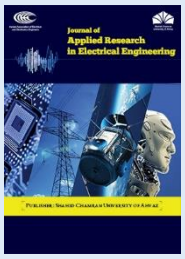
Shahid Chamran University of Ahvaz

Iranian Association of Electrical and Electronics Engineers

Journal of Applied Research in Electrical Engineering

E-ISSN: 2783-2864
P-ISSN: 2717-414X
Homepage: https://jaree.scu.ac.ir/



Research Article

Investigating Robust Tracking of Type 1 Diabetes Control Using Model-Free Controllers

Peyman Vafadoost Sabzevar[1], Ahmad Hajipour[1,*], and Hamidreza Tavakoli[2]

[1] *Biomedical Engineering Department, Electrical and Computer Faculty, Hakim Sabzevari University, Sabzevar, Iran*

[2] *Electronic Engineering Department, Electrical and Computer Faculty, Hakim Sabzevari University Sabzevar, Iran*

** Corresponding Author: a.hajipour@hsu.ac.ir*

Abstract: One of the main challenges in the field of control is the use of a stable controller and its lack of dependence on the system model and dynamics, so that the input signal is applied to the system based on the existing needs. One of the areas that needs controlling and applying the input signal is type 1 diabetes, where people with this disease need constant and regular insulin injections based on blood glucose concentration. Based on this, in this article, two free model methods called the Q-learning algorithm and PID have been used to determine insulin dose, and the results of insulin dose injection show the results and high performance of the Q-learning algorithm in determining insulin dose. This algorithm is one of the methods based on artificial intelligence that discovers the optimal policy based on trial and error. Finally, the Q-learning algorithm has been investigated in the presence of noise, and its stability has been proven to ensure the performance of the controller.

Keywords: Q-Learning, PID controller, model-free, injection insulin, tracking blood glucose.

Article history
Received 26 July 2024; Revised 15 October 2024; Accepted 17 October 2024; Published online 20 April 2025.

How to cite this article
P. Vafadoost Sabzevar, A. Hajipour, and H. Tavakoli, "Investigating robust tracking of type 1 diabetes control using model-free controllers," *J. Appl. Res. Electr. Eng.*, vol. 3, no. 2, pp. 232-239, 2024.
DOI: 10.22055/jaree.2024.47542.1126

Check for updates

1. INTRODUCTION

The human body needs energy to perform daily activities, and the most important source of this energy is glucose, which enters the body through daily nutrition. Glucose provides the necessary energy for cells, making physical and mental activities possible. The concentration of glucose in the body must be maintained at a certain level. The pancreas secretes the hormones insulin and glucagon to regulate blood glucose (BG), as the functions of these two hormones complement each other. Insulin helps lower plasma glucose when it is high, and glucagon raises it when plasma glucose is low. Diabetes is one of the most common endocrine diseases that occurs due to damage to the beta cells in the pancreas, so insulin is not secreted in sufficient amounts to regulate BG. As a result, the patient's BG level increases from the normal range of 80-110 mg/dL. Hyperglycemia results from anomalies in either insulin secretion or insulin action or both and manifests in a chronic and heterogeneous manner as carbohydrate, fat, and protein metabolic dysfunctions [1,2].

In general, diabetes is divided into two main types and several subtypes:

Type 1 diabetes (T1D), formerly known as juvenile-onset diabetes or insulin-dependent diabetes, in which the body's immune system mistakenly attacks and destroys beta cells in the pancreas, resulting in reduced insulin production, or it stops completely. People with this type of diabetes need insulin injections. Type 2 diabetes (T2D) is more common in adults. In this type of diabetes, the body does not use insulin effectively or does not produce enough insulin. The cause of this type of diabetes can be obesity, inactivity and improper diet and lifestyle. Gestational diabetes (GD) is a type of diabetes that occurs during pregnancy, and the hormones released during this period cause the body to resist insulin, which usually resolves after the birth of the baby. There are

other types of diabetes that are less often seen in people who have chemotherapy due to drug use [3].

T1D is the third most common chronic disease of childhood, affecting 1 in 300 children, and there is a consensus that its incidence is increasing [4]. Although significant progress has been made in the timeline of diagnosis, medical management and prevention and treatment of complications, T1D is still a disease with a significant burden with psychological, medical and financial damages for sufferers and their families [5]. Considering that in patients with diabetes, people with T1D require continuous insulin injections, this category of patients needs special attention. In T1D, the pancreas is unable to produce insulin or produces very little insulin, so these patients must inject insulin regularly to keep their BG levels within a normal range.

Many studies have been presented in the field of T1D control and optimal insulin injection.

Different controllers and methods have been used in different fields using machine learning techniques such as neural networks, deep learning and their combination. Also, in various studies, various types of traditional controllers have been used to determine the dose of insulin, and a number of mathematical models related to the diagnosis of diabetes have been reviewed and presented. Therefore, the collection of these models helps to determine the amount of insulin needed to control the disease. The goal of controllers should be to determine insulin dosage based on non-maximization of the model and achieve that goal through interaction with the desired model.

During their research, Babar *et al.* [9] designed an artificial pancreas using Bergman's minimal model and sliding mode control (SMC) and second-order sliding mode control (SOSMC) control techniques. In their results, the use of SOSMC led to better results and fewer complications than the SMC method. Matamoros-Alcivar *et al.* [10] used the model predictive control (MPC) controller and compared it with the proportional–integral–derivative (PID) controller in order to investigate and compare the effects of diets, disorders and other factors related to T1D patients. Single-network adaptive critical neural networks (SNAC), which are based on linear optimum control, were used in the research by Faruque and Padhi [11]. This article's main goal is to simulate how the human pancreas works, which is to continuously detect BG levels and then inject insulin in response to those findings. Tornese *et al.* [12] used a Hybrid Closed-Loop (HCL) programmed into an insulin pump to limit the spread of the coronavirus as well as the high vulnerability of people with T1D in this pandemic. In this method, insulin is injected automatically and semi-automatically based on the BG concentration measured by the sensors. The results of their research indicated that despite the quarantine, diabetes was controlled well and with acceptable results. Mosavi *et al.* [13] have presented a new approach in the control of T1D, which includes fuzzy logic and the modified Bergman model. They have used second type fuzzy logic system (T2FLS) to compensate the error and guarantee the stability. In this research, meal, patient activities and disorders are also considered to evaluate the stability of the controller. The results show that the BG level using this method, compared to other methods, returns to its base and reference value after a short period of time. Nimri *et al.* [14] used a smart method to compare with doctor's prescriptions. The proposed method was to use decision support system (AI-DSS) and studies were conducted to determine whether frequent adjustments in this system are as effective as the doctor's prescription or not. During the six-month trial, different races and food styles were used on patients, the results of which indicated that during this research, severe complications of diabetes were reported by the doctor in three people, and no case was found in the proposed method. In conclusion, using an automated decision support tool to optimize insulin pump settings resulted in better outcomes than physician prescribing. For individuals with T1D, Patra *et al.* employed a continuous time model predictive controller (CMPC). They carried out a comparison analysis with H-infinity, a PID controller, a linear quadratic regulator (LQR/LQT), and linear quadratic Gaussian (LQG) control to support the efficacy of the controller. The correctness and robustness of the controllers' efficiency have been verified by simulation. The suggested controller's performance is described in terms of its capacity to monitor 81 mg/dL of BG in the presence of random and Gaussian noise [15]. Reference [16] addresses the problem of developing control algorithms for type 1 diabetic patients that provide an automatic connection between continuous glucose monitoring and insulin injection with model free adaptive controller. Reference [17] presents in-silico design and verification of an advanced multi-agent reinforcement learning (RL) strategy for personalized glucose regulation in individuals diagnosed with type 1 diabetes (T1D).

Complications of diabetes include two categories, acute and chronic. One of the acute complications of people with diabetes is diabetic ketoacidosis, which is caused by an increase in blood sugar concentration of more than 250 mg/dL and acidification of the blood, and the use of fat and protein by cells as an energy source leads to the release of acids. Free fat, cholesterol enters the bloodstream and can lead to coma and death. This complication occurs mainly in T1D and sometimes in T2D. Chronic complications can be kidney complications due to high BG and destruction of glomeruli as kidney purifiers. Also, diabetes can include severe complications such as blindness caused by retinal damage, heart diseases, digestive diseases, etc. [6-8].

It is evident from the literature review that different studies have employed different approaches to manage diabetes. Some of these techniques are based on the system model, which has drawbacks because of its unique structure and is unable to adequately take into account all the intricate details of managing diabetes. Linear models are typically utilized in other studies, however because of their lack of comprehensiveness, they are unable to account for all illnesses and variations in the patients' bodies. However, several studies have employed artificial intelligence techniques in place of conventional models. These techniques can handle massive volumes of data and offer more flexible and ideal diabetes management solutions. Artificial intelligence-based decision support systems, for instance, have improved the precision of BG control over conventional techniques by making necessary adjustments. All of these approaches have advantages and disadvantages, and the best approach will rely on the particular circumstances of the patients as well as the objectives of the researchers.

The main goal of this study is to improve and optimize the dose of injectable insulin for these patients. To achieve this goal, model free controller based on reinforcement learning (RL) method is used to calculate and adjust the appropriate dose of insulin by continuously monitoring the BG level and taking into account the daily activities, diet and individual needs of each patient.

According to the above mentions, in the following points, the contribution of this paper can be summarized as:

- Model free RL method has been used to adjust the dose of insulin.
- The performance of proposed method has been compared with performance of PID controller.
- The ability of the proposed controller in handling noise has been investigated

This paper is presented as follows: methodology is described in Section 2. Section 3 is presented the control methods. Simulations and results are presented in Section 4. Finally, Section 5 concludes the paper.

2. METHODOLOGY

According to the review of the literature and the methods used in the control of BG concentration in diabetic patients, in some cases controllers have been used that are dependent on the system model or they have used non-linear and non-comprehensive models in their studies that lead to gaps. In this regard, this paper uses two model-free methods based on classical PID controller, Q-learning algorithm as a sub-branch of machine learning. The desired process is done by measuring the BG concentration by the sensors and comparing it with the reference value, and then the difference value is delivered to the proposed controller and by applying insulin through the insulin pump to the diabetic patient, the BG concentration value until the time Its stability continues.

3. CONTROL METHODS

In this section, RL based on Q-Learning and PID controller methods, which are based on model-free controller, are presented.

3.1. Q-Learning

By examining and conducting studies on the behavior of living organisms, various algorithms and methods have been presented by modeling these systems. One of the desired algorithms used in this research is the Q-learning algorithm, which is presented as a sub-branch of RL. This algorithm optimally discovers its strategy independently of the environment and by interacting and receiving rewards or penalties. This policy is such that the bonus or penalty received reaches its maximum or minimum amount. Q-learning algorithm generally includes the following concepts [18]:

Agent: The agent performs various actions in the environment by using the stimuli defined in him and acts first as a learner and then as a decision maker in the environment after completing the learning.

State Space: The state space is a set of different states that the agent can be in. In this research, the state space depends on the patient's BG concentration. 144 states of the state space are defined in which the agent is placed in that state if the BG concentration falls within any given interval.

Action Space: The action space is called the set of actions of the agent in the state space. The dose of injectable insulin has been introduced as an action that can be performed by the agent, which can perform 120 different values from 0 to 12 μU.

Reward: Reward is one of the key and decisive components in the agent's performance. Reward as an immediate feedback signal that is presented to the agent and indicates the success rate of its performance in the environment. The amount of reward in this process is calculated based on the following formula, if there is a difference between the output and the reference signal, the agent receives a penalty:

$$R = -|G_{ref} - G| \quad (1)$$

Policy: Optimal policy as a situation where the agent in the desired state should perform an action. The optimal policy may be a function or a lookup table, and this concept is referred to as the core of RL algorithms.

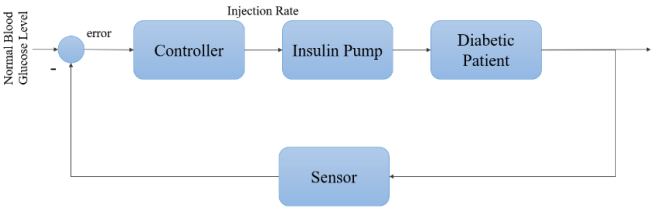


Fig. 1: Feedback regulation of BG.

State	Glucose
State 1	$80 > Glucose$
State 2	$80 \leq Glucose < 81$
State 3	$82 \leq Glucose < 83$
State 4	$83 \leq Glucose < 84$
.	.
.	.
.	.
State 142	$219 \leq Glucose < 220$
State 143	$220 \leq Glucose < 221$
State 144	$Glucose \geq 221$

Fig. 2: State space.

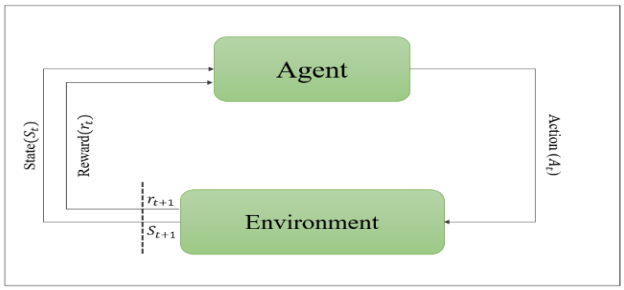


Fig. 3: Schematic of reinforcement learning operation.

Maximizing reward or penalty during the learning process is a primary objective of Q-learning, and it is characterized by the following formula:

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} = R_{t+1} + \gamma R_{t+2+\cdots} \quad (2)$$

where γ is referred to as the discount factor, which is defined as a value between 0 and 1. The closer this value is to 1, the more important the factor is to long-term rewards, and conversely, the closer it is to 0, the more important short-term rewards are given. Considering that in this study it is necessary that the BG concentration of the patient has a higher stability in the long term, we use the value of 0.95.

To find the optimal policy in Q-learning, the state-action space function is defined, which indicates the value of the amount of action performed in that state, which is determined according to the following formula:

$$q_\pi(s,a) = E[G_t|S_t = s,\ A_t = a] \quad (3)$$

The value function of the optimal state-action in the presence of the optimal policy can be computed by replacing equation 2 in 3.

$$q_*(s,a) = max_\pi q_\pi(s,a) \quad (4)$$

The optimal policy is defined based on value functions. When the state-action-value function is available, it selects the action factor that has the highest value among all states. The optimal policy is defined based on value functions according to the following formula:

$$\pi_*(s) = argmax_a q_*(s,a) \quad (5)$$

Considering that at the beginning of learning, the agent does not understand the environment, it performs its actions based on the ε policy. This means that the action with the highest value is performed with a probability of $1-\varepsilon$, and an action is randomly selected and applied in the environment with a probability of ε. At the beginning of the process, due to the agent's lack of complete understanding of the environment, the value of ε is considered to be equal to 1 to search the environment based on random actions, and then with the completion of the learning process, its value is reduced using the following formula It finds that its minimum value is considered equal to 0.01:

$$\varepsilon = min\varepsilon + (max\varepsilon - min\varepsilon)e^{-0.01*episode} \quad (6)$$

It is always possible to improve an existing policy, because a better policy leads to higher values. By determining the state-action value function relative to the initial policy, a better policy can be found. After determining the improved policy, the state-action value function is calculated and using this function, a better policy is created.

This process of evaluating and improving the policy is repeated until the optimal policy is reached. Any new policy is usually better than the previous policy unless the optimal policy is reached. Fig. 4 shows the performance of the Q-learning, which seeks to find the best solution by choosing different actions and receiving rewards for each action. Learning rate in the Q-learning algorithm is defined as alpha α. The amount that the new information replaces the old information is determined by this value. To put it another way, α indicates the ratio of the algorithm's reliance on prior knowledge to that gained from new events. This value is used in this research based on trial and error based on 0.8. The important point is that all the parameters in the Q-learning algorithm have been evaluated through the process of trial and error. In this process, it has been tried to obtain the most optimal settings to improve the performance of the algorithm by checking and comparing the values of different parameters.

3.2. PID

PID is one of the most popular controllers in industrial systems because of its adaptability and simplicity; studies have shown that PID is successful and long-lasting [19]. This controller operates on closed loop control, which is composed of three basic components: proportional, integral, and derivative. It is independent of environmental conditions. The block diagram of this controller's overall operation is displayed in Fig. 5. The controller does the following tasks [20]:

Proportional controller: This type of controller has an output that is directly proportional to the current error. The controller's coefficient determines how strongly the controller reacts to the current error.

Integral controller: this component's output is based on the total amount of errors over time, which establishes how strongly the controller responds to previous errors.

Derivative controller: Its coefficient shows how the controller responds over time to changes in the system's error rate and is proportionate to the error change rate.

The control signal in this method is calculated according to the following formula:

Q-Learning Algorithm

Set values learning rate $\alpha \in (0,1]$, discount factor $\gamma \in (0,1], \varepsilon > 0$, reward matrix R
Initialize $Q(s,a)$ to zeros
for each episode: **do**
  Initialize s
  for each step of episode: **do**
    Choose a from using policy derived from $Q(e,.g,\varepsilon - greedy)$
    Take action ,obtain reward r from R and next state s'
    $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma max_a Q(s',a') - Q(s,a)]$
    $s \leftarrow s'$
    until s is terminal
  end for
end for

Fig. 4: Q-Learning algorithm.

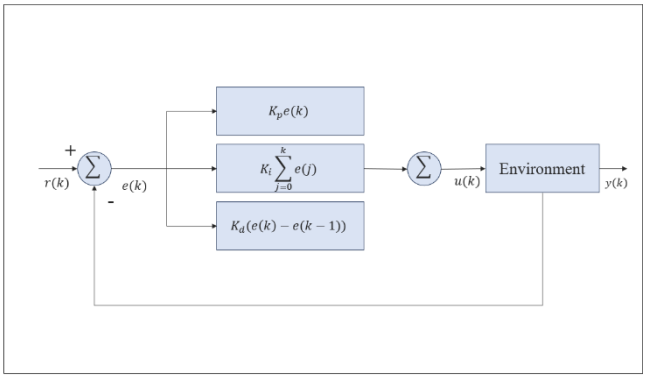


Fig. 5: PID control system's structure.

$$u(k) = K_p e(k) + K_i \sum_{j=0}^{k} e(j) + K_d(e(k) - e(k-1)) \quad (7)$$

The error considered in order to track the reference signal is calculated according to the following formula:

$$e(k) = r(k) - y(k) \quad (8)$$

The controller parameters of PID are set based on the studies done by Chengwei *et al* .PID parameters are $K_p = 0.09, K_i = 0, K_d = 0.04$ [21].

4. Simulations and Results

Considering that the two control methods are not dependent on the model and do not need to know the parameters of the system, therefore, in this research, due to the fact that the possibility and conditions of testing on the human biological system were not available, a non-linear comprehensive model called Bergman's minimal model was used in This research is used only to receive feedback and to apply insulin dosage, whose formula is as follows [22]:

$$\begin{aligned} \frac{dG}{dt}(t) &= -p_1[G(t) - G_b] - X(t)G(t) \\ \frac{dX}{dt}(t) &= -p_3[I(t) - I_b] - p_2X(t) \\ \frac{dI}{dt}(t) &= -n[I(t) - I_b] + \gamma[G(t) - h]^+ + u(t) \end{aligned} \quad (9)$$

The variables and parameters used in this model are thoroughly detailed and explained in Table 1. This table provides a comprehensive overview, listing each variable and parameter alongside its corresponding definition, unit of measurement used in the analysis. One of the most often used models for physiological study on the mechanism of glucose and insulin, which is used to characterize the concentration of blood glucose and insulin, is Bergman's minimum model. This model, which has two components to illustrate the behavior of glucose and insulin secretion following an intravenous injection of the sample, is called minimal because it uses the fewest parameters feasible to mimic diabetes individuals for the intravenous glucose tolerance. In equation 9, the sign "+" indicates the absorption of glucose by the body. When the value of $G(t)$ is higher than h, the desired relationship acts as a regulator in the body, which is not considered in insulin dynamics due to the lack of a regulator or its lack of influence in patients with diabetes.

For simulation purposes, MATLAB version 2021b software has been used to investigate the control of BG concentration in T1D patients. For this purpose, first, using the mathematical equations of Bergman's minimum model and the initial values of its parameters in Fig. 6, the changes in BG concentration for a healthy person and a T1D patient have been investigated. Fig. 7 shows that having an external injector is necessary for people with T1D.

Finally, based on the definitions in the problem description section, the insulin injection dose has been applied to the existing model by two controllers, and the reference signal is defined as follows in order to compare and improve the insulin injection:

$$G_{ref} = 80 + (200 - 80)e^{0.05t} \quad (10)$$

Fig. 8 depicts the outputs produced by two algorithms, namely the cue learning algorithm and the PID controller. This graph clearly shows that the Q-learning algorithm has a very strong and effective performance in tracking the reference signal compared to PID. Q-learning algorithm has been able to follow system changes well and achieve higher accuracy in setting control parameters.

The superior performance of the Q-learning algorithm is due to its ability to learn by interacting with the environment and continuously updating the Q-values, which leads to

Parameters	Healthy	T1D
$G(0)$	200	200
$X(0)$	0	0
$I(0)$	364.8	50
G_b	80	80
I_b	7	7
p_1	0.0317	0.0
p_2	0.123	0.0
p_3	4.92×10^{-6}	1.54×10^{-5}
n	0.2655	0.2814
h	79.0353	79.0353
γ	0.0039	0

Fig. 6: Values of model parameters for a healthy person and a person with T1D [23].

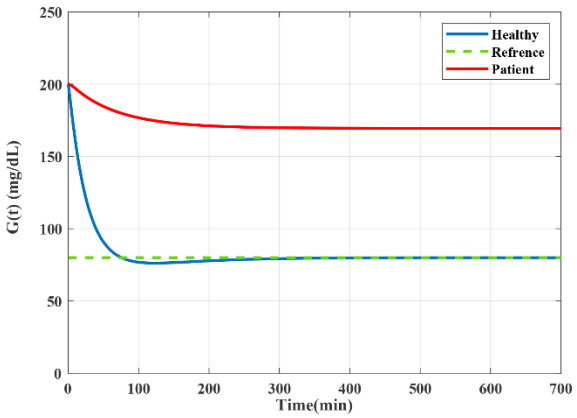


Fig. 7: Changes in BG concentration in healthy individuals and T1D patients.

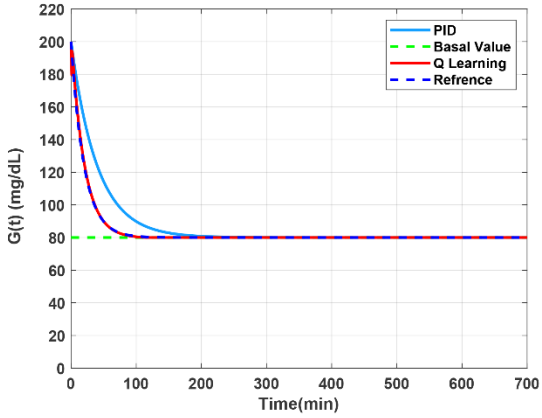


Fig. 8: BG concentration control using Q-learning and PID.

continuous improvement of decision making and control. This algorithm has been able to minimize system errors and create more stability in process control. The accuracy of the proposed algorithms is calculated according to the following formula:

$$Accuracy\ (\%) = \frac{\max|G(t) - G_{ref}(t)|}{G_{ref}(t)} \times 100 \qquad (11)$$

According to (11), the accuracy of Q learning algorithm is 94.6% and PID is 74.3%.

To evaluate the robustness and stability of this algorithm, investigations have also been done by adding noise to the system. These noises have been applied in order to simulate more realistic conditions and evaluate the performance of the algorithm in the face of unexpected changes and environmental noises.

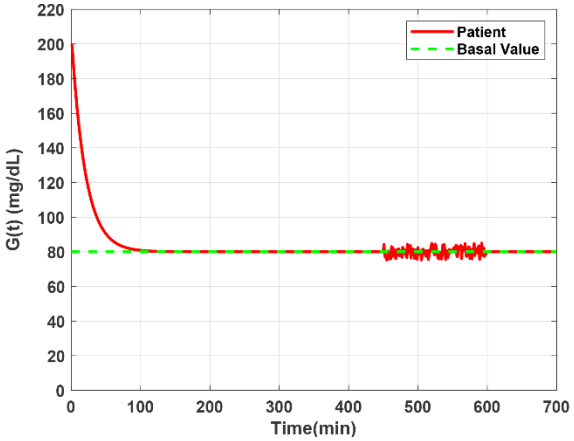


Fig. 9: Regulation of BG levels with Q-learning in noisy environments.

5. Conclusion

In this article, the application and efficiency of two control methods, one based on RL and the other PID, as model-free algorithms that do not depend on the system model, were investigated. One of the other primary goals of this article was to track the BG concentration of T1D patients. In particular, due to the lack of insulin secretion, this article focused on the parameters of T1D so that the BG concentration of these people is the same as that of healthy people. In the simulations and results, it was shown that the Q-learning algorithm, due to its continuous updating, had a much higher and more acceptable accuracy in tracking and maintained its stability and resistance against abnormal conditions in the presence of noise. In the absence of inappropriate conditions in his biological system, the patient should not suffer from severe complications and a sudden drop or increase in BG concentration. One of the main advantages of this algorithm compared to PID is its compatibility with the environment, and if the appropriate reward is defined, the optimal policy can be converged to the desired problem. This adaptability makes them suitable for environments where traditional control methods may have difficulty finding a solution. Although the Q-learning algorithm has a high potential for optimizing the insulin dose, but due to these limitations, such as the fact that each person's body's response to insulin is complex and variable and various factors are involved, it requires a large set of different data. Also, during the process of learning and adjusting the parameters of the algorithm, there are health risks such as a severe drop in BG or an excessive increase in BG. These risks can threaten the patient's health during the implementation of an algorithm that is not yet optimized. Therefore, its use requires caution and the use of large data sets to be used in real environments with sufficient safety.

Credit Authorship Contribution Statement

Peyman Vafadoost Sabzevar: Conceptualization, Data curation, Investigation, Methodology, Software, Validation, Writing - review & editing. **Ahmad Hajipour**: Conceptualization, Data curation, Formal analysis, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Hamidreza Tavakoli**: Formal analysis, Investigation, Software, Visualization, Writing - original draft, Writing - review & editing.

Declaration Of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

Table 1: Description of Bergman's minimal model parameters [22].

Parameters	Description	Unit
$G(t)$	concentration of blood glucose in plasma at time t	$[mg/dL]$
$X(t)$	the effect of insulin on the disappearance of glucose at time t	$[1/min]$
$I(t)$	concentration of insulin in plasma at time t	$[\mu U/mL]$
G_b	basal value of glucose level	$[mg/dL]$
I_b	basal value of insulin level	$[\mu U/mL]$
p_1	rate of glucose absorption in tissues independent of insulin	$[1/min]$
p_2	rate of reduction of absorption ability Glucose in tissues	$[1/min]$
p_3	rate of the ability of tissues	$I_b[(\frac{\mu U}{mL})^{-1}min^{-1}]$
n	rate of insulin reduction	$[1/min]$
h	threshold value Glucose, insulin secretion if the glucose concentration exceeds	$[mg/dL]$
γ	rate of insulin secretion by beta cells when the blood glucose level exceeds the threshold value	$[(\mu/mL)(mg/dL)^{-1}min^{-2}]$

REFERENCES

[1] American Diabetes Association, "Diagnosis and classication of diabetes mellitus," *Diabetes Care*, 2014, vol. 37, pp. S81-90.

[2] American Diabetes Association, "Introduction: Standards of medical care in diabete," *Diabetes Care*, 2018, vol. 41, pp. S1-2.

[3] M. Z. Banday, S. S. Aga, and N. Saniya, "Pathophysiology of diabetes: An overview," *Avicenna Journal of Medicine*, vo. 10, no. 4, pp. 174-188, 2020.

[4] C. C. Patterson *et al.*, "Worldwide estimates of incidence, prevalence and mortality of type 1 diabetes in children and adolescents: Results from the international diabetes federation diabetes atlas." *Diabetes Research and Clinical Practice*, vol. 157, p. 107842, 2019.

[5] T. Quattrin, L. D. Mastrandrea, and L. S. K. Walker, "Type 1 diabetes." *The Lancet*, vol. 401, no. 10394, pp. 2149-2162, 2023.

[6] A/ H. A. Abu-Rmileh, "Control and modeling techniques in biomedical engineering: the artificial pancreas for patients with type 1 diabetes," PhD Thesis, Universitat de Girona, 2013.

[7] M. Bryer-Ash, *100 Questions & answers about diabetes*. Jones & Bartlett Publishers, 2009.

[8] C. S. Marathe et al., Gastrointestinal disorders in diabetes. [Online]. (2003), Available: https://www.ncbi.nlm.nih.gov/books/NBK553219/

[9] S. A. Babar, A. Iftikhar, and I. S. Mughal, "Sliding - mode-based controllers for automation of blood glucose concentration for type 1 diabetes." *IET Systems Biology*, vol. 15, no. 2 pp. 72-82, 2021.

[10] E. Matamoros-Alcivar, T. Ascencio-Lino, R. Fonseca, G. Villalba-Meneses, A. Tirado-Espín, L. Barona, and D. Almeida-Galárraga, "Implementation of MPC and PID control algorithms to the artificial pancreas for diabetes mellitus type 1," in *2021 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT)*, IEEE, 2021.

[11] S. F. Ali, and R. Padhi. "Optimal blood glucose regulation of diabetic patients using single network adaptive critics," *Optimal Control Applications and Methods*, vol. 32, no. 2, pp. 196-214, 2011.

[12] G. Tornese, V. Ceconi, L. Monasta, C. Carletti, E. Faleschini, and E. Barbi. "Glycemic control in type 1 diabetes mellitus during COVID-19 quarantine and the role of in-home physical activity." *Diabetes Technology & Therapeutics*, vol. 22, no. 6, pp. 462-467, 2020.

[13] A. H. Mosavi *et al.*,,"Deep learning fuzzy immersion and invariance control for type-I diabetes," *Computers in Biology and Medicine*, vol. 149, p. 105975, 2022.

[14] R. Nimri *et al.*, "Insulin dose optimization using an automated artificial intelligence-based decision support system in youths with type 1 diabetes," *Nature Medicine*, vol. 26, no. 9, pp. 1380-1384, 2020.

[15] A. K. Patra, and P. K. Rout. "Adaptive continuous-time model predictive controller for implantable insulin delivery system in Type I diabetic patient," *Optimal Control Applications and Methods*, vol. 38, no. 2, pp. 184-204, 2017.

[16] B. Selma, H. Abouaïssa, S. Chouraqui, H. Kadem, D. Mehdeb, and M. Elaffifi, "Toward a model-free feedback control of blood glucose induced by meals for type-1 diabetics: in silico studies," *Iran Journal of Computer Science*, pp.1-11, 2024..

[17] M. Jaloli, and M. Cescon, "Basal-bolus advisor for type 1 diabetes (T1D) patients using multi-agent reinforcement learning (RL) methodology," *Control Engineering Practice*, vol. 142, p.105762, 2024.

[18] J. C. H. Christopher, "Watkins and peter dayan. Q-Learning." *Machine Learning*, vol. 8, no. 3, pp. 279-292, 1992.

[19] K. H. Ang, G. Chong, and Y. Li. "PID control system analysis, design, and technology." *IEEE Transactions on Control Systems Technology*, vol. 13, no. 4, pp. 559-576, 2005.

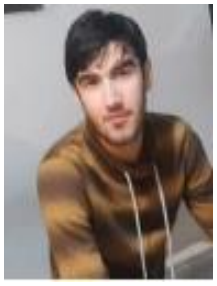
[20] M. A. Johnson, and M. H. Moradi, *PID control*. London, UK: Springer-Verlag London Limited, 2005.

[21] C. Li, and R. Hu. "Simulation study on blood glucose control in diabetics," in *2007 1st International Conference on Bioinformatics and Biomedical Engineering*, pp. 1103-1106. IEEE, 2007.

[22] K. E. Andersen, and M. Højbjerre, "A bayesian approach to bergman's minimal model," *in International Workshop on Artificial Intelligence and Statistics*, pp. 1-8, 2003.

[23] P. S. Vafadoost, H. Sadrian, and A. Hajipour, "Tracking blood glucose concentration of type 1 diabetic patients using reinforcement learning," in *2023 9th International Conference on Control, Instrumentation and Automation (ICCIA)*, IEEE, 2023, pp. 1-6..

BIOGRAPHY



Peyman Vafadoost Sabzevar received his B.Sc. degree in Computer Engineering and his M.Sc. degree in Biomedical Engineering in 2020 and 2023 from Hakim Sabzevari University, Sabzevar, Iran, respectively. His research interests include internet of things and machine learning.

Ahmad Hajipour received the B.Sc. degree in control engineering from the Ferdowsi University of Mashhad, Iran, in 2002, and the M.Sc. and Ph.D. degrees in control engineering from the Shahrood University of Technology, Iran, in 2004 and 2009, respectively. Since 2011, he has been an Associate Professor with the Department of Electrical

Engineering, Hakim Sabzevari University. His research interests include fractional calculus, robotics, and machine learning.

Hamidreza Tavakoli received the B.Sc. degree in electronic engineering from the Ferdowsi University of Mashhad, in 2000, and the M.Sc. and Ph.D. degrees in electronic engineering from the Iran University of Science and Technology, in 2003 and 2014, respectively. Since 2015, he has been an Assistant Professor with the Department of Electrical Engineering, Hakim Sabzevari University. His research interests include robotics, machine learning, and machine vision.