Safe Data-Driven Optimal control for type-1 Diabetes

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Abstract— **This work introduces a safe data-driven control methodology, Data-Enabled Predictive Control (DeePC), for the control of blood glucose in type-1 diabetic patients. DeePC utilizes input-output trajectory data directly without requiring a system model or state estimation like other model-based algorithms. The control strategy is validated using the Bergman Minimal Model, a well-established framework for glucose-insulin dynamics. Comparative simulations are conducted against Proportional-Integral-Derivative (PID) and Model Predictive Control (MPC) strategies. Results show that DeePC achieves comparable or superior glycemic regulation, particularly under model uncertainty, by maintaining normoglycemia and reducing hypoglycemia risk. The findings demonstrate the robustness and potential of DeePC in biomedical applications where model accuracy is uncertain. Future works would include computational efficiency improvements and handling uncertainties in meal estimation.**

I. INTRODUCTION

Type 1 Diabetes (T1D) is a long-term condition that requires insulin from outside sources (like injections or a pump) to keep blood sugar levels in a healthy range, preventing both hyperglycemia i.e., high Blood Glucose (BG) levels ($BG > 180$ mg/dL) and hypoglycemia i.e. , low BG levels ($BG < 70$ mg/dL) [1], [2], [3]. The Artificial Pancreas (AP), integrating continuous glucose monitoring, an insulin pump, and a control algorithm, has emerged as a promising solution for automating insulin delivery in real-time [2], [3].

An essential element of an AP system is the control law responsible for determining the appropriate amount of insulin to administer. Traditionally, glucose regulation has relied on control strategies such as Proportional-Integral-Derivative (PID) control, Model Predictive Control (MPC) [4], [2], and Linear Parameter-Varying (LPV) control [5], [6]. In recent years, however, the growing capabilities of artificial intelligence (AI) in handling complex, nonlinear systems [7] have opened the door to novel approaches. Such approaches include control strategies based on machine learning techniques [8], [9] and fuzzy logic [10], [11], which offer increased flexibility and adaptability in dynamic and uncertain environments.

Among various control strategies, MPC has been widely adopted, in many applications, for its ability to handle constraints and optimize states trajectories [12], [13], [4]. However, MPC relies on accurate patient-specific models, and designing robust controllers adaptable to inter-patient variability remains a major challenge.

To address this, Data-enabled Predictive Control (DeePC) has recently been proposed as a powerful data-driven alternative that bypasses explicit model identification by leveraging historical input-output data for prediction and control [14]. DeePC builds on Willems' behavioral systems theory [15] and has been successfully extended for noisy systems, non-linear dynamics [16], and real-time control applications [14].

In the context of T1D, DeePC offers a novel pathway for developing personalized and adaptive control algorithms, capable of managing glucose dynamics based on patient data without the need for detailed physiological modeling. This can significantly enhance the safety and usability of AP systems in real-world, free-living conditions.

To design a robust and effective controller, it is essential to have a model that accurately captures the glucose-insulin dynamics of the patient. However, directly measuring the individual physiological parameters of a person with Type 1 Diabetes is often invasive and costly, making it impractical for routine clinical use. For this reason, the Bergman minimal model is commonly employed as a simplified yet representative description of the glucose-insulin regulatory system [17].

The main research objective is to develop an implementable safe data-driven control strategy for glucose regulation in Type 1 Diabetes by applying a method known as Data-enabled Predictive Control. Unlike traditional model-based approaches, DeePC does not require an explicit mathematical model of the system. Instead, it directly utilizes input-output data to predict system behavior and compute optimal control actions. Using historical data from the Bergman mathematical model, this approach enables the synthesis of a predictive controller capable of managing the complex glucose-insulin dynamics while inherently accommodating the variability and constraints of the system.

The application of DeePC to the regulation of blood glucose in T1D represents a significant shift in control strategy. This study highlights the following main contributions:

- **Model-free control based on data**: DeePC bypasses the need for explicit model identification by leveraging historical input-output data (e.g., insulin administration and measurements of the glucose) to predict and regulate glucose dynamics.
- **Enhanced robustness and adaptability**: Due to its data-driven nature, DeePC is less sensitive to parameter uncertainties and physiological variability, which are common among T1D patients and can change over time.

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- **Direct handling of clinical constraints**: Similar to MPC, DeePC allows for the direct inclusion of constraints on insulin delivery, glucose levels, and other physiological variables within the optimization problem, improving safety and clinical relevance.
- **Demonstration of personalized, data-driven control**: Even when applied to a simplified model such as Bergman's, DeePC achieves competitive performance, supporting its potential use in more complex scenarios or with real patient data.

The remainder of the document is organized as follows: Section II presents the method used to control the system from data; Section III describes the T1D mathematical model; Section IV shows the results of the DeePC methodology; Section V draws conclusions and outlines future research directions.

II. Data-Enabled Predictive Control

Data-Enabled Predictive Control (DeePC) is a data-driven technique that optimizes control inputs using input-output trajectories without requiring an explicit system-state representation of the model [14]. It represents an alternative to the indirect system identification followed by a model-based control, e.g. Model Predictive Control (MPC). In the classic framework of the MPC, considering to have a discrete linear time-invariant (LTI) dynamical model:

$$\begin{aligned} x(t+1) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t) \end{aligned} \tag{1}$$

where $t \in \mathbb{N} \geq 0$ $x \in \mathbb{R}^n$ is the state, $u \in \mathbb{R}^m$ is the control input, $y \in \mathbb{R}^p$ is the output, $A \in \mathbb{R}^{nxn}$, $B \in \mathbb{R}^{mxn}$, $C \in \mathbb{R}^{pxn}$ and $D \in \mathbb{R}^{pxm}$. The goal is to find the optimal control sequence u^* that minimizes a given cost function $J(u, y)$ while satisfying some constraints. It can be mathematically formulated as follows:

$$u^* = \arg\min_{u,y} \sum_{i=0}^{N-1} \left(||y_i - r_{t+i}||_Q^2 + ||u_i||_R^2 \right) \tag{2a}$$

subject to

$$x_{i+1} = Ax_i + Bu_i \tag{2b}$$
$$y_i = Cx_i + Du_i \tag{2c}$$
$$x_0 = \hat{x}(t), \tag{2d}$$
$$u_{min} \leq u_i \leq u_{max} \tag{2e}$$
$$y_{min} \leq y_i \leq y_{max} \tag{2f}$$
$$\forall i \in \{0, \ldots, N-1\}$$

where $u = [u_0, \ldots, u_{N-1}]^T$, $y = [y_0, \ldots, y_{N-1}]^T$, $r \in \mathbb{R}^p$ is the desired reference for the output, $Q \in \mathbb{R}^{p \times p}$ is the weight matrix of the tracking error and $R \in \mathbb{R}^{m \times m}$ is the weight matrix associated to the control effort. $|| \cdot ||_Q$ represents the norm in a quadratic form with the weight Q, t is the time at which the optimal control problem should be solved by minimizing the total cost function described by (2a). Finally, $\hat{x}(t)$ is the estimation of the system's initial state calculated from the past input and output data. If all the states are measurable, then it is the actual measurement of the state. This process is re-iterated at each time step t, and, usually, only the first control is applied to the system, then the new measurements are acquired, and the optimization is performed again.

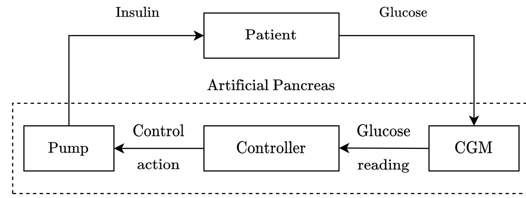

Fig. 1. Block scheme of the Artificial Pancreas control framework [18].

In the standard MPC setting, the optimal control is evaluated based on the measured system state and its model-driven predicted evolution. In other words, to find the optimal control, it is necessary to have access to an accurate model to predict the future evolution of the system given a specific input sequence. If the model is not accurate, the performance of the controller is not guaranteed and it can lead to instability or the violation of some constraints, which may be not acceptable in some critical applications, e.g., medical and electrical systems.

To overcome this problem, DeePC is adopted to learn the behaviors of the system without the need of a system identification or a state estimation. DeePC is based on the behavioral system theory, where the system state representation is not essential, but the signal space in which the trajectories of the system live is the main focus.

The key idea behind DeePC is to collect enough data (trajectories of length L), having certain characteristics, in order to capture the input-output dynamics of the system. The past trajectories are used to construct the Hankel Matrix of the form:

$$\mathcal{H}_L(u) := \begin{pmatrix} u_1^1 & \cdots & u_1^d \\ \vdots & \ddots & \vdots \\ u_L^1 & \cdots & u_L^d \end{pmatrix} \tag{3}$$

where $u^i = [u_1^i, u_2^i \ldots, u_{L-1}^i, u_L^i]^T$ is the i-th trajectory of length L, $u_j^i \in \mathbb{R}^m$ $d \gg L$, and the matrix $\mathcal{H}_L(u)$ has a full-row rank. The input Hankel matrix $\mathcal{H}_L(u)$ is then paired with its corresponding output trajectory Hankel matrix $\mathcal{H}_L(y)$.

According to [14], under some assumptions, the input/output trajectories can be considered as input/output of a minimal input-state-output representation. Moreover, the Hankel matrices can be divided in past trajectories and future trajectories:

$$\mathcal{H}_L(u) =: \begin{pmatrix} U_p \\ U_f \end{pmatrix} \qquad \mathcal{H}_L(y) =: \begin{pmatrix} Y_p \\ Y_f \end{pmatrix}, \tag{4}$$

where $U_p \in \mathbb{R}^{m \cdot T_{ini} \times d}$ and $Y_p \in \mathbb{R}^{p \cdot T_{ini} \times d}$ represent the past input and output data (first $m \cdot T_{ini}$ rows of the Hankel matrices), $U_f \in \mathbb{R}^{m \cdot N \times d}$ and $Y_f \in \mathbb{R}^{p \cdot N \times d}$ represent the future input and output data (last $m \cdot N$ rows of the Hankel matrices), T_{ini} is the number of steps used to identify the current state of the system and N is the number of future prediction steps of the evolution of the system's output.

Considering Lemma 4.2 in [14], the construction of any input-output trajectory of length L is possible by solving the following equality constraints:

$$\begin{pmatrix} U_p \\ Y_p \\ U_f \\ Y_f \end{pmatrix} g = \begin{pmatrix} u_p \\ y_p \\ u_f \\ y_f \end{pmatrix} \tag{5}$$

where u_p, y_p represent the first T_{ini} steps of the reconstructed trajectory and u_f, y_f represent the last N steps which are the predicted ones. In other words, knowing the past T_{ini} steps of the input and output of the system allows the reconstruction of the future output y_f by adequately choosing the future input u_f. $g \in \mathbb{R}^{T-T_{ini}-N+1}$ is the decision variable that maps the past input/output to the collected trajectories, T is the number of steps of the collected trajectories, and $L = T_{ini} + N$.

Thus, the model-based problem described in (2) can be reformulated as follows:

$$u^* = \arg\min_{u,y,g} \sum_{i=0}^{N-1} \left(||y_i - r_{t+i}||_Q^2 + ||u_i||_R^2 \right) \tag{6a}$$

subject to

$$\begin{pmatrix} U_p \\ Y_p \\ U_f \\ Y_f \end{pmatrix} g = \begin{pmatrix} u_p \\ y_p \\ u \\ y \end{pmatrix} \tag{6b}$$

$$u_{min} \leq u_i \leq u_{max} \tag{6c}$$

$$y_{min} \leq y_i \leq y_{max} \tag{6d}$$

$$\forall i \in \{0, \ldots, N-1\}$$

where u_p, y_p are the last T_{ini} inputs/outputs of the system and the others are the same as defined previously in (2).

The presence of the noise and the effect of nonlinearities of the system can lead to infeasibility of the optimization problem defined in (6). To address these problems, regularization terms are introduced as discussed in [14], [19] and a selection criterion is used to get the most important trajectories for each operating point. Therefore, the extended version is described as follows:

$$u^* = \arg\min_{u,y,g,w_u,w_y} \sum_{i=0}^{N-1} \left(||y_i - r_{t+i}||_Q^2 + ||u_i||_R^2 \right) + \\ + \lambda_u ||w_u||^2 + \lambda_y ||w_y||^2 + \lambda_g |g| \tag{7a}$$

subject to

$$\begin{pmatrix} \tilde{U}_p \\ \tilde{Y}_p \\ \tilde{U}_f \\ \tilde{Y}_f \end{pmatrix} g = \begin{pmatrix} u_p \\ y_p \\ u \\ y \end{pmatrix} + \begin{pmatrix} w_u \\ w_y \\ 0 \\ 0 \end{pmatrix} \tag{7b}$$

$$u_{min} \leq u_i \leq u_{max} \tag{7c}$$

$$y_{min} \leq y_i \leq y_{max} \tag{7d}$$

$$\forall i \in \{0, \ldots, N-1\}$$

TABLE I

PARAMETERS OF THE BERGMAN MINIMAL MODEL [17]

Parameter	Description	Unit
G	Plasma glucose concentration	$\mathrm{mg/dl}$
X	Insulin's effect on the net glucose disappearance	min^{-1}
I	Insulin concentration in plasma	$\mu\mathrm{U/ml}$
$\mathrm{G_b}$	Basal glucose plasma concentration	$\mathrm{mg/dl}$
$\mathrm{I_b}$	Basal insulin plasma concentration	$\mu\mathrm{U/ml}$
$\mathbf{u}_i(\mathbf{t})$	Insulin infusion rate	$\mu U/\mathrm{min}$
$\mathrm{p_1}$	Insulin-independent glucose disappearance rate	min^{-1}
$\mathrm{p_2}$	Spontaneous decreased rate of tissue glucose uptake ability	min^{-1}
$\mathrm{p_3}$	Insulin-dependent increase in tissue glucose uptake ability per unit of insulin concentration increase over basal insulin	$\frac{\mathrm{min}^{-2}}{(\mu\mathrm{U/ml})}$
h	Threshold value of glucose above which the pancreatic β-cells release insulin (only for DMT2)	$\mathrm{mg/dl}$
γ	Rate of the pancreatic β-cells' release of insulin after the glucose concentration is above the threshold h	$\frac{(\mu\mathrm{U/ml})}{\mathrm{min}^2(\mathrm{mg/dl})}$
n	Disappearance rate of insulin	(min^{-1})

where $\tilde{U}_p, \tilde{Y}_p, \tilde{U}_f, \tilde{Y}_f$ are selected columns of the complete matrices U_p, Y_p, U_f, Y_f. The selection is performed according to the distance of the trajectories of the Hankel matrices with respect to the past trajectory defined by u_p and y_p. $\lambda_u, \lambda_y, \lambda_g$ are the regularization weights for the input noise, output noise and the trajectory selection variable g, respectively. Finally, $|g|$ is the l-1 norm of the decision variable g which provides a better performance than the l-2 norm. The selection of the columns can be interpreted as finding a local input-output linear relationship of the considered system.

The solution of the optimization problem in (7) represent the optimal control u^* to the given system calculated by means of the observed data without the need of any knowledge of the model of the system. The only requirement is to have good excitation inputs of the system to capture most of the system's behaviors. To note that the number of control steps to perform can be variable depending on the computational cost of the optimization problem. More details related to the theoretical aspect and the different assumptions and proofs can be found in [14].

III. BERGMAN MINIMAL MODEL

The Bergman Minimal Model represents the most basic yet effective mathematical framework for describing the glucose-insulin regulatory system. It has demonstrated both accuracy and utility in various applications. It has been extensively used in numerous studies to investigate the impact of insulin sensitivity on glucose tolerance and the risk of developing diabetes and to evaluate the role of insulin production.

Furthermore, insights into the kinetics of insulin in vivo and the critical role of β-cell dysfunction in the pathogenesis of diabetes are derived from the basic assumptions of the Bergman Minimal Model. The dynamics of this model are expressed through the following set of equations:

$$\begin{aligned}\dot{G} &= -\, p_1 \left[G - G_{\mathrm{b}}\right] - GX + d(t), \\ \dot{X} &= -\, p_2 X + p_3 \left[I - I_{\mathrm{b}}\right], \\ \dot{I} &= -\, n \left[I - I_{\mathrm{b}}\right] + \gamma[G - h]t + u_i(t).\end{aligned} \tag{8}$$

The insulin input function $u(t)$ is an externally controlled experimental signal and does not affect the behavior or solution of the model, as long as $u(t)$ remains non-negative, i.e. $u_i : [0, \infty) \to \mathbb{R}_+$ instead $d(t)$ represents the disturbance signal. Both the control signal and disturbance signal are non-negative.

In Table I are provided the descriptions of the parameters and variables of the model.

However, physiological constraints must be considered to prevent hypoglycemic episodes, since excessive insulin administration can be harmful. The maximum tolerable amount of insulin depends on the individual's initial glucose concentration and physiological condition.

Note that $\gamma = 0$ for type 1 diabetic patients.

Insulin sensitivity is defined as $S_I = \frac{p_3}{p_2}$, which quantifies the body's responsiveness to insulin. The term $\gamma[G - h]^+ t$ represents the pancreatic insulin secretion in response to a meal at time $t = 0$. The parameter p_1, also known as glucose effectiveness (S_G), reflects the ability of glucose to enhance its own utilization and inhibit endogenous production independently of insulin [17]. Both S_G and S_I are objective markers used to assess a patient's glycemic regulation and diabetic condition.

IV. Simulation and Results

The DeePC algorithm is deployed to control the blood glucose level of a type-1 diabetic patient described by the Bergman Minimal Model. In the framework of the DeePC algorithm, the output $y(t)$ is the blood glucose, while the input $u(t)$ is a concatenation of the insulin injection $u_i(t)$ (controlled input) and the amount of carbohydrates the patient is having $d(t)$ (known disturbance); the input of the DeePC is defined as $u(t) = [u_i(t), d(t)]^T$. The input noise is not present as we assume the knowledge of the input and the disturbance; consequently, the variable w_u is not added.

To evaluate the performance of the proposed methodology and to proof the effectiveness of the control strategy, a simulation is performed over the Bergman Minimal Model presented in Section III. The simulations are performed in Python using Google Colab. The dynamics of the Bergman model are discretized through the fifth order of the Runge-Kutta method and the sampling time is $dt = 1\ min$. A day-scenario is simulated in which a patient has three meals: breakfast, lunch and dinner at 7:00, 13:00 and 20:00, respectively. The three meals contain 70g, 170g and 130g of carbohydrates respectively. For the DeePC algorithm, a different random scenario is considered to generate the trajectories of the Hankel matrices. The considered scenarios represent a real-world scenario of a nominal patient. The collected data has a length of a single day, the number of steps is $T = 60 * 24 = 1440$. The data are then put in trajectories of length $L = T_{ini} + N$ with $T_{ini} = 60$ and $N = 100$ to create the Hankel matrix:

$$\mathcal{H}_L(a) = \begin{pmatrix} a_1 & a_2 & \cdots & a_{T-L} & a_{T-L+1} \\ a_2 & a_3 & \cdots & a_{T-L+1} & a_{T-L+2} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{L-1} & a_L & \cdots & a_{T-2} & a_{T-1} \\ a_L & a_{L+1} & \cdots & a_{T-1} & a_T \end{pmatrix} \tag{9}$$

where a_i is the input/output at the time step i used to create the input/output Hankel matrix . Using all the collected data would not lead to acceptable results due to the nonlinearities of the system and the computational cost expense. Thus, at each time step, all the columns are ordered as described in Section II and only the first $n\_cols = 300$ columns are considered to solve the optimization problem in (7).

The nominal values of the Bergman Model parameters [17] are given in table II. While the weights of the DeePC are $Q = \mathbb{1}_N$, $R = 10^{-1} \cdot \mathbb{1}_N$, $\lambda_u = 0$, $\lambda_y = 10^4$ and $\lambda_g = 3 \cdot 10^2$.

TABLE II
Nominal Parameter Values of the Bergman Minimal Model[17]

Parameter	Value	Unit
G_b	120	mg/dl
I_b	20.11	μU/ml
p_1	0.026	$\min^{-1}$
p_2	0.088	$\min^{-1}$
p_3	$0.63 \cdot 10^{-3}$	$\frac{\min^{-2}}{(\mu\mathrm{U/ml})}$
n	0.09	$(\min^{-1})$

In order to evaluate the performance of the proposed controller, benchmark comparisons are performed with respect to other control logics. The first control algorithm is the Proportional Integral Derivative (PID) control [20], a very widely used control method in which the control depends on the past, present and derivative of the error. The control input in the discrete framework is calculated as:

$$u(t) = K_P e(t) + K_I \sum_{j=0}^{t} e(j) + K_D\big(e(t) - e(t-1)\big), \tag{10}$$

where the error is calculated as $e(t) = G(t) - G_b$, $K_P = 6 \cdot 10^{-3}, K_I = 25 \cdot 10^{-6}$ and $K_D = 18 \cdot 10^{-2}$. The parameter tuning is performed according to [21] and the nominal parameters of the model in table II. The second control algorithm is the Model Predictive Control; to make the comparison fair, only the output (glucose measurement) of the system was provided to the MPC and not the full state. The future disturbance was also passed to the MPC, the amount of future meals is assumed to be known in this setup. The initial state is estimated by making use of the inputs $u(t) = [u_i(t), d(t)]^T$ and the output of the previous step through the Extended Kalman Filter (EKF). The prediction horizon of the MPC is the same as DeePC, $N = 100$. The control effort is limited in all the controllers $0 \le u_i(t) \le 20$ and the state is limited to $50 \le G(t) \le 400$. The advantage of using DeePC is the possibility of capturing system

TABLE III

PERFORMANCE COMPARISON IN THE NOMINAL CASE

KPI	MPC	PID	DeePC
Percentage Normoglycemia time	99.78%	95.22%	96.87%
Percentage Hyperglycemia time	0%	4.78%	3.13%
Percentage Hypoglycemia time	0.22%	0%	0%
Maximum G	151	339	289
Minimum G	55	106	72
Control effort $\sum u_i(t)$	71	176	299

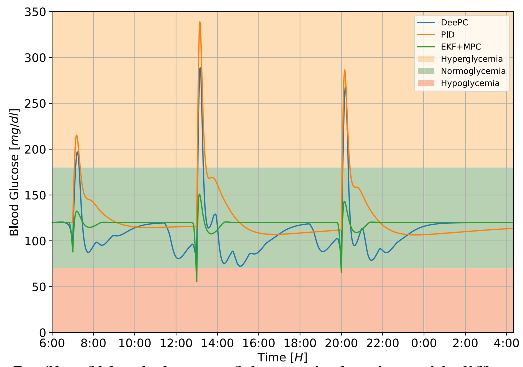

Fig. 2. Profile of blood glucose of the nominal patient with different control strategies.Parameters are provided in table II

dynamics without the need of the model. To this purpose, a first simulation is performed to compare the performance of the three controllers in case the model to control is the nominal one. A second simulation is performed to prove the effectiveness of DeePC when the model parameters are different from the nominal ones, demonstrating its robustness also in the biomedical field.

A. Nominal Patient Simulation

In the first simulation, the nominal model parameters in table II are considered to collect the data, tune the PID controller and find the optimal control of the MPC controller. After collecting the data, the DeePC algorithm is deployed to control the blood glucose level. The profile of the blood glucose is provided in figure 2 for all three controllers, while the control effort is given in figure 3. The best profile is the one of the MPC, as we can expect, it has a full knowledge of the model and the disturbances and it is optimized considering a long prediction horizon. The PID controller performs good as well with an overshoot during the first instances of each meal. The DeePC has a lower overshoot than the PID and captures successfully the system's dynamics by only observing the insulin, carbs and blood glucose trajectories of the past data. The main difference in the control effort is the amount of injected insulin, which is very high for the DeePC. A more analytic comparison is provided in table III.

B. Specific Patient Simulation

As introduced previously, a second simulation is performed to prove the robustness of the DeePC and compare its performance to other model-based (e.g. MPC) and model-free (e.g. PID) controllers. To note that the tuning of the PID is done according to the nominal patient parameters. The new

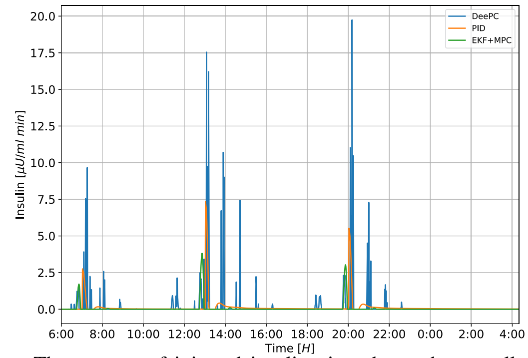

Fig. 3. The amount of injected insulin given by each controller for the nominal patient. Parameters are provided in table II

TABLE IV

PERFORMANCE COMPARISON OF THE SPECIAL PATIENT CASE

KPI	MPC	PID	DeePC
Percentage Normoglycemia time	85.30%	81.64%	84.70%
Percentage Hyperglycemia time	0%	2.76%	6.34%
Percentage Hypoglycemia time	14.70%	15.60%	8.95%
Maximum G	120	323	313
Minimum G	34	52	65
Control effort $\sum u_i(t)$	134	99	63

parameters are given from [17] and provided in table V. The setup is the same as the previous simulation.

The profile of the blood glucose is reported in figure 4 while the injected insulin is provided in figure 5. The performance of the MPC and the PID controllers is worse than the nominal simulation, as we can expect. The PID has an overshoot in the first steps of the meal while the MPC anticipates the effect of the meal by injecting insulin before the meal. The anticipation worked well in the nominal case, while in the specific parameter simulation, it leads to infeasibility of the optimization problem. As a matter of fact, the hard constraint related to the minimum value of the blood glucose is made soft with a very high penalty to guarantee the feasibility. Even if the estimation of the state is always acceptable, the difference in the model's parameters gives rise to a critical behaviour that threatens the safety of the patient. This problem does not exist for the DeePC due to its ability to capture the behavior from the data directly. In particular, this patient seems to be more sensitive to insulin injection, which leads to constraint violations for the MPC. More analytic comparison details are provided in table IV.

V. CONCLUSIONS

This work deploys a safe data-driven control algorithm with constraints on the blood glucose level for a diabetic patient. The proposed method is deployed for the first time in a medical field where the constraints are stiff and can not be violated. The DeePC controller is validated on the Bergman Minimal Model proving its capabilities to capture its dynamics. The performance is similar to that of the MPC and PID controllers in the nominal parameter values. When the parameters are different, the DeePC outperforms the other controllers by keeping the blood glucose in the safe

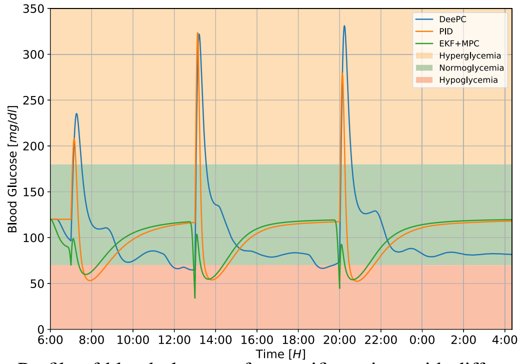

Fig. 4. Profile of blood glucose of a specific patient with different control strategies. Parameters are provided in table V

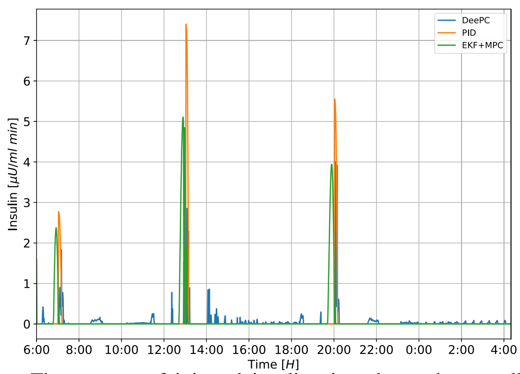

Fig. 5. The amount of injected insulin given by each controller for a specific patient. Parameters are provided in table V

range, avoiding hypoglycemia. This work represents the first step toward the data-driven control of blood glucose while guaranteeing the satisfiability of the constraints without the need for an explicit model.

Future works would define a better methodology to choose better the columns of the Hankel matrix in order to reduce the computational cost of the optimization problem. In addition, the assumption of knowing perfectly the meal amount can be managed in a probabilistic way in order to allow more robustness in the framework.

TABLE V
PERSONALIZED BERGMAN MINIMAL MODEL PARAMETERS[17]

Parameter	Value	Unit
$\mathrm{G_b}$	120	mg/dl
$\mathrm{I_b}$	13.75	μU/ml
$\mathrm{p_1}$	0.01	min^{-1}
$\mathrm{p_2}$	0.058	min^{-1}
$\mathrm{p_3}$	$1{\cdot}10^{-3}$	$\frac{\mathrm{min}^{-2}}{(\mu\mathrm{U/ml})}$
n	0.056	(min^{-1})

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