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Enhancement of the Blood Glucose Level for Diabetic Patients Based on an Adaptive Auto-Tuned PID Controller via Meta-Heuristic Methods

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Abstract: This work proposes an intelligent method that uses an adaptive auto-tuned proportional-integral-derivative (PID) controller to track and regulate the blood glucose level of diabetic patients. The suggested controller seeks to provide the optimal insulin control action, which is in charge of swiftly, precisely, and accurately managing the blood glucose level. To train this controller, two meta-heuristic techniques are employed. The first technique is the particle swarm optimization (PSO), which has been widely used in both data estimation and training because of its quick computing speed, while the second one is an intrusion detection technique called grey wolf optimization (GWO), which was created to categorize data and effectively find multiple intrusions. The mean square error performance index is used in the two distinct meta-heuristic algorithm types to determine and optimize the optimal or nearly optimal gain parameters of the adaptive PID controller. The results of the MATLAB simulations for three different patients demonstrated the efficacy and resilience of the proposed control algorithm in tracking the dynamic behaviour of the diabetic patients' blood glucose levels by minimizing overshoot in the transient state to zero value, maintaining the steady-state blood glucose level in the normal physiological level of (60-120) mg/dl. These characteristics were particularly evident when we added a meal as a disturbance effect. Moreover, the comparison results showed that the proposed PID-GWO and PID-PSO algorithms enhanced the time (96 and 88) minutes to reach the blood glucose level at a normal physiological level by 4% and 12%, respectively, when compared to the fractional order PID and fuzzy logic control algorithms that the blood glucose level reached at a normal physiological level at 100 minutes and improved the time by 20% and 27%, respectively, when compared to the type-2 fuzzy control algorithm that the blood glucose level reached at a normal level at 120 minutes. In particular, the blood glucose level was kept at the desired normal physiological level without any oscillation.

Keywords: Blood glucose level, Type-1 diabetic patient, Adaptive PID controller, Particle swarm optimization, Grey wolf optimization.

1. Introduction

Millions of individuals across the world suffer from diabetes, which is a chronic metabolic illness [1]. Particularly, patients with diabetes can be classified as having either type 1 or type 2, where the body cannot adequately use the insulin that it generates and requires insulin injections to survive [2]. In this regard, complications of all kinds can include renal failure, heart attacks, strokes, amputations of legs, eyesight loss, and damage to nerves [3]. In addition, uncontrolled diabetes during pregnancy raises the possibility of fetal mortality. Accordingly, numerous organizations have proclaimed this illness a worldwide pandemic and projected that by 2030, where the yearly cost of managing diabetes and its complications will rise from 171 million in 2000 to 366 million [4]. Therefore, it is imperative to precisely, quickly, and affordably monitor and regulate those patients' blood glucose levels. Specifically, patients with type 1 diabetes mellitus (T1DM) are being studied in great detail by experts. As a result, a great deal of study has gone into creating several mathematical models of glucose and insulin that, to some extent, accurately represent the physiological behaviour of the human body. To this end, the most important model was the Bergman minimal model, and there are other glucose-insulin models, such as those in [4, 5]. Moreover, many types of insulin controllers were developed in the artificial pancreas to keep the patient's blood glucose level at a normal level of 80 mg/dl. For instance, the authors in [6] proposed a complex-order PID controller for enhanced blood glucose level in a T1D patient model and used a fractional-order PID controller to improve the blood glucose tracking error and regulate the blood glucose of the patient. However, the drawbacks of these controllers are tuning the control parameters using numerical optimization and the initial values depending on the designer's experience. In addition, in [7], the authors presented a digital PID controller for the blood glucose level of diabetic patients with a linear Bergman model. They used the Ziegler-Nichols (Z-N) tuning method to find the control parameters, which led to an overshoot in the response of the blood glucose of the patient because the Z-N tuning method is not suitable for exploring and exploiting the global extreme solution of the problem. Furthermore, the authors in [8] employed the fractional order PID controller and the fuzzy logic controller for regulating the blood glucose level of a T1D patient, and they used many types of meta-heuristic algorithms for tuning the control gain parameters of the FOPID. However, the limitation of this work is that these controllers have been built for the linear Bergman model and only for one patient, and they used only five rules for the membership function, with a try-and-error method to obtain the gain in the input-output fuzzy logic controller. Therefore, the controller generates a fast and non-optimal value of the insulin control action that leads to an overshoot in the response of the blood glucose level. In [9], the researchers described the design and implementation of a digital PID controller based on the Xilinx system generator for regulating the blood glucose level of the T1D patient with a PSO algorithm to tune the gain parameters in continuous time, and not in discrete time with a small search space. These different values of the control gain parameters lead to obtaining different responses with high overshoot, especially in the digital PID controller. In addition, the authors in [10, 11] exploited the type-2 fuzzy controller for tracking and stabilizing the blood glucose level in T1D patients. On the other hand, a radial basis function neural network was utilized in [12] as an intelligent controller for an automated insulin delivery system for a virtual patient model to monitor and control the blood glucose level within days. In another work, the authors in [13] illustrated the estimation of the T1D patient model based on a UVA/Padova metabolic simulator and designed control algorithms using an intelligent predictive control model with linear and nonlinear controllers to regulate the blood glucose level for the linear third-order patient model. In [14], the authors proposed a model predictive controller using a Laguerre function and a linearized structure for the T1DM patient with an insulin pump to build an artificial pancreas system that automates insulin and stabilizes the blood glucose level for the patient. Moreover, the author in [15] designed a physiological system using an observer-based back-stepping controller for an intravenous glucose tolerance test model of a T1DM patient with an extended Bergman model to estimate the insulin concentration and the plasma level. These estimations are then applied as feedback to the controller to keep the patient's blood glucose at a normal physiological level. In this work, the problem definition is that the type-1 diabetes mellitus (T1DM) patient has a challenging disorder that essentially involves the regulation of the blood glucose levels to avoid hyperglycemia as well as hypoglycemia. Moreover, determining the quantity of the insulin-infusion level is essential to regulate and stabilize the blood glucose level to the normal physiological level within the minimum amount of time possible. Specifically, the main objective of this research is to determine the fast and optimal insulin-infusion control action value in order to enhance the performance of the blood glucose level in the patient model in terms of regulation and stabilization of the blood glucose at the normal physiological level by implementing the proposed off-line adaptive PID controller using two meta-heuristic methods. In particular, the main contribution of this research is to find and tune the optimal or near-optimal control gain parameters of the adaptive PID controller to obtain the fast and optimal value of the insulin-infusion control action that will be injected into the nonlinear Bergman model of the T1DM patients to quickly track and stabilize the patient's blood glucose level and keep it at a normal physiological level within suitable time to avoid the hyperglycemia and hypoglycemia states.

The structure of this paper is as follows: The nonlinear mathematical model of the Bergman Minimal Model is presented in section 2. The control mechanism using the optimization algorithms is explained in section 3. The results of the simulation are presented in section 4. In section 5, the main conclusions from this work are provided.

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Table 1. The parameters' values of the Bergman model [8, 10, 17, 18].

Parameters Units	Normal	First Patient	Second Patient	Third Patient
$P_1(1/min)$	0.031	0	0	0
$P_2(1/min)$	0.012	0.011	0.007	0.014
$P_3(mUL^{-1}/min^2)$	4.92^{-6}	5.3^{-6}	2.16^{-6}	9.94^{-6}
$n(min^{-1})$	0.265	0.26	0.246	0.281
$G_b(mg/dl)$	70	70	70	70
$I_b(mU/min)$	7	7	7	7
$G_0(mg/dl)$	280	230	220	210
$I_0(mU/min)$	364.8	50	55	60

2. Patient bergman minimal model

In general, the link between the distant insulin compartment level I(t) in mU/dL and the plasma glucose compartment level G(t) in mg/dl is described by the Bergman glucose insulin minimum model, which is based on nonlinear ordinary differential equations. It was believed that insulin, a hormone, and blood glucose were housed in two distinct compartments and interacted with one another. In this context, several studies examined how insulin is distributed and blood glucose is controlled using the Bergman glucose-insulin basic model, which lacks the biological complexity observed in [16]. This model can be described as follows [8 and 17]:

$$\dot{G}(t) = -P_1[G(t) - G_b] - X(t)G(t) + d(t) \quad (1)$$

$$\dot{X}(t) = -P_2X(t) + P_3[I(t) - I_b] \quad (2)$$

$$\dot{I}(t) = -n[I(t) - I_b] + Y[G(t) - h]^+ t + u(t) \quad (3)$$

Since diabetic patients cannot manage their blood sugar levels $Y[G(t) - h]^+ t$ =0, this factor will not be taken into account when determining the transfer function; instead, a given parameter will be determined on the presumption of a steady state condition. Consequently,

$$I(\dot{t}) = -n[I(t) - I_b] + u(t) \quad (4)$$

Where the definitions and units of the equations parameters are shown below:

Equations Parameters	Definitions with units
$G(t)$	The blood glucose concentration variable mg/dl
$X(t)$	The effect of active insulin in the remote compartment variable mU/L
$I(t)$	The blood-insulin concentration variable mU/dl
$d(t)$	The meal disturbance input variable mg/dl
$u(t)$	The manipulated insulin-infusion rate variable mU/dl
G_b	The basal blood glucose concentration
I_b	The basal blood-insulin concentration
n	The first-order decay rate of plasma insulin
h	The threshold value of glucose above which the pancreatic β-cells release insulin
Y	The rate of the pancreatic β-cells' release of insulin after the glucose injection with glucose concentration
P_1	The glucose effectiveness factor *(1/min)*
P_2	The delay in insulin actions *(1/min)*
P_3	The patient parameter mUL^{-1}/min^2)

Table 1 shows the parameters of the Bergman model equations that describe normal, first, second, and third patients as follows [8, 10, 17, 18].

3. Adaptive PID controller design

Fig. 1 illustrates the structure and methods of the blood glucose level PID controller and presents the suggested meta-heuristic technique, which is suitable for exploring and exploiting the global extreme solution to find and tune the gain control parameters of the PID controller.

According to Eq. (5) [19], the discrete PID controller is defined as follows:

$$Insulin(k) = Insulin(k-1) + Kp(Error(k) - Error(k-1)) + Ki(Error(k)) + Kd(Error(k) - 2Error(k-1) + Error(k-2)) \quad (5)$$

The error signal between the desired and the actual blood glucose levels is the input for the adaptive blood glucose level PID controller. The insulin-infusion level, which serves as the control action and regulates the patient's blood glucose levels, is the output of the PID controller. The control gain parameters of the PID controller (k_p, k_i, and k_d) can be found and tuned by the off-line (PSO and GWO) algorithms in order to obtain the optimal or near-optimal insulin control action for the nonlinear

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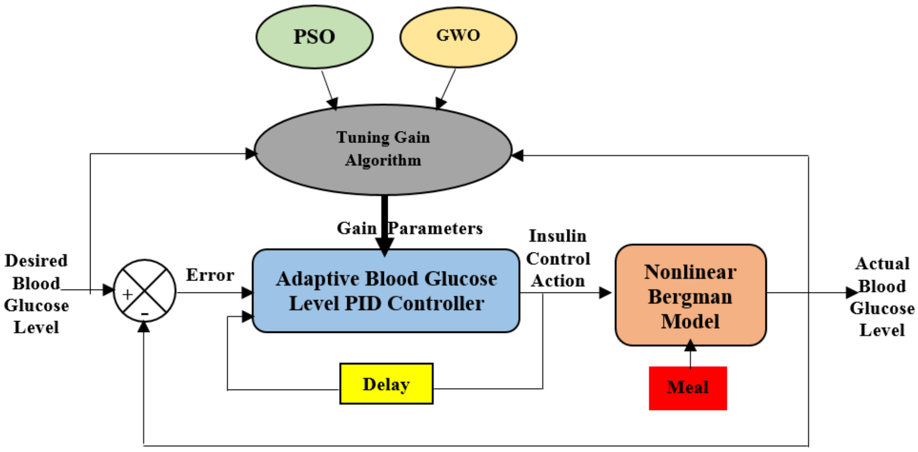

Figure 1. The diagram of the proposed adaptive PID controller for the blood glucose level

Bergman model to keep the blood glucose level in the normal state to avoid the hyperglycemia and hypoglycemia states.

3.1 Gain tuning control algorithms

In recent decades, many meta-heuristic methods have been proposed and developed to find optimal or near-optimal parameters. In this work, two meta-heuristic methods will be exploited, including the PSO and the GWO algorithms. As the cost function, the mean square error of each solution in both optimization algorithms is calculated using Eq. (6) [20]:

$$MSE = \frac{1}{P}\sum_{i}^{P}((Desired(i) - Actual(i))^{2}) \quad (6)$$

3.1.1. The PSO algorithm

The PSO method belongs to the population-based evolutionary algorithms, which draw inspiration from studies on swarms, including fish schools and bird flocks [21]. The PSO algorithm makes an effort to mimic the common communication mechanism that emerges during the gathering, feeding, and movement of individuals within such swarms [21]. Specifically, for high-dimensional, multiple-optimum, nonlinear, and non-differentiable optimization problems, the PSO is a trustworthy meta-heuristic method [22]. A few more advantages of the PSO are its excellent processing efficiency, constant convergence properties, and relatively easy implementation [23]. More specifically, the PSO process is started with a set of (N) randomly chosen particles. As every particle in the group symbolizes a point that moves across a (D)-dimensional search space, the positions of the particles indicate multiple potential sets of unknown parameters that need to be idealized. The rate at which the particle's location changes is determined by its velocity, while its fitness or quality measure is determined by its position inside the search space. The vector ($X_{particlei}$) = {$x_{\text{particle},i1}$, $x_{\text{particle},i2}$, …, $x_{\text{particle},iJ}$}, where (i) is the particle's index and (J) is its parameter, represents the location, while the vector ($V_{\text{particle},i}$) = {$v_{\text{particle},i1}$, $v_{\text{particle},i2}$, …, $v_{\text{particle},iJ}$}, which is limited within the range of $Vmax_{\text{particle}}$ = {$vmax_{\text{particle},1}$, $vmax_{\text{particle},2}$, …, $vmax_{\text{particle},J}$}, represents the velocity. The velocity is forced to its proper value if it is beyond certain limits. The i^th particle can seek its local optimal place by altering its velocity in this manner. Based on its own flight expertise, each particle modifies its trajectory toward a particular place and disseminates collective knowledge among the particles. Each particle has an iteration that varies its speed from one location to another, and it retains the best position it has found thus far in the vector $L\_best_{\text{particle},i}$ = {$L\_best_{\text{particle},i1}$, $L\_best_{\text{particle},i2}$, …, $L\_best_{\text{particle},iJ}$}. The best global particle or solution up to this point is represented by the global best position, which is then kept in the vector G_best_{particle} = {$G\_best_{\text{particle},1}$, $G\_best_{\text{particle},2}$, …, $G\_best_{\text{particle},J}$} among all the best individual locations of particles. Each iteration modifies each particle's location and velocity in accordance with Eqs. (7) and (8), and the parameters' definitions are shown in Table 2 [19-22].

$$v_{i,k+1} = w_{i,k}v_{i,k} + c_1r_1\left(L\_best_{\text{particle},i,k} - x_{\text{particle},i,k}\right) + c_2r_2(G\_best_{\text{particle},k} - x_{\text{particle}i,k}) \quad (7)$$

$$x_{i,k+1} = x_{i,k} + v_{i,k+1} \quad (8)$$

By swarming the particles (kp, ki, and kd) toward the best correct solution found in the previous iterations,

Table 2. Parameters' definition of the PSO

Symbols	Definition
$w_{i,k}$	Inertia weight of the i^{th} particle at iteration k
$v_{i,k}$	Particle speed at iteration k
c_1, c_2	Acceleration constants ($(c_1+c_2)<4$)
r_1, r_2	Random values between (0,1)
$L_{best,k}$	Reflects the best local position
$G_{best,k}$	Reflects the best global position
$x_{i,k}$	The current position of the i^{th} particle at iteration k

the aim is to effectively search the result space, eventually converge on a single minimum blood glucose level error solution, and discover better solutions along the way based on the PID controller. The fundamental procedures of the PSO algorithm for finding and tuning the parameters of the PID controller are described in Fig. 2.

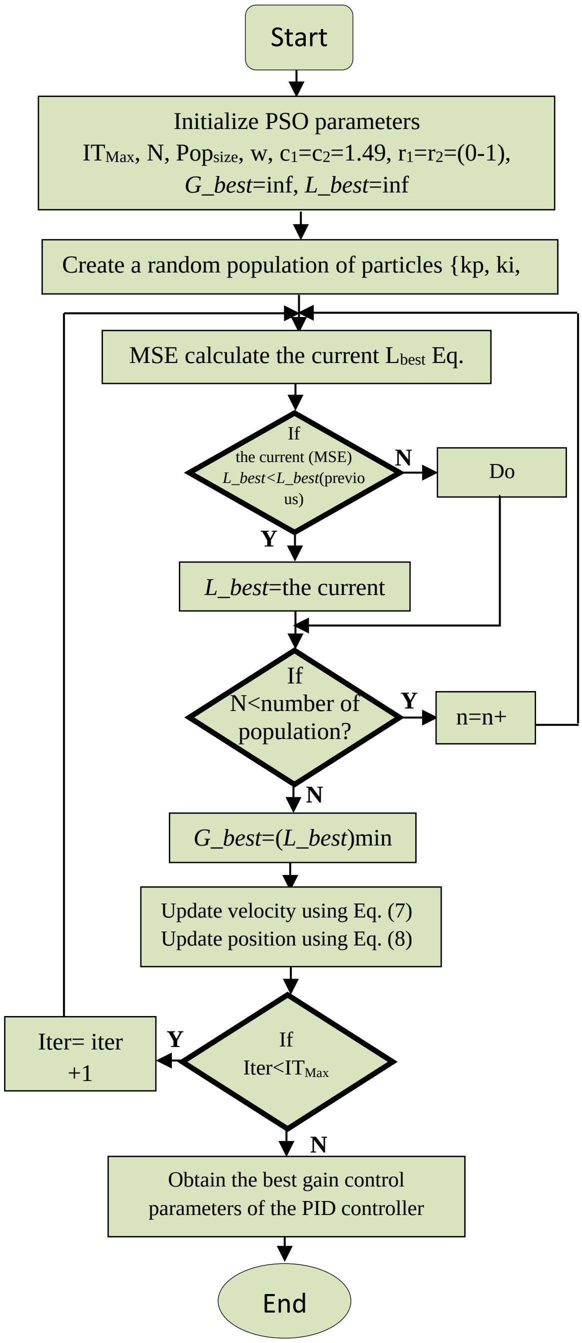

Figure. 2 The flowchart of the off-line PID-PSO control algorithm.

3.1.2. The GWO algorithm

An intelligent algorithm based on grey wolf predation is called the GWO algorithm. Like other smart algorithms, the prey points to the best answer, and each grey wolf's position points to a workable one. When attempting to find the optimal solution, grey wolves are ranked based on the value of their fitness function [23]. It is possible to construct hierarchical commands with three distinct types of grey wolf groups. The leader group, or the alpha (α) group, consists of grey wolves with the greatest fitness function value. Making decisions on hunting, waking hours, sleeping locations, and other matters falls within the purview of the alphas. Strangely, the alpha has to be the best pack manager, even if they are not the strongest member of the group. Because they support the alpha in decision-making and pack activities, the beta (β) group, which is the second echelon of leadership, is often referred to as co-leaders. They are followed by the delta (Δ) groups. The position of the likely prey is closer to the wolves α, β, and Δ [24]. One unique aspect of GWO is the hierarchy of gray wolves during predation. In order to maximize efficiency, three main hunting stages are carried out, namely searching for the prey, encircling the prey, and attacking the prey. Gray wolves are guided by α groups to encircle their victim; β and Δ groups attack the prey; and finally, the prey is captured. This procedure leads to excellent convergence performance for the method, which lacks specific search parameters, is easy to construct, and has few parameters [25].

A predetermined number of grey wolves are used at the start of the procedure, and their locations are chosen at random. The following mathematical equations [26] dictate how each group in the pack will encircle one another [27]:

$$D = \left|C \times X_p(iter) - X(iter)\right| \tag{9}$$

$$X(iter+1) = \left|X_p(iter) - A \times D\right| \tag{10}$$

where the distance between the grey wolf individual and its prey is represented by Eq. (9). The gray wolf's

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position update formula is found in Eq. (10), where iter denotes the current iteration, A and C are coefficient vectors, and Xp and X are the prey's and the grey wolf's respective position vectors [24]. The following are the formulae used to calculate A and C:

$$A = 2a \times r_1 - a \tag{11}$$

$$a = 2 \times (1 - It_{Max}) \tag{12}$$

$$C = 2 \times r_2 \tag{13}$$

It is represented by the convergence factor, where r_1 and r_2 are random vectors selected at random within the interval (0,1). It_{Max} is the total number of iterations. As stated by the following equations [23-27], the prey position *Xp (iter + 1)* update is determined by averaging the locations of grey wolves α, β, and Δ (the three temporarily ideal solutions), while the others are discarded for position update:

$$X_p(iter + 1) = \frac{X_1 + X_2 + X_3}{3} \tag{14}$$

Where:

$$\left.\begin{aligned} X_1(iter) &= X_\alpha(iter) - A_1 \times D_\alpha \\ X_2(iter) &= X_\beta(iter) - A_2 \times D_\beta \\ X_3(iter) &= X_\Delta(iter) - A_3 \times D_\Delta \end{aligned}\right\} \tag{15}$$

And:

$$\left.\begin{aligned} D_\alpha &= |C_1 \times X_\alpha(iter) - X(iter)| \\ D_\beta &= |C_2 \times X_\beta(iter) - X(iter)| \\ D_\Delta &= |C_3 \times X_\Delta(iter) - X(iter)| \end{aligned}\right\} \tag{16}$$

The distances between α, β, and Δ and other individuals are represented by D_α, D_β, and D_Δ in Eq. (16), respectively, and the random vectors C_1, C_2, and C_3 describe the ultimate positions of individuals. In addition, Eq. (13) specifies their starting and ending positions. The grey wolf attacks to end the hunt when the victim finally stops moving [23-27]. The basic approach to developing a process model is to progressively lower the value of an, which lowers the range of A's fluctuations. In other words, during the iterative process, the equivalent value of A varies in the interval (-*a*, *b*) in a manner similar to how the value of a drops linearly in the interval [2, 0]. The fundamental procedures of the GWO algorithm for finding and tuning the parameters of the PID controller are described in Fig. 3.

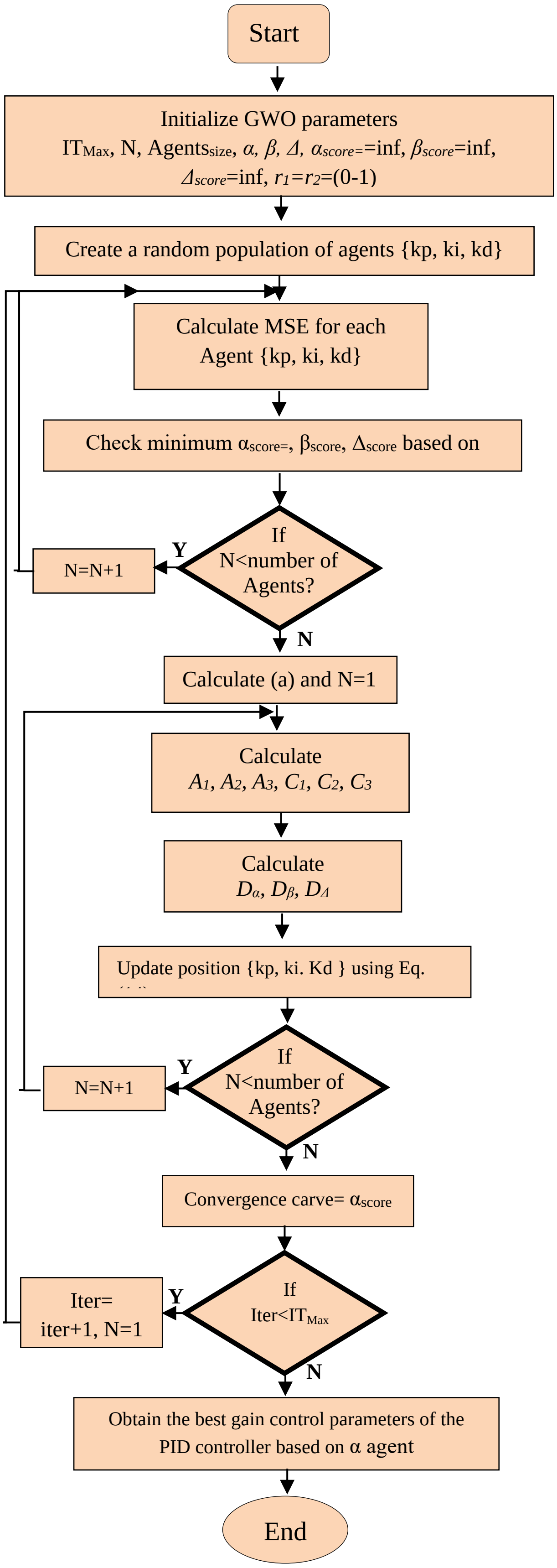

Figure. 3 The flowchart of the off-line PID-GWO control algorithm

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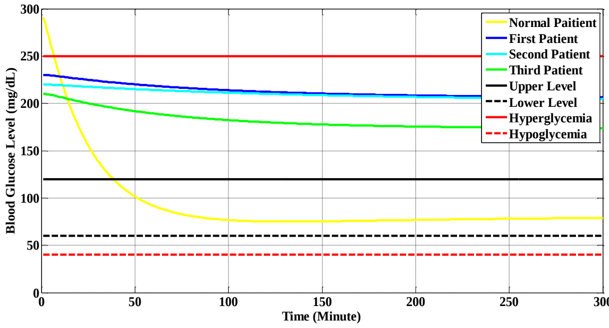

Figure. 4 The behaviour of a normal person and different types of patients in an open loop with hyperglycemia and hypoglycemia levels

4. Simulation results

Using the numerical fourth-order Runge Kutta (4RK) method based on the MATLAB package with a one-minute sampling time, we implemented the proposed off-line adaptive insulin-infusion PID controller with two meta-heuristics (PSO and GWO) methods for the nonlinear Bergman model. In particular, normal and different types of patients were considered in order to improve the performance of the blood glucose level of diabetic patients. Fig. 4 demonstrates how the blood glucose level performs as an open loop for a healthy individual as well as for three distinct categories of diabetic patients who are dependent on the glucose starting levels (G0) of 280, 230, 220, and 210) mg/dl, respectively.

Since the healthy person curve shows a normal glucose level dropping from a high value to the physiological level, or the normal glucose level (between the upper level of 120 mg/dl and the lower level of 60 mg/dl), consuming high blood sugar is not harmful. On the other hand, the glucose value is exceedingly high and well beyond the physiological range, putting the patient in danger mode with hyperglycemia (250 mg/dl) and hypoglycemia (40 mg/dl). The blood glucose level in the patient's model started high, decreased very slowly, and would never return to the normal state. Therefore, we examined the efficacy and performance of the adaptive PID controller using the off-line method for tuning the parameters based on GWO and PSO. In this regard, the suggested adaptive PID controller settings for the search space areas are displayed for each patient in Table 3, which is suitable for exploring and exploiting the global extreme solution to find and tune the gain control parameters of the PID controller. The response of the suggested closed-loop adaptive insulin-infusion PID-GWO controller is shown in Fig. 5.

Table 3. The suggested regions of the control parameters' search spaces for each patient.

Kp	Ki	Kd
-0.5 to +0.5	-1 to +1	-10 to +10

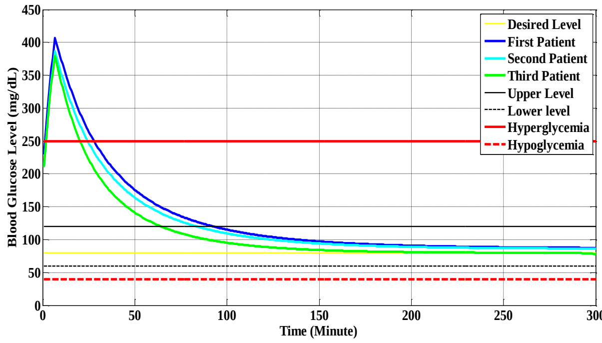

Figure. 5 The glucose level response for each patient's closed loop PID-GWO controller

To demonstrate the efficacy of the insulin-infusion control action, a meal disturbance effect was added for a period of time equal to 10 minutes for all patients. Specifically, the proposed meal disturbance value is equal to 20 mg/dL. The proposed controller enhances the patients' glucose level response as follows: the glucose level of the first patient, indicated by the blue color line, is shown to be stabilized by the insulin action, as it decreases from 230 mg/dl to 120 mg/dl (the upper normal physiological level) and stays there for 96 minutes. On the other hand, the second patient's glucose level is reduced from 220 mg/dl to 120 mg/dl, which is the upper normal physiological level, and it stabilizes there after 84 minutes, where the second patient is shown by the cyan color line. The third patient's glucose level is finally reduced from 210 mg/dl to 120 mg/dl, or the upper normal physiological level, and stabilized there for 65 minutes, where the third patient is shown by the green color line. It is worth noticing that the blood glucose levels for the first and the second patients did not reach an exact value of 80 mg/dL at steady state at 300 minutes. However, they are still at the normal physiological level.

The best-proposed values of the GWO algorithm in terms of the agent number are 5 and the maximum iteration is 50, which leads to generating the best PID-GWO controller parameters for the first patient, the second patient, and the third patient models, as displayed in Table 4. For each patient model, the proposed controller is in charge of producing optimal or near-optimal insulin control action, which lowers the blood glucose levels and maintains them within an acceptable range.

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Table 4. The PID-GWO controller parameters optimal values for three patient classes

Type of patients	K_p	K_i	K_d
The First Patient	-0.0079	0.2155	2.3557
The Second Patient	0.0007	0.0525	-9.0112
The Third Patient	0.0338	0.2394	2.6836

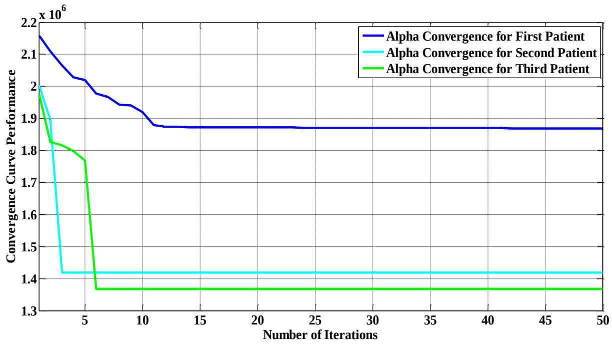

Figure. 6 The convergence curve performance of the closed loop PID-GWO controller for the three patients

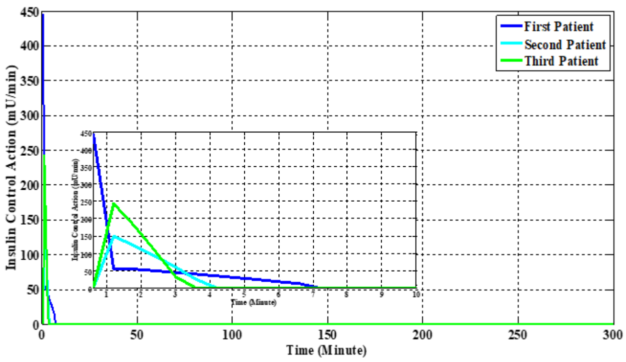

Figure. 7 The insulin PID-GWO controller's output response

Fig. 6 shows the response of the best alpha convergence for the three patients in order to obtain the best control gain parameters of the PID-GWO controller.

Fig. 7 shows the output response of the insulin PID-GWO controller when the blood glucose level suddenly increases during the first 10 minutes. For the three patients, the PID-GWO quickly and optimally calculates the insulin action value to monitor the abrupt rise in blood glucose levels. For the first patient, the second patient, and the third patient, the maximal values of the insulin control action are 450 mU/min, 250 mU/min, and 150 mU/min, respectively.

The remote insulin level for all patients is shown in Fig. 8, which represents the insulin level in the entire body.

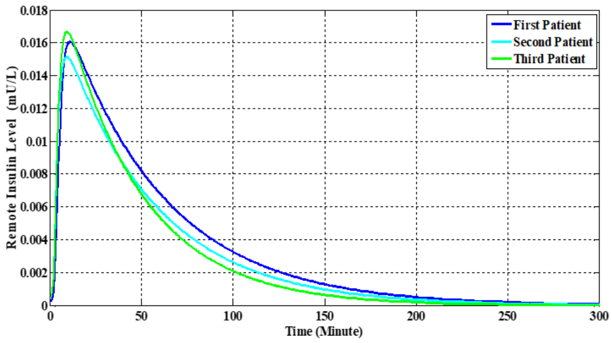

Figure. 8 The remote insulin level for all patients

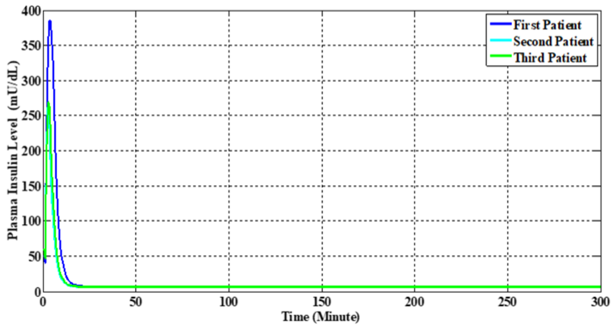

Figure. 9 The plasma insulin level for all patients

Table 5. The proposed parameters' definition of the PSO.

Symbols	Value
W	0.739
N	50
Particle weights Kp, ki, kd	3
c_1,c_2	1.39, 1.39
r_1,r_2	Random value between (0,1)
It_{Max}	50

The plasma insulin level for all patients is shown in Fig. 9, which represents the fast spread of the plasma insulin level throughout the body during 300 minutes.

The best-proposed PSO values for the PID controller parameters are shown in Table 5, and the best values of the PID control parameters for the first patient, the second patient, and the third patient models are displayed in Table 6. In particular, the particle swarm optimization (PSO) technique has quick computing speed. For each patient, the controller is in charge of producing optimal or near-optimal insulin control action, which lowers the blood glucose levels and maintains them within an acceptable range.

Fig. 10 illustrates the response of the proposed closed-loop adaptive insulin-infusion PID-PSO controller. When adding a meal disturbance effect at a time equal to 10 minutes for all patient cases, the suggested controller improves the patients' response

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Table 6. The PID-PSO controller parameters optimal values for the three patient classes.

Type of patients	K_p	K_i	K_d
The First Patient	0.0153	0.6164	3.8567
The Second Patient	0.0031	0.6466	3.1336
The Third Patient	0.0512	0.4622	3.3123

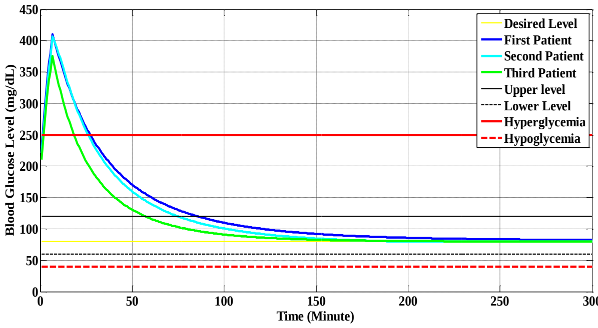

Figure. 10 The glucose level response for each patient's closed loop PID-PSO controller

to glucose by raising the effectiveness of the insulin-infusion control action. Specifically, the proposed meal disturbance value equals 20 mg/dL. The first patient's glucose level, represented by the blue color line, drops from 230 mg/dl to 120 mg/dl (the upper normal physiological level) and remains there for 88 minutes, demonstrating that the insulin action has stabilized the glucose level. After 75 minutes, the second patient's glucose level stabilizes at 120 mg/dl, which is the upper normal physiological level, after being dropped from 220 mg/dl. The second patient is shown by the cyan color line. The third patient is indicated by the green color line. The third patient's glucose level was eventually lowered from 210 mg/dl to 120 mg/dl, or the upper normal physiological level, and it stabilized there for 56 minutes. The blood glucose level for all patients reached an exact value of 80 mg/dL at steady state after 300 minutes.

Fig. 11 shows the output response of the insulin PID-PSO controller when the blood glucose level suddenly increases during the first 10 minutes. For the three patients, the PID-PSO quickly and optimally calculates the insulin action value to monitor the abrupt rise in blood glucose levels. For the first patient, the second patient, and the third patient, the maximal levels of the insulin control action are 225 mU/min, 50 mU/min, and 333 mU/min, respectively.

As demonstrated in Table 7, we compared the simulation results of the suggested off-line adaptive PID controller with the results of other types of controllers that are taken from [8] and [10] with the same dataset as in Table 1 in order to validate the efficacy of the two optimization algorithms (GWO and PSO) for tuning the parameters of the PID controller in this work in terms of reaching the blood glucose level at a normal physiological level at a minimum time and for showing the time enhancement percentage by using Eq. (16):

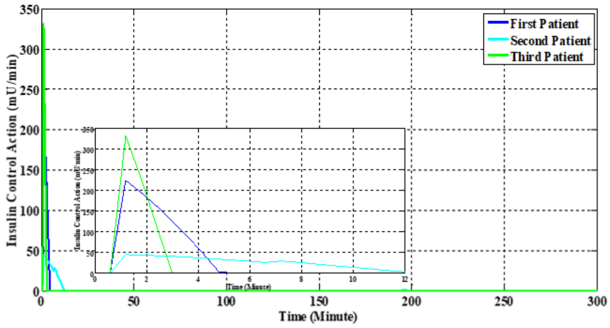

Figure. 11 The insulin PID-PSO controller's output response.

Table 7. Simulation results comparing the suggested controller to other designs.

Type of control algorithm	Tuning algorithm	Steady- State Error Overshoot OS(%) Time to reach normal physyological level	The proposed algorithms enhance the time to reach the blood glucose level at a normal physiological level (%)
Fractional order PID and Fuzzy logic controllers [8]	GA, ACO, BAT, IWO	No oscillation E_{ss}=0 OS=20% T=100 min	4% when using GWO 12% when using PSO
Type-2 Fuzzy controller [10]	Try and error	Small oscillation E_{ss}=0 OS=0 T=120 min	20% when using GWO 27% when using PSO
The proposed PID-GWO	GWO	No oscillation E_{ss}=0 OS=0 T=96 min	
The proposed PID-PSO	PSO	No oscillation E_{ss}=0 OS=0% T=88 min	

$$Time\ Enhancement\ (\%) = \left(1 - \frac{Time\ to\ reach\ normal\ level\ by\ proposed\ method}{Time\ to\ reach\ normal\ level\ by\ other\ method}\right) \times 100\% \qquad (16)$$

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The fractional order PID and the fuzzy logic controllers in [8] were built for the linear Bergman model and only for the first patient, using only five rules for the membership function and using the try-and-error method for obtaining the gain in the input-output fuzzy logic controller. Therefore, the controller generates a fast and non-optimal value of the insulin control action that leads to an overshoot in the response of the blood glucose level. In contrast, the proposed adaptive PID controller using the two heuristic methods (GWO and PSO) is used with a nonlinear Bergman model, and the controller has generated optimal or near-optimal insulin control action based on the best parameters obtained by the optimization algorithms that lead to reaching the blood glucose level to a normal physiological level without any overshooting and no oscillation in the response. By using Eq. (16), the comparison results showed that the PID-GWO and the PID-GPSO algorithms enhance the time (96 and 88) minutes to reach the blood glucose level in a normal state by 4% and 12%, respectively, when compared to the fractional order PID and the fuzzy logic controller algorithms [8] that reached the blood glucose level in a normal state at 100 minutes when taken with the same Bergman model parameters and the same operation conditional.The type-2 fuzzy controller in [10] was designed for the linear patient Bergman model and only for the first patient. It uses the try-and-error method to obtain the four control gains in the control law. As a result, the controller generates a quick and suboptimal value of the insulin control action, which causes a slight oscillation in the blood glucose level response. When a nonlinear patient Bergman model is used with the proposed adaptive PID controller with the two heuristic methods (GWO and PSO), the controller generates an optimal or near-optimal insulin control action based on the best parameters found by the optimization algorithms, which results in the blood glucose level being brought to a normal physiological level without oscillating or overshooting. According to the comparative results when used Eq. (16), the PID-GWO and the PID-PSO algorithms outperform the type-2 fuzzy controller algorithm in terms of how long it takes to achieve a normal blood glucose level (20% and 27%, 96 and 88 minutes respectively) [10] that reached the blood glucose level in a normal state at 120 minutes when taken with the same Bergman model parameters and the same operation conditional.

In summary, the simulation results demonstrate that the suggested adaptive PID controller with PSO and GWO algorithms can generate the best insulin control action, which allows the nonlinear patient Bergman model to track the required blood glucose level with the least amount of tracking error and to achieve optimal performance without oscillation in the various patient types' output blood glucose levels.

5. Conclusions

This study presented the design and simulation of an offline adaptive PID controller using PSO and GWO algorithms for blood glucose level monitoring and control in a nonlinear patient Bergman model. In order to track and stabilize the blood glucose level response in diabetes patients by figuring out the ideal insulin-infusion level and maintaining the blood glucose level at the normal physiological level, three distinct patient models were used as a nonlinear model to solve the problem statement. As a result, the auto-tuned control strategy of the adaptive PID controller with PSO and GWO algorithm was suggested, and it is very effective in resolving the following issues:

- At the target level of 80 mg/dl, the blood glucose level is superbly monitored and sustained at a typical physiological level of 60–120 mg/dl without oscillation.
- Without reaching the saturation state, an ideal or nearly ideal smooth value of the insulin-infusion control action was produced to improve the blood glucose level response in diabetic patients.
- The suggested controller, which is based on PSO and GWO algorithms, has offline tuning control settings that provide smooth insulin action without a large spike or a saturation state, which results in a high tracking precision of the measured blood glucose level.
- When tracking blood glucose, the maximum span tracking error level approaches zero.
- By comparing the proposed PID-GWO and the PID-PSO algorithms with the fractional order PID and the fuzzy logic control algorithms, the proposed controllers enhance the time by 4% and 12%, respectively, to reach the blood glucose level at a normal physiological level, and they improve the time by 20% and 27%, respectively, compared to the type-2 fuzzy control algorithm.

In the future, the experimental work of the proposed off-line adaptive PID controller with an optimization algorithm will be implemented in an embedded system based on an FPGA development board with an insulin pump device in order to manufacture an artificial pancreas.

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Conflicts of interest

The authors declare no conflict of interest.

Author contributions

For the nonlinear Bergman model, Khulood E. Dagher and Joseph Haggege improved an off-line adaptive PID controller algorithm using two meta-heuristic techniques. For patients with type 1 diabetes, Khulood E. Dagher outlined the suggested control strategy based on PSO and GWO. The Bergman model was described by Joseph Haggege. The suggested simulation findings from this work were addressed by the two authors.

References

[1] M. M. Rivai and F. Kurniawan, "Diabetes Detection Using Carbon Nanomaterial Coated QCM Gas Sensors and a Convolutional Neural Network through Urine Sample", *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 5, pp. 417-427, 2023, doi: 10.22266/ijies2023.1031.36.

[2] S. E. Engell, T. B. Aradottir, H. Bengtsson, M. Magnus, and J. B. Jorgensen, "Glucose Response to Fast-and –Long-Acting Insulin in people with Type 2 Diabetes", *IFAC Paper Online*, Vol. 54, No. 15, pp. 496-501, 2021.

[3] H. Qteat and M. Awad, "Using Hybrid Model of Particle Swarm Optimization and Multi-Layer Perceptron Neural Networks for Classification of Diabetes", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 3, pp. 11-23, 2021, doi: 10.22266/ijies2021.0630.02.

[4] C. Hettiarachchi, N. Malagutti, C. J. Nolan, H. Suominen, and E. Daskalaki, "G2P2C—A Modular Reinforcement Learning Algorithm for Glucose Control by Glucose Prediction and Planning in Type 1 Diabetes", *Biomedical Signal Processing and Control*, Vol. 90, No. 105839, pp. 1-19, 2024.

[5] W. Liu, "A Mathematical Model for the Robust Blood Glucose Tracking", *Mathematical Biosciences and Engineering*, Vol. 16, No. 2, pp. 759-781, 2019.

[6] O. Saleem and J. Iqbal, "Complex-order PID Controller Design for Enhanced Blood-Glucose Regulation in Type-I Diabetes Patients", *Measurement and Control*, Vol. 56, No. 9, pp. 1811-1825, 2023.

[7] R. Sharma, A. Basu, and S. Mohanty, "Designing of Digital PID Controller for Blood Glucose Level of Diabetic Patient by using Various Tuning Methods", *International Journal of Electrical and Electronics Engineering*, Vol. 9, No. 2, pp. 1-5, 2022.

[8] S. Benzian, A. Ameur, and A. Rebai, "Design and Optimal Fractional Order PID Controller based on New Algorithm and a Fuzzy Logic Controller to Regulate Type 1 Diabetes Patient", *Journal Europeen Des Systemes Automatises*, Vol. 54, No. 3, pp. 381-394, 2021.

[9] S. Benzian, A. Rebai, and A. Ameur, "Optimal Digital PID Controller Design for regulating Blood Glucose Level of Type-I Diabetic Patients", *International Journal of Signals and Systems*, Vol. 3, Nos. 1-3, pp. 137-149, 2019.

[10] S. R. Yan, K. A. Alattas, M. Bakouri, A. K. Alanazi, A. Mohammadzadeh, S. Mobayen, A. Zhilenkov, and W. Guo, "Generalized Type-2 Fuzzy Control for Type-I Diabetes: Analytical Robust System", *Mathematics*, Vol. 10, No. 690, pp. 1-20, 2022.

[11] A. Sayed, B. A. Zalam, M. Elhoushy, and E. Nabil, "Optimized Type-2 Fuzzy Controller based on IOMT for Stabilizing the Glucose level in Type-1 Diabetic Patients", *Scientific Report*, Vol. 13, No. 14508, pp. 1-21, 2023.

[12] J. L. C. Farias and W. M. Bessa, "Intelligent Control with Artificial Neural Networks for Automated Insulin Delivery Systems", *Bioengineering*, Vol. 9, No, 664, pp. 1-19, 2022.

[13] A. Khaqan, A. Nauman, S. Shuja, T. Khurshaid, and K. Kim, "An Intelligent Model-Based Effective Approach for Glycemic Control in Type-1 Diabetes", *Sensor*, Vol. 22, No. 7733, pp. 1-18, 2022.

[14] A. K. Patra and A. Nanda, "Model Predictive Controller Design based on the Laguerre Functions for Blood Glucose Regulation in TIDM Patient", *Journal of the Institution of Engineers (India): Series B*, Vol. 102, No. 2, pp. 237-248, 2021.

[15] M. Homayounzade, "Positive Input Observer-based Controller Design for Blood Glucose Regulation for Type 1 Diabetic Patients: A Backstepping Approach", *The Institution of Engineering and Technology Systems Biology*, Vol. 16, No. 5, pp. 157-172, 2022.

[16] R. N. Bergman, L. S. Phillips, and C. Cobelli, "Physiologic Evaluation of Factors Controlling Glucose Tolerance in Man: Measurement of Insulin Sensitivity and Beta-Cell Glucose Sensitivity from the Response to Intravenous Glucose", *The American Society for Clinical Investigation*, Vol. 68, No. 6, pp. 1456-1467, 1981.

[17] F. Hassan, M. Adil, A. Khaqan, S. Shuja, M. I. Tiwana, Q. Hassan, S. Malik, and R. A. Riaz,

"Closed Loop Blood Glucose Control in Diabetics", *Biomedical Research*, Vol. 28, No. 16, pp. 7230-7236, 2017.

[18] N. Sivaramakrishnan, S. K. Lakshmanaprabu, and M. V. Muvvala, "Optimal Model Based Control for Blood Glucose Insulin System Using Continuous Glucose Monitoring", *Journal* of *Pharmaceutical Sciences* and Research, Vol. 9, No. 4, pp. 465-469, 2017.

[19] K. E. Dagher and M. N. Abdullah, "Airborne Computer System Based Collision-Free Flight Path Finding Strategy Design for Drone Model", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 6, pp. 234-248, 2021, doi: 10.22266/ijies2021.1231.22.

[20] K. E. Dagher, "Design of an Adaptive Neural Voltage-Tracking Controller for Nonlinear Proton Exchange Membrane Fuel Cell System Based on Optimization Algorithms", *Journal of Engineering and Applied Sciences*, Vol. 13, No. 15, pp. 6188-6198, 2018.

[21] P. D. Kusuma, and A. Dinimaharawati, "Extended Stochastic Coati Optimizer", *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 3, pp. 482-494, 2023, doi: 10.22266/ijies2023.0630.38.

[22] M. N. Abdullah and K. E. Dagher, "Airborne Computer System Path-Tracking Based Multi-PID-PSO Controller Design", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 3, pp. 403-411, 2021, doi: 10.22266/ijies2021.0630.33.

[23] E. S. P. Krishna and T. Arunkumar, "Hybrid Particle Swarm and Grey Wolf Optimization Algorithm for IoT Intrusion Detection System", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 4, pp. 66-74, 2021, doi: 10.22266/ijies2021.0831.07.

[24] B. Gao, H. Guan, W. Shen, and Y. Ye, "Application of the Grey Wolf Optimization Algorithm in Active Disturbance Rejection Control Parameter Tuning of an Electro-Hydraulic Servo Unit", *Machines*, Vol. 10, No. 599, pp. 1-20, 2022.

[25] H. Kraiem, F. Aymen, L. Yahya, A. Triviño, M. Alharthi, and S. S. M. Ghoneim, "A Comparison between Particle Swarm and Grey Wolf Optimization Algorithms for Improving the Battery Autonomy in a Photovoltaic System", *Applied Sciences (Basel)*, Vol. 11, No. 7732, pp. 1-19, 2021.

[26] H. Almazini and K. R. K. Mahamud "Grey Wolf Optimization Parameter Control for Feature Selection in Anomaly Detection", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 2, pp. 474-483, 2021, doi: 10.22266/ijies2021.0430.43.

[27] H. F. Almazini, K. R. K. Mahamud, and H. Almazini, "Heuristic Initialization Using Grey Wolf Optimizer Algorithm for Feature Selection in Intrusion Detection", *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 1, pp. 410-418, 2023, doi: 10.22266/ijies2023.0228.36.