Gharyan University Journal of Engineering Science (GUJES)
ISSN (3105-4560)
Website:http://journals.gu.edu.ly
email: gujes@gu.edu.ly

Comparative Analysis of PID Control Structures for Glucose Regulation in Type 1 Diabetes: A Simulation-Based Study Using the Bergman's Model

Aleisawee Mohamed Alsseid*[1], Issa Eldbib[2], Shefaallah Melad[3], Haneeyah Omran[4], Nehal A. Alsseid[5]
[1-5] Control Engineering Department , College of Electronic Technology, Bani Walid, Libya

*Corresponding author: dr.Aleisawee@gmail.com

Received: 07 Feb 2026	Accepted: 26 Feb 2026	Published: 01 March 2026

Abstract

Regulation of blood glucose levels is a critical challenge in the management of Type 1 Diabetes (T1D), where endogenous insulin production is impaired. This study presents a comprehensive comparative analysis of various classical control strategies for glucose regulation, based on the Bergman Minimal Model. We evaluate the performance of Proportional (P), Proportional-Integral (PI), Proportional-Derivative (PD), and Proportional-Integral-Derivative (PID) controllers, implemented in both series and parallel configurations. The system is subjected to physiological disturbances, including meal intake, to simulate real-world conditions. Controller performance is rigorously assessed using a suite of metrics, including the Integral of Absolute Error (IAE), Integral of Squared Error (ISE), Integral of Time-weighted Absolute Error (ITAE), Integral of Time-weighted Squared Error (ITSE), and Integral of Control Effort (ICE), alongside time-domain specifications such as settling time, overshoot, rise time, and steady-state error. Our findings indicate that while the series PID controller demonstrates the most effective regulation, it demands a control effort that may be clinically impractical. In contrast, the parallel PID controller provides the best compromise between accuracy, stability, and insulin utilization, making it a more suitable candidate for automated glucose control systems. These results underscore the critical importance of controller structure in biomedical applications and highlight the potential of PID-based designs in the development of future artificial pancreas technologies The investigated system with applied different control strategy is implemented in MATLAB.

Keywords: Type 1 Diabetes, Glucose Control, PID Controller, Bergman Minimal Model, Artificial Pancreas, Control Structures

1. Introduction

Diabetes mellitus is a major global health burden and ranks among the top ten causes of mortality in the adult population. According to established epidemiological estimate, the global prevalence of diabetes among adults is approximately 463 million, consequent to 9.3% of the world's adult demographic. Projections suggest this figure will rise to 700 million, or 10.9% of the global adult population, in the coming decades. The impact of diabetes is not limited to health; it also involves significant financial costs. In 2019, global spending on diabetes care was about 760 billion US dollars. This cost is expected to increase to 825 billion dollars by 2030 and could reach 845 billion dollars by 2045 [1]. Evidently, diabetes is a growing problem, and a great amount of research goes into understanding the development of the disease additionally prevent and treat the diabetes are extremely the most important issue. It is well known that; the human being body consists of various organs. Those organs have their own specific functions and play their roles in maintaining relevant biological activities in the body. To carry through its function, each organ needs a stable and adequate glucose supply from the blood. It is therefore important to keep the optimal blood glucose level under normal metabolic conditions [2]. In general, the whole-body glucose regulation mechanism is described by the following sequence of events: the elevated glucose level in the glucose-insulin regulation system stimulates insulin secretion from the pancreatic β-cells, thus raising the plasma insulin level. Such a high insulin level promotes glucose consumption in the glucose consuming organs and suppresses glucose production in the liver. This in turn induces reduction of the plasma glucose level, which inhibits gradually insulin secretion from the pancreas. Otherwise, the decline in the blood glucose level tends to promote secretion of glucagon, which activates glucose production in the liver. In this manner, the combined effects of glucose, insulin and glucagon regulate the blood glucose level, to which a number of mathematical approaches have been devoted. Insulin is among the most important hormones. It regulates glucose transport into the muscle and adipose tissues and hepatic glucose output as well as controls secretion of itself in pancreatic β-cells. If the β-cells do not secrete insulin sufficiently or the insulin does not work properly, the body is prone to diabetes, [3] which develops such complications as retinopathy, nephropathy, peripheral neuropathy and blindness [4]. Therefore, for the assessment of the β-cell function and insulin sensitivity/resistance, various glucose tolerance tests have been performed in experiments as well as in clinics.2. Bergman,[5],[6]. The use of mathematical models as an approach to aid our understanding of glucose regulation has grown rapidly over recent years, providing new insights into the underlying mechanisms involved and the dynamic behaviour of the complex biological system. Type 1 diabetes is a chronic condition that requires careful management of insulin levels to maintain stable blood glucose levels. The effective regulation of insulin is crucial for the health and well-being of individuals with type 1 diabetes. This study explores the use of Proportional-Integral-Derivative (PID) controllers as a potential solution for automated insulin delivery and improved glycaemic control in individuals with type 1 diabetes. The project investigates the performance of various PID controller configurations in regulating insulin levels, providing valuable insights into the viability and effectiveness of this approach for type 1 diabetes management. According to the International Diabetes Federation (IDF), in 2014, 385 million people worldwide suffered from diabetes, with many of them living in the Western Pacific regions, including countries like Malaysia, China, and Cambodia [7]. Because of these numbers and future predictions, research is essential to prevent diabetes, develop better treatment methods, and eventually find a cure for Type 1 Diabetes Mellitus

(T1D). The T1D is a condition where people must manage their blood sugar levels using insulin because their bodies can't produce enough insulin on their own. This differs from people without diabetes, who can naturally produce insulin in their pancreases. In 2019, about 1.4 million adults in the United States were newly diagnosed with diabetes. This means 5.9 new cases were found for every 1000 people. Research shows that many people with Type 2 Diabetes (T2D) already have other diabetes-related health issues when they are diagnosed [8],[9]. For example, more than 30% of veterans had chronic kidney disease even before they knew they had diabetes [10]. The T1D is one of the main kinds of diabetes, alongside T2D and gestational diabetes mellitus (GDM) [11]. By 2019, about 1.1 million kids and young people under 20 had T1D. In this condition, the immune system attacks and destroys the β cells in the pancreas that produce insulin [12]. Insulin is crucial because it helps lower blood sugar levels, which the body needs to make energy [13]. People with T1D lose a lot of insulin and a hormone called amylin secretion. Though the small percentage of T1D patients are monogenic, until now, there was no therapy to surpass the ultimate cause of diabetes. The available treatments are the sole option to maintain blood glucose within the target normal level (70-180 mg/dL) [14]. Around 100 years ago, scientists created insulin that could be taken from outside the body, which helped people with T1D live much longer. Today, treatments include insulin shots and insulin pumps that deliver a steady flow of insulin [15]. Numerical techniques and mathematical models have been applied in the area of biomedical sciences as theoretical tools traditionally to analyse major aspects of various healthcare and biomedical processes and to formulate healthcare policies [16]. Diabetes mathematical modelling is a valuable technique for nations to keep track of diabetes prevalence over time and to derive cost-effective policies aimed at both diabetes incidence and complication control. Today, the use of sophisticated physiological modelling and control techniques is very applicable in biomedical engineering [17]. Various areas exist where such solutions are implemented. Clear examples are the control of anesthesia [18], the regulation of blood glucose (BG) levels in diabetes mellitus (DM) patients, also referred to as the Artificial Pancreas (AP) challenge [19], and the regulation of tumor growth. In the case of diabetes mellitus, many difficult factors come into play that need to be taken into account when devising solutions to treatment. In the last several decades there have been a number of research studies on the diabetes illness, which can be of the type 1 diabetes or type 2 diabetes, and the associated blood hormones using different approaches [20-24]. In [16 - 25] developed a model for the motion of the glucose and insulin hormones. It has been referred to as the minimal model since it was as simple as possible with the minimum of the biological intricacies. The minimal model is also referred to as an open-loop model since it lacks an equation for the insulin secretion by the pancreatic beta cells, which can operate when the plasma level of glucose is elevated. Glucose-insulin interaction mathematical models have been researched within the past 50 years. These models range from uncomplicated linear models to very detailed mathematical models. Such as non-linear model [25], and detailed models [26]. [27]. Glucose-insulin interaction models have been widely applied in the research of diabetic patients' physiological behavior. Thus, regulation and management of blood glucose for a diabetic patient is an open research issue. Multiple injection doses are the most common therapy, wherein a patient must manually calculate the dosage intake each time prior to or after meal [28]. In [29] linear model is investigated. In control engineering, closed-loop control involves the design of an automatic controller that at the appointed time responds when blood glucose levels go astray from the established threshold. The controller's purpose is to guarantee that glucose levels remain within the normal glycemic range for an extended period. The control of blood glucose (BG) levels in a closed-loop system has been a subject of research for decades, with experiments carried out under both mathematical settings (see, e.g., [12]– [14], and others) and empirical settings (see, e.g., [15]). The empirical setting employed clinical knowledge and experience, while the mathematical setting employed models that explain the endogenous regulation of glucose carried out by the endocrine pancreas to derive suitable strategies for BG control. The most common controller applied to identify the system's dynamics is the PID controller. The modelling is easier and more practical. Minimum assumptions are taken like the association of insulin and blood glucose as well as the disturbance that acts upon the blood glucose. There was no relative detection of risk associated with hyperglycemia and hypoglycemia [29, 33]. The linear control methods considered for the control of glucose concentration in people with type 1 diabetes are basically based on Proportional Integral Derivative (PID) control algorithms [31], including a robust PID control method [32], a digital PID controller [33], an expert PID controller [34], and a genetic control algorithm based on the PID control strategy [35]. Some other linear control techniques for glucose level control include a feed forward-feedback control approach [36], a control law based on pole placement, and a discrete model predictive algorithm-based controller [37]. There can be no doubt that diabetes is an increasing problem, and there is a substantial amount of research aimed at discovering the trajectory of the disease and prevention and intervention strategies. The application of mathematical models to improve our insights into glucose regulation has grown significantly in recent years, offering new understanding of the underlying mechanisms and dynamic properties of this intricate biological system [38]. The analysis of different structures of Proportional-Integral-Derivative (PID) controllers in insulin control systems for the regulation of Type 1 Diabetes (T1D) is a significant field of study, with the ultimate goal of enhancing blood glucose regulation and patient outcomes. In this study, we present a comprehensive comparative analysis of various PID controller structures specifically P, PI, PD, and PID in both series and parallel configurations for automated insulin delivery in T1D. Utilizing the established Bergman Minimal Model as our physiological framework, all controller configurations are

Gharyan University Journal of Engineering Science (GUJES)
ISSN (3105-4560)
Website:http://journals.gu.edu.ly
email: gujes@gu.edu.ly

evaluated and compared under standardized zero initial conditions within a transfer function framework. This standardized approach provides a fair and critical benchmark for evaluating transient dynamics and steady-state performance, which is an essential step in identifying the most viable and promising controllers for the development of a safe and effective artificial pancreas system.

2. Mathematical Model and Methodology

The Bergman Minimal Model is a widely accepted mathematical representation of glucose-insulin dynamics in the human body. It provides a simplified yet powerful framework for simulating the physiological responses to glucose and insulin, making it an ideal platform for the development and testing of control algorithms for an artificial pancreas. The model consists of two main components: glucose dynamics and insulin dynamics. Glucose Dynamics**,** The rate of change of glucose concentration in the blood is described by the following differential equation:

$$(dG(t)) / dt = -(\alpha\_1 + X(t)) * G(t) + \alpha\_1 * G\_b \quad (1)$$

$$dX(t)/dt = -\alpha_2 * X(t) + (I(t) - I_b) * \alpha_3 \quad (2)$$

Where: ***G(t)*** = Actual glucose concentration (mg/dl)., G_b Basal glucose level (mg/dl). X(t) = Effect of active insulin (1/min). α_1 = Rate of insulin-independent glucose consumption (1/min) and $I(t)$ = Actual insulin level (U/ml)., I_b = Basal insulin level (U/ml)., α_2 = Decay rate of insulin effect (1/min). α_3 = Insulin-dependent glucose consumption rate (1/U). The dynamics of insulin in the plasma are described by equation

$$dI(t)/dt = -n * (I(t) - I_b) + \gamma * [G(t) - h]^{+t} \quad (3)$$

Where: ***n*** is the First order decay rate (1/min). ***γ*** is the secretion rate of insulin (µU·mg/(ml·min²·dl)) and ***h*** is the threshold value for glucose (mg/dl). For the purpose of this study, the model was linearized around a nominal operating point to obtain a transfer function representation, which is more amenable to classical control design techniques. The resulting transfer function from the insulin infusion rate u(s) to the glucose concentration G(s) is given by:

$$G(s) = -G_b / ((s + \alpha_1)(s + \alpha_2)(s + n)) \quad (4)$$

The parameters (***a_1, a_2, a_3, n, γ, h, G_b, I_b***) are not estimated from individual patient data in this study but are taken from established literature as shown in Table 1. These values represent typical or average physiological values. In a real clinical implementation, these would be personalized for each patient (e.g., n and insulin sensitivity could be estimated from patient data). A block diagram of the closed-loop control system for a Type 1 diabetes patient is presented in Figure 1. The reference input $R(s)$ represents the desired basal glucose set point. The measured output $Y(s)$, obtained from a continuous glucose monitor (CGM), is fed back and compared to $R(s)$ at a summing junction. This junction computes the error signal $E(s)=R(s)-Y(s)$. The PID controller processes $E(s)$ to generate the control signal $U(s)$, the commanded insulin infusion rate. This control signal serves as the input to the plant $G(s)$, which models the patient's glucose regulatory dynamics via a linearized Bergman minimal model. An disturbance input $D(s)$, representing metabolic perturbations such as meal consumption, physical exercise, or physiological stress, is introduced as an additive term to the plant's output. The resulting variable $Y(s)$ is the resultant blood glucose concentration, which is subsequently measured by the sensor to close the feedback loop. The control objective is for the controller to continuously regulate the plant input $U(s)$ to drive the error signal $E(s)$ asymptotically to zero. This ensures the maintenance of normoglycemia (a normal blood glucose level) by compensating for the effect of disturbances $D(s)$. This modelling paradigm provides a rigorous and mathematically tractable framework for simulation, analysis, and performance comparison of various control strategies. This constitutes a fundamental step in the design cycle of biomedical control systems, enabling extensive testing prior to clinical human trials.

Table 1. Nomenclature

Symbol.	Description	Val.	Units
α_1	Rate of insulin-independent glucose consumption	0.72	1/min
G_b	Basel value of glucose	80	Mg/dl
α_2	Decay rate of insulin effect	0.05	1/min
α_3	Insulin-dependent glucose consumption rate of glucose	1	1/U
I_b	Basel level of insulin	7	U/ml
h	Threshold value of glucose	79.0353	Mg/dl
n	First order decay rate	0.31	1/min
Y	Secretion rate of insulin	0.0039	μU.mg/ml.$\mathbf{min^2}$.dl

Gharyan University Journal of Engineering Science (GUJES)
ISSN (3105-4560)
Website:http://journals.gu.edu.ly
email: gujes@gu.edu.ly

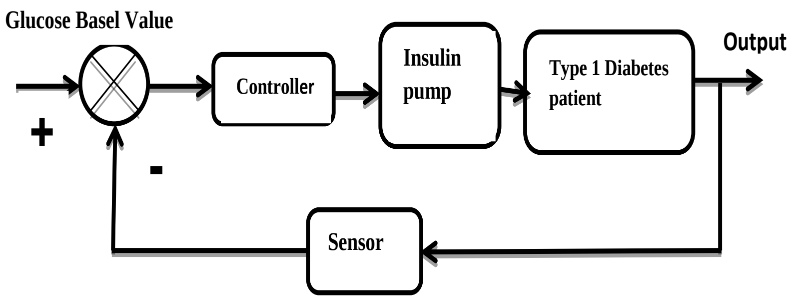

Figure 1: The Block Diagram of Type 1 Diabetes Patient

3. PID Controller Configurations

The Proportional-Integral-Derivative (PID) controller is a feedback control mechanism that calculates a corrective action based on the present, past, and predicted future state of the error signal. The error signal, e(t), is defined as the difference between the desired set point (the basal glucose level, e.g., 80 mg/dL) and the measured process variable (the actual glucose concentration). The general form of a PID controller is given in (5).

$$U(t) = k_p(e(t) + k_i * \int e(t)\,dt + k_d * \frac{de(t)}{dt}) \quad (5)$$

Where U(t) is the control signal $e(t)$ is the error signal (difference between the desired set point and the actual output) ,k_p is the proportional gain, k_i is the integral gain and K_d is the derivative gain. The PID controller generates a corrective output by combining three distinct actions based on the error signal, ***e(t)***, defined as the deviation between a desired set point (e.g., basal glucose) and the measured process variable. The ***Proportional (P)*** term provides an immediate control action proportional to the current error magnitude, enabling a rapid response to disturbances. However, P-only control inherently results in steady-state error, as the corrective effort diminishes as the error decreases, preventing complete elimination of the offset. ***Integral (I)*** **Term:** Eliminates steady-state error by integrating past errors, ensuring long-term accuracy. However, excessive integral gain can induce overshoot and oscillations, posing a risk of hypoglycemia due to continued insulin infusion after the set point is reached. The **Derivative (D)** term anticipates future error trends by responding to the rate of change of the error signal, providing a damping action that mitigates rapid glucose excursions. However, its high sensitivity to high-frequency noise necessitates careful implementation, often requiring signal filtering to avoid control signal instability. Equations (6-12) highlight the mathematical form of applied controller

Parallel PID $U(s) = (k_p + \frac{k_i}{s} + k_d * s)E(s)$ (6)

Series PID $U(s) = k * \left(1 + \frac{1}{\tau_{i*}s}\right)(1 + \tau_d * s) * E(s)$ (7)

Parallel PI : $U(s) = (k_p + k_i/s) * E(s)$ (8)

Series PI : $U(s) = k * \left(1 + \frac{1}{Ti*s}\right) * E(s)$ (9)

Parallel PD: $U(s) = (k_p + k_d * s)E(s)$ (10)

Series PD: $U(s) = K * (1 + Td * s) * E(s)$ (11)

Proportional (P) : $U(s) = Kp * E(s)$ (12)

In this study, all PID configurations were compared using zero initial conditions within a transfer function framework. This provides a standardized and fair benchmark to evaluate them. This deliberate standardization is essential for generating a reasonable, and allowing accurate assessment and direct comparison of transient dynamics and steady-state performance across different controller designs. The gains of the controllers all manually tuned.

4. Performance Evaluation Metrics

To provide a comprehensive and quantitative comparison of the different controller configurations, we employed a set of widely used performance indices. Integral of Absolute Error (IAE): Measures the cumulative absolute error over time. A smaller IAE indicates better overall performance. Integral of Squared Error (ISE), Penalizes larger errors more heavily than smaller ones. A smaller ISE indicates a more precise response. Integral of Time-weighted Absolute Error (ITAE), Emphasizes errors that persist for a longer time. A smaller ITAE suggests a faster response. Integral of Time-weighted Squared Error (ITSE): A combination of ISE and ITAE, which strongly penalizes large and persistent errors. Integral of Control Effort (ICE), Measures the total control action applied over time. A smaller ICE is desirable for efficiency and to minimize the risk of actuator saturation. In addition to these integral performance indices, we also analyzed the time-domain specifications of the system's response, including: Settling Time: The time it takes for the response to reach and stay within a certain percentage (typically 2% or 5%) of the final value. Overshoot: The maximum peak value of the response curve measured from the desired response. Rise Time: The time it takes for the response to rise from 10% to 90% of its final value. Steady-State Error: The difference between the desired final value and the actual final value of the system's response.

5. Results and Analysis

To evaluate the performance of the different PID controller configurations, a series of simulations are conducted using the linearized Bergman Minimal Model. In this study, the model is subjected to the following highly considerable factors that should be taken in consideration. Muscle and liver glycogen dynamics are modelled with their respective maximum storage, utilization, and release rates. Meal disturbances with varying magnitudes are introduced at specified times using an exponential absorption function to simulate glucose influx. Hormonal influences (glucagon, epinephrine), exercise intensity profiles, and stress disturbances are incorporated to add realism to the glucose response under different physiological conditions. Patient-specific parameters like insulin sensitivity, basal glucose, and beta-cell response determine the control objectives. Accordingly, the simulation results are analyzed based on the performance metrics and time-domain specifications described in the previous section. The primary objective of the control system is to maintain the blood glucose level as close as possible to the basal level in the presence of disturbances. *Case I* , the model was subjected to a disturbance with magnitude of seven at different period of time where as second and third case are subjected to a disturbance with magnitude of ten and thirteen respectively. the Throughout this study, the controller gains are manually tuned. Figure 2, demonstrates the initial blood glucose concentration in mg/dl against time interval which is taken into minutes to match the practical approach of the diabetic. As can be seen in Fig.2, the behaviour response of blood glucose concentration is clearly influenced according to the controller configuration a detailed comparison is highlighted in Table 1. Fig.ure 3 visualizes the blood glucose concentration from 50 min to 1000 min. In this the model are subjected to the following highly considerable factors that should be taken in consideration. Glucose and insulin limits define safe operating bounds. The insulin infusion profiles are shown in Figure 4. Figure 5 highlighted the dynamic response of control signal over time with disturbance magnitude of 7. As can seen from Figure 6. the series configuration of PID shows high-amplitude oscillations compared with the rest of configuration. Time-domain specification analysis With reference to the obtained results and the figures presented in Table

Gharyan University Journal of Engineering Science (GUJES)
ISSN (3105-4560)
Website:http://journals.gu.edu.ly
email: gujes@gu.edu.ly

1 the following observation are noticed and the **key findings are presented. The** PID controllers, especially in the parallel configuration, are optimal for glucose regulation. consistently demonstrated superior performance in terms of minimal overshoot, fast rise time, and zero steady-state error. It achieved the best performance compared with other configuration with acceptable insulin usage. The PID Series controller while

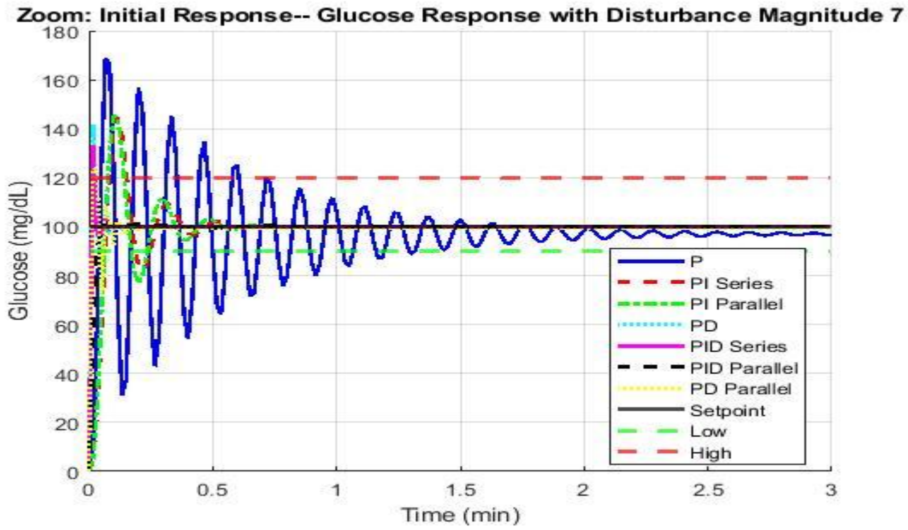

Figure 2: Initial Blood Glucose Response for Different Controller Configurations.

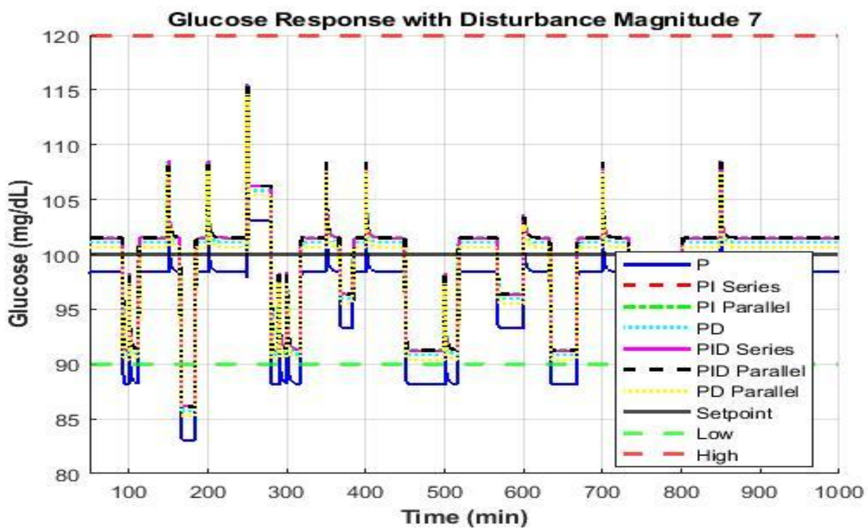

Figure 3: Blood Glucose Response for Different Controller Configurations

Gharyan University Journal of Engineering Science (GUJES)
ISSN (3105-4560)
Website:http://journals.gu.edu.ly
email: gujes@gu.edu.ly

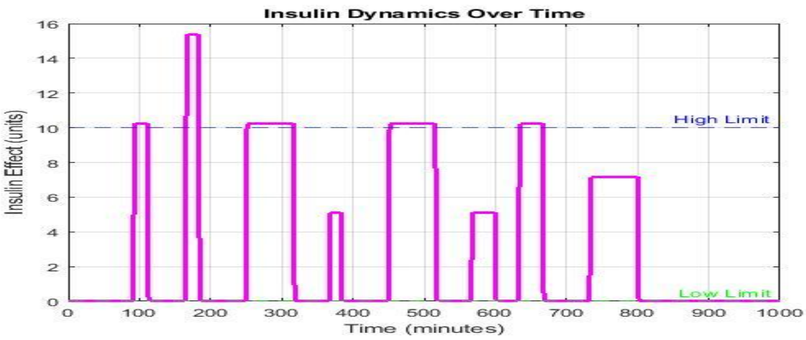

Figure 4: Insulin Infusion Profiles Vertime

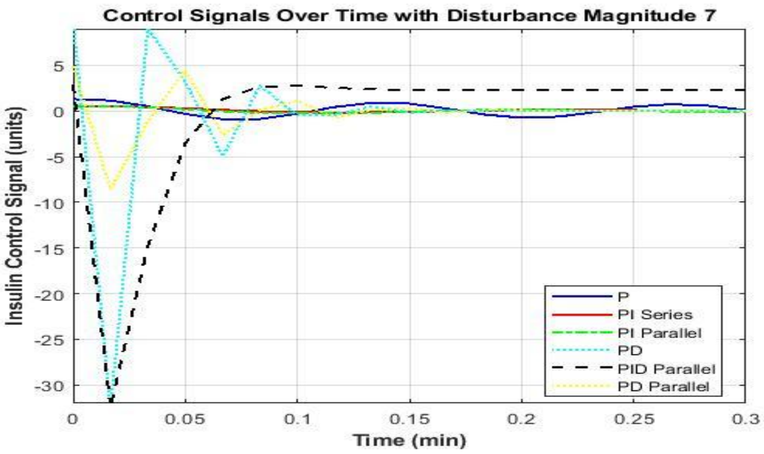

Figure 5: Initial Response Control Signal Over Time with Disturbance

achieving slightly better performance metrics, consumes significantly more control effort, raising clinical safety and feasibility concerns. Controllers without integral action (P, PD) failed to maintain glucose within safe limits over long periods. This reinforces the necessity of integral control in any closed-loop artificial pancreas system. Furthermore, the model's incorporation of real-world phenomena—meals, stress, exercise—enhances the validity of the conclusions. The study's rigorous use of time-domain and integral error metrics ensures robustness in the evaluation. Control Dynamics , is one of the most important factors that should be well addressed, the PID Parallel controller exhibited the shortest settling time and the least overshoot, highlighting its effectiveness in achieving rapid stabilization without excessive oscillation. The results suggest that the choice of controller configuration significantly impacts the system's ability to maintain glucose levels within desired limits. Key findings from the time-domain analysis include: The **parallel PID controller** achieves the fastest settling time and the lowest overshoot, indicating a rapid and stable response. The **series PID controller** also performs well, with a fast settling time and low overshoot, but not as well as the parallel configuration. The **P and PD controllers** have unacceptably high steady-state errors and large overshoots. The **PI controllers** effectively eliminate the steady-

Gharyan University Journal of Engineering Science (GUJES)
ISSN (3105-4560)
Website:http://journals.gu.edu.ly
email: gujes@gu.edu.ly

state error but have a slower response compared to the PID controllers. Performance Indices Analysis as illustrated in figures 6, 7 ,8, and 9. The integral performance indices provide a quantitative measure of the controllers' performance. The calculated values for IAE, ISE, ITAE, ITSE, and ICE for each controller and disturbance magnitude are summarized in Table 2. From these results, several key observations can be made. The **P controller** consistently exhibits the poorest performance across all indices, with large errors and slow response times. The **PI controllers** show a significant improvement over the P controller, effectively eliminating the steady-state error. The series and parallel configurations have comparable performance. The **PD controllers**, like the P controller, fail to eliminate the steady-state error and are generally not well-suited for this application. The **PID controllers** demonstrate the best overall performance. The **series PID controller** achieves the lowest error values (IAE, ISE, ITAE, ITSE), indicating superior regulation. Higher ICE is a trade-off for superior performance.PID Series exhibits ICE values exceeding 50 million (e.g., 53,618,602.6 at DM=7), likely due to aggressive integral gain.PID Controllers Parallel Configuration Slightly inferior to series but still excellent. It observed that Lower ICE than series PID in most cases.

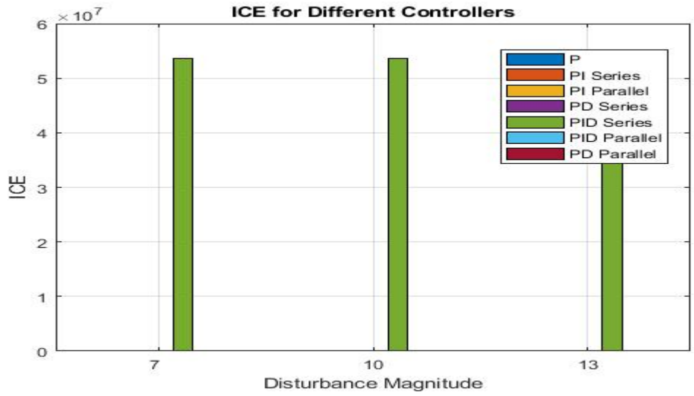

Figure 6: ICE for Different Controller Configuration

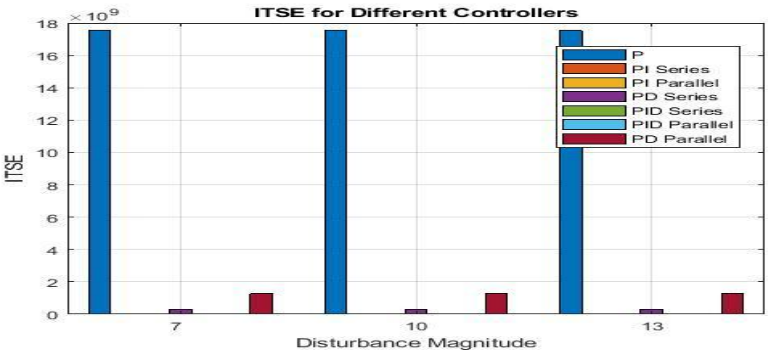

Figure 7: ITSE for Different Controller Configuration

Gharyan University Journal of Engineering Science (GUJES)
ISSN (3105-4560)
Website:http://journals.gu.edu.ly
email: gujes@gu.edu.ly

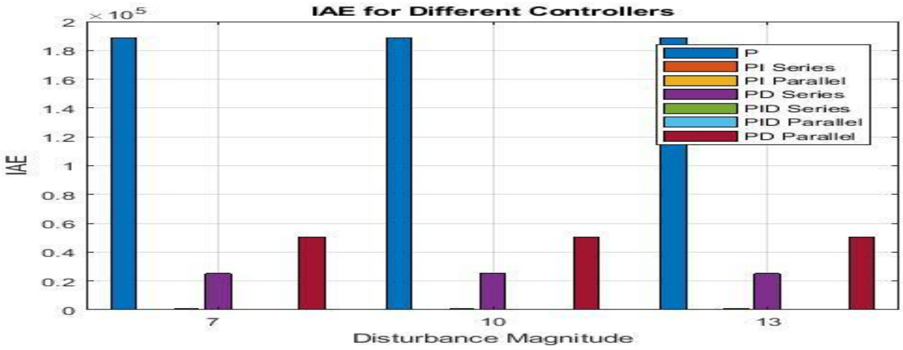

Figure 8: IAE for Different Controller Configuration

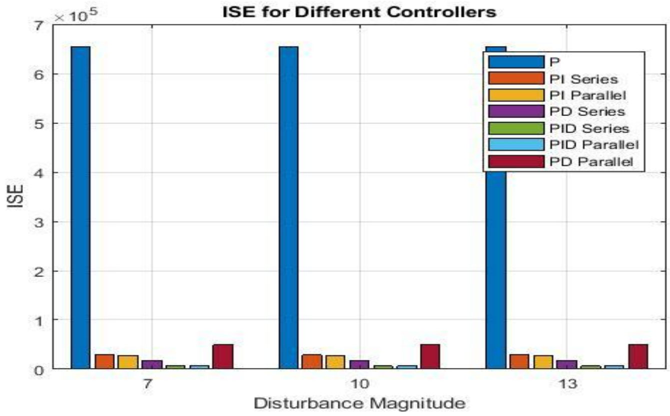

Figure 9: ISE for Different Controller Configuration

6. Discussion

The results of this simulation study provide valuable insights into the selection and design of PID controllers for glucose regulation in Type 1 Diabetes. Our findings clearly demonstrate that the choice of controller structure has a profound impact on the performance of the closed-loop system, with significant implications for the safety and efficacy of an artificial pancreas. The superior performance of the PID controllers, in both series and parallel configurations, compared to the P, PI, and PD controllers, underscores the importance of all three control actions (proportional, integral, and derivative) for effective glucose regulation. The proportional action provides a rapid response to errors, the integral action eliminates steady-state errors, and the derivative action anticipates future errors, leading to a more stable and accurate response. The inability of the P and PD controllers to eliminate steady-state error makes them unsuitable for this application, as persistent hyperglycemia or hypoglycemia can have serious health consequences. One of the most significant findings of this study is the trade-off between performance and control effort, as exemplified by the comparison between the series and parallel PID controllers. The series PID controller consistently achieved the best performance in terms of error minimization as indicated by the lower IAE, ISE, ITAE, and ITSE values. However, this superior performance was achieved at the cost of a dramatically higher control effort (ICE). In a clinical context, a high control effort translates to **larger** and more frequent insulin doses, which can increase the risk of hypoglycemia and may not be well-tolerated by patients. Furthermore, a high control effort can lead to actuator saturation, where the insulin pump is unable to deliver the required amount of insulin, potentially compromising the controller's performance. In contrast, the parallel PID controller provided a more balanced performance, with only slightly higher error values than the series configuration but with a significantly lower control effort. This suggests that the parallel PID controller is a more practical and clinically viable option for an artificial pancreas, as it can achieve effective glucose regulation without excessive insulin administration. The faster settling time and lower overshoot of the parallel PID controller are also highly desirable characteristics, as they indicate a more stable and predictable response. These findings are consistent with previous studies that have highlighted the importance of controller design in the development of an artificial pancreas. Our study adds to this body of knowledge by providing a detailed and quantitative comparison of different PID controller structures, which has not been extensively explored in the context of glucose regulation.

7. Conclusion

This study has presented a comprehensive comparative analysis of various PID controller structures for glucose regulation in Type 1 Diabetes, using the Bergman Minimal Model as a simulation platform. Our findings demonstrate that the parallel PID controller offers the most promising solution, providing an optimal balance between glycemic control, stability, and insulin utilization. While the series PID controller exhibited slightly better error metrics, its high control effort raises concerns about its clinical feasibility and safety. The P, PI, and PD controllers were found to be inadequate for this application due to their inability to effectively manage the complex dynamics of glucose metabolism. As a result, This research underscores the critical role of controller structure in the design of effective and safe artificial pancreas systems. The insights gained from this study can guide the development of more advanced control algorithms for automated glucose management in T1D. Accordingly, the PID Parallel controller demonstrates a robust, efficient, and clinically viable approach for automated glucose management. It balances fast system response, minimal overshoot, zero steady-state error, and manageable insulin effort, making it highly suitable for integration into artificial pancreas systems and next-generation insulin pump designs. This underscores the essential role of precise controller design in advancing biomedical control systems and improving patient outcomes

Table 2: Comparison of Time-Domain Specifications

Controller	Settling Time	Overshoot	Steady-State Error	Rise Time
Disturbance Magnitude 7				
P	00.0	68.64	3.52	1.57
PI Series	30.89	44.59	0.001	2.65
PI Parallel	30.98	45.43	0.001	2.49
PD Series	5.55	41.88	0.43	0.57
PID Series	4.45	33.44	0.0001	0.62
PID Parallel	2.85	1.73	0.0001	2.01
PD Parallel	9.27	23.97	0.81	0.59
Disturbance Magnitude 10				
P	55	68.61	3.12	1.59
PI Series	31.89	44.58	0.00	2.64
PI Parallel	30.58	45.40	0.00	2.47
PD Series	5.58	41.77	0.42	0.56
PID Series	4.25	33.24	0.00	0.60
PID Parallel	2.83	1.70	0.00	1.88
PD Parallel	9.95	23.77	0.84	0.56
Disturbance Magnitude 13				
P	**56**	**69.11**	**3.15**	**1.61**
PI Series	**33.86**	**45.99**	**0.001**	**2.59**
PI Parallel	**30.52**	**44.95**	**0.001**	**2.09**
PD Series	**5.49**	**42.01**	**0.45**	**0.52**
PID Series	**4.82**	**32.94**	**0.00001**	**0.65**
PID Parallel	**2.91**	**1.73**	**0.00001**	**1.98**
PD Parallel	**9.31**	**23.11**	**0.65**	**|0.84**

References

[1] International Diabetes Federation, IDF Diabetes Atlas Ninth Edition 2019.
[2] Ajmera, I., Swat, M., Le Novere, N. And Chelliah, V. (2013) 'The impact of mathematical modelling on the understanding of diabetes and related complications' *CPT Pharmacometrics& Systems Pharmacology*, vol. 2, no. 2, pp. E54.
[3] Z. Trajanoski and P. Wach, "Neural predictive controller for insulin delivery using the subcutaneous route," *IEEE Trans. Biomed. Eng.*, vol. 45,no. 9, pp. 1122–1134, Sep. 1998.
[4] R. S. Parker, F. J. Doyle III, and N. A. Peppas, "A model-based algorithm for blood glucose control in type I diabetic patients," *IEEE Trans. Biomed. Eng.*, vol. 46, no. 2, pp. 148–157, Feb. 1999.
[5] Chew YH, Shia YL, Lee CT, Majid FA, Chua LS, Sarmidi MR, et al. Modeling of oscillatory bursting activity of pancreatic β-cells under regulated glucose stimulation. Mol Cell Endocrinol 2009; 307:57- 67; PMID:19524127; http://dx.doi.org/10.1016/j. mce.2009.03.005.

[6] Han K, Kang H, Choi MY, Kim J. Mathematical model of the glucose-insulin regulatory system: From the bursting electrical activity in pancreatic β-cells to the glucose dynamics in the whole body. (preprint).
[7]G. W. Swan, "An optimal control model of diabetes mellitus," *Bull.Math. Biol.*, vol. 44, no. 6, pp. 793–808, 1982.
[8] World Health Organization. Classification of Diabetes Mellitus; World Health Organization: Geneva, Switzerland, 2019.
[9] Boutayeb, A.; Chetouani, A. A population model of diabetes and prediabetes. Int. J. Comput. Math. **2007**, 84, 57–66. [CrossRef]
[10] An, J.; Nichols, G.A.; Qian, L.; Munis, M.A.; Harrison, T.N.; Li, Z.;Wei, R.;Weiss, T.; Rajpathak, S.; Reynolds, K. Prevalence and incidence of microvascular and macrovascular complications over 15 years among patients with incident type 2 diabetes. BMJ Open Diabetes Res. Care **2021**, 9, e001847. [CrossRef]
[11] Gatwood, J.; Chisholm-Burns, M.; Davis, R.; Thomas, F.; Potukuchi, P.; Hung, A.; Kovesdy, C.P. Evidence of chronic kidneydisease in veterans with incident diabetes mellitus. PLoS ONE **2018**, 13, e0192712.
[12] P. Saeedi, I. Petersohn, P. Salpea, B. Malanda, S. Karuranga, N. Unwin,S. Colagiuri, L. Guariguata, A.A. Motala, K. Ogurtsova, J.E. Shaw, D. R. Williams, Global and regional diabetes prevalence estimates for 2019 andprojections for 2030 and 2045: results from the international diabetes federation diabetes Atlas, 9th edition, Diabetes Res. Clin. Pract. 157 (2019), 107843.
[13] M.A. Atkinson, G.S. Eisenbarth, A.W. Michels, Type 1 diabetes, Lancet 383 (2014)69–82.A.D. Cherrington, Banting lecture 1997, Diabetes 48 (1999) 1198–1214.
[14] A. Cinar, Advances in artificial pancreas control systems, J. Process Control 81(2019) 221–222.
[15] J.C. Pickup, H. Keen, J.A. Parsons, K.G. Alberti, Continuous subcutaneous insulin infusion: an approach to achieving normoglycaemia, Br. Med. J. 1 (1978) 204–207.
[16] El Haout, S.; Fatani, M.; Farha, N.A.; AlSawaftah, N.; Mortula, M.; Husseini, G.A. Modeling the Effects of Chemotherapy and Immunotherapy on Tumor Growth. J. Biomed. Nanotechnol. **2021**, 17, 2505–2518. [CrossRef]
[17] Centers for Disease Control and Prevention. Incidence of Newly Diagnosed Diabetes. Available online: https://www.cdc.gov/ diabetes/data/statistics-report/newly-diagnosed-diabetes.html (accessed on 9 October 2022).
[18] F. Chee, T. Fernando, and P. V. van Heerden, "Closed-loop glucose control in critically-ill patients using continuous glucose monitoring system (CGMS) in real-time," *IEEE Trans. Inf. Technol. Biomed.*, vol. 7, no. 1, pp. 43–53, Mar. 2003.
[19] Bergman, R. N., Ider, Y. Z., Bowden, G. R. &Cobelli, C. (1979). Quantitative estimation of insulin sensitivity, Am. J. Physiol. Vol. 236, pp. E667-E677
[20] Bergman, R. N. &Cobelli, C. (1980). Minimal modeling, partition analysis and the estimation of insulin sensitivity, Fed. Proc. Vol. 39, pp. 110-115.
[21] Bergman, R. N., Bortolan, G., Cobelli, C. &Toffolo, G. (1980). Identification of a minimal model of glucose disappearance for estimating insulin sensitivity, in Proceedings of the 5th IFAC Symposium on Identification and System Parameter Estimation, (Isermann, Ed.), Bergman, Oxford, Vol. 2, pp. 883-890
[22] Mitsis, G. D., Markakis, M. G., &Marmarelis, V. Z. (2009). Nonlinear modeling of the dynamic effects of infused insulin on glucose: comparison of compartmental with Volterra models, IEEE Transactions on Biomedical Engineering, Vol. *56*, No. 10, pp. 2347-2358.
[23] Gyorgy, E., Jozef, K. T. &Levente, K. (2015). Adaptive control solution for type 1 diabetes control. Applied Computational Intelligence and Informatics, IEEE 10th Jubilee Int. Symposium, 215-220.

[24] Gomez, A. M., Marin Carrillo, L. F., &MunosVelandia, O. M. (2017). Long-term efficacy and safety of sensor augmented insulin pump therapy with low-glucose suspend feature in patients with type 1 diabetes. Diabetes Tech. Ther. Vol. 19, No. 2, pp. 109-114

[25]Forlenza, G. P., Pinhas-Hamiel, O., &Liljenquist, D. R. (2019). Safety evaluation of the Minimed 670G System in children 7-13 years of age with type 1 diabetes, Diabetes Tech. Ther. Vol. 21, No. 1, pp. 11-19

[26] Gomez, A. M., Marin Carrillo, L. F., &MunosVelandia, O. M. (2017). Long-term efficacy and safety of sensor augmented insulin pump therapy with low-glucose suspend feature in patients with type 1 diabetes. Diabetes Tech. Ther. Vol. 19, No. 2, pp. 109-114

[27] Hassan, F. U., Adil, M., Khaqan, A., Shuja, S., Tiwana, M. I., Hassan, Q. U., Malik, S. and Riaz, R. A. (2017). Closed loop blood glucose control in diabetics. Biomedical Research, Vol. *28*, No.16, pp. 7230-7236.

[28] Kwach, B., Ongati, O., &Simwa, R. (2011). Mathematical model for detecting diabetes in the blood, Applied Mathematical Sciences, Vol. *5*6, pp. 279-286

[29] J. D. Bronzino and D. R. Peterson, *The Biomedical Engineering Handbook*, 4th ed. Boca Raton, FL, USA: CRC Press, 2015.

[30] C. Ionescu, Y. Zhou, and J. A. T. Machado, ``Special Issue: Advances in fractional dynamics and control," *J. Vib. Control*, vol. 22, no. 8, pp. 1969_1971, 2016.

[31] A. Haidar, ``The arti_cial pancreas: How closed-loop control is revolutionizing diabetes," *IEEE Control Syst. Mag.*, vol. 36, no. 5, pp. 28_47, Oct. 2016.

[32] E.Ackerman,L.C.Gatewood,J.W.Rosevear,G.D.Molnar. “Model studies of blood glucose regulation, ” Bull. Math. Biophys.vol.27,pp.21-37,1965

[33] R.N.Bergman,L.S.Phillips,C.Cobelli. “Physiologic evaluation of factors controlling glucose tolerance in man,” J.Clin.Invest,vol.68,pp.1456- 1467,1981.

[34] C.Cobelli, A.Mari. “Validation of mathematical models of complex endocrine-metabolic systems. A case study on a model of glucose regulation, ” Med. Biol. Eng. Comput,vol.21,pp.390-399,1983.

[35] R.Hovorka, V.Canonico, L.J.Chassin, U.Haueter, M.MassiBenedetti, M.O.Federici, T.R.Pieber, H.C.Schaller, L.Schaupp, T.Vering, M.E.Wilinska, “Non-linear model predictive control of glucose concentration in subjects with type 1 diabetes,”Physiol.Meas,vol.25, pp.905-920,2004.

[36] Lind, M., Polonsky, W., Hirsch, I.B, *et al.*: ‘Continuous glucose monitoring vs. conventional therapy for glycemic control in adults with type 1 diabetes treated with multiple daily insulin injections: the gold randomized clinical trial’, *J. Am. Med. Assoc.*, 2017, **317**, (4), pp. 379–387.

[37] Steil, G.M., Rebrin, K., Janowski, R., *et al.*: ‘Modeling-cell insulin secretion implications for closed-loop glucose homeostasis’, *Diabetes Technol. Ther.*, 2003, 5, (6), pp. 953–964

[38] Athena Makroglou, Jiaxu Li, Yang Kuang, Mathematical models and software tools for the glucose-insulin regulatory system and diabetes: an overview, Applied Numerical Mathematics, Volume 56, Issues 3–4, 2006, Pages 559-573, ISSN 0168-9274,https://doi.org/10.1016/j.apnum.2005.04.023.