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Blood glucose adaptive generalized predictive control for critical care patients

Gholam Reza Alikhani[1], Saeed Balochian[2]

[1]*Department of Electrical engineering, Gonabad Branch 1, Islamic Azad University Gonabad, Iran,*
[2]*Department of Electrical engineering, Gonabad Branch 2, Islamic Azad University Gonabad, Iran,*
e-mail: reza.alikhani@chmail.ir, saeedbalochian@gmail.com

Abstract: Blood glucose (BG) concentration control for diabetic patients is a useful tool to reduce death and emergence of serious complications. But glucose control in patients with high variation and uncertainty with physiological conditions is harder. A generalized predictive control based on adaptive control strategy with frequent glucose measurements is proposed for blood glucose illness. Estimation of the parameters of the model is performed with an identification algorithm based on Recursive Least Squares (RLS) in on-line manner. The adaptive generalized predictive control is performed and the results have shown that our proposed method is superior and effective in controlling the concentration of blood glucose, contrary to the high variations in the blood glucose response.

Keywords: Blood glucose control, Adaptive control, Adaptive Generalized predictive control

1. Introduction

Diabetes mellitus (DM) is a metabolic disorder in which pancreas is unable to secrete sufficient insulin. Poor maintenance of normoglycemia (defined as blood glucose 70-100 mg/dL) with elevated blood glucose concentrations is the result of the most important hormone adjustment glucose metabolism. Patients that experience induced stress hyperglycemia (Blood glucose with high level) accepted in intensive care unit (ICU) [1].

There are two situations in blood glucose problems. Because of the hypoglycemia is correlated with critical patients in the ICU, it should be avoided [2]. Performing an effective control for BG is difficult duo to complexity of the response for each patient in ICU manner. For regulation of the BG several attempts has been done [3-7].

A nonlinear optimal control based on H-infinity under parametric and model uncertainty is proposed in [2]. The results get better insulin infusion administered for patients in regulation of BG levels in ICU.

In [6] a sliding mode controller based on fractional order backstepping is provided for BG regulation using Bergman minimal model for type I diabetes. The robustness is achieved by fractional sliding mode control. The backstepping is controller has been able to overcome to uncertainties.

In [7] the LOGIC-Insulin BG control method is compared with blood glucose control by expert nurses. The LOGIC-Insulin results have shown that to be effective and secure when used in ICUs in clinical practice.

ICU applications of BG control techniques are based on computers including PID and model based controllers [8-13]. These control strategies can be used to determine insulin infusion rate.

An Adaptive PID control strategy has been proposed by Ottavian et al for blood glucose control [8]. A simulation study verifies this technique and control strategy based on self-tuning is designed for 200 virtual patients. Simulations for 200 patients verify efficiency of this method. In this paper, measurement noise is not considered in simulations.

A blood glucose concentration regulation in Type 1 diabetes using multi model multi parametric model predictive control has been studied in [9]. From the Hovarka's 8^{th} order virtual patient model, a Glucose – Insulin steady state static map has been obtained. A multi model multi- parametric model predictive control has been designed using delay time compensations strategies for pure dynamics of each linear region. The blood glucose concentration has been regulated by the gain scheduled controller within the acceptable range (80mg/dL TO 160 MG/dL) during multiple meal disturbances, but the effect of the measurement noise is not considered in [9].

A data based model predictive controller with state and disturbance estimation has been proposed in [10] to control the blood glucose concentration in type-I diabetic patients in the presence of meal disturbances considering patient-model mismatch. In this paper, simulation studies are performed on three individual patient models. This control technique has become able to control the blood glucose concentration in acceptable ranges as a result of sensitivity analysis, and it has compensated the mild parametric drift. But in [10] the adaptive strategy is not used.

A new cost function has been proposed by Lee et al for an MPC based on clinical requirements in [11] and the algorithm has been validated under *in silico* and advisory mode assessments. Their formulation has improved eluding hypoglycemia within a wide range of *in silico* scenarios significantly. However, noise effect and adaptive method were not studied in [11].

In [12], a linear zone model predictive controller with moving horizon state estimation and output regulation has been developed. Lin et al have proposed a physiological intensive control insulin- nutrition- glucose model [13]. The mentioned model has been validated in critical care patients. In an observational study, critical care patient data was used to build virtual patients. Closed-loop control in these virtual patients unlike clinical practice standard, increases the time spent in the target glucose zone significantly and enhances targeted glucose control on critically ill patients in silico substantially. So, the clinical decision making and patient results have been improved.

Considering development of technology in BG measurement, a BG control system that works automatically can be very profitable. So, in [14] some types of accurate glucose sensors have been proposed. Employing such sensors might improve ICU blood glucose significantly since insulin infusion rate can be adjusted more frequently. Due to high rise of nursing staff workload, control techniques like high BG sampling rate cannot be implemented manually.

Main challenge of automatic glucose control in ICUs is designing controllers since information of the ICU patients is limited. Very little prior information of a patient is available when an individual is admitted to an intensive care unit emergently.

Stress-induced hyperglycemia might change considerably in response to insulin infusion due to surgery.

In [15] the control of Blood glucose and identification of rapid mode using particle swarm optimization has been proposed. The proposed method is shown that economic and effective in blood glucose control.

In [16] the control of Glycemic in patients of critically ill surgical has been proposed. The aim of glycemic control in the ICU is treat hyperglycemia safely and mitigates hypoglycemia effectively.

Ding et al in [17] combined just-in- time learning and extreme learning machine to present a mortality prediction for ICU patients. A two-step framework including clustering and mortality prediction was also proposed to establish a more personalized model [17]. The new method including just-in-time learning (JITL) combined with extreme learning machine

(ELM) has been proposed for mortality prediction. The extreme learning machine is an instance of neural network but its shortcoming is that establishing neural network requires data training and it cannot be implemented easily.

Locally weighted principal component analysis LWPR-JPCA was proposed by Ding et al in [18] to monitor health status of ICU patients. The results obtained using LWPR indicates that the best monitoring performance including adaptation of the patient to changes, sensitivity of abnormality detection, fast learning speed and low computational complexity can be achieved. But patients with no or little prior information cannot be administered successfully. So, a significant study is required to monitor status of the patient with no prior history. Furthermore, authors of [18] have conducted no predictive or adaptive control for controlling blood glucose.

Authors of [19] have proposed an adaptive online monitoring without blood glucose control for ICU patients through combining just-in-time learning and principal analysis. A novel combination of just-in-time learning (JITL) and PCA called learning type PCA (L-PCA), has been proposed for adaptive online monitoring of ICU patients. A comparison was performed between the proposed method and the traditional PCA and fast moving-window PCA (Fast MWPCA).

In [20] an intelligent control based on Takagi- Sugeno (TS) Fuzzy logic was proposed regulate plasma glucose in type 1 Diabetic Mellitus (T1DM) patients in the presence of known meal disturbance and parametric variations. In order to describe the influence of glucose and insulin, the modified Bergman minimal model is considered as a mathematical model. Simulation results of the plasma glucose concentration and insulin infusion rate verify effectiveness of the designed control law. Despite suitability of fuzzy control for controlling nonlinear and time-variant systems and empirical derivation of the fuzzy rules and membership functions of fuzzy control, design of the controller is more complicated than adaptive predictive control; its implementation and popularization is also difficult [21].

Industry has employed a wide variety of control methods. One of the most well-known control methods is MPC which has become one of the main control strategies due to its intuitive control concept. It has been implemented successfully in various applications including food processing, automotive, chemical and aerospace applications. Three factors contribute in success of MPC [22]:

(1) Reconciliation of an explicit process mode to handle all features of the plant dynamics directly.

(2) Considering the plant behavior over a future time horizon in time to predict and eliminate disturbances.

(3) Considering process input, state and output constraints directly in control calculations to avoid control violations.

The Generalized predictive control (GPC) which was first proposed in 1987 [23] is a well-known control methods which is favorite at both universities and in industry. GPC can be applied to time delays systems, non-minimum-phase, unknown order systems and unstable systems. In predictive control algorithm the future control actions is computed. Therefore, the reference trajectory can be tracked by the system output with minimum error

The adaptive control method is robust for removing or reducing of noise and disturbances effects in a system model. Blood glucose has steady variations in continuous processes, which is a suitable model for using of adaptive control. Unlike classical control, adaptive control adjusts its control parameters or the control law online.

In order to benefit from both GPC and adaptive control simultaneously, these methods are combined for blood glucose control in this paper. To our knowledge, such blood glucose control combining GPC and adaptive control method has not been reported. Also, proposed method is designed and validated in popular model of [8].

Purpose of this paper is to design an adaptive generalized predictive control for blood glucose system. It is illustrated that this adaptive controller is more robust against measurement noise and sets point tracking characteristics better.

This paper is organized as follows. In the section 2 the introduced system model is presented. In the section 3 the generalized predictive control algorithm is described. The fourth section explains the adaptive control algorithm. Section 5 demonstrates the superiority and effectiveness of the proposed method through simulation. Finally, the paper is concluded in section 6.

2. System model

The developed model for the glucose-insulin dynamics of ICU patients has been proposed by chase et al [8]. This model is as follows:

$$\dot{G_1}(\mathrm{t}) = -\mathrm{p}_G \mathrm{G}_1(\mathrm{t}) - \mathrm{S}_I [\mathrm{G}_1(\mathrm{t}) + \mathrm{G}_E] \frac{Q(\mathrm{t})}{1+\alpha_G Q(\mathrm{t})} + \frac{P(\mathrm{t})}{V_P} \tag{1}$$

$$\dot{Q}(\mathrm{t}) = -\mathrm{k}_I \, Q(\mathrm{t}) + \mathrm{k}_I \, I(\mathrm{t}) \tag{2}$$

$$\dot{I}(\mathrm{t}) = -\frac{nI(\mathrm{t})}{1+\alpha_I(\mathrm{t})} + \frac{u(\mathrm{t})}{V_I} \tag{3}$$

The variables $\dot{\mathrm{G}}_1(\mathrm{t}), \dot{Q}(\mathrm{t}), \dot{I}(\mathrm{t})$ are the derivatives of G_1, *Q*, *I* that are the state variables of the blood glucose model. $\mathrm{G}_1(t)$ is the concentration of plasma glucose. $\mathrm{G_E}$ (mg/dL) is an equilibrium level; p_G and S_I ($L/mU/\min$) are the fractional glucose clearance rate and the insulin sensitivity respectively; I(t) is the concentration of plasma insulin (mU/L); The insulin interstitial concentration (mU/L) is *Q*(t) that considering previous infusion; The rise rate of insulin concentration from plasma and decay rate of insulin concentration is k_I ($\min^{-1}$); The distribution volumes of glucose is $V_P(L)$; The insulin distribution volumes is V_I (L) ; n ($\min^{-1}$) is decay rate of insulin and α_I is the Michaelis – Menten saturation parameter for plasma insulin disappearance; α_G is the parameter of the Michaelis – Menten saturation; *P*(t) is the appearance rate of exogenous plasma glucose ($mg/\min$) [8]; *u*(t) is the input of total insulin into plasma ($mU/\min$).The values of parameters are shown in Table 1 [8].

TABLE 1. The parameters of Chase model

Parameter	*Value*	*Units*
K_I	0.0099	$\min^{-1}$
p_G	0.02	$\min^{-1}$
$S_I(t=0)$	0.002	$L/mU/\min$
n	0.16	$\min^{-1}$
α_I	0.0017	L/mU
α_G	1/16	L/mU
V_p	15	L
V_I	12	L

After linearizing the above model about equilibrium point $(100,0,0)$, the transfer function is obtained. The model that described in Equations (1-3) is linearizing for $\mathrm{G_E}$=200 mg/dl at a steady-state value of 100 mg/dl to find

$$\begin{bmatrix} \dot{G}_1 \\ \dot{Q} \\ \dot{I} \end{bmatrix} = \begin{bmatrix} -0.02 & -0.002 & 0 \\ 0 & -0.0099 & 0.0099 \\ 0 & 0 & -0.16 \end{bmatrix} \begin{bmatrix} G_1 \\ Q \\ I \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0.0833 \end{bmatrix} u$$
$$y = \begin{bmatrix} 20 & 0 & 0 \end{bmatrix} \begin{bmatrix} G_1 \\ Q \\ I \end{bmatrix} \tag{4}$$

then the following transfer function is obtained:

$$G_2 = \frac{0.00033}{10.42\mathrm{s}^3 + 1.978s^2 + 0.0519s + 0.00033} \tag{5}$$

where $G_2 = \dfrac{G_1(\mathrm{s})}{u(\mathrm{s})}$, u is the insulin infusion which is a control input.

The location of the poles in transfer function of (5) are $\{-1.1599,\ -0.02,\ -0.0099\}$. The system of G_2 can be controlled using the PID controller. But the PID controller has not prediction ability for events in the future and smooth control signal. For more details about comparison between PID and GPC in the industrial process refer to [27]

3. Control algorithm

With considering of operating point, a local linearized model is admitted generally [23-25].

$$A_1(q_1^{-1})y_1(t) = B_1(q_1^{-1})u_1(t-1) + w_1(t) \tag{6}$$

where, A_1 and B_1 are polynomials in operator q_1^{-1}:

$$A_1(q_1^{-1}) = 1 + a_1 q_1^{-1} + \ldots + a_{na} q_1^{-na}$$
$$B_1(q_1^{-1}) = b_0 + b_1 q_1^{-1} + \ldots + b_{nb} q_1^{-nb}$$

The $[a_1, a_2, \ldots a_{na}]$ and $[b_1, b_2, \ldots b_{na}]$ are polynomials coefficients of A_1 and B_1. In (6) control input is $u_1(t)$, The measured variable is $y_1(t)$ or output, and a disturbance term is $w_1(t)$.
The disturbance $w_1(t)$ has been considered as follows:

$$w_1(t) = C_1(q_1^{-1})N(t) \tag{7}$$

where, $C_1(q_1^{-1}) = 1 + c_1 q_1^{-1} + \ldots + c_{nc} q_1^{-nc}$

In this equation, $[c_1, c_2, ...c_{na}]$ are polynomial coefficients of C_1, N (t) is random sequences combining with (5) and integral operator we can get the CARIMA (Controlled Auto-regressive and Integrated Moving Average) model [23]:

$$A_1(q_1^{-1})y_1(t) = B_1(q_1^{-1})u_1(t-1) + \frac{C_1(q_1^{-1})}{\Delta_1(q_1^{-1})}N(t) \tag{8}$$

where, the differencing operator is Δ_1 and the backward shift operator is $1-q_1^{-1}$. And $q_1^{-1}y_1(t) = y_1(t-1)$. Also, $\frac{1}{\Delta_1(q_1^{-1})}$ is the integral operator. For simplicity, $C_1(q_1^{-1}))$ is 1.

The main idea of GPC controller is that the $y_1(t)$ follows the reference signal y_1^*. The cost function (9) for GPC controller is as follows [25]:

$$\begin{aligned} &J(H_i, H_p, H_c, t) = \\ &E\{\sum_{j=H_i}^{H_p}[y_1(t+j) - y_1^*(t+j)]^T R[y_1(t+j) - y_1^*(t+j)] \\ &+ \sum_{j=H_i}^{H_c} \Delta u_1^T(t+j-1) Q_c \Delta u_1(t+j-1)\} \end{aligned} \tag{9}$$

where the initial horizon is H_i; The prediction horizon is H_p; The control horizon is H_c; The output reference is $y_1^*(t)$; R is the output weighing factor; The weighting factor of control is Q_c.

The purpose of this problem is to find an appropriate control input, so that the cost function of *J* is minimized.

Two cases have been presented:

Case 1: $H_c = H_p, H_i = 1$

The following Diophantine equation with *j*-step ahead predictors are as follows (for more details about *j*-step ahead predictors refer to [23, 25]):

$$\begin{aligned} &1 = E^j(q_1^{-1})A_1(q_1^{-1})\Delta_1(q_1^{-1}) + q_1^{-j}F^j(q_1^{-1}) \\ &j = 1, ..., H_p \end{aligned} \tag{10}$$

where

$$E^j(q_1^{-1}) = 1 + e_1 q_1^{-1} + ... + e_{j-1} q_1^{-(j-1)}$$
$$F^j(q_1^{-1}) = f_0^j + f_1^j q_1^{-1} + ... + f_{na}^j q_1^{-na}$$

The polynomials $E^j(q_1^{-1})$ and $F^j(q_1^{-1})$ are defined by: $A_1(q_1^{-1}), \Delta_1(q_1^{-1})$ and j. With use of equations (6) and (10) we can get:

$$y_1(t+j) = E^j(q_1^{-1})B_1(q_1^{-1})\Delta u_1(t+j-1) + F^j(q_1^{-1})y_1(t) + E^j(q_1^{-1})N(t+j) \quad (11)$$

The predictor gives output data in time t:

$$\hat{y}_1(t+j/t) = G_1^j(q_1^{-1})\Delta u_1(t+j-1) + F^j(q^{-1})y_1(t) \quad (12)$$

where $G^j(q_1^{-1}) = E^j(q_1^{-1})B_1(q_1^{-1})$

That $G^j(q_1^{-1})$ is:

$$G^j(q_1^{-1}) = g_0^j + g_1^j q_1^{-1} + ... + g_{j-1}^j q_1^{-(j-1)}$$

So, the above equations are written as follows:

$$\hat{Y_1} = G\Delta U_{1t} + Y_0 \quad (13)$$

The vectors are $H_p \times 1$:

$$\hat{Y_1}^T = [\hat{y}_1^T(t+1).....\hat{y}_1^T(t+h_p)],\ \Delta U_{1t}^T = [\Delta U_{1t}^T(t).....\Delta U_{1t}^T(t+H_p-1)].$$

$$Y_0^T = [y_0^T(t+1).....y_0^T(t+h_p)]$$

Note that $G^j(q_1^{-1}) = B_1(q_1^{-1})[1-q_1^{-j}F^j(q_1^{-1})]/A_1(q_1^{-1})\Delta_1$. Therefor for obtaining of G^j is to compute Z-transform of the plant's step response and to taking the first j terms and $g_i^j = g_j$ for $j = 0,1,2,... < i$ that are independent the polynomial G_1.

Then, the G_1 is lower-triangular matrix with dimension $H_p \times H_p$:

$$G = \begin{bmatrix} g_0 & 0 & ... & ... & 0 \\ g_1 & g_0 & ... & ... & 0 \\ . & .. & ... & ... & . \\ \vdots & & & & \vdots \\ g_{H_p-1} & g_{H_p-2} & & & g_0 \end{bmatrix}$$

If H_i is assumed to be equal to d, the leading element is non-zero.

From the above definitions of the vectors and with:

$Y_1^{*T} = [y_1^{*T}(t+1).....y_1^{*T}(t+h_p)]$

The cost function (9) can be written as follows:

$$J(H_i, H_p, H_c, t) = (G\Delta U_{1t} + Y_0 - Y_1^*)^T R(G\Delta U_{1t} + Y_0 - Y_1^*) + \Delta U_{1t} Q_c \Delta U_{1t}^T \quad (14)$$

The solution ΔU_t that minimizes the cost function can be found as follows:

$$\frac{\partial J}{\partial \Delta U_{1t}} = 0 \quad (15)$$

where:

$$\Delta U_{1t}^* = (G_1^T G_1 + Q_c)^{-1} G_1^T R(Y_0 - Y_1^*) \quad (16)$$

Therefore, the control $u_1(t)$ is:

$$u_1(t) = u_1(t-1) + (G^T G + Q_c)^{-1} G^T R(Y_0 - Y_1^*) \quad (17)$$

Case 2: $H_c < H_p, H_i = 1$

Reducing the computational burden is possible. In order to do it, a constant control input vector is imposed after a fixed horizon H_c, $\Delta u_1(t+j-1) = 0 for \quad j > H_c$.

where the ΔU_{1t} and G_1 will be as follows:

$\Delta U_{1t}^T = [\Delta U_{1t}^T(t).....\Delta U_{1t}^T(t+H_c-1)]$

$$G = \begin{bmatrix} g_0 & 0 & \dots & \dots & 0 \\ g_1 & g_0 & \dots & \dots & 0 \\ . & .. & \dots & \dots & g_0 \\ \vdots & & & & \vdots \\ g_{H_p-1} & g_{H_p-2} & & & g_{H_p-H_c} \end{bmatrix}$$

4. Design of adaptive control method algorithm

Suppose that we have not system parameters of Equation (6). In this paper, the indirect adaptive controller is proposed. The unknown system parameter $\theta = (a_1, ..., a_{na}, b_0, ..., b_{nb})^T$ is estimated by the recursive least squares (RLS). Then, the system parameters $\hat{\theta}_t$ are estimated. Then, the control signal will be generated by adaptive generalized predictive controller Equation (17). The RLS algorithm is as follows:

$$\hat{\theta}(t_1) = \hat{\theta}(t_1 - 1) + \frac{\varepsilon(t_1)\Delta\Phi_1(t_1 - 1)F_1(t_1 - 1)}{1 + \Delta\Phi_1^T(t_1 - 1)F_1(t_1 - 1)\Delta\Phi_1(t_1 - 1)} \tag{18}$$

$$\varepsilon_1(t_1) = \Delta y_1(t_1 - 1) - \hat{\theta}(t_1 - 1)\Delta\Phi_1(t_1 - 1) \tag{19}$$

$$F_1(t_1) = \frac{1}{\lambda_1(t_1)}\left[F(t_1 - 1) - \frac{\Delta\Phi_1(t_1 - 1)\Delta\Phi_1^T(t_1 - 1)F(t_1 - 1)}{\frac{\lambda_1(t_1)}{\lambda_2(t_1)} + \Delta\Phi_1^T(t_1 - 1)F_1(t_1 - 1)\Delta\Phi_1(t_1 - 1)}\right] \tag{20}$$

Where,

$\hat{\theta}(t_1) = [\hat{a}_1, ..., \hat{a}_{na}, \hat{b}_0, ..., \hat{b}_{nb}]^T$

$\Phi_1(t) = [y_1^T(t_1 - 1), ..., y_1^T(t_1 - na), u_1^T(t_1 - 1), ..., u_1^T(t_1 - n_b)]^T$

where $\varepsilon_1(t_1)$ is the error of estimation between the estimated output and plasma glucose concentration and $\hat{\theta}(t_1)$ is a vector of parameter estimates. This vector should be estimated well, in order to $\varepsilon_1(t_1)$ is reduced. The vector of data input-output is $\Phi_1(t_1)$. $F_1(t_1)$ is the gain of adaptation. The forgotten factors are $\lambda_1(t)$ and $\lambda_2(t)$. For more details about RLS algorithm refer to [25, 26].

5. Simulation and results

After linearization of plant, the system identification technique in system identification toolbox in Matlab is used. Therefore, we can reach to Equation (21) from (5). After that we use RLS technique in order to adaptive estimation of the system parameters that consist of A_1, B_1, polynomials coefficients.

In order to show the behavior of the proposed adaptive generalized predictive controller, the blood glucose model obtained by using Equation (5) can be written by:

$$\begin{aligned} y_1(t_1) - 1.5314y_1(t_1 - 1) + 0.6107y_1(t_1 - 2) - 0.0224y_1(t_1 - 3) \\ = 0.0189u_1(t_1 - 1) + 0.0349u_1(t_1 - 2) + 0.003u_1(t_1 - 3) \end{aligned} \tag{21}$$

The simulations are done with these considerations:

- T_1=20 min is the sampling time.
- The structure of plant mode: $na = 3, nb = 2, time \quad delay = 0$

- A square wave is chosen as reference
- The $C_1(q_1^{-1})$ is chosen as $C_1(q_1^{-1}) = 1$.
- The matrix of initial covariance $F_1(0) = 10^6$
- The design parameters in control objectives are:

$H_p = H_c = 3,\ H_i = 1,$

$Q_c = 0.01,\ R = 1$

Case 1: The results of simulation without considering of noise.

The generalized predictive control performance and the adaptive GPC controller are shown in Figs 1-3. It can be observed that the oscillations of the adaptive GPC are lower than traditional GPC.

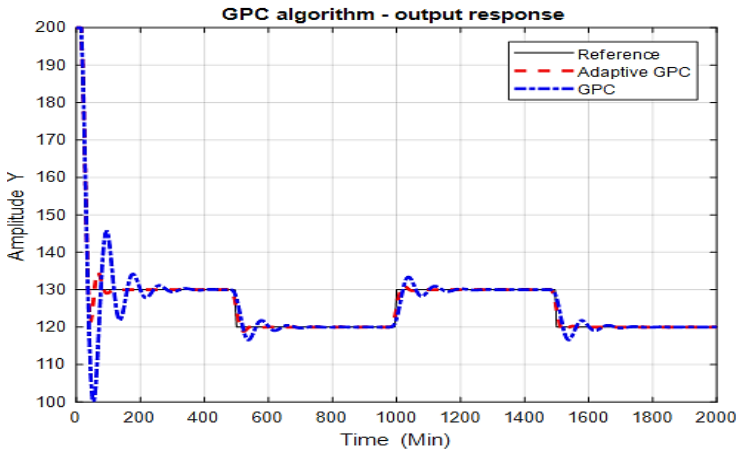

FIGURE 1. Output of plant Y_1 in without noise conditions: Adaptive GPC and GPC.

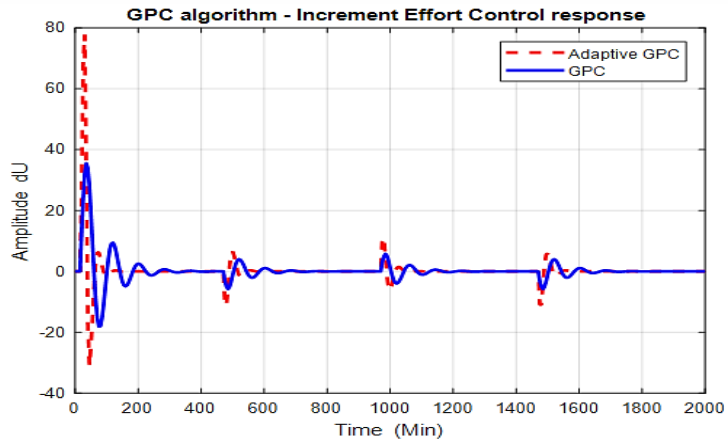

FIGURE 2. Input control in without noise condition: Adaptive GPC and GPC.

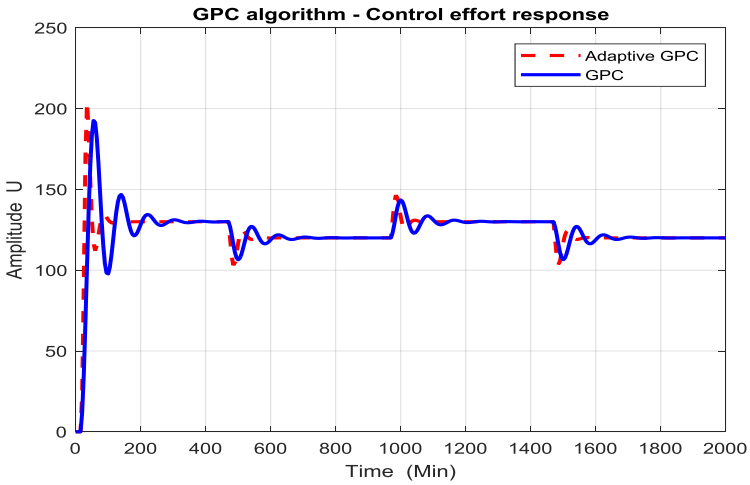

FIGURE 3. Control effort in without noise condition: Adaptive GPC and GPC.

From Figs. 1-3 it can be seen that adaptive GPC can get better output response in compare to traditional GPC in terms of accuracy and the reference tracking speed. Also, the overshoot in adaptive GPC is lower than traditional GPC. In compare to other papers our proposed method can obtain faster reference tracking speed.

Case 2: Simulation results in presence of noise conditions:

The performance of the control strategies in presence of noise conditions has been evaluated too. The white noise ($\sigma^2 = 0.01$) is used and the results are presented in Figs 4-6.

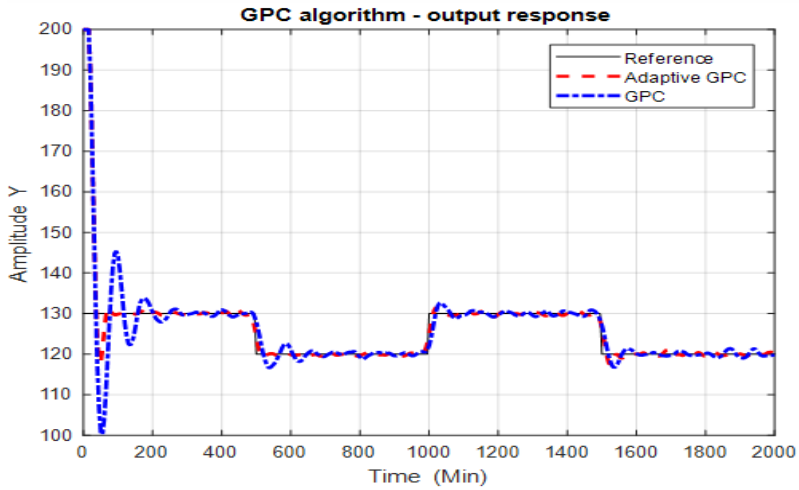

FIGURE 4. Plant output in presence of noise conditions Adaptive GPC and GPC.

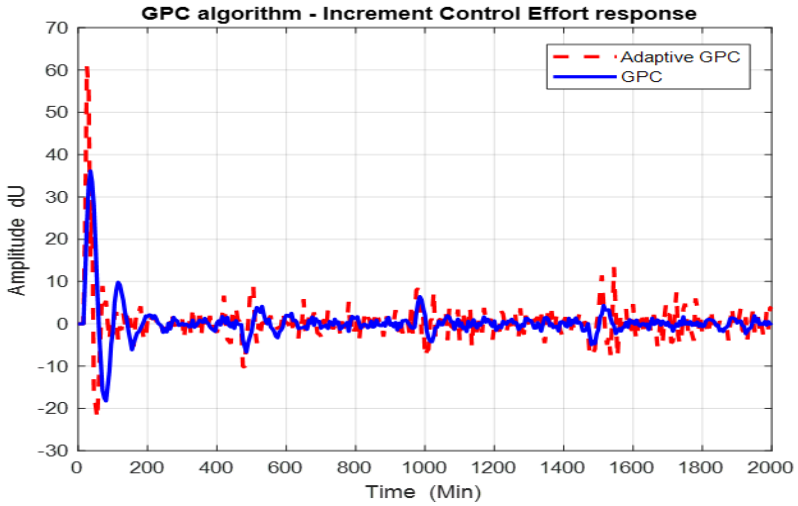

FIGURE 5. Increment control effort in presence of noise conditions: Adaptive GPC and GPC.

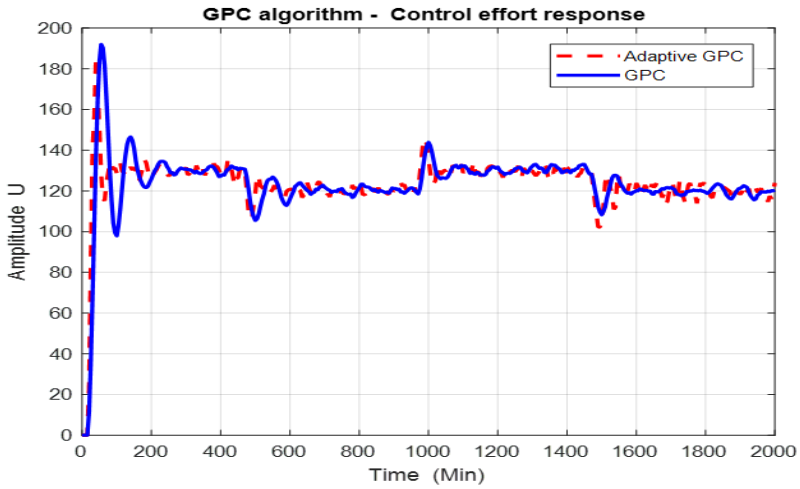

FIGURE 6. Control effort in presence of noise conditions: Adaptive GPC and GPC.

From Figures 4-6, the results between adaptive GPC and traditional GPC are showed. From these figures, the adaptive GPC gets better results in terms of overshoot and fast tracking responses. Also the oscillations of the output obtained by adaptive GPC are lower than traditional GPC. It can be observed from Figure 5 that the adaptive GPC uses more effort control than normal GPC to reduce noise effect. So, the simulation results by proposed technique for intensive care applications have been validated. This proposed controller also provides more efficient control, faster tracking speed, more robustness against noise for the BG concentration in contrast of the other papers methods.

6. Conclusions

In this paper, a blood glucose control model is presented by applying an adaptive generalized predictive control. It is shown that even by changing the plant output, the proposed method performs efficiently in terms of tracking speed, accuracy and overshoot reduction. The adaptive GPC is robust in the presence of noise and eliminating oscillations. Thus, the adaptive GPC has many benefits for the applications of ICU.

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