Design Optimal Modified Internal Model Controller of Blood Glucose for Type I Diabetes

Ekhlas H. Karam, Eman H. Jadoo

Abstract*— Type I diabetic patients is a chronic condition marked by an abnormally large level of glucose in the blood. Persons with diabetes characterized by no insulin secretion within the pancreas (ß-cell) which also referred to as insulin-dependent diabetic Mellitus (IDDM). The treatment of type I diabetes counting on the delivery of exogenous insulin to succeed in the blood glucose level near the natural ranges (70-110mg/dL). In this paper, a Modified Internal Model Controller (MIMC) has been developed based on three different nonlinear functions to control the concentration of blood glucose levels under a disturbing meal. The parameters of the proposed control design are optimized by using Chaotic Particle Swarm Optimization (CPSO) technique. The model which is used to represent the artificial pancreas is a minimal model for Bergman. Simulations, based on MATLAB/Simulink, were performed to verify the performance of the proposed controller. The results showed the effectiveness of the proposed MIMC in controlling the behavior of glucose deviation to a sudden rise in blood glucose.

Keywords*— Type 1diabetes,Internal Model Control (IMC), Bergman minimal model, Chaotic Particle Swarm Optimization (CPSO), BGL.

I. INTRODUCTION

Diabetes mellitus is one of the most important chronic diseases which results from a high blood sugar for a long time due to insufficient insulin generation in the blood [1]. The concentration of glucose in the bloodstream is naturally regulated by two hormones: insulin and glucagon. Both of these hormones are secreted by β-cells and α cells in the Langerhans islands of the pancreas, respectively. The concentration of glucose ranges from 70 to 110 (mg / dl). Accordingly, there are two states, hyperglycemia (glucose concentration is above the normal ranges) and hypoglycemia (low glucose concentration than the normal ranges) [2]. Diabetes is classified into two common types. Type 1 diabetes mellitus (T1DM) is caused by the autoimmune destruction of (β-cells) in the pancreas that produce insulin deficiency. Therefore, patients with insulin-dependent Type 1 diabetes mellitus, they need insulin injections to regulate the external glucose concentration they have to a normal level. Type 2 diabetes begins with insulin resistance, a condition in which cells do not respond to insulin properly. This model is noninsulin-dependent diabetes-dependent diabetes. The most common cause is excessive body weight and not enough exercise [3].

The close loop control system is designed to normalize the high blood glucose level for diabetes patients. The closed-loop of the blood glucose control system, one needs the use of a glucose sensor that can measure blood glucose level. This information will passed to a control system to calculate the necessary insulin delivery rate to keep the blood glucose level in a stable range and hence a mechanical pump can deliver the desired amount of insulin. As shown in Fig.(1) the closed-loop method is more reliable in maintaining the level of blood glucose and also is close to the normal pancreas [4].

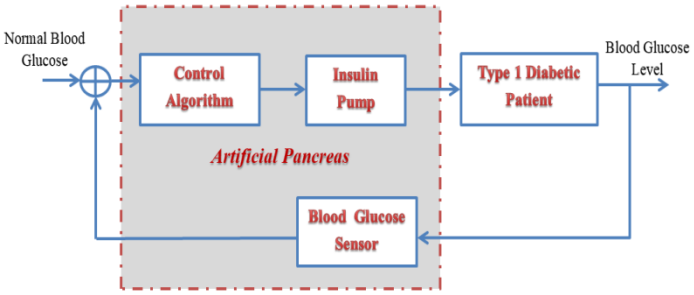

Fig.(1): Closed loop insulin regulation system block.

The internal model controller (IMC) is one of the well-known based controls and has been widely used to design the biomedical systems because of simplicity, strength and good control performance. therefore has been widely used to design the feedback controller for type I diabetes in order to determine the delivery of exogenous insulin to reach the blood glucose level near the normal range of insulin delivery. Different IMC has been used suggested to feedback controller for insulin delivery as PSO-PD & PSO-IMC controller [2] and EIMC (Enhances Internal model Controller) [5], optimal IMC controller based on Genetic Algorithm (GA) [6] as well as robust SMC controller with internal model controller (SMC-IMC) [7]. In this paper, optimal modified IMC is suggested and designed based on different nonlinear functions for the glucose concentration level control problem in diabetic patients under meal disturbance.

The paper is categorized into four sections. In Section 2, Bergman's minimal model has been formulated. Section 3 presents the internal model controller (IMC) and the modified internal model controller (MIMC). In section 4, simulation results have been provided with thorough discussion. Finally, the conclusion is presented in section 5.

II. Insulin-Glucose Regulation model

Different mathematical models have been proposed to understand the dynamics of diabetes and to correlate the relationship between glucose and insulin distribution models that help design a diabetes
model. Among these models, the minimal Bergman model, a common reference model in the literature, approaches the dynamic response of blood glucose concentration in a diabetic to insulin injections. Bergman model consists of three differential equations as follows [3, 6]:

$$\begin{aligned}\dot{G}(t) &= -p_1(G(t)-G_b) - X(t)G(t) + D(t)\\ \dot{X}(t) &= -p_2X(t) + p_3(I(t)-I_b)\\ \dot{I}(t) &= -n(I(t)+I_b) + \gamma[G(t)-h]^+t + u(t)\end{aligned} \quad (1)$$

where G(t) is the plasma glucose concentration in [mg/dL], $X(t)$ proportional to the insulin concentration in the remote compartment [1/min], $I(t)$ is the plasma insulin concentration in [mU/dL], and $u(t)$ is injected insulin rate in [mU/min], $(p_1, p_2, p_3, n, h, \gamma)$ are parameters of the model. The term, $\gamma[G(t)-h]^+$ in the third equation of this model, serves as an internal regulatory function that formulates insulin secretion in the body, which does not exist in diabetics, the $u(t)$ represent the rate of exogenous insulin . The value of p_1 will be significantly reduced; therefore it can be approximated as zero [9,10]. The $D(t)$ is disturbance signal (meal disturbance) can be modeled by a decaying exponential function of the following form [7]:

$$D(t) = Aexp(t - t_{meal}) \quad (2)$$

The nonlinear mathematical model (Eq.(1)) become linear around steady state values of the model the transfer function of overall system is given below [10]:

$$\frac{G(s)}{u(s)} = \frac{-p_3G_b}{(s+p_1)+(s+p_2)+(s+n)} \quad (3)$$

$$\frac{G(s)}{u(s)} = \frac{-p_3G_b}{s^3+s^2(n+p_1+p_2)+s(np_1+np_2+p_1p_2)+p_1p_2n} \quad (4)$$

III. Classical Internal Model Control (CIMC) Design

The IMC is a method that depend on using plant model to build the controller. It is a commonly used technique that provides a transparent mode for the designing and tuning of various types of control architecture. The IMC has many advantages including the simple structure and only parameter tuning. Due to simple design principle and convenient parameter tuning [11]. The block diagram of internal model control is given below (Fig.2).

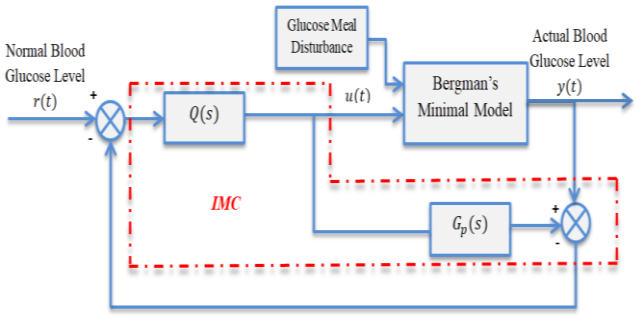

Fig.(2): Classical Internal Model Control.

The $Q(s)$ is the primary controller IMC transfer function, $u(s)$ is manipulated variable, *r(t)* the reference
input and G_p(s) is the approximate linear reduction model.
The process model G_p(s), must first be factored into invertible and non-invertible parts, that is [11]:

$$G_p(s) = G_{p+}(s) \times G_{p-}(s) \quad (5)$$

where G_{p+}(s)is non-invertible part containing all non-minimum phase elements (delays and right half plane (RHP) zeros).And G_{p-}(s)is a invertible model without delays and right hand zero .
Then using only the invertible component of the process model,

$$q(s) = G_{p-}(s)^{-1} \quad (6)$$

(the controller is the inverse of the process model)
Augment $q(s)$ with an IMC filter, (s). The final IMC controller is defined as:

$$Q_c(s) = G_{p-}(s)^{-1} \times f(s) \quad (7)$$

with

$$f(s) = \frac{1}{(\lambda s+1)^n} \quad (8)$$

In order to design the IMC the parameters value of (Table I) are used, the approximate transfer function for glucose insulin regulatory mechanism becomes:

$$G(s) = \frac{-0.00155}{s\text{^}3 + 0.3099\,s\text{^}2 + 0.01209\,s + 0.0001037} \quad (9)$$

The above equation is reduced to second order transfer function by using Matlab command (reduce instruction), therefore the resulted reduction equation is:

$$G_p(s) = \frac{a_0s+a_1}{s^2+b_1s+b_2} = \frac{0.003055\,s - 0.001205}{s^2+\,0.04111\,s+0.0003642} \quad (10)$$

In order to simplified the design of IMC, the zero of Eq.(10) numerator is replaced by scalar k as illustrated in Eq.(11):

$$G_p(s) = \frac{b_0s+b_1}{s^2+a_1s+a_2} = \frac{k}{s^2+m_1s+m_2} \quad (11)$$

The obtained transfer function become:

$$G_p(s) = \frac{-0.001089}{s^2+\,0.03799s+\,0.0003291} \quad (12)$$

Therefore, the IMC controller $Q_c(s)$ is:

$$G_p(s) = \frac{s^2+\,0.03799s+\,0.0003291}{-0.001089(\lambda s+1)^2} \quad (13)$$

The filter time constant λ is must be selected, in this paper this parameter is tuned by Chaotic Particle Swarm Optimization (CPSO) algorithm.

TABLE I. Bergman Minimal Model Parameters [9].

Parameter	normal	Patient1	Patient2	Patient3
p_1	0.0317	0	0	0
p_2	0.0123	0.02	0.0072	0.0142
p_3	4.92	5.3×10^{-6}	2.16×10^{-6}	9.94×10^{-5}
n	0.2659	0.3	0.2465	0.2814
γ	0.0039	-	-	-
h	79.0353	-	-	-
G_b	70	70	70	70
I_b	7	7	7	7

IV. Modified Internal Model Controller (MIMC)

In this section a modified internal model controller structures are developed to regulate the blood glucose concentration as shown in Fig.(3). Where the CIMC is modified by adding a simple nonlinear function $f\big(e(t)\big)$, thus the performance of the overall controlled system will be enhanced. Three nonlinear are used, the first $f\big(e(t)\big)$ is [12]:

$$f\big(e(t)\big) = m_1 * \big(1 - e^{m_2 e(t)}\big) \quad (14)$$

$$e(k) = r(t) - y(t) \quad (15)$$

where $e(t)$ is the error between the normal blood glucose concentration level $(r(t))$ and the actual blood glucose level $(y(t))$ and (m, m_2) are small positive numbers which can be tuned by using the CPSO algorithm as shown below:

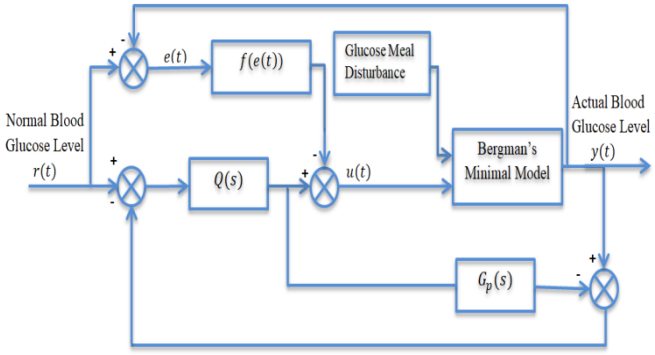

Fig. (3): The MIMC controller block diagram.

The second nonlinear function $f\big(e(t)\big)$ is:

$$f\big(e(t)\big) = K_n \tanh\big(e(t)\big) \quad (16)$$

where $\tanh(.)$ is tangent hyperbolic function which is nonlinear function, the parameters K_n is positive numbers tuned by the CPSO algorithm. The third nonlinear function is $fal(.)$ [13]:

$$fal(e,\alpha,\delta) = \begin{cases} \frac{e}{\delta^{(1-\alpha)}}, & |e| \le \delta \\ |e|^{\alpha} sign(e), & |e| > \delta \end{cases} \quad (17)$$

where δ is a small number used to express the length of the linear part, and $0 < \alpha < 1$.

Fig.(4) depicts the characteristics of the $fal(e,\alpha,\delta)$ function. The parameters $(\delta,\ \alpha)$ are tuned by CPSO algorithm.

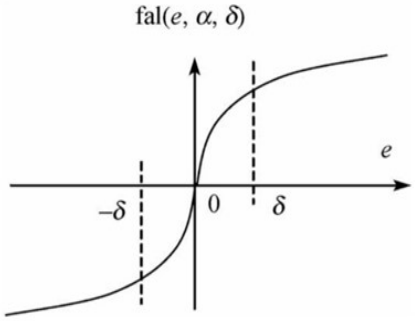

Fig. (4): Block diagram of $fal(e,\alpha,\delta)$ function characteristics.

V. Chaotic Particle Swarm Optimization (CPSO) Algorithm

The Particle Swarm Optimization algorithms (PSO) is the common evolutionary techniques. Which is adopt a random sequence for their parameter. The PSO algorithm is initialized with a population of candidate solutions which is called a particle. N particles are moving around in a D-dimensional search space of the problem [14].

The position of the i^{th} particle at the i^{th} iteration is represented by $x_i(t) = (x_{i1}, x_{i_2}, \ldots, x_{iD})$.The velocity for the i^{th} particle can be written as $v_i(t) = (v_{i1}, v_{i_2}, \ldots, v_{iD})$.The best position that has so far been visited by the i^{th} particle is represented as $pi=(p_{i1}, p_{i_2}, \ldots, p_{iD})$ which is also called pbest. The global best position attained by the whole swarm is called the global best (gbest) and represented as $p_g(t)=(p_{g1}, p_{g2}, \ldots, p_{gD})$. The velocity vector at the i^{th} iteration is represented as $v_i(t)=(v_{g1}, v_{g2}, \ldots, v_{gD})$. At the next iteration, the velocity and position of the particle are calculated according to (21,22)

$$v_i(t+1) = wv_i(t) + c_1 r_1\big(\text{pbest}_i(t) - x_i(t)\big) + c_2 r_2\big(\text{gbest}_i(t) - x_i(t)\big) \quad (18)$$

$$x_i(t+1) = x_i(t) + v_i(t) \quad (19)$$

Where c_1, c_2 are called acceleration coefficients. w is called inertia weight, and r_1, r_2 are random value in the range [0, 1].

The parameters $w, r_1\ and\ r_2$ is the key factors that effected the convergence behavior [15]. In the Chaotic Particle Swarm Optimization algorithms (CPSO) the parameters $c_1\ and\ c_2$ are modified by using logistic map based on the following equation:

$$M(t+1) = \mu * M(t) * \big(1 - M(t)\big) \quad 0 \le M(t) \le 1 \quad (20)$$

Where $M(0)$ generated randomly for each independent run and $= 4$. Then introduce a new velocity update as in equations (21).

$$v_i(t+1) = wv_i(t) + M \times r_1\big(\text{pbest}_i(t) - x_i(t)\big) + (1 - M) \times r_2\big(\text{gbest}_i(t) - x_i(t)\big) \quad (21)$$

important advantages of the chaotic optimization algorithm (COA) are summarized as: easy implementation, short execution time and speed-up of the search. Observations, however, reveal that the COA also has some problems including: (i) COA is effective only for small decision spaces; (ii) COA easily converges in the early stages of the search process. Therefore, hybrid methods have attracted attention by the researchers [16] The flowchart that represented this algorithm illustrated below.

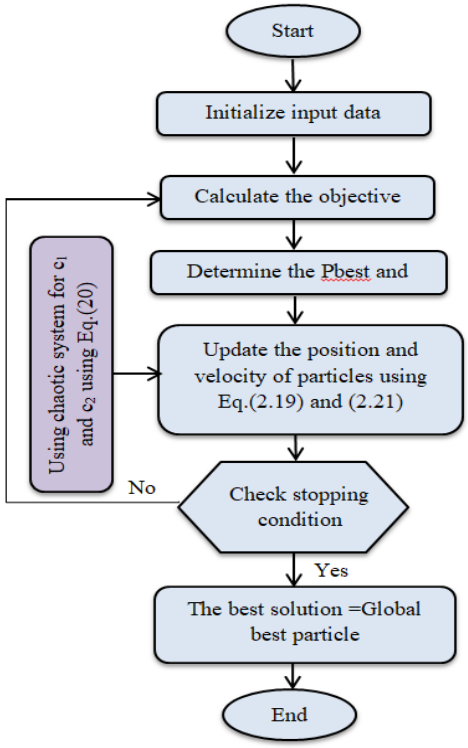

Fig.(5): General flowchart of the CPSO algorithm.

VI. Simulation and Results

The closed-loop system simulates using MATLAB to prove the suggested design confirmation. The simulation result is based on meal glucose disturbance of Eq.(2) and the numerical values of the parameters used in this paper are given in Table I. Firstly the system of (Eq.1) without controller has been simulated for normal and patient person to show the difference between their glucose regulatory systems, the results for this simulation are shown in figure (5).

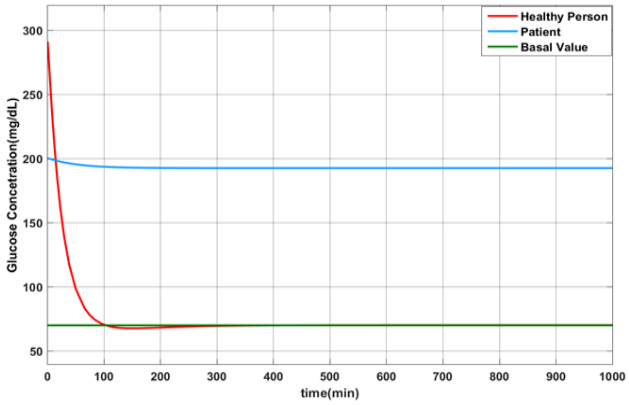

Fig.(6): Glucose output of a normal person and patient (open-loop glucose regulatory system).

It can be noted from Fig. (6) that the glucose value of the normal person is stabilized at the basal (desired=70) level, while the patient's glucose level remains dangerous outside the range. Secondly the simulation of Bergman model controlled by (CIMC, MIMC with the three nonlinear functions) are carried out dynamically for three patients (see Table (I)) with the initial conditions 290, 200 and 180 mg/dl for patients 1, 2 and 3, respectively. The parameters of meal glucose disturbance of Eq.(2) is $A = 0.5$ start at $t_{meal} = 400min$. The optimal parameters for CIMC, and MIMC tuned by CPSO algorithm are illustrate by Table (II). The results for this simulation are shown in Figs. (7-11).

TABLE II the optimal parameters for CIMC, and the suggested MIMC tuned by CPSO algorithm.

Controller	Parameter	Value
Classical IMC	λ	9.93
MIMC Structure #1	m_1	0.65
	m_2	0.054
MIMC Structure #2	k_n	0.0134
MIMC Structure #3	α	0.45
	δ	0.5

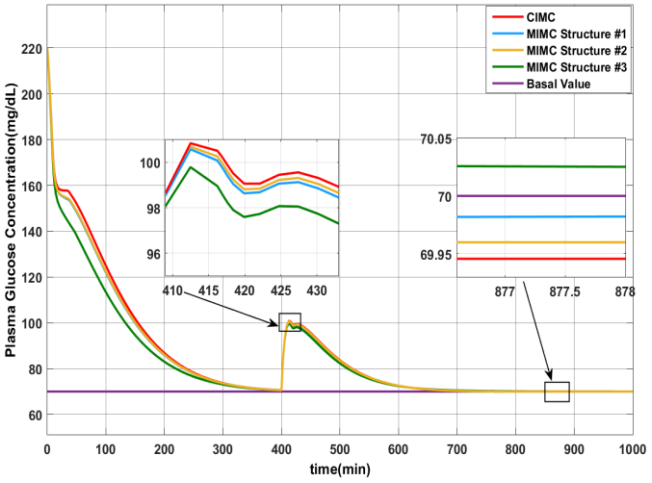

Fig.(7): Glucose regulatory system for patient1 with CIMC and the suggested MIMCs.

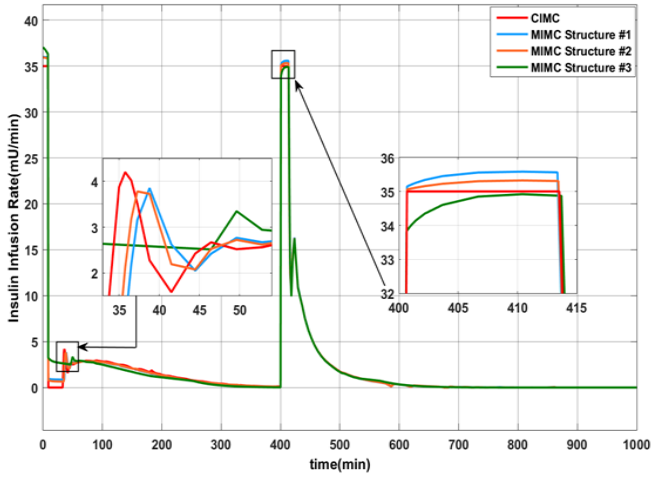

Fig.(8): Insulin infusion rate for patient1 with CIMC and the suggested MIMCs.

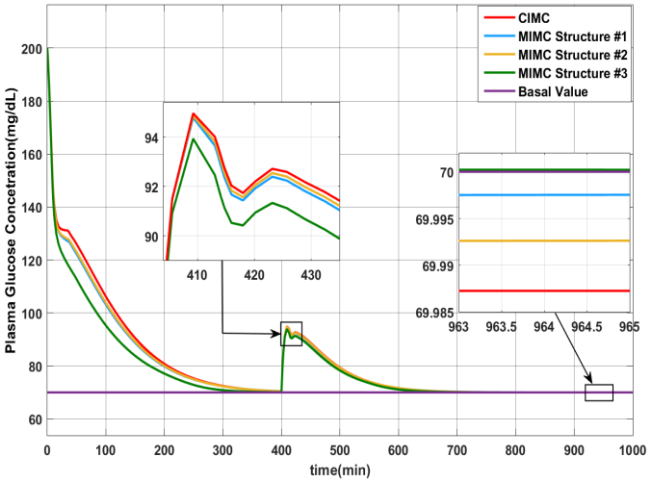

Fig.(9): Glucose regulatory system for patient2 with CIMC and the suggested MIMCs.

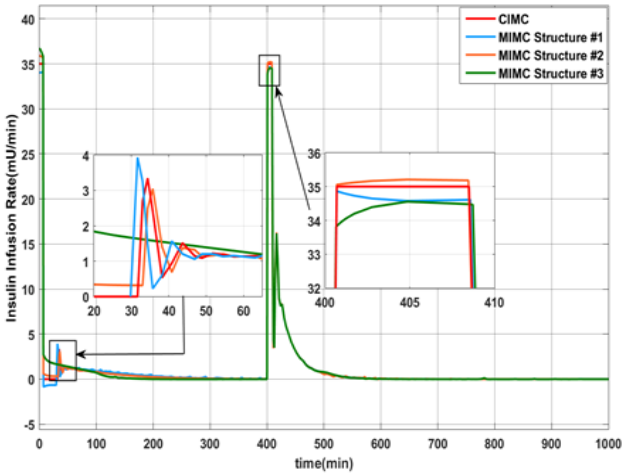

Fig.(10): Insulin infusion rate for patient2 with CIMC and the suggested MIMCs.

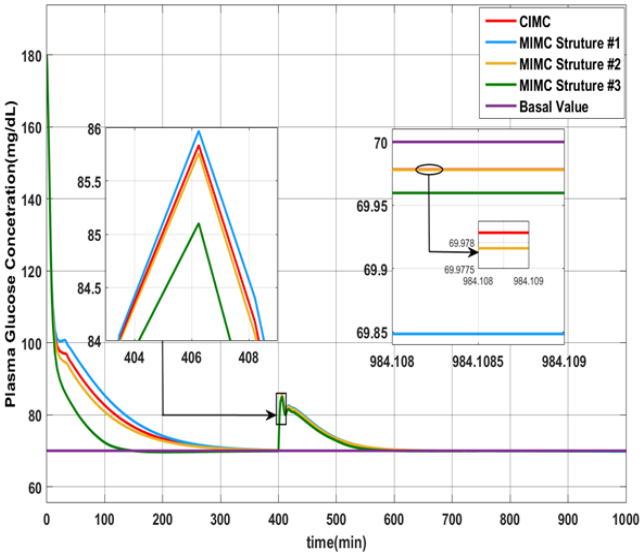

Fig.(11): Glucose regulatory system for patient3 with CIMC and the suggested MIMCs.

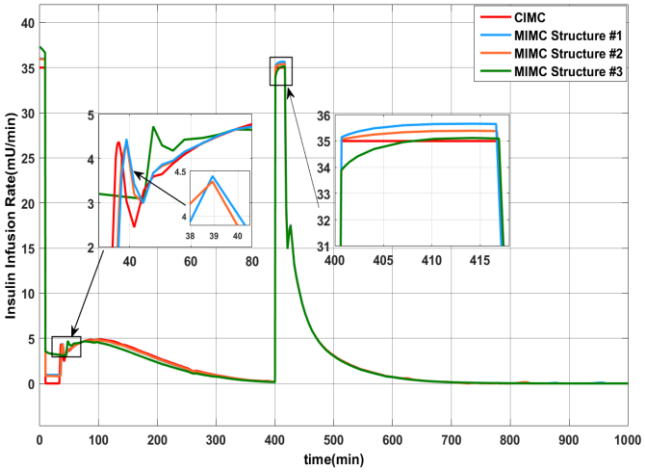

Fig.(12): Insulin infusion rate for patient3 with CIMC and the suggested MIMCs.

The comparison between performance of the CIMC and three different MIMC structures all for the three patients are shown in Table III to Table V. It can be noticed from Figs (7 to 12) and Table III to Table V that the CIMC gives performance of maximum glucose level for all patients and the MIMC structure#3 shows the best robustness characteristics than all the other controllers with less glucose level for the three patients In addition, the rate of insulin injection rate simulation results confirmed that the proposed controller has a good promising performance in terms of insulin injection rate and TM in comparison with the results of other researches.

TABLE III. The simulation result's evaluation parameters for patient 1.

The controller used	t_s(min.)	$MAPE\%$	$e_{s.s.}$
CIMC	590.93	22.5	0.054
MIMC Structure #1	590.47	21.6	0.0132
MIMC Structure #2	590.78	21.8	0.0364
MIMC Structure #3	586.59	19.3	0.0045

TABLE IV. The simulation result's evaluation parameters for patient 2.

The controller used	t_s(min.)	$MAPE\%$	$e_{s.s.}$
CIMC	574.99	15.6	0.0127
MIMC Structure #1	574.54	14.8	0.0023
MIMC Structure #2	574.85	15	0.005
MIMC Structure #3	562.94	8.8	0.0002

TABLE V. The simulation result's evaluation parameters for patient 3.

The controller used	t_s(min.)	$MAPE\%$	$e_{s.s.}$
CIMC	520.64	6.6	0.0218
MIMC Structure #1	521.81	7.4	0.1583
MIMC Structure #2	520.1	6.11	0.022
MIMC Structure #3	508.04	3.3	0.026

VI. Conclusions

In this paper, a simple modified internal model controller has been suggested based on three nonlinear function and CPSO algorithm. The performance analysis of the suggested control strategy concerning plasma glucose-insulin stabilization is comprehensively demonstrated by computer simulations. To validate the robustness of the suggested controller, the diabetic patient is exposed to external disturbance, that is, a meal. The closed-loop system has been simulated for different patients with different parameters, in the presence of the food intake disturbance and it has been shown that the glucose level is stabilized at its base value in a reasonable amount of time. The effectiveness of the suggested controller compared with the
classical IMC are verified by simulation results for three different patients.

Acknowledgment

The authors thank all the colleagues in the Computer Engineering Department, College of Engineering, Mustansiriyah University, for their unlimited support.

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