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Chattering-free hybrid adaptive neuro-fuzzy inference system-particle swarm optimisation data fusion-based BG-level control

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Abstract: In this study, a closed-loop control scheme is proposed for the glucose–insulin regulatory system in type-1 diabetic mellitus (T1DM) patients. Some innovative hybrid glucose–insulin regulators have combined artificial intelligence such as fuzzy logic and genetic algorithm with well known Palumbo model to regulate the blood glucose (BG) level in T1DM patients. However, most of these approaches have focused on the glucose reference tracking, and the qualitative of this tracking such as chattering reduction of insulin injection has not been well-studied. Higher-order sliding mode (HoSM) controllers have been employed to attenuate the effect of chattering. Owing to the delayed nature and non-linear property of glucose–insulin mechanism as well as various unmeasurable disturbances, even the HoSM methods are partly successful. In this study, data fusion of adaptive neuro-fuzzy inference systems optimised by particle swarm optimisation has been presented. The excellent performance of the proposed hybrid controller, i.e. desired BG-level tracking and chattering reduction in the presence of daily glucose-level disturbances is verified.

1 Introduction

The two main types of diabetes include type 1 and type 2. In type-1 diabetes (T1D), destruction of beta cells, in the pancreas leads to defects in insulin production, whereas in type-2 diabetes, the progressive body resistance to insulin may eventually lead to full defects in insulin production. The field of glucose regulation in patients with T1D is divided into three main categories: (i) diabetic diagnosis and glucose monitoring, (ii) insulin–glucose modelling and (iii) insulin–glucose control.

Continuous glucose monitoring has been demonstrated in randomised trials to improve glucose control in patients with T1D [1–4]. In the last four decades, mathematical models have become of great importance in the context of diabetes treatment planning. Some of the most important useful models that have been proposed for glucose–insulin regulatory system include the Bergman minimal model (BMM) presented in [5], the Sorensen model in [6], the Kuang model in [7], the Dalaman model in [8, 9] and the Liu–Tang model [10]. A novel blind identification approach has been introduced to model T1D patients and to effectively recover the unmeasured input signals such as food, physical activity and emotions [11]. During the last decade, more attention has been to delay differential equation (DDE) because of their compliance with diagnostic testing of patients [12, 13]. The advantage of the DDE model is that the delay of insulin effects is considered as the time interval between blood glucose (BG)-level rise and insulin injection time.

Many studies have shown that the artificial pancreas systems can control BG concentrations (BGCs) in T1D patients [14–16]. Glucagon is the natural secretory product of pancreatic alpha cells in the body and is normally released in response to hypoglycaemia. Some papers have addressed the issue of avoiding hypoglycaemic events by incorporating a second pump that delivers glucagon [17–19]. A new control strategy has been proposed based on individualised optimal insulin delivery that consists of a patient-specific model predictive controller, a state estimator, a personalised scheduling level and an open-loop optimisation problem [20]. A multiple model probabilistic predictive controller has been assessed on T1D patients that do not require meal announcement [21].

By modifying the pancreatic insulin secretion based on the Liu–Tang model, the model could be transformed to describe type-1 diabetic mellitus (T1DM) [22]. Then, using adaptive neuro-fuzzy inference system (ANFIS) which combines the artificial neural network (NN) adaptive approach and the fuzzy logic qualitative features, the BG system will be regulated for a normal T1D patient. Also, the FIS structure was constructed using subtractive clustering approach [22]. Classical and traditional ANFIS-based methodologies have some intrinsic problems that in the presence of input disturbances such as food intake and physical activity often yield chattering.

In [23], by switching on Bergman model (BM) and setting appropriate parameters and overshoot time, the suggested proportional–integral–derivative (PID) controller will be able to reach the BG levels into a reference level. Controllers based on induced $L2$-norm minimisation of glucose–insulin system [24], improved PID [25], fuzzy logic [26] and H_∞ robust control approach [27] have been studied and tested in clinical trials. However, most of the previously mentioned studies have focused on error reduction of the glucose reference tracking, and the qualitative of this tracking in T1D patients such as chattering reduction has not been well-studied.

Palumbo *et al.* [28] have proposed one of the complete control methods in the field of glucose–insulin regulatory system based on feedback linearisation. This method is based on locus location of the desired closed-loop poles and needs to be the trial and error experiment. To overcome this drawback, a hybrid approach of the fuzzy logic controller and the genetic algorithm (GA) as an optimisation tool called hybrid method was proposed to control the BG level in T1DM patients [29]. To date, only a few studies have investigated the chattering phenomena of real-time insulin infusion and its complications. Higher-order sliding mode (HoSM) control techniques such as super-twisting algorithm were used to eliminate the effect of chattering and obtain continuous control [30–34]. These controllers were generally based on BM, which is not counted as a DDE model and has less compliance with diagnostic testing of a diabetic patient. Another primary drawback to almost all traditional insulin–glucose regulatory approaches is that they are not able to recover or to systematically account for the various disturbances that affect T1D patients. These various unmeasured disturbances such as food, physical activity, emotions and actuator errors are main sources of the glucose fluctuating and cause the chattering phenomena in the insulin infusion rate.

Recently, an adaptive fractional-order sliding mode control (AFOSMC) has been designed for BG regulation based on BM in the presence of the external disturbances such as food intake, critical initial condition, parameters uncertainties and sensor noises [34]. Although the simulation results have shown that the AFOSMC has a good BG tracking in appropriate time, but insulin injections suffer from some fluctuating behaviours [34].

In this paper, a data fusion of ANFISs optimised by particle swarm optimisation (PSO) has been suggested to overcome these drawbacks. The rest of this paper is organised as follows. A well known mathematical model for glucose–insulin regulatory system is reviewed in Section 2. In Section 3, a brief description of Palumbo non-linear control is presented. Sections 4 and 5 describe the hybrid control method and a typical HoSM controller, respectively. In Section 6, the proposed chattering-free hybrid ANFIS-PSO (HANFIS-PSO) data fusion methodology is explained. Simulation of glucose–insulin system is presented in Section 7. Finally, the conclusions of this paper are discussed in Section 8.

2 Methods

2.1 DDE mathematical model of diabetic patient

Nowadays, the insulin therapy is based on discrete BG measurements and either multiple daily insulin injections or an implementation of a continuous subcutaneous insulin injection pump for T1D patients [35]. The delayed non-linear model for glucose–insulin regulatory system is considered as follows [12]:

$$\dot{G}(t) = -K_{xgi}I(t)G(t) + \frac{T_{\mathrm{gh}}}{V_{\mathrm{g}}} \tag{1}$$

$$\dot{I}(t) = -K_{xi}I(t) + \frac{T_{ig\max}}{V_i}f\big(G(t-\tau_{\mathrm{g}})\big) + u(t) + d_{\mathrm{I}}(t) \tag{2}$$

$$f(G) = \frac{(G/G^*)^{\gamma}}{1+(G/G^*)^{\gamma}} \tag{3}$$

where the delayed pancreatic insulin delivery rate is modelled as the non-linear function $f(G)$. Here, $u(t)$ and $d_{\mathrm{I}}(t)$ are considered as a control input and an unavoidable actuator disturbance, respectively. The purpose of the proposed control law is the reduction of plasma glucose concentration above the normal level and keeps this value at the normal level. That is possible through intravenous insulin infusion. Palumbo delayed non-linear model parameters are described as follows [12]:

- $G(t)$, mM is the plasma glucose.
- $I(t)$, pM is the plasma insulin.
- K_{xgi}, $\mathrm{min}^{-1}\,\mathrm{pM}^{-1}$ denotes the degree of insulin resistance as a linear function of the plasma glycaemia.
- V_{g}, L/kg BW is the apparent glucose distribution volume.
- T_{gh}, min^{-1} (mmol/kg BW) denotes the net balance between hepatic glucose output and insulin-independent zero-order glucose tissue uptake.
- K_{xi}, min^{-1} is the apparent first-order disappearance rate constant for insulin.
- $T_{ig\max}$, min^{-1} (pmol/kg BW) is the maximal rate of second-phase insulin release.
- V_i, L/kg BW is the apparent insulin distribution rate for insulin.
- τ_{g}, min is the delay with which the pancreas varies secondary insulin release in response to increased plasma glucose concentrations.
- G^*, mM corresponds to the glycaemia at which the insulin rate is half of its maximal volume.
- γ, denotes the progressivity with which the pancreas reacts to circulating glucose concentrations.

As mentioned before $d_{\mathrm{I}}(t)$ in (2) denotes the actuator error. This disturbance is assumed measurable and generally considered as a sinusoidal variable [12]

$$d_{\mathrm{I}}(t) = a_{\mathrm{I}}\sin(w_{\mathrm{I}}t), \quad t > 0 \tag{4}$$

To consider the glucose disturbances such as meal intake at $t = t_{\mathrm{m}}$, another disturbance term $d_{\mathrm{G}}(t)$ is considered in (1) as below:

$$\dot{G}(t) = -K_{xgi}I(t)G(t) + \frac{T_{\mathrm{gh}}}{V_{\mathrm{g}}} + d_{\mathrm{G}}(t) \tag{5}$$

This disturbance is generally modelled by a decaying exponential function [30]

$$d_{\mathrm{G}}(t) = \alpha\exp(-\beta(t-t_{\mathrm{m}})), \quad t > t_{\mathrm{m}} \tag{6}$$

This model does not consider other unmeasured input signals such as physical activities and emotions, which is a common relevant problem to the traditional controllers based on DDE models. In the diabetes context, an important problem is about the not easily measurable inputs, while the conventional glucose–insulin control techniques do not consider or be able to handle such disturbances [33, 34]. In our proposed approach, to show the complete dynamics of the glucose–insulin regulatory system, the $d_{\mathrm{G}}(t)$ is considered as below:

$$\begin{aligned} d_{\mathrm{G}}(t) &= \alpha\exp(-\beta(t-t_{\mathrm{m}})) + a_{\mathrm{G}}\sin(w_{\mathrm{G}}t) \\ &\quad +\gamma\Pi\Big(\frac{t-t_0}{T}\Big) + \delta v(t) \end{aligned} \tag{7}$$

where the normal physical activity is defined by a sinusoidal function, the constant physical activity is considered as a rectangular function with duration T and $v(t)$ as a Gaussian white random process is considered for sensor noise.

2.2 Palumbo non-linear control method

$$u(t) = \frac{S\big(G(t),\, I(t),\, G(t-\tau_{\mathrm{g}})\big) - v(t)}{K_{xgi}G(t)} \tag{8}$$

$$\begin{aligned} &S\big(G(t),\, I(t),\, G(t-\tau_{\mathrm{g}})\big) \\ &\quad = -K_{xgi}I(t)\Big(-K_{xgi}I(t)G(t) + \frac{T_{\mathrm{gh}}}{V_{\mathrm{g}}}\Big) \\ &\qquad -K_{xgi}G(t)\Big(-K_{xi}I(t)\frac{T_{ig\max}}{V_i}f\big(G(t-\tau_{\mathrm{g}})\big)\Big) \end{aligned} \tag{9}$$

Palumbo *et al.*, after presenting the above-mentioned non-linear model of glucose–insulin, provided a glucose–insulin regulatory system based on feedback linearisation to eliminate the non-linear terms [13]. This control approach based on the feedback linearisation is as follows:

$$v(t) = \ddot{G}_{\mathrm{ref}}(t) + Ke(t) \tag{10}$$

$$e(t) = \begin{bmatrix} e_1(t) \\ e_2(t) \end{bmatrix} = Z(t) - Z_{\mathrm{ref}}(t) \tag{11}$$

$$Z(t) = \begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix} = \begin{bmatrix} G(t) \\ -K_{xgi}I(t)G(t) + \frac{T_{\mathrm{gh}}}{V_{\mathrm{g}}} \end{bmatrix} \tag{12}$$

$$Z_{\mathrm{ref}}(t) = \begin{bmatrix} G_{\mathrm{ref}}(t) & \dot{G}_{\mathrm{ref}}(t) \end{bmatrix}^{\mathrm{T}} \tag{13}$$

where $G_{\mathrm{ref}}(t)$ denotes the glucose reference level, and in (10), vector $\boldsymbol{K} \in R^{1*2}$ is determined in such a way that the matrix $\boldsymbol{H}$ in (14) has the eigenvalues located on the left-hand side of the imaginary axis

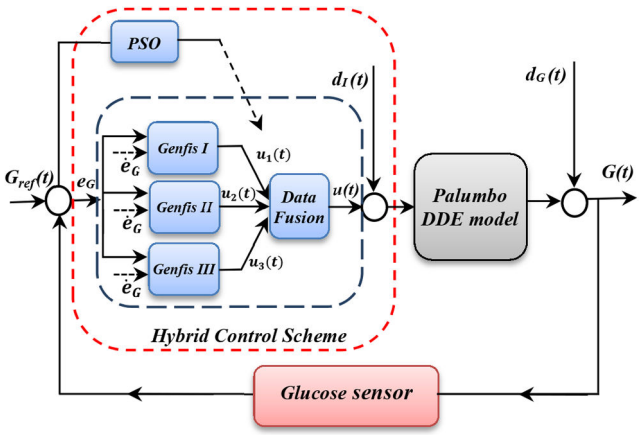

Fig. 1 *Block diagram of hybrid proposed ANFIS-PSO data fusion scheme*

$$\boldsymbol{H} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \boldsymbol{K} \tag{14}$$

This method is based on trial and error to find the desired location of closed-loop poles. To overcome this problem, a hybrid of the fuzzy logic controller and feedback linearisation has been suggested [29].

2.3 Hybrid method for glucose–insulin control [29]

The collection of sufficient, well-distributed and accurately measured input data of glucose–insulin regulatory mechanism is the basic requirement to obtain an accurate HANFIS-PSO model. Therefore, we use the hybrid controller provided in [29] as a complete control approach to obtain the input–output data set for our proposed HANFIS-PSO training. This input–output data set would be obtained from a complete methodology such as hybrid control system suggested in [29]. This hybrid approach regulates the BG level of the patient via an insulin injection by employing a feedback linearisation and fuzzy logic. To better stabilise BG to the reference level, a Mamdani type of the fuzzy logic controller is provided including two inputs and one output

$$e_{\mathrm{G}} = G(t) - G_{\mathrm{ref}}(t) \tag{15}$$

$$e_{\dot{\mathrm{G}}} = \dot{G}(t) - \dot{G}_{\mathrm{ref}}(t) \tag{16}$$

Fuzzy controller inputs include both the difference between the glucose level and its reference value $e_{\mathrm{G}} = G(t) - G_{\mathrm{ref}}(t)$ and rate of changes in this difference $e_{\dot{\mathrm{G}}} = \dot{G}(t) - \dot{G}_{\mathrm{ref}}(t)$ and the output of the fuzzy controller is defined as the insulin infusion rate $u(t)$ as follows.

Besides, the successful reference glucose tracking by using the hybrid method, the finite implemented membership functions related to fuzzy control produces chattering in insulin infusion rate. Therefore, such input control fluctuations must be strictly avoided in biological systems, which can cause damage to the patient body. To solve the contradiction between the reference glucose tracking and smooth insulin infusion rate, the HoSMCs were proposed [30–32].

2.4 HoSM control [30]

The tracking error is defined as the difference between the glucose value and the glucose reference value in T1D patient's blood as in (15). The controller $u(t)$ would be designed such that e_{G} goes to zero in the presence of all noises and disturbances. At first, the relative degree of the system for HoSM control must be calculated. For dynamic (1), a relative degree r means the first appearance of control $u(t)$ explicitly in the rth successive differentiation of tracking error e_{G}. Considering (1) without disturbances and noises, the control variable appears in the derivatives after the second differentiation, i.e.

$$\begin{aligned} \ddot{G}(t) = & -K_{xgi}\dot{I}(t)G(t) - K_{xgi}I(t)\dot{G}(t) \\ = & -K_{xgi}\left[-K_{xi}I(t) + \frac{T_{ig\max}}{V_i} f\big(G(t-\tau_{\mathrm{g}})\big) + u(t)\right]G(t) \\ & -K_{xgi}I(t)\dot{G}(t) \end{aligned} \tag{17}$$

The above equation could be considered as below:

$$\ddot{G}(t) = \varnothing(G,\, I,\, t) - K_{xgi}G(t)u(t) \tag{18}$$

where

$$\begin{aligned} \varnothing(G,\, I,\, t) = & K_{xgi}K_{xi}I(t)G(t) \\ & + \frac{T_{ig\max}}{V_i} f\big(G(t-\tau_{\mathrm{g}})\big)G(t) - K_{xgi}I(t)\dot{G}(t) \end{aligned} \tag{19}$$

On the basis of the relative degree $r = 2$ (the relative degree for BM is $r = 3$ [30]) the sliding surface s is defined as follows:

$$S = \left(\frac{\mathrm{d}}{\mathrm{d}t} + \lambda\right) e_{\mathrm{G}} \tag{20}$$

To ensure that the tracking error e_{G} converges to zero, the sliding variable and its derivatives must converge to zero. This condition means the remaining of sliding surface s. Here, λ is a positive constant, is defined by frequency bound of unmeasurable uncertainties. $\dot{s}$ can be calculated as follows:

$$\begin{aligned} \dot{S} = & \left[\ddot{G}(t) - \ddot{G}_{\mathrm{ref}}(t)\right] + \lambda\left[\dot{G}(t) - \dot{G}_{\mathrm{ref}}(t)\right] \\ = & -K_{xgi}\left[-K_{xi}I(t) + \frac{T_{ig\max}}{V_i} f\big(G(t-\tau_{\mathrm{g}})\big) + u(t)\right]G(t) \\ & -K_{xgi}I(t)\dot{G}(t) - \ddot{G}_{\mathrm{ref}}(t) + \lambda\left[\dot{G}(t) - \dot{G}_{\mathrm{ref}}(t)\right] \end{aligned} \tag{21}$$

By considering the input control $u(t)$ as below:

$$\begin{aligned} u(t) = & -\frac{T_{ig\max}}{V_i} f\big(G(t-\tau_{\mathrm{g}})\big) + K_{xi}I(t) \\ & + \frac{\left[-K_{xgi}I(t)\dot{G}(t) + \ddot{G}(t) + \lambda\big(\dot{G}(t) - \dot{G}_{\mathrm{ref}}(t)\big)\right]}{\big(K_{xgi}G(t)\big)} \end{aligned} \tag{22}$$

By substituting $u(t)$ in (21), it would be seen that $\dot{S} = 0$.

2.5 Proposed HANFIS-PSO data fusion scheme

An ANFIS generally refers to an adaptive artificial NN, which performs such as an FIS [36]. ANFIS uses a hybrid learning method to update parameters of Sugeno-type FIS. The HANFIS-PSO data fusion algorithm combines the advantages of the optimised FISs and artificial NN to identify NN unknown parameters. The flexibility and individuality of each FISs, when added to the optimisation solidity of adaptive networks, give the new scheme its significant power of modelling and control set (see Fig. 1).

The motivation of using the ANFIS is that it uses a hybrid learning method to update its inference system parameters. The ANFIS has the advantages of both NNs and FISs. Some of the ANFIS advantages are the ability to capture the non-linear structure of an unknown and complex process, adaptation capability in membership functions and rapid learning capacity of unknown parameters. Also, the PSO approach has the advantage of being less computationally expensive compared with other well known evolutionary algorithms such as GA, firefly algorithm and Grey Wolf optimisation.

The new proposed algorithm applies a combination of the intrinsic least-squares-back-propagation gradient descent methods and the evolutionary stochastic search approach of PSO to emulate a given training data. One of the advantages of the proposed HANFIS-PSO approach besides preventing the chattering phenomena from the insulin infusion rate is the robustness control

against the uncertainty and disturbance. The overall operation of the HANFIS-PSO data fusion algorithm is illustrated by three stages, according to Fig. 1.

2.5.1 Hybrid FISs (first stage): *Genfis1:* This kind of FIS generates a single-output Sugeno-type fuzzy system using a grid partition on the data. In almost all optimisation algorithms, there are some alignment parameters, which significantly degraded its performance. Genfis1 uses a number of membership functions for each input based on equal grid partitioning method. The important alignment parameter for this kind of FIS is the number of membership functions (m_i) for each input. Here, $\boldsymbol{m} \in R^{1*_2}$ is a vector whose coordinates specify the number of membership functions associated with e_G and $e_{\dot{G}}$ inputs.

Genfis2: Genfis2 is based on an FIS structure using subtractive clustering approach, where a set of rules is extracted that models the input–output data set behaviour. The subtractive clustering method was first introduced in the field of extracting fuzzy rules [37]. The subtractive clustering method considers each data point as a potential cluster centre and defines a measure of the potential of a data point x_i to serve as a cluster centre as

$$P_i = \sum_{j=1}^{N} \exp\left[(x_i - x_j)^2 / f_i^2\right] \tag{23}$$

where for N data points f_i is a positive constant defined as the range of influence. The potential of data point is a function of its distance to all other data points. Thus, a high potential data sample would be data with many neighbouring data samples. By selecting the range of influence, the data points with the highest potential are determined so that the feature space is covered. Therefore, the alignment parameter for Genfis2 is the range of influence (f_i) in each of the data dimensions. So the $\boldsymbol{f}_i \in R^{1*3}$ is a vector which specifies the ranges of influence in the first, second and third data dimensions [i.e. e_G, $e_{\dot{G}}$ and the insulin infusion rate $u(t)$].

Genfis3: Genfis3 generates an FIS structure using fuzzy C-means clustering algorithm by producing a set of rules that models the data set behaviour. Alignment parameter for Genfis3 is the number of clusters ($c_i \in R^{1*1}$). The number of clusters determines the number of rules and membership functions in the generated FIS.

2.5.2 Data fusion of FIS outputs (second stage): As shown in Fig. 1, the outputs of these three FISs would be combined by a data fusion method. Data fusion approach is used to find a proper amount of altered information, which may be arisen from different viewpoints to glucose regulatory in the presence of disturbances [38]. By fusion of these types of information, besides optimisation of above-mentioned FISs parameters, results with proper improvement and high stability could be achieved. There are several methodologies in the field of data fusion. The most common methods of data fusion, which are called the weighted mean method, is used in this paper. In this methodology, the final estimation value in a specified sample time is determined from weighted averaging of the extracted data in that sample time

$$u(t) = \frac{1}{\mu_1 + \mu_2 + \mu_3} \sum_{i=1}^{3} \mu_i u_i(t) \tag{24}$$

where $u_i(t)$ denotes the output of the ith Genfis and $\boldsymbol{\mu} \in R^{1*3}$ is determined by PSO.

2.5.3 PSO (third stage): PSO is a stochastic, metaheuristic evolutionary method, which is inspired by the social behaviour of bird flocking and is originally attributed to Eberhart and Kennedy [39]. A PSO algorithm maintains a swarm of individuals, where each particle represents a candidate solution. Particles follow a simple behaviour based on both the success of neighbouring particles and their own achieved success. The PSO approach has the advantage of being less computationally expensive compared with other well known evolutionary algorithms such as GA. Particle position x_i^k is updated as below:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{25}$$

where indices i and k show the ith particle at the kth sample time. The PSO concept consists of changing the velocity of each particle toward its personal best position (pbest) and global best position (gbest), at each sample time. Velocity is weighted by the separate random terms rand_p, $\text{rand}_g \in U(0, 1)$. So the velocity update relation is calculated by

$$\begin{aligned} V_i^{k+1} = C_0 V_i^k + C_1 \text{rand}_p^k\left(\text{pbest}_i^k - x_i^k\right) \\ + C_2 \text{rand}_g^k\left(\text{gbest}_i^k - x_i^k\right) \end{aligned} \tag{26}$$

where C_0 is an inertia weight and C_1, C_2 are the positive velocity constants. In this paper, hybrid FISs and data fusion scheme employ PSO algorithm to adjust the previously mentioned parameters. Therefore, the ith particle position vector would be optimised by PSO defined as below:

$$\boldsymbol{x}_i = \begin{bmatrix} m_1 & m_2 & f_1 & f_2 & f_3 & c_1 & \mu_1 & \mu_2 & \mu_3 \end{bmatrix} \in R^{1*9} \tag{27}$$

Different types of fitness functions could be used for validation of particles. In this paper, the mean square error (MSE) and mean absolute error (MAE) are used for glucose reference tracking defined as

$$\begin{aligned} \text{MSE}(\boldsymbol{E}_G) &= [\boldsymbol{E}_G - \overline{\boldsymbol{E}_G}]^T [\boldsymbol{E}_G - \overline{\boldsymbol{E}_G}] \\ \text{MAE}(\boldsymbol{E}_G) &= \text{sum}[\boldsymbol{E}_G - \overline{\boldsymbol{E}_G}]/N \end{aligned} \tag{28}$$

where $E_G = [e_{G1}\ e_{G2} \ldots e_{GN}]^T$ is the glucose reference tracking error for N data points and $e_{Gk} = G(t) - G_{\text{ref}}(t)$, $t = kT$, $T = 2$ min means the kth glucose reference error and $sum[E_G - \overline{E_G}] = \sum_{i=1}^{N} |e_{Gi} - \bar{e}_{Gi}|$. Also, another important criterion for the glucose–insulin controller is the amount of insulin infusion rate well known as the control effort. Therefore, the control effort can be defined as follows:

$$\begin{aligned} MSE(\boldsymbol{U}) &= [\boldsymbol{U} - \bar{\boldsymbol{U}}]^T \left[\boldsymbol{U} - \bar{\boldsymbol{U}}\right] \\ MAE(\boldsymbol{U}) &= sum\left[\boldsymbol{U} - \bar{\boldsymbol{U}}\right]/N \end{aligned} \tag{29}$$

where $U = [u_1\ u_2 \ldots u_N]^T$ is the insulin infusion rate for N sample times. The best fitness function considers the glucose–insulin controller that balances between reference glucose tracking errors and insulin infusion rates is as follows:

$$\begin{aligned} \text{MSE(GU)} &= [\boldsymbol{E}_G - \overline{\boldsymbol{E}_G}]^T Q [\boldsymbol{E}_G - \overline{\boldsymbol{E}_G}] + \left[\boldsymbol{U} - \bar{\boldsymbol{U}}\right]^T R \left[\boldsymbol{U} - \bar{\boldsymbol{U}}\right] \\ \text{MAE(GU)} &= \text{sum}(Q[\boldsymbol{E}_G - \overline{\boldsymbol{E}_G}])/N + \text{sum}\left(R\left[\boldsymbol{U} - \bar{\boldsymbol{U}}\right]\right)/N \end{aligned} \tag{30}$$

where $\boldsymbol{Q}$ and $\boldsymbol{R}$ are weighted matrices.

3 Results

The numerical values of a T1D patient based on the Palumbo DDE model are used for simulations [12]. Besides, to train the proposed HANFIS-PSO data fusion controller, the input–output data set obtained by the hybrid controller (Section 2.3) is used [29].

The plasma glucose level $G(t)$ is directly measured, and then the plasma insulin $I(t)$ could be estimated. It must be noted that the simulation results are based on this assumption that plasma insulin value is estimated precisely, i.e. $\hat{I}(t) = I(t)$ and the dynamics of the insulin pump is neglected. Some parameters such as G^*, V_i, γ, V_g, K_{xi}, τ_g, K_{xgi}, T_{gh} and $T_{ig\max}$ are estimated or calculated according to patient steady-state relations [40–43].

Table 1 Numerical values of a T1D patient based on the Palumbo DDE model [12]

$G_b = 12.37$ mM	$I_b = 93.669$ pM
$K_{xgi} = 2.51 \times 10^{-5}$ min^{-1} pM^{-1}	$G^* = 9$ mM
$T_{gh} = 0.003$ min^{-1} (mmol/kg BW)	$\tau_g = 24$ min
$V_g = 0.187$ L/kg BW	$\gamma = 3.205$
$K_{xi} = 1.211 \times 10^{-2}$ min^{-1}	$V_i = 0.25$ L/kg BW
$T_{ig\max} = 0.242$ min^{-1} (pmol/kg BW)	BMI = 50

Table 2 Numerical values of insulin actuator and glucose disturbances [40, 47]

$a_I = 0.03$ pM	$w_I = 0.08$ rad/ min
$\beta = -0.02$ min^{-1}	$t_m = 160$ min
$w_G = 0.08$ rad/ min	$\gamma = -0.03$ mM
$T = 200$ min	$\delta = 0.012$ mM
$\alpha = 0.09$ mM	$a_G = 0.03$ mM
$t_0 = 350$ min	—

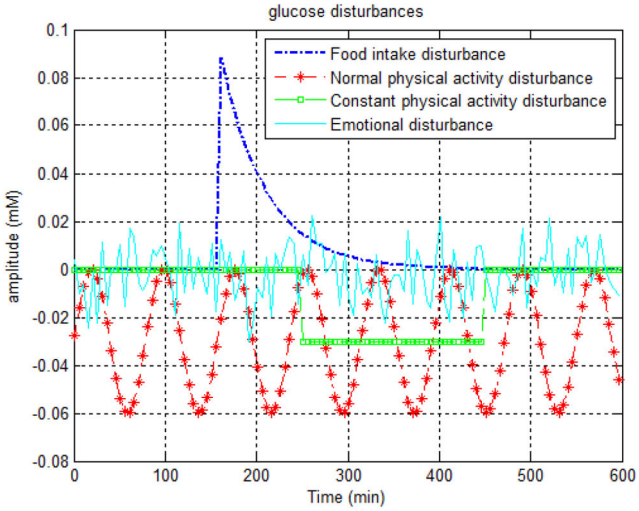

Fig. 2 *BG disturbances profile*

Table 3 Numerical values of the PSO alignment parameters

$n_{var} = 9$	$n_{iter} = 300$	$n_{pop} = 20$
$C_0 = 1$	$C_1 = 2$	$C_2 = 2$
$x_{min} = [3 \quad 3 \quad 0.1 \quad 0.001 \quad 1 \quad 3 \quad 0.1 \quad 0.1 \quad 0.1]$		
$x_{max} = [20 \quad 20 \quad 2 \quad 0.2 \quad 10 \quad 30 \quad 4 \quad 4 \quad 4]$		

To compare the proposed HANFIS-PSO method performance and the other glucose–insulin regulatory methodologies, the parameters of a typical T1DM patient are used in this paper as shown in Table 1. This selected T1DM patient has a body mass index (BMI) =50 and the base BG level is $G_b = G(0) = 12.37$ mM that indicates a higher BG level compared with the normal level. K_{xgi} is the rate of glucose uptake by insulin-dependent tissues per pM of plasma insulin concentration is $<10^{-4}$ that shows a sub-normal insulin delivery rate [44–46].

A single meal disturbance is provided and the initial BGC of T1DM patient is considered to be 12.37 mM at $t = 0$ min. The reference signal of plasma glucose has a decreasing exponentially profile from the value of 12.37 to the final value 4.7 as below:

$$G_{ref}(t) = 4.7 + (12.37 - 4.7) \times \exp(-0.01t) \tag{31}$$

The hypoglycaemia and hyperglycaemia were reduced in the presence of parametric variability and exogenous meal disturbance in [33]. The effects of sensor and actuator noises, critical initial condition, physical activity and emotions have been neglected in [33]. Control of BG level was investigated in the presence of food intake, critical initial condition, parameters uncertainties and sensor noise in [34]. The effects of physical activities such as exercise and emotional behaviour were not considered in [34]. Only meal disturbances, sensor and actuator noises were considered and try to be rejected in [45]; the effects of physical exercise by the patient was not considered.

In our proposed approach, a complete list of uncertainties such as food intake, physical exercise, emotion effects, critical initial condition, parameters uncertainties and sensor and actuator noises are considered. Table 2 shows the numerical values chosen for the insulin actuator and glucose disturbance parameters mentioned in (4) and (7).

Fig. 2 shows the glucose disturbances profile due to food intake, normal and constant physical activities and emotional disturbances. The numerical values of two variables e_G and e_G obtained by the hybrid controller [29] are used as the input data set and insulin injection rate $u(t)$ is considered as the output to train the HANFIS-PSO controller. The parameters associated with PSO algorithm are shown in Table 3.

Where n_{var}, n_{pop} and n_{iter} are the number of variables, the number of particles and the number of iterations, respectively. Also, x_{min} and x_{max} control the minimum and maximum permissible values of each particle through the algorithm. In total, 600 training sample data sets in 1200 epochs are taken to train the proposed HANFIS-PSO model.

In the following, there are some details about three different FISs used in the proposed hybrid scheme. After 300 iterations, the applied PSO found the globally best particle as below:

$$x_{gbest} = [7 \quad 7 \quad 0.5 \quad 0.005 \quad 4 \quad 20 \quad 0.79 \quad 2.12 \quad 2.89] \tag{32}$$

Therefore, seven membership functions determined as the optimal number of membership functions for each input of Genfis1 (i.e. $m = [7\ 7]$). Thus, 49 rules are generated to track glucose reference level. Here, $f_1 = 0.5$ and $f_2 = 0.005$ are found as the range of influence for the first and second input data sets, and $f_3 = 4$ was determined as the range of influence for the output data by PSO. Consequently, 25 membership functions were considered for each input by MATLAB software, and totally $25 \times 25 = 625$ rules are generated. The number of clusters determined by PSO is $c_1 = 20$; consequently, the number of rules generated by Genfis3 is 20. Finally, $\mu = [0.79\ 2.12\ 2.89]$ is determined as the optimal weighted coefficients for data fusion.

As illustrated in Fig. 3, without applying controller, the BG level remains in the range 12.37 mM while by using closed-loop controller the BG level gets closer to the normal or reference amount. Fig. 3*a* shows the stabilisation of the patient's BG level into the normal level by using HANFIS-PSO data fusion approach compared with fuzzy, fuzzy-genetic, Palumbo, hybrid and HoSM controllers. Fig. 3*b* illustrates the error obtained from the difference between patient's BG and normal glucose levels in the proposed approach compared with the other control methods. All of the insulin dosing control is based on a $T = 2$ min glucose sample time. The difference between the different controller performances is apparent on finer scale as shown in Fig. 4. The fuzzy controller approach cannot control the BG very well, but by using fuzzy-GA controller, where the fuzzy membership functions are optimised by GA, the BG can better get to the normal level.

In Table 4, the error rate of each controller is given in terms of criteria MSE and MAE based on (28). Table 4 shows a comparison between the HANFIS-PSO data fusion approach and five other approaches for glucose reference tracking. The obtained results by the HoSM control are comparable with those obtained by fuzzy control and fuzzy-genetic approach controllers. The error of hybrid and HANFIS-PSO controllers are less than others. Table 4 reflects the improving performance of the HANFIS-PSO data fusion controller compared with the other methodologies. These results are computed ignoring initial transitions. Fig. 5 shows excellent control performances by applying Palumbo, hybrid and HANFIS-

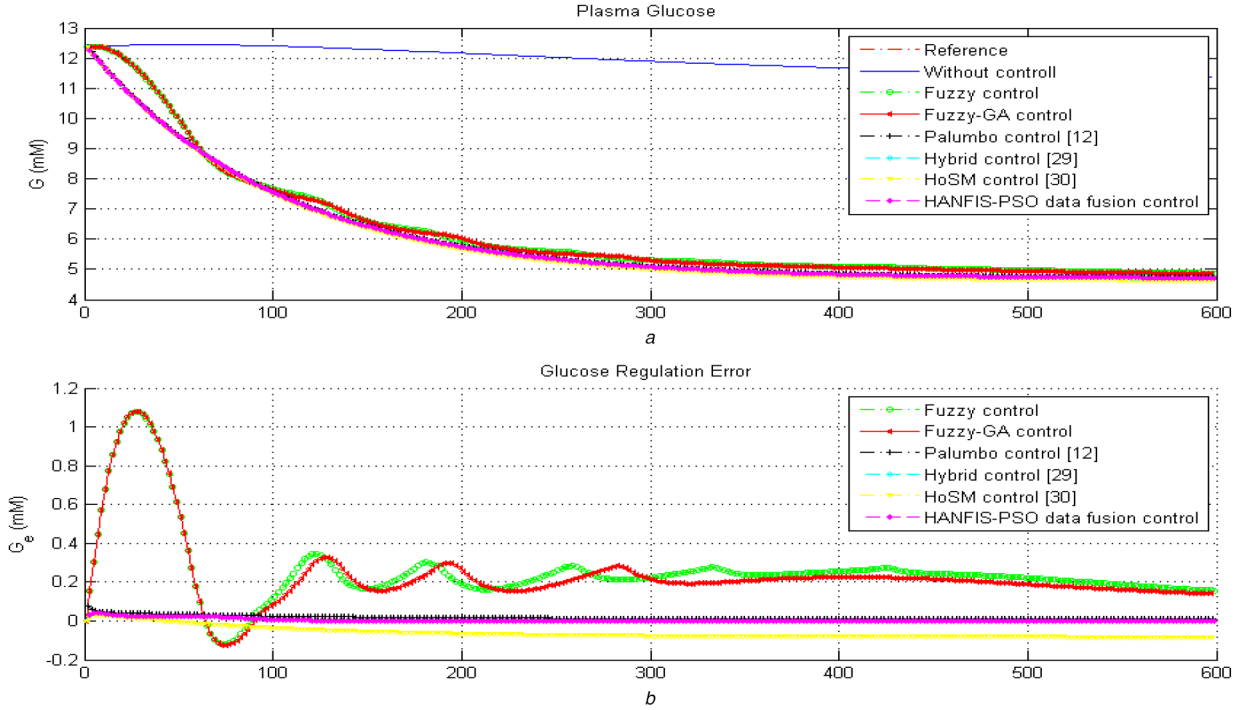

Fig. 3 *The stabilisation of the patient's BG level*

(a) Regulation of plasma glucose by applying HANFIS-PSO data fusion controller, ***(b)*** The error of blood glucose tracking respect to the reference glucose

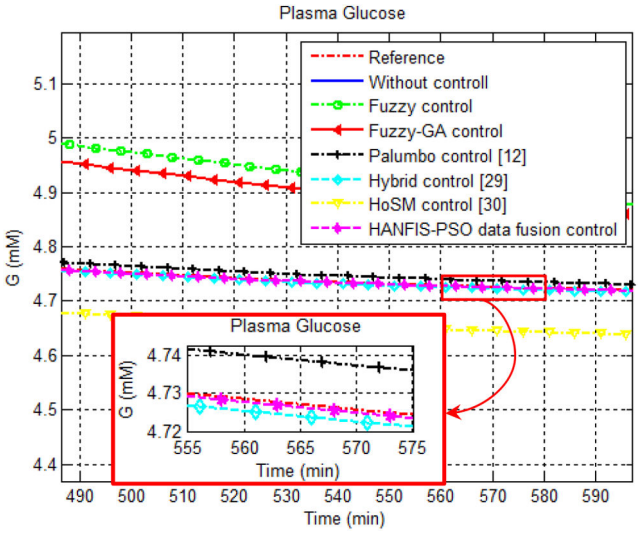

Fig. 4 *Regulation of plasma glucose by applying HANFIS-PSO data fusion controller (finer scale)*

Table 4 Error of glucose control (ignoring initial transitions)

Control method	MSE(E_G)	$MAE(E_G)$
fuzzy control	0.051516	0.218197
fuzzy-GA control	0.042534	0.196960
Palumbo control [11]	0.000272	0.015499
hybrid control [27]	0.000036	0.003677
HoSM control [30]	0.004901	0.067432
HANFIS-PSO data fusion control	0.000034	0.003255

PSO data fusion controllers. Although the hybrid control approach has comparable performance based on Table 4, this algorithm has acceptable performance, but not excellent as illustrated in Fig. 5.

One important aspect of the proposed HANFIS-PSO based on hybrid FISs optimised by PSO is desired BG-level tracking while preventing chattering behaviour of the insulin infusion rate. This property of the proposed method is a vital feature for T1DM patients. Although the Palumbo, hybrid and HoSM approaches provide acceptable performances in glucose reference tracking, all of them suffer the chattering phenomena in their insulin infusion rates. Fig. 6 shows the injected insulin infusion rate while preventing chattering by the HANFIS-PSO approach, especially over the steady-state time interval.

Fig. 7 indicates the body insulin changes by applying each controller for this T1DM patient, respectively. In Table 5, the control efforts (i.e. the insulin injected rate) of each controller are also given and compared with HANFIS-PSO data fusion controller regarding the MSE and MAE criteria. Although fuzzy and optimised fuzzy methods are counted as the typical controllers (as seen in Table 4), but this decreasing glucose tracking error would be with a corresponding increment in control effort (as shown in Table 5).

In contrast to fuzzy-based controllers, the HoSM controller has a better performance of glucose reference tracking (Table 4) and its control effort generally has an acceptable level and even lower than that of by hybrid method. Improvements in MSE of the control effort for the proposed approach for the Palumbo, hybrid and HoSM approaches are 12.8, 31.4 and 17.5%, respectively.

As mentioned before, the best criterion should be considered a trade-off between reference glucose tracking error and the control effort was presented in (30). In Table 6, the results of six different methods are summarised regarding the MSE and MAE criteria, $\boldsymbol{Q}$ and $\boldsymbol{R}$ are set to 100 and 1, respectively.

Improvements in MSE for the proposed approach for Palumbo, hybrid and HoSM methodologies are 61.9, 26.6 and 96.85%, respectively.

4 Discussion

T1D patients rely on insulin injection at regular periods to maintain the BGC near the normal level. So the ability of smooth insulin delivery is considered as a vital feature of a typical glucose–insulin controller to prevent some of complications such as hypo or hyperglycaemia in diabetic patients. One of the main drawbacks to almost all traditional insulin–glucose regulatory approaches is that they are not able to stabilise the glucose level in the presence of disturbances. These various unmeasured disturbances such as food, physical activity, emotions and actuator errors are the main sources of the glucose fluctuating and cause the chattering phenomena in the insulin infusion rate. In this paper, a hybrid technique for BG

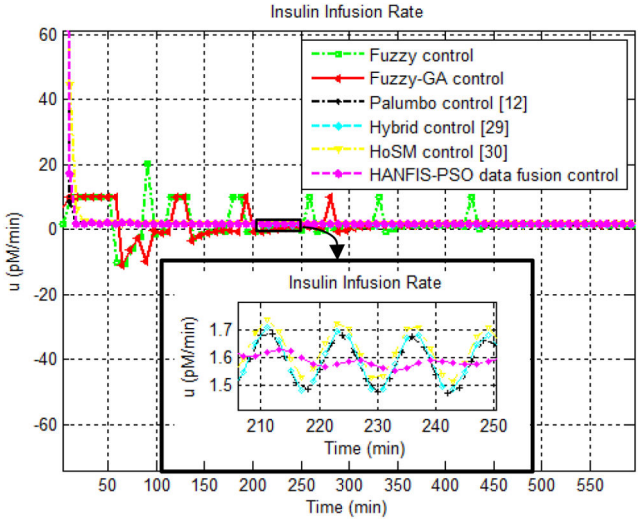

Fig. 5 *Insulin injection rate by using chattering-free HANFIS-PSO data fusion controller compared with the other controllers*

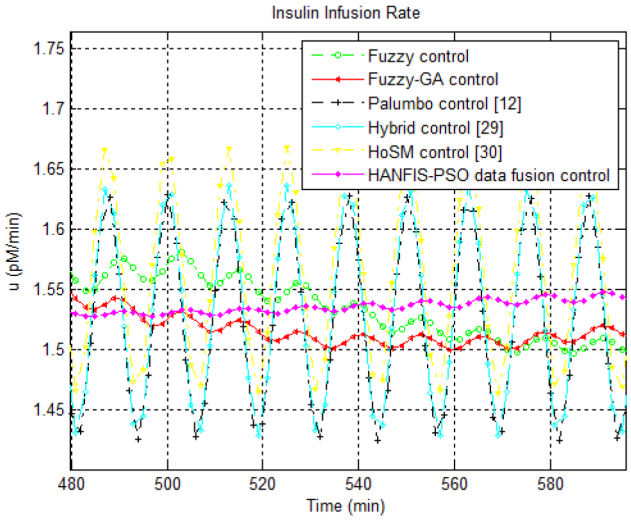

Fig. 6 *Injected insulin infusion rate by applying chattering-free HANFIS-PSO data fusion controller compared with the other control methods (finer scale, steady-state condition)*

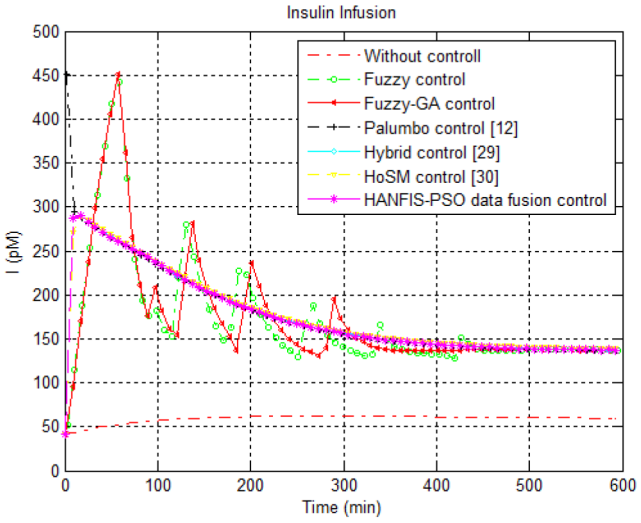

Fig. 7 *Patient's plasma insulin changes by applying each controller*

regulation by insulin injections is proposed to overcome these drawbacks.

One important aspect of the new ANFIS-PSO control scheme is glucose tracking to the desired level as well as the preventing chattering behaviour in insulin injection rate. Although the simulation results showed the acceptable performances in glucose reference tracking for Palumbo, hybrid and HoSM control approaches, all of them suffer the chattering phenomena in their insulin infusion rates. It is shown that the proposed technique adequately address the issue of reducing chattering phenomena of insulin delivery.

Another vital aspect of the new hybrid technique is the preventing of hypo or hyperglycaemia events. The regulated glucose levels are <8.5 mM/L or 154 mg/dl and more than 3.88 mM/L or 70 mg/dl for all simulation results which are following recommendations made by the American Diabetes Association [48]. The simulation results in 100 different runs showed the preventing hypoglycaemia and hyperglycaemia events of the proposed algorithm compared with other methodologies. Although the simulation results showed (based on Table 4) the acceptable performances in glucose reference tracking for Palumbo, hybrid and HoSM control approaches, these decreasing glucose tracking error could be with corresponding increase in control efforts (shown in Table 5).

The advantages of our proposed control scheme make it different from [12, 28–30] were:

i. A delayed non-linear model was used here with a complete list of uncertainties such as food intake, physical activities and emotions, sensor and actuator noises, whereas in [12, 29, 30] uncertainty was only considered as glucose disturbance. The effects of sensor and actuator noises, critical initial condition, physical activity and emotions were neglected in [33, 34]. The effects of physical exercise by the patient are not considered in [45].
ii. The proposed intelligent control scheme on the well known Palumbo model was done, whereas in [33, 34, 45–47], based on BM [34], BMM [47], modified BMM [33, 46] and Dalla Man model [45] which are not counted as a DDE model and have less compliance with diagnostic testing of a diabetic patient.
iii. For the first time, an intelligent combination of ANFISs optimised by PSO as a control signal was used. This new control law could simultaneously guarantee the desired BG-level tracking and chattering reduction.
iv. The new HANFIS-PSO data fusion technique has avoided any occurrences of several hypoglycaemia or hyperglycaemia events given satisfactory performance under uncertainties.
v. Another advantage of the proposed control technique besides preventing the chattering phenomena from the insulin infusion rate is the robustness control against the uncertainty and disturbance.

Some of the further developments and disadvantages of the newly proposed control technique are:

i. Further study is required to evaluate the performance of the HANFIS-PSO scheme in a more realistic case, where insulin value must be estimated from the available glucose value.
ii. The limitation of the Palumbo DDE model is that the effects of growth hormone and glucagon and so on have not been considered, whereas in [45] based on Dalla Man model.
iii. Additional requirement is about the dynamics of the insulin pump that should be considered.
iv. Another development such as the use of fault detection techniques to detect pump malfunctions should be considered before moving to the clinical use of any suggested controller.

5 Conclusion

The application of the proposed hybrid method to Palumbo DDE model is both novel and effective. By applying an intelligent combination of ANFISs optimised by PSO as a control signal on the well known Palumbo model, more stabilisation of glucose tracking and preventing of insulin chattering would be achieved. The simulation results reported in Tables 4–6 show the excellent performance of the proposed controller, especially on control effort

Table 5 Control input efforts of each controller

Control method	MSE(U)	MAE(U)
fuzzy control	15.4681	2.5022
fuzzy-GA control	13.3525	2.3602
Palumbo control [11]	0.0140	1.5897
hybrid control [27]	0.0178	1.5982
HoSM control [30]	0.0148	1.6328
HANFIS-PSO data fusion control	0.0122	1.5989

Table 6 Glucose-level control and control input efforts

Control method	MSE(GU)	MAE(GU)
fuzzy control	20.6198	24.3219
fuzzy-GA control	17.6060	22.0562
Palumbo control [11]	0.0413	3.1397
hybrid control [27]	0.0214	1.9659
HoSM control [30]	0.5049	8.3760
HANFIS-PSO data fusion control	0.0157	1.9244

besides the preventing chattering phenomena on the insulin–glucose regulatory system.

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7 References

[1] Foster, N.C., Miller, K.M., Tamborlane, W.V., *et al.*: 'Continuous glucose monitoring in patients with type 1 diabetes using insulin injections', *Diabetes Care*, 2016, **39**, (6), pp. 81–82

[2] Ubeyli, E.D.: 'Automatic diagnosis of diabetes using adaptive neuro-fuzzy inference systems', *Expert Syst.*, 2010, **27**, (4), pp. 259–266

[3] Polonsky, W.H., Hessler, D., Ruedy, K.J., *et al.*: 'The impact of continuous glucose monitoring on markers of quality of life in adults with type 1 diabetes: further findings from the DIAMOND randomized clinical trial', *Diabetes Care*, 2017, **40**, (6), pp. 736–741

[4] Renard, E., Place, J., Cantwell, M., *et al.*: 'Closed-loop insulin delivery using a subcutaneous glucose sensor and intraperitoneal insulin delivery feasibility study testing a new model for the artificial pancreas', *Diabetes Care*, 2010, **33**, (1), pp. 121–127

[5] Bergman, R.N., Ider, Y.Z., Bowden, C.R., *et al.*: 'Quantitative estimation of insulin sensitivity', *Am. J. Physiol.*, 1979, **236**, (6), pp. E667–E677

[6] Sorensen, J.T.: 'A physiologic model of glucose metabolism in man and its use to design and assess improved insulin therapies for diabetes'. PhD thesis, Department Chemical Engineering, Massachusetts Institute of Technology (MIT), Cambridge, 1985

[7] Li, J., Kuang, Y., Mason, C.C.: 'Modelling the glucose–insulin regulatory system and ultradian insulin secretory oscillations with two explicit time delays', *J. Theor. Biol.*, 2006, **242**, (3), pp. 722–735

[8] Dalla Man, C., Rizza, R.A., Cobelli, C.: 'Meal simulation model of the glucose–insulin system', *IEEE Trans. Biomed. Eng.*, 2007, **54**, (10), pp. 1740–1749

[9] Piccinini, F., Dalla Man, C., Vella, A., *et al.*: 'A model for the estimation of hepatic insulin extraction after a meal', *IEEE Trans. Biomed. Eng.*, 2016, **63**, (9), pp. 1925–1932

[10] Liu, W., Tang, F.: 'Modeling a simplified regulatory system of blood glucose at molecular levels', *J. Theor. Biol.*, 2008, **252**, (4), pp. 608–620

[11] Novara, C., Mohammad Pour, N., Vincent, T., *et al.*: 'A nonlinear blind identification approach to modeling of diabetic patients', *IEEE Trans. Control Syst. Technol.*, 2016, **24**, (3), pp. 1092–1100

[12] Gaetano, A., Panunzi, S., Palumbo, P.: 'Qualitative behavior of a family of delay-differential models of the glucose–insulin system', *Discret. Continuous Dyn. Syst., B*, 2006, **7**, (2), pp. 399–424

[13] Palumbo, P., Pepe, P., Panunzi, S., *et al.*: 'Time-delay model-based control of the glucose–insulin system, by means of a state observer', *Eur. J. Control*, 2012, **18**, (6), pp. 591–606

[14] Sherr, J., Cengiz, E., Palerm, C., *et al.*: 'Reduced hypoglycemia and increased time in target using closed-loop insulin delivery during nights with or without antecedent afternoon exercise in type 1 diabetes', *Diabetes Care*, 2013, **36**, (10), pp. 2909–2914

[15] Steil, G., Palerm, C., Kurtz, N., *et al.*: 'The effect of insulin feedback on closed-loop glucose control', *J. Clin. Endocrinol. Metab.*, 2011, **96**, (5), pp. 1402–1408

[16] Breton, M., Farret, A., Bruttomesso, D., *et al.*: 'Fully integrated artificial pancreas in type 1 diabetes: modular closed-loop glucose control maintains near normoglycemia', *Diabetes*, 2012, **61**, (9), pp. 2230–2237

[17] Russell, S., El-Khatib, F., Nathan, D., *et al.*: 'Blood glucose control in type 1 diabetes with a bihormonal bionic endocrine pancreas', *Diabetes Care*, 2012, **35**, (11), pp. 2148–2155

[18] Haidar, A., Legault, L., Dallaire, M., *et al.*: 'Glucose-responsive insulin and glucagon delivery (dual-hormone artificial pancreas) in adults with type 1 diabetes: a randomized crossover controlled trial', *Can. Med. Assoc. J.*, 2013, **185**, (4), pp. 297–305

[19] Battelino, T., Nimri, R., Dovc, K., *et al.*: 'Prevention of hypoglycemia with predictive low glucose insulin suspension in children with type 1 diabetes: a randomized controlled trial', *Diabetes Care*, 2017, **40**, (6), pp. 764–770

[20] Zavitsanou, S., Mantalaris, A., Georgiadis, M.C., *et al.*: 'In-silico closed loop control validation studies for optimal insulin delivery in type 1 diabetes', *IEEE Trans. Biomed. Eng.*, 2015, **62**, (10), pp. 2369–2378

[21] Cameron, F., Niemeyer, G., Wilson, D., *et al.*: 'Inpatient trial of an artificial pancreas based on multiple model probabilistic predictive control with repeated large unannounced meals', *Diabetes Technol. Ther.*, 2014, **16**, (11), pp. 728–734

[22] Gyorgy, A., Szalay, P., Benyo, Z., *et al.*: 'ANFIS regulated type 1diabetic model for different glucose absorption scenarios'. Proc. IEEE Conf. Intelligent Engineering Systems, Las Palmas, Spain, 2010, pp. 327–332

[23] Hariri, A., Wang, L.: 'Identification and low-complexity regime-switching insulin control of type I diabetic patients', *J. Biomed. Sci. Eng.*, 2011, **04**, (4), pp. 297–314

[24] Kovács, L., Benyó, B., Bokor, J., *et al.*: 'Induced *L*2-norm minimization of glucose–insulin system for type I diabetic patients', *Comput. Methods Programs Biomed.*, 2011, **102**, (2), pp. 105–118

[25] Marchetti, G., Barolo, M., Jovanovic, L., *et al.*: 'An improved PID switching control strategy for type 1 diabetes', *IEEE Trans. Biomed. Eng.*, 2008, **55**, (3), pp. 857–865

[26] Mauseth, R., Hirsch, I., Bollyky, J., *et al.*: 'Use of a 'Fuzzy Logic' controller in a closed-loop artificial pancreas', *Diabetes Technol. Ther.*, 2013, **15**, (8), pp. 628–633

[27] Colmegna, P., Sánchez Peña, R.S., Gondhalekar, R., *et al.*: 'Reducing risks in type 1 diabetes using H_∞ control', *IEEE Trans. Biomed. Eng.*, 2014, **61**, (12), pp. 2939–2947

[28] Palumbo, P., Pepe, P., Panunzi, S., *et al.*: 'Robust closed-loop control of plasma glycemia: a discrete-delay model approach', *Discret. Continuous Dyn. Syst., B*, 2009, **12**, (2), pp. 455–468

[29] Hydari, V., Karsaz, A.: 'Feedback linearization and intelligent combination control method to blood glucose level control based on Palumbo delayed model', *Iran J. Control*, 2016, **10**, (1), pp. 14–24

[30] Kaveh, P., Shtessel, Y.: 'Blood glucose regulation using higher-order sliding mode control', *J. Robust Nonlinear Control*, 2008, **18**, (4–5), pp. 557–569

[31] Feng, Y., Han, F., Yu, X.: 'Chattering free full-order sliding-mode control', *Automatica*, 2014, **50**, (4), pp. 1310–1314

[32] Bartolini, G., Ferrara, A., Usai, E.: 'Chattering avoidance by second-order sliding mode control', *IEEE Trans. Autom. Control*, 1998, **43**, (2), pp. 241–246

[33] Nath, A., Dey, R.: 'Robust observer based control for plasma glucose regulation in type 1 diabetes patient using attractive ellipsoid method', *IET Syst. Biol.*, 2019, **13**, (2), pp. 84–91

[34] Delavari, H., Heydarinejad, H., Baleanu, D.: 'Adaptive fractional-order blood glucose regulator based on high-order sliding mode observer', *IET Syst. Biol.*, 2019, **13**, (2), pp. 43–54

[35] Fabietti, P., Canonico, V., Federici, M., *et al.*: 'Control oriented model of insulin and glucose dynamics in type 1 diabetics', *Med. Biol. Eng. Comput.*, 2006, **44**, (2), pp. 69–78

[36] Jang, J.: 'ANFIS: adaptive-network-based fuzzy inference system', *IEEE Trans. Syst. Man Cybern.*, 1993, **23**, (3), pp. 665–685

[37] Chiu, S.: 'Fuzzy model identification based on cluster estimation', *J. Intell. Fuzzy Syst.*, 1994, **2**, (3), pp. 267–278

[38] Yu, S., Tranchevent, L., Liu, X., *et al.*: 'Optimized data fusion for kernel *k*-means clustering', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2012, **34**, (5), pp. 1031–1039

[39] Eberhart, R., Kennedy, J.: 'A new optimizer using particle swarm theory'. Proc. Sixth Int. Symp. Micro Machine Human Science, Nagoya, Japan, 1995, pp. 39–43

[40] Zhang, N., Yang, G.H.: 'Mixed frequency small gain state feedback control with application to insulin pumps', *Int. J. Control Autom. Syst.*, 2009, **7**, (2), pp. 319–324

[41] Palumbo, P., Ditlevsen, S., Bertuzzi, A., *et al.*: 'Mathematical modeling of the glucose–insulin system: a review', *Math. Biosci.*, 2013, **244**, (2), pp. 69–81

[42] Colmegna, P., Sanchez Pena, R., Gondhalekar, R., *et al.*: 'Switched LPV glucose control in type 1 diabetes', *IEEE Trans. Biomed. Eng.*, 2016, **63**, (6), pp. 1192–1200

[43] Colmegna, P., Sánchez Peña, R., Gondhalekar, R.: 'Linear parameter-varying model to design control laws for an artificial pancreas', *Biomed. Signal Proc. Control*, 2018, **40**, pp. 204–213

[44] Ramezanzadeh, R., Baygi, S.M.H., Farzaneh, J., *et al.*: 'Chattering-free blood glucose level control based on ANFIS'. Proc. IEEE Int. Conf. Fuzzy Systems (FUZZ-IEEE), Naplez, Italy, 2017

[45] Mandal, S., Sutradhar, A.: 'Robust multi-objective blood glucose control in type-1 diabetic patient', *IET Syst. Biol.*, 2019, **13**, (3), pp. 136–146

[46] Nath, A., Deb, D., Dey, R., *et al.*: 'Blood glucose regulation in type 1 diabetic patients: an adaptive parametric compensation control-based approach', *IET Syst. Biol.*, 2018, **12**, (5), pp. 219–225

[47] Batmani, Y.: 'Blood glucose concentration control for type 1 diabetic patients: a non-linear suboptimal approach', *IET Syst. Biol.*, 2017, **11**, (4), pp. 119–125

[48] American Diabetes Association: 'Standards of medical care in diabetes – 2014', *Diabetes Care*, 2014, **37**, pp. S14–S80