Gain-Scheduled Observer-Based Finite-Time Control Algorithm for an Automated Closed-Loop Insulin Delivery System

WAQAR ALAM, QUDRAT KHAN, RAJA ALI RIAZ, RINI AKMELIAWAT, ILYAS KHAN, AND KOTTAKKARAN SOOPPY NISAR

1Department of Electrical and Computer Engineering, COMSATS University Islamabad, Islamabad 45550, Pakistan
2Centre of Advanced Studies in Telecommunications (CAST), COMSATS University Islamabad, Islamabad 45550, Pakistan
3School of Mechanical Engineering, The University of Adelaide, Adelaide, SA 5005, Australia
4Faculty of Mathematics and Statistics, Ton Duc Thang University, Ho Chi Minh City 700000, Vietnam
5Department of Mathematics, College of Arts and Sciences, Prince Sattam bin Abdulaziz University, Wadi Al-Dawaser 11991, Saudi Arabia

Corresponding author: Ilyas Khan (ilyaskhan@tdtu.edu.vn)

ABSTRACT In diabetes mellitus, the efficient alleviation of hyperglycemia, an elevated glycemic concentration, is quite crucial to avoid persistent complications. Thus, it is of prime importance to have an automated closed-loop insulin delivery system, often termed as an artificial pancreas, in the patient’s body. The requisite amount of exogenous insulin bolus must be determined by a control algorithm, which is the primary constituent of the closed-loop system. In this article, a finite-time synergistic control approach, based on a gain-scheduled Luenberger observer (GSLO), is introduced. The proposed control strategy establishes a closed-loop insulin delivery system, which confirms the glycemic regulation that is quite obligatory in type-1 diabetic (T1D) patients. The control law is synthesized by using a recursive backstepping with a sliding mode control (SMC) approach. Besides, the nonlinear terms are incorporated, in the pseudo control inputs, which provide the finite-time convergence of the system’s trajectories. Since the proposed control law relies on the system’s information, thus, a virtual patient simulator, presented by Bergman minimal model (BMM), is transformed into an equivalent dynamic structure, which facilitates the design of GSLO. The observer’s gains, which modify in each iteration, are based on the updated values of the system’s states. Also, it endorses the separation principle, thus proving the closed-loop system’s stability. The proposed closed-loop insulin delivery system confirms the suppression of postprandial hyperglycemia and hypoglycemic events in T1D patients. The efficacy is demonstrated via in-silico testing, which is executed in MATLAB/Simulink environment.

INDEX TERMS Gain-scheduled Luenberger observer, glucose-insulin stabilization, recursive backstepping method, sliding mode control approach, closed-loop insulin delivery system, Bergman minimal model, external disturbances, controllable canonical system.

I. INTRODUCTION

Diabetes mellitus (DM) is an acute metabolic syndrome, which is caused either by the body’s inability to produce insulin or the autoimmune reaction of the body against insulin [1]. This lack of primary glycemic regulator results in hyperglycemic, a prolonged elevated plasma glucose concentration (PGC) [2]–[4]. The tolerable glycemic concentration rests in 70 – 180 mg/dl, often referred to as euglycemic range [5], [6]. The plasma glucose excursion across the either side of euglycemic range leads to hyperglycemia (when PGC > 180 mg/dl) or hypoglycemia (when PGC < 50 mg/dl) [5]. These extreme glycemic conditions, when existed for a long time, may lead to certain fatal disorders, such as cardiovascular diseases, joint diseases, and kidney failure [7], [8]. To avoid the complications as mentioned above, the infusion of exogenous insulin bolus in T1D patients is mandatory. The insulin injection therapy, which is currently in practice, includes the discrete-time measurement of glycemic concentration and the injection of exogenous insulin bolus into the
The artificial pancreas (AP) is an automated closed-loop mechanism, which ensures the controlled injection of exogenous insulin bolus into the patient’s body [11]. The quantity of exogenous insulin, to be injected, must be determined by a control algorithm according to the measurement provided by the continuous glucose monitoring (CGM) sensor [12]. However, the issues of various parametric variations and external perturbations (i.e., meal intake and exercise) cause the escalation of PGC in a realistic environment. Consequently, an untreated, excessive glycemic concentration, if existed for a long time, may cause many complexities and even lead to patient’s death. The above challenges posture a serious hindrance to the design of a control algorithm, which constitutes the core theme of an AP mechanism. The working procedure of an AP mechanism is illustrated in Fig. 1 [9].

The nonlinear control algorithms, implanted in the AP mechanism, are based on the patient’s physiological model, which are categorized into either intravenous or subcutaneous model [13]. In this context, a prominent BMM [14], also termed as the intravenous glucose tolerance test (IVGTT) model, is considered for the design of a nonlinear control algorithm. The significant features behind the selection of BMM are: (i) the macroscopic response of the glucose-insulin dynamics in plasma is modeled via simple non-linearity [15], (ii) it has a broad scope of applications in the Bed-side AP [16], and (iii) the significant physiological factors, such as glucose sensitivity and insulin effectiveness can be easily modeled in terms of its parameters [15].

To deal with a nonlinear system, the effective treatment of the substantial constraints are needed, e.g., the presence of immeasurable states, and the effects of the external perturbations. In many biological systems, it is not possible to measure all the states due to the difficulty associated with the installation of sensors at various locations within the human body. Also, if there exists an easy way to install sensors, then the availability of a bio-compatible sensor and its cost will be a huge concern. Due to the above factors, the problem of glycemic regulation in T1D patients is quite challenging. Therefore, the design of an appropriate observer is quite essential to provide the information of the unavailable states to the controller [17].

Several attempts have been made to address the problem of state estimation in T1D patients while considering the BMM [15]. In the existing literature related to the glucose-insulin dynamics, two types of states estimators, i.e., Kalman filter (KF) and Luenberger observer, have been employed. In [18], a Luenberger observer is designed for the BMM in the presence of external disturbances like glucose intake. After estimation, the states are then utilized in a linear quadratic regulator. In [19], a nonlinear observer-based feedback linearization control law is proposed where the robustness against the parametric uncertainty is ensured via numerical simulations. However, the authors did not incorporate the observer-based controller, which is somewhat non-appealing. Furthermore, multiple variants of KFs are introduced for BMM, which include the unscented Kalman filter (UKF) and the extended Kalman filter (EKF) [20]. However, these strategies were performed for the linear model, which generally doesn’t reflect the practical scenarios. In addition, the KF-based state estimators need precise information regarding the system and error distribution, which may not be easily available, and thus, if not provided, may lead to approximation error.

Numerous model-based control strategies have been employed to develop a closed-loop insulin delivery system for the stabilization of glycemic concentration in T1D patients. These strategies are categorized into linear and nonlinear control algorithms. Linear control Strategies includes; conventional PID controller [21], an $H_{\infty}$ control algorithm [22], and model predictive control (MPC) strategy [23]. These control algorithms result in appealing performances. However, they suffer from numerous issues, i.e., the PID scheme remains valid in the vicinity of equilibrium points, the $H_{\infty}$ not only operates on linear modal but also exceeds the feasible range of the manipulated input. The MPC law also faces the same restriction. Now, the nonlinear control techniques designed for the closed-loop AP system include; SMC approach presented in [24], provides a robust glucose regulation but the state unavailability and chattering phenomenon challenge its candidature to AP mechanism. Few synergistic strategies of fuzzy logics and SMC were focused in [25], [26]. However, these techniques required a long settling time and often degraded in uncertain situations. In addition, the existence of chattering was also witnessed. States-dependent Riccati equation (SDRE) approach was investigated in [27], which provides acceptable results around the equilibrium point, but this method does not claim to be able in a realistic environment. A feedback linearization-based nonlinear control algorithm is designed in [28]. The simulation results are acceptable. However, the stability of internal dynamics...
was not confirmed. Conventional and Super twisting-based SMC algorithms are employed for plasma glucose regulation in T1D patients [7], [29]. However, the manipulated input remains out of the feasibility bound.

The motivation behind the current work is based on the standard literature [5], [7], [30], where the presented control strategies are deficient of the salient features, which play a vital role in the diabetic research community. To ensure a reliable solution, a finite-time tracking problem is presented, which, in the last decade, has captivated a significant consideration in the research community. Contrary to the classical stability, the finite-time stability confirms the convergence of the system’s trajectories towards the desired equilibrium point in a finite-time, which can feature an accelerated transient response with an excellent tracking performance [31]–[34]. The designed control law, which confirms a finite-time tracking of the system’s states, is derived using the synergistic backstepping SMC approach. The Backstepping control scheme (BCS) offers an accurate recursive stabilization of the system’s states, presented in a strict-feedback form. However, the SMC approach is in fact a variable structure control (VSC) strategy, mostly employing to stabilize an uncertain nonlinear systems. In SMC approach, a switching manifold is defined, upon which the system’s trajectories are enforced. This phase is termed as a reaching phase. Once the reaching phase is achieved, the system’s trajectories are then driven along the switching surface towards the desired equilibrium point. This phase is termed as a sliding phase. In other words, one can term the sliding phase, a constrained motion. It is quite worthy to explain that once the sliding mode is achieved, then the performance of the system relies on the switching gradients [32], [35]. The proposed synergistic control strategy, which incorporates the nonlinear terms in the pseudo-control inputs, guarantees the finite-time stabilization of the system’s states towards the desired equilibrium point.

To increase the applicability of the proposed model-based control law, in a practical scenario, a quasi-linear decomposition-based GSLO is synthesized. The GSLO estimates the immeasurable states’ information via the available state variable. The proposed control scheme offers a finite-time convergence and provides the robustness in the presence of an external disturbances. The theoretical claims are justified via computer simulations. For the sake of clearance, the main features of the current work are:

1) A robust synergistic control law, based on the recursive backstepping SMC approach, is designed for glycemic regulation in T1D patient subjected to external perturbations.

2) The proposed control law, which incorporates the nonlinear terms in the pseudo-control inputs, provides the finite-time convergence of the system’s states towards the desired trajectory.

3) In a practical scenario, the model-based control strategy needs the system’s information, which may not be available. Thus a robust GSLO is presented to provide the estimates of the immeasurable states.

4) The proposed observer is based on a quasi-linear decomposition method. A quasi-linear modal, obtained via a convex optimization approach, provides an efficient decomposition of the system at each arbitrary point.

5) The proposed control scheme thus leads to an automated closed-loop insulin delivery system, which is tested in MATLAB/Simulink environment.

The detailed representation of an automated closed-loop insulin delivery system in T1D patient is demonstrated in Fig. 2. The rest of the manuscript is categorized as follows: In section II, the mathematical model, representing the glucose-insulin dynamics within a human body, is concisely described. The design procedure of the proposed synergistic control structure is briefly investigated in section III. In section IV, the results obtained via computer simulation are discussed. The conclusion of the paper is presented in section V.

II. PROBLEM FORMULATION

This section presents the detailed model description, the design procedure of the stabilizing control law, and GSLO.

A. MATHEMATICAL MODEL OF T1D-PATIENT

To design a proposed control strategy, the mathematical model of T1D Patient, which acts as a virtual patient simulator, is quite essential [7], [36]. Thus, in this subsection, BMM is briefly discussed. The graphical overview of BMM is illustrated in Fig. 3.

BMM, also termed as IVGTT model, takes into consideration the glucose and insulin dynamics within a normal human body. The glucose dynamics are governed by the following nonlinear differential equations

\[
\frac{dG(t)}{dt} = -(p_1 + X(t))G(t) + p_1G_b \quad G(0) = G_0
\]

\[
\frac{dX(t)}{dt} = -p_2X(t) + p_3(I(t) - I_b) \quad X(0) = 0, \quad (1)
\]

where \(G(t)\) is PGC, \(G_b\) is the basal glycemia. \(X(t)\) is the effect of active insulin in plasma, \(p_1, p_2,\) and \(p_3\) are the constant parameters that represent the insulin-independent glucose consumption by liver and periphery, the decline of glucose utilization in tissues, and the insulin-dependent glucose
absorption in tissues, respectively. The insulin dynamics that are governed by the first-order differential equation can be written as

\[ \dot{I}(t) = -n(I(t) - I_0) + \rho[G(t) - h]^+t \quad I(0) = I_0, \]

where \( I(t) \) depicts the PIC while \( I_0 \) represents the optimal value of plasma insulin. \([G(t) - h]^+t\) is the internal glucose regulatory (IGR) function, while \( h \) shows the threshold value of glucose above which the insulin secretion is initiated. The positive value of IGR function decides the secretion of insulin while its rate is decided by \( \rho \). The \( t \) term defines the glucose stimulation time in plasma. Furthermore, the factors that play an essential role in the interpretation of IGVTT model are glucose effectiveness and insulin sensitivity, which are represented by \( S_G \) and \( S_I \), respectively. The glucose effectiveness \( S_G \) is the ability of glucose to cause its own disposal, while insulin sensitivity \( S_I \) is the ability of the insulin to enhance the disposal of PGC. These two factors are measured during the interpretation of IGVTT model. It is quite worthy to mention that in T1D patient, the IGR function gets destroyed due to which the PGC exceeds the basal value. To find out an efficient solution, the IGR function in IGVTT model is replaced with alternate exogenous insulin injection term \( u(t) \), which mimics the natural behavior of the IGR function. The dynamics reported in 1 and 2 can be expressed, in a generalized form, as

\[ \dot{\xi} = \phi(\xi, t) + \gamma(\xi, t)u + \Delta(\xi, t), \]

where \( \xi = [\xi_1, \xi_2, \xi_3]^T = [G(t), X(t), I(t)]^T \) define the system’s states, \( \phi(\xi, t) \) and \( \gamma(\xi, t) \) are the sufficient smooth vector fields, which are defined as follows

\[
\phi(\xi, t) = \begin{bmatrix}
-(p_1 + \beta_2)\xi_1 + p_1G_b \\
-p_2\xi_2 + p_3\xi_3 - \beta_3 I_b \\
-p_4(\xi_3 - I_b)
\end{bmatrix},
\]

\[
\gamma(\xi, t) = \begin{bmatrix}
0 \\
0 \\
1
\end{bmatrix},
\]

The term \( \Delta(\xi, t) \), which provides information about the external perturbation, can be presented as

\[ \Delta(\xi, t) = \begin{bmatrix} D(t) \\ 0 \\ 0 \end{bmatrix}, \]

where \( D(t) \) is the external meal intake, described by Fisher [37]. Mathematically, it can be written as

\[ D(t) = Ae^{-\beta t}, \]

where \( A \) corresponds to the initial constant value of glucose, injected into T1D patient while \( \beta \) is the exponential decaying rate of glucose in plasma. The graphical representation of (4) is illustrated in Fig. 11. Before proceeding to the control design, the following assumption is stated.

**Assumption 1**: The disturbances \( \Delta(\xi, t) \) is supposed to be bounded with sufficient continuous derivatives.

In the next subsection, the design steps of nonlinear control approach is described.

### B. Controller Design

In this subsection, a finite-time backstepping SMC strategy is introduced. In this process, the design of Lyapunov-based control law is accomplished systematically in a recursive procedure where the state variables are considered as “virtual controls” or “pseudo controls”, depending on the dynamics of each state. The reported description is the summary of materials presented in [38], [39].

Consider the system (3), where the principal objective is to design a control strategy that must ensure the finite-time convergence of the system’s trajectories \( \xi_1, \xi_2, \xi_3 \) towards the desired equilibrium point. Here, the design procedure is outlined step by step.

In the very first phase, the tracking error \( \xi_1 \) needs to be diminished, i.e., \( \xi_1 = \xi_1 - \xi_d \to 0 \), as \( t \to 0 \), where \( \xi_d \) represents the desired glycemia concentration. Consider a Lyapunov candidate function (LCF) as follow

\[ V_1(\xi_1) = \frac{1}{2} \xi_1^2 \]

The time derivative of the Lyapunov function along the trajectory of \( \xi_1 \), can be expressed as

\[ \dot{V}_1(\xi_1) = \xi_1(-p_1\xi_1 - \xi_2\xi_1 + p_1G_b - \xi_d) \]

Now, treating \( \xi_2 = \alpha_1(\xi_1) \) with \( \alpha_1(0) = 0 \) as a stabilizing control law. It will lead to

\[ \dot{V}_1(\xi_1) = -c_1\xi_1^2 \eta_1|\gamma_1|^{\gamma_1+1} - \eta_2|\xi_1|^{\gamma_2+1}, \]

where \( c_1, \eta_1, \eta_2, \gamma_1, \gamma_2 \) depict the positive gains.

Now, proceeding towards the next step where \( \xi_2 = \xi_2 - \alpha_1(\xi_1) \) must be minimized. The first derivative of the denoted error can be written as

\[ \dot{\xi}_2 = -p_2\xi_2 + p_3\xi_3 - p_4I_b - \dot{\alpha}_1, \]

where

\[ \dot{\alpha}_1 = \frac{\partial \alpha_1}{\partial \xi_1}[-p_1\xi_1 - \xi_2\xi_1 + p_1G_b - \xi_d] \]
To confirm the error convergence in the second step, let $V_2 = V_1 + \frac{1}{2} \xi_3^2$ be the desired Lyapunov function. The time derivative of second Lyapunov function along $8$ becomes

$$\dot{V}_2 = -c_1 \xi_1^2 - \eta_1 |\xi_1|^{\gamma_1+1} - \eta_2 |\xi_1|^{\gamma_2+1} + \xi_2 (-p_2 \xi_2 + p_3 \xi_3 - p_3 I_b - \alpha_1)$$  \hspace{1cm} (9)

In this step, the main purpose is to design a pseudo control input $\alpha_2(\xi_1, \xi_2)$ with $\alpha_2(0) = 0$. Consequently, the obvious choice of $\alpha_2(\xi_1, \xi_2)$ would be

$$\alpha_2 = \frac{1}{p_3} (p_2 \xi_2 + p_3 I_b - \alpha_1 - c_2 \xi_2) - \eta_3 |\xi_2|^{\gamma_3} sign(\xi_2) - \eta_4 |\xi_2|^{\gamma_4} sign(\xi_2).$$  \hspace{1cm} (10)

where $c_2, \eta_3, \eta_4$ are the positive constant terms. After Substituting (10) in (9), the following equation is obtained

$$\dot{V}_2 = -c_1 \xi_1^2 - c_2 \xi_2^2 - \eta_1 |\xi_1|^{\gamma_1+1} - \eta_2 |\xi_1|^{\gamma_2+1} - \eta_3 |\xi_2|^{\gamma_3+1} - \eta_4 |\xi_2|^{\gamma_4+1}$$  \hspace{1cm} (11)

The assumption $\xi_1 = \alpha_2(\xi_1, \xi_2)$ leads to $\dot{V}_2(\xi_1, \xi_2) \leq -W_2(\xi_1, \xi_2)$, where $W_2$ is a positive function for every $\xi_1, \xi_2 \in \mathbb{R}$. Thus, to confirm the positive definiteness, the error $\xi_3 = \xi_3 - \alpha_2$ must reach to zero. The first time derivative of $\xi_3$ can be expressed as

$$\dot{\xi}_3 = -p_4 \xi_3 + p_4 I_b + u(t) - \dot{\alpha}_2,$$  \hspace{1cm} (12)

where

$$\dot{\alpha}_2 = \frac{\partial \alpha_2}{\partial \xi_1} \xi_1 + \frac{\partial \alpha_2}{\partial \xi_2} \xi_2$$

Let the final Lyapunov candidate function be

$$V_3 = V_2 + \frac{1}{2} \xi_3^2$$  \hspace{1cm} (13)

Taking the first derivative and after incorporating the respective values, the expression obtained as

$$\dot{V}_3 = -c_1 \xi_1^2 - c_2 \xi_2^2 - \eta_1 |\xi_1|^{\gamma_1+1} - \eta_2 |\xi_1|^{\gamma_2+1} - \eta_3 |\xi_2|^{\gamma_3+1} - \eta_4 |\xi_2|^{\gamma_4+1} + \xi_2 (-p_4 \xi_3 + p_4 I_b + u),$$  \hspace{1cm} (14)

where $u$ is the actual input, which is realized as

$$u(t) = p_4 \xi_3 - p_4 I_b + \dot{\alpha}_2 - p_3 \xi_2 - c_3 \xi_3 - \eta_5 |\xi_3|^{\gamma_5} sign(\xi_3) - \eta_6 |\xi_3|^{\gamma_6} sign(\xi_3).$$  \hspace{1cm} (15)

Thus, the choice of $u$ will lead to

$$\dot{V}_3 = -c_1 \xi_1^2 - c_2 \xi_2^2 - c_3 \xi_3^2 - \eta_1 |\xi_1|^{\gamma_1+1} - \eta_2 |\xi_1|^{\gamma_2+1} - \eta_3 |\xi_2|^{\gamma_3+1} - \eta_4 |\xi_2|^{\gamma_4+1} - \eta_5 |\xi_3|^{\gamma_5+1} - \eta_6 |\xi_3|^{\gamma_6+1},$$  \hspace{1cm} (16)

where $c_3, \eta_5, \eta_6$ shows the positive constant gains. The final control law (15) confirms the finite-time convergence of the system’s trajectories towards the desired equilibrium point. The final LCF (16) is summarized in the below theorem, and the finite-time is computed.

**Theorem 1:** If the control law (15) is applied to the dynamic system (3), then all the closed-loop system’s trajectories, i.e., $\xi_1, \xi_2, \xi_3$ converge to the desired equilibrium point in a finite-time.

**Proof:** Consider the LCF presented in (16), which can be expressed as

$$\dot{V}_3 = -\sum_{i=1}^{3} c_i \xi_i^2 - \sum_{i=1}^{3} \eta_{2i-1} |\xi_i|^{\gamma_{i+1}} - \sum_{i=1}^{3} \eta_{2i} |\xi_i|^{\gamma_{2i+1}}$$  \hspace{1cm} (17)

Employing the inequality, i.e., $V_3 \geq \frac{1}{\gamma_i} \xi_i^2$, $i = 1, \ldots 3$ [40], (17) can be written as

$$\dot{V}_3 \leq -\alpha V_3 - \beta_1 V_3^{\frac{\gamma_1+1}{2}} - \beta_2 V_3^{\frac{\gamma_2+1}{2}},$$  \hspace{1cm} (18)

where

$$\alpha = min(2c_1, 2c_2, 2c_3)$$

$$\beta_1 = min(2^{\frac{\gamma_1+1}{2}}, 1, 2^{\frac{\gamma_1+1}{2}} \eta_1, 2^{\frac{\gamma_1+1}{2}} \eta_3, 2^{\frac{\gamma_1+1}{2}} \eta_5)$$

$$\beta_2 = min(2^{\frac{\gamma_2+1}{2}}, 2^{\frac{\gamma_2+1}{2}} \eta_2, 2^{\frac{\gamma_2+1}{2}} \eta_4, 2^{\frac{\gamma_2+1}{2}} \eta_6)$$  \hspace{1cm} (19)

The time taken from $V_3(\xi(t) = 0)$ to $V_3(\xi(T)) = 0$ can be determined by integrating the differential inequality (18), the computed bounded finite-time can be expressed as

$$T \leq max \left( \int_0^T \frac{dV_3}{-\alpha V_3 - \beta_1 V_3^{\frac{\gamma_1+1}{2}} - \beta_2 V_3^{\frac{\gamma_2+1}{2}}} \right)$$  \hspace{1cm} (20)

where $\alpha, \beta_1, \beta_2, r_1, r_2$ are the positive gains such that $0 < r_1 < 1$ and $r_2 > 1$. The inequality expressed in (18), which is equipped with nonlinear terms, confirms the finite-time convergence of the system’s trajectories towards the desired equilibrium point.

**Remark 1:** In the virtual/pseudo control inputs, considered at each iteration of the process, some nonlinear terms are incorporated. It is because, when the system’s trajectories are initially far-off the desired point, the nonlinear terms having power greater than unity deviate the system’s trajectories towards the desired equilibrium point, thus dominating the convergence rate. Once the trajectories reach near the desired point, then the terms having power less than unity sustain the supremacy of the convergence rate. It is entirely well-meaning that the proposed control strategy possesses the property of bi-homogeneity [41], which provides the finite-time convergence of the states’ trajectories.

It is worthy of mentioning that the designed control law significantly requires the system’s states for the practical applicability, thus an observer is quite mandatory for the state estimation process [42]. To cope with this situation, GSLO is presented in the next subsection.

**C. GAIN-SCHEDULED LUEMBERGER OBSERVER (GSLO)**

Consider a system (3) which can be re-written as

$$\dot{\xi} = \phi(\xi) + \gamma(\xi) u + \Delta(t)$$  \hspace{1cm} (21)
The vector fields $\phi(\xi)$, $\gamma(\xi)$ and $\Delta(t)$ are already defined. Similarly, the output is as follow

$$y = h(\xi), \quad (22)$$

where $h(\xi)$ is a smooth vector field. Note that in our case

$$h(\xi) = [1 \ 0 \ 0]^T \in R^{3} \quad (23)$$

The design procedure of GSLO is based on a quasi-linear decomposition approach presented in [43], [44]. The conventional linearization process is based on either the Jacobean method or first-order tailor series approximation, which is no more valid for any arbitrary operating point. To resolve issue, a constrained convex optimization problem is formulated, which proposes a quasi-linear model and can provide the exact decomposition of the system at any arbitrary point, i.e., $\xi_o$. Referring to the quasi-linear decomposition approach, the system (21) can be represented as

$$\dot{\xi} = \phi(\xi) + \gamma(\xi)u + \Delta(t) \approx A(\xi)\xi + Bu + \Delta(t) \quad (24)$$

At any arbitrary point $\xi_o$, (24) can be expressed as

$$\dot{\xi} = A(\xi_o)\xi_o + Bu + \Delta(t_o) \quad (25)$$

Referring to (24) and (25), the principal objective is to find out the state-dependent matrix, i.e., $A(\xi) \in \mathbb{R}^{3 \times 3}$, in the close vicinity of $\xi_o$ such that

$$\phi(\xi) \approx A(\xi)\xi \quad (27)$$
$$\phi(\xi_o) = A(\xi_o)\xi_o \quad (28)$$

In (27) and (28), the $i_{th}$ component of $\phi(\xi)$, i.e., $\phi_i(\xi) \in \mathbb{R}^{3}$ is $\phi_i(\xi)$. Using tailor’s series expansion method on left side of (27) with respect to $\xi_o$, while avoiding the high order terms, one gets

$$\phi(\xi_o)\nabla^T \phi(\xi_o)(\xi - \xi_o) \approx r_i^T \xi, \quad (29)$$

where $\nabla \phi(\xi_o) \in \mathbb{R}^{3}$ represents the gradient of $\phi(\xi)$ with respect to $\xi$. Substituting (28) in (29), the following expression is obtained as

$$\nabla^T \phi(\xi_o)(\xi - \xi_o) = r_i^T (\xi_o)(\xi - \xi_o), \quad (30)$$

where $\xi$ is the arbitrary point but close to $\xi_o$. The aim is to sort out a constant matrix $r_i$, thus a constrained optimization problem can be defined as

$$\min_{r_i} \mathcal{E} = \frac{1}{2} \|\nabla \phi(\xi_o) - r_i(\xi_o)\|^2, \quad (31)$$

such that

$$\phi(\xi_o) = r_i^T (\xi_o)\xi_o$$

As (31) presents the convex optimization problem (COP), thus a first-order condition for a minimum $\mathcal{E}$ is also sufficient. Consequently, the first order condition for the COP can be expressed as

$$\nabla_r \mathcal{E} + \lambda \nabla r_i (r_i^T \xi_o - \phi_i(\xi_o)) = 0 \quad (32)$$
$$r_i^T \xi_o = \phi_i(\xi_o) \quad (33)$$

where $\lambda$ is the Lagrange multiplier. After performing the necessary differentiation of (32), it gives

$$r_i - \nabla \phi(\xi_o) + \lambda \xi_o = 0 \quad (34)$$

By considering $\xi_o \neq 0$ and multiplying (34) by $\xi_o^T$ with substituting (33) in the result, one may get the following expression

$$\lambda = \frac{\xi_o^T \nabla \phi(\xi_o) - \phi(\xi_o)}{\|\xi_o\|^2}. \quad (35)$$

substitution (35) in (34) yields

$$r_i = \nabla \phi(\xi_o) + \frac{\phi(\xi_o) - \xi_o^T \nabla \phi(\xi_o)}{\|\xi_o\|^2} \xi_o \quad (36)$$

Similarly, $h(\xi)$ in (22) is linearized to get $C(\xi) \in \mathbb{R}^{1}$. Thus, the $i_{th}$ column of $C(\xi)$ is as follow

$$c_i = \nabla h_i(\xi_o) + \frac{h_i(\xi_o) - \xi_o^T \nabla h_i(\xi_o)}{\|\xi_o\|^2} \xi_o \quad (37)$$

It is worthy of mentioning that if the arbitrary point is only the origin in the state space, i.e., $\xi_o = 0$, then the task of finding $A(\xi)$ and $C(\xi)$ reduces to the Jacobean of the nonlinear function $\phi(\xi)$ and $h(\xi)$ along with the system’s states, respectively. The system (21) and (22), in quasi-linear decomposition form, can be expressed as

$$\dot{\xi} = A(\xi)\xi + Bu + \Delta(t)$$
$$y = C(\xi)\xi \quad (38)$$

In light of the results investigated in (36) and (37), the matrices $A(\xi)$ and $C(\xi)$ can be expressed as

$$A(\xi) = \begin{bmatrix} a_1 & a_2 & a_3 \\ \vdots & \vdots & \vdots \\ \end{bmatrix} \quad (39)$$
$$C(\xi) = \begin{bmatrix} c_1 & c_2 & c_3 \\ \vdots & \vdots & \vdots \\ \end{bmatrix}$$

The ansatz of the corresponding GSLO is following

$$\dot{\xi} = A(\xi)\xi + Bu + L(\xi)(y - C(\xi)\xi) + \Delta(t), \quad (39)$$

where $L(\xi) \in \mathbb{R}^{3 \times 1}$ is the gain matrix, which is computed by an observer via a linear quadratic regulator (LQR) approach. Moreover, It can also be computed via an adaptive optimal approach [45], [46]. It is worthy to mention that the structure of the above observer is quite similar to the conventional one. However, in this work $L(\xi)$ is adapted according to the state-dependent matrix $A(\xi)$ and $C(\xi)$, which
varies at each operating point $\hat{\xi}_o$. In the LQR process, the cost of the following quadratic function is minimized as follow

$$J = \int_0^T \hat{\xi}^T C(\hat{\xi}) \hat{\xi} d\tau,$$

where $Q \in \mathbb{R}^{3 \times 3}$ and $R \in \mathbb{R}^{1 \times 1}$ are the weighting matrices and can be written as

$$Q = \text{diag}(\Pi_i^2), \quad R = \tilde{\Omega}^2,$$

where the $\Pi_i$ and $\tilde{\Omega}$ are chosen to be

$$\Pi_i = \sigma \left( \frac{\pi_i}{\xi_i^2, \text{max}} \right) \quad \text{and} \quad \tilde{\Omega} = \left( \frac{\omega}{e_y, \text{max}} \right),$$

where $e_y = y - \hat{y}$ denotes the error between the actual and estimated output. The parameters $\pi_i$ and $\omega$ are chosen to endorse the estimation process and convergence of the measurement error, respectively. Moreover, the relative weighting between $Q$, i.e., state reconstruction, and $R$, i.e., measurement error convergence, is set by varying $\sigma$. Since the state-dependent matrices, i.e., $A(\hat{\xi})$ and $C(\hat{\xi})$, varies at each arbitrary point $\hat{\xi}_o$. Therefore, the gain matrix $L(\hat{\xi})$ varies correspondingly.

**Remark 2:** A finite-time backstepping sliding mode control approach is designed in the present work. In addition, a GSLO is formulated for the estimation of immeasurable states. Consequently, it is worthy to examine the closed-loop stability of the system. Since the BMM is represented by an equivalent quasi-linear form such that the system becomes linear time-invariant in each iteration of the simulation/implementation. Based on these facts, it is claimed that the separation principle holds for the closed-loop system, including the plant, controller, and observer. Thus, the individual stability of the controller and observer will ensure the overall closed-loop stability, which is confirmed earlier in their studies.

### III. CONTROL IMPLEMENTATION SCHEME

The closed-loop control strategy, equipped with a finite-time control law and GSLO, is illustrated in Fig. 4.

**Remark 3:** The saturation block is employed to restrict the control efforts, i.e., the exogenous insulin bolus, within the bounds of the feasible range. The virtual patient simulator, i.e., BMM, demonstrates the plasma glucose-insulin dynamics while the quasi-linear model block, in parallel, represents the equivalent linear representation of BMM at each iteration of the simulation. The $L(\hat{\xi})$ depicts the gain matrix, which is adapted in each iteration for the modified linear system.

### IV. RESULTS AND DISCUSSION

In this section, the performance analysis of the proposed control scheme is carried out for glycemic regulation in T1D patients. The acquired results are briefly demonstrated to authenticate the theoretical claims. The initial conditions, analogous to plasma glucose-insulin dynamics, are considered as $[220, 0, 0.3]$. The model parameters are presented in Table 1.

To discuss the effectiveness of the designed closed-loop control strategy for the stabilization of PGC in T1D patient, it is quite crucial to have some familiarity with the function of IGR system in both healthy and T1D person which are illustrated in Fig. 5. It is obvious that initially (at $t = 0$), the glycemic concentration in a healthy person is above the basal value. However, euglycemia is attained efficiently. In contrast, the hyperglycemia in sick person existed for a long time span because of the impaired IGR system. Thus, to acquire the basal PGC, an automated closed-loop insulin delivery system is obligatory that can mimic the natural
behaviour of the IGR system. The closed-loop insulin mechanism confirms the intravenous injection of exogenous insulin bolus in the patient body to keep the required basal level. To claim the proposed algorithm as a potential strategy for the development of closed-loop AP mechanism, the two possible scenarios are considered.

A. SCENARIO I: PERFORMANCES ANALYSIS IN THE NOMINAL ENVIRONMENT

The potentiality of the proposed control scheme, for glycemic regulation in T1D patient, is examined in this subsection. The control objective is to maintain the standards, i.e., $G_b = 80$, $I_b = 7$ while avoiding the hypoglycemic events.

Discussion: The glycemic regulation, under the influence of the proposed control law, in T1D patient, is illustrated in Fig. 6. In this figure, the euglycemic range ($70 < \text{PGC} < 180$), hyperglycemia ($\text{PGC} > 180$) and hypoglycemia ($\text{PGC} < 50$) are also clearly portrayed. It is quite evident that initially (at $t = 0$), the T1D patient is experiencing a hyperglycemic situation. In such a case, the proposed control strategy quite efficiently regulated the PGC in the euglycemic range while achieving the desired basal value in a practicable period ($t = 310 \text{ min}$). Moreover, no hypoglycemic events are observed. Similarly, the effectiveness of the proposed strategy for the regulation of PIC is displayed in Fig. 7. Initially (at $t = 0$) the PIC is quite minimum (i.e., $0 \leq 3 \mu U/ml$). However, the proposed control law delivered the excessive amount of insulin bolus to alleviate hyperglycemia, i.e., depicted in Fig. 6. Consequently, it initially exceeds the basal insulin concentration, which is accurately regulated thereafter. The corresponding manipulated input, which is the exogenous insulin infusion rate, determined by the proposed control algorithm, is illustrated in Fig. 8. It is quite clear that the control efforts effectively mitigated the existed hyperglycemia while staying in a practically realizable range, i.e., $[0 - 10]ml/l/min$. As the control input is non-negative, therefore, it excludes the need for any extra glucose or glucagon infusion in the blood plasma.

In a practical context, the controller may only be available with PGC, i.e., the first state variable $\xi_1$, whereas, the second and third states are immeasurable, which must be estimated via robust GSLO. The GSLO utilizes the available information for the estimation purpose. Fig. 9 shows the estimated insulin effect, whereas Fig. 10 displays the estimated plasma insulin profile via the proposed observer. These figures demonstrate the estimation performance of the robust GSLO.
B. SCENARIO II: PERFORMANCES ANALYSIS IN THE PERTURB ENVIRONMENT

In this subsection, the potency of the proposed control approach is demonstrated for T1D patient subjected to an external perturbation. Generally, in the diabetic patient, meal intake is considered an external perturbation. In this study, the disturbance, as depicted in Fig. 11, appears in the system at $t = 400$ min, which is reported as Fisher’s meal disturbance.

**Discussion:** The effectiveness of the proposed control scheme, in the perturbed system, is depicted in Fig. 12. It is obvious that the proposed control strategy quite efficiently mitigates the existed hyperglycemia at $t = 0$. However, when the system is suddenly exposed to an external disturbance, it quite efficiently tackled the agitated scenario while achieving the euglycemic range in a feasible time instant. The regulation profile of PIC is demonstrated in Fig. 13. It shows that the PIC scales up initially because of the injected exogenous insulin, which gets stabilized once the objective of euglycemia is met. Similarly, the uprising of PIC, in the perturb environment at $t = 400$ min, is promptly regulated by the designed control law at the desired value. The control effort required to maintain the regulated PGC and PIC, in the perturbed environment, is portrayed in Fig. 14. It is obvious once again that the control effort, which is the insulin injection rate by the proposed control law in T1D patients, is practically realizable.

Remark 4: The discussion described above, thus, reveals that the proposed control strategy, via realistic control efforts, achieves the euglycemic range and the basal PIC.
in a practically realizable time. Moreover, It also shows robust performance in the perturbed environment. In addition, the robust GSLO quite efficiently estimates the unavailable states’ information, which are required for the successful implementation of the designed control law. Due to the appealing performance, in both the scenarios, the designed control strategy proves as a better candidate for the development of an automated closed-loop insulin delivery system.

V. CONCLUSION

In this article, a stabilizing finite-time control algorithm with a gain-scheduled Luenberger observer is introduced. The proposed control law, which constitutes the core of an automated closed-loop insulin delivery system, affirms the glycemic regulation in T1D patients. The synergistic control law is derived using the recursive Backstepping approach. However, the incorporation of nonlinear terms, in the pseudo control law, which constitutes the core of an automated closed-loop insulin delivery system, affirms the glycemic regulation in type 1 diabetic patient using atactic ellipsoid method,” IEEE Control Syst. Mag., vol. 38, no. 1, pp. 84–91, Apr. 2019.

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WAQAR ALAM was born in Bajkata, Pakistan, in April 1992. He received the B.Sc. degree in electronics engineering from UET Peshawar, Abbottabad Campus, in 2014, and the M.S. degree in electrical engineering from COMSATS University Islamabad, in 2017, where he is currently pursuing the Ph.D. degree in electrical engineering. His research interests include robust nonlinear control algorithms, adaptive control approaches, and non-linear exact differentiator and observers. He has published several articles and presented various papers in the conferences. In addition, he also serves as a Referee in the Elsevier research community.

QUDRAT KHAN (Member, IEEE) received the B.Sc. degree in mathematics and computer science from the University of Peshawar, in 2003, the M.Sc. and M.Phil. degrees in mathematics from Quaid-i-Azam University, Islamabad, in 2006 and 2008, respectively, and the Ph.D. degree in the area of nonlinear control systems from Mohammad Ali Jinnah University, Islamabad, in November 2012. He has been working as an Assistant Professor at COMSATS University Islamabad, since July 2013. He worked as a Post-doctoral Fellow at the Department of Mechatronics Engineering, International Islamic University, Malaysia, from September 2015 to August 2016. He has published more than 50 research articles (with impact factor more than 40) in refereed international journals and conference proceedings. His research interests include robust nonlinear control design, observers design, fault detection in electro-mechanical systems, and multi agent system's control. He was a postgraduate scholarship holder during Ph.D., from 2008 to 2011, and an IRSIP scholarship holder during Ph.D. (as a Visiting Research Scholar at the University of Pavia, Italy). He was selected for Young Author Support Program, IFAC, World Congress, Milan, Italy, in 2011. He is listed in the young productive scientists of the Pakistan in the year of 2017 and 2018.

RAJA ALI RIAZ received the B.Eng. degree from the National University of Sciences and Technology (NUST), Pakistan, in 1998, the M.Sc. degree in electrical engineering degree from CASE, UET Taxila, Pakistan, in 2003, specializing in telecommunications, the M.Sc. degree in electrical engineering from the National University of Sciences and Technology (NUST), Pakistan, specializing in the area of controls of dynamic systems, and the Ph.D. degree in the field of ultra wide-band communications from the School of Electrical and Computer Sciences, University of Southampton, U.K., in 2010. He is an author of more than ten IEEE publications during his Ph.D. studies. His research interests include channel coding, communication systems, and stochastic processes. Moreover, he was a recipient of the various foreign Ph.D. Scholarship from the Government of Pakistan. He received the Silver Medal for his B.Eng. degree.

RINI AKMELIAWATI (Senior Member, IEEE) received the B.Eng. degree (Hons.) in electrical engineering from the Royal Melbourne Institute of Technology (RMIT) University, Australia, in 1997, and the Ph.D. degree in electrical and electronic engineering from the University of Melbourne, Australia, in 2002. She was a Full Professor with the Department of Mechatronics Engineering, International Islamic University Malaysia, from 2012 to 2018. She joined the Department as an Associate Professor, in 2008. She was a Lecturer at RMIT University, from 2001 to 2004, and Monash University, from 2004 to 2008. She is currently an Associate Professor with the School of Mechanical Engineering, The University of Adelaide, Australia. She is a Fellow of Engineers Australia and a member of International Federation of Automatic Control (IFAC) Technical Committees. She was the Vice President of the Malaysian Society of Automatic Control Engineers (MACE), from 2016 to 2018.
ILYAS KHAN works at Majmaah University, Saudi Arabia. He is also a Visiting Professor at the Department of Mathematical Sciences, Faculty of Science, Universiti Teknologi Malaysia, Skudai, UTM Johor Bahru, Malaysia, and the Faculty of Mathematics and Statistics, Ton Duc Thang University, Ho Chi Minh City, Vietnam. He is working on both analytical and numerical techniques. He has published more than 300 articles in various reputed journals. He is also the author of several books and book chapters. His areas of interests include boundary layer flows, Newtonian and non-Newtonian fluids, heat and mass transfer, renewable energy, and nanofluids.

KOTTAKKARAN SOOPPY NISAR is currently working as an Associate Professor with the Department of Mathematics, College of Arts and Science, Prince Sattam bin Abdulaziz University, Wadi Al-Dawaser, Saudi Arabia. His areas of specialization are partial differential equations, fractional calculus, and numerical solutions for nonlinear PDEs. He has published more than 200 articles. He is also a referee of several journals.