ROBUST ARTIFICIAL PANCREAS SYSTEM
CONTROLER FOR TYPE - 1 DIABETES PATIENTS

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Abstract

Type 1 Diabetes (T1D) is a global health concern, impairing insulin production and leading to high blood sugar levels. Current treatment methods, including insulin therapy, diet, and physical activity, pose daily challenges in maintaining optimal blood glucose levels. This study proposes a theoretical solution, the Robust Artificial Pancreas System Controller (RAPSC), employing Fuzzy Logic technology to automate blood glucose regulation and mitigate daily disturbances. Additionally, a user-friendly web application allows easy monitoring of T1D-related vitals. The proposed solution has the potential to alleviate the burden of blood glucose management and reduce health risks for T1D patients. Further research is needed to evaluate its clinical effectiveness.

Keywords: Type 1 Diabetes, insulin therapy, blood glucose regulation, artificial pancreas, Fuzzy Logic, web application, personalized healthcare.

1. Introduction

Type 1 Diabetes (T_1D) 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]. 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].
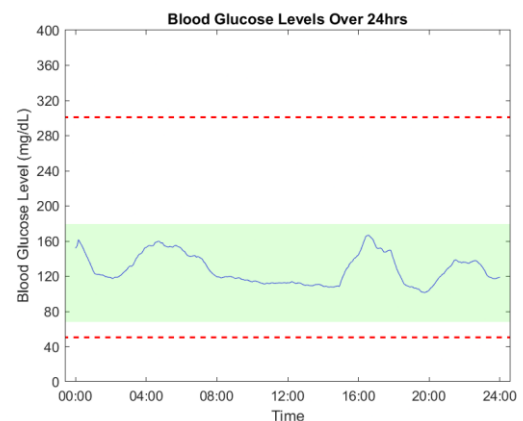

Figure 1- Blood glucose level controlled by older version of the proposed system, where 70-180 mg/dL (in green) is normoglycemia

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], 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] API[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]. 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].

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:

$$BGR_i = (BGL_i - BGL_{i-1}) \div \Delta t$$

Figure 2 - 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,

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[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].

[2] Representational State Transfer (REST) is a software architecture that imposes conditions on how an API should work [4.2]

[3] RESTful API is an interface that two computer systems use to exchange information securely over the internet [4.3].

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]. 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

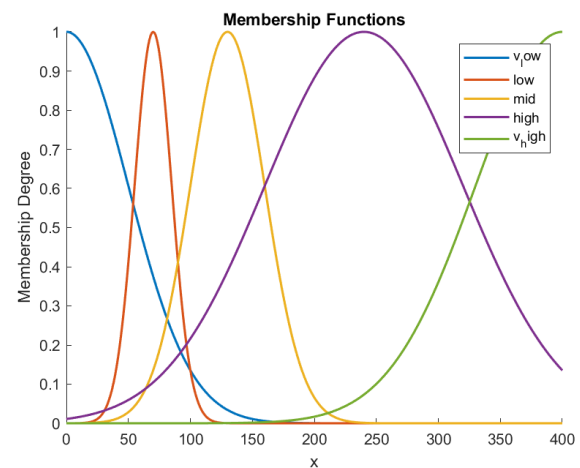glucose dynamics and insulin dosage over the 24-hour period.

Figure 3 - 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]. 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 7, Figure 8).

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

Integrating a RESTful API into a project with a MATLAB backend and a vanilla JS/HTML/CSS frontend brings numerous advantages. It establishes a seamless connection and facilitates efficient data exchange between the backend and frontend components. The computational power of MATLAB for backend operations and lightweight frontend technologies, allow great optimization of the project's performance and flexibility.

This section of the program underwent small yet significant changes that allowed for an easier and more standards compliant communication between server and client. Key changes that impacted the functionality and efficiency of the RESTful API:

- Data Storage: The old version used to write JSON data to a file using the fs module (Figure 10), while the new version maintains the data dynamically in memory. This shift eliminates the need for file read/write operations, reducing overhead and enabling faster data retrieval (Figure 9).
- CORS Integration: The new version incorporates the cors module, which enables cross-origin resource sharing. This change allows the API to securely interact with client-side.
- Simplified Endpoint Handling: In the old version, the code handles the '/patient' endpoint by writing JSON data to a file and providing a response based on the success or failure of the operation. In the new version, the code responds to a GET request to '/patient' by directly returning the JSON data from the dynamic memory. For a POST request, the code updates the JSON contents and acknowledges the successful processing. These modifications streamline the endpoint handling process and eliminate unnecessary file I/O operations.

- Performance Optimization: By storing data in memory rather than writing it to a file, the new version offers improved performance. Retrieving data from memory is faster compared to reading from the file system, resulting in reduced response times and enhanced efficiency.

2.3 Fronted

Both the initial and final designs of the app exhibit similar functionality but with some notable differences (Figure 11, Figure 12, Figure 13). The initial draft underwent testing on T1D patients, and based on their feedback, adjustments were made. Initially, the app consisted of three separate pages: one dedicated to blood glucose tracking, another for analytics of the collected data, and a third serving as a personal cabinet with notifications and information about connected devices. However, after consulting with a UI/UX designer and gathering valuable feedback, it was decided to merge the blood glucose tracking and analytics pages. This consolidation ensures that all necessary information is readily available to the patient. It's worth noting that while the personal cabinet is still considered part of the design, it has not been implemented in the current prototype as it does not provide any additional useful functionality for the testing phase.

In the new version (Figure 14), additional considerations have been taken into account, including handling edge cases. For instance, when the continuous glucose monitoring (CGM) reading fails due to various reasons, resulting in the unavailability of data for display, the app gracefully falls back to default expressions. This ensures that the user still receives meaningful information or feedback even in scenarios where real-time data is not accessible (Figure 15). By implementing this fallback mechanism, the app enhances its robustness and user experience by providing alternative expressions when specific data is unavailable.

3. Development Lifecycle

The development lifecycle of the project embraced an Agile software development methodology, known for its iterative and collaborative approach. Agile principles such as continuous feedback, adaptive planning, and incremental development were incorporated into the process. This allowed for flexibility and responsiveness to changing requirements and enabled the team to deliver value early and frequently.

3.1 Methodology

To address the potential impact of Parkinson's Law on time management, the Scrum methodology for a single developer was adopted. Parkinson's Law suggests that work expands to fill the time available, which can lead to inefficiencies and delays. To counteract this effect it was decided to implement shorter sprints lasting two to four days. A dynamic backlog was utilized to facilitate task grouping and prioritization, ensuring that the most valuable and critical items were addressed within each sprint. This approach helped prevent unnecessary task expansion and fostered a sense of urgency, promoting increased productivity and timely progress.

3.2 Major stages of development

To ensure a comprehensive understanding of the project's progress and to facilitate future analysis, every stage of the development process has been meticulously recorded.

This documentation serves as a valuable resource to assess the current state of the work and identify areas for further improvements. This systematic approach to documentation enhances transparency, fosters collaboration, and enables effective project management throughout the development lifecycle.

3.2.1 Requirements gathering

For the proposed system, the primary users will be type-1 diabetic patients who require an automated and convenient method for managing their condition. These users will have the ability to set up and register the CGM (Figure 17) device and SIP (Figure 18). They will also be able to access and interpret information about their blood glucose levels and insulin delivery. Additionally, the

system may be used by third parties such as parents, doctors, and guardians who need to track the condition of the diabetic patient (Figure 16). These users will have access to information about the patient's blood glucose levels and receive alerts if the levels approach hypoglycemic or hyperglycemic levels.

3.2.2 System Design

The system design of the project underwent significant changes, driven by the challenges encountered during the initial implementation phase. The decision to use C++ as the language of implementation initially proved to be slow and inefficient, primarily due to the complexities of the proposed system design. The development team lacked experience in building such systems with multiple programming interfaces, making it difficult to make progress effectively.

As a result, the production process faced a hurdle when considering alternative approaches. After careful evaluation, the team made the strategic decision to transition to MATLAB and leverage its built-in functionality for communication with RESTful APIs. While this decision required an additional learning curve, it significantly reduced the production time and provided a more efficient development environment.

The new system design was developed with a clear vision of the end goal, taking into account the gathered requirements. This shift allowed the team to align the system design more effectively with the desired outcomes and ensure that the development process would be smoother and more streamlined.

3.2.3 Implementation

By reassessing the language of implementation and leveraging MATLAB's capabilities for interacting with RESTful APIs, the project was able to overcome the initial challenges and proceed with a more viable and efficient development approach. The solid vision and consideration of requirements during the system design phase contributed to a more focused and effective development process moving forward.

During the implementation phase, a significant challenge emerged with the initially chosen framework. Extensive research and reading articles on various approaches for creating an artificial pancreas controller, such as ANFIS and RDL, introduced distractions from the original FIST framework. This created uncertainty regarding whether to proceed with the existing framework or explore alternative implementations.

To make a well-informed decision, thorough exploration of other approaches was undertaken to assess their potential. However, it became clear that transitioning to a new framework would require rebuilding the entire system, posing substantial risks and complexities. The potential benefits of alternative approaches needed to be carefully weighed against the cost and effort involved in such a significant change.

3.3 Validation and Verification

After careful consideration, the decision was made to stick with the initial framework. Rather than starting from scratch, the focus shifted to improving the existing system through comprehensive testing. This approach utilized the strengths of the chosen framework while incorporating valuable insights gained from exploring other approaches.

To ensure the reliability and functionality of the API, the initial implementation involved storing the received JSON data in a file. However, as the development progressed, it was realized that this approach had limitations and could impact performance. As a result, the implementation was revised to incorporate GET and POST methods for data handling, along with dynamic memory storage.

In terms of frontend data handling, simple unit tests were conducted to verify the proper functioning of the system. These tests included various scenarios, including cases where data was corrupted or inappropriately formatted, ensuring robustness in handling different inputs.

124 mg/dL	-- mg/dL
13/05/2023 - 13/05/2023	--/--/--
Average Glucose Level	Average Glucose Level
132 mg/dL	-- mg/dL
Standard Deviation	Standard Deviation
14.33 mg/dL	-- mg/dL
GMI	GMI
7.14 %	-- %
Time in range	Time in range
High	High
22 %	--
In range	In range
65 %	--
Low	Low
13 %	--

Figure 4 - Fronted view when connection to the API was successful (no CSS)

Figure 5 - Fronted values when connection to the API was unsuccessful (no CSS)

For backend testing, MATLAB's built-in plot functions were utilized to assess the newly implemented carbs distribution system. Additionally, the impact of updates made to the FIST's membership functions on system performance was evaluated through extensive testing. Over a thousand tests were executed to achieve optimal tuning of the FIST (Figure 3).

Furthermore, a simulation environment was utilized to generate a comprehensive history of tests. This allowed for the visualization of the patient's blood glucose levels over a 24-hour period, providing insights into the overall performance of the system (Table 1, Table 2).

By conducting these various tests, the project team was able to validate the functionality, stability, and performance of both the API and the system as a whole.
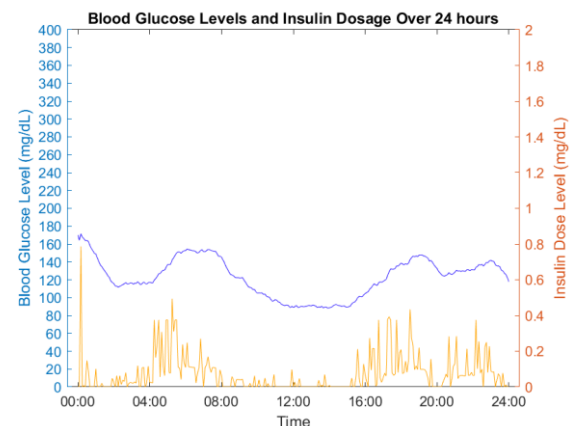
Figure 6 - Simulation results from FIST fed with a normal diet dataset

4. Critical Analysis

4.1 Tools Used

In terms of the tools used throughout the development process, there were several key choices that facilitated the creation of the closed-loop system. Starting with MATLAB, it proved to be an excellent platform for gaining a comprehensive understanding of the development concepts involved. Its capabilities and ease of use were instrumental in getting started.

Looking ahead to future development, Rust emerged as a compelling choice. With its emphasis on speed, safety, and networking capabilities, it holds great potential as the next checkpoint for the RAPSC. The language's unique features make it a promising option for further enhancing the system.

GitHub as always played a crucial role in system's succession by providing remote capabilities to the project. Its project feature allows developers to create and maintain a very convenient backlog for sprints as well as setting goals and achieving them. Great management tool overall.

It's important to note that the system was developed on an x64 Windows system and has certain prerequisites, including MATLAB 2020b or higher, NodeJS, and npm, to ensure compatibility and smooth operation.

4.2 Approach

The Fuzzy Inference System (FIS) has emerged as a promising framework for the management of Type 1 Diabetes (T1D). Its ease of implementation and efficient training process make it an attractive choice for T1D management. One of the notable advantages of FIS is its ability to utilize natural language for the implementation of rulesets, providing a crucial component of abstraction that gives FIS a distinct edge.

However, when it comes to developing a robust artificial pancreas controller, certain limita-

tions within the FIS framework need to be addressed. Firstly, FIS requires specialized expertise and meticulous tuning, making it more suitable for personalized use rather than widespread applicability. This lack of adaptiveness and generality restricts its potential in accommodating diverse individuals and varying circumstances.

Another critical aspect that demands attention is the absence of an accurate blood glucose level prediction model within the project. While there exist FDA licensed simulators that offer moderately reliable data for testing controllers, their usage is accompanied by limitations that confine the research predominantly to the theoretical realm.

Nevertheless, the thorough tuning of FIS's verbose ruleset has provided valuable insights into the intricacies of insulin administration, taking into account parameters such as blood glucose level, blood glucose rate, and blood glucose acceleration. This knowledge serves as a valuable asset for future developments and paves the way for further advancements in this field.

As the field of T1D management and artificial pancreas controllers continues to evolve, efforts are underway to overcome the limitations of FIS and enhance the accuracy of blood glucose prediction models. By addressing these challenges, researchers aim to forge a path towards more adaptive, personalized, and effective T1D management systems.

4.3 Appraisal

In my ongoing research endeavors, I intend to explore the utilization of deep reinforcement learning with the Q-Learning algorithm, which has gained significant prominence in recent times. This study has shed light on the inadequacy of a system lacking adaptiveness and generality, making it unsuitable for a broader spectrum of patients. Such limitations are deemed unacceptable, considering that the primary objective of closed-loop artificial pancreas system controllers is to alleviate the daily burden of insulin administration for numerous adults, adolescents, and even children. Consequently, it becomes imperative to de-

velop a system that is both versatile and safe, ensuring long-term viability and, above all, safety.

This work serves as a commendable foundation for further investigation in the expansive domain of biotechnology. Notably, the project has successfully attained a significant portion of its predetermined objectives. I find satisfaction in the encountered challenges throughout the journey, as they have contributed invaluable experiences and knowledge that will significantly inform the subsequent stages of development.

Drawing upon these achievements, future research endeavors can explore the intricate landscape of biotechnology with greater depth. My fervent aspiration is that these ongoing efforts will culminate in the development of a holistic, flexible, and robust artificial pancreas system controller that can effectively cater to the diverse requirements of individuals living with Type 1 Diabetes. Such an advanced controller holds the potential to revolutionize T1D management, offering improved quality of life and empowering patients with enhanced control over their condition. By harnessing the power of cutting-edge technologies and integrating them seamlessly into clinical practice, we can pave the way for a future where individuals with T1D can lead healthier, more fulfilling lives.

5. Conclusion

In conclusion, the Robust Artificial Pancreas System Controller (RAPSC) presents a promising solution for individuals with Type 1 Diabetes (T1D) in managing their blood glucose levels effectively. By leveraging Fuzzy Logic technology, the developed RAPSC offers personalized and automated blood glucose regulation, alleviating the daily challenges faced by T1D patients. The inclusion of a user-friendly web application further enhances the monitoring and management of T1D-related vitals, providing a convenient and accessible tool for patients. While the proposed system shows great potential, further research and clinical trials are necessary to validate its effectiveness and ensure its safe implementation in real-world settings. Overall, the RAPSC holds

promise as an innovative approach to improving the quality of life for T1D patients by mitigating health risks associated with uncontrolled blood glucose levels.

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Once again, I express my deepest appreciation to everyone who has helped me throughout this journey, and I hope that this research will contribute significantly to the development of more effective and robust artificial pancreas systems for type-1 diabetes patients.

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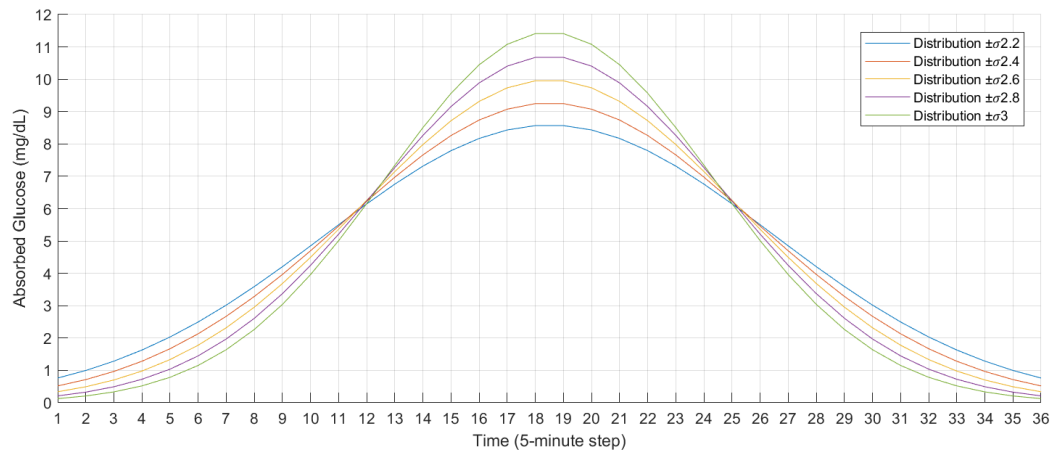
Appendices

Figure 7 - Different variations of carbohydrates distribution based on variative standard deviations

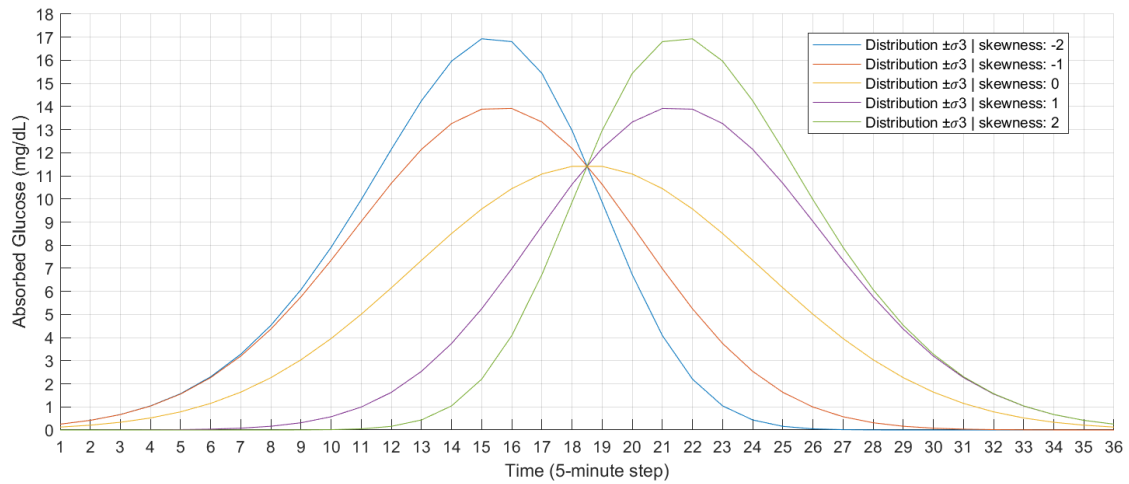*Figure 8 - Different variations of carbohydrates distribution based on variative skewness*

Figure 9 - Internal server error due to inability to access the specified file location

Figure 10 - Showcase of the server startup on port 8080 and successful write operation to JSON file
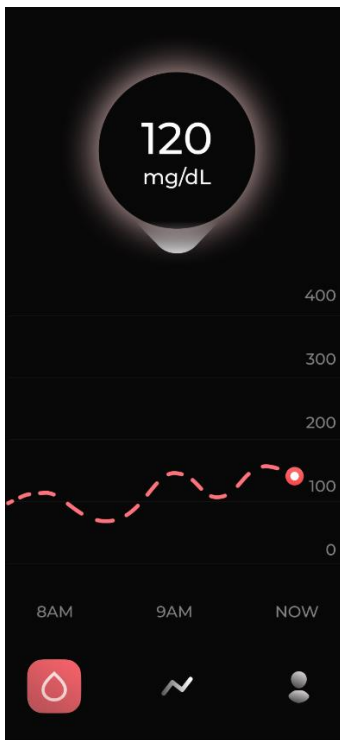
Figure 11 - Initial Design: Virtual CGM tab in the app with real-time blood glucose tracker and trend line up showing glucose level history

Figure 12 - Initial Design: Statistics tab in the app showing collected data about patient within 3 months period; share button that allows to export presented data
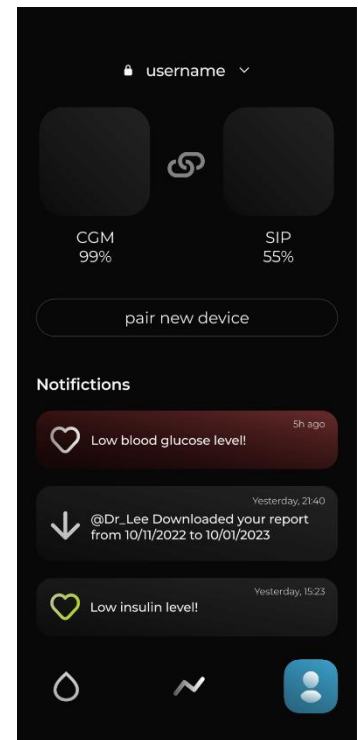
Figure 13 - Initial Design: Profile tab in the app showing APSC devices connected to smartphone, latest notifications history as well as button to pair new device
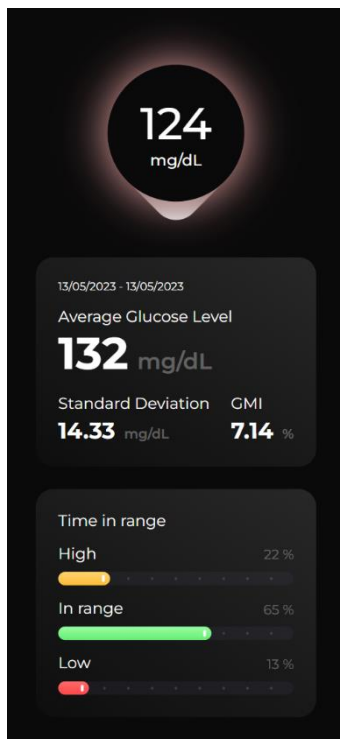

Figure 14 - Current Design: Joined analytics and CGM readings pages for better user espirience

Figure 15 - Current Design: Edge case when CGM reading fails but the whole system still works
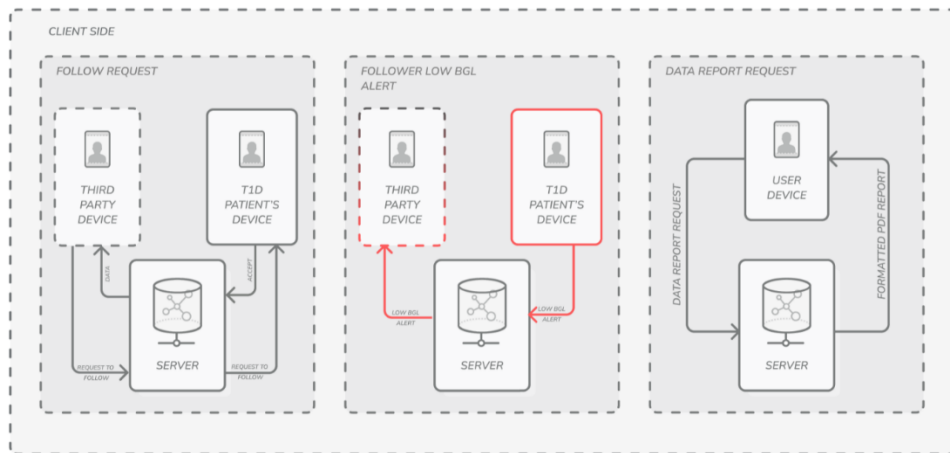
Figure 16 - Client-side functionality for patient and third parties with three use cases diagrams
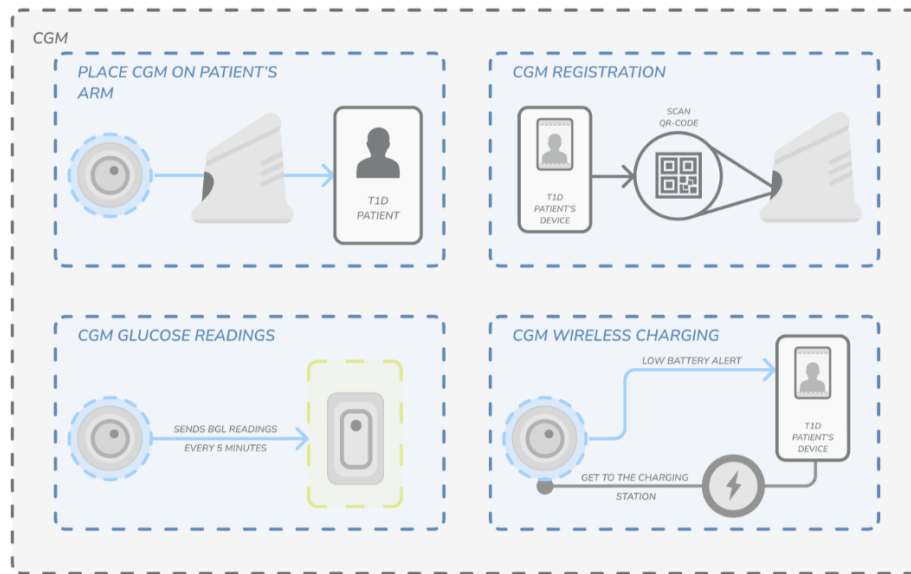

Figure 17 - Use case diagrams of continuous glucose monitor (CGM) interactions with software, hardware and client
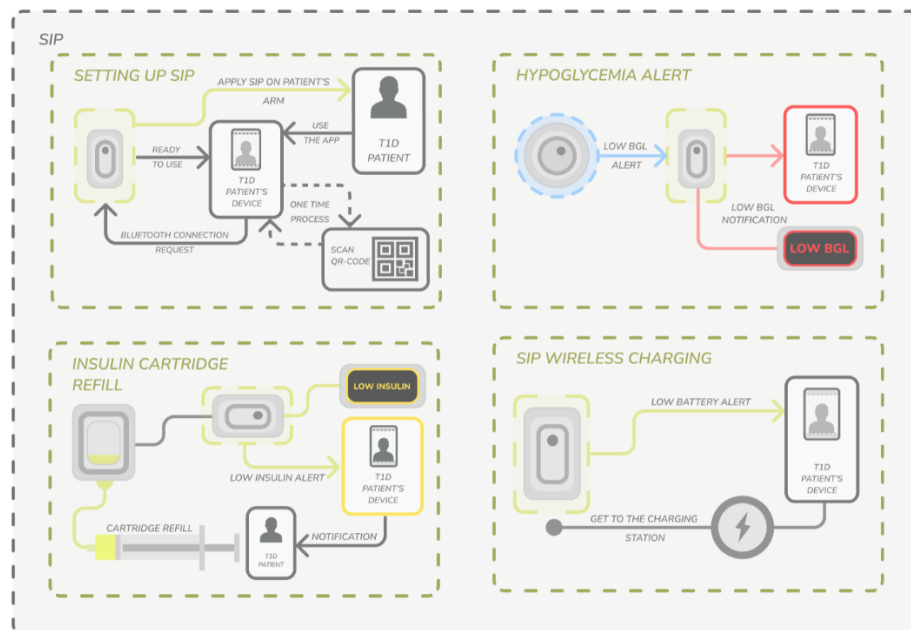

Figure 18 - Use case diagrams of smart insulin pump (SIP) interaction with software, hardware and client
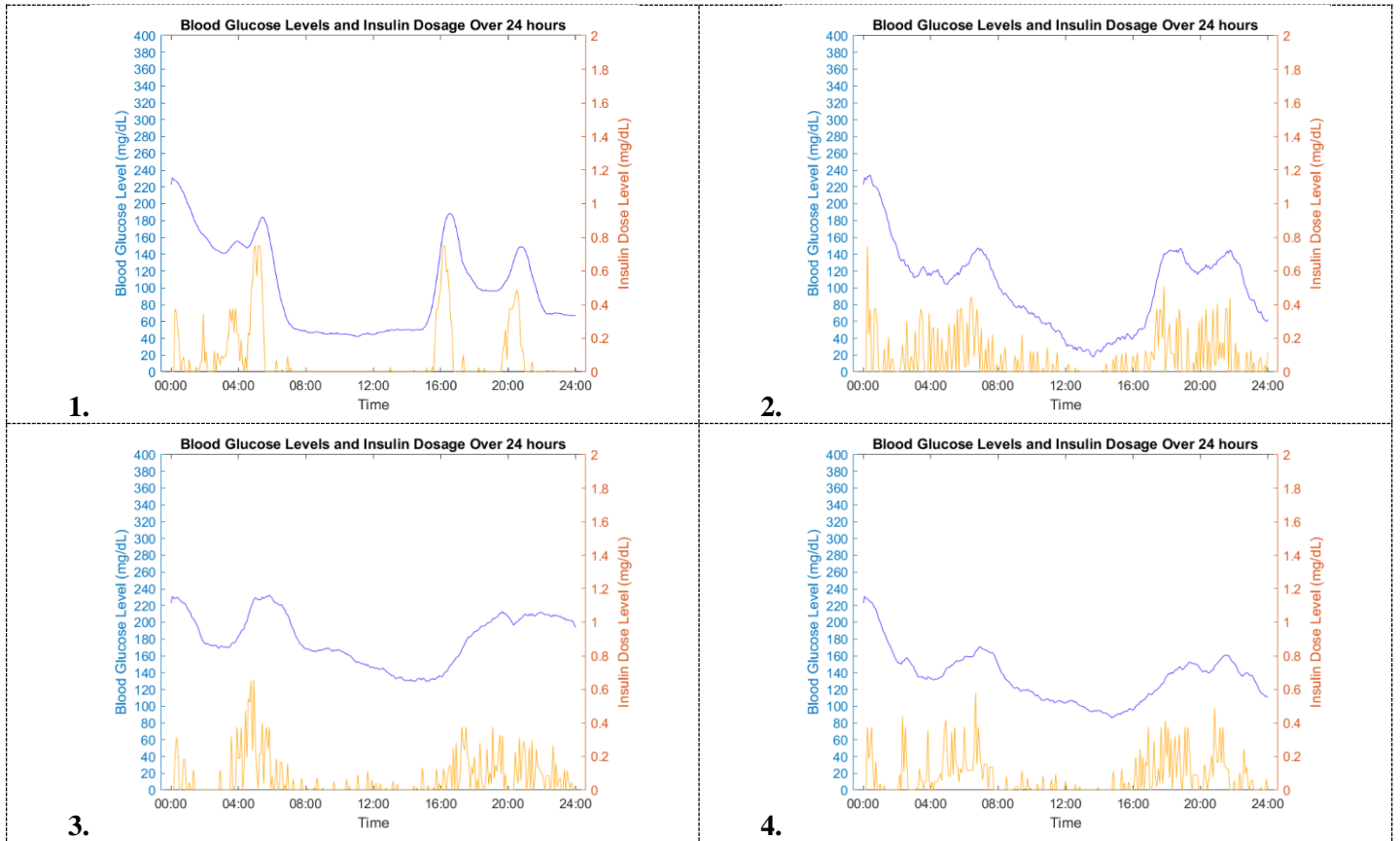
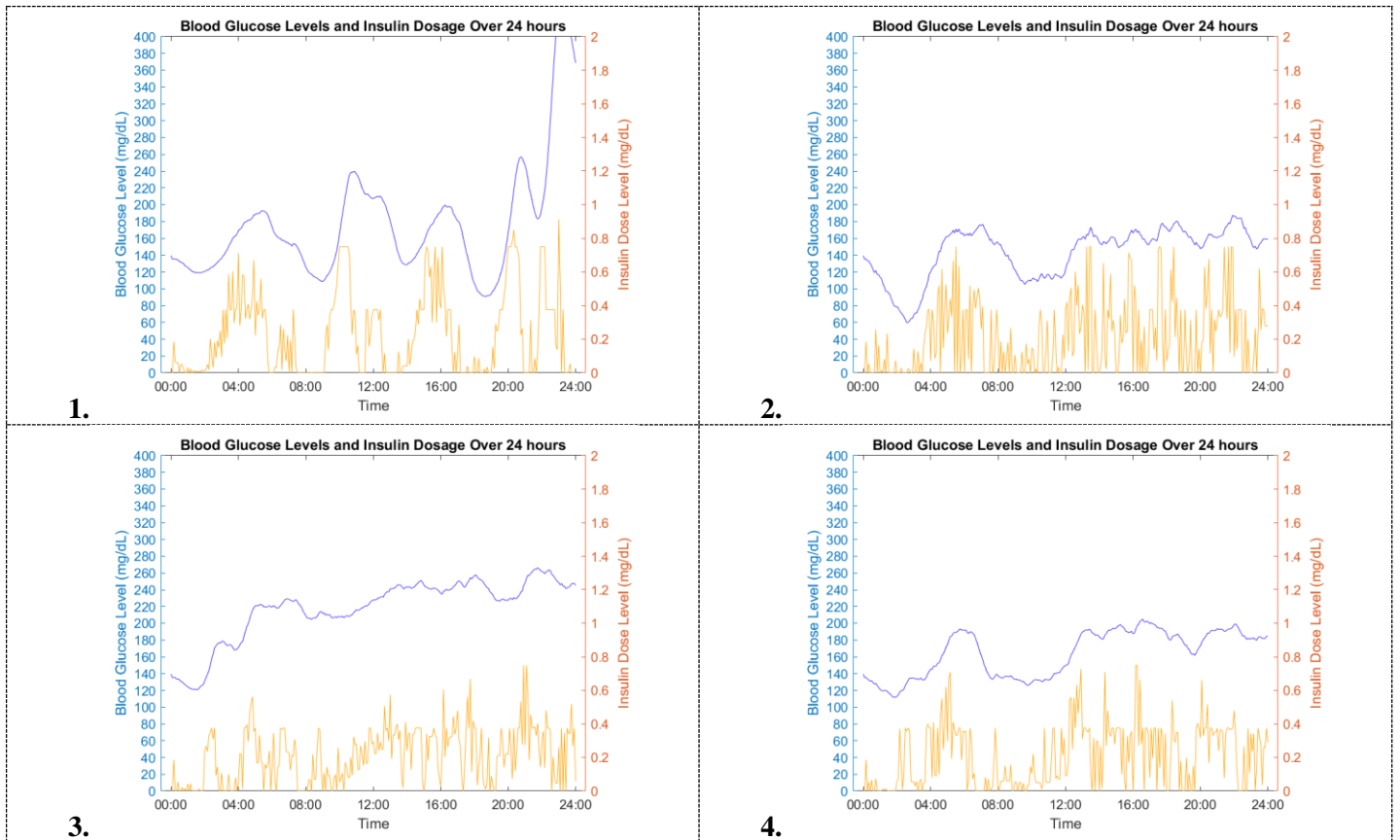*Table 1 - Progress of FIST tuning on a dataset with high blood glucose level*

Table 2 - Progress of FIST tuning on a dataset with high carbohydrate intake