International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 05 May 2026
Page No: 3529-3533
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0458

Model Predictive Control of Physical Activity for Long-Term Diabetes Risk Reduction

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Abstract

This paper presents an output-feedback Model Predictive Control (MPC) framework designed to support long-term diabetes prevention through personalized physical activity planning. A physiological glucose–insulin dynamic model is used to predict how the human body responds to variations in physical activity. In this approach, physical activity is treated as a controllable input that can influence glucose regulation. Since continuous measurement of all physiological states is not feasible in practical healthcare settings, an output-feedback strategy combined with a state estimation technique is implemented to estimate unmeasured variables. The proposed controller dynamically adjusts the intensity, duration, and timing of physical activity to keep glucose levels within a healthy physiological range. At the same time, it considers realistic lifestyle constraints and safety limits for individuals. Simulation results show that the proposed MPC-based strategy improves long-term glycaemic regulation and maintains stability under uncertainties in physiological parameters. The study highlights the potential of control-theoretic approaches as effective tools for preventive healthcare and personalized diabetes management.

1. Introduction

Diabetes is a major global health concern caused mainly by sedentary lifestyles, unhealthy diet, and genetic predisposition. Preventing the onset of diabetes through lifestyle modification has become an important research focus.[2], in their study published in The New England Journal of Medicine, lifestyle interventions such as increased physical activity and dietary changes can significantly reduce the risk of developing type 2 diabetes. Their findings demonstrate that structured physical activity programs improve glucose metabolism and insulin sensitivity in high-risk individuals. Diabetes prevention can be supported through regular physical activity that improves glucose metabolism and insulin sensitivity, Carlos Bordon's enables personalized activity strategies for long-term metabolic health [3][6]. It is a growing global health concern highlighted in the World Health Organization report on diabetes. Integrating systems engineering approaches, as discussed by Ali Cinar, enables better modelling and management of metabolic processes. By combining physiological models with Model Predictive Control, personalized physical activity strategies can be developed to monitor metabolic responses and support long-term diabetes prevention [11],[3].

2. Background and Motivation

a) Impact of Physical Activity on Glucose Regulation:

Physical activity plays a vital role in maintaining glucose homeostasis and improving insulin sensitivity, which are essential for preventing type 2 diabetes. The quantitative analysis of glucose–insulin dynamics introduced by American Journal of Physiology demonstrated how insulin sensitivity can be estimated through mathematical modelling. These models highlight how metabolic responses change with physiological conditions. Since regular exercise enhances glucose uptake and insulin efficiency, integrating such physiological insights with predictive control strategies can support personalized activity planning for long-term diabetes prevention [1]. Regular physical activity improves glucose uptake and insulin sensitivity, supporting effective diabetes prevention. structured exercise enhances metabolic regulation and helps maintain stable blood

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glucose levels in individuals at risk of diabetes [10]. As Shown in Figure 1.

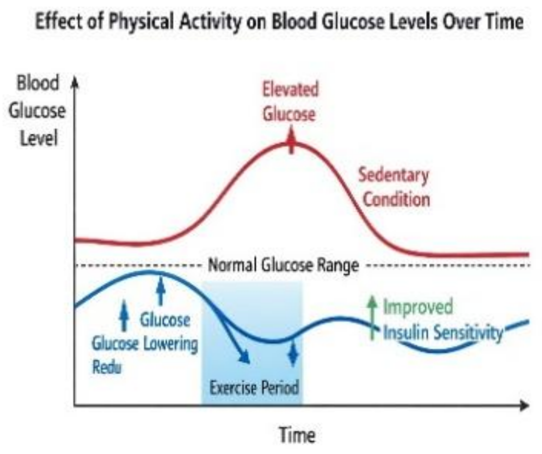

Figure 1 Effect of physical activity on blood glucose levels over time. The graph shows blood glucose levels over time comparing sedentary and exercise conditions. Physical activity lowers glucose during the exercise period and improves insulin sensitivity, keeping levels closer to the normal range

b) Need for Personalized Prevention:

The global prevalence of diabetes continues to rise, highlighting the urgent need for effective prevention strategies. Personalized physical activity interventions, guided by predictive control approaches, can improve metabolic regulation and reduce long-term diabetes risk [5]. Model Predictive Control enables systematic optimization of dynamic systems. In diabetes prevention, integrating physiological glucose–insulin models with predictive control can personalize physical activity strategies, improving long-term metabolic regulation [6], [8].

3. Related Work

Nonlinear Model Predictive Control (NMPC) has been widely applied to complex physiological systems due to its ability to handle nonlinear dynamics and constraints. Such approaches provide a foundation for designing predictive strategies that regulate metabolic responses and support personalized diabetes prevention [7]. Model Predictive Control (MPC) has been extensively studied for regulating dynamic systems with constraints and uncertainties. The theoretical foundations of MPC, presented by Rawlings and Mayne, highlight its capability to predict future system behavior and optimize control actions based on model-based predictions. In healthcare applications, such predictive strategies have been explored to manage physiological processes, including glucose insulin dynamics. [11] [9]. These methods enable adaptive decision-making that can support personalized interventions. Furthermore, global health studies emphasize the growing burden of diabetes and the need for preventive strategies that incorporate lifestyle modifications such as physical activity. According to the World Health Organization (2016), effective prevention approaches must integrate monitoring, prediction, and personalized guidance to reduce long-term diabetes risk and improve population health outcomes [11].

4. Glucose–Insulin Dynamic Model

The human metabolic system is represented using a non-linear state-space model:

$$X(t)=f(x(t), u(t)) +W(T) \tag{1}$$

$$Y(t)=h(x(t)) +v(t) \tag{2}$$

where x(t) denotes the internal metabolic states, including glucose and insulin dynamics, u(t) represents the physical activity input, and y(t) is the measured blood glucose concern- traction. The terms w(t) and v(t) represent process disturbances and measurement noise, respectively. The glucose insulin dynamic model represents interactions between blood glucose and insulin to predict metabolic responses. In [13], such models support personalized control strategies for diabetes prevention. The diagram illustrates the glucose insulin dynamic system. Physical activity acts as the input, influencing metabolic states. Disturbances and measurement noise affect the system, while glucose measurements represent the output for monitoring regulation. As Shown in Figure 2.

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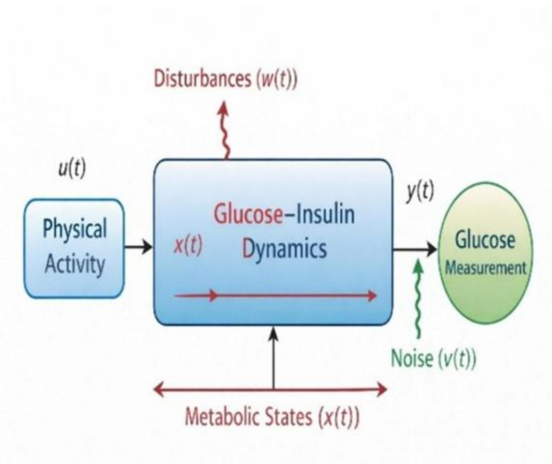

Figure 2 Block diagram of the glucose insulin dynamic system

5. Problem Formulation

The problem focuses on developing a control strategy to regulate long-term blood glucose levels through optimized physical activity recommendations. The objective is to minimize the risk of diabetes by predicting glucose–insulin responses and adjusting activity levels accordingly. structured lifestyle interventions, particularly increased physical activity, significantly reduce the incidence of type 2 diabetes in high-risk individuals [4].

a) Problem Statement:

The rising prevalence of Type 2 Diabetes requires effective prevention strategies. Based on findings from the Diabetes Prevention Program by William C. Knowler in the New England Journal of Medicine (2002), this work formulates a predictive control approach that optimizes physical activity to regulate glucose levels and reduce diabetes risk [4].

b) Mathematical Model of Diabetes Progression:

The progression toward Type 2 Diabetes can be modelled using dynamic state-space equations that describe glucose insulin interactions and the effect of physical activity. Based on principles from Model Predictive Control: Theory and Design by James B. Rawlings [12], the system can be expressed as.

$$G(t) = -k^1G(t) - X(t)G(t) + D(t) \qquad (3)$$

$$X(t) = -k^2X(t) + k^3I(t)A = \pi r^2 \qquad (4)$$

$$x^{k+1} = Ax^k + Bu^k \qquad (5)$$

Where:

(G(t)) represents glucose concentration, (I(t)) insulin level, (X(t)) insulin action, and denotes physical activity input used in predictive control for long-term diabetes prevention [12]. The control input reflects the beneficial effect of exercise in slowing the degradation of insulin sensitivity.

c) Control Objective:

The goal is to determine an optimal exercise strategy u_v (t)that maintains the glucose level near a desired reference value G_d [15]. This objective can be formulated as the minimization of the cost function.

$$J(\chi, u_v) = \| \chi_1(t) - G_d \mid u_v - u_{v,b} \mid^2 \qquad (6)$$

Where:

G_d represents the desired or target glucose level that the body aims to maintain for normal metabolic function. u_(v,b) denotes the baseline physical activity level influencing energy expenditure and glucose utilization. a weighting factor that balances the importance of maintaining glucose regulation while minimizing the effort associated with physical activity [15]. This formulation ensures that the system maintains safe glucose levels while avoiding unrealistic exercise recommendations.

d) Measurement Constraints:

According to the American Diabetes Association guidelines in Diabetes Care (2021), glucose monitoring for Type 2 Diabetes must consider sensor accuracy, sampling intervals, and physiological variability to ensure reliable measurements [15]. Measurement of glucose dynamics is limited by sensor noise and sampling delays, as discussed by Claudio Cobelli in IEEE Transactions on Biomedical Engineering. The observed glucose output can be modelled as: [8]

$$Y^K = Cx^K + V^K \qquad (7)$$

$$G^m(k) = G(k) + n(k) \qquad (8)$$

where (y^k) is measured output, (v^k) represents measurement noise, (G^2 m(k)) is measured glucose,

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and (n(k)) denotes sensor error.

e) Optimization Problem:

The optimization framework regulates glucose dynamics by adjusting activity inputs based on the minimal model. The MPC cost function is [1]

$$G(t) = -p^1 G(t) - X(t)G(t) + D(t) \qquad (9)$$

subject to:

1) System dynamics

$$\dot{\chi}(t) = f(\chi(t)) + g(\chi(t))u_v(t) \qquad (10)$$

2) Physical activity constraints

$$0 \leq u_v(t) \leq 1 \qquad (11)$$

3) Measurement limitations

$$y(t) = G(t) \qquad (12)$$

The Optimization minimizes diabetes risk via lifestyle control [4].

f) Research Objective:

Objective is to design an output-feedback predictive control strategy that regulates glucose dynamics and optimizes physical activity using Model Predictive Control principles described by James B. Rawlings and David Q. Mayne. [9].

6. Model Predictive Control Design

a) Cost Function:

The MPC cost function minimizes glucose deviation and excessive activity input while maintaining safe metabolic conditions recommended [15].

$$\mathrm{J} = \mathrm{k} = 0 \sum_{k=0}^{n} N\,[(\,G^k - G^{ref}\,)2 + \lambda\mathrm{uk}2] \qquad (13)$$

where (G^k) is predicted glucose level, (G^{ref}) desired reference glucose, and represents physical activity input used for long-term diabetes prevention [15]. The diagram illustrates an output-feedback Model Predictive Control (MPC) framework where glucose measurements and estimated metabolic states guide the optimizer to determine optimal physical activity for regulating glucose–insulin dynamics [3]. As shown in Figure 3.

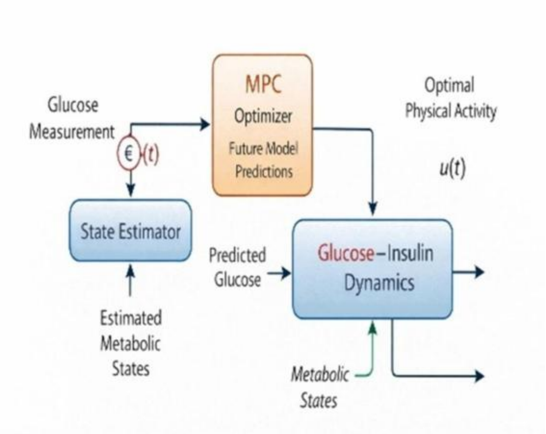

Figure 3 Output-feedback MPC structure for physical activity regulation

7. Output-Feedback and State Estimation

Output-feedback control estimates unmeasured metabolic states from glucose measurements to regulate system dynamics; observers reconstruct internal states for improved diabetes monitoring and predictive control [13] Output-feedback control estimates metabolic states using measured glucose levels and physical activity data. As discussed, physical activity significantly influences glucose regulation and metabolic state prediction [10].

8. Implementation Algorithm

The implementation algorithm integrates glucose measurements, state estimation, and predictive optimization to recommend physical activity for diabetes prevention. Evidence from the Finnish Diabetes Prevention Study led, Type 2 Diabetes [2]. The algorithm predicts glucose dynamics, estimates system states, and optimizes activity inputs using Model Predictive Control principles described [6] Algorithm applies predictive optimization and state estimation based on MPC principles [9].

9. Simulation Results

Simulation results demonstrate improved glucose regulation and reduced long-term risk of Type 2 Diabetes through optimized physical activity. These findings support global trends reported [5]. Simulation validates predictive control performance for glucose regulation using MPC methods

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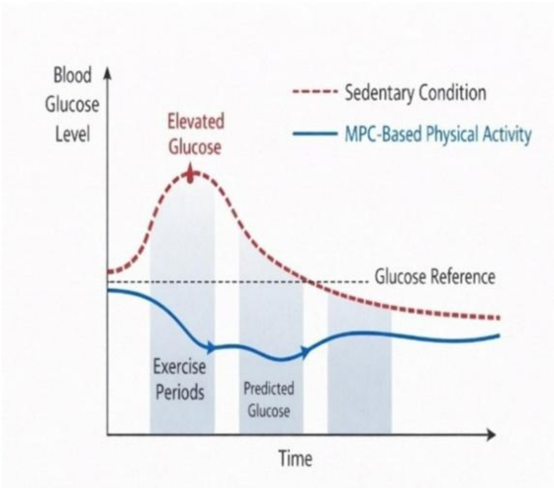

Figure 4 Simulated glucose trajectories with and without MPC-based physical activity

10. DISCUSSION

Results support physical activity–based control strategies for preventing Type 2 Diabetes, consistent with global trends reported in the IDF Diabetes Atlas [14] The proposed predictive control approach highlights the importance of physical activity in reducing the risk of Type 2 Diabetes, aligning with global prevention strategies reported [11].

Conclusion

The proposed output-feedback Model Predictive Control framework enables personalized physical activity planning for long-term diabetes prevention. By predicting metabolic responses and updating control actions through feedback, MPC optimizes activity levels under constraints, improving glucose regulation and supporting sustainable lifestyle interventions [12].

Future Work

Future work will focus on integrating wearable sensors, real-time glucose monitoring, and data-driven models to enhance personalized activity recommendations. Large-scale clinical validation and adaptive learning strategies can further improve prediction accuracy and support global diabetes prevention efforts [14].

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