International Journal of Pharmacy and Biological Sciences
ISSN: 2321-3272 (Print), ISSN: 2230-7605 (Online)
IJPBS | Volume 8 | Issue 2 | APR-JUN | 2018 | 668-682
Research Article | Biological Sciences | Open Access | MCI Approved| ज्ञान-विज्ञान विमुक्तये
|UGC Approved Journal |

ENHANCEMENT OF INSULIN DOSAGE IN TYPE 1 DIABETES PATIENTS: PRECISION MEDICINE THROUGH A FUZZY-LOGIC BASED SYSTEM

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ABSTRACT

Type 1 diabetes mellitus (T1DM) with an ever-expanding global incidence rate relies heavily on traditional insulin therapy, which lacks the scope of fully emulating a 'normoglycemic' state in the patients' physiology. The present paper examined the persistent, explicit and accurate outcome among the population of 25 T1DM patients undergoing insulin therapy through utilization of fuzzy logic - a potential solution to achieving exquisite precision over approximation. A previous study was conducted by our research group considering the same patient population that considered three patient-specific factors, i.e. patient weight, body mass index (BMI) and daily carbohydrate intake as inputs and concluded obtaining better glycemic control through this technique as compared to the conventional insulin dose determining approach [1]. These patients were supervised in this study, where two new patient-reported factors i.e. average fasted blood glucose and physical activity were monitored for an extended time and in conjunction with the previously adjusted dose was used to achieve superior glycemic control. Using appropriate membership functions, which are a means of defining this system, specific rules were developed in MATLAB for the input/output relationship. Analyzing the previously computed insulin dosage and two additional factors as inputs, the system further refined the daily insulin dosage for these patients. These outputs were later compared to the prescribed insulin dosage recommended by their respective physicians and notably revealed the numerical differences between adjusted predicted insulin dose (APID) and physician's prescribed dose (PPD) for each specific patient. Accordingly, this method suggested a more credible and optimum insulin measurement which in turn mitigates the episodes of two prominent mortal complications, e.g. hypoglycemia or hyperglycemia among T1DM patients and thus improved their quality of life.

KEY WORDS

Insulin, Fuzzy Logic, MATLAB, Type 1 Diabetes (T1DM), Dose Adjustment, Drug Dosing, Blood Glucose, Diabetic Lifestyle

INTRODUCTION

Type 1 diabetes represents an epidemiological conundrum with a global incidence of 79,000 children annually and its propensity to affect people of all ages [2]. The incidence of type 1 diabetes diverges by two important factors such as- age and geographical location, starting from 4.2 per 1,00,000 people in Bangladesh to 61.7 per 1,00,000 people in the USA [3,4]. However, a report of Changing Diabetes in Children (CDiC) program at BIRDEM shows an elevated trend in

the newly diagnosed case of type 1 diabetes among children in Bangladesh, numerically from 112 cases to 319 cases from the year 2008 to 2013 respectively [3]. It has been assessed that roughly 40% of diabetes patients have progressed this condition later 30 years of age [5]. Age is hence no longer being considered as an impeded factor in its symptomatic onset [6]. Notably, 86,000 new type 1 diabetes cases are diagnosed worldwide per year [7]. Type 1 diabetes imitates 5% of all diagnosed diabetes, according to National Diabetes Statistics Report, 2017. If the rate of incidence expands in its actual manner, the global rate will be doubled over the next 10 years [8]. Although for all aged group of people, the increase in incidence has not resulted uniformly and children less than 5 years old exert the most significant upturn [9,10]. In the U.S. closely 5 million people are predicted to have type 1 diabetes by 2050, counting additional 6,00,000 youth [11].

The symptoms of type 1 diabetes comprise of polyphagia, glycosuria, polyuria, polydipsia [12]. Polyphagia results from the catabolic states of a person where adipose tissue breaks down fats and muscle tissue break down proteins even though there is enough glucose in the blood of the patient. Due to the presence of high glucose levels in the blood, when blood gets filtered through the kidneys some of it starts to squirt into the urine. This symptomatic phenomenon is known as glycosuria. Due to the osmotic power of glucose, water aims to follow it. In effect, this upsurge of urination is termed as polyuria. Consequently, increased urination will produce dehydration or polydipsia, another suggestive incidence of type 1 diabetes. The clinical onset of this type extends up to 2-3-week period for both children and adolescents generally [13]. However, relating to age, numerous studies have demonstrated that the symptoms of type 1 diabetes can arise from 1 to 180 days [14].

The primary differences between type 1 and type 2 diabetes may be limned through genetic and environmental factors, history of the disease and the reduction in beta cell mass [14]. Pointedly, type 2 diabetes is a non-human leukocyte antigen-related system holding obesity as the environmental trigger. The percentage of the decrease of beta cell mass in type 2 diabetes is 25-50 whereas, in type 1 diabetes, this number is 70-80 [16, 17]. The observation theorizes that the reduction of beta cell mass is higher in type 1 diabetes patients than in type 2 diabetes patients. The range of BMI of patient's exhibits diversified values in both types. Here, BMI in Type 1 diabetes remains low or normal since the value lies in the obese range in type 2 [18]. Type 2 diabetes mostly diagnosed in patients over 30 years of age. The diagnosis of type 1 diabetes usually linked with elevated ketone levels whereas type 2 diabetes cases include a high blood pressure and/or higher levels of cholesterol [19].

Treatment of type 1 diabetes aims to achieve better glucose control and reduce the associated risks. Diet and physical activity, weight management, counseling and foot care are non-pharmacological options in treating T1DM. Pharmacological intervention starts with basal and rapid-acting insulin therapy [20]. In general, insulin therapy is the mainstay of treatment for T1DM where insulin dosage frequently depends on patient-related factors (PRFs) such as body weight, height, BMI (body mass index), age, daily carbohydrate intake, protein intake, fat intake, physical exercise, duration of diabetes and pubertal status [1,21]. Still, this therapy lacks the capacity to fully imitate a "normoglycemic" (regular glucose homeostasis) state in the patient's body as physicians prescribe the insulin dosage by considering patient-related factors discretely and sometimes considering the only factor that causes faulty administration of insulin in case of type 1 diabetes [22]. Resultantly, episodes of abnormally decreased or increased blood glucose level considered respectively as hypoglycemia or hyperglycemia take place [23]. These two incidences increase the mortality rates of type 1 diabetes patients, especially the risk of permanent damage to the central nervous system due to hypoglycemia [24]. The avoidance and amelioration of the above mentioned mortal complications have been the primary goals of contemporary research [25].

Fuzzy logic, a branch of computer-based artificial intelligence, is the technique of reasoning, thinking and assuming that perceives and practices the true world phenomena through consideration of each input as a matter of degree [26]. Our group has previously demonstrated the utility of artificially intelligent systems in aiding the physiologic complexities in diabetic care through the use of fuzzy logic-based dose adjustments. [27, 28]. Our previous study followed 25 type 1 diabetes patients undergoing insulin therapy where certain patient related factors i.e. patient weight, body mass index (BMI) and daily carbohydrate intake were incorporated as inputs for developing the system

[1]. In this present study, a follow-up comprising the interpretation of data from two additional factors such as – average fasted blood glucose and physical activity of the same patient population for acquiring a superior control with more sophisticated insulin dosing for these patients. The more patient-related factors are accumulated together in the fuzzy system, the more precise the insulin dose would be as the output. Here, we examined fasted blood glucose and physical activity in conjunction with other factors to enhance insulin dosage in type 1 diabetes patients. We hypothesized that the significance of utilizing fasted blood glucose and physical activity as new factors is their possible link to beta cell function. Previous studies have shown a positive correlation between fasted blood glucose and insulin sensitivity [29, 30]. Furthermore, investigations have also shown that patients with impaired glucose tolerance have improved insulin sensitivity upon regular exercise training [31,32].

MATERIALS AND METHODS

2.1. Patients population

The pool of patient data came from 25 randomly selected type-2 diabetes patients living in Dhaka, Bangladesh. The gender composition is 15 males and 10 females. The dataset from each patient contained the following body-demographic information: weight, height, and average carbohydrate intake per day over a period of a month. Other information relevant to the study includes the number of minutes of physical activity per day and average fasting blood glucose levels every day for one month and the respective prescribed insulin dose by the physician. To determine the insulin dose for the patient a physician would first use the body weight of the patient to estimate the first dose of insulin. Then according to the consultation with patient's activity and fasting blood glucose level the second and consequent dosages would be determined. A score was determined based on the intensity of physical activity of patients was given to be used in the method explored which is further described in section 2.3. Consent form and full disclosure of the study was given to patients to sign so that we can use this data for publication purposes.

2.2. Insulin dosage from previous study

Predicted insulin dose is one of the inputs used in this study. The values were obtained from our previous studies [1]. The goal is to refine the results using the new data obtained through this study. Table 1 shows the predicted insulin dose in comparison to the physician prescribed insulin dose. The predicted value was calculated based on the patient's weight, BMI and average carbohydrate intake.

One of the inputs used for this study was the predicted insulin dosage from our previous study [1] with the goal of refinement. The original dosage output from the fuzzy based system is listed in Table 1 and was calculated based on the patient's weight, BMI and average carbohydrate intake using formula described in [1].

Table 1. Predicted dose vs. prescribed dose of daily insulin units for each of the 25 patients [1]

Patient number	Predicted insulin dose by the fuzzy system	Physician prescribed insulin dose
1	39.6	38.0
2	40.0	45.0
3	40.0	35.0
4	46.5	45.0
5	39.5	38.0
6	46.5	50.0
7	40.0	38.0
8	39.5	40.0
9	39.5	35.0
10	52.4	50.0
11	40.0	45.0
12	40.0	44.0
13	46.5	44.0
14	33.0	44.0
15	52.6	55.0
16	39.6	38.0
17	40.0	40.0
18	46.5	52.0
19	39.5	52.0
20	39.5	38.0
21	39.5	40.0
22	40.0	28.0
23	46.5	40.0
24	39.5	35.0
25	46.5	40.0

2.3 Physical Activity Score

Insulin dose requirement varies not only with the body-demographics but also with physical activities [31, 32] which could be physician recommended or part of the patient's daily routine. Such activities may include jogging, running, cycling, climbing, sports, etc. A scoring system based on a number between 0 and 3 (to one decimal place) is assigned according to table 2. This number is important to emphasize the inverse relationship between insulin dosage and physical activity during the construction of our fuzzy logic decision matrix.

Table 2. Physical Activity Reference Scores based on duration of physical activity

Patient Reported Physical Activity (minutes)	Physical Activity Reference Score
0	0
20	1
40	2
60	3

2.4. Average fasting blood glucose level

A month-long measurement of fasting blood glucose level (FBGL) was performed by a respondent. They would measure every day and report the weekly average for four weeks. This value is used to calculate the cumulative average FBGL for the month in standard units of mmol/L. The membership functions in the fuzzy based system was adjust as recommended in [33, 34, 35] if higher FBGL was detected that indicated a beta cell dysfunction in the pancreas.

2.5. Fuzzy logic membership function definition

The input variables of the system are Predicted Insulin Dose (PID), Average Fasting Blood Glucose Level (AFBGL), and Physical Activity (PA) score. The output variable is considered to be the Insulin Dose (insulin Dose). The membership functions of the input and output variables are defined in the MATLAB Fuzzy Logic

Designer Toolbox. The triangular membership functions are used to define every input and output variable. All input variables, i.e. PID, AFBGL, and PA, have three membership functions, namely Low (L), Optimum (O), and High (H). However, the output variable, insulin Dose, has five membership functions- A, B, C, D, and E. Table 3 illustrates the ranges of the PID, AFBGL, PA, and insulin Dose; and Table 4 provides the membership function ranges of input variables.

Table 3. Input and output variable ranges

Input			Output
PID	**AFBGL**	**PA**	**insulin Dose**
30 - 55	4 - 12.5	0 - 3	30 - 55

Table 4. Ranges and Unity membership points of PID, AFBGL, and PA

		PID		AFBGL		PA	
		Range	**Unity membership point**	**Range**	**Unity membership point**	**Range**	**Unity membership point**
Fuzzy values	**L**	30 - 40	30	4 - 8	4	0 - 1.5	0
	O	35 - 45	40	6 - 10	8	0.5 - 2.5	1.5
	H	45 - 55	55	8.5 - 12.5	12.5	1.5 - 3	3

The "Unity membership points" on Table 4 represents the points where the corresponding variable has a fuzzy membership of 1, e.g. the PID is perfectly Low at PID=30, perfectly Optimum at PID=40, and so on. Other values in the range, where the fuzzy membership is not unity, implicates the membership of the corresponding variable to have a lower degree of membership. For example, PID=35 implies that PID falls in the Low range but is not perfectly Low.

Table 5 shows the breakdown of the ranges and unity membership points of the output variable- insulin Dose.

		insulin Dose	
		Range	**Unity membership point**
Fuzzy values	**A**	30 - 37	33.5
	B	33 - 40	36.5
	C	38 - 45	41.5
	D	43 - 50	46.5
	E	48 - 55	51.5

Figure 1 shows the triangular membership functions constructed for PID in MATLAB Fuzzy Logic Toolbox, as per Table 4.

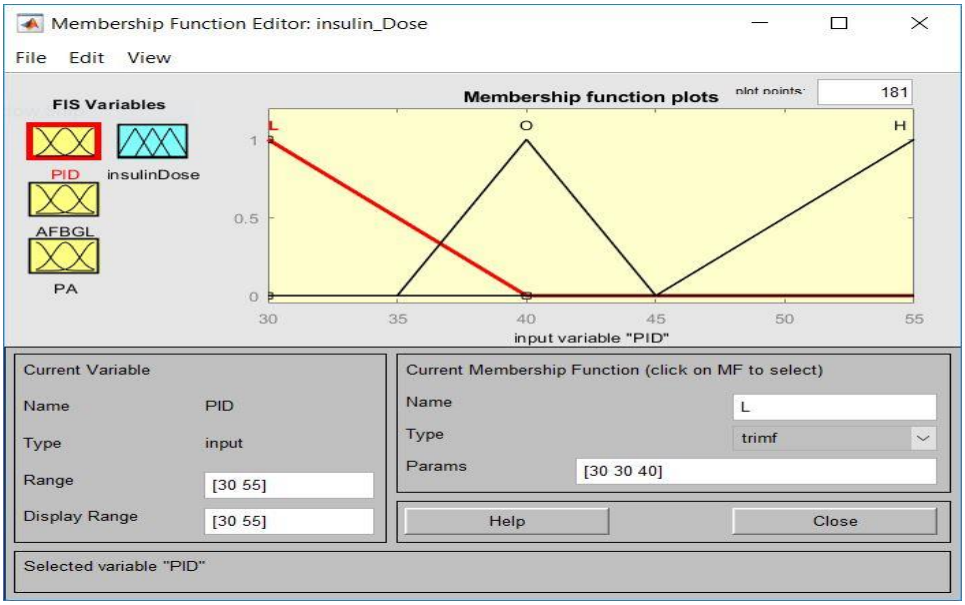

Figure 1. Membership functions for PID

Illustrated in Figure 2 are the membership functions constructed, in accordance with Table 4, for the input variable AFBGL.

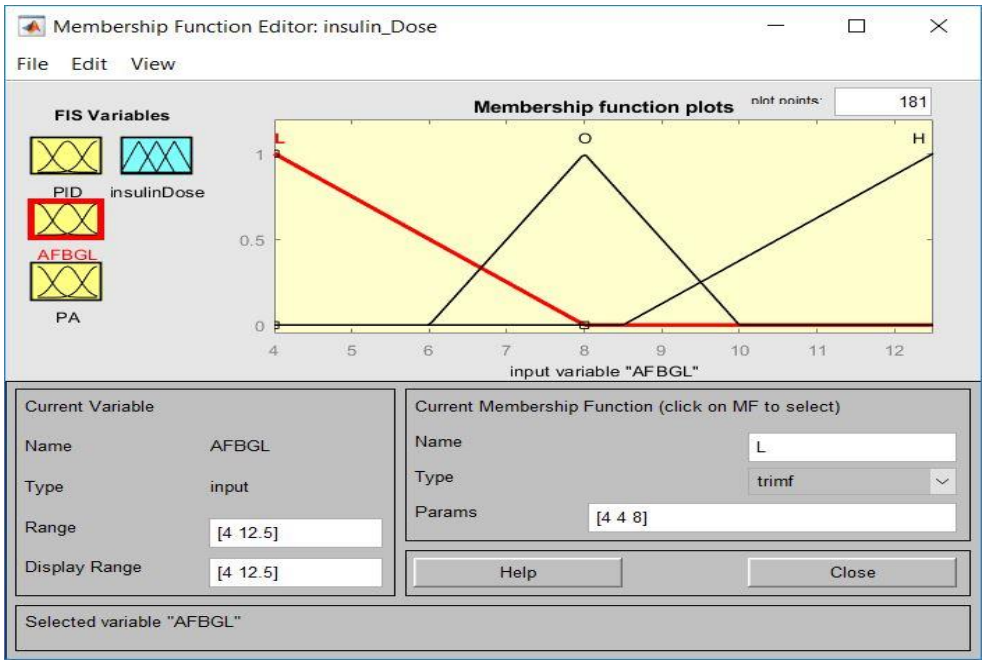

Figure 2. Membership functions for AFBGL

The last input variable PA also has three membership functions given in Figure 3. The Ranges and Unity membership points for the membership functions of PA is also taken from the Table 4 for their construction.

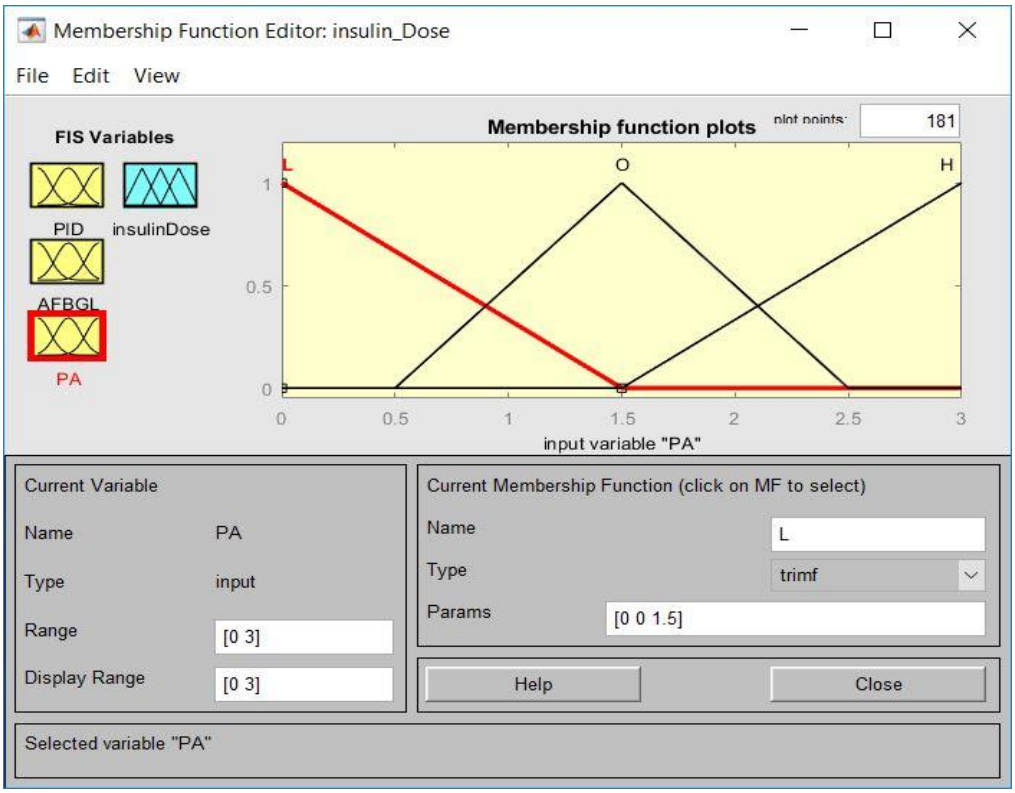

Figure 3. Membership functions for PA

The constructions of the membership functions for the output variable insulinDose is done considering the Ranges and Unity membership points delineated in Table 5. The membership functions of insulinDose is depicted in Figure 4.

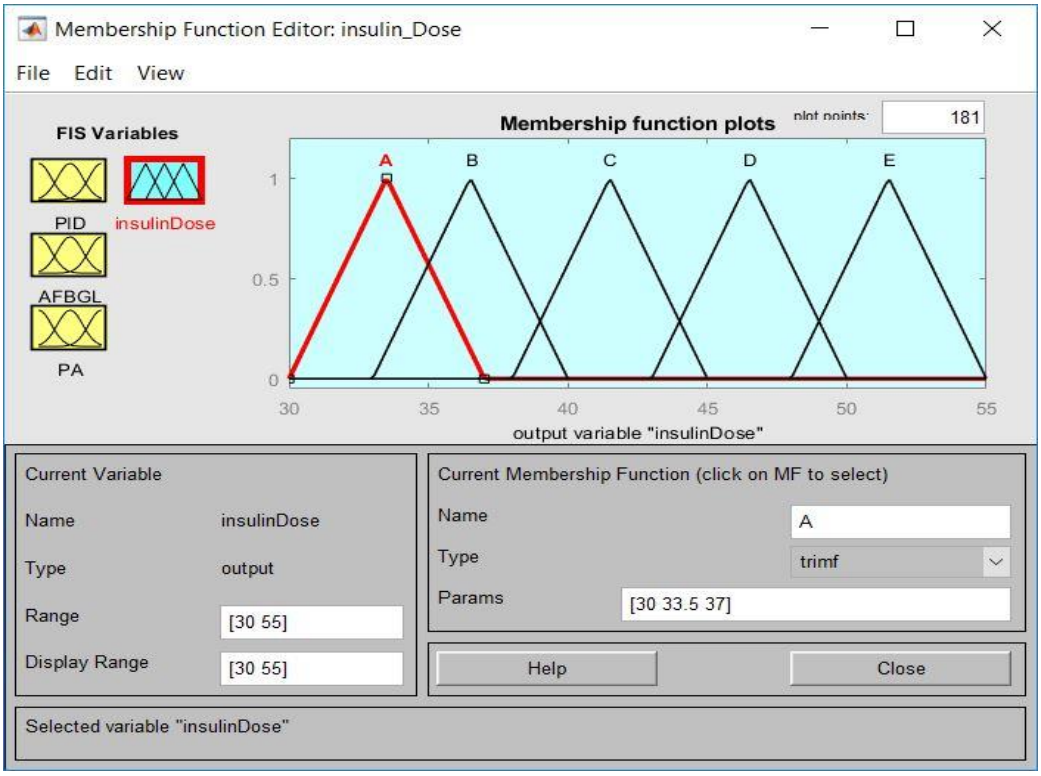

Figure 4. Membership functions for insulin Dose

In summary, Table 3 through Table 5 provides an insight about the assignment of Fuzzy values, Ranges, and Unity membership points of the input and output variables. Figure 1 through Figure 4 illustrates the actual membership functions constructed as per the Tables. It is evident that it is a three input-one output system with varying ranges and degree of memberships for different variables.

2.6. Rules for fuzzy inference definition

Till now, only the membership functions are defined; however, the system will not function unless the relationships among the membership functions are not defined. This step is called "Setting Rules" for the fuzzy inference. In order to set rules, the membership functions of the input and output variables must be mapped to each other with the if/then rules. The decision matrices provided on Table 6 through Table 8 outlines the mappings using which the if/then rules are set.

Table 6. Decision matrix, considering PID= L

		PA		
		L	**O**	**H**
AFBGL	**L**	A	B	B
	O	D	C	B
	H	D	C	C

Table 7. Decision matrix, considering PID= O

		PA		
		L	**O**	**H**
AFBGL	**L**	B	C	C
	O	C	C	B
	H	D	B	A

Table 8. Decision matrix, considering PID= H

		PA		
		L	**O**	**H**
AFBGL	**L**	B	D	C
	O	D	E	D
	H	C	D	D

Interpreting the provided decision tables is quite simple. For example, if the insulin Dose for a subject with High PID, High AFBGL, and Optimum PA is to be determined, then we refer to Table 8 (because this represents the table for PID=H) and map to the point where AFBGL=H, and PA=O. The resulting output for insulin Dose is D. Therefore, as subject with PID=H, AFBGL=H, and PA=O should take an insulin dose in the range insulin Dose=D. However, taking an insulin dose in a range does not make sense, which is why there is one more step called defuzzification (discussed in section 2.7) in the fuzzy inference system. When read linguistically, the if/then rule is to be read as "*If* (PID is H) *and* (AFBGL is H) *and*

(PA is O) *then* (insulin Dose is D)". All the if/then rules are set as per the decision matrices and are provided below:

1. *If* (PID is L) *and* (AFBGL is L) *and* (PA is L) *then* (insulin Dose is A)
2. *If* (PID is L) *and* (AFBGL is L) *and* (PA is O) *then* (insulinDose is B)
3. *If* (PID is L) *and* (AFBGL is L) *and* (PA is H) *then* (insulinDose is B)
4. *If* (PID is L) *and* (AFBGL is O) *and* (PA is L) *then* (insulinDose is D)
5. *If* (PID is L) *and* (AFBGL is O) *and* (PA is O) *then* (insulinDose is C)
6. *If* (PID is L) *and* (AFBGL is O) *and* (PA is H) *then* (insulinDose is B)
7. *If* (PID is L) *and* (AFBGL is H) *and* (PA is L) *then* (insulinDose is D)
8. *If* (PID is L) *and* (AFBGL is H) *and* (PA is O) *then* (insulinDose is C)
9. *If* (PID is L) *and* (AFBGL is H) *and* (PA is H) *then* (insulinDose is C)
10. *If* (PID is O) *and* (AFBGL is L) *and* (PA is L) *then* (insulinDose is B)
11. *If* (PID is O) *and* (AFBGL is L) *and* (PA is O) *then* (insulinDose is C)
12. *If* (PID is O) *and* (AFBGL is L) *and* (PA is H) *then* (insulinDose is C)
13. *If* (PID is O) *and* (AFBGL is O) *and* (PA is L) *then* (insulinDose is C)
14. *If* (PID is O) *and* (AFBGL is O) *and* (PA is O) *then* (insulinDose is C)
15. *If* (PID is O) *and* (AFBGL is O) *and* (PA is H) *then* (insulinDose is B)
16. *If* (PID is O) *and* (AFBGL is H) *and* (PA is L) *then* (insulinDose is D)
17. *If* (PID is O) *and* (AFBGL is H) *and* (PA is O) *then* (insulinDose is B)
18. *If* (PID is O) *and* (AFBGL is H) *and* (PA is H) *then* (insulinDose is A)
19. *If* (PID is H) *and* (AFBGL is L) *and* (PA is L) *then* (insulinDose is B)
20. *If* (PID is H) *and* (AFBGL is L) *and* (PA is O) *then* (insulinDose is D)
21. *If* (PID is H) *and* (AFBGL is L) *and* (PA is H) *then* (insulinDose is C)
22. *If* (PID is H) *and* (AFBGL is O) *and* (PA is L) *then* (insulinDose is D)
23. *If* (PID is H) *and* (AFBGL is O) *and* (PA is O) *then* (insulinDose is E)
24. *If* (PID is H) *and* (AFBGL is O) *and* (PA is H) *then* (insulinDose is D)
25. *If* (PID is H) *and* (AFBGL is H) *and* (PA is L) *then* (insulinDose is C)
26. *If* (PID is H) *and* (AFBGL is H) *and* (PA is O) *then* (insulinDose is D)
27. *If* (PID is H) *and* (AFBGL is H) *and* (PA is H) *then* (insulinDose is D)

2.7. Defuzzification for the fuzzy inference

"Defuzzifaction" is the last step of the fuzzy inferencing. As mentioned in the previous section, insulin dose in a range does not make sense. To counter such problem, the defuzzification is carried out. After defuzzification, the system will return a crisp value as a recommendation for the insulin dose. Illustrated on Figure 5 is the defuzzification, carried out for a set of input values in the Rule Viewer feature of MATLAB Fuzzy Logic Toolbox.

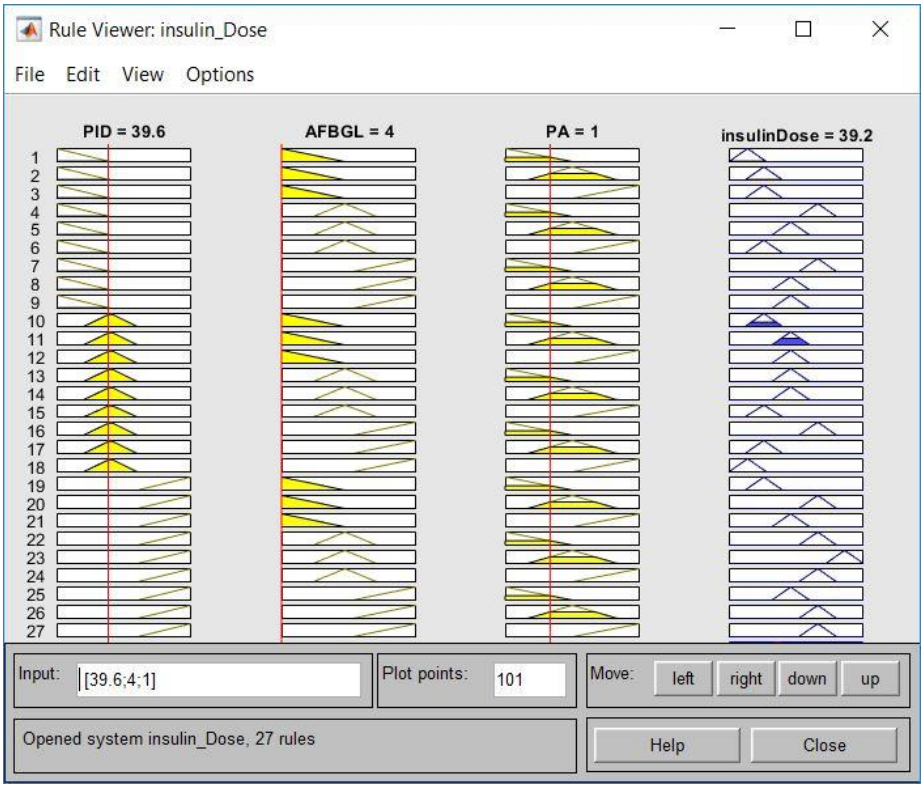

Figure 5. Defuzzification in the Rule Viewer

The figure shows the insulin dose recommendation, after defuzzification, for a subject with PID=39.6, AFBGL=4, and PA=1 is insulinDose=39.2 units. The system would not have returned this crisp number of insulin Dose=39.2 without the defuzzification step.

The MATLAB Fuzzy Logic Toolbox provides another feature that enables us to visually depict the whole system by means of three-dimensional surface, namely Surface Viewer. The Surface Viewer shows the relationships among any two input variables and the output variable at a time. Figure 6 through Figure 8 illustrates all surface diagrams for this system.

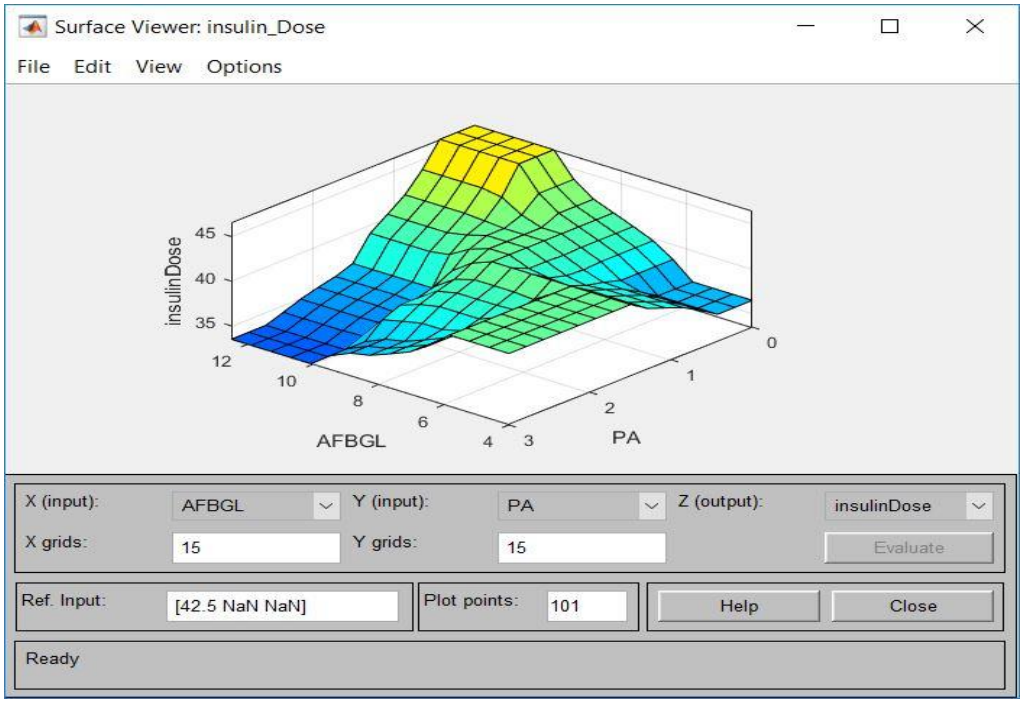

Figure 6. Surface diagram for AFBGL, PA, and insulinDose

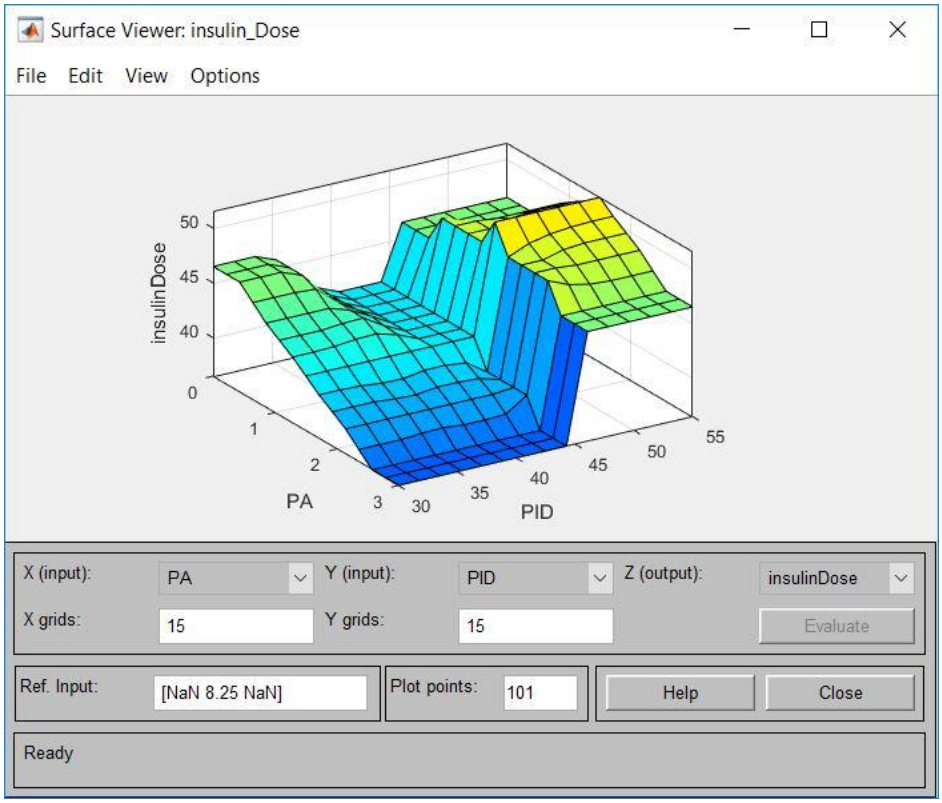

Figure 7. Surface diagram for PA, PID, and insulinDose

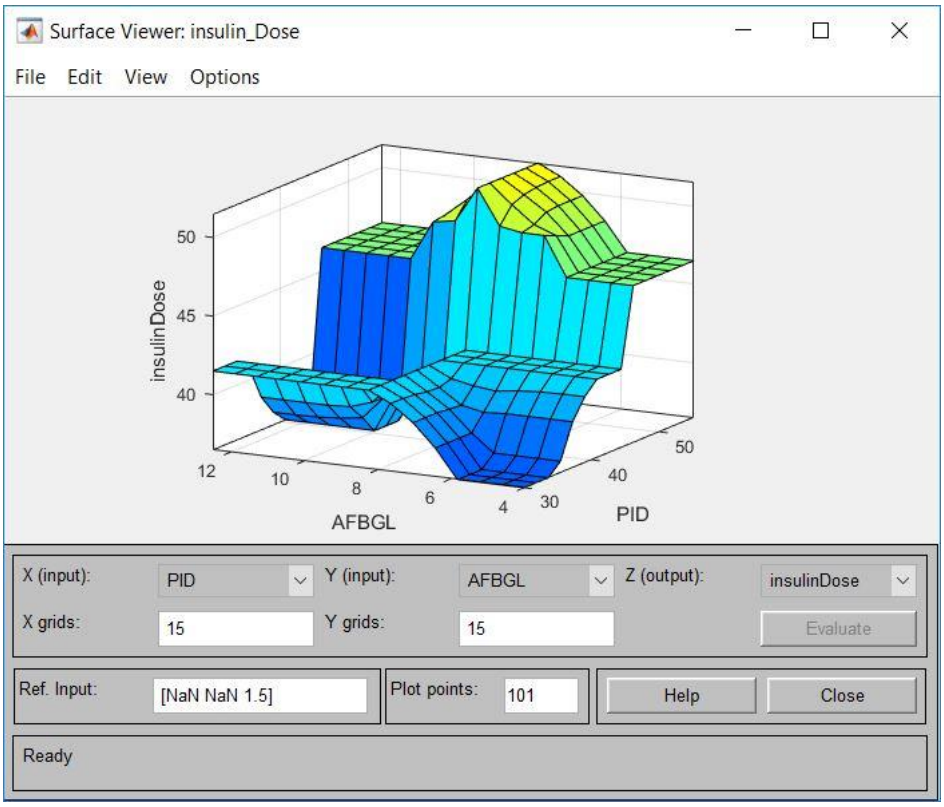

Figure 8. Surface diagram for PID, AFBGL, and insulinDose

RESULTS AND DISCUSSION

All patients in this research study were randomly selected from various parts of Dhaka city. They were all long-time type 1 diabetic (T1DM) patients undergoing insulin therapy. These patients were experiencing difficulty maintaining insulin homeostasis and therefore their insulin dosage was adjusted using a fuzzy logic based computational system. This adjustment was done in two phases. In the first phase of our study (Phase 1), their daily dose was adjusted based on their weight, BMI and average carbohydrate intake i.e. PID in Table 9 [1]. The adjustment in Phase 1 improved the quality of life of some of the patients but further refinement was warranted to serve a wider patient population of T1DM patients. In this study, the focus was directed at the second phase of dose adjustment (Phase 2); wherein the predicted dose from the first study i.e. PID was used along with patient's fasting blood glucose level and level of physical activity to further refine the daily insulin dose. Table 9 shows the PIDs for the 25 patients with prescribed insulin doses by physicians (PPD) and the newly adjusted insulin doses (APID) as well as the numerical difference between PPD and PID along with PPD and APID i.e. ND1 and ND2, respectively.

Table 9. Prescribed dose predicted dose and Adjusted Predicted dose of Insulin for each of the 25 patients

Patient number	Predicted Insulin dose (PID) by Fuzzy System (Phase 1)	Physician's Prescribed Dose (PPD)	Numerical Difference between PID and PPD (ND1)	Adjusted Predicted Insulin Dose (APID) by Fuzzy System (Phase 2)	Numerical Difference between APDI and PPD (ND2)
1	39.6	38.0	1.6	39.2	1.2
2	40.0	45.0	-5.0	39.4	-5.6
3	40.0	35.0	5.0	39.4	4.4
4	46.5	45.0	1.5	44.0	-1.0
5	39.5	38.0	1.5	38.3	0.3
6	46.5	50.0	-3.5	47.5	-2.5
7	40.0	38.0	2.0	37.8	-0.2
8	39.5	40.0	-0.5	38.6	-1.4
9	39.5	35.0	4.5	41.1	6.1
10	52.4	50.0	2.4	44.4	-5.6
11	40.0	45.0	-5.0	36.1	-8.9
12	40.0	44.0	-4.0	39.4	-4.6
13	46.5	44.0	2.5	49.0	5.0
14	33.0	44.0	-11.0	41.5	-2.5
15	52.6	55.0	-2.4	46.5	-8.5
16	39.6	38.0	1.6	35.1	-2.9
17	40.0	40.0	0.0	39.4	-0.6
18	46.5	52.0	-5.5	46.5	-5.5
19	39.5	52.0	-12.5	38.1	-13.9
20	39.5	38.0	1.5	39.4	1.4
21	39.5	40.0	-0.5	35.6	-4.4
22	40.0	28.0	12.0	40.5	12.5
23	46.5	40.0	6.5	41.5	1.5
24	39.5	35.0	4.5	40.8	5.8
25	46.5	40.0	6.5	47.9	7.9

The purpose of this study was to further enhance the consistency of the patients total daily insulin dosage that could be applied to a wider population of type 1 diabetes patients. A comprehensive summary highlighting the differences among PPD, PID and APID in both phases 1 and 2 is shown in Table 9. In order to compare the utility of PPD, PID and APID, the respective numerical difference between the doses ND1 and ND2 were the defining parameters. The observed numerical differences i.e. ND1 from the previous study advocate that there was a dose correction based on the provided original three patient related factors (PRFs). This study was very successful in practice for most of the patients but more difficult to infer compared to the previous studies done by our group. Out of the 25 patients, 18 reported that the adjusted insulin dose had a positive

impact on their lives either physically or financially or both. The most intriguing was that of patient number 14. For this patient, ND1 was -11.0 which indicated that the originally prescribed dose was significantly higher than the one predicted by the fuzzy logic-based system. However, after consulting with the patient, in this particular case, he had more success with the PPD rather than the PID in terms of treating T1DM symptoms. For his case, a refinement of the insulin dose was very necessary. Upon incorporating the two new PRFs i.e. average fasting blood glucose levels and the patent's physical activity score to the fuzzy system, the numerical difference, ND2, was reduced and the dose i.e. APID was calculated closer to the original PPD to be 41.0 units. After a month of monitoring the patient, the APID was reported to be useful since the patient reported a better quality of life with a lower dose of insulin compared to PPD that was predicted by this refined model. Patient 14's case was pivotal in terms of identifying the utility of this novel refinement process.

In the case of patient no. 19, she was experiencing hypoglycemic events when taking the PPD. After the first adjustment i.e. PID, her hypoglycemic events were significantly decreased even though she reported one particular instance of hypoglycemia [1]. This initially accounted for a numerical difference, ND1 (between PPD and PID) of -12.5. However, in Phase 2, upon further refinement with the two additional factors, the APID reduced the dose to 38.1 units per day, which accounted for a numerical difference, ND2, of -13.9 (between PPD and APID). Post follow-up i.e. after a period of one month after the initiation of Phase 2, the patient reported that there were no occurrences of hypoglycemic events whatsoever and a continued good quality of life in general. It was thus inferred that the APID provided an improved dose considering the fact that there was a better balance with fewer units of insulin units but still enough effectiveness for the patient in terms of controlling T1DM symptoms. This patient's case posits the utility of a fuzzy logic-based system in insulin dosing in general as well as the added benefits of this refinement process. It is worthwhile to consider the very interesting fact that the APID was significantly superior compared to the PPD, even though the PPD was used in part to develop the membership functions of this system.

When our group conducted this study on 39 type 2 diabetes patients, a general trend was observed in most cases where ND2 was lower compared to ND1 and there were no reports of hypoglycemia or hyperglycemia instances [27]. This trend often corresponded to better blood glucose regulation and a higher quality of life for those patients. Even for those who did not benefit greatly from this system, we hypothesized that other factors such as dietary habits, lifestyle, etc. might have impaired its precision. However, this was not the case for these 25 type 1 diabetes patients. Figure 9 shows the ND1 and ND2 values for each of the 25 patients. Since it is highly probable that the final number will likely tend to a different value other than that of PPD, it may be that only 25 patients were not enough to conduct this study and in this particular case, the ND1 and ND2 values were less reliable in terms of predicting a better outcome. In accordance to the study on type 2 diabetes patients, this discrepancy may have been brought about by the fewer number of patients that were studied in comparison. This especially makes sense since any artificially intelligent system works better with a higher number of data points. Setting aside this limitation, the dose refinement actually worked very well for a number of patients in the clinical sense and those who were given a lower dose because of it also benefitted financially.

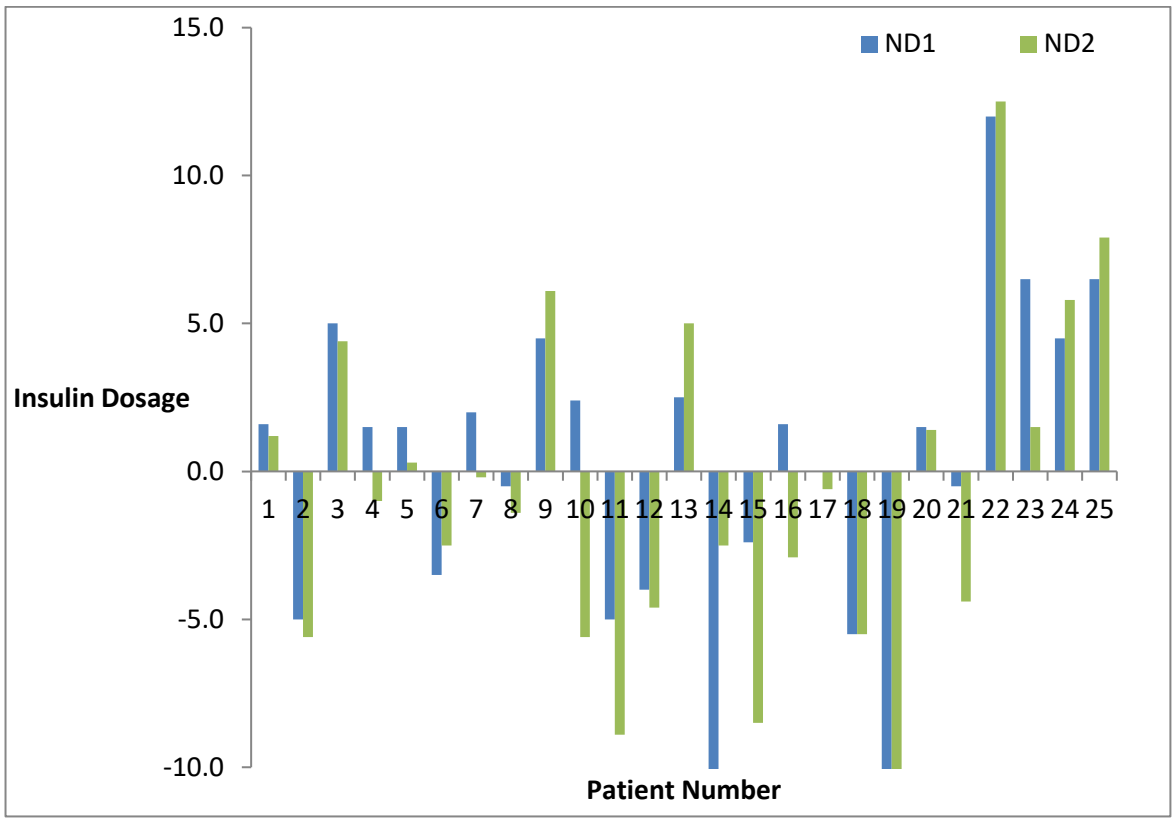

Figure 9: Numerical difference between ND1 and ND2

CONCLUSION

This fuzzy logic-based insulin dosing system posited a refinement process that turned out to be critical for a number of type 1 diabetes mellitus (T1DM) patients. The superior control of blood sugar regulation was clinically observable as well as financially beneficial for those who had to take lower number of units of insulin. Due to the nature of this approach, being highly personalized in calculating the daily insulin doses, it has shown significant promise for better management of type 1 diabetics. After monitoring the patients for a significant amount of time, the merits of this system have been demonstrated quite reasonably. Specific patient data such as the ones from patient no. 14 and 19 were critical in identifying these utilities. Therefore, it can be reasonably concluded that our fuzzy-based insulin dosage system may be very effective for diabetes management in a clinical setting. However, there are still a number of anomalies and discrepancies that need to be resolved further, especially in terms of identifying the likelihood of whether this system can provide an "ideal" insulin dose or not. But so far it seems that Artificial Intelligence is a promising tool which can be used to ameliorate insulin management. Our experimental approach may also be very financially beneficial to future patients since lower predicted doses means lower usage of insulin and hence lower purchases. In this study, a more refined dose was computed out of the 25 patients' data, but of course further studies are warranted with more patient related factors with the inclusion of a more sophisticated artificially intelligent system. For now, it can be reasonably concluded that our system is able to provide a relatively safe and effective method to identify individualized insulin dosage.

CONFLICT OF INTEREST

The authors report no declaration of interest.

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