University of Baghdad
College of Engineering
JOURNAL OF ENGINEERING

Journal of Engineering

journal homepage: www.jcoeng.edu.iq

Volume 31 Number 6 June 2025

A Half Decade Reviews and Controller Design for the Bergman Diabetic Patient Model

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ABSTRACT

With an emphasis on individuals with Type 1 diabetes, this study reviews blood glucose management techniques during the last five years. A brief introduction is provided to show how this biological issue turns out to be a control system issue in terms of plasma blood glucose management. This paper discusses new research on automated insulin delivery using the Bergman mathematical model. An attempt has been made to undertake a systematic review of the research that has been done so far in the development of artificial pancreas systems. The conclusion describes the development of a cognitive glucose-insulin controller and provides a fundamental grasp of how the nonlinear Bergman model for blood glucose regulation can be used to establish a control system for this biomedical control challenge. When compared to other current methods, the proposed cognitive controller shows a quicker response in terms of blood glucose maintenance. Additionally, the comparison results demonstrated that the suggested cognitive glucose-insulin control algorithm improved the time to reach a normal physiological blood glucose level for the first patient by 10% compared to the fuzzy logic and the fractional-order PID control algorithms, by 25% compared to the type-2 fuzzy control algorithm.

Keywords: Control strategy, Diabetes mellitus, Insulin action, Plasma blood glucose.

1. INTRODUCTION

One of the most important and common chronic diseases in the world is diabetes, sometimes referred to as diabetes mellitus, which is mostly brought on by elevated blood glucose levels. Diabetes can be fatal or significantly impair a person's quality of life, regardless of gender. Diabetes is a chronic illness that only develops when blood glucose levels are too high. The

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Peer review under the responsibility of University of Baghdad.
https://doi.org/10.31026/j.eng.2025.06.01

Article received: 18/01/2025
Article revised: 09/05/2025
Article accepted: 14/05/2025
Article published: 01/06/2025

body uses glucose as an energy source, and the hormone insulin, which is released by the pancreas, regulates the amount of glucose that cells may use as fuel **(Chinnababu and Jayachandra, 2024)**. Diabetes mellitus (DM) is becoming more and more common worldwide; by 2045, there will likely be over 783 million cases, mostly in low- and middle-income nations **(Gudiño-Ochoa et al., 2024)**. About 90% of cases are Type 2 diabetes mellitus (T2DM), with the remaining instances being Type 1 diabetes mellitus (T1DM) and gestational diabetes mellitus (GDM). Serious side effects include nerve damage, cardiovascular problems, and an elevated risk of dying young are linked to these disorders. Thus, accurate, timely, and cost-effective blood glucose monitoring and control are essential for those individuals. Experts are specifically studying the diabetes sufferers with type 1 diabetes mellitus (T1DM) in great depth. Because of this, a lot of research has been done to develop a number of the diabetes sufferer mathematical models of insulin and glucose that, to a certain degree, accurately depict the physiological behavior of the human body **(Kalaimani and Jeyakumar, 2024)**.

The first generally recognized classification was released by the WHO in 1980 (**Rivai and Kurniawan, 2023)**. IDDM (Type I) and NIDDM (Type II) were proposed as the two main classifications of diabetes mellitus. Because patients were categorized based on treatment rather than pathophysiology, it was suggested that the names "insulin-dependent diabetes mellitus" and "non-insulin-dependent diabetes mellitus" be dropped. The cases were referred to as Type I and Type II, with the former mostly originating from the death of pancreatic islet beta-cells and the latter from the common primary form of diabetes caused by abnormalities in insulin secretion (**Rivai and Kurniawan, 2023)**. Even though type I diabetes only makes up 5–10% of all cases, its incidence is rising globally and it has major short- and long-term effects. According to the definition, diagnosis, and classification of diabetes mellitus and its complications **(Engell et al., 2021)**, type I denotes the process of beta-cell destruction in the pancreas that may eventually result in diabetes mellitus, where "insulin is required for survival" to avoid the development of ketoacidosis, coma, and death. For Type I diabetes, which requires constant attention to several areas such insulin delivery, blood glucose monitoring, meal planning, and diabetes-related problem screening, a multidisciplinary health team is the best setting. These effects, which include microvascular and macrovascular disease, are the main cause of morbidity and mortality associated with Type I diabetes **(Qteat and Awad, 2021)**. The most prevalent type of diabetes is type II. Type II diabetes has been identified in millions of people worldwide, and many more are still undiagnosed. If diabetes is not identified or is not adequately managed, people with the condition are more likely to get heart attacks and strokes. They also have a higher chance of losing their sight, having their feet and legs amputated because of damage to their blood vessels and nerves, and developing renal failure that necessitates dialysis or a transplant **(Hettiarachchi et al., 2024)**. When blood glucose levels are higher than normal but not high enough to be considered diabetes, people almost invariably have "prediabetes" before developing Type II diabetes. Recent research suggests that prediabetes may already be permanently damaging the body, especially the heart and circulatory system **(Liu, 2019)**. Insulin is either ignored by the cells or the body does not make enough of it in Type II diabetes. For the body to be able to use glucose as fuel, insulin is required. The body converts all sugars and starches into glucose, the fundamental fuel for cells, when food is consumed. Blood sugar is transported into the cells by insulin. Diabetes problems may arise when glucose accumulates in the circulation rather than entering the cells. The purpose of this work is to demonstrate how the diabetes sufferers with type 1 diabetes, whose bodies

cannot properly utilize the insulin they produce, need insulin injections in order to survive. Many studies have been conducted to develop a number of mathematical glucose-insulin control models that determine the prompt and optimal insulin-infusion control action value in order to improve the performance of the plasma blood glucose level in the diabetes sufferer model with regard to regulation and stabilization of the plasma blood glucose at the normal physiological level within a suitable time to avoid the hyperglycemia and hypoglycemia states. People with diabetes have a challenging disease that essentially involves regulating plasma blood glucose levels to prevent both hyperglycemia and hypoglycemia, according to the study's description of the issue. Furthermore, determining the amount of insulin-infusion level is essential for controlling and stabilizing the blood glucose level to the normal physiological level in the shortest amount of time.

2. THE NONLINEAR DIABETIC PATIENT MODEL

Generally speaking, the intestine, where carbs are absorbed from digested food, and the liver are the two places where glucose enters the plasma blood **(Benzian, 2021)**. The pancreas produces the hormones insulin and glucagon, which have opposing effects and are necessary for the body to maintain a steady blood glucose level, as shown in **Fig. 1 (Benzian, 2021)** and **(Chinnababu and Jayachandra, 2024).**

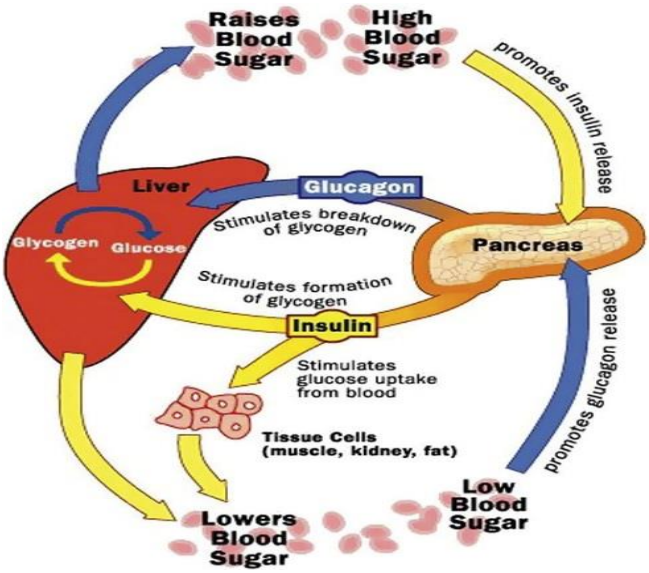


Figure 1. The general diagram of the insulin-glucagon system **(Benzian, 2021; Chinnababu and Jayachandra, 2024)**.

The beta cells of the pancreatic islets, which are tiny islands of endocrine cells in the pancreas, produce and secrete insulin. The pancreatic islets' alpha cells produce and excrete glucose. Glycogen is stored by the liver, which then transforms it back into glucose and delivers it into the bloodstream. By secreting insulin, the pancreas helps cells absorb blood glucose. According to **(Benzian et al., 2021; Chinnababu and Jayachandra, 2024)**, this reduces blood glucose levels. A normal blood glucose level is required for the organs to function properly because glucose is the cell's primary fuel. Diabetes is a metabolic disease in which the body either produces insufficient insulin or develops resistant to its effects, resulting in abnormally high blood glucose levels. Two widely used tests, the oral tolerance

test (OGTT) and the intravenous glucose tolerance test (IVGTT), can identify the abnormally elevated blood glucose levels associated with diabetes **(Benzian, 2021; Chinnababu and Jayachandra, 2024)**.

In our work, a model of the glucose-insulin system based on the Bergman glucose insulin minimum model has been taken. In particular, the three important compartments in this model are shown in **Fig. 2**, which describes the relationship among the concentration level of the distant insulin compartment *Ins(k)* in (mU/L), the level of the plasma blood glucose compartment *Gp(k)* in (mg/dl), and *Xp(k)* is the variable which describes the insulin effect on net glucose disappearance and the unit of *Xp(k)* is (1/min). Blood glucose, a hormone, and insulin were thought to be stored in two separate compartments and to interact with each other. In this context, several research works used the Bergman glucose-insulin basic model, which lacks the biological complexity shown in **(Chinnababu and Jayachandra, 2024)**, to study the distribution of insulin and the regulation of blood glucose **(Bergman et al., 1981)**.

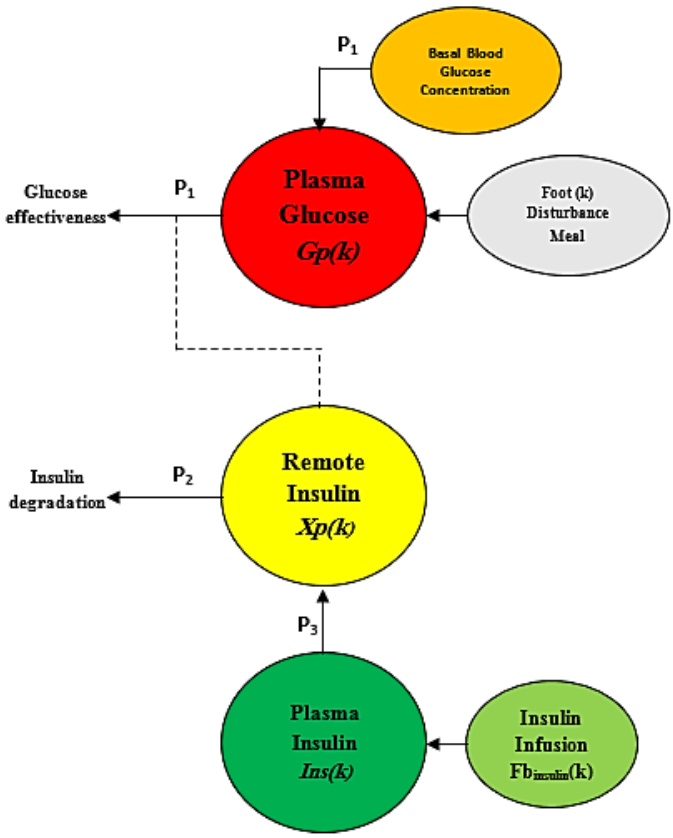


Figure 2. The compartments of the Bergman glucose insulin minimal model.

The following is a description of this model, which is based on nonlinear ordinary differential equations **(Pujol-Vázquez et al., 2023; Kaçar et al., 2020; Yazdani and Moghaddam, 2021; Nath et al., 2018; Alkahtani et al., 2018)**:

$$\dot{Gp}(k) = -P_1[Gp(k) - G_b] - Xp(k)Gp(k) + Food(k) \quad (1)$$

$$\dot{Xp}(k) = -P_2 Xp(k) + P_3 Ins(k) \quad (2)$$

$$\dot{Ins}(k) = -n[Ins(k) - I_b] + Y[Gp(k) - h]^+ t + Fb_{\text{Insulin}}(k) \quad (3)$$

Since diabetic people are unable to regulate their blood sugar levels, this factor $Y[Gp(k) - h]^+ \ t$ =0 will not be taken into account while developing the transfer function. Instead, a given parameter will be derived based on the assumption of a steady-state condition, as given below **(Pujol-Vázquez et al., 2023; Kaçar et al., 2020; Yazdani and Moghaddam, 2021):**

$$\dot{Ins}(k) = -n[Ins(k) - I_b] + Fb_{Insulin}(k) \quad (4)$$

Table 1 displays the parameters of the nonlinear Bergman model equations that describe the normal individual and three models of people with diabetes. (**Incremona et al., 2018; Pujol-Vázquez et al., 2023; Bergman et al., 1981; Abadi et al., 2014)**.

Table 1. The diabetes sufferers' parameters of the nonlinear Bergman model **(Bergman et al., 1981; Incremona et al., 2018; Pujol-Vázquez et al., 2023; Abadi et al., 2014)**.

Parameters Units	Normal Person	Patient #1	Patient #2	Patient #3
P_1 *(1/min)*	0.031	0	0	0
P_2 *(1/min)*	0.012	0.011	0.007	0.014
P_3 *(L/mUmin²)*	4.92×10^{-6}	5.3×10^{-6}	2.16×10^{-6}	9.94×10^{-6}
Y(mU/mg.min²)	0.0039	0.0042	0.0038	0.0046
h (mg/dl)	79.035	80.2	77.578	82.937
n (min^{-1})	0.265	0.26	0.246	0.281
G_b *(mg/dl)*	70	70	70	70
I_b *(mU/L)*	7	7	7	7
G_o *(mg/dl)*	280	230	220	210
I_o *(mU/L)*	364.8	50	55	60
$S_I=P_3/P_2$	492×10^{-6}	481×10^{-6}	308×10^{-6}	710×10^{-6}

where *Xp(k)* is the effect of active insulin in the distant compartment variable 1/min, and *Gp(k)* is the blood glucose concentration variable mg/dl. *Food(k)* is the meal disturbance input variable mg/dl.min^{-1}, $Fb_{\text{Insulin}}(k)$ is the controlled insulin-infusion rate variable, mU/L.min^{-1}, and *Ins(k)* is the blood-insulin concentration variable mU/L.

P_1 is the glucose effectiveness factor, P_2 and P_3 are the fractional transfer coefficients of insulin into and out of the remote compartment where insulin action is expressed, *Gb* is the basal concentration of the plasma blood glucose, I_b is the basal concentration of the plasma blood-insulin, *n* denotes to the first-order decay rate of plasma insulin, *h* denotes the glucose threshold value above which the pancreatic β-cells release insulin, and *Y* is the rate of the pancreatic β-cells' release of insulin following the glucose injection with glucose concentration. Insulin sensitivity S_I is calculated as P_3/P_2.

To check the nonlinear diabetic patient model based on the Bergman minimal model is stable in each patient's parameters as in **Table 1**, the Lyapunov function **(Ogata, 2010)** is proposed as follows:

$$V(x_1, x_2, x_3) > 0.5x_1(t)^2 + 0.5x_2(t)^2 + 0.5x_3(t)^2 \quad (5)$$

Clearly, $V \geq 0$ if all states $(x_1, x_2\ x_3) \geq 0$, the function is positive definite in all values of the states.

The nonlinear Bergman minimal mode can be expressed as in Eq. (6) based on the Eq. (1), Eq. (2), Eq. (3), and Eq. (4).

$$\begin{bmatrix} \dot{x_1} \\ \dot{x_2} \\ \dot{x_3} \end{bmatrix} = \begin{bmatrix} -p_1 & -x_1 & 0 \\ 0 & -p_2 & p_3 \\ 0 & 0 & -n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \tag{6}$$

where, $x_1, x_2\ x_3$ are *Gp, Xp,* and *Ins,* respectively. The time derivative of Eq. (5) becomes:

$$\dot{V}(x_1, x_2, x_3) < x_1\dot{x_1} + x_2\dot{x_2} + x_3\dot{x_3} \tag{7}$$

Substituting Eq. (6) in Eq. (7), the derivative state vector becomes as follows:

$$\dot{V}(x_1, x_2, x_3) < x_1(-p_1x_1 - x_1x_2) + x_2(-p_2x_2 - p_3x_3) + x_3(-nx_3) \tag{8}$$

$$\dot{V}(x_1, x_2, x_3) < -p_1x_1x_1 - x_1x_1x_2 - p_2x_2x_2 - p_3x_2x_3 - nx_3x_3 \tag{9}$$

$$\dot{V}(x_1, x_2, x_3) < -p_1x_1^2 - p_2x_2^2 - nx_3^2 - x_2x_1^2 - p_3x_2x_3 \tag{10}$$

Clearly, if all states $(x_1, x_2\ x_3) = 0, \dot{V} = 0$, and if all states $(x_1, x_2\ x_3) > 0, \dot{V} < 0$, the function $\dot{V}$ is negative definite in all values of the states, and the system is globally asymptotically stable with four weighting parameters $(p_1, p_2, n, p_3)$of the normal person model. But, when the parameter p_1 is equal to the zero value of the Bergman patient model, $\dot{V}(x_1, x_2, x_3)$ is expressed as in Eq. (11) as follows:

$$\dot{V}(x_1, x_2, x_3) < -p_2x_2^2 - nx_3^2 - x_2x_1^2 - p_3x_2x_3 \tag{11}$$

The effect of $x_1$in Eq. (11) is still appears, so $\dot{V}$ is negative definite in all values of the states, and the system is globally asymptotically stable with three weighting parameters (p_2, n, p_3) of the different types of patient models.

3. HALF DECADE STUDIES

In a half decade, in the artificial pancreas, numerous kinds of glucose-insulin controllers were created to maintain the patient's blood glucose levels within the normal range of 80–100–120 mg/dl. Using a PSO algorithm to adjust the gain parameters in continuous time rather than discrete time with a small search space and the design and implementation of a digital PID controller based on the Xilinx system generator for regulating the T1D patient's blood glucose level were detailed by **(Benzian et al., 2019).** Different controllers are obtained as a result of these variations in the control gain parameters. Sorensen created a single MPC for dual model infusion of insulin and glucagon with an unmeasured disturbance at a random moment in **(Dias et al., 2020)**, a thorough physiological model. The suggested controller's efficacy is evaluated using average tracking error (ATE), which gives the average blood glucose deviation from the threshold. While the set point is believed to be 90 mg/dl, the usual limit, where the blood glucose can deviate for optimal performance, is 14.4 mg/dl. This approach offers a better and more effective way to control blood sugar levels. Moreover, **(Benzian et al., 2021)** used a fractional-order-PID (FOPID)controller and a fuzzy-logic (FL)

controller to control a T1D patient's blood glucose level. They also used a variety of meta-heuristic methods to adjust the FOPID's control gain parameters. This work's drawback is that the controllers were only developed for a single patient and the linear Bergman model, and they only employed five rules for the membership function. They also utilized a trial-and-error approach to determine the input-output fuzzy logic controller's gain. As a result, the controller produces an insulin control action value that is too quick and suboptimal, which causes the blood glucose level to respond too quickly. In **(Babar et al., 2021)** designed a control glucose-insulin system using a sliding mode-back-stepping controller with three control gain parameters that were adjusted by trial-error method to achieve quick response and reduced chattering in a T1DM patient model for an intravenous glucose tolerance test.

Additionally, an artificial pancreas system was developed by the authors **(Patra and Nanda, 2021)** that automatically releases insulin and maintains the patient's blood glucose level by suggesting a model predictive controller for T1DM patients with insulin pumps that uses a Laguerre function and a linearized structure. However, a digital PID controller for diabetes patients' blood glucose levels using a linear Bergman model was introduced by **(Sharma et al., 2022)**. Because the Ziegler-Nichols (Z-N) tuning method is not appropriate for investigating and utilizing the global extreme solution of the issue, they used it to determine the control settings, which resulted in an overshoot in the patient's blood glucose response. An intelligent controller using a radial basis function neural network for an automated insulin delivery system for a virtual the diabetes sufferer model was described in **(Barbosa de Farias et al., 2022)** for monitoring and regulating the plasma blood glucose level in a matter of days.

The estimation of the T1D patient model was demonstrated in **(Khaqan et al., 2022)** using a UVA/Padova metabolic simulator. For the linear third-order diabetes sufferer model, control algorithms that managed the blood glucose level were designed using an intelligent predictive control model with linear and nonlinear controllers. A physiological system was created in **(Homayounzade, 2022)** utilizing an observer-based bbackstepping controller for an intravenous glucose tolerance test, the diabetes sufferer model with type 1 diabetes using an expanded Bergman model to estimate the plasma level and insulin concentration. The controller then uses these estimates as feedback to maintain the patient's blood glucose levels within a typical physiological range. A generalized type-2 (GT2) fuzzy-logic system (FLSs) controller was created in **(Yan et al., 2022)** specifically for the first diabetes sufferer model and the linear diabetes sufferer Bergman model. To get the four control gains in the control law, it employs the trial-and-error technique. Because the controller generates a quick and less-than-ideal value of the insulin control action, this causes a slight oscillation in the plasma blood glucose level response. The optimal interval type-2 fuzzy (IT2F) controller was suggested by **(Sayed et al., 2023)** for the nonlinear Bergman model in patients with type 1 diabetes. The eight control gains in the control law are obtained using the grey wolf optimization (GWO) technique. This results in a minor oscillation in the blood glucose level response as the controller produces a rapid and suboptimal value of the insulin control action. Futhermore, a fractional-order-PID (FOPID) controller was utilized to improve the tracking plasma blood glucose error and control the diabetes sufferer's blood glucose level, while a complex-order PID (COPID) controller was suggested for higher blood glucose levels in a T1D diabetes sufferer model in **(Saleem and Iqbal, 2023)**. However, these controllers have two drawbacks: the control parameters are modified by numerical optimization, and the beginning settings are dependent on the designer's experience. Additionally, the

adaptive Tilt Integral-Derivative Filter controller was developed in **(Patra and Panigrahi, 2023)** using a Romora optimization technique. Its four controller gains parameters are adjusted for the blood glucose levels of patients with type 1 diabetes mellitus. The precision, consistency, robustness, noise reduction, and enhanced uncertainty handling of the proposed patient model with RO-TIDF are evaluated. But in the Lehman-Based Diabetic Patient Model (LBDPM). (**Kalaimani and Jeyakumar, 2024)** created and investigated adaptive controllers to control blood sugar levels through insulin administration. This work utilizes the ANYA fuzzy rule-based system, an online adaptive type controller that uses the N-BEATS algorithm, for the application of diabetes. Normal blood glucose levels are monitored by the model using the suggested controller, even in the event of unanticipated external disturbances. Using data from simulated diabetic patient models, the primary goal in type 1 diabetes research is to increase the accuracy of a deep learning system. The linear blood glucose-insulin model in type 1 diabetes was enhanced by (**Shenbagam et al., 2024)**, who also proposed a fractional-order PID (FOPID) controller with a genetic algorithm to modify the five control parameters. This improved the tracking plasma blood glucose error and aided the plasma blood glucose levels of the diabetes sufferer model.The previous works related to the glucose-insulin control algorithm can be summarized in **Table 2,** in terms of the algorithms used, the simulation results, and the drawbacks in their research works.

Table 2. The previous works related to the glucose-insulin control algorithm

Author Names	Algorithms	Simulation Results	Drawback
(Benzian et al., 2019)	PID controller with PSO	High overshoot response of plasma blood glucose level	Small search space for the gain parameters
(Dias et al., 2020)	Single MPC	Blood glucose level was good performance	Trial-error method for tuning parameters
(Benzian et al., 2021)	Fractional order PID controller and the fuzzy logic controller	Overshoot in the response of the blood glucose level	The linear Bergman model and they used only five rules for the membership function, with a trial-and-error method
(Babar et al., 2021)	Back-stepping-sliding mode controller	Quick response and less chattering in an intravenous glucose level	Trial-error method for tuning three control gain parameters
(Patra and Nanda, 2021)	Model predictive controller	Stabilizes the blood glucose level for the diabetes sufferer	Linearization model of Bergman diabetes sufferer model
(Sharma et al., 2022)	Using Ziegler-Nichols (Z-N) tuning, a digital PID controller	Overshooting, the response of the blood glucose	The optimized algorithm lacked intelligence.
(Barbosa de Farias et al., 2022)	Intelligent controller with a radial basis function neural network	Blood glucose level was good performance	The automated insulin delivery system was a big value
(Khaqan et al., 2022)	Intelligent predictive control model	Stabilizes the plasma blood glucose level for the diabetes sufferer model	Linearization model of Bergman diabetes sufferer

(Homayounzade, 2022)	Observer-based back-stepping controller	Fast glucose level response	Linearization model of Bergman diabetes sufferer
(Yan et al., 2022)	Generalized type-2 (GT2) fuzzy-logic system (FLSs) controller	The slight oscillation in the blood glucose level response.	Linear patient Bergman model. It uses the trial-and-error method
(Sayed et al., 2023)	Optimized interval type-2 fuzzy (IT2F) controller with GWO	Quick and suboptimal value of the insulin control action	The tuning algorithm has many iterations
(Saleem and Iqbal, 2023)	Complex-order PID controller	The blood glucose tracking error was a small value	Tuning the control parameters using numerical optimization
(Patra and Panigrahi, 2023)	Controller for Adaptive Tilt Integral-Derivative Filters	Quick response to the glucose level of the diabetes sufferer model	The tuning algorithm has many iterations
(Kalaimani and Jeyakumar, 2024)	Adaptive Fuzzy Controller	Track the diabetes sufferer model's normal blood glucose levels.	Deep learning algorithm has a long time for tuning parameters.
(Shenbagam et al., 2024)	Fractional-order PID controller with a genetic algorithm	Quick response of the diabetic patient model's plasma blood glucose level	Linearization model of the diabetes sufferer Bergman model

4. PROPOSED CONTROLLER

The general structure of the proposed cognitive plasma blood glucose-insulin control strategy is shown in **Fig. 3**, which demonstrates the three layers for achieving the optimal insulin-infusion level for the nonlinear diabetic patient model to avoid the hyperglycemia and hypoglycemia states and to stablize the plasma blood glucose level of the diabetes sufferer in the desired normal state.

This three-layer structure consists of:

- Layer #1: The cognitive dataset that represents the attributes of the control system, and it depends on three different types of diabetic patients, such as the first patient has high insulin sensitivity. The second patient has low insulin sensitivity, and the third patient has very high insulin sensitivity.
- Layer #2: The neural network identifier patient model that represents the different types of nonlinear diabetic patients with different types of meal disturbances.
- Layer #3: The feedback neural network controller based on the radial basis function neural network model to find the optimal insulin-infusion value and to keep the plasma blood glucose level for the diabetes sufferer in the normal state.

The identifier model is based on the NARMA-L2 neural network model that will represent the different types of the nonlinear diabetic patient model. Three different types of the nonlinear Bergman glucose-insulin model are used with the input-output dataset, including insulin *Ins(k)* in (mU/L) and glucose *Gp(k)* in (mg/dl), as well as the dataset in layer #1 to build the proposed nonlinear identifier neural network glucose-insulin model. Therefore, the modelling of the nonlinear glucose-insulin is the primary aim of the proposed cognitive blood glucose-insulin control strategy, which is utilized to provide the preconditions for analysis and will be used in the third layer of the control design.

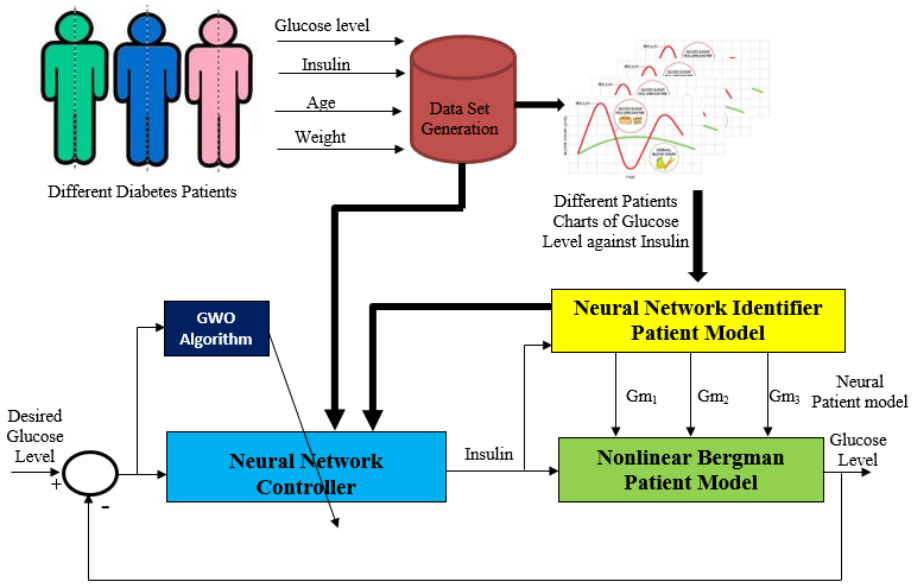


Figure 3. Cognitive plasma blood glucose-insulin control strategy for the nonlinear diabetic patient model.

In fact, the purpose of the nonlinear glucose-insulin identification is to find a mathematical model of the different types of the nonlinear Bergman glucose-insulin model whose output corresponds to the output of the nonlinear diabetic patient models. In this regard, neural networks are mathematical models with excellent fault tolerance, adaptiveness, and associative memory capacities that can process data concurrently. In order to establish the neural network glucose-insulin model, the identifier model of the nonlinear diabetic patient model is constructed using the NARMA-L2 neural network model, as seen in **Fig. 4**.

For the proposed identification, the NARMA-L2 model was selected among several traditional neural networks due to its unique advantages. More specifically, strong robustness performance, no output oscillation, high dynamic representation, and an increasing degree of the nonlinear glucose-insulin model performance are provided by the two networks of *FH[-]* and *GH[-]*, which are raised in the order of the hidden units. The cognitive attributes input is represented in Eq. (12), therefore, the number of input to each network is equal to 7 that lead to the number of neurons in each network is equal to 15 based on equation 2n+1 **(Narendra and Parthasarthy, 1990; Al-Araji et al, 2019)** where n is the number of inputs.

$$B_i(k) = [Go(k) \quad I_o(k) \quad Food(k) \quad I_{max}(k) \quad Gp(k) \quad Xp(k) \quad Ins(k-1)] \tag{12}$$

The proposed NARMA-L2 model of the nonlinear glucose-insulin model can be described in Eq. (13).

$$G_m(k+1) = FH[Gp(k), Xp(k), Ins(k-1), Food(k), I_o(k), Go(k), I_{max}(k)] + GH[Gp(k), Xp(k), Ins(k-1), Food(k), I_o(k), Go(k), I_{max}(k)] \times Ins(k) \tag{13}$$

The $FH[-]$ and GH [-] network weights can be represented as follows: FV_{ai} represents the weight matrix of $FH[-]$ in the hidden layer, FW_b represents the weight matrix of $FH[-]$ in the output layer, GV_{ai} represents the weight matrix of GH [-] in the hidden layer, and GW_b represents the weight matrix of GH [-] in the output layer.

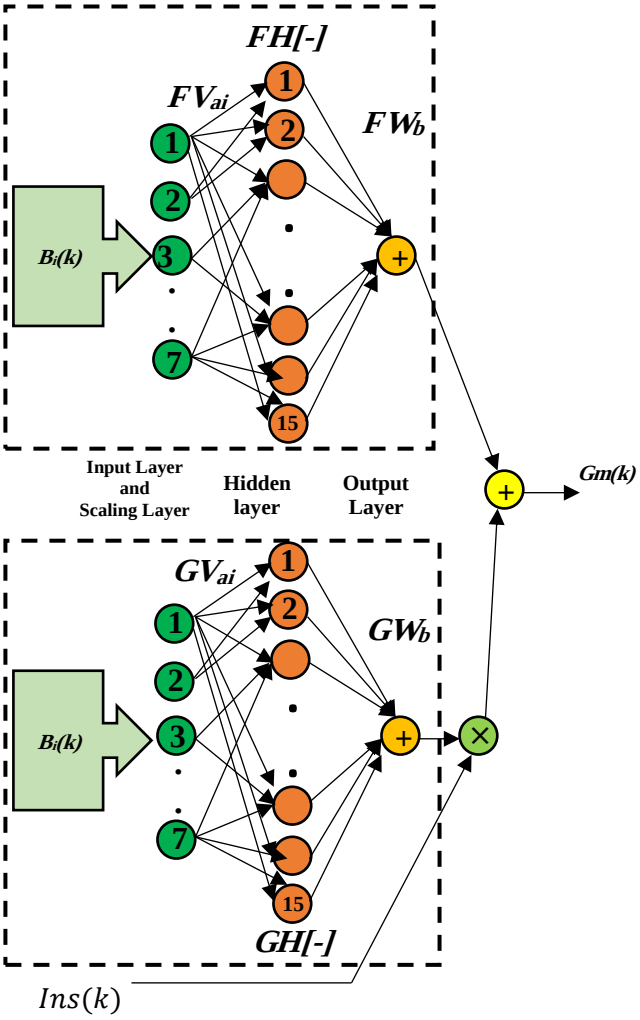


Figure 4. FH[−] and GH[-] neural network structure.

To illustrate the calculations in the hidden layer based on the fifteen neurons, firstly, we will sum the net of the weights of FV_{ai} and GV_{ai} using Eq. (14) and Eq. (15).

$$FHnet_a = \sum_{a=1}^{nfh} FH_{ai} \times \overline{B}_i \quad (14)$$

$$GHnet_a = \sum_{a=1}^{ngh} GH_{ai} \times \overline{B}_i \quad (15)$$

Where *nfh* and *ngh* represent the hidden nodes' number, which is equal to fifteen nodes. Secondly, the neuron outputs of both FH_a and GH_a are calculated as a continuous unipolar sigmoid activation function of the $FHnet_a$ and $GHnet_a$, as illustrated in Eq. (16) and Eq. (17), respectively.

$$FH_a = \frac{1}{1+e^{-FHnet_a}} \quad (16)$$

$$GH_a = \frac{1}{1+e^{-GHnet_a}} \quad (17)$$

Thirdly, to calculate the weighted sum $Fnet_o$ and $Gnet_o$ of the output layers, Eq. (18) and Eq. (19) are used, respectively.

$$Fnet_o = \sum_{a=1}^{nfh} FW_b \times \overline{FH_a} \quad (18)$$

$$Gnet_o = \sum_{a=1}^{ngh} GW_b \times \overline{GH_a} \quad (19)$$

The one linear neuron passes the sum of both (*Fnetfo*) and (*Gnetgo*) through a linear function of slope 1, as shown in Eq. (20) and Eq. (21).

$$FO = Linear(Fnet_o) \quad (20)$$

$$GO = Linear(Gnet_o) \quad (21)$$

The neural network output is the glucose level of the modelling *Gm(k)* that can be expressed as given in Eq. (22):

$$Gm(k) = FO + GO \times Ins(k) \quad (22)$$

The identifier model based on NRMA-L2 will produce the same actual response of the glucose level after using the neural network's training procedure.

The mean square error is used as the cost function to evaluate each solution in the GWO algorithm:

$$MSE = \sum_{It=1}^{IT_{max}} [\frac{1}{K} \sum_{i=1}^{K} ((Gp(i) - Gm(i))^{2})] \quad (23)$$

where IT_{max} is the maximum number of iterations and K denotes the maximum number of samples.

The NARMA-L2 neural network model serves as the foundation for the feedforward neural network controller, which calculates the maximum insulin-infusion amount $Umax$ for each meal as shown in **Fig. 5.**

The control law that indicates the maximum insulin-infusion level for every meal is provided by the Jacobian, which is also known as the GH[-] neural network. This law will be utilized in the closed loop control system's multi-objective function to lower the value of the feedback-insulin control action.

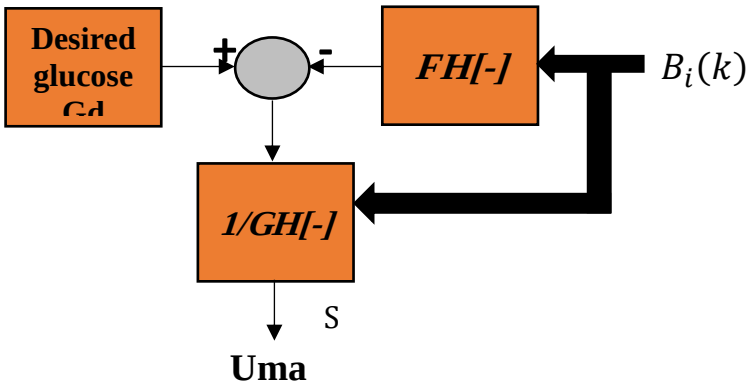


Figure 5. The structure of the feedforward neural network controller.

It has the sign definite in the nonlinear Bergman glucose-insulin model operation region to ensure the uniqueness of the model inverse at that operating region, which can be expressed in Eq. (24) and Eq. (25) based on Eq. (22) and Eq. (13).

$$Umax = \frac{Gd - FH[-]}{GH[-]} \tag{24}$$

$$Umax(k+1) = (Gd(k+1) - FH[Gp(k), Xp(k), Ins(k-1), Food(k), I_o(k), Go(k), I_{max}(k)])/ \\ GH[Gp(k), Xp(k), Ins(k-1), Food(k), I_o(k), Go(k), I_{max}(k)] \tag{25}$$

Where, $Gd(k+1)$: denotes the desired blood glucose level.

The GWO algorithm is a clever algorithm that is based on grey wolf predation. Similar to other intelligent algorithms, each grey wolf's position indicates a feasible response, and the prey indicates the optimal one. Grey wolves are ranked according to the value of their fitness function in an effort to identify the best solution **(Gao et al., 2022).** With three different kinds of grey wolf groups, hierarchical commands can be created. The grey wolves with the highest fitness function value make up the leader group, often known as the alpha (α) group. The alphas are in charge of making judgments about hunting, waking times, sleeping spots, and other things. Ironically, despite not being the strongest person in the group, the alpha must be the best pack manager. The beta (β) group, the second echelon of leadership, is frequently called co-leaders since they assist the alpha in pack activities and decision-making. The delta (Δ) groups come after them. The probable prey is located nearer the wolves α, β, and Δ **(Kraiem et al., 2021)**. Figure 6 illustrates the hierarchy of gray wolves during predation, which is one distinctive feature of GWO. The three primary phases of hunting, finding the prey, encircling the prey, and attacking the prey, are carried out to optimize efficiency.

After α groups lead gray wolves to encircle their victim, β and Δ groups assault the prey, and the prey is eventually taken. This process results in a method with few parameters, no special search parameters, and good convergence performance **(Almazini and Ku-Mahamud, 2021).** It is very easy to design. At the beginning of the process, a fixed number of grey wolves are used, and their locations are selected at random.

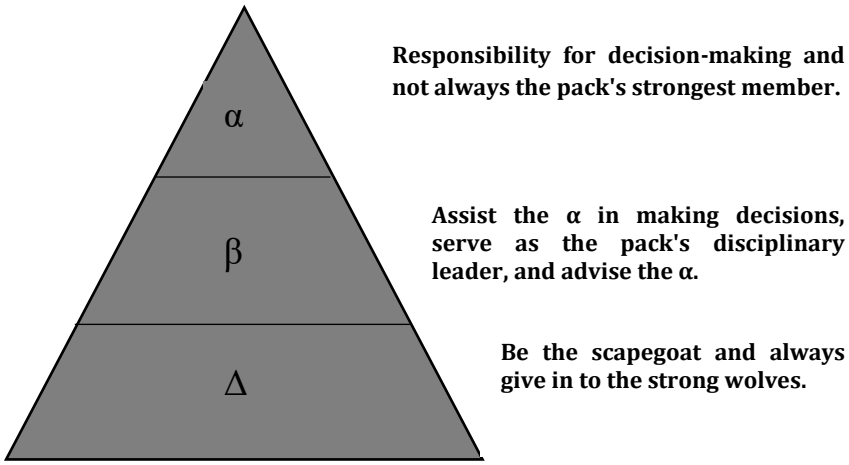


Figure 6. The hierarchy of gray wolves.

Each group in the pack will encircle the others according to the following mathematical equations **(Almazini et al., 2023; Almazini and Ku-Mahamud, 2021):**

$$D = \left|C \times X_p(iter) - X(iter)\right| \quad (26)$$

$$X(iter+1) = \left|X_p(iter) - A \times D\right| \quad (27)$$

where Eq. (26) represents the distance between the grey wolf individual and its prey. Eq. (27) contains the formula for the gray wolf's position update, where iter represents the current iteration, A and C are coefficient vectors, and Xp and X are the position vectors of the prey and the grey wolf, respectively **(Almazini and Ku-Mahamud, 2021; Almazini et al., 2023)**. The formulas used to determine A and C are as follows:

$$A = 2a \times r_1 - a \quad (28)$$
$$a = 2 \times (1 - iter/It_{Max}) \quad (29)$$
$$C = 2 \times r_2 \quad (30)$$

The basic steps of the GWO methodology for figuring out and modifying the weights of the FH[-] and GH[-] neural networks are shown in **Fig. 7**.
The convergence factor serves as its representation, and the random vectors r1 and r2 are chosen at random from the interval (0,1). The total number of iterations is called ItMax. The following equations **(Gao et al., 2022; Kraiem et al., 2021; Almazini and Ku-Mahamud, 2021; Almazini et al., 2023)** state that the prey position Xp (iter + 1) update is calculated by averaging the grey wolf locations α, β, and Δ (the three temporarily ideal solutions), with the remaining locations being discarded for position update:

$$X_p(iter+1) = \frac{X_1+X_2+X_3}{3} \quad (31)$$

Where:

$$\left.\begin{aligned} X_1(iter) &= X_\alpha(iter) - A_1 \times D_\alpha \\ X_2(iter) &= X_\beta(iter) - A_2 \times D_\beta \\ X_3(iter) &= X_\Delta(iter) - A_3 \times D_\Delta \end{aligned}\right\} \quad (32)$$

and:

$$\left.\begin{aligned} D_\alpha &= |C_1 \times X_\alpha(iter) - X(iter)| \\ D_\beta &= \left|C_2 \times X_\beta(iter) - X(iter)\right| \\ D_\Delta &= |C_3 \times X_\Delta(iter) - X(iter)| \end{aligned}\right\} \quad (33)$$

The random vectors C1, C2, and C3 characterize the final positions of people, whereas Dα, Dβ, and DΔ in Eq. (26), respectively, indicate the distances between α, β, and Δ and other individuals. Furthermore, their beginning and finishing positions are specified by Eq. (27). When the victim eventually stops moving, the grey wolf attacks to put an end to the search **(Gao et al., 2022; Kraiem et al., 2021; Almazini and Ku-Mahamud, 2021; Almazini et al., 2023)**. By gradually decreasing the value of an, the range of A's fluctuations is reduced. This is the fundamental method for creating a process model. Put another way, the analogous value of A changes in the interval (-a, b) during the iterative process in a way that is comparable to the linear decrease of an in the interval (2, 0).

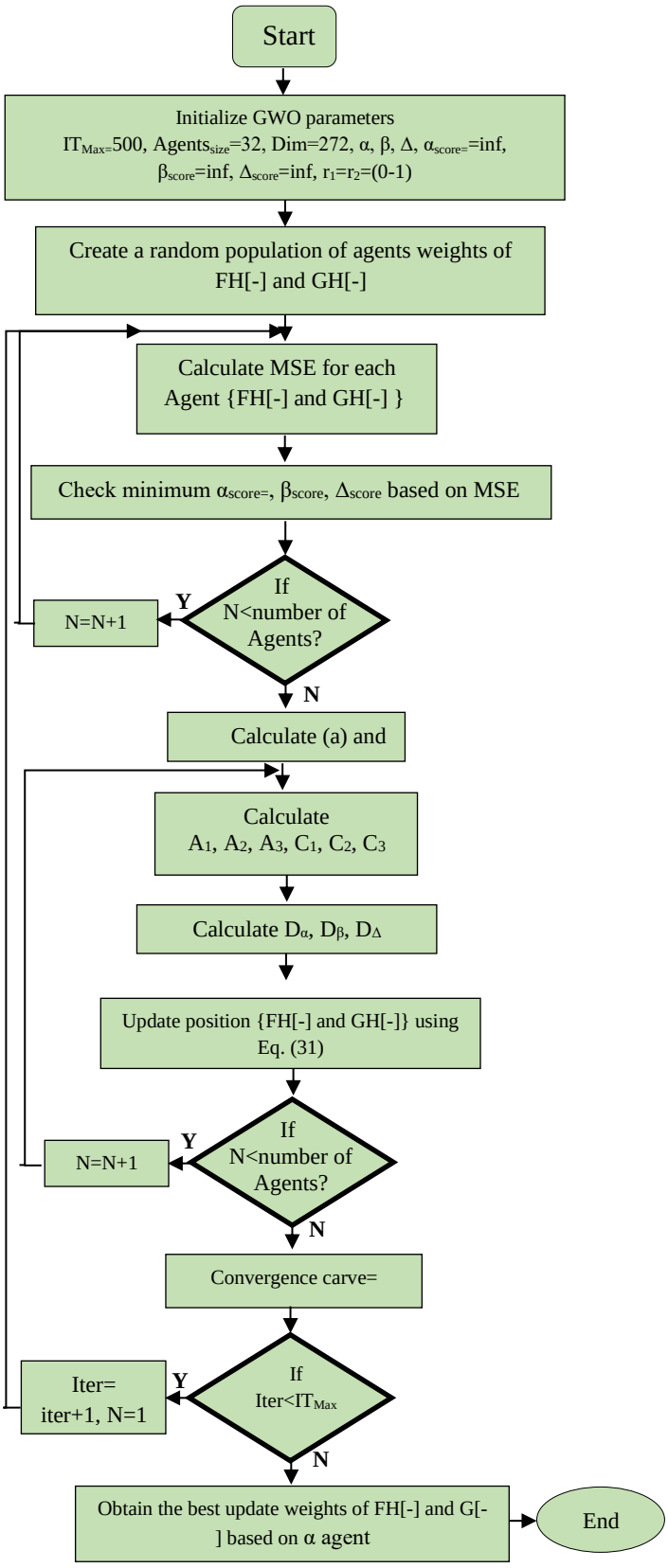


Figure 7. The flowchart of updating the weights for the identifier patient model based on the GWO algorithm.

5. SIMULATION RESULTS

In this work, the numerical fourth-order Runge-Kutta (4RK) method based on the MATLAB package with a half-minute sampling time was utilized for implementing the cognitive blood glucose-insulin control strategy for the nonlinear diabetic patient model in **Fig. 3**. This control strategy will achieve the optimal insulin-infusion level for the different types of nonlinear diabetic patient models to avoid the hyperglycemia level and hypoglycemia level and to keep the plasma blood glucose level of the diabetes sufferer in the desired normal state. Specifically, five steps are implemented, as illustrated below:

The first step is to determine the cognitive attributes dataset, with the blood glucose level of the patient *Gp(k)*, the blood-insulin concentration level *Ins(k)*, and the active insulin in the remote compartment performs *Xp(k)*, as an open-loop patient model for a healthy individual as well as for three distinct categories of the diabetes sufferers (NP, P#1, P#2, and P#3) who are dependent on the glucose starting levels (Go) of (280, 230, 220, and 210) mg/dl, respectively. **Fig. 8** demonstrates the plasma blood glucose level of different types of three patients ($Gp_1(k)$, $Gp_2(k)$, *and* $Gp_3(k)$), with the same initial glucose levels *Go*. However, the disturbance meal at breakfast is equal to 15 mg/dl.min^{-1} blood glucose level.

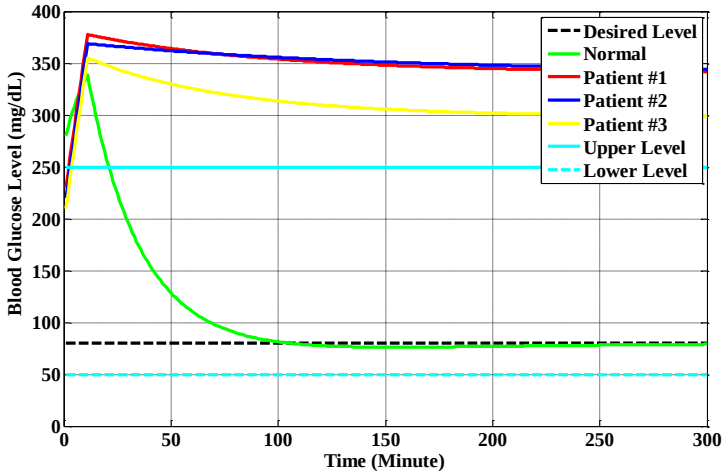


Figure 8. The diabetes sufferers (P#1, P#2, and P#3) and a normal person (NP) of the plasma glucose level responses in the breakfast-meal state.

Fig. 9 demonstrates the dynamic behaviour of the Bergman glucose insulin minimum model for the three different types of diabetic patients, representing the blood glucose level with the same initial glucose levels Go, but the disturbance meal at lunch is equal to 20 mg/dl.min^{-1} blood glucose level.

Fig. 10 demonstrates another dataset, which includes adding the disturbance meal at dinner with a blood glucose level equal to 5 mg/dl.min^{-1} for the three different types of diabetic patients with the same initial glucose levels Go.

In step two, the nonlinear glucose-insulin the diabetes sufferer model is displayed in **Fig. 3** using the structure of the NARMA-L2 neural network **(Dagher, 2018)**. Accordingly, the suggested number of nodes in each of the networks, which have three layers, including the input layer, the hidden layer, and the output layer, is as follows: [7: 15: 1], respectively **(Narendra and Parthasarthy, 1990; Al-Araji et al., 2019)**.

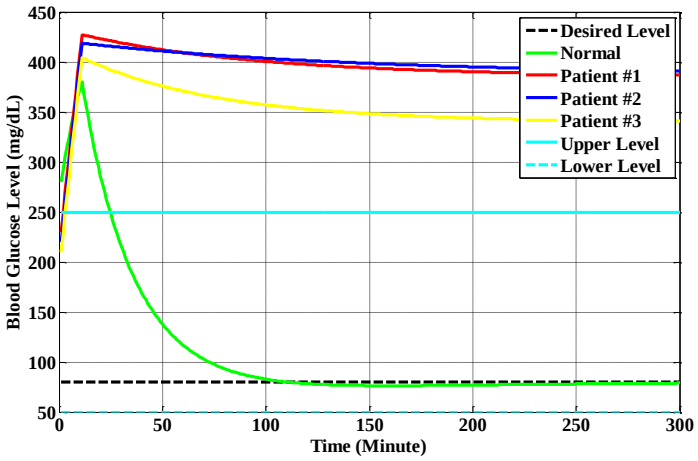


Figure 9. The diabetes sufferers (P#1, P#2, and P#3) and a normal person (NP) of the plasma glucose level responses in the lunch-meal state.

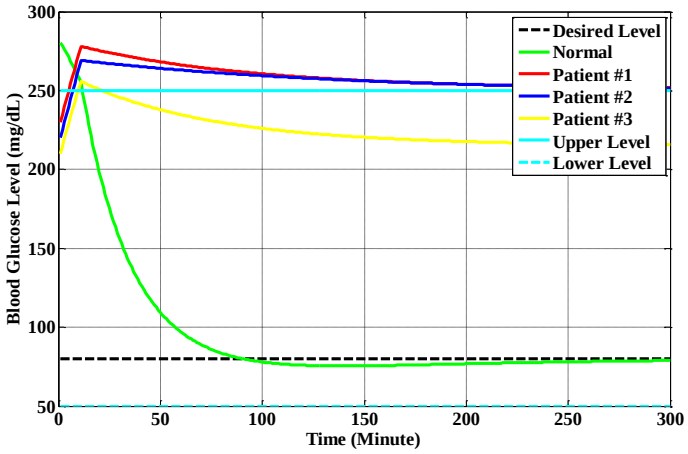


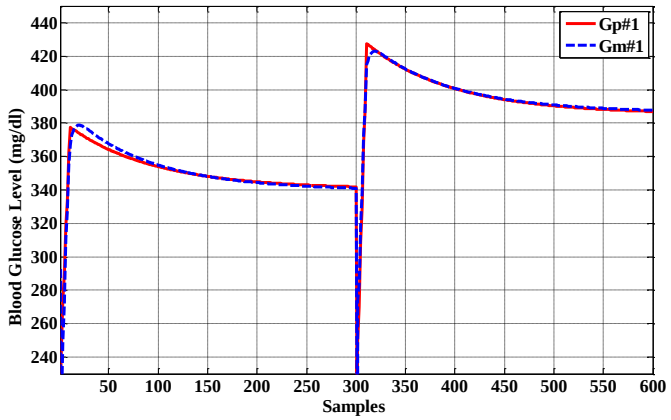
Figure 10. The diabetes sufferers (P#1, P#2, and P#3) and a normal person (NP) of the plasma glucose level responses in the dinner-meal state.

The number of nodes in the hidden layer is equal to twice the number of nodes in the input layer plus one. The third step involves learning the identifier model of the nonlinear glucose-insulin the diabetes sufferer using the GWO off-line algorithm and then tuning the models online. Signals entering or exiting the neural network (NN) have been considered to lie between (-1) and (+1) in order to solve numerical issues pertaining to actual values **(Al-Araji et al., 2019; Dagher, 2018)**. As a result, the neural network terminals' first and last layers (input-output) require the application of scaling functions, respectively, such that the ranges of these inputs are as follows: Gp(k)=(50 to 500) mg/dl; Xp(k)=(0 to 0.05) 1/min; Ins(k)=(0 to 700) mU/L; Food(k)=(5 to 25) mg/dl.min^{-1}; I_o(k)=(50 to 60) mU/L; Go(k)=(210 to 280) mg/dl; and Imax(k)=(0 to 70) U/min.

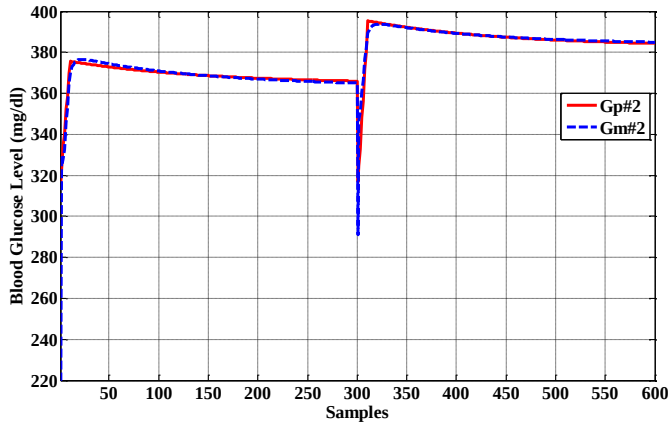
In the learning mode, the responses of the different types of the nonlinear neural network glucose-insulin the diabetes sufferer models (Gm_1, Gm_2, and Gm_3) are shown in **Figs. 11-a, b, c** for three models with two cases the breakfast and the lunch meals learning dataset.

These models have a very small error value in the modelling between the Bergman glucose level and the diabetic patient neural network model (Gm_1, Gm_2, and Gm_3) for 600 patterns as a learning set, and they have good responsiveness of the identifier models with a very

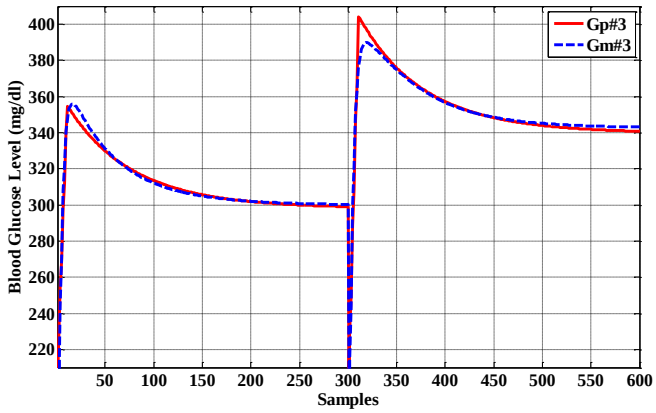
good dynamical behaviour during the different cases of disturbance meal inputs (breakfast meal and lunch meal) for the three different types of the nonlinear glucose-insulin patient models. The performance of the best convergence curve is depicted in **Fig. 12**.



(a)



(b)



(c)

Figure 11. The response of the different types of the nonlinear neural network glucose-insulin patient models for the breakfast meal learning set and the lunch meal learning set, a) The first diabetes sufferer model Gm_1, b) The second diabetes sufferer model Gm_2, c) The third diabetes sufferer model Gm_3.

It is based on the off-line GWO algorithm for three different types of patient models with 500 iterations and with an agents' number equal to 32 for the neural networks. In addition, the number of weights is 272. Specifically, the best alpha convergence curve for the optimal updated weights of the identifier neural network is presented in **Fig. 12**.

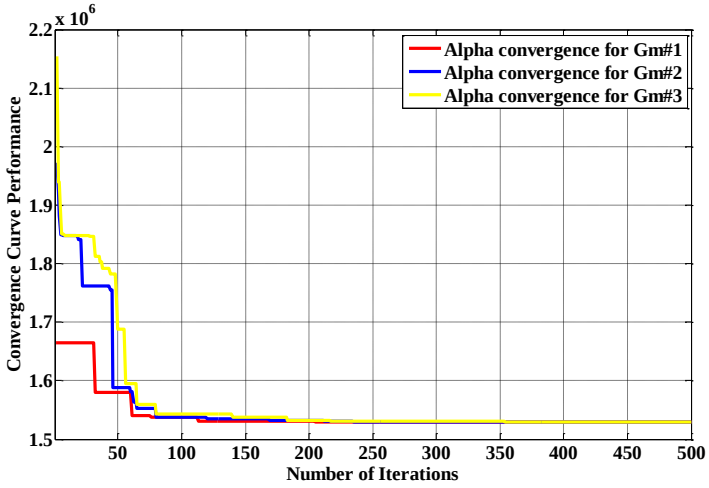
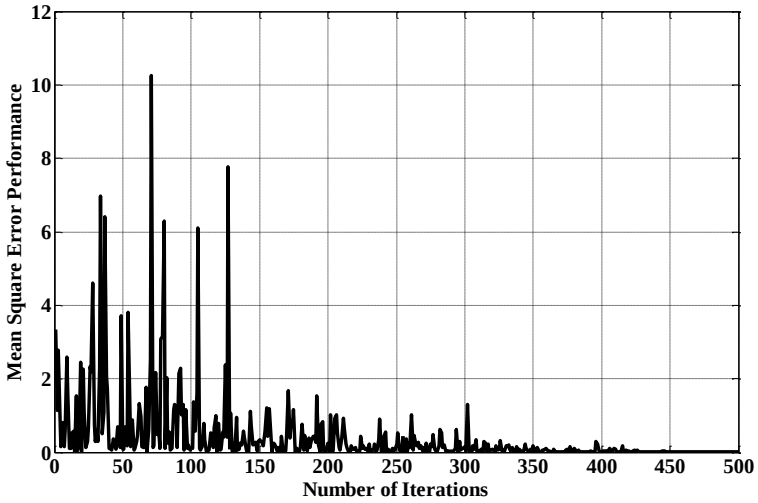


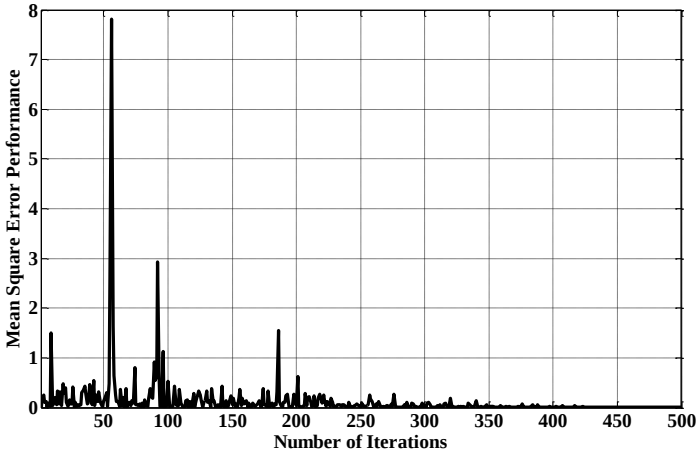
Figure 12. The best alpha convergence curve response of the different types of nonlinear neural network glucose-insulin patient models.

The mean square error response for the optimal updated weights of the identifier neural network patients in the learning mode are presented in **Figs. 13-a, b, c.** To verify that these neural network models have remarkable learning, the testing mode in our work is essentially for the nonlinear glucose-insulin patient models to prove that these neural models have been learned in all the excitation and active regions of the real models and eliminated the overlearning problem. This problem means that the network learns on a part of the region and forgets other regions during the learning mode. However, the meta-heuristic GWO algorithm learning cycle was excellent because this algorithm is ideal for investigating and taking advantage of the problems' global extreme solutions. **Figs. 14-a, b, c** demonstrate the dynamical behaviour of the nonlinear glucose-insulin patient models during the testing mode using dinner meal. To verify that these neural network models have remarkable learning, the testing mode in our work is essentially for the nonlinear glucose-insulin patient models to prove that these neural models have been learned in all the excitation and active regions of the real models and eliminated the overlearning problem. This problem means that the network learns on a part of the region and forgets other regions during the learning mode. However, the meta-heuristic GWO algorithm learning cycle was excellent because this algorithm is ideal for investigating and taking advantage of the problems' global extreme solutions. **Figs. 15-a, b, c** demonstrate the dynamical behaviour of the nonlinear glucose-insulin patient models during the testing mode using dinner meal. The mean square error response of the different types of nonlinear neural network glucose-insulin patient models, a) The first diabetes sufferer model Gm_1, b) The second diabetes sufferer model Gm_2, c) The third diabetes sufferer model Gm_3. The fourth step involves representing the closed-loop control system for the nonlinear Bergman model based on the proposed NN controller with the GWO meta-heuristic method using the objective function **(Al-Bayati et al., 2020)**. This function will reduce the error between the desired glucose level and the patient's glucose level, and at the same time, it will reduce the value of the insulin control action for each

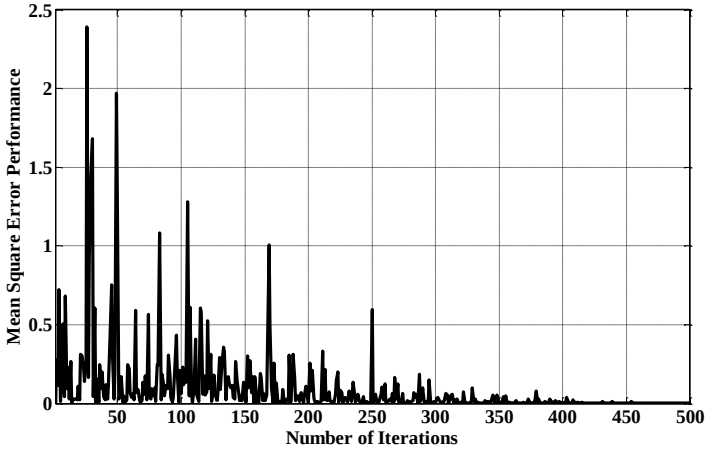
solution of the control gain parameters for the NN controller to find the best value of the insulin-infusion control action in the transient and the steady-state regions.



(a)

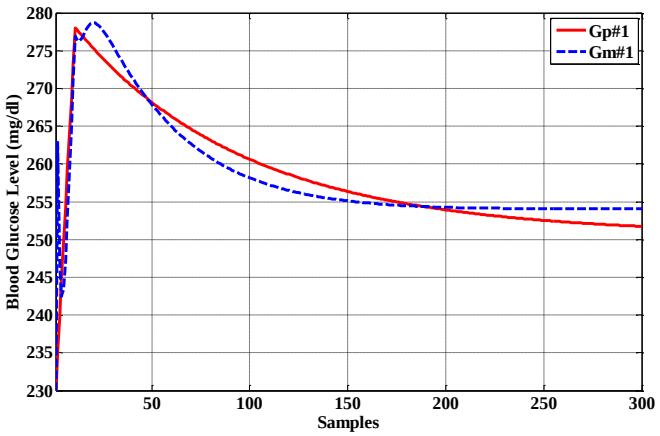


(b)

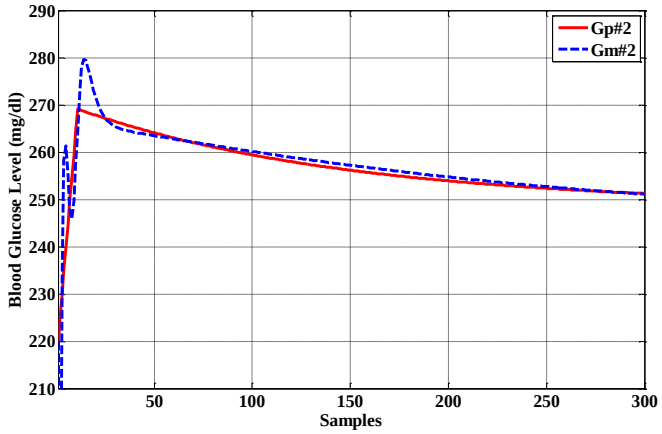


(c)

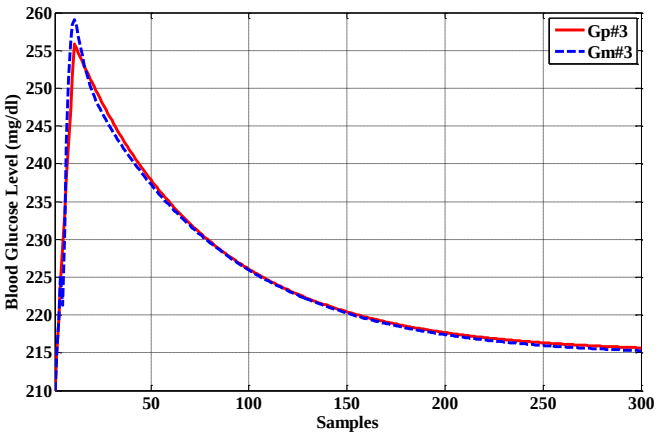
Figure 13. The mean square error response of the different types of nonlinear neural network glucose-insulin patient models, a) The first diabetes sufferer model Gm_1, b) The second diabetes sufferer model Gm_2, c) The third diabetes sufferer model Gm_3.



(a)



(b)



(c)

Figure 14. The response of the different types of the nonlinear neural network glucose-insulin patient models for the dinner meal testing set, a) The first diabetes sufferer model Gm_1, b) The second diabetes sufferer model Gm_2, c) The third diabetes sufferer model Gm_3.

The fourth step involves representing the closed-loop control system for the nonlinear Bergman model based on the proposed NN controller with the GWO meta-heuristic method using the objective function **(Al-Bayati et al., 2020)**. This function will reduce the error between the desired glucose level and the patient's glucose level, and at the same time, it will

reduce the value of the insulin control action for each solution of the control gain parameters for the NN controller to find the best value of the insulin-infusion control action in the transient and the steady-state regions. **Fig. 15** displays the response of the proposed closed-loop insulin-infusion neural network controller, when the Bergman diabetic patient model adds the breakfast meal as a disturbance. It is important to note that at 200 minutes, the plasma blood glucose levels of the first diabetes sufferer model and second diabetes sufferer model did not precisely reach 80 mg/dl at steady state. They remain at their typical physiological level.

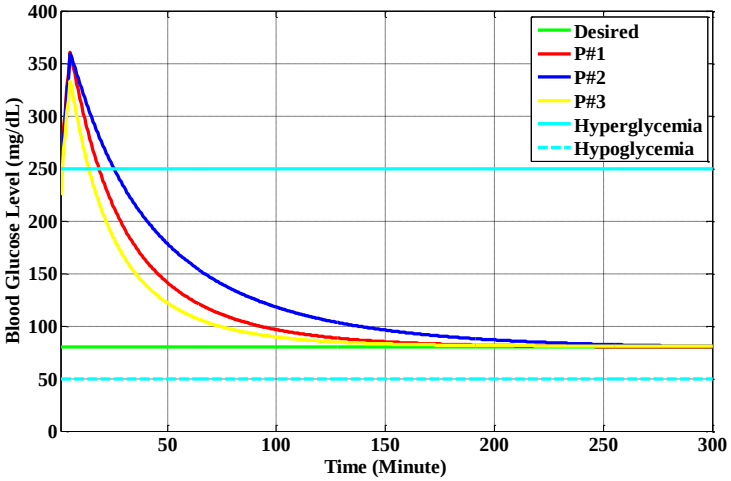


Figure 15. The plasma blood glucose responses for each Bergman diabetes sufferer model based on the closed-loop cognitive NN controller with the breakfast disturbance.

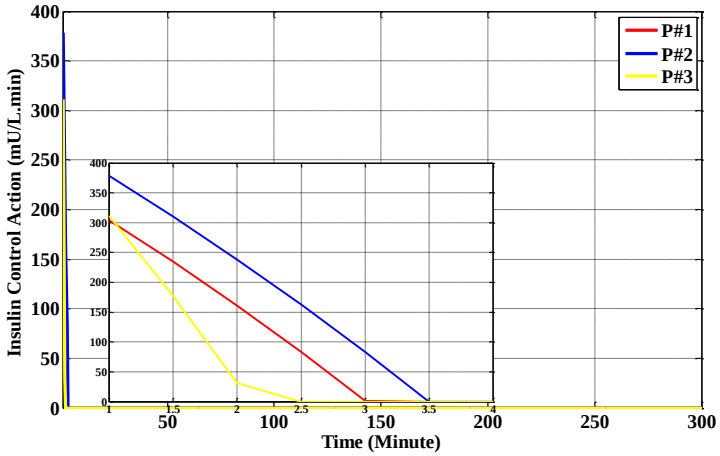


Figure 16. The insulin action of the proposed controller for the three different types of Bergman models with the breakfast disturbance.

The output response of the insulin-infusion NN controller during the first ten samples is displayed in **Fig. 16** when the blood glucose level abruptly rises. The NN efficiently and rapidly determines the insulin action value for each of the three diabetes sufferer model to track the sudden increase in the blood glucose levels.

To determine the optimal control gain settings of the NN controller, **Fig. 17** shows the response of the best alpha convergence for the three diabetes sufferers.

The lunch disturbance effect was introduced for a duration of ten samples for each patient to show the effectiveness of the insulin-infusion control action. In particular, 20 mg/dl.min^{-1} is the suggested lunch disturbance value. The following points indicate that the suggested

overall controller improves the diabetes sufferer's glucose level response as shown in **Fig. 18.**

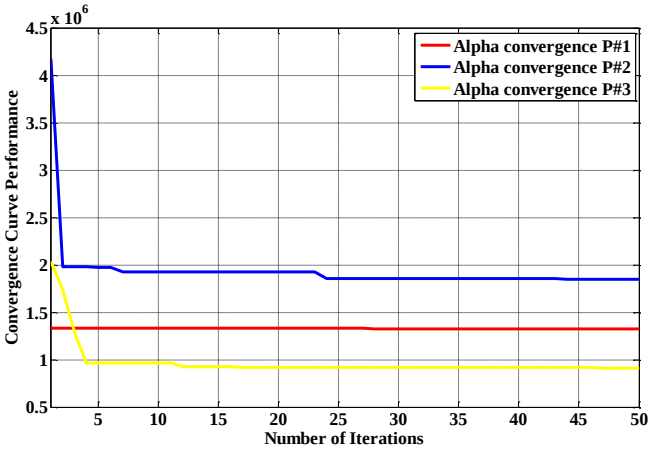


Figure 17. The best alpha fitness curve response of the NN controller for the diabetes sufferers models (P#1, P#2, and P#3) of Bergman patient models with the breakfast distubance.

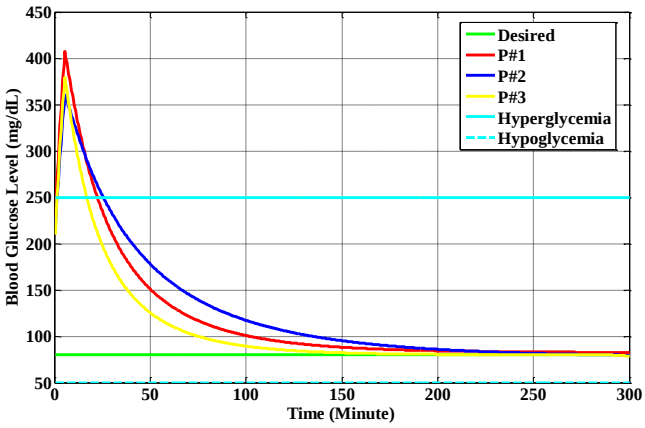


Figure 18. The plasma blood glucose responses for each Bergman diabetes sufferer model based on the closed-loop cognitive NN controller with the lunch disturbance.

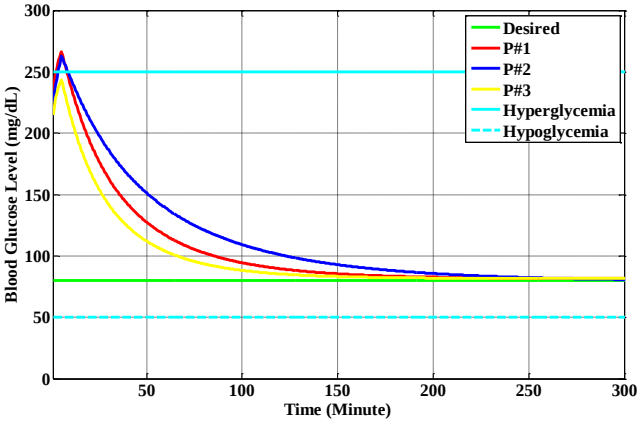


Figure 19. The plasma blood glucose responses for each Bergman diabetes sufferer model based on the closed-loop cognitive NN controller with the dinner disturbance.

The suggested closed-loop insulin-infusion cognitive controller's response to the addition of dinner as a perturbation in the Bergman diabetic patient model is shown in **Fig. 19**. Specifically, the recommended dinner disturbance value is 5 mg/dl.min^{-1}.

To confirm the effectiveness of the optimization algorithm (GWO) for modifying the parameters of the NN controller in this work, the simulation results of the proposed cognitive neural controller are compared with the results of other controller types that have taken from **(Benzian et al., 2021; Yan et al., 2022)**. The results are shown in **Table 3**.

Table 3. Simulation results contrasting alternative architectures with the proposed controller.

Type of control algorithm	**Tuning algorithm**	**Steady- State Error Overshoot OS(%) Time to reach normal physyological level**	**Enhance the time to reach the blood glucose level at 100 mg/dl**
Fractional order PID and Fuzzy logic controllers (Benzian et al., 2021) for 20 mg/dl lunch-meal disturbance	GA, ACO, BAT, IWO	No oscillation E_{ss}=0 T=100 min	10% for patient#1 T=90 min
Type-2 Fuzzy controller (Yan et al., 2022) for 20 mg/dl lunch-meal disturbance	Trial and Error	Small oscillation E_{ss}=0 T=120 min	25% for patient#1 T=90 min
The proposed cognitive neural networks controller	GWO	No oscillation E_{ss}=0	

The fractional-order PID (FOPID) and fuzzy-logic (FL) controllers in **(Benzian et al., 2021)** were built for the linear Bergman model and only for the first the diabetes sufferer (P#1), using only five rules for the membership function and the trial-and-error method to determine the gain in the input-output fuzzy logic controller. As a result, the controller produces an insulin control action value that is too quick and suboptimal, which causes the plasma blood glucose level to respond too quickly. The suggested controller, on the other hand, employs the nonlinear Bergman model, the feedback NN with the GWO heuristic method. Based on the optimum parameters identified by the optimization algorithm, the controller has generated optimal or nearly optimal insulin control action, resulting in the reduction of blood glucose levels to a normal physiological level without overshooting or response oscillation. In contrast to fuzzy-logic controller algorithms and fractional-order-PID algorithms, the comparison findings demonstrated that the NN with the GWO algorithm improved the time to attain the blood glucose level in a normal condition for patient #1 by 10% **(Benzian et al., 2021)**.

In **(Yan et al., 2022)**, the type-2 fuzzy controller was created only for the first diabetes sufferer (P#1) using the linear patient Bergman model. Trial and error is how the four control gains in the control law are acquired, which results in a minor oscillation in the blood glucose level response as the controller produces a rapid and suboptimal value of the insulin control action. The proposed cognitive neural controller, which consists of the feedback NN controller with the heuristic GWO method, works with a nonlinear patient Bergman model. The controller produces an ideal or nearly optimal insulin control action based on the best parameters found by the optimization algorithms, bringing the blood glucose level to a physiologically normal level without fluctuating or overshooting. When compared to the type-2 fuzzy controller algorithm, the comparison findings demonstrated that the NN with the GWO algorithm improved the time to attain the blood glucose level in normal conditions for patient #1 by 25% **(Yan et al., 2022)**.

The simulation's findings demonstrate that the optimal insulin control action can be achieved by the suggested cognitive neural network glucose-insulin controller using the

GWO algorithm. This makes it possible for the nonlinear diabetes sufferer Bergman model to track the necessary plasma blood glucose level with the least degree of tracking error and to attain optimal performance without oscillation in the output blood glucose levels of the different diabetes sufferer types.

Furthermore, to show the effectiveness of the proposed cognitive glucose-insulin controller, we will take another parameter of the minimal glucose model, especially to show the effect of the glucose effectiveness factor P_1, which is the rate constant for the glucose uptake in muscles and liver, which is not equal to zero. In the Bergman minimal model, the parameter P_1 also known as glucose effectiveness (S_G), quantifies glucose's ability to facilitate its own uptake and suppress its production, independent of insulin action. A number of factors, including model simplifications, individual variability in insulin secretion and sensitivity, and underlying physiological conditions impacting glucose metabolism, can cause variations in the estimated values of P1, including zero or extremely tiny. The impacts of P1 zero versus small values on a few features are displayed in **Table 4**.

Table 4. The effects of P_1 zero vs small value.

Feature	P_1 = 0 (No Glucose Effectiveness)	P_1 = Small (Minimal Glucose Effectiveness)
Muscle Glucose Uptake	Fully dependent on insulin	A very small amount occurs independently
Liver Glucose Suppression	No suppression without insulin	Slight suppression, but still needs insulin
Impact on Blood Sugar	Extreme glucose instability	Slightly better glucose clearance, but still requires insulin

Table 5 demonstrates **t**he parameters of the minimal glucose model for the fourth patient **(Xavier et al., 2022)**. The response of the suggested closed-loop insulin-infusion proposed controller is shown in **Fig. 20** based on the Bergman diabetic patient model parameters as in **Table 5**. In particular, Go is equal to 200 mg/dl value in the blood at beginning, the insulin-infusion action stabilizes patient #4's glucose level, as indicated by the red-colour line, which drops from 200 mg/dl to 80 mg/dl (the normal physiological level) and takes up 42 minutes. While the open loop response of patient #4 as indicated by the purple-colour line, decreases from 200 mg/dl to 120 mg/dl during 100 minutes, then remains at a level of 120 mg/dl blood glucose to 300 minutes.

Table 5. The parameters' values of the minimal model for the fourth patient **(Xavier et al., 2022)**.

Parameters Units	**Patient #4**
P_1 *(1/min)*	0.028735
P_2 *(1/min)*	0.028344
P_3 *(L/mUmin²)*	5.0353×10^{-6}
n (min^{-1})	0.1
G_b *(mg/dl)*	120
I_b *(mU/L)*	10
G_o *(mg/dl)*	200
I_o *(mU/L)*	10
$S_I=P_3/P_2$	177.65×10^{-6}

To monitor the abrupt rise in blood glucose levels as shown in **Fig. 21**, the proposed neural networks quickly and effectively calculate the insulin action value for the initial blood glucose level, Go. The maximum insulin-infusion control action value of 34.5 mU/L.min^{-1}, then the rating insulin action is 8 mU/L.min^{-1}.

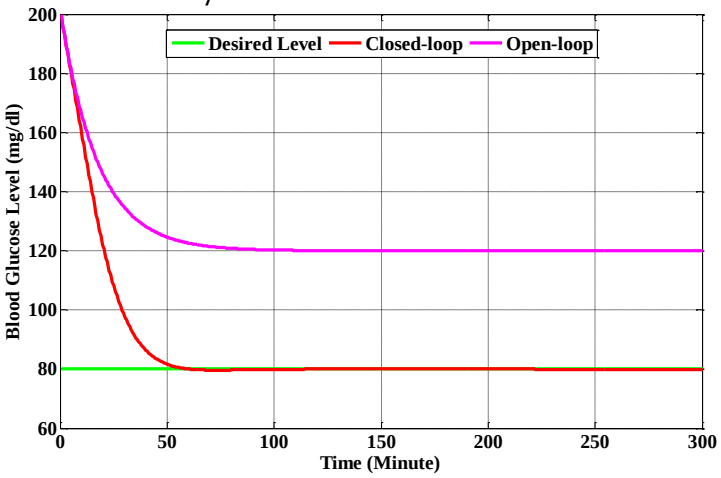


Figure 20. The glucose responses for patient #4 model based on the closed-loop cognitive controller with the p1 effect.

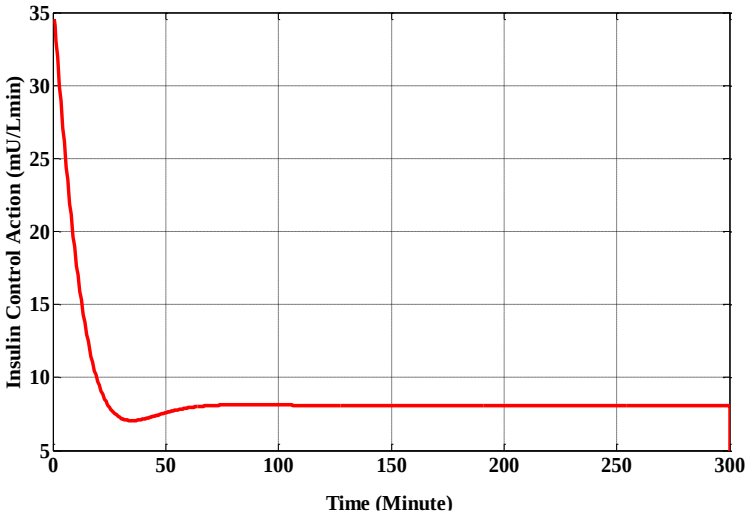


Figure 21. The insulin action of the proposed controller for the fourth patient with the p1 effect.

6. CONCLUSIONS

The cognitive blood glucose-insulin control technique is presented in this work, which uses three layers in the controller's structure to monitor and control the plasma blood glucose levels of various diabetic patients' types. The first layer was the cognitive dataset that represented the attributes of the control system. The second layer was the identifier neural network model that represented the different types of nonlinear Bergman diabetic patient models. The third layer was the feedback NN controller based on the radial basis function neural network model to find the optimal insulin-infusion value and to maintain a normal level of blood glucose. The grey wolf optimization (GWO) meta-heuristic technique was used to train this controller. Due to its rapid processing speed and capacity to detect multiple invasions, GWO has been widely used in both data estimation and training. The following

problems can be effectively resolved by using the glucose-insulin management technique based on the suggested three layers:

- The blood glucose level is effectively tracked and kept steady at the target level of 80 mg/dl, which is within the normal physiological range of 60–120 mg/dl.
- An ideal or almost ideal smooth value of the insulin-infusion control action was generated in order to enhance the blood glucose level response in diabetes patients without reaching saturation.
- The suggested controller, which is based on the NN controller with the GWO algorithm, attains a high level of tracking accuracy for the plasma blood glucose level that is observed. Its offline and online tuning control settings offer smooth insulin action without a significant spike and no saturation state.
- At intervals longer than 220 minutes, the maximum tracking error level for plasma blood glucose monitoring gets closer to zero.
- The suggested controller improved the time by 10% to bring the blood glucose level back to a normal physiological level with the lunch disturbance as compared to the fractional-order PID controller method. Furthermore, the suggested controller improved the time by 25% in comparison to the type-2 fuzzy control algorithm to get the plasma blood glucose level to a physiologically normal level with the lunch disturbance.

To create an artificial pancreas, the suggested glucose-insulin control strategy based on offline and online neural network controller with the GWO algorithm will be experimentally implemented in the future utilizing an FPGA development board with an insulin pump device.

Credit Authorship Contribution Statement

Khulood E. Dagher and Joseph Haggege studied and analysed the Bergman diabetic patient models. Khulood E. Dagher developed a cognitive glucose-insulin control algorithm using the GWO meta-heuristic technique. Joseph Haggege described the Bergman model. The two writers discussed the proposed numerical simulation results from this work.

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.

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مراجعات نصف عقد وتصميم وحدة التحكم لنموذج بيركمان لمريض السكري

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الخلاصة

مع التركيز على الأفراد المصابين بداء السكري من النوع الأول، تستعرض هذه الدراسة تقنيات إدارة نسبة الكلوكوز في الدم من خلال السنوات الخمس الماضية. ان في فقرة المقدمة توضح موجزة لكيف حول هذه المشكلة البيولوجية إلى مشكلة في نظام التحكم فيما يتعلق بإدارة نسبة الكلوكوز في بلازما الدم. في هذا البحث تم مناقشة دراسة جديدًة حول توصيل الأنسولين الآلي باستخدام نموذج بيركمان الرياضي اللاخطي. لقد جرت محاولات كثيرة من خلال المراجع المنهجية للأبحاث التي تم إجراؤها حتى الآن في مجال تطوير أنظمة البنكرياس الاصطناعية. يصف الاستنتاج تطوير جهاز التحكم المعرفي في الكلوكوز والأنسولين ويوفر فهمًا أساسيًا لكيفية استخدام نموذج بيركمان اللاخطي لتنظيم الكلوكوز في الدم لإنشاء نظام سيطرة لهذا التحدي في مجال التحكم الطبي الحيوي. عند مقارنتها بالطرق الحالية الأخرى، تظهر وحدة السيطرة المعرفية المقترحة استجابة أسرع من حيث الحفاظ على نسبة الجلوكوز في الدم. بالإضافة إلى ذلك، أظهرت نتائج المقارنة أن خوارزمية التحكم المعرفي بالجلوكوز والأنسولين المقترحة قد حسنت الوقت اللازم للوصول إلى مستوى جلوكوز الدم الفسيولوجي الطبيعي للمريض الأول بنسبة 10% مقارنة بخوارزميات التحكم المنطقي الضبابي وخوارزميات التحكم PID ذات الترتيب الكسري، وبنسبة 25% مقارنة بخوارزمية التحكم الضبابي من النوع الثاني.

الكلمات المفتاحية: ستراتيجية السيطرة ، داء السكري ، فعل الانسولين ، بلازمة سكر الدم.