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# Design of Optimized PID Controller for Blood Glucose Level Using CSA

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**Abstract:** ***The present paper aims to design an optimized Proportional Integral Derivative (PID) controller for diabetic patients. External insulin injection is required in patients suffering from diabetes to aid quickly. Insulin injection for diabetic patients is a topic of major research to improve their life with the help of a controller. As diabetic patients are increasing at an alarming rate, the classical controllers fail to live up to the challenges and expectations. To accurately inject external insulin into the patients, PID controllers are used. The controller helps the patient in many ways as it works on the difference between the desired output and the actual output. In the present work, the Crow Search Algorithm (CSA) is implemented to optimize the error of PID controllers and the results have been compared with Cohen-Coon Method, Astrom-Hagglund (AMIGO Method) and Chien-Hrones-Reswik method. The results indicate the superiority of the proposed techniques.***

**Keywords:** PID controller, Blood Glucose, MATLAB, Crow Search Algorithm

## 1. Introduction

The changed lifestyles and eating habits of humans have made them prone to many diseases, diabetes being one of them. Despite advancements in the field of medicine, people are still dying because of such chronic diseases [1]. In a recent survey conducted in 2012, it was estimated that around 347 million people suffered from this problem, and the number is expected to rise more alarmingly by 2031. In this world, a large chunk of the population suffers from diabetes mellitus everywhere, a disease that affects people of all ages.

The three main types of diabetes are Type 1, Type 2, and gestational diabetes [2]. Type 1 Diabetes usually occurs in childhood when a person's pancreas is unable to produce enough insulin i.e. Blood Glucose level, which should be between 60mg/dl to 120mg/dl for a healthy person. Type 1 diabetes is also called childhood Diabetes. Digital PID (Proportional integral derivative) controller automatically manages the amount of insulin provided for Type 1 diabetes.

Type 2 Diabetes usually occurs in middle-aged persons, mainly due to overweight. It generally occurs very slowly. It is a condition when a patient's body is unable to secrete enough insulin because it has developed resistance to insulin. Gestational diabetes usually occurs in pregnant women. If a person has high blood glucose levels, then it is known as hyperglycemia whereas if a person has low blood glucose level then it is known as hypoglycemia.

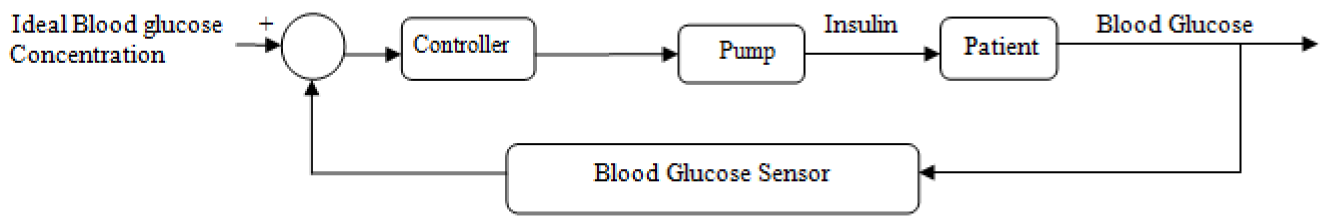


**Figure 1:** Closed-loop glucose control of diabetic [3].

Figure 1shows a closed-loop device that is fully capable of maintaining the insulin, consisting of three main components, namely: - i) pump, ii) Glucose sensor, iii) a mathematical control algorithm [4]. This three compartment-minimal model has been explained by Bergman *et al*. [5]. Ideal Blood Glucose concentration is checked by all these components in closed loop as shown in Figure 1.

Diabetes mellitus is caused when the pancreas are unable to secrete insulin. Such patients require to check their glucose levels manually on a regular basis. The glucose level is required to be measured by a test strip. If the level is found higher or lower than the required level of glucose in the blood, insulin can be inserted directly into the insulin pump. The PID controller is optimized to avoid situations in which high variations in glucose concentration are found [1].

This paper consists of 7 sections. Section 1 gives a brief introduction of the work. Modeling of Blood Glucose level **(**BGL) is done in section 2. Section 3 describes a brief literature survey of related work. While section 4 deals with design of PID controller. Section 5 describes the Crow Search Algorithm in brief. Section 6 describes the simulation results and section 7 concludes the paper.

## 2. Modelling of Bloood Glucose Level (BGL) From Differential Equation: Mathematical Overview

The differential equation of blood glucose is given below[6] [7] :

$$\text{r (t)} = \frac{d^3 c}{dt^3} + 6\frac{d^2 c}{dt^2} + 5\frac{dc}{dt} \qquad (1)$$

Now converting this differential equation into the Laplace domain by using forward Laplace transform. This transform can be applied as:

$C(s) \longrightarrow L\{C\ (t);\ t \longrightarrow s\}$

$R(s) \longrightarrow L\{r\ (t);\ t \longrightarrow s\}$

By applying this substitution above, we get

$$\text{R(s)} = s^3\text{C(s)} + 6s^2 C(s) + 5s\text{C(s)} \qquad (2)$$

Simplifying the above equation in transfer function form, we get:

$$\text{Gc(s)} = \frac{\text{R(S)}}{C(s)} = \frac{1}{s^3 + 6s^2 + 5s} \qquad (3)$$

**Table 1:** Control objectives of the blood glucose-insulin system

| | |
|---|---|
| From 70 to 99 | Normal glucose tolerance |
| From 100 to 125 mg/dL | Pre-diabetes |
| More than 126 mg/dL | Diabetes |

## 3. Related Work

PID controllers are widely used in industries and research. These are also used for diabetic-related applications. This section helps us to understand some of the contributions in this area. Afroza Shirin [8] implemented optimal regulation of blood glucose level in Type 1 diabetes using insulin and glucagon. Firas H. El-Khatib [9] implemented a Bi-hormonal Closed-Loop Blood Glucose (BG) Control for Type 1 Diabetes in which a "closed-loop" BG control system utilizing both insulin and glucagon were used. Robert S. Parker [4] developed a model-based predictive control algorithm to maintain normoglycemia in Type 1 diabetic patients using a closed-loop insulin infusion pump. Larry Brown [10] designed to avert episodes of low blood sugar in patients with insulin-dependent diabetes. Pia V [11] summarized the interplay of the pancreas with various other organs and tissues that maintain glucose homeostasis. Rohit Sharma [7] improvised the tuning techniques of Digital PID Controller. Pinky Dua [12] presented a Model-Based Blood Glucose Control for Type 1 Diabetes via Parametric Programming. Mojtaba [13] designed an ARO based fuzzy PID controller for Type 1 diabetes. Qi Li [14] developed a portable, economy blood glucose meter for self-monitoring of blood glucose.

## 4. Designing of PID Controller

PID controller is mainly used in industries to control different loops in various processes. It works on the error between the desired output and the actual output

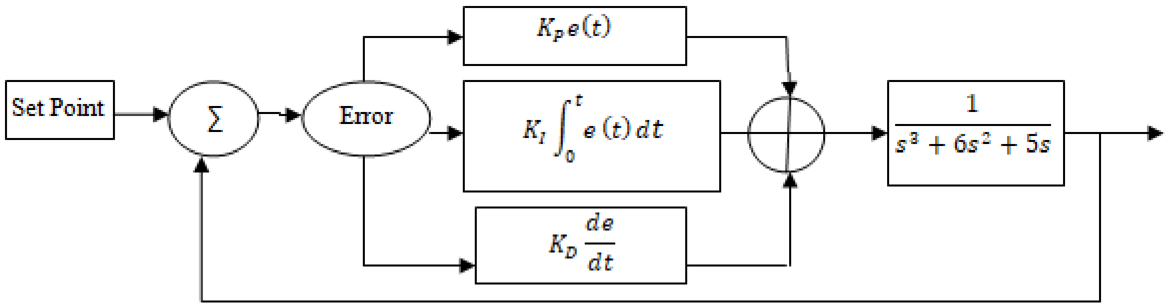


**Figure 2:** Block Diagram of Blood Glucose Insulin System with Digital PID Controller

The externally applied insulin dosage helps in controlling the sugar level automatically. The controller detects the patient need and automatically gives the appropriate amount of insulin dosage; it can be more or less. Proportional, Integrative and Derivative are the three main parameters of a PID Controller [6]. Below $K_P$ = proportional gain, $K_I$ = integral gain, $K_D$= derivative gain

$$u(t) = K_P e(t) + K_I \int e\,(t)dt + K_D \frac{de}{dt} \qquad (4)$$

For equation (4), the transfer function of PID controller is-

$$Gc(s) = K_P + \frac{K_I}{S} + K_D\ S \qquad (5)$$

Above Figure 2 shows the block diagram of the PID controller. PID controller provides a control strategy. It works on the error between the desired output and the actual output. Based on the error, various performance indicators are defined as follows:

a) Integral square error (ISE)

$$\text{ITSE} = \int_0^\infty e^2\,(t)dt \qquad (6)$$

b) Integral absolute error (IAE)

$$IAE = \int_0^\infty |e(t)|dt \qquad (7)$$

c) Integral time absolute error (ITAE)

$$IATE = \int_0^\infty t|e(t)|dt \qquad (8)$$

d) Integral time squared error (ITSE)

$$\text{ITSE} = \int_0^\infty te^2\,(t)dt \qquad (9)$$

## 5. Crow Search Algorithm (CSA)

It was Askarzadeh [15] who proposed the technique of CSA, which is defined as a metaheuristic population founded optimizer on the basis of the cognitive behavior of crows. CSA's working principle is based on a crow's ability to hide surplus food and retrieve it as per its own needs. It can be said that the technique is suitable for the complex objective function. CSA is totally suitable for various engineering design problems as it takes less computation time for convergence.

When the crow *j* finds that another crow *i* is following it and can find its hiding place, the crow *j* moves to a false position. This state is known as awareness probability. CSA works with two mainly adjustable parameters *fl* (flight length) and *AP* (Awareness probability). After adjusting these two, the *N* (Flock size) and *t* (No of iteration) are assumed as well. Awarness probability is known as $AP_{(j,t)}$. Each crow takes its position in as follow:

$$x_{(i,t+1)} = \begin{cases} x_{(i,t)} + r_i * fl_{(i,t)} * \left[m_{(j,t)} - x_{(i,t)}\right] & r_j > AP_{(j,t)} \\ random\ position & otherwise \end{cases} \quad (10)$$

Each crow can update its own memory according to its fitness value. If the new value is better than the previous one then it updates itself.

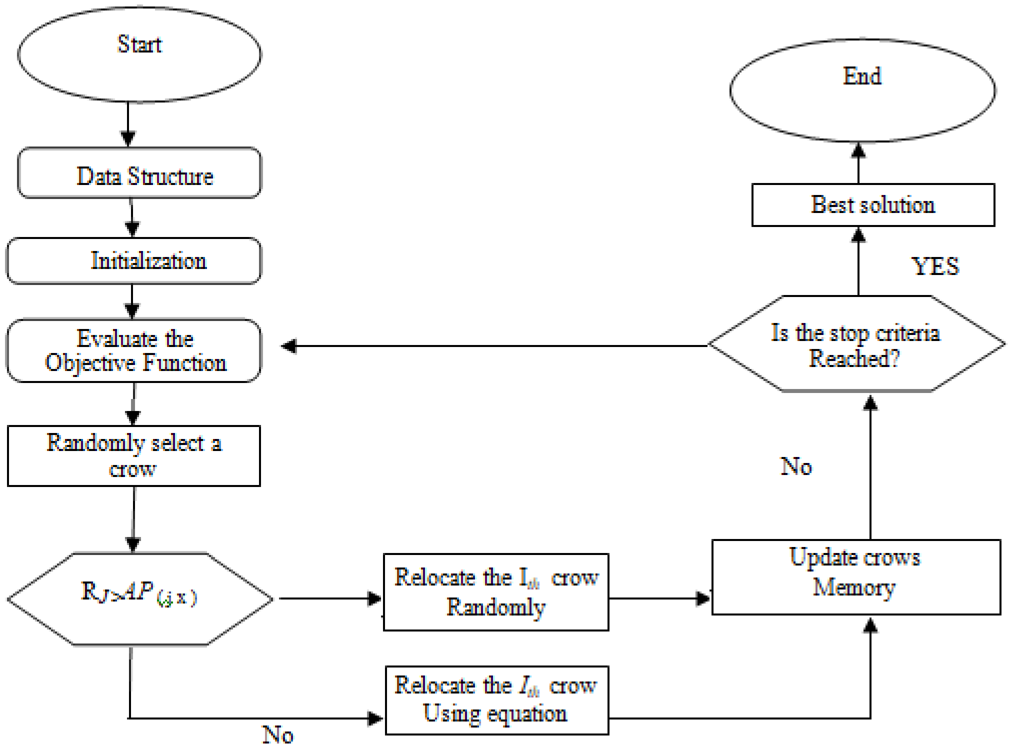


**Figure 3:** Flowchart of the standard CSA [16]

The procedure of memory updation is described as:

$$m_{(i,t)} = \begin{cases} x_{(i,t+1)}\ if\ f\left[x_{(i,t+1)}\right]\ is\ better\ than\ f\left[m_{(i,t)}\right] \\ m(i,t)\ otherwise \end{cases} \quad (11)$$

Steps of CSA are given below [17] [18] . These stages are further explained below.

Step 1. The optimization problem or objective function, decision variables and constraints values are defined. Subsequently, the flock size (*N*), maximum number of iterations, flight length (*fl*), and awareness probability (*AP*) are defined. Crow's positions are set randomly between the given ranges.

Step 2. The Fitness value is calculated using the different sets of decision variables for the given flock.

Step 3. As per requirement crow's position is updated, using the equations.

Step 4. The utility of a new position is tested by comparing the limits in stage 1.

Step 5. The new fitness value is compared and calculated with the previous one.

Step 6. Redo steps 4 and 5 until we get the targeted value of $iter_{max}$.

## 6. Simulation Results

This section shows the result of an optimized PID controller of the diabetic patient using the CSA algorithm. Firstly the control parameters of CSA are tuned with 20 runs of 100 iterations each with two sets of experiments a) keeping *AP* fixed and varying *fl* between 1 and 2 and b) varying *AP* between 0 and 1 by keeping *fl* fixed

### 6.1 Tuning of control parameters *AP* and *FL* for optimization

The best ten values out of these runs are then tabulated. Corresponding to the minimum integral indices values, *AP* and *fl* are fixed and then actual optimization for PID tuning begins. 20 runs of 100 iterations are taken and the minimum value of $K_P$, $K_I$ and $K_D$ corresponding to minimum integral indices is recorded and then the results are compared with existing techniques as discussed further.

### 6.1.1 With *AP*=0.1 and varying values of 1≤ *fl* ≤ 2.

As CSA depends upon two control parameter *AP* and *fl*. So, in the first case, the value of *AP* is fixed as 0.1 and *fl* is varied between 1 and 2 by an increment of 0.1. Best ten values of $K_P$, $K_I$, $K_D$ are recorded as shown in Table 2 corresponding to minimum integral indices- ISE and ITSE.

**Table 2:** Best values of ISE & ITSE by fixing *AP* and varying *fl*

| *AP=0.1,1≤fl≤ 1.9* | ISE | ITSE | $K_P$ | $K_I$ | $K_D$ |
|---|---|---|---|---|---|
| *fl*=1.9 | 2.722 | 10.62 | 2.014853 | 1.899334 | 2.010862 |
| *fl* =1.8 | 1.863 | 6.085 | 2.554277 | 1.982696 | 2.836527 |
| *fl* =1.7 | 1.957 | 7.7 | 1.306268 | 0.803837 | 2.971441 |
| *fl* =1.6 | 1.018 | 1.883 | 3.394472 | 0.85153 | 3.340289 |
| *fl* =1.5 | 1.963 | 4.907 | 2.549603 | 0.525416 | 0.42303 |
| *fl* =1.4 | 1.367 | 1.906 | 3.428109 | 0.326923 | 0.652712 |
| *fl* =1.3 | 1.977 | 5.328 | 2.698563 | 0.802912 | 0.763275 |
| *fl* =1.2 | 1.56 | 2.71 | 1.24005 | 0.04210 | 2.79567 |
| *fl* =1.1 | 1.32 | 3.483 | 2.659477 | 1.045455 | 3.12968 |
| *fl* =1 | 1.209 | 1.47 | 1.642517 | 0.103166 | 3.197946 |

**6.1.2 With *fl*=2 and varying values of 0≤*AP*≤1.** Similarly, by fixing the value of *fl* as 2 and varying value of *AP* between 0.1 and 1 by an increment of 0.1 the values of PID parameters corresponding to minimum integral indices have been tabulated as in Table 3. The best ten values of $K_P$, $K_I$, $K_D$ and corresponding ISE & ITSE have been tabulated in Table 3.

As the minimum value of ISE and ITSE have been obtained at *AP*=0.1 and *fl*=2 so corresponding values of PID controller gives the optimum results and have been considered as final values for comparing against existing techniques.

**Table 3:** Best values of ISE& ITSE by fixing *fl* and varying *AP*

| *Fl=2,0.1≤AP≤1* | ISE | ITSE | $K_P$ | $K_I$ | $K_D$ |
|---|---|---|---|---|---|
| *AP*=0.1 | 1.335 | 1.399 | 2.1536 | 0.0216 | 1.6945 |
| *AP*=0.2 | 1.824 | 3.643 | 0.707212 | 0.119163 | 2.912672 |
| *AP*=0.3 | 2.431 | 8.788 | 3.496431 | 2.174476 | 1.417886 |
| *AP*=0.4 | 1.792 | 3.488 | 0.824727 | 0.098586 | 2.799694 |
| *AP*=0.5 | 1.828 | 6.263 | 2.007533 | 1.674089 | 3.267199 |
| *AP*=0.6 | 3.784 | 17.83 | 0.83321 | 0.567227 | 0.765945 |
| *AP*=0.7 | 1.448 | 1.94 | 1.837801 | 0.156082 | 1.649939 |
| *AP*=0.8 | 2.919 | 13.53 | 1.055296 | 0.815036 | 1.916135 |
| *AP*=0.9 | 1.643 | 2.423 | 1.674244 | 0.153373 | 1.221031 |
| *AP* =1 | 2.028 | 8.323 | 1.376437 | 0.982473 | 3.109644 |

After careful investigation of Tables 2 and 3 it has been found that the best output of PID has been obtained when *AP* is kept at 0.1 and *fl* is set at 1 and 2. So further 10 runs of 100 iterations have been taken and three best values have been tabulated in Table 4.

**Table 4:** Values of ISE& ITSE by fixing *AP*

| | $K_P$ | $K_I$ | $K_D$ | ISE | ITSE |
|---|---|---|---|---|---|
| *AP*=0.1 *fl*=1 | 3.3513 | 0.089923 | 3.398887 | 0.837 | 0.576 |
| | 3.104189 | 0.089524 | 2.952478 | 0.9163 | 0.6896 |
| | 2.997662 | 0.031432 | 2.821309 | 0.951 | 0.717 |
| *AP*=0.1 *fl*=2 | 3.297756 | 0.000321 | 2.279794 | 0.9711 | 0.7004 |
| | 3.499731 | 0.518722 | 3.283052 | 0.9144 | 1.236 |
| | 3.477261 | 0.01139 | 3.3658 | 0.8305 | 0.5403 |

### 6.2 Comparison with other technique

In this section, CSA-PID is compared with other techniques to analyze its performance and efficiency as tabulated in Table 5.

**Table 5:** Comparison with other technique

| Techniques | $K_P$ | $K_I$ | $K_D$ | ISE | IAE | ITSE | ITAE |
|---|---|---|---|---|---|---|---|
| Without Controller | - | - | - | 3.121 | 5 | 6.921 | 19 |
| CSA-PID(PROPOSED) | 3.477261 | 0.01139 | 3.3658 | 0.832 | 1.792 | 0.6144 | 20.83 |
| Cohen-Coon Method | 3.66987 | 0.798213 | 2.49714 | 1.093 | 2.562 | 1.861 | 9.532 |
| Astrom-Hagglund (AMIGO Method) | 1.21993 | 0.0826917 | 1.12484 | 2.338 | 6.329 | 9.989 | 75.72 |
| Chien-Hrones-Reswik Method | 3.25316 | 0.882044 | 2.51964 | 1.216 | 2.977 | 2.567 | 13.75 |

Comparison with other techniques show that the step response of CSA-PID is much better than the remaining techniques in terms of least integral indices values. It can be easily seen that the overshoot, IAE, ISE and ITSE values of CSA-PID, are much lesser than Cohen-coon, AMIGO, and Chien-Hrones-Reswik method. The graphs of comparison of step response of blood glucose meter with different techniques are given in Figure 4.

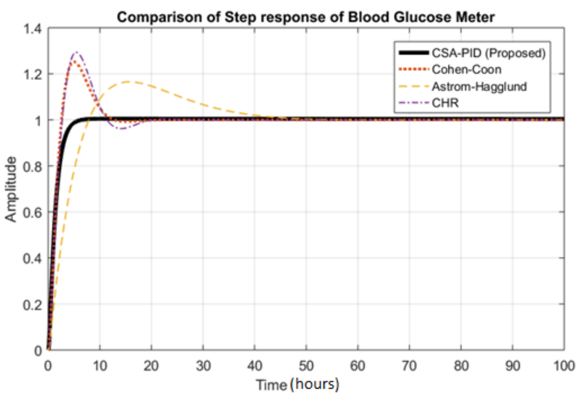


**Figure 4:** Comparison of step response of Blood Glucose Meter

### 6.3 Robustness Analysis

Glucose in the blood gets varied with the food intake by the patient. A designed controller should be able to handle the variation in the blood glucose level, for this a load disturbance corresponding to food intake of breakfast, lunch and dinner has been introduced.

### 6.3.1 Load Disturbance Analysis after breakfast

Intake of food is the main factor for the variation of blood glucose levels. So, to check which technique or method is better, a comparison is made after intake of food. The normal range of blood glucose after eating should be 140 mg/dl. The meal distribution is applied as a pulse at 5$^{th}$ hours. The graph of the comparison of load disturbance with other techniques is shown below.

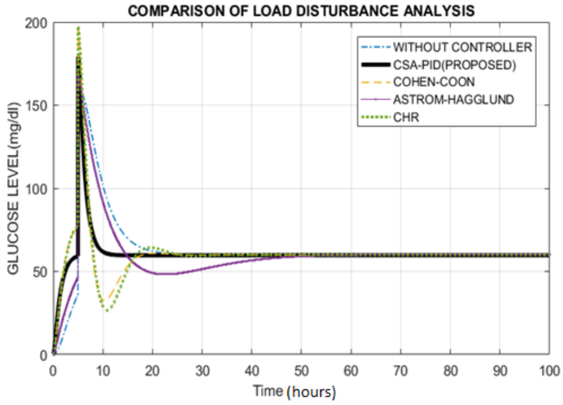


**Figure 5:** Comparison of load disturbance analysis after breakfast

As can be seen from the Figure 5, that blood glucose is coming down to its nominal value but the main difference is the time
taken for settling back to normal value. To further strengthen this investigation, integral indices in terms of IAE, ITAE, ISE and ITSE have been recorded for load disturbance capabilities of these controllers in Table 5. It can be easily seen that integral error function values and settling time are much lesser for CSA-PID in comparison to other techniques.

**Table 6:** Load Disturbance Comparison after breakfast

| Techniques | ISE | IAE | ITSE | ITAE |
|---|---|---|---|---|
| Without Controller | 4.302e+4 | 737.2 | 2.579e+5 | 5064 |
| CSA-PID(PROPOSED) | 1.488e+4 | 277.2 | 6.941e+4 | 2325 |
| Cohen-Coon Method | 2.316e+4 | 427.3 | 1.298e+5 | 2934 |
| Astrom-Hagglund or AMIGO Method | 3.503e+4 | 796.1 | 2.366e+5 | 9833 |
| Chien-Hrones-Reswik Method | 2.655e+4 | 496.3 | 1.598e+5 | 3855 |

### 6.3.2 Comparison of output after lunch and dinner

Further, to check the effect of both lunch and dinner, corresponding disturbances are provided and the output is again compared of all these techniques. The normal range of blood glucose after eating should be 140mg/dl. The meal distribution is applied as a pulse at 200 min for lunch and at 500 min for dinner. The graph of the comparison of load disturbance with other techniques is shown aside.

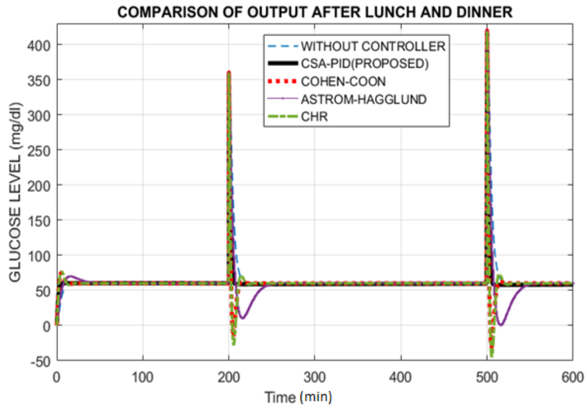


**Figure 6:** Comparison of output after lunch and dinner

Figure7 represents the magnified view of comparison of output after lunch and dinner. Lunch and dinner varies the blood glucose level heavily and so are the main factors in the variation of blood glucose levels. It can be easily seen from Figure 6 and the magnified view in Figure 7 that CSA-PID takes the least time for settling back to its nominal value as compared to Cohen and Coon, Astrom and Hagglund and CHR.

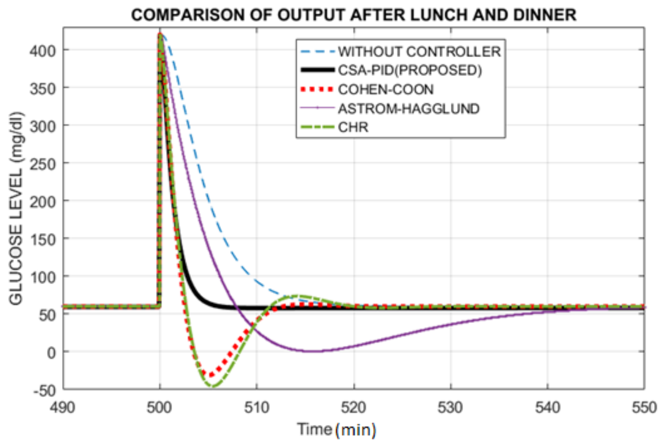


**Figure 7:** Magnified view of comparison of output after lunch and dinner

In view of the above results, CSA-PID based glucometer has been found to be more robust and fastest amongst compared techniques and can easily handle abnormalities in blood glucose in lesser time.

### 6.4 Convergence Rate

The CSA optimized PID glucosometer have been found to converge to its minimum fitness value before 25$^{th}$ iterations when the optimization has run for 100 iteration per run.

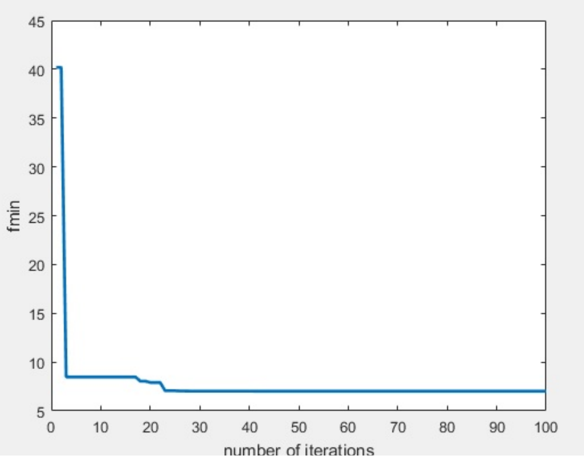


**Figure 8:** Convergence of CSA-PID

As the global minimum is achieved in 25th iteration, so less time and memory is utilized in optimization to get optimal CSA-PID glucosometer.

## 7. Conclusions

An optimized PID controller is designed for diabetic patients using CSA. Different algorithms can be used to obtain the best design of the PID controller, however, in our case, CSA has been used because of the presence of only two control parameters namely, *fl* (flight length) and *AP* (Awareness probability). This algorithm works on the dynamic interrelationship between these two parameters and which was something not available in the traditional methods used previously. It can be easily seen in the above analysis, that CSA-PID can efficiently handle the blood glucose level of a diabetic patient very efficiently utilizing least time amongst the compared techniques.

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## References

[1] S. L. Katrin Lunze, Tarunraj Sing, Marian Walter, Mathias D.Brendel, "Blood glucose control Algorithm for type 1 diabetics patient: A methodological review," 2012.

[2] S. Dan L.Longo, Anthony S. Fauci, Dennis L. Kasper and J. L. L.Hauser, J.Larry Jamenson, "Harrison's principle of Internal Medicine",18th Edition textbook."

[3] R. Hu and C. Li, "A fuzzy-PID glucose control strategy for insulin therapy in type 1 diabetics," *2015 IEEE Int. Conf. Mechatronics Autom. ICMA 2015*, pp. 447–452, 2015, doi: 10.1109/ICMA.2015.7237527.

[4] R. S. Parker, F. J. Doyle, and N. A. Peppas, "A model-based algorithm for blood glucose control in type I diabetic patients," *IEEE Trans. Biomed. Eng.*, vol. 46, no. 2, pp. 148–157, 1999, doi: 10.1109/10.740877.

[5] R. N. Bergman, "Minimal model: Perspective from 2005," *Horm. Res.*, vol. 64, no. SUPPL. 3, pp. 8–15, 2005, doi: 10.1159/000089312.

[6] V. Anilkumar and R. Phadke, "Design of Digital PID Controller for Blood-Glucose Monitoring System," vol. 3, no. 12, pp. 307–311, 2014.

[7] R. Sharma, S. Mohanty, and A. Basu, "Tuning of digital PID controller for blood glucose level of diabetic patient," *2016 IEEE Int. Conf. Recent Trends Electron. Inf. Commun. Technol. RTEICT 2016 - Proc.*, vol. 6, no. 2, pp. 332–336, 2017, doi: 10.1109/RTEICT.2016.7807837.

[8] A. Shirin, F. Della Rossa, I. Klickstein, J. Russell, and F. Sorrentino, "Optimal regulation of blood glucose level in Type I diabetes using insulin and glucagon," *PLoS One*, vol. 14, no. 3, pp. 1–23, 2019, doi: 10.1371/journal.pone.0213665.

[9] F. H. El-Khatib, S. J. Russell, D. M. Nathan, R. G. Sutherlin, and E. R. Damiano, "Bi-hormonal closed-loop glucose control for type 1 diabetes," *Sci. Transl. Med.*, vol. 2, no. 27, pp. 1–17, 2010, doi: 10.1126/scitranslmed.3000619.Bi-hormonal.

[10] L. Brown and E. R. Edelman, "Optimal control of blood glucose: The diabetic patient or the machine?," *Sci. Transl. Med.*, vol. 2, no. 27, pp. 1–5, 2010, doi: 10.1126/scitranslmed.3001083.

[11] P. V. Röder, B. Wu, Y. Liu, and W. Han, "Pancreatic regulation of glucose homeostasis," *Exp. Mol. Med.*, vol. 48, no. December 2015, p. e219, 2016, doi: 10.1038/emm.2016.6.

[12] P. Dua, F. J. Doyle, and E. N. Pistikopoulos, "Model-based blood glucose control for type 1 diabetes via parametric programming," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 8, pp. 1478–1491, 2006, doi: 10.1109/TBME.2006.878075.

[13] M. Kazemi and M. B. Menhaj, "An ARO based fuzzy PI+D controller for type 1 diabete," *2016 4th Int. Conf. Control. Instrumentation, Autom. ICCIA 2016*, no. January, pp. 190–195, 2016, doi: 10.1109/ICCIAutom.2016.7483159.

[14] L. Qi and Y. Jingqi, "Development of the portable blood glucose meter for self-monitoring of blood glucose," *Annu. Int. Conf. IEEE Eng. Med. Biol. - Proc.*, vol. 7 VOLS, pp. 6735–6738, 2005, doi: 10.1109/iembs.2005.1616050.

[15] A. Askarzadeh, "A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm. Computers & Structures, 169," pp. 1–12, 2016.

[16] O. Bozorg-Haddad, "Advanced Optimization by Nature-Inspired Algorithms," *Springer*, pp. 1–159, 2018, doi: 10.1007/978-981-10-5221-7.

[17] S. Kumar, A. Kumar, and G. Shankar, "Crow search algorithm based optimal dynamic performance control of SVC assisted SMIB system," *2018 20th Natl. Power Syst. Conf. NPSC 2018*, 2018, doi: 10.1109/NPSC.2018.8771814.

[18] U. S. B. Surya Samantha , M. Trupthi, "A Review on Using Crow Search Algorithm in Solving the Problems of Constrained Optimization," *Int. J. Sci. Res. Sci. Technol.*, vol. 4, no. 2, pp. 1374–1387, 2018.

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