental health consequences such as hypoglycemia and hyperglycemia. The total time spent between blood glucose levels of 70-180 mg/dL (3.9-10mmol/L) is referred to as Time in Range (TIR), and optimizing TIR is a lifelong problem that requires continuous management (Figure 1).

The existing treatment methods, such as Multiple Daily Injections (MDI), Sensor Augmented Pump (SAP) therapy, and hybrid closed-loop systems, require exogenous insulin to be infused into the body manually. Moreover, MDI and SAP therapies use a rule-based mechanism designed by clinicians for insulin infusion. This involves calculating patient-specific characteristics such as Total Daily Insulin (TDI), Carbohydrate Ratio (CR), and Factor (F), which must be closely monitored and periodically adjusted. Although hybrid closed-loop systems use Proportional Integral Derivative (PID) control and Model Predictive Control (MPC) techniques to automatically control basal insulin levels, they still require manual bolus insulin to counter meals and are affected by disturbances arising through daily events, such as exercise and stress [[2]](#_C._Hettiarachchi,_N.).

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Figure - Blood glucose level controlled by older version of the proposed system, where 70-180 mg/dL (in green) is normoglycemia

In this work, I propose a theoretical solution to the challenges associated with current treatment methods for Type 1 Diabetes. The proposed solution involves the development of a personalized Robust Artificial Pancreas System Controller (RAPSC), utilizing Fuzzy Logic technology to automatically regulate blood glucose levels and mitigate daily disturbances. Additionally, a web application will be designed and implemented to enable end-users to easily monitor their T1D-related vitals through a user-friendly interface, accessible via a server-side RESTful API. This proposed solution has the potential to significantly improve the lives of T1D patients by reducing the daily burden of managing their blood glucose levels and minimizing the risk of serious health complications. However, it should be noted that this solution is only theoretical and further research is needed to fully assess its effectiveness in a clinical setting.

# 2. Major Components

The system is locally hosted, with both the client and server components running on the localhost. The client component operates on port 5500, while the server component operates on port 8080. This configuration enables efficient communication and data transfer between the frontend and the backend during the simulation process.

By combining the power of the MATLAB backend, the flexibility of the API [[1]](#footnote-1), and the user-friendly frontend interface, the system functions as a cohesive unit, facilitating effective simulations while ensuring a seamless user experience. In the following subsections, I will delve deeper into each component, exploring their functionalities and interactions in detail.

## 2.1 Backend

The backend of the system is built upon the MATLAB programming language, serving as the computational core responsible for executing essential calculations as well as simulate the T-1D patient. The system uses RESTful[[2]](#footnote-2) API[[3]](#footnote-3) to allow communication between MATLAB and Client.

### 2.1.1 Simulation

The simulation function aims to model the behavior of blood glucose levels and insulin dosage over a 24-hour period in a T-1D patient.

The initial step involves the initialization of the FIS tree using patient-specific data. By employing fuzzy logic, a flexible and robust modeling technique, the component can effectively capture the intricate relationships and uncertainties inherent in blood glucose dynamics [[3]](#_Bibliography). The inclusion of the FIS initialization enables the system to simulate the nonlinear dependencies between blood glucose levels, rates of change, and insulin dosage, thereby enhancing the accuracy of the simulation.

To introduce realism and flexibility into the simulation, the component reads data from a database that represents the selected diet for simulation. This capability allows for the integration of real or hypothetical dietary scenarios, enabling the observer to investigate the effects of different diets on blood glucose dynamics. The optional randomization functionality further enriches the simulation by introducing variability in the initial blood glucose levels and their rates of change. This variation mimics the inherent physiological diversity observed in individuals, enabling researchers to examine a wider range of scenarios [[5][6]](#_Bibliography).

During each step of the simulation, the FIS system undergoes evaluation by receiving inputs including the patient's current blood glucose level, the rate of change of blood glucose, and the acceleration of blood glucose. These inputs are derived using the following equations:

Figure - Where BGR(i) represents the blood glucose rate at the i-th step, BGL(i) denotes the blood glucose level at the i-th step, BGL(i-1) represents the blood glucose level at the previous step, and t represents the time interval between consecutive steps.

The calculated insulin dosage resulting from the FIS evaluation is then recorded in the database. This functionality empowers the simulation to dynamically adapt the insulin dosage based on the patient's unique blood glucose dynamics.

In light of the challenges associated with clinically testing potential algorithms for carbohydrates distribution, the simulation component adopts a non-standard model in this regard. This decision stems from the limitations in obtaining clinical validation for alternative approaches [[7][8]](#_Bibliography). Instead, the simulation relies on the methodology that will be discussed in detail in the upcoming Carbohydrates Distribution section.

While acknowledging that the chosen model may deviate from established standards, it was deemed necessary in the absence of clinically validated alternatives. By adhering to the methodology outlined in the subsequent section, the simulation endeavors to provide valuable insights into the dynamics of carbohydrates absorption and its consequential impact on blood glucose levels.

Following the simulation process, data transmission to the API is facilitated through MATLAB's ‘webwrite’ function. It allows for seamless communication between the simulation component and external systems or applications.

To ensure the synchronization between the simulated time and real-time scenarios, the simulation design incorporates a fixed time duration of 5 minutes per iteration. Although each simulation step takes approximately 1 second to complete in real time, the simulation effectively emulates the occurrence of CGM readings, which are typically obtained at 5-minute intervals.

Upon completion of the simulation, the component stores the results in a dedicated ‘results’ table. This enables subsequent analyses, comparisons, and data exploration. Additionally, the generation of visualizations in the form of figures enhances the interpretability of the simulated data (Figure 3). These visual representations assist in identifying patterns, trends, or anomalies in blood glucose dynamics and insulin dosage over the 24-hour period. A picture containing text, diagram, plot, line

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Figure - The most recent version of Gaussian membership function used in Fuzzy Interference System to predict insulin dose

### 2.1.2 Carbohydrates Distribution

In the initial development stage of the prototype, the carbs distribution was implemented as a straightforward linear function, upon which the entire system heavily relied [[9]](#_Bibliography). However, this approach presented limitations in terms of further development and the ability to accurately simulate the complexities of carbohydrate absorption. Recognizing the need for a more sophisticated and flexible solution, a new approach was adopted, leveraging the concept of probability density function (PDF). By incorporating a mathematical function that represents the PDF, the updated method provides a means to simulate the absorption rate of carbohydrates. This shift to a probabilistic modeling approach was driven by the recognition that determining an accurate and comprehensive representation of carbohydrate absorption dynamics posed significant challenges. The adoption of the PDF-based approach offers a simplified yet effective means to capture the essential characteristics of carbohydrate absorption within the simulation framework (Figure 4, Figure 5).

Here's the intuition behind the implementation of the PDF-based approach for simulating the distribution of glucose absorption over time:

1. Understanding the problem: The goal is to create a mathematical function that represents the variability of glucose absorption over time.
2. Leveraging probability density functions (PDFs): PDFs are commonly used to model the probability distribution of continuous random variables. They provide a way to mathematically describe the likelihood of different outcomes.
3. Choosing the Gaussian (normal) distribution: The Gaussian distribution is a versatile choice for modeling variables that exhibit a bell-shaped curve and are influenced by multiple factors. It is commonly used in various scientific and statistical applications.
4. Selecting the parameters: The mean and standard deviation are important parameters in a Gaussian distribution. In this case, a mean of 0 is chosen, indicating that the distribution is centered around zero. A standard deviation of 1 represents the spread or variability of the distribution.
5. Generating x-values: The code generates equally spaced x-values using the ‘linspace’ function. These values cover the desired range of absorption time intervals, determined by the Glucose Absorption Time and the step size.
6. Calculating y-values using the PDF equation: The PDF equation for the Gaussian distribution is applied to calculate the corresponding y-values. This equation involves the mean, standard deviation, and the x-values generated in the previous step.
7. Normalizing the y-values: To ensure that the distribution matches the desired total glucose absorption, the y-values are normalized. This step scales the distribution so that the sum of the y-values equals the Total Glucose Absorbed.

### 2.1.3 Fuzzy Interference System

The Fuzzy Inference System (FIS) is a major component of the backend system that plays a crucial role in determining the insulin dosage for a given patient. The functionality of the FIS is as follows:

* Maximum Insulin Per Day (MIPD): The system calculates the maximum amount of insulin a patient can receive per day based on their weight and insulin requirement coefficient (IRC).
* Carbs Coverage Ratio (CCR): This ratio is calculated by dividing the patient's available carbs count (ACC) by the MIPD. It represents the amount of insulin needed to cover a certain amount of carbohydrates.
* Insulin Dose Range (MDI): The system defines a range of insulin doses, which in this case is between 0 and 1.5 units.
* Blood Glucose Rate Range (BGR\_R): The range of blood glucose rate is determined to be between -2 and 2 mg/dL/min.
* Blood Glucose Acceleration Range (BGA\_R): The range of blood glucose acceleration is set between -0.7 and 0.7 mg/dL/min^2.

The FIS employs membership functions to represent linguistic variables. Two sets of membership functions are used: mf5\_nzp (negative, slightly negative, zero, slightly positive, positive) and mf5\_lmh (very low, low, medium, high, very high).

The FIS consists of two main parts: fPrecalcDose and fInsulinDose:

* fPrecalcDose: This component is responsible for pre-calculating the insulin dose based on the patient's blood glucose level (BGL) and blood glucose rate (BGR). It uses Gaussian membership functions to define the relationships between BGL and the precalculated dose. The rules in the rule base associate specific combinations of BGL and BGR values with corresponding precalculated doses.
* fInsulinDose: This component takes the precalculated dose and the blood glucose acceleration (BGA) as inputs to determine the final insulin dose. Similar to fPrecalcDose, it uses membership functions and rule-based logic to calculate the insulin dose.

The FIST (Fuzzy Inference System Tree) is initialized by connecting the output of fPrecalcDose to the input of fInsulinDose. This tree structure allows for the propagation of information between the two components.

## 2.2 RESTful API

# 3. Development Lifecycle

* Software development methodology
* Major stages of development
* Validation and verification

# 4. Critical Analysis

* Evaluating of successes and failures (Fuzzy logic is good but only suitable for personalized use, because requires expertise)
* Suggestions for improvement (Use of deep reinforcement learning with Q-alg)
* Appraisal of the product
* Analysis of approach taken
* Analysis of tools used

# 5. Conclusion

* Summary of key-findings and recommendations for future work

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Figure - Variations of carbohydrates distribution with different deviation steps

Figure - Different variations of carbohydrates distribution with added skewness

1. An application programming interface (API) defines the rules that you must follow to communicate with other software systems. Developers expose or create APIs so that other applications can communicate with their applications programmatically [[4.1]](https://aws.amazon.com/what-is/restful-api/). [↑](#footnote-ref-1)
2. Representational State Transfer (REST) is a software architecture that imposes conditions on how an API should work [[4.2]](https://aws.amazon.com/what-is/restful-api/) [↑](#footnote-ref-2)
3. RESTful API is an interface that two computer systems use to exchange information securely over the internet [[4.3]](https://aws.amazon.com/what-is/restful-api/). [↑](#footnote-ref-3)