Proceedings of the 2nd World Congress on Electrical Engineering and Computer Systems and Science (EECSS'16)
Budapest, Hungary – August 16 – 17, 2016
Paper No. EEE 130
DOI: 10.11159/eee16.130

Comparison of PID based Control Algorithms for Daily Blood Glucose Control

Selim Soylu, Kenan Danisman
Department of Electrical & Electronics Engineering, Faculty of Engineering,
Erciyes University, 38039, Kayseri, Turkey
selimsoylu@ erciyes.edu.tr; danismak@ erciyes.edu.tr

Abstract - Type 1 Diabetes Mellitus (T1DM) is a worldwide disease. Although a complete cure has not been found yet, an artificial pancreas (AP), also known as a closed-loop insulin therapy, is becoming more important for the treatment of this disease. Controller part of the AP can compute insulin infusion rate that will keep blood glucose concentration (BGC) in normoglycemic ranges for patients with T1DM. In this paper, three different control algorithms are proposed as a controller part of the AP. These control algorithms include genetic algorithm based proportional-integral-derivative (GA-PID) control, artificial bee colony algorithm based PID (ABC-PID) control, and particle swarm optimization algorithm based PID (PSO-PID) control. In silico control studies are implemented through a virtual diabetic patient based on the Stolwijk-Hardy's glucose-insulin regulation model. Simulations are performed to assess control function in terms of tracking BGC profile of a healthy person against to a daily food intake of three meals. In order to demonstrate robustness, sensor noise test is implemented. Simulation results are promising in terms of regulating the daily BGC.

***Keywords*:** T1DM, blood glucose concentration, artificial pancreas, PID based control methods, virtual diabetic patient.

1. Introduction

Diabetes Mellitus (DM) is a widespread disease characterized by chronic hyperglycaemia stemming from the failure of the pancreas in insulin secretion, insulin action, or both. Type 1 Diabetes Mellitus (T1DM) and Type 2 Diabetes Mellitus (T2DM) are two types of DM. T1DM is characterized by absolute deficiency of insulin caused by autoimmune system damage to the insulin producing beta cells. On the other hand, the insulin does not function properly due to resistance to insulin in patients with T2DM. There are some complications arising from DM: neuropathy, blindness, nephropathy, and other long-term vascular complications [1]. According to the International Diabetes Federation (IDF), there are approximately half a million children living with T1DM around the world. In 2013, Turkey has the highest diabetes national prevalence (14.8%) in Europe [2].

For glucose uptake and utilization, patients with T1DM need exogenous insulin. Exogenous insulin should be infused at an appropriate rate to keep the BGC in normoglycemic ranges (0.6 mg/mL $\leq$ BGC $\leq$ 1.6 mg/mL [3]). Nowadays, measurements of the BGC 3-5 times in a day and the injections of an equal amount of insulin subcutaneously are proposed as medical treatment. However, this method is unsuitable and painful. Furthermore, it is difficult to deliver right amount and type of the insulin. For this reason, much research is being performed to cope with the deficiencies of the current medical treatment. In this study, we focused on a closed-loop control system for insulin injections. The closed-loop control system known as the artificial pancreas (AP) includes a continuous glucose monitor (CGM) or a glucose sensor, a controller, and an insulin pump. CGM signals are transmitted to the controller which determines the required insulin injection rate to maintain the BGC in normoglycemic ranges. Required amount of insulin can be delivered by the insulin pump. The block diagram of the closed-loop control system for patients with T1DM is shown in Fig. 1.

Thanks to advances in biomedical system modelling, several models have been introduced to investigate the glucose-insulin regulatory system. These models are crucial in terms of better understanding the glucose-insulin regulatory system. Moreover, clinical over crowdedness increases the importance of the modelling. Some of these models such as minimal model, Hovorka model, meal simulation model, and the Stolwijk-Hardy glucose-insulin regulation model are common in the literature and referred to in [4]-[7], respectively. In this paper, the modified Stolwijk-Hardy glucose-insulin regulation model is considered [7]. The model is used to obtain both virtual diabetic patient and the healthy person data.

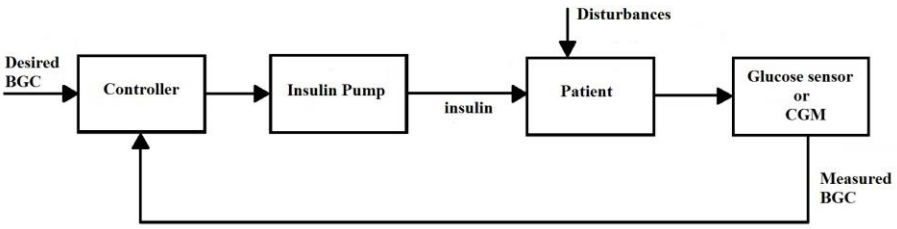

Fig. 1: A closed-loop glucose control system (Artificial Pancreas).

Various control algorithms have been proposed to control the BGC of patients with T1DM through usage of the mathematical models. Some of these algorithms include PID (proportional-integral-derivative) controller [8], model-based and model-predictive controller (MPC) [9], and fuzzy logic controller (FLC) [10]. On the other hand, there are many studies based on the combination of different control algorithms. In [11], performances of the FLC and the Fuzzy-PID controller are compared versus single glucose infusion based on the modified Stolwijk-Hardy glucose-insulin regulation model. In [12], the authors proposed a FLC that is optimized by particle swarm optimization (PSO) algorithm to follow the glucose profiles of a healthy person with minimum infused insulin. For this purpose, a nonlinear delay differential model is used. Based on the same model, a genetic algorithm based PI-FLC is proposed in [13].

In this paper, we performed three different control strategies to regulate the BGC of a patient with T1DM. GA-PID, PSO-PID, and ABC-PID controllers are implemented on the virtual diabetic patient described by the modified Stolwijk-Hardy glucose-insulin regulation model. In contrast to [11], single exogenous glucose intake is not used. To assess the performance of the control algorithms against daily food intake, three meals (breakfast, lunch and dinner) are added to the model as disturbances.

2. The Modified Stolwijk-Hardy Model

In silico control trials are conducted on the Stolwijk-Hardy's glucose-insulin regulation model version as presented by Khoo [7]. It is one of the simple models when examined in terms of mathematical complexity. The model comprises just two state variables, *G(t)* and *I(t)*. The model was modified by adding a term for exogenous insulin infusion $U_I(t)$ [14]. The glucose dynamics are expressed as:

$$\begin{aligned} C_G \frac{dG(t)}{dt} &= U_G(t) + Q_G(t) - \lambda G(t) - \nu G(t) I(t), && G(t) \le \theta \\ C_G \frac{dG(t)}{dt} &= U_G(t) + Q_G(t) - \lambda G(t) - \nu G(t) I(t) - \mu(G(t) - \theta), && G(t) > \theta \end{aligned} \tag{1}$$

It is important to note that the cross-product term between *G(t)* and *I(t)*, the blood insulin concentration (BIC), makes the above equations nonlinear. The corresponding dynamic mass balance for insulin is defined as:

$$\begin{aligned} C_I \frac{dI(t)}{dt} &= U_I(t) - \alpha I(t), && G(t) \le \varphi \\ C_I \frac{dI(t)}{dt} &= U_I(t) - \alpha I(t) + \beta(G(t) - \varphi), && G(t) > \varphi \end{aligned} \tag{2}$$

Parameters and coefficients of the model are taken from [7, 11, 14]. It should be emphasized that the coefficients and parameters are related to physiology. In this model, the total volume of plasma and interstitial fluid was given in a single compartment (15 L, in a healthy adult). Steady-state concentrations of the BGC and the BIC in this compartment were 0.81 mg/mL and 0.055 mU/mL, respectively. As mentioned before, for patients with T1DM, the main problem is the inadequacy of beta cells to produce the necessary amount of insulin. In the model, this situation was performed by reducing the sensitivity of insulin response to glucose. From this modelling for patients with T1DM, glucose and insulin concentrations were obtained as 1.28 mg/mL and 0.029 mU/mL in the steady state, respectively [7].

2.1. Open-loop simulation of the model

An open-loop simulations of the Stolwijk-Hardy model (i.e. without exogenous insulin infusion $U_I(t)$), given by the aforementioned equations, are conducted in MATLAB/SIMULINK (The MathWorks, Inc.). Simulations are performed for 24 hours (from 06.00 am to 06.00 am). In the model, exogenous glucose infusion $U_G(t)$ is considered as daily three meals: A meal of 40 g glucose at 07.00 am. for breakfast, a meal of 60 g glucose at 12.00 for lunch, a meal of 60 g glucose at 17.00 pm. for dinner. Simulation studies are evaluated for the healthy person and the virtual diabetic patient (a patient with T1DM). The BGC and the BIC profiles are shown in Fig. 2 and Fig. 3, respectively.

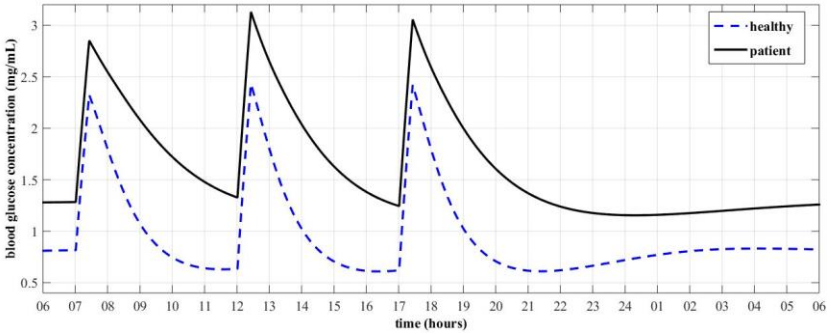

Fig. 2: Blood glucose concentration signals of the model (open-loop).

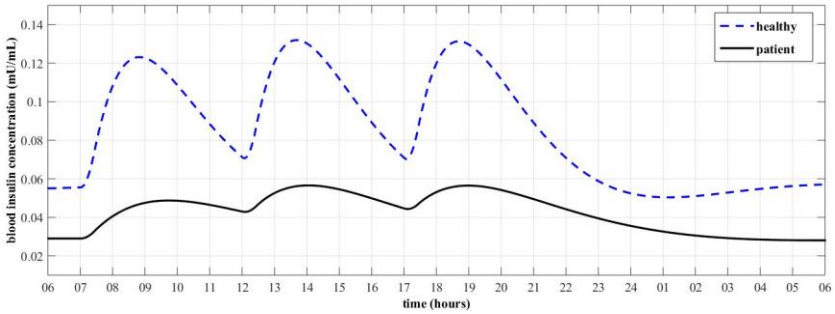

Fig. 3: Blood insulin concentration signals of the model (open-loop).

In Fig. 2, the abrupt rises in the BGC with $U_G(t)$ are considered as food intakes. After a certain time from the meals, they settle down to the steady-state values determined by the model. Furthermore, the secreted level of insulin changes according to the BGC and it is shown in Fig. 3.

3. Design of Proposed Control Methods

The modified model, with the addition of the exogenous insulin infusion term $U_I(t)$, can be thought of as a dynamic system that includes two-inputs ($U_I(t)$ and $U_G(t)$) and two-outputs ($G(t)$ and $I(t)$). For the patient with T1DM, the BGC can be regulated by $U_I(t)$. In this context, we proposed three different closed-loop control techniques. These control techniques are based on a traditional PID controller. The transfer function of a PID controller is as follows:

$$G(s) = Kp + Ki\frac{1}{s} + Kd \cdot s \tag{3}$$

Three parameters (proportional gain, Kp; integral gain, Ki; derivative gain, Kd) affect the robustness of the controller via certain specifications. Some of these specifications are rise time, settling time, overshoot, stability, and steady-state error. The individual effects of the parameters on these specifications are presented in [15].

To implement a PID controller, three parameters (Kp, Ki, Kd) must be determined carefully. For this purpose, efficient tuning methods based on GA, PSO algorithm, and ABC algorithm are proposed to achieve controller tuning in order to

regulate the BGC of the virtual diabetic patient. The block diagram of the proposed GA-PID, PSO-PID, and ABC-PID control techniques is shown schematically in Fig. 4.

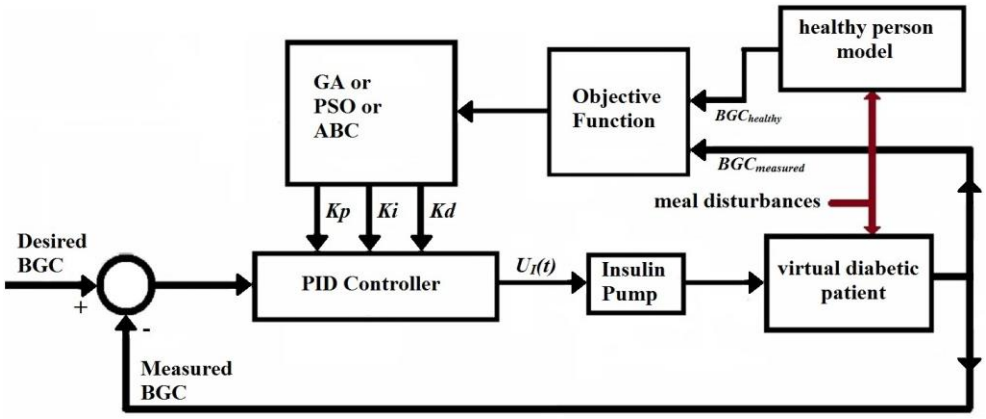

Fig. 4: Block Diagram of GA-PID, PSO-PID, and ABC-PID controllers.

3.1. Brief explanation of optimization algorithms

3.1.1 Genetic Algorithm (GA)

Basic principles of GA were first conceived by Holland [16]. The technique was inspired by the concepts of natural selection and genetics. GA uses stochastic transition rules instead of deterministic rules, and handle a population of potential solutions known as chromosomes that evolve iteratively. Each iteration of the algorithm is known as a generation. An objective function and genetic operators such as selection, crossover, and mutation function perform effectively to simulate the evolution of a solution. The selection operator is used to copy the large number of most fit solutions into the next generations. Thus, an increase in quality for better solutions is ensured. The crossover operator is the second operator that mimics mating in populations. It provides an opportunity for the chromosomes to mix and match their most favourable qualities in forming offspring. Diversity in the population characteristics is provided by the mutation operator. The mutation operator prevents the algorithm from getting trapped in local minima and paves the way for global search. A detailed description of the GA can be found in [17]. In order to apply the GA for tuning PID parameters (*Kp*, *Ki*, *Kd*) values given in Table 1 are used in this study.

3.1.2 Particle Swarm Optimization (PSO) Algorithm

PSO, first introduced by Kennedy and Eberhart [18], is a modern heuristic algorithm that inspired by behaviours in nature such as bird flocking and fish schooling. Unlike the GA, the PSO has no evolution operators such as crossover and mutation. The PSO is less prone to getting trapped in local minima and has good computational efficiency [19]. The PSO starts with an initial population of randomly generated solutions called particles which fly through the search space. The particles correspond to the chromosomes in the GA. Each particle, which has a position and a velocity, serves as a candidate solution to the problem. The best previous position is kept and called Pbest (*Pb*). The best particle among all particles in the population is the overall best value, and its position is called Gbest (*Gb*). The position and the velocity of each particle are updated according to Eqs. (4) - (5).

$$V_i^{(k+1)} = w_i \cdot V_i^{(k)} + c_1 \cdot r_1 \cdot (P_b - X_i^{(k)}) + c_2 \cdot r_2 \cdot (G_b - X_i^{(k)}) \quad (4)$$

$$X_i^{(k+1)} = X_i^{(k)} + V_i^{(k+1)} \quad (5)$$

where $X_i^{(k)}$ is the *k*th position of the particle i; $V_i^{(k)}$ is the *k*th velocity of the particle *i*; c_1 and c_2 are cognitive and social constant; r_1 and r_2 are uniformly distributed random numbers in [0 1], and *w* is the inertia weight. The inertia weight is used to achieve a balance in the exploration and exploitation of the search space. In this paper, linearly decreasing inertia weight (LDIW) [20] is used. The LDIW demonstrates its superiority in the computational complexity, success rate, and solution quality as follows:

$$w_i = w_{\min} + \frac{iter_{\max} - iter}{iter_{\max}} \cdot (w_{\max} - w_{\min}) \quad (6)$$

where w_i is the inertia weight of i. iteration, $iter_{max}$ is the maximum number of iterations, and $iter$ is the i. iteration. The PSO parameter values used in this paper are given in Table 1.

3.1.3 Artificial Bee Colony (ABC) Algorithm

ABC algorithm, which was inspired by the foraging behaviour of honeybees, is a global optimization algorithm that was developed by Karaboga in 2005 [21, 22]. Forager bees work collaboratively to gather a greater amount of nectar into the hive. This operation is performed intrinsically without a central control mechanism. Further information and detailed behaviour of real bees can be found in [21].

Each solution is the position of the food source in ABC algorithm. The honeybees in the colony are categorized into three groups: employed bees, onlooker bees and scout bees. This categorization is determined according to how they select the food source to utilize. Half of the colony contains employed bees and the other half is made up of the onlooker bees. The number of employed bees or onlooker bees is equal to the number of solutions in the population. Employed bees exploit the nectar sources already explored and provide information to the onlooker bees about the quality of the food source site they are exploiting. Onlooker bees don't have any source region in their memory and select probably profitable food source regions. Information about the profitability of the sources is gathered from the experiences of the employed bees. Scout bees perform the job of exploration in order to find a new food source [22]. In order to obtain PID parameters (Kp, Ki, Kd) using ABC algorithm, the values given in Table 1 are used in this paper.

Table 1: Parameter values of GA, PSO, and ABC.

GA		PSO		ABC	
Parameters	Method / Value	Parameters	Value	Parameters	Value
Generation Size	30	Maximum İteration	30	Maximum Cycle	30
Population Size	1000	Size of the swarm	1000	Size of the colony	1000
Bounds	[0 – 5]	Bounds	[0 – 5]	Bounds	[0 – 5]
Mutation	Uniform / 0.01	Cognitive parameter c_1	2	Limit	1500
Crossover	Heuristic / 0.8	Social parameter c_2	2	-	-
Selection Method	Roulette Wheel	Inertia weight [$w_{max} – w_{min}$]	[0.9 – 0.4]	-	-

3.2. Choosing of an objective function

While designing the closed-loop controller for blood glucose control, we assume that difference between the BGC of the healthy person and the BGC of the virtual diabetic patient as an error. Our main purpose is to minimize the error and to mimic the glucose-insulin dynamics in healthy person. Several performance criteria can be used as an objective function for the time domain optimization of PID controllers using heuristic algorithms. In this paper, mean absolute percentage error (MAPE) is chosen as an objective function for the optimization algorithms. The main purpose is to minimize the MAPE as in [12, 13, 23]:

$$MAPE = \frac{1}{n} \sum_{t=0}^{n} \left| \frac{BGC_{healthy} - BGC_{measured}}{BGC_{healthy}} \right| \quad (7)$$

where n is the duration of simulation, $BGC_{healthy}$ is the BGC of the healthy person and $BGC_{measured}$ represents the BGC of the virtual diabetic patient.

4. Simulation Results

In order to demonstrate the performance of the proposed controllers, MATLAB software is utilized. In a similar manner to open-loop simulations, simulations of closed-loop control studies are performed for 1440 min (24 h) which contain daily three meals. The BGC and the BIC profiles of the healthy person, the virtual diabetic patient, GA-PID, PSO-PID, and ABC-PID controllers are shown in Figs. 5 - 6, respectively.

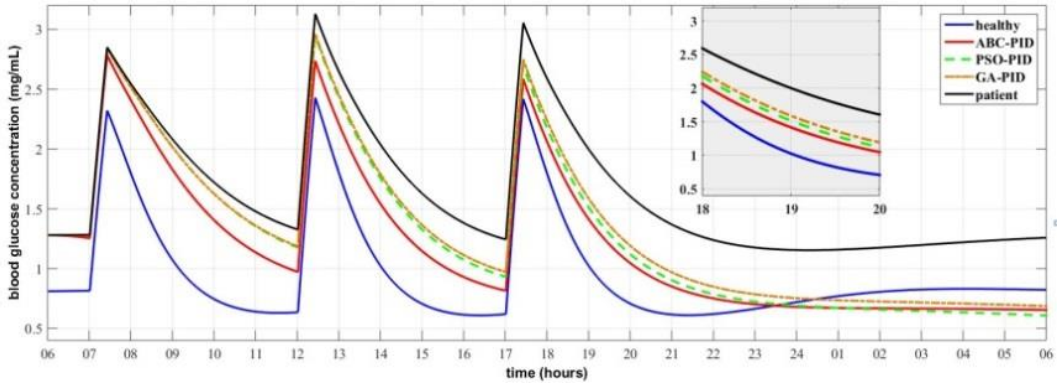

Fig. 5: Comparison of the BGC profiles.

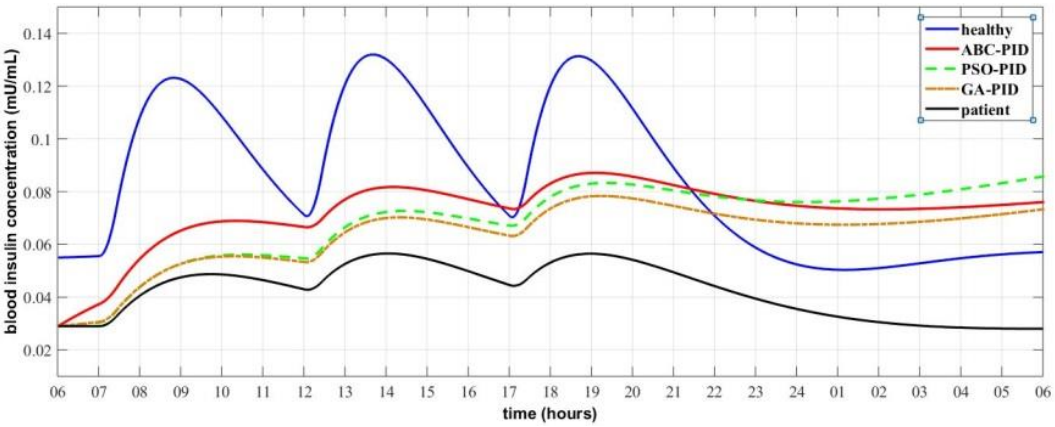

Fig. 6: Comparison of the BIC profiles.

In the light of simulations, comparisons of the performance criteria are presented in Table 2. Moreover, obtained minimum and maximum BGC levels from simulations are given in Table 3.

Table 2: Comparison of performance criteria of the proposed controllers.

	GA-PID	PSO-PID	ABC-PID
MAPE	0.5575%	0.4844%	0.4725%
MAPE (with sensor noise)	0.6235%	0.5326%	0.5207%

As can be clearly seen in Table 3 and Fig. 5, the minimum BGC levels of the proposed controllers are higher than the minimum BGC level of the healthy person. From this point of view, no hypoglycaemic event occurred during simulations. To show the differences of the BGC profiles clearly, an enlarged image of a two hour (from 18.00 pm to 20.00 pm) simulation period is also given in Fig. 5.

As shown in Table 2, the ABC-PID controller has the minimum fitness function value among the proposed controllers. It can be claimed that the ABC-PID controller gives more effective results than the other proposed controllers in terms of regulation the BGC the virtual diabetic patient. Through the implementation of the ABC-PID controller, BGC of the virtual diabetic patient better converges to the BGC profile of the healthy person.

Table 3: Obtained minimum and maximum BGC levels through simulations.

	minimum BGC (mg/mL)	maximum BGC (mg/mL)
Healthy person	0.6194	2.4303
Patient	1.1546	3.1302
GA-PID	0.6873	2.9648
PSO-PID	0.6284	2.9501
ABC-PID	0.6551	2.7834

4.1. Sensor Noise

In this case, the effect of measurement noise is considered. A white Gaussian noise with mean equal to 0 and variance equal to 0.3 is assumed. Comparison of the performance criteria in the presence of sensor noise are also presented in Table 2.

As pointed out in Table 2, the ABC-PID controller has the minimum fitness value among the proposed controllers against measurement of sensor. Thus, the ABC-PID controller gives highly effective results in dealing with sensor noise. More importantly, these results are promising in terms of practical applications such as an insulin pump by means of the efficacious performance of the ABC-PID control technique. It should be noted that, choosing the proper insulin pump is crucial with regards to the usage of such controllers for real-life applications.

Simulation results of the ABC-PID controller that consist of all situations (three meal intake and sensor noise) are then given together in Fig. 7.

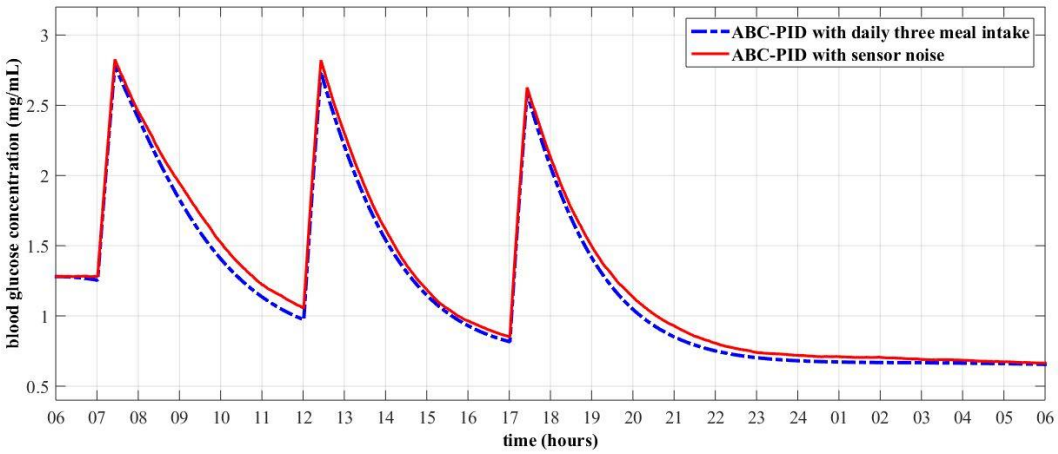

Fig. 7: BGC profiles of the ABC-PID controller against all situations.

5. Conclusion

In this study, we consider a virtual diabetic patient (a patient with T1DM) for regulating the BGC. For this purpose, PID based control techniques such as GA-PID, PSO-PID, and ABC-PID controllers are proposed. These controllers are implemented on the virtual diabetic patient generated from the modified Stolwijk-Hardy glucose-insulin dynamic model of a patient with T1DM and compared to a healthy person. Through 24 hour simulations, the proposed controllers are tested against daily food intake of three meals. To compare the performance of the proposed controllers, MAPE is used.

Simulation results show that heuristic algorithms give better results in terms of regulating the BGC. The ABC-PID controller is more successful within the proposed controllers. The ABC-PID controller deals with difficulties such as meal disturbances and sensor error effectively. Moreover, hypoglycaemia, which is one of the major challenges for the AP, did not occur throughout simulation studies. It should be emphasized that the ABC-PID control technique used in this study is adapted to the considered problem for the first time in the literature.

References

[1] C. Cobelli, et al., "Diabetes: models, signals, and control," *IEEE Rev. Biomed. Eng.*, vol. 2, pp. 54-96, 2009.

[2] F. Aguiree, et al., *IDF Diabetes Atlas: sixth edition.* Switzerland: International Diabetes Federation, 2013.

[3] T. Koschinsky, et al., "Parameters affecting postprandial blood glucose: Effects of blood glucose measurement errors," *J Diabetes Sci. Technol.*, vol. 2, no. 1, pp. 58-66, 2008.

[4] R. N. Bergman, et al., "Quantitative estimation of insulin sensitivity," *Amer. J. Physiol. Endocrinol. Metab.*, vol. 236, no. 6, pp. E667-E677, 1979.

[5] R. Hovorka, et al., "Nonlinear model predictive control of glucose concentration in subjects with type 1 diabetes," *Physiological Measurement*, vol. 25, no. 4, pp. 905-920, 2004.

[6] C. Dalla Man, et al., "Meal simulation model of the glucose-insulin system," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 10, pp. 1740-1749, 2007.

[7] M. Khoo, *Physiological Control Systems; Analysis, Simulation, and Estimation*. New York: IEEE Press, 2000.

[8] G. Marchetti, et al., "An improved PID switching control strategy for type 1 diabetes," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 3, pp. 857-865, 2008.

[9] L. Magni, et al., "Model predictive control of type 1 diabetes: an in silico trial," *J Diabetes Sci. Technol.*, vol. 1, no. 6, pp. 804-812, 2007.

[10] E. Atlas, et al., "MD-Logic Artificial Pancreas System A pilot study in adults with type 1 diabetes," *Diabetes Care*, vol. 33, no. 5, pp. 1072-1076, 2010.

[11] S. Soylu, et al., "Closed-loop control of blood glucose level in type-1 diabetics: A simulation study," in *Proc. IEEE 8th Int. Conf. on Elect. and Electron. Eng. (ELECO)*, Bursa, TURKEY, 2013, pp. 371-375.

[12] M. H. Khooban, et al., "Swarm optimization tuned Mamdani fuzzy controller for diabetes delayed model," *Turk. J. Elect. Eng. & Comput. Sci.*, vol. 21, pp. 2110-2126, 2013.

[13] M. Al-Fandi, et al., "Optimal PID-Fuzzy Logic Controller for type 1 diabetic patients," in *Proc. IEEE 8th Int. Symp. on Mechatron. and its Applicat. (ISMA)*, Sharjah, UAE, 2012, pp. 1-7.

[14] N. W. Chbat and T. K. Roy, "Glycemic Control in Critically Ill Patients Effect of Delay in Insulin Administration," in *Proc. IEEE 27th Annu. Conf. of Eng. in Med. and Biol.Society (EMBS)*, Shangai, CHINA, 2005, pp. 2506-2510.

[15] K. H. Ang, et al., "PID control system analysis, design, and technology," *IEEE Trans. Control Syst. Technol.*, vol. 13, no. 4, pp. 559-576, 2005.

[16] J. H. Holland, "Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence," Cambridge, MA, USA: MIT Press, 1992.

[17] K.F. Man, et al, "Genetic algorithms: concepts and applications," *IEEE Trans. Ind. Electron.*, vol. 43, no. 5, pp. 519-534, 1996.

[18] R. Eberhart and J. Kennedy, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Netw.*, Perth, WA, 1995, pp. 1942-1948.

[19] S. Bouallègue, et al., "PID-type fuzzy logic controller tuning based on particle swarm optimization," *Eng. Applicat. of Artificial Intell.*, vol. 25, no. 3, pp. 484-493, 2012.

[20] A. Ratnaweera, et al., "Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients," *IEEE Trans. Evol. Comput.*, vol. 8, no. 3, pp. 240-255, 2004.

[21] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Computer Engineering Department, Engineering Faculty, Erciyes University, Kayseri, Tech. Rep. TR06, 2005.

[22] D. Karaboga, "Artificial bee colony algorithm," *Scholarpedia*, vol. 5, no. 3, pp. 6915, 2010.

[23] M. Al-Fandi, et al., "Optimal PI-fuzzy logic controller of glucose concentration using genetic algorithm," *Int J Knowledge-based and Intelligent Eng. Syst.*, vol. 15, no. 2, pp. 99-117, 2011.