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Design of Robust Evolving Cloud-Based Controller for Type 1 Diabetic Patients Using n-Beats Algorithm

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HIGHLIGHTS

- RECCo is an online adaptive type controller, represents a notable recent innovation in the field of diabetes management.
- RPME is an online parameter estimation technique into the Adaptive Model Predictive Controller based on real-time data, making it more adaptive to changes in the patient's condition.
- The proposed N-BEATS algorithm is used for model validation. Comparing the performance of this algorithm with other conventional machine learning algorithms adds novelty to the study's approach.

Abstract: Designing and analyzing adaptive controllers to control blood glucose levels by giving insulin in the Lehman-Based Diabetic Patient Model (LBDPM) while considering diverse stochastic environments in gaining popularity is challenging task. RECCo, a notable recent innovation that implements the concept of the ANYA fuzzy rule-based system, is an online adaptive type controller that is used in this study for the application of diabetes. The simulation results show that the suggested controller is used in the model to track standard blood glucose values even in the presence of some unexpected external disturbances. The primary concern in the field of type 1 diabetes is achieving higher accuracy using a deep learning algorithm with data obtained from simulated patient models. To achieve better accuracy, validation of the model is performed using the N-BEATS algorithm. By utilizing an online parameter estimation technique, the RPME is integrated to improve the performance of the adaptive model predictive controller. The system identification technique is used to attain a transfer function that is designed further for implementation of the controller. The experimental validation of the proposed N-BEATS algorithm method is compared with other conventional machine learning algorithms. The proposed controller method attains excellent blood glucose set point tracking and the proposed algorithms give accuracy rates of 97.4% and 96% for the data obtained. It outperforms other state-of-the-art methods with an increase in the accuracy percentage compared with other Benchmark Pima Indian Diabetes Datasets (PIDD).

Keywords: Adaptive Model Predictive Control (AMPC); Glucose-Insulin (GI); Lehman Based Diabetic Patient Model (LBDPM); Neural Network (NN); Neural Basis Expansion Analysis for Interpretable Time Series (N-BEATS).

INTRODUCTION

Diabetes is a common chronic disease, and every year, billions of dollars are spent for its treatment. The total amount of expenses was estimated at approximately 133 billion dollars in 2002. The estimation has been increased to 245 billion dollars by 2014. Studies show that the number of patients suffering from diabetes around the world may increase to 400 million by 2025. This situation has motivated many researchers to find new ways of treatment for diabetes patients. Generally, the standard value of blood glucose is an approximately 80-120 mg/dl, and this phenomenon is termed normoglycemia. To avoid hypo and hyperglycemia, significant control of blood glucose is essential [1]. A cure for the disease is often prescribed with a suitable daily dosage of insulin injection. The advanced method is the usage of an insulin pump, which requires a closed-loop system for maintaining sugar levels for injecting insulin manually and a usage of the sensor to calculate the concentration level of blood glucose. The major physiological models that are considered for the representation of the study are a very simple state of the models, the Lehman Based Diabetic Patient Model (LBDPM) [2-4], in which the design procedure includes a model based on external disturbances such as meals, exercise, and measurement noise that may cause a sudden fluctuation in the glucose/sugar level. In this research conventional types of controllers such as PID is compared with recent AMPC is tested to overcome sudden changes and its controller performance was evaluated with one more adaptive proposed new controllers such as RECCo to regulate the variation of glucose level even in case of disturbances. The simulated data taken from developed system is further evaluated using the N-BEATS algorithm for its performance analysis. The Proposed model includes the different kinds of impact of characteristics such as time-varying parameters, uncertainty cases, lack of sensitivity to glucose are also considered for the present design work for patient and controller.

The model proposed by [5] is applied for simulation using various control techniques that give a satisfactory performance. In this category, working patient model include systems considering both types of linear and nonlinear systems [6]. In [7] extended the glucose-insulin (GI) dynamics in type I diabetic patients who include effects associated with exercise [8]. introduced the technology for validating the above model with the values of blood glucose in an off-line study and parameter estimation which revealed a standard deviation between majored and simulated blood glucose values. In [9] described a state estimation technology with online linearization of a nonlinear rigorous dynamic model. There are certain limitations that were found in the previous literature study and are given below in which practical studies based on the evaluation of controller performance have yet to be explored. The recent optimal methods with glucose monitoring issues are Fuzzy control, Sliding Mode (SM) control, Linear Quadratic Gaussian (LQG) control, H∞ control, Model Predictive Control with Lagrangian Function (MPC/LF) control and MP control, Fractional Order PID with JAYA (FOPIDC/JAYA) control, Genetic-Algorithm-PI-Controller (GA-PICExisting methods of patient model with its controller and validation techniques algorithms are shown including its merits and demerits listed in tables (1&2).

Table 1. Existing Controller algorithms

Authors	Diabetes Type	Controller Types	Merits / Demerits
(Bahremand et al., 2019) [10]	Type-1	Neural Network based Model Predictive Controller (MPC)	The practical implementation is very difficult using NN-based MPC.
(Colmegna, Bianchi, & Sánchez-Peña, 2020) [11]	Type-1	Switched Linear Parameter Varying (SLPV) Controller	Different meal scenarios were tested under various condition which overcomes risk of hypo and hyperglycemia.
(Alfian et al., 2020) [12]	Type-1	Artificial Neural Network (ANN)	The future blood glucose values can be predicted which provides alert in critical cases.
(Khaqan, Nauman, Shuja, Khurshaid, & Kim, 2022) [13]	Type-1	Sliding Mode Controller (SMC)	The brief comparison between (PID & LQR) and Nonlinear method SMC provides good efficiency.
(Belmon & Auxillia, 2020) [14]	Type-1	Grasshopper Optimization Algorithm (GOA) based Proportional Integral Derivative (PID)	Compared to conventional controllers GOA based PID provides good results with best accuracy.

Table 2. Existing Classification methods used for Type-1 Diabetes Mellitus

Authors	Diabetes Type	Classification methods	Merits / Demerits
Sun, Jankovic, Bally, & Mougiakakou, 2018 [15]	Type-1	Bidirectional LSTM (Bi-LSTM)	In this method future values can be predicted which satisfy the evaluation criteria.
De Bois, El Yacoubi, & Ammi, 2019 [16]	Type-1	Long Short Term Memory (LSTM)	Performs well when compared to other state of art methods.
Li, Yeh, Chen, & Chung, 2019 [17]	Type-1	Deep Convolution Neural Networks (DCNNs)	Based on the computer assisted method used in Diabetic Retinopathy applications.
Freiburghaus, Rizzotti, & Albertetti, 2020 [18]	Type-1	Multi layer Convolution Recurrent Neural Network (CRNN)	This method provides data driven technique which provides long term health support during complications.
Alazwari et al., 2022 [19]	Type-1	Random forests (RF) and Relief feature evaluation algorithms	It provides knowledge about how the future weights get integrated.

Based on the review made from existing - works, the experiment is limited to limited number of patients that has been overcome by the implementation of the N-BEATS Algorithm that contains data collected from a developed simulated diabetic patient model with 31,000 trained data by using Neural Network (NN) techniques that comes under type-1 diabetes which is suitable to obtain excellent accuracy-level and efficiency.

Motivation and Challenges:

- The study motivates to introduce RECCo, an online adaptive type controller based on the ANYA fuzzy rule-based system. RECCo is used in the LBDPM to control blood glucose levels effectively justified in section 4.
- Validation with N-BEATS Algorithm is most important challenges: To achieve better accuracy, the proposed model is validated using the N-BEATS algorithm. N-BEATS is a deep learning algorithm used for time series forecasting justified in section 5.
- Integration of RPME for Parameter Estimation: An online parameter estimation technique called RPME (Recursive Prediction Error) is integrated into the Adaptive Model Predictive Controller. This improves the controller's performance is an Challenging task by updating parameters based on real-time data is clearly visualized in Figure (6).
- System Identification and Transfer Function: System Identification technique is used to obtain the transfer function, which is further designed for implementing the controller. This ensures that the control system is accurately represented in Figures (9).

The rest of the paper has been framed as follows: Section 2 describes a brief account of the implementation of the research methodology. Section 3 derives the mathematical modeling of the diabetic patient model including disturbances. Section 4 presents the proposed RECCo-based control approach for TIDM monitoring. Section 5 demonstrates the experimental validation of simulated diabetes data using the proposed N-BEATS algorithm. Section 6 concludes based on the previous investigation performed.

PROPOSED METHODOLOGY

In this proposed work, an extended mathematical patient model is developed for treating Type 1 Diabetic Mellitus patients, which is named as the Lehman Based Diabetic Patient Model (LBDPM) system. In addition to the original model, the proposed model includes external disturbances such as meal, exercise, and noise disturbances. To regulate blood glucose by automatically giving insulin, sudden fluctuations can be overcome using three controllers, PID, AMPC, and RECCo, as shown in Figure 1. in which (AMPC & RECCo) acts as adaptive controller of the system. The basic procedure involved in the proposed technology is data collection from developed simulated patient model, preprocessing (removal of unwanted blood glucose values from collected data or round-off decimal values), feature selection based on forward/backward selection technique that leads to the highest accuracy with minimum number of features selected as a sample of blood glucose values, insulin concentration, age of the patient, time period), hyper parameter tuning that improves accuracy level, classifier method (gives confusion matrix, accuracy, precision, recall, F1-score).

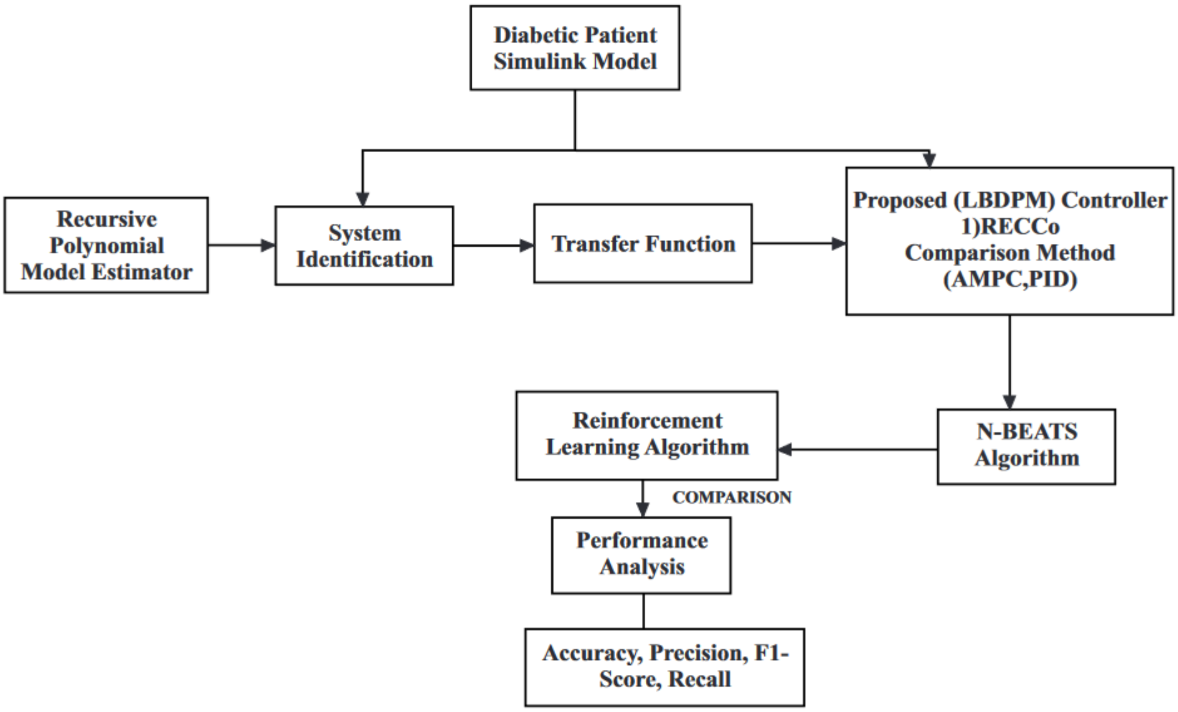


Figure 1. Block Diagram of Proposed Methodology

MATERIALS AND METHODS

One of the more difficult tasks is monitoring diabetes patients utilizing RECCo and artificial intelligence (AI) methods with mathematical modeling of the diabetic patient model. It is described briefly with the following steps.

3.1 Novel Lehman Based Diabetic Patient Model (LBDPM)

The design of the Lehman Based Diabetic Patient Model (LBDPM) is described in a detailed manner considering all other disturbances such as measurement noise, physical activity, and meals.[20] The glucose-insulin (GI) processes of the model consist of six different compartments: kidney, gut, heart/lungs, periphery, brain, and liver. The steps involved in designing the Lehman (9^{th} order model) process are as follows:

Step 1: Insulin Action: The pancreas provides a suitable amount of insulin absorbed, which is called the absorption rate of insulin I_{absa}. The filter required for the calculation of insulin in plasma is given as,

$$\frac{dI_{Pa}}{dta} = \frac{I_{absa}}{V_{Ia}} - K_{ea} * I_{Paa} \tag{1}$$

$$I_{paa} = \frac{1}{s}(I_{absa}/V_{Ia}) - (K_{ea} * I_{Paa}) \tag{2}$$

Where I_{paa} - is the insulin concentration in plasma in terms of (mU/dl), I_{absa}– is the insulin absorption rate (mU/min), K_{ea} – is the rate constant of amount of insulin eliminated, & V_{Ia} – is the insulin distribution volume (dl). I_{aa}- termed as a concentration of plasma in terms of insulin which is called as insulin active. The rate of change of active insulin is defined as

$$\frac{dI_{aa}}{dt} = ((K_{1a} * I_{Paa}) - K_{2a}) * I_{aa} \tag{3}$$

$$I_{aa} = \frac{1}{s}((K_{1a}) * I_{Paa} - K_{2a}) * I_{aa} \tag{4}$$

Here I_{aa} - is the insulin active concentration in terms of (mU/dl), I_{absa}– is the insulin absorption rate (mU/min), K_{1a}– denotes insulin elimination rate constant, & K_{2a}– denotes delay rate in insulin action. The two important types of insulin are as follows: Effective Active Insulin (I_{ea1}): Effective Plasma Insulin (I_{ep1}).

$$I_{ea1} = S_{p1a}\left(\frac{K_{2a}}{K_{1a}}\right) * I_{a1} \tag{5}$$

$$I_{ep1} = S_{h1a}\left(\frac{I_{Paa}}{I_{basal}}\right) \tag{6}$$

The above dynamic equations are used for the simulation of insulin in the diabetic patient model.

Step 2: Glucose action: Glucose which is generated by the gastric emptying subsystem increases up to 360 mg/min and decreases up to the value of 0. During the ingestion of the meal to the model, the intake of carbohydrates must be less than 10.8 gm. calculated by the equations

$$\mathrm{Ch_{criticala}} = \frac{[(\mathrm{Tasc_{gea}} + \mathrm{Tdes_{gea}})\mathrm{Vmax_{gea}}]}{2} \tag{7}$$

$$\mathrm{Tasc_{gea}} = \mathrm{Tdes_{gea}} = \mathrm{Cha} / \mathrm{Vmax_{\ gea}} \tag{8}$$

$$\mathrm{Tmax_{gea}} = [\mathrm{Cha} - \left(\frac{1}{2}\right)\mathrm{Vmax_{\ gea}} \frac{[(\mathrm{Tasc_{gea}} + \mathrm{Tdes_{gea}})\mathrm{Vmax_{gea}}]}{2}] \tag{9}$$

The gastric emptying rate is described by mathematical equations as follows:

$$\mathrm{G_{empta}} = ((\mathrm{Vmax_{\ gea}}) / \mathrm{Tasc_{gea}})\mathrm{t} \tag{10}$$

$$\mathrm{G_{guta}} = \frac{1}{s} * \left(\mathrm{G_{empta}} - \mathrm{G_{ina}}\right) \tag{11}$$

$$\mathrm{G_{ina}} = \mathrm{K_{gabsa}}\,\mathrm{G_{guta}} \tag{12}$$

Where, $\mathrm{G_{guta}}$ – is the absorption amount of glucose by gut in (mg), G_{ina}- amount of glucose intake, K_{absa}- is the constant of glucose absorption, $Tmax_{gea}$ - is the rate of time duration of gastric emptying system & $Tasc_{gea}$, $Tdes_{gea}$ - is the rate at which time duration has default values as 30 mins.

$$G_{rena} = CCR\ (G\text{-}RTG) \tag{13}$$

Where, G – is the amount of plasma glucose values present in the blood. The function of the kidney is to extract a lesser volume of glucose from blood, results in the Creatinine clearance rate (CCR). Glucose is utilized by certain organs such as the central nervous system, red blood cells, and peripheral cells, and is excreted through the kidney.

Step 3: The insulin delivery system is represented by the following transfer function with the components of the system described in paper. The system should contain the following subsystems: the gastric emptying system, central nervous subsystem, kidney subsystem, and also insulin dispenser system. The responses are analyzed using dynamic equations from 1-13 with its parameters described in table 3. and their responses are tested using Simulink tool results are depicted in Figure 3. Step 4: In the general form any human patient model can be represented using linearization technique in which state-space analysis is performed using a differential equation with white noise as shown in Figure 2.

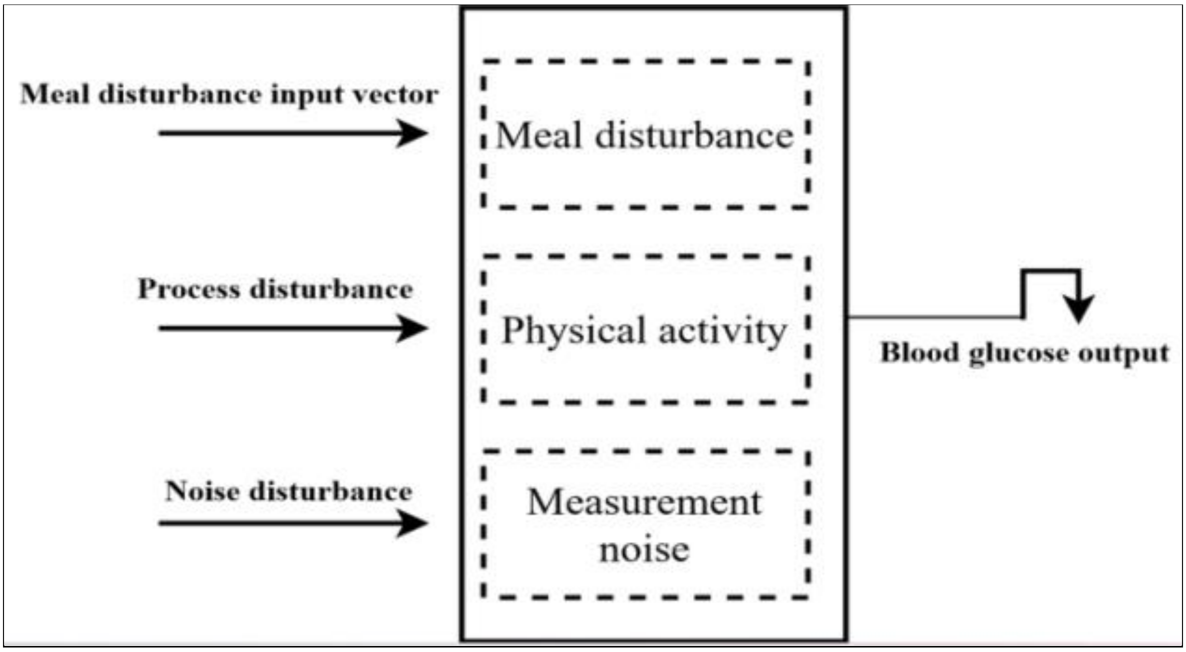
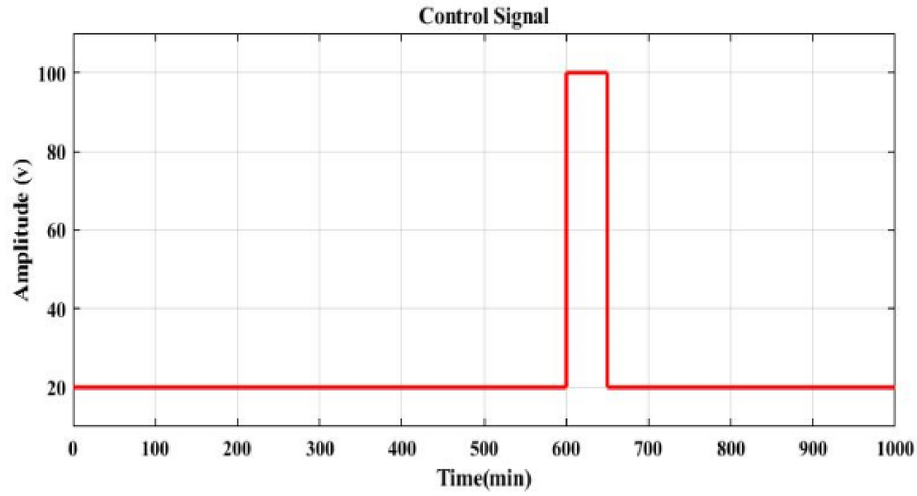
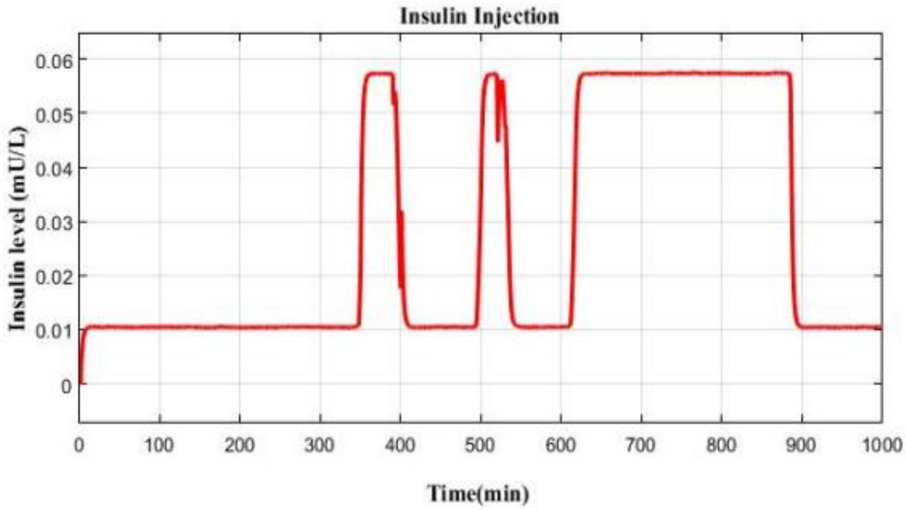


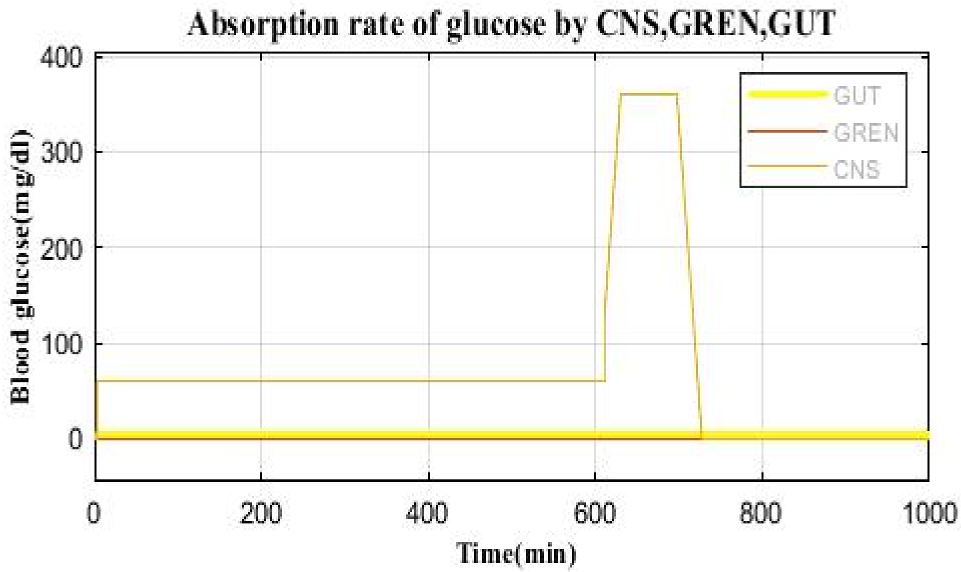
Figure 2. General representation of (Lehman) model


Control Signal
Amplitude (v)
100
80
60
40
20
0
100
200
300
400
500
600
700
800
900
1000
Time(min)

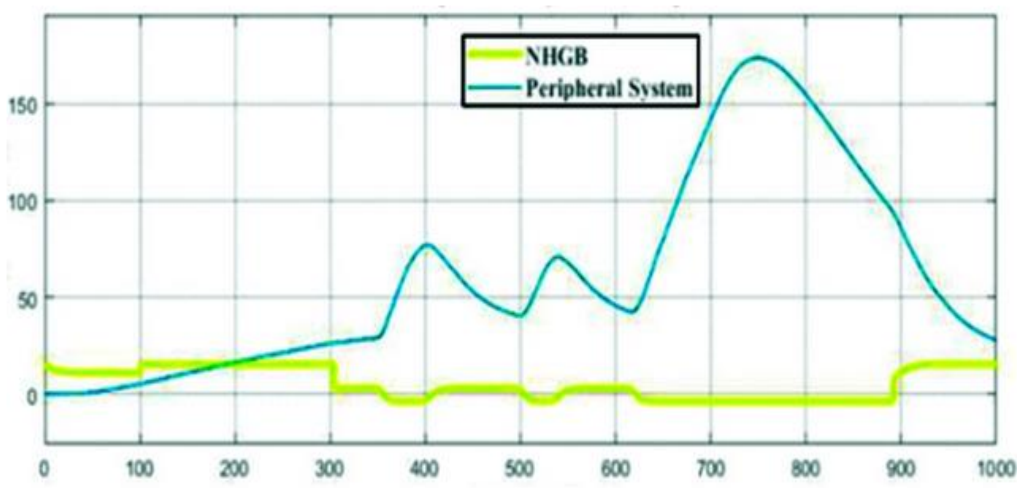
(a)


Insulin Injection
Insulin level (mU/L)
0.06
0.05
0.04
0.03
0.02
0.01
0
0
100
200
300
400
500
600
700
800
900
1000
Time(min)

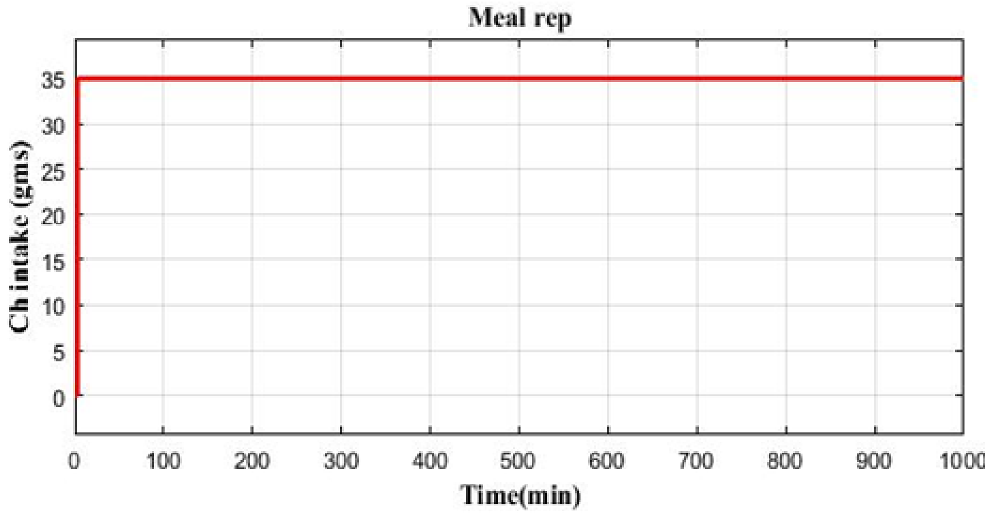
(b)


Absorption rate of glucose by CNS,GREN,GUT
Blood glucose(mg/dl)
400
300
200
100
0
0
200
400
600
800
1000
Time(min)
GUT
GREN
CNS

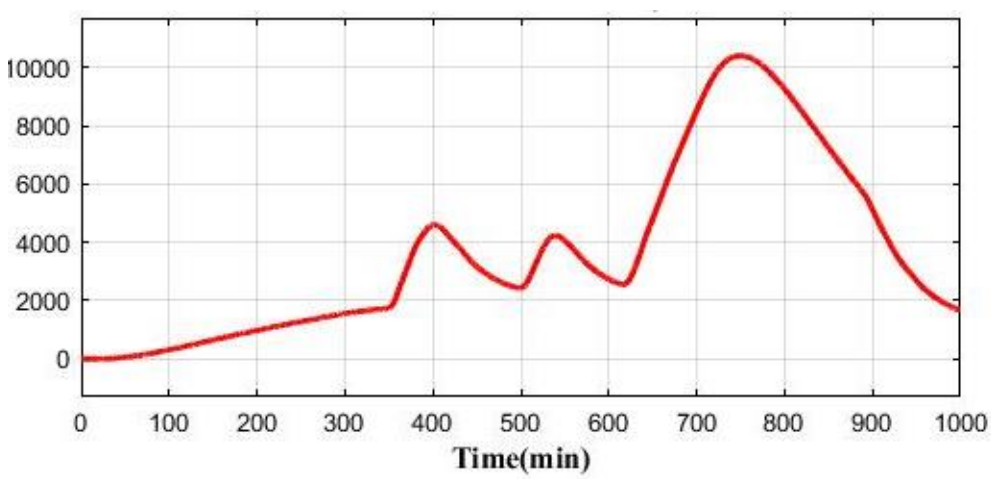
(c)



(d)



e)



(f)

Figure 3. a) Amplitude of the control signal b) Insulin level (mU/L) c) Glucose absorption rate by organs (CNS,GREN,GUT) (mg/min) d) Utilization of glucose by the net haptic glucose balance rate by the liver (mg/min) & Peripheral system e) Carbohydrates meal intake (60gms) f) Glucose absorption by RTG.

Table 3. Model parameters for patient design

Parameters considered in simulation	Symbol	Values	Unit
Constant rate of Insulin Elimination	K_{ea}	6.3	h^{-1}
I_pInsulin action delay rate	K_{1a}	0.025	h^{-1}
I_aInsulin action delay rate	K_{2a}	1.550	h^{-1}
Reference value of plasma insulin	I_{basal}	1.0	mU/dl
Constant rate of glucose by Gut	K_{gabsa}	1.000	h^{-1}
Rate of Gastric emptying system	$Vmax_{gea}$	360.0	mg/min
Distribution of Insulin volume in whole body weight	V_{Ia}	1.42 * 80	dl
Distribution of insulin volume in whole bodyweight	V_{Ga}	2.21 *80	dl
For reaching $Vmax_{gea}$, rise time	$Tasc_{gea}$	30	min
From $Vmax_{gea}$ to 0 falling time	$Tdes_{gea}$	30	min
Creatinine Clearance Rate	CCR	1.0	dl/min
Renal Threshold Glucose Value	RTG	162	mg/dl

Model Identification

To use the developed model using a feedback scheme, some of the parameters are to be identified to achieve the requirements of patients. The RPME technique which is an online parameter estimation technique that has to be implemented for Adaptive Model Predictive Control (AMPC). The detailed parameters values are listed in Appendix for reference

Model Validation

Testing a given model with appropriate values of blood glucose using the system identification method is called model validation. The quality of work is estimated from the model using a mean-square error criterion, by comparing the estimated output value of blood glucose to the measured value. The obtained transfer function is used to linearise the patient model that is designed to simulate the system, which helps to tune the controller to get the reference input. The Transfer function obtained is given by,

$$\frac{0.072S-7.2e^{-3}}{S^2+0.12S+4.01e^{-6}} \tag{13}$$

Controller Design and Mechanism

In this study the novel Lehman Based Diabetic Proposed Patient Model (LBDPM) is designed and tuned with the help of a PID controller, to check and evaluate its better controller performance. Further the model is implemented with Robust controllers adaptive MPC, RECCo depicted in Figure 4.

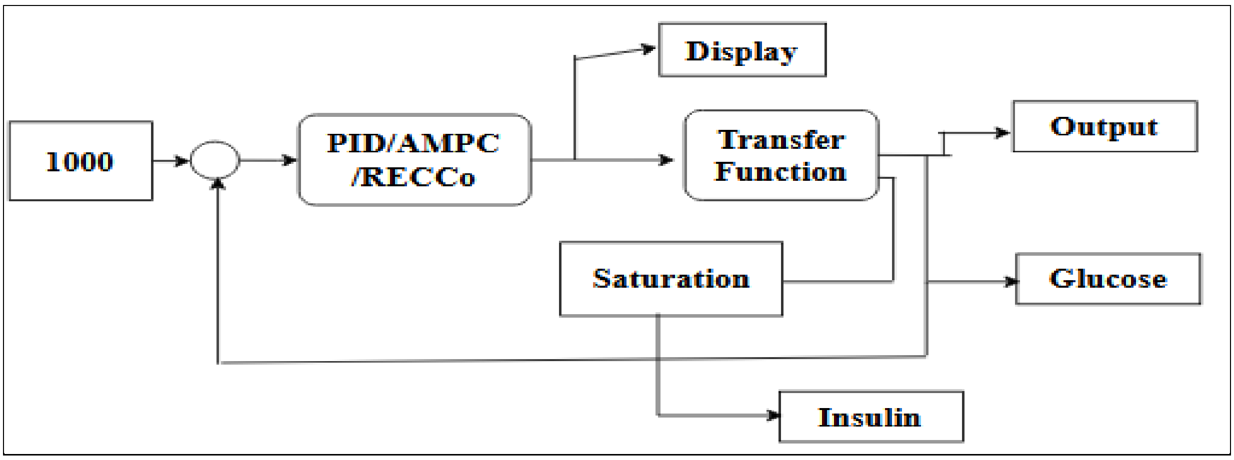


Figure 4. Methodology of the proposed controller algorithm*Adaptive Model Predictive Controller (AMPC)*

The recursive polynomial model estimated algorithm library has been realized in Matlab/Simulink. The general steps involved in the state estimation technique is represented by the block diagram using the continuous-time transfer function of the controlled system as given in Figure 5. A necessary input such as blood glucose parameters should be fed through the transfer function block obtained which represents the linearized model of the patient. The value given in the transfer function is denoted with polynomials degree & time period in which output contains the parameter estimate state values, covariance matrix values, and data measurement vector listed in Table 4. The algorithms mentioned above were tested in a closed loop system with a self-tuning Linear Quadratic (LQ) controller as shown in Figure 6 (a, b). The controller is based on the minimization of quadratic criterion with the penalization of the output control signal. This method is applied in the current work which represents automatic online parameter adaptation of values even though under various disturbances.

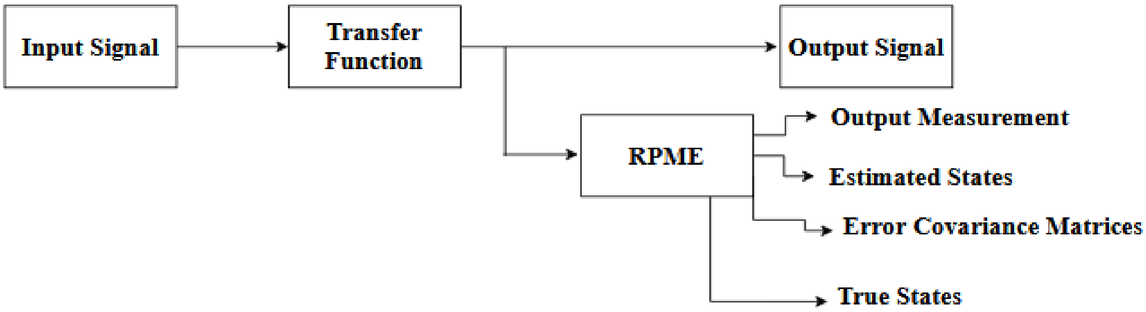
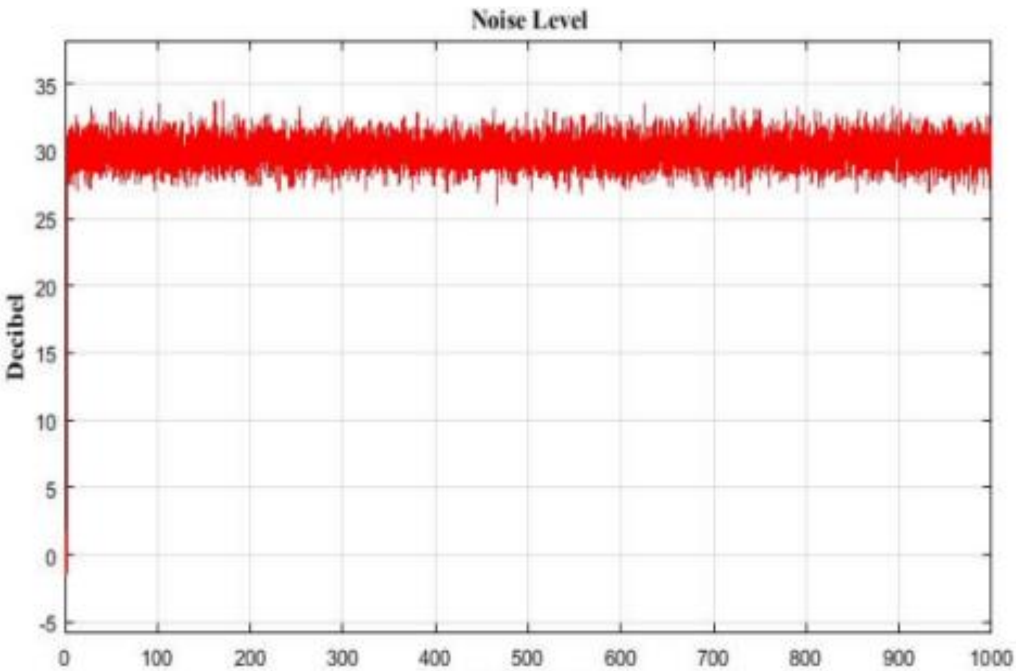
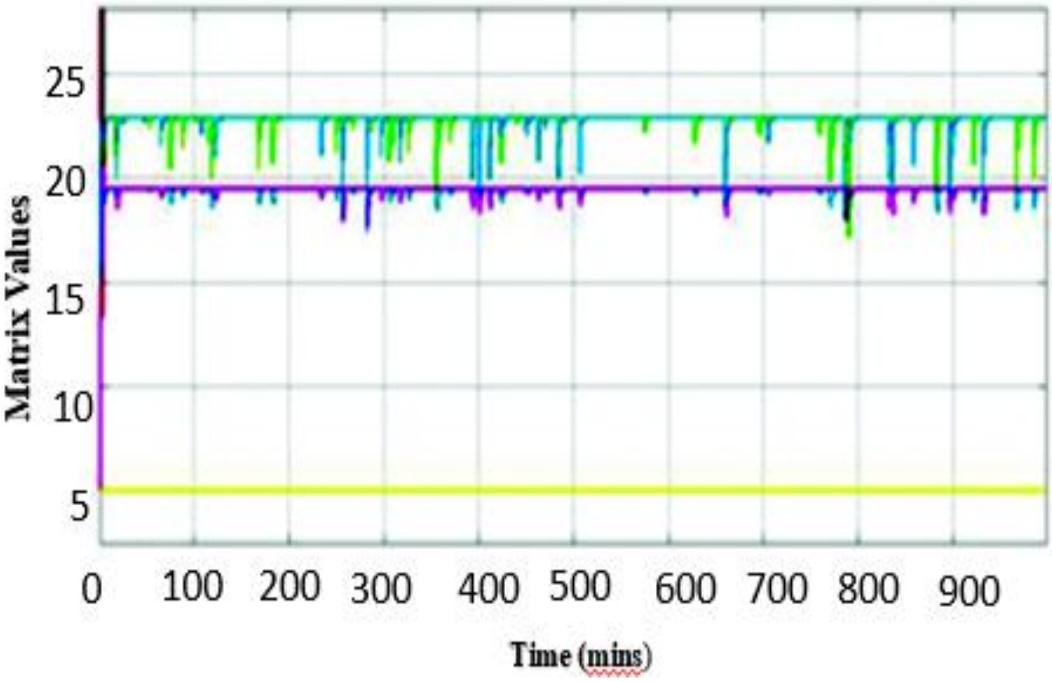


Figure 5. State Estimation Method

Adaptive Model Predictive Controller uses an Extended Kalman Filter (EKF) and substitutes the gain value, at each interval with the updated patient model parameters to maintain consistency of blood glucose values. The response of the blood glucose and insulin shows that AMPC performs well with less peak overshoot and oscillation with a faster settling rate of the glucose graph when compared to the PID controller shown in Table 5.



(a)



(b)

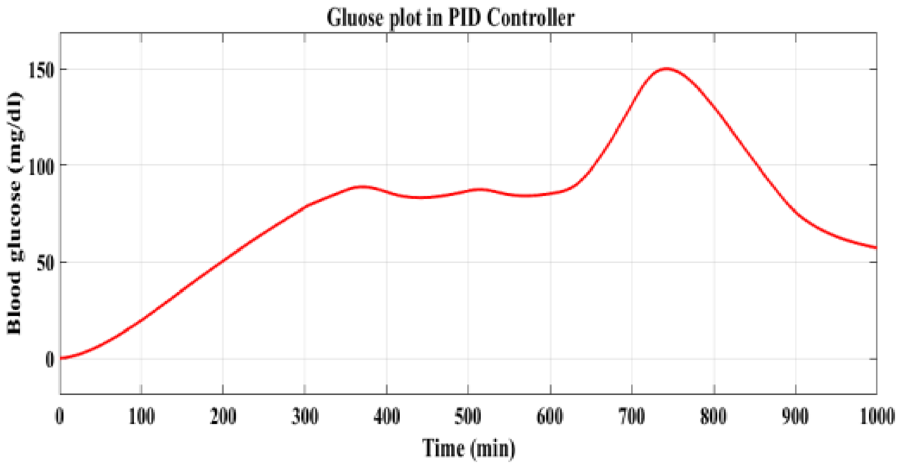
Figure 6. Adaptive Control plot: **a)** Measurement of Noise Signal, **b)** Representation of parameter estimated values

The proposed estimation parameters technique (RPME) was validated at epochs 8 training and analyzed using neural network tools. The response plot of parameter estimation technique using RPME method is given in Figure 6 (a,b).

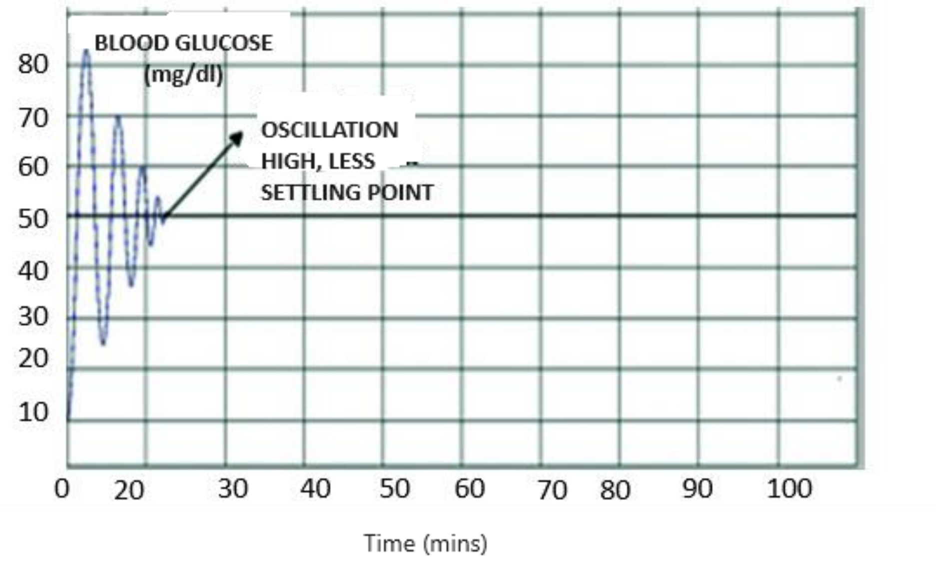
Table 4. Recursive polynomial model estimated values

Error Covariance matrix value				Estimated state values	True state values	Measurement states	
30.84	0	14.52	0	14.33	16.07	20.1	6.994
0	30.83	0	14.5	5.068	0		
14.52	0	17.87	0	0.8892	30		
0	14.5	0	17.86	0.9774			

Adaptive Model Predictuve Controller [21, 22] is preferable under a linear patient model in which parameter is obtained during process of run time. Error covariance matrix values, estimated states values, true states values, and measurement states values are calculated as shown in Figure 6. On comparison with PID controller [23][24], blood glucose plot reaches a steady state at a faster rate and peak overshoot is very less with respect to the PID controller as shown in Figure 6(a,b).



(a)



(b)

Figure 7. Blood glucose plot for: (a) PID Controller – (b) AMPC

The response of blood glucose and insulin shows AMPC performs well with less peak overshoot and oscillation with faster settling rate of glucose graph when compared to PID controller [25][26] shown in table 4. The frequency response analysis of the model is justified in Figure 7.

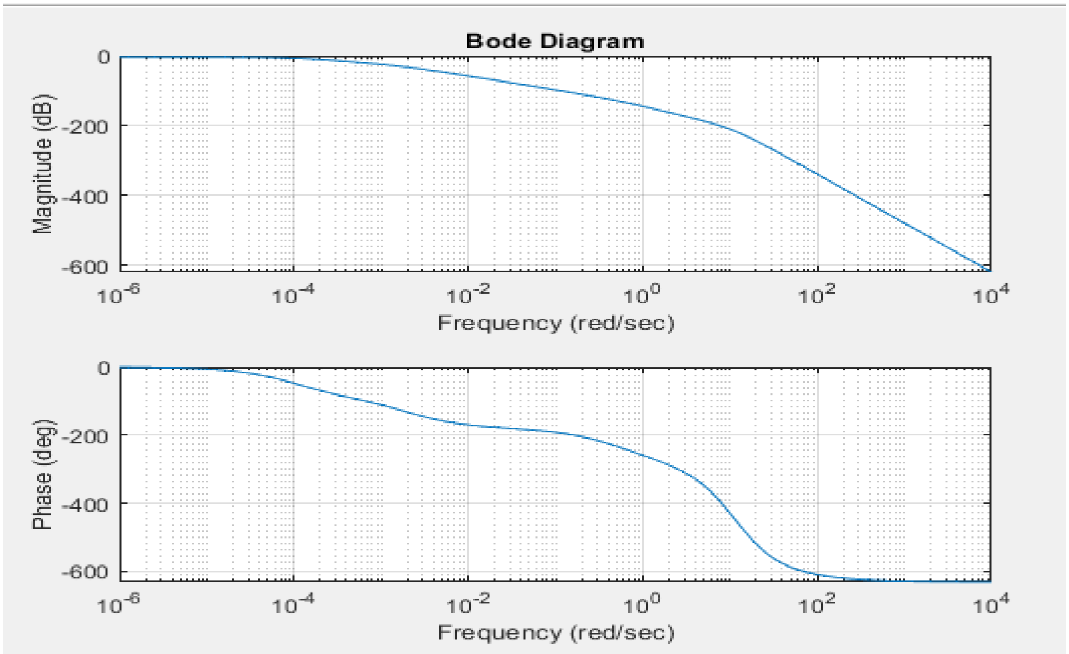


Figure 8. Bode plot response

Table 5. Comparative investigation with other recent controllers

Name of Controller	Peak Overshoot Time (min)	Settling Time (min)	Meal intake (gm)	Insulin Dose (mU/L)	Noise (%)	Error (%)
Proportional Integral Derivative (PID)	800 min	650 min	60	59.6	10	0
Adaptive Model Predictive Controller (AMPC)	20 min	120 min	60	59.2	5	0
RECCo (Proposed method controller)	Minimzed Justified in graph (Figure 12)	50 min	60	59	1	0

System Identification approach

The parameters of the proposed model with all the three disturbances are estimated repeatedly using System Identification method. From the workspace, the values of blood glucose and insulin are taken for estimating transfer function. It provides better fit transfer function in assuming the number of zeroes and poles as shown in Figure (9) to linearise the system.

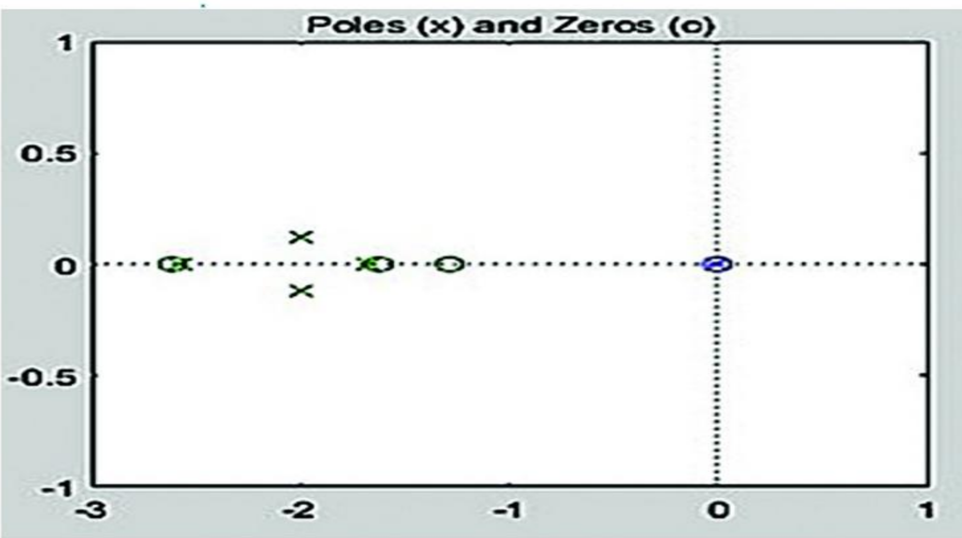


Figure 9. Poles (x) and Zeros(O)

Proposed RECCO - based control approach for TIDM monitoring

It is a kind of fuzzy rule-based (FRB) system that contains non parametric parts of the antecedent. The main concept behind this controller is to obtain the membership value of the current value to the existing data clouds that apply the terms fuzzy data and relative data density. The clouds denote previous blood glucose samples that are very close to each other. The analyses of incoming blood glucose data samples are performed in an online method, every sample value is associated with each cloud and the parameters are updated automatically. The RECCo controller [27] is described here and comprises three stages: reference model, evolving, and adaptation law. The entire control structure procedure is depicted in Figure 10. From the initial received data sample, the controller has started. Any previous data related to the controlled process are used for initializing the constant ‘τ', design parameters of ‘u_{min}','u_{max}'input range, sampling time ‘T_S' and output range of 'y_{min}' ,'y_{max}'. For each incoming sample after initialization, adapted controller gains are performed and a newer data cloud or fuzzy rule is included if specific conditions are satisfied.

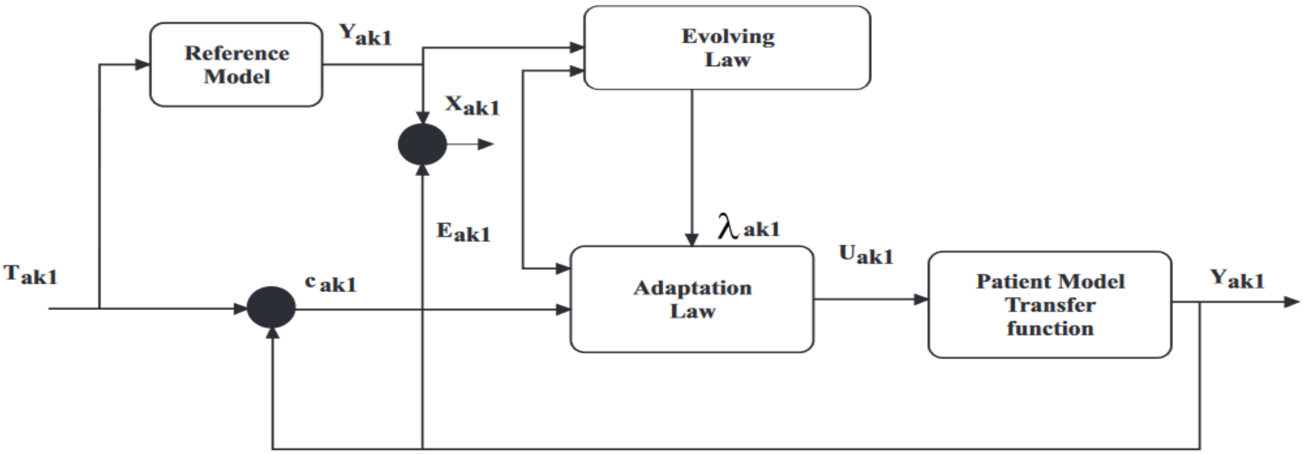


Figure 10. RECCo Control Structure procedure

Reference model

The RECCo controller reference model explains the expected trajectory $\mathrm{y_{ak1}}^{\mathrm{r}}$and $\mathrm{y_{ak1}}$the plant output dynamics. A basic 1st order linear reference model is expressed as,

$$\mathrm{y_{ak+1}}^{\mathrm{r}} = \mathrm{a_{r1}}\ \mathrm{y_{ak1}}^{\mathrm{r}} + (1 - \mathrm{a_{r1}})\ \mathrm{r_{ak1}} \tag{15}$$

From the above Eq. (17) the range is, $0 < \mathrm{a_{r1}} < 1$, $\mathrm{a_{r1}}$is the pole parameter of the model, and reference signal is$\mathrm{r_{ak1}}$. It has been estimated to $1 - \frac{\mathrm{T_{ak1}}}{\tau}$, process sampling period is $\mathrm{T_{ak1}}$and time constant is τ. The major aim of controller gives effective performance which assures the smaller error from tracking

$$\varepsilon_{\mathrm{ak1}} = {y_{ak1}}^{r} - y_{ak1} \tag{16}$$

Evolving law

The controller fuzzy structure has been further addressed by evolving law. The algorithm is based on the ANYA fuzzy rule and the model is expressed as,

$$\mathcal{R}^{\mathrm{i}} = \mathrm{IF}\ \left(\mathrm{x} \sim \mathrm{X}^{\mathrm{i}}\right)\ \mathrm{THEN}\ \ (\mathrm{u^i}) \tag{17}$$

From Eq.(19), $\mathcal{R}^{\mathrm{i}}$ is the number of rules which is the same as the total count of clouds in the data space, $\mathrm{i} = 1, \ldots., \mathrm{C}$. Evolving law plays a major role in the antecedent part determined through the ~operator. The present data $\mathrm{x} = [\mathrm{x_1}, \mathrm{x_2}, \ldots, \mathrm{x_n}]\mathrm{T}$ compared with $\mathrm{X}^{\mathrm{i}} \in \mathcal{R}^{\mathrm{n}}$ of i-th cloud. The subsequent part is determined through C control operations in local u_i data and is described in 2-D space as

$$\mathrm{x_{ak1}} = \left[\frac{\varepsilon_{\mathrm{ak1}}}{\Delta\varepsilon_{\mathrm{ak1}}}, \frac{\mathrm{y_{ak1}}^{\mathrm{r}} - \mathrm{y_{min}}}{\Delta \mathrm{y_{ak1}}}\right]^{\mathrm{T}} \tag{18}$$

From Eq.(20),$\Delta\mathrm{y_{ak1}} = \mathrm{y_{max}} - \mathrm{y_{min}}$ and $\Delta\varepsilon_{\mathrm{ak1}} = \frac{\Delta \mathrm{y_{ak1}}}{2}$. Based on the values taken from Table 6, the clouds are generated and cloud points are associated with glucose samples as shown in Figure 11, for the simulated diabetes patient model system using the properties stated.

Table 6. Data cloud properties

Normalized Relative Density	λ_{ak1}^{i} $=\gamma_{ak1}^{i}/\Sigma_{j=1}^{c}\gamma_{ak1}^{i}$ i=1,2,3..C where γ_{ak1}^{i}- local density of ith cloud
Local Density	γ_{ak1}^{i}=1/ 1+ ‖‖x_{ak1} - μ_{ak1}^{i} ‖‖^2 + σ_{ak1}^{i} - ‖‖ μ_{ak1}^{i} ‖‖^2
Mean Value	μ_{ak1}^{i}= ((M^i - 1/ M^i) μ_{k-1}^{i} + 1/$M^i{}_*$ (x_{ak1}) [M^i= No of data points]
Mean Square Length	σ_{ak1}^{i}= ((M^i - 1/ M^i) σ_{k-1}^{i} + 1/ M^i ‖‖ x_{ak1} ‖‖^2 [Initial condition M^i = 1], mean value μ_1^i= x_1, σ_1^i= ‖‖ x_1 ‖‖^2

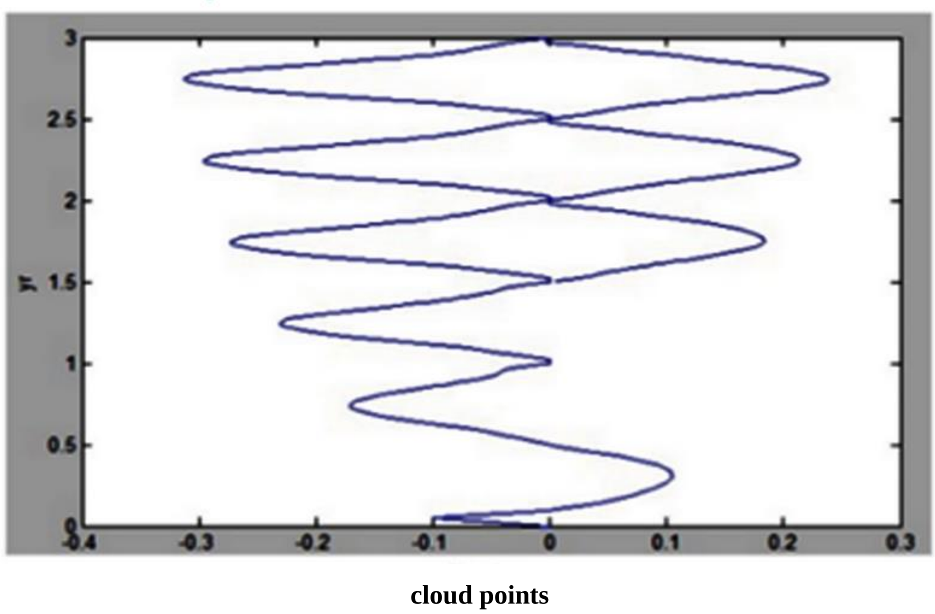


Figure 11. Cloud points generated

Adaptation Law

In the case of the consequent part, the PID-R type of RECCo based controller is expressed using the following terms:

$$u_{ak1}{}^{i} = P_k{}^{i}\varepsilon_{ak1} + I_k{}^{i}\Sigma^{\varepsilon}_{ak1} + D_k{}^{i}\Delta^{\varepsilon}_{ak1} + R_k{}^{i},\quad i = 1, \ldots.. C \tag{19}$$

From Equation (21) the controller gains are $P_k{}^i$, $D_k{}^i$ and $I_k{}^i$, and the operating point compensation is $R_k{}^i$. $\Delta^{\varepsilon}_{ak1}$ and $\Sigma^{\varepsilon}_{ak1}$ are tracking error derivatives and the discrete time integral signal is measured as follows:

$$\Sigma^{\varepsilon}_{ak1} = \begin{Bmatrix} \Sigma^{\varepsilon}_{k-1} + \varepsilon_{ak1}, u_{min} < u(k) < u_{max} \\ \Sigma^{\varepsilon}_{k-1,}, u(k) = u_{max}\ or\ u_{min} \end{Bmatrix} \tag{20}$$

$$\Delta^{\varepsilon}_{ak1} = \varepsilon_{ak1} - \varepsilon_{ak1-1} \tag{21}$$

The definition of adaptation gain values for other parameters are given by,

$$\Delta P_k{}^{i} = \alpha_P\, G_{sign}\, \lambda^{i}_{ak1}\ |\ e_{ak1}\, \varepsilon_{ak1}\ |\ /\ (1+ r^2_{ak1})\quad \Delta I_k{}^{i} = \alpha_I\, G_{sign}\, \lambda^{i}_{ak1}\ |\ e_{ak1}\, \Delta^{\varepsilon}_{ak1}\ |\ /\ (1+r^2_{ak1})$$

$$\Delta D_k{}^{i} = \alpha_D\, G_{sign}\, \lambda^{i}_{ak1}\ |\ e_{ak1}\, \Delta^{\varepsilon}_{ak1}\ |\ /\ (1+r^2_{ak1})$$

$$\Delta R_k{}^{i} = \alpha_R\, G_{sign}\, \lambda^{i}_{ak1}\ |\ \varepsilon_{ak1}\ |\ /\ (1+ r^2_{ak1}) \tag{22}$$

The adaptive law uses the tracking product and error processing as normalization with a cost function. After parameter adaptation, weighted average defuzzification is utilized, and then the control variables are given

by, $$u_{ak1} = \sum_{i=1}^{c} \lambda_{ak1}{}^{i}\, u_{ak1}{}^{i} = \frac{\sum_{i=1}^{c} \gamma_{ak1}{}^{i} u_{ak1}{}^{i}}{\sum_{i=1}^{c} \gamma_{ak1}{}^{i}} \tag{23}$$

The default adaptation gain value is 0.1 when the control range is between u_{min1} = 0 and u_{max1} = 100

$$\alpha_{new} = (u_{max1} - u_{min1}/20) * 0.1 = 0.5 \tag{24}$$

Table 7. Formulas for the instability protection mechanism

(i) Dead zone in adaptation law (function to switch off algorithm when value of tracking error is lower that threshold value)	$\Delta\bar{\theta}^{i}_{k} = \begin{Bmatrix} \Delta\theta^{i}_{k}, & \Vert\varepsilon_{ak1}\Vert \geq d_{dead} \\ 0, & \Vert\varepsilon_{ak1}\Vert < d_{dead} \end{Bmatrix}$ i=1,….c (25)
(ii) Parameter projection (it is converged to get optimal parameters values)	$\theta^{i}_{k} = \begin{Bmatrix} \theta^{i}_{k-1} + \Delta\theta^{i}_{k}, & \underline{\theta} \leq \theta^{i}_{k-1} + \Delta\theta^{i}_{k} \leq \bar{\theta} \\ \underline{\theta}, & \theta^{i}_{k-1} + \Delta\theta^{i}_{k} < \underline{\theta} \\ \bar{\theta} & , \theta^{i}_{k-1} + \Delta\theta^{i}_{k} > \bar{\theta} \end{Bmatrix}$ i=1,….c (26)
(iii) Leakage in adaptation law (σ- modification)	$\theta^{i}_{k} = (1- \sigma_L)\theta^{i}_{k-1} + \Delta\theta^{i}_{k}$ i=1,….c (27)
(iv) Interruption of adaptation law	$\Delta\bar{\theta}^{i}_{k} = \begin{Bmatrix} \Delta\theta^{i}_{k}, & u_{min} < u(k) < u_{max} \\ 0, & \text{otherwise} \end{Bmatrix}$ i=1,….c (28)

where $\Delta\theta^{i}_{k}$, σL, , d_{dead} has certain constraints such as $\Delta\theta^{i}_{k}$-Tracking error must be smaller than a threshold value, σL - Leakage value must be approximately 10^-6 ,d_{dead}- value should be kept larger than noise level, αP,αI,αD, αR - adaptation gains as given in table 7&8. The transfer function is taken from the designed diabetic patient model which is analyzed by applying equations (14) to (27) using the simulation platform.

Table 8: Control parameters for RECCo used in the simulation

Process Parameters	Values	Evolving Parameters	Values	Adaptation Parameters	Values
u_{min}	0	γ_{max}	0.93	G_{sign}	± 1
u_{max}	100	k_{add1}	1	α_{pa},α_{Ia}, α_{Da},α_{Ra}	0.1
y_{min}	20	n_{add1}	20		
y_{max}	70	C	0		
T_S (SamplingRate)	2	C_{max}	20		
τ (Time Constant)	40	γ_{max}	0.93		

Steps involved in the algorithm

Step 1: Initialize process parameters
Step 2: Initialize evolving parameters
Step 3: Initialize adaptation parameters, Repeat.
Step 4: Measure the output y_{ak1}.
Step 5: Compute the reference system outputr_{ak1}..
Step 6: Evaluate ε_{ak1}, e_{ak1}, $\Sigma^{\varepsilon}_{ak1}$,$\Delta^{\varepsilon}_{ak1}$
Step 7: Calculate x_{ak1}
Step 8: if C=0 Increment C
Step 9: Store k_{add1}
Step 10: Initialize $\mu_0{}^1$,σ_0^1, $\theta_0^1$for cloud1 by using the above properties
Step 11: else
Step 12: Calculate λ^i_{ak1}, μ^i_{ak1} for i=1,2,…C
Step 13: if ($max_i\gamma^i_k$<γ_{max} and K > (k_{add1} + n_{add1})) then, increment C, store k_{add1}.
Step 14: Initialize $\mu_0{}^c$, σ_0^c, θ_0^c , else
Step 15: Associate sample $x_{ak1}$with cloud
Step 16: Update μ^i_{ak1}, $\sigma^i_{ak1}$for the cloud, end if, end if.
Step 17: Adaptation of PID controller gain from the transfer function taken using the diabetic patient model.
Step 18: Compute the control code using scripts, end.

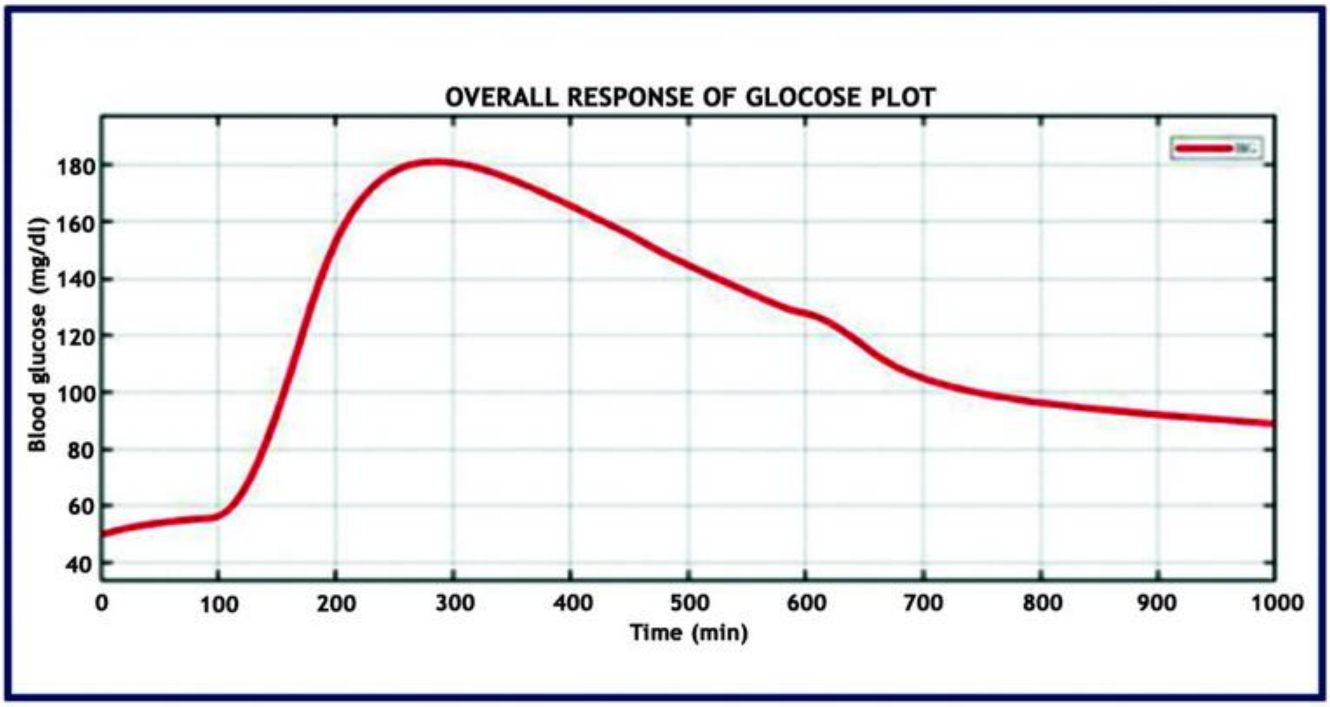


Figure 12. RECCo controller output results: Overall response of Blood Glucose plot (after RECCo implementation)

On Comparison of RECCo controller with other recent popular method of controller such as AMPC the settling time of output response from RECCo is about 50 minutes and thereby oscillations has been completely vanished entirely as shown in Figure 12.

Experimental setup of the proposed work using the N-BEATS algorithm:

The research was implemented using the Windows 10 operating system, and an Intel Core CPU. The algorithm was designed and tested with Python version 3.7. NBEATS [28], a pure deep learning method for time series predictions which beat Recurrent Neural Network's score with an accuracy rate of 97.4%. with the help of the datasets taken from the Simulink model as represented in Figure 13.

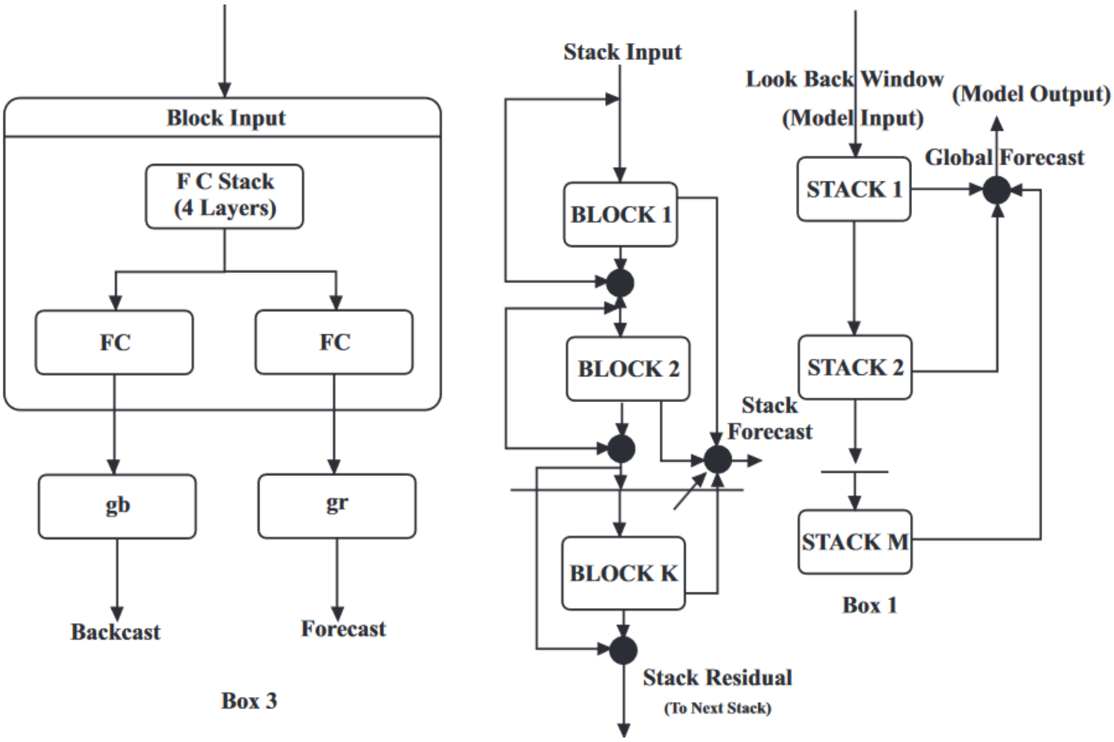


Figure 13. Architecture of the N-BEATS algorithm

Basic Operation:

The basic block operation is described with block index 'l'. The 'lst' block accepts its input 'X_l' and output vectors such as $\widehat{X}_l$and $\widehat{Y}_l$. For the remaining blocks, their inputs X_l are the output residual of previous blocks. Each block contains two outputs $\widehat{Y}_l$ block the forward forecast of length H. $\widehat{X}_l$- the block estimate of length X_l is called a back-cast with certain constraints of the space that the block is used for approximate signals. The first part is the fully connected network that produces forward θ_l^f and backward θ_l^b of the expansion coefficient to note that block index '1' is denoted with a drop of θ_l^f, θ_l^b, g_l^b, g_l^f. The second part contains backward $g_l^b$and forward g_l^f with basic layers that accept forward θ_l^f and backward θ_l^b coefficient expansion that projects them internally on basis functions that produce back-cast outputs $\widehat{X}_l$and forecast output $\widehat{Y}_l$. The second part of the networks corresponds to expansion coefficients of θ_l^f and θ_l^bthat send outputs through the following function: $\hat{y}_l = g_l^f(\theta_l^f)$ and $\hat{x}_l = g_l^b(\theta_l^b)$.

The 4 layered fully connected stack is expressed as, Layer 1: $h_{l,1}$= FC $_{l,1}$ (X_l) ; Layer 2: $h_{l,2}$= FC $_{l,2}$ ($h_{l,1}$); Layer 3:$h_{l,3}$= FC $_{l,3}$ ($h_{l,2}$); Layer 4: $h_{l,4}$= FC $_{l,4}$ ($h_{l,3}$). FC layer with RELU non-linearity is said to be the fully connected layer. $h_{l,1} = RELU\ (W_{l,1}X_1 + b_{l,1})$ (29) Using ${g_l}^b$ as the basis vector, x_l backward data are estimated. Through ${g_l}^f$, the following similar path $y_l$has been produced. $\hat{x} = {g_l}^b({\theta_l}^b)$ and $\hat{x} = {g_l}^f({\theta_l}^f)$,used for mapping the extension of forward and backward data coefficients calculated by using equations 28 and 29.

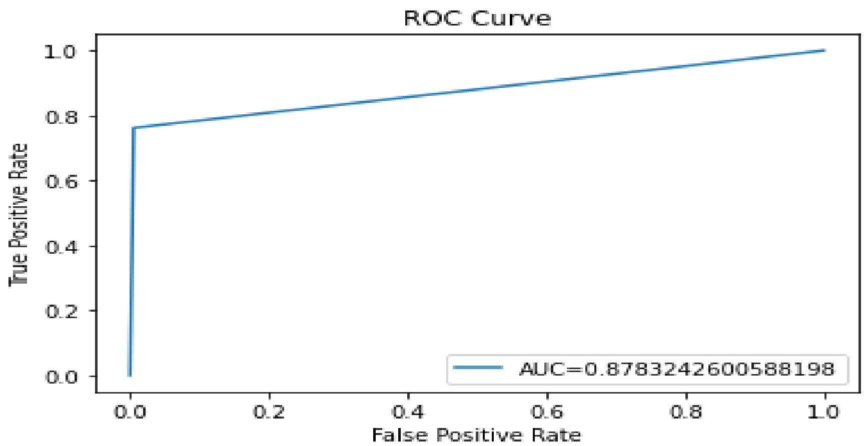


Figure 14. N-BEATS ROC Curve

Table 9. Indication of performance indices using different machine learning algorithms:

Algorithms Used	Precision	Recall	F1-Score	Mean Square Error	Accuracy	Training Accuracy	Testing Accuracy
N-BEATS	**0.969**	**0.966**	**0.973**	**0.152**	**97.4%**	**0.974**	**0.971**
XGB	0.929	0.924	0.921	0.346	93%	0.91	0.92
SVM	0.919	0.915	0.912	0.469	91%	0.86	0.91
Decision Tree	0.921	0.927	0.922	0.217	92%	0.81	0.90
KNN	0.898	0.863	0.869	0.521	89%	0.93	0.92
Reinforcement Learning	0.964	0.867	0.878	0.174	96.1%	0.87	0.89

The experimental validation of the proposed N-BEATS algorithm method is compared with other conventional algorithms [29][30] as shown in Table 9. Its ROC Curve for N-BEATS is depicted as shown in Figure 14. The Stability analysis of the proposed model with different condition of patients were tested based on the simulated datasets which is depicted in Figure. The normal, abnormal, critical condition of patients [31] were informed to doctors based on the analysis of standard deviation factor by automatic indication. The proposed stability controller condition under uncertainty cases is also tested for patients with real time datasets collected from Thanjavur Government hospital with ethical clearance approval number (578) and its results are shown in Figure 15.

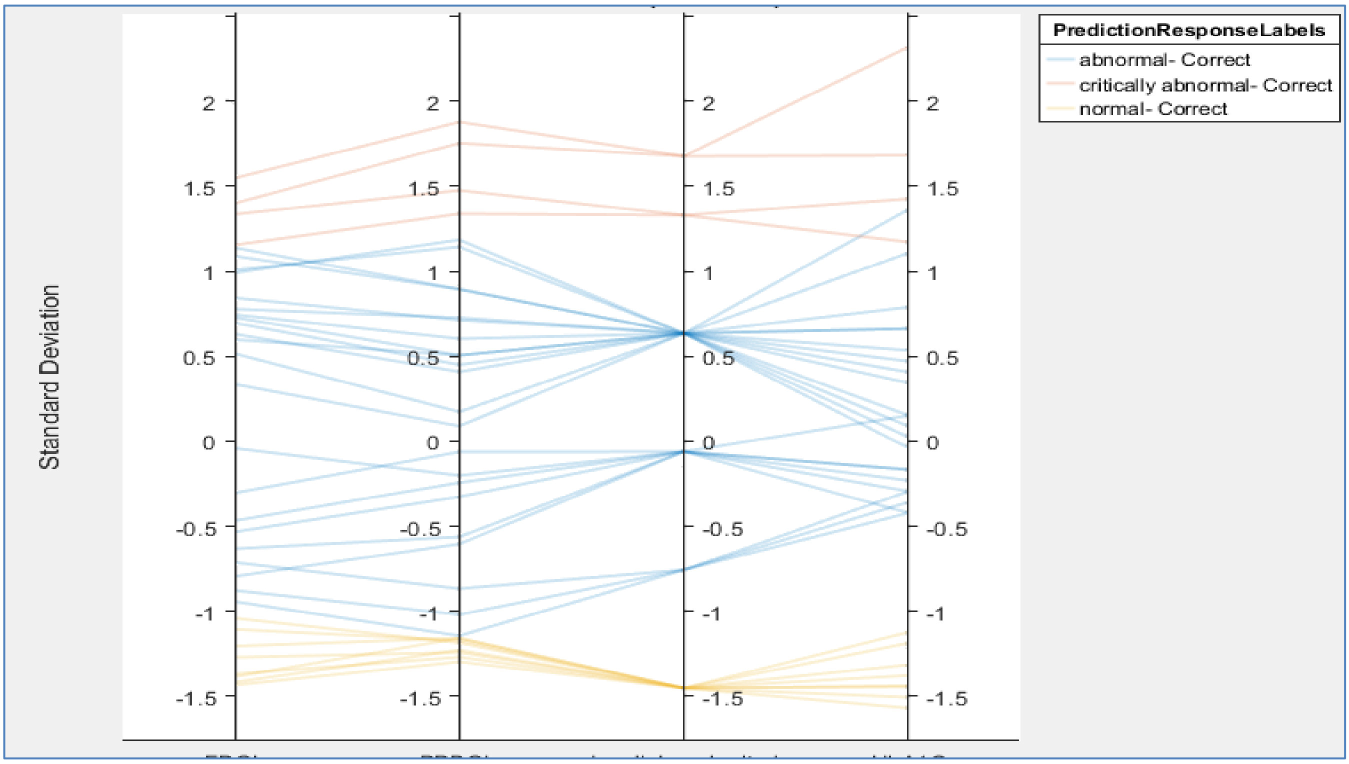


Figure 15. Stability analysis of the proposed model under different patient conditions

CONCLUSION

The proposed Lehman Based Diabetic Patient Model (LBDPM) system was developed under different cases with PID, adaptive MPC, and RECCo controllers are implemented to regulate blood glucose even during sudden fluctuations. The developed model is further validated using the N-BEATS algorithm for performance analysis. A novel N-BEATS algorithm increases the accuracy rate but the value of mean square error rate has been reduced. The simulation analysis shows that proposed model using Robust RECCo Controllers has less settling time 50 minutes when compared with other recent adoptive controller such as AMPC and conventional controller such as PID there by the main objective is to track the desired blood glucose value with their corresponding models. The proposed method is further evaluated on simulated diabetes datasets that achieve greater accuracies of 97.4% and 96% with lower mean squared error rates of 0.15% and 0.2%, which infers low computation time. In the future, the work will be extended further for real-time implementation of controller namely Reinforcement Learning Human Feedback Controller which will be further implemented and tested.

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