Application of Fuzzy Controller to Adjust the Appropriate Injection Rate of Insulin with Alpha Sections and Genetic Algorithm

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Abstract

Controlling the rate of insulin injection is very important in diabetic patients who are equipped with an insulin pump. The challenges of proper insulin injection into the body can be exacerbated by the presence of uncertainties (due to different physiological differences in individuals) and the different daily activities of each person. Insulin control has also become more complex due to the delayed effect of carbohydrate entry on the body's blood sugar levels, and may lead to dangerous conditions of hyperglycemia or hypoglycemia. In this paper, the aim is to reduce the effect of inherent uncertainties in the patient. The patient model is based on the Hurca mathematical model. General type 2 fuzzy controllers with alpha cuts are proposed. A neural network system with a linear regression model is used to predict blood sugar levels in the following hours. Also the adjustment of a number of controlling parameters has been done using genetic algorithm. To investigate the controlling behavior, several disturbances in the model and the entry of carbohydrates into the closed-loop system have been considered. The simulation results show that the proposed controller can control blood sugar under different conditions. The designed controller also prevents the occurrence of two dangerous states of hyperglycemia and hypoglycemia.

Keywords: control insulin injection rate, fuzzy control, genetic algorithm, neural network
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1. Introduction

Unfortunately, many people around the world have diabetes. The disease is divided into two types, one (insulin-dependent diabetes) and two [1,2]. In type 2, fortunately, insulin is still produced by the pancreas, but it may not be enough, that people are treated with diet and exercise [3,4]. The risk of severe hypoglycemia and severe hyperglycemia is dangerous for people and may lead to death or coma. Regulation of blood sugar in diabetic patients reduces other side effects [5,6].

A closed-loop control scheme for the glucose-insulin regulatory system in type 1 (T1DM) diabetic patients has been proposed in [7], where some innovative hybrid glucose-insulin regulators have combined artificial intelligence with the well-known Palumbo model to predict blood glucose (BG) levels. adjust in T1DM patients.

A complete model of the glucose-insulin regulation system, which is a nonlinear delay differential model, has been used in [8], which aims to investigate the glucose profiles of a healthy individual with minimal injectable insulin. Therefore, an intelligent fuzzy controller based on Mamdani structure is proposed for type 1 diabetic patients.

The aim of this paper is to design a fuzzy controller, which can regulate blood sugar levels according to existing uncertainties, and defined in a specific range. A predictive model based on the neural network is designed to prevent hyperglycemia and hypoglycemia. Optimal response can reduce insulin consumption, so some system parameters are determined using a genetic algorithm. The structure of the article is as follows. In the second part, the model is mentioned and in the third part, the proposed structure is mentioned. The results and

discussion are presented in the fourth section. At the end and in the fifth section, the conclusion is stated.

2. System Model Equations

In this paper, Horca as shown in fig. 1, is used to examine changes in mood in three areas: insulin uptake, carbohydrate uptake, and blood sugar regulation [9,10]. The different modes of the model are:

$S_1(t)$: Insulin levels in the stomach
$S_2(t)$: Insulin levels in the large intestine
$x_1(t)$: Carrier and distribution of glucose
$x_2(t)$: Glucose excretion
$x_3(t)$: Production of endogenous glucose
$D_1(t)$: The amount of glucose in the stomach
$D_2(t)$: The amount of glucose in the large intestine
I(t): Plasma insulin concentration
$Q_1(t)$: Glucose concentration in accessible areas
$Q_2(t)$: Glucose concentration in inaccessible areas

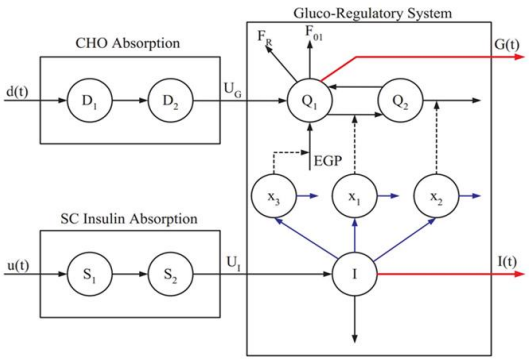

Fig 1. Diagram of Hovorka model

The system equations are:

$$\frac{dS_1(t)}{dt} = u(t) - \frac{S_1(t)}{\tau_s} \quad (1)$$

$$\frac{dS_2(t)}{dt} = \frac{S_1(t)}{\tau_s} - \frac{S_2(t)}{\tau_s} \quad (2)$$

$$\frac{dD_1(t)}{dt} = A_G D(t) - \frac{D_1(t)}{\tau_d} \quad (3)$$

$$\frac{dD_2(t)}{dt} = \frac{D_1(t)}{\tau_d} - \frac{D_2(t)}{\tau_d} \quad (4)$$

$$\frac{dx_1(t)}{dt} = -k_{a1}x_1(t) + k_{b1}I \quad (5)$$

$$\frac{dx_2(t)}{dt} = -k_{a2}x_2(t) + k_{b2}I \quad (6)$$

$$\frac{dx_3(t)}{dt} = -k_{a3}x_3(t) + k_{b3}I \quad (7)$$

$$\frac{dI(t)}{dt} = \frac{U_I(t)}{V_I} - K_e I(t) \quad (8)$$

$$\frac{dQ_1(t)}{dt} = U_G(t) - F_{01,c} - F_R - x_1(t)Q_1(t) + k_{12}Q_2(t) + EGP_0\left[1 - x_3(t)\right] \quad (9)$$

$$F_{01}^c = \begin{cases} F_{01} & if \quad G \geq 4.5 \quad mmol/l \\ F_{01}G/4.5 & otherwise \end{cases} \quad (10)$$

$$F_R = \begin{cases} 0.003(G-9)V_G & if \quad G \geq 9 \quad mmol/l \\ 0 & otherwise \end{cases} \quad (11)$$

$$\frac{dQ_2(t)}{dt} = x_1Q_1(t) - \left[k_{12} + x_2(t)\right]Q_2(t) \quad (12)$$

$$G(t) = \frac{Q_1(t)}{V_G} \quad (13)$$

3. Proposed Model Structure

The structure of the proposed model used for the study in this paper is shown in fig. 2.

In the proposed model, the information used for the controller, in addition to the error signal and error changes, is also affected by the output of the controller block.

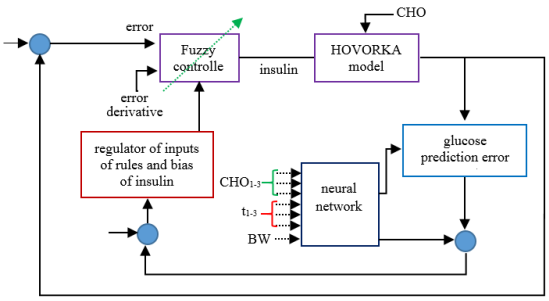

Fig 2. Block diagram of the structure of the proposed model

The purpose of the neural network block is to estimate the patient's blood sugar level in the next hour. The output of this block is the estimation of blood sugar level at the same time and in the next hour.

First, to create a database showing insulin-glucose interaction, 50 patient models (different weights for patients, different time and amount of carbohydrate intake) for 48 hours, and insulin levels in random numbers (between 5 and 15 milli-units) is considered and their insulin, carbohydrate and glucose levels are stored.

In this paper, the predictive model of glucose with neural network with two structures RBF and MLP is investigated, which shows the better estimation of blood sugar by the MLP network. To more accurately estimate this parameter, which plays a decisive role in how the controller is adjusted, using the actual amount of blood sugar at the time of the test, and the amount of blood sugar obtained through the neural network, a second degree model is determined using regression

methods, which reduces the amount of estimation error:

$$e_{G+1} = \alpha_2 x^2 + \alpha_1 x + \alpha_0 \quad (14)$$

To increase the controller efficiency and high sensitivity of the system in the areas of hyperglycemia and hypoglycemia, the fuzzy rules used have been weighted according to (15).

$$\text{if } e \text{ is } A_{ie}^{j}(e) \text{ and } \Delta e \text{ is } B_{i\Delta e}^{j}(\Delta e) \text{ then } y^{j} = I^{j} \text{ with weight } = W^{j} \quad (15)$$

An example of a fuzzy rule is shown in (15), where j represents the j-th rule and represents the i-th fuzzy set for error and the i-th fuzzy set for error change.

The output of the type-1 fuzzy model, which determines the amount of insulin entering the system, is obtained from the following equation:

$$y = \frac{\sum_{j=1}^{R} \mu^j y^j w^j}{\sum_{j=1}^{R} \mu^j} + b_0 \quad (16)$$

In this regard, the amount of bias is a constant amount of insulin that the insulin pump enters the body and changes only in the areas of increased and decreased blood.

The fuzzy control block of the proposed model is designed and compared with three methods [11-16], which are: fuzzy controller type-1, fuzzy controller type -2 interval and general type 2 fuzzy controller with alpha sections.

In the model presented with fuzzy type-2, the interval shape of fuzzy sets has an indefinite footprint (FOU). FOU levels are evenly distributed in type 2 interval fuzzy models as opposed to general type 2 fuzzy models. In these models, the output of the following relation is obtained:

$$y = \frac{Y_l + Y_r}{2} + b_0 \quad (17)$$

$$Y_l = \min \frac{\sum_{i=1}^{R} y_i \mu_i}{\sum_{i=1}^{R} \mu_i} \quad (18)$$

$$Y_r = \max \frac{\sum_{i=1}^{R} y_i \mu_i}{\sum_{i=1}^{R} \mu_i} \quad (19)$$

In the above relation, each of the outputs representing the right and left limits of the output of the type-2 fuzzy controller is determined using Mendel's Karnik algorithm [17,18].

4. Simulation of Neural Network

In this section, the neural network with two structures of MLP and RBF for estimating glucose one hour later and regression model were examined that MLP network with a hidden layer and 15 intermediate nodes provided the best answer for estimation. For regression model, coefficients of -0.001, 0.76 and 1.16 are considered. The input CHO rate to the model is as shown in Table 1. The values expressed are nominal. Changes have been made to create a database of up to 30% of the nominal amount of food input per meal. Also, the body insulin level was injected into the body in random numbers between 7.4±1.4 mU/min. Glucose output was calculated for 50 different samples with random weights between 56 and 84 kg measured in 24 hours. Fig. 3 shows the glucose output.

To investigate the behavior of the proposed controllers against the uncertainties entered into the system, four different modes have been considered, each of which includes 30 patient samples.

A- The first case: the time of receiving CHO is the same, but the amount of receiving them has changed between 30 30% and with random weights between 56 and 84 kg.

B- The second case: in addition to the change in the amount of CHO intake (according to the first case), there was a time delay in each meal.

C- Third case: they have received CHO 30% more than the nominal amount of consumption time.

D- Fourth case: consumption time and amount of CHO consumption is 30% less than the nominal value.

Four membership functions are considered for error according to fig. 4 (four ranges of severe hyperglycemia [400-250], hyperglycemia [250-150], conventional [150-60] and hypoglycemia] less than 60 mg/dL. There are also 5 membership functions for error changes that generate a total of 20 fuzzy rules. The baseline blood sugar is 110 mg / dl.

To investigate the effect of matching the weights of the rules and adjusting the amount of output insulin bias, the type-1 fuzzy controller is identified in three modes as shown in Table 3.

The weights of the rules are adjusted to the values of 0.6, 0.8 and 1, depending on which of the four areas (severe hyperglycemia, hyperglycemia, normal and hypoglycemia) is in the next hour. And the rules for the predicted area gain more weight.

The output bias in the predictive state of hyperglycemia and hypoglycemia will be 0.9 and 0.5, respectively. According to the table, it can be seen that in fuzzy type-1, in the first case, the average glucose in 24 hours under study is better for all samples. Fig. 5 shows a glucose chart for every 120 people for the first case (bias and weight are both adaptive). Figs. 6 and 7 show the maximum and minimum injected glucose and insulin, respectively. As it is known, the phenomenon of severe hyperglycemia or hypoglycemia has not been observed.

According to the results, it is clear that the use of bias and weights of adaptive rules has improved the performance of the controller. Therefore, in

order to develop fuzzy control of type-2 interval and type-2 general, the amount of bias and the weights of the rules have been used comparatively. The results in tables (4) and figs. 8 and 9 show the mean glucose and injectable insulin for the type-2 phase interval, respectively.

The following are the results for the general type-2 fuzzy controller in three modes with 5 sections (GT2-5α), 3 sections (GT2-3α) and 2 sections (GT2-2α).

Comparing the results in tables (3), (4) and (5), it can be seen that the mean glucose in all individuals belonging to the four groups of 30 is better for GT2-5α than in the other cases. Also, according to fig. 10 and 11, it has been determined that hypoglycemia has not occurred for any of the samples under study. Severe hyperglycemia is also seen only in some cases where people have either changed their diet time (30 people) or have taken in a lot of carb-ohydrates (30 people). Fig. 12 shows the average insulin injection rate for every 120 patients in GT2-5α.

Table.1.
Daily usage Carbohydrate,Schedule of meals during the day

Food turns	***Period***	***g CHO***
Breakfast	15	90
Snack	10	40
Lunch	30	150
Evening meal	10	40
Dinner	40	200

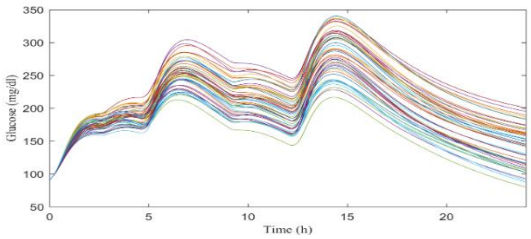

Fig 3. Glucose amount in patient's diet responses

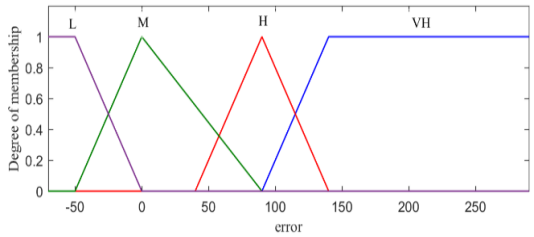

Fig 4. T1-Membership functions for input "error"

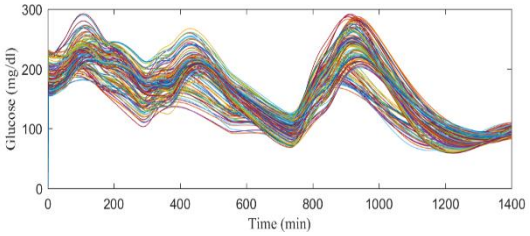

Fig 5. Mean of glucose in adaptive case

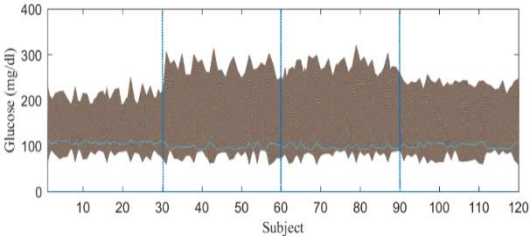

Fig 6. Glucose diagram for 120 persons

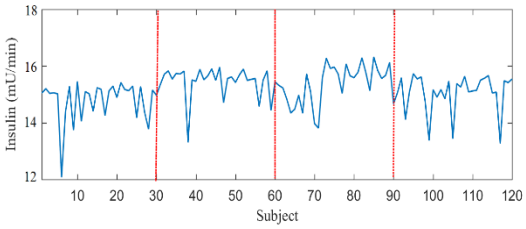

Fig 7. Delivered insulin for 120 persons in adaptive case

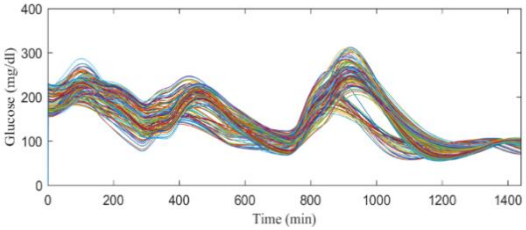

Fig 8. Mean of Glucose in IT2

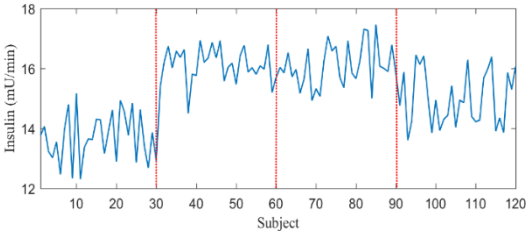

Fig 9. Mean of Insulin for 120 persons in IT2

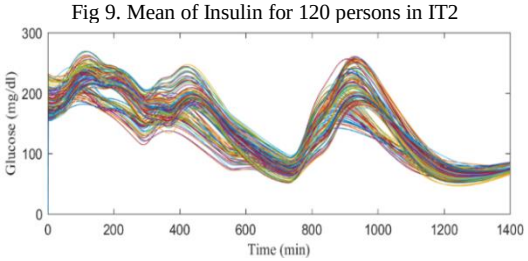

Fig 10. Mean of glucose in GT2-5α

Table.2.
Linguistic Variables

Language variable (error)	Meaning of language variable (error)	Language variable (error change)	Meaning of language variable (error change)
L	Low	N	Negative
		SN	Small Negative
M	Medium		
		Z	Zero
H	High	SP	Small Positive
VH	Very High	P	Positive

Table.3.
Insulin and glucose, T1 fuzzy controller results

Fuzzy controller type	Bios	Weight of rules	Average	1-30	31-60	61-90	91-120
Type 1	Adaptive	Adaptive	Glucose	125.3	147	149.8	137
			Insulin	13.6	15.9	15.8	14.8
Type 1	Fixed	Adaptive	Glucose	137.7	165.3	169.1	151.7
			Insulin	13	14.8	14.7	13.9
Type 1	Fixed	Fixed	Glucose	140.7	172	169	151
			Insulin	12.9	14.7	14.7	13.8

Table.4.
Insulin and glucose comparison in IT2

Fuzzy controller type	Bios	Weight of rules	Average	1-30	31-60	61-90	91-120
Type 1	Adaptive	Adaptive	Glucose	126.68	149.27	150.98	138.56
			Insulin	13.69	16.12	16.09	14.99

Table.5.
Comparison between results with different alpha planes

Fuzzy controller type	Bios	Weight of rules	Average	1-30	31-60	61-90	91-120
GT2-5α	Adaptive	Adaptive	Glucose	122.6	144.9	146.7	133.8
			Insulin	13.9	16.40	16.40	15.35
GT2-2α	Fixed	Adaptive	Glucose	122.58	145	146.8	133.93
			Insulin	13.9	16.42	16.41	15.35
GT2-3α	Fixed	Fixed	Glucose	126.4	148.8	151.04	137.09
			Insulin	13.66	16.13	16.08	15.02

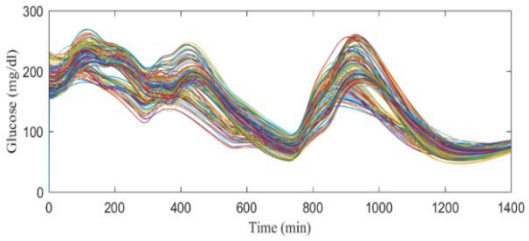

Fig 11. Mean of glucose in GT2-5α

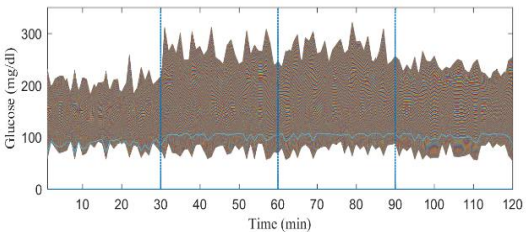

Fig 12. Mean of glucose for 120 persons with GT2-5α

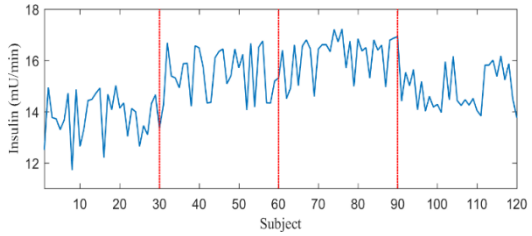

Fig 13. Delivered insulin for 120 persons with **GT2-5α**

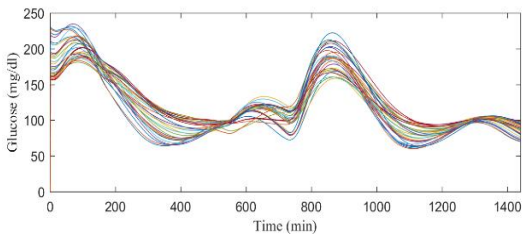

Fig 14. Daily glucose in first 30 persons with **GT2-5α**

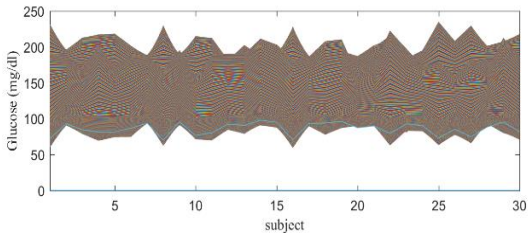

Fig 15. Glucose for 30 persons with **GT2-5α**

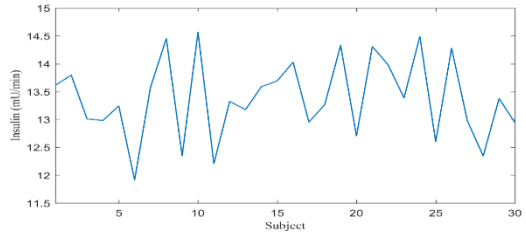

Fig 16. Delivered insulin for 30 persons with **GT2-5α**

5. Investigation of closed loop system against uncertainties

To further investigate the closed-loop system, different uncertainties were considered. For this purpose, the type 2 fuzzy controller, which provided the best answer, was applied to the first 30 people with uncertainty. In this section, it is assumed that the first 30 people of the sample have skipped one of their main meals. Tables (6), (7), (8) and (9) show the effects of skipping one meal on the glucose of GT2-5α, GT2-3α, GT2-2α and IT2, respectively. These tables show the highest and lowest blood sugar levels, as well as the highest and lowest average for the first 30 people during 24 hours.

As it is known, skipping lunch can bring a diabetic person closer to the hypoglycemic area (52.27 lowest blood sugar obtained). This value is almost equal for all control modes. In addition, by considering the amount of insulin consumed, it is determined that the amount of insulin consumed has increased. Figs. 13 and 14 show glucose concentration by skipping lunch with the first 30 and GT2-5α, and fig. 15 shows a chart of injected insulin for the first 30.

In tables (10), (11) and (12) the changes of injected insulin with error of 10%, 20% and 30% of the amount determined by the controller are examined. For example, if the controller sets the insulin intake to 0.8, an error of 10%, 20%, and 30%, respectively, causes injectable insulin in the areas of [0.88, 0.72], [0.96, 0.64] and [0.56, 10.4]. Comparing the relevant tables, it is clear that with fuzzy controller's type-2 GT2 and IT2, hyperglycemic and hypoglycemic phenomena are not observed, and based on this, it is clear that the system is resistant to possible uncertainties.

Table.6.
Results for injection error equal to 10%

Fuzzy controller type	Highest blood sugar	Lowest blood sugar	Highest mean blood sugar	Lowest average blood sugar	Average insulin
GT2-5α	242.69	56.87	204.73	67.69	13.9
GT2-3α	242.68	56.88	204.74	67.66	13.9
GT2-2α	242.67	56.41	204.76	67.68	13.9
IT2	242.6	56.79	204.75	68.23	13.95
Type 1	242.68	56.66	204.81	67.56	13.97

Table.7.
Results for injection error equal to 20%

Fuzzy controller type	Highest blood sugar	Lowest blood sugar	Highest mean blood sugar	Lowest average blood sugar	Average insulin
GT2-5α	242.38	53.93	204.31	65.69	13.9
GT2-3α	242.38	53.99	204.31	65.26	14.16
GT2-2α	242.41	53.83	204.32	65.35	14.15
IT2	242.3	54.26	204.33	65.58	14.2
Type 1	242.41	54.56	204.09	65.1	14.23

Table.8.
Results for injection error equal to 30%

Fuzzy controller type	Highest blood sugar	Lowest blood sugar	Highest mean blood sugar	Lowest average blood sugar	Average insulin
GT2-5α	242.10	52.83	203.09	62.8	14.41
GT2-3α	242.09	52.85	203.09	63.01	14.41
GT2-2α	242.09	53.11	203.91	63.03	14.42
IT2	242.03	51.59	203.92	63.05	14.46
Type 1	242.412	51.97	203.97	62.99	14.49

6. Conclusion

Diabetes leads to high mortality, and careful control of blood glucose is important in this type of disease. The design of a fuzzy controller to control the closed loop of blood sugar in type 1 diabetic patients is mentioned in this article. To predict blood glucose, in the next hour to prevent the increase and decrease of blood pressure, a neural network system with two structures RBF and MLP was used, the results of which show that the MLP system has a better ability to predict glucose. The behavior of the proposed controllers against the uncertainties entered into the system was examined for four different cases, each of which included 30 patient samples.

In type 1 fuzzy control, mean glucose and insulin are considered for different states. Which includes (a) the bias and weight of both are adaptive, (b) the bias is constant and the adaptive weight is

variable, and (c) the bias and weights of the rules are both constant. As the results showed, the use of bias and weights of adaptive rules has improved the controller performance.

Then the results of fuzzy type 1 controller, interval type 2 fuzzy and general type 2 fuzzy in three modes with 5 sections, 3 sections and 2 sections were compared, and it was observed that the mean glucose for general type 2 fuzzy with 5 slices is better than all modes. Then the results of fuzzy type 1 controller, interval type 2 fuzzy and general type 2 fuzzy in three modes with 5 sections, 3 sections and 2 sections were compared. And it was observed that the mean glucose for general type 2 fuzzy with 5 slices is better than all modes. The closed-loop system with different uncertainties was investigated. The system was shown to be robust and reliable against possible uncertainties. The simulation results showed that the proposed controller has a good function in controlling blood sugar.

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