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A Deep Q-Network-Assisted Artificial Hummingbird Optimized PID Controller with Derivative Filter for Blood Glucose Regulation

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ABSTRACT Blood glucose regulation is one of the most critical challenges in artificial pancreas systems due to the nonlinear characteristics of glucose-insulin dynamics and the difficulty of maintaining appropriate controller performance under varying operating conditions. This study proposes a hybrid control strategy combining the Artificial Hummingbird Algorithm (AHA) and a Deep Q-Network (DQN)-assisted PID controller with derivative filter for nonlinear blood glucose regulation. Initially, the controller parameters were optimally tuned using the AHA according to the Integral Square Error (ISE) performance criterion. Subsequently, instead of redesigning the entire controller, the DQN was employed to adaptively determine a weighting factor for the derivative gain during online operation, while the remaining controller parameters remained fixed. The proposed controller was evaluated using the nonlinear APMonitor blood glucose regulation model under identical simulation conditions. In addition, the proposed approach was compared with a nonlinear Model Predictive Control (MPC) strategy under the same simulation scenario to provide a comprehensive performance assessment. The simulation results demonstrated that the proposed approach improved blood glucose tracking performance by reducing the tracking error and oscillatory behavior compared with the conventionally optimized PID controller. Furthermore, the proposed hybrid controller outperformed the MPC approach by providing lower tracking error and smoother glucose regulation under identical operating conditions. DQN training process exhibited stable convergence within a limited number of training episodes, indicating the effectiveness of the proposed adaptive learning framework. By combining offline global optimization with online adaptive learning, the proposed method preserves the simplicity and robustness of the classical PID controller while enhancing its regulation capability for nonlinear blood glucose systems. The obtained results indicate that the proposed hybrid strategy provides an effective and computationally efficient solution for intelligent blood glucose regulation.

KEYWORDS
Deep Q-Network
Blood glucose regulation
Artificial hummingbird algorithm
PID
Model predictive control

INTRODUCTION

Diabetes mellitus (DM) is one of the most widespread chronic metabolic diseases worldwide and continues to pose a major public health challenge because of its increasing prevalence and the severe complications associated with poor glycemic regulation. Among its different forms, Type 1 Diabetes Mellitus (T1DM) is characterized by the autoimmune destruction of pancreatic $\beta-$cells, resulting in an absolute deficiency of insulin secretion and lifelong dependence on exogenous insulin administration. Maintaining blood glucose (BG) concentration within the physiological range is therefore essential, since prolonged hyperglycemia and hypoglycemia may lead to serious complications such as cardiovascular diseases, nephropathy, retinopathy, neuropathy, coma, and even death. Consequently, accurate and reliable blood glucose regulation has become one of the primary objectives in diabetes treatment and biomedical control engineering (Acikgoz and Diwekar 2010; Dagher and Haggege 2025; Pompa *et al.* 2021).

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Conventional diabetes management generally relies on multiple daily insulin injections or continuous subcutaneous insulin infusion using insulin pumps. Although these treatment strategies have significantly improved patients' quality of life, insulin dosage is still largely determined according to periodic glucose measurements, meal estimation, and patient experience. Such manual decision-making is often insufficient under rapidly changing physiological conditions caused by meal disturbances, physical activity, stress, and inter-patient variability. Therefore, considerable research efforts have been devoted to the development of Artificial Pancreas (AP) systems, which integrate continuous glucose monitoring (CGM), insulin infusion pumps, and automatic control algorithms to emulate the glucose regulation mechanism of a healthy pancreas. The primary objective of these systems is to maintain blood glucose concentration within a safe physiological range while minimizing both hyperglycemic and hypoglycemic events under various operating conditions (Acikgoz and Diwekar 2010; Dagher and Haggege 2025; Friis-Jensen 2007; Çetkin 2013).

The performance of an artificial pancreas system is directly related to the mathematical model employed to describe glucose-insulin dynamics. During the past several decades, numerous

mathematical models with different physiological complexities have been proposed for blood glucose regulation. Among these, the Bergman Minimal Model has become one of the most widely adopted models in control engineering because of its simple mathematical formulation, relatively small number of parameters, and ability to represent the fundamental dynamics of glucose-insulin interaction with satisfactory accuracy. Owing to its computational efficiency and straightforward implementation, the Bergman model has served as the foundation for numerous controller design, optimization, and artificial pancreas studies (Pompa *et al.* 2021; Friis-Jensen 2007; Soylu and Danışman 2017).

To achieve higher physiological fidelity, more comprehensive mathematical models have subsequently been introduced. The Hovorka model incorporates detailed descriptions of glucose absorption, insulin kinetics, and meal disturbances, making it particularly suitable for advanced model-based control strategies. Similarly, the UVa/Padova simulator provides a highly realistic virtual patient environment that has been extensively employed for the pre-clinical evaluation of artificial pancreas algorithms. Although these models provide more detailed physiological behavior than the Bergman model, their increased complexity generally leads to higher computational requirements during controller design and simulation. Consequently, the Bergman model remains one of the most preferred mathematical models for developing and evaluating control algorithms owing to its balanced compromise between physiological accuracy and computational simplicity (Pompa *et al.* 2021; Friis-Jensen 2007; Dua *et al.* 2006).

The availability of these mathematical models has enabled researchers to investigate numerous control methodologies for automated blood glucose regulation. Nevertheless, the nonlinear characteristics of the glucose-insulin system, together with patient-dependent parameter variations, external meal disturbances, and physiological uncertainties, continue to make the design of high-performance glucose controllers a challenging control problem. These challenges have encouraged the development of increasingly sophisticated control strategies, ranging from conventional PID-based approaches to intelligent optimization and reinforcement learning-based algorithms.

The availability of reliable mathematical models has enabled researchers to investigate a wide range of control strategies for automated blood glucose regulation. Among these approaches, the Proportional-Integral-Derivative (PID) controller remains one of the most commonly employed techniques because of its simple structure, ease of implementation, and satisfactory performance in many engineering applications. Owing to these advantages, PID-based controllers have been extensively applied to glucose-insulin regulation using Bergman and other physiological models. Nevertheless, the nonlinear dynamics of the glucose-insulin system, together with parameter uncertainties and external meal disturbances, often degrade the performance of conventional PID controllers, leading to oscillatory responses, increased settling time, or larger steady-state errors. Consequently, improving the control performance of PID-based algorithms has remained an active research topic in artificial pancreas systems (Dagher and Haggege 2025; Çetkin 2013; Farahmand *et al.* 2019).

To overcome the limitations of conventional PID control, numerous advanced control methodologies have been proposed in the literature. Model Predictive Control (MPC) has become one of the most successful approaches because of its capability to explicitly consider system constraints and predict future glucose trajectories. Sliding Mode Control (SMC) has demonstrated superior robustness against modeling uncertainties and external disturbances, whereas fuzzy logic controllers have been successfully employed to regulate blood glucose without requiring highly accurate mathematical models. Furthermore, neural network-based and adaptive control techniques have also been investigated to improve glucose regulation performance under nonlinear physiological dynamics. Although these control strategies generally provide better performance than conventional PID controllers, they are usually associated with increased computational complexity, sophisticated controller structures, or higher implementation costs, which may limit their practical applicability (Pompa *et al.* 2021; Dua *et al.* 2006; Tašić *et al.* 2022; Mirzaee *et al.* 2023). Besides developing more sophisticated controller structures, another important research direction has focused on determining optimal controller parameters using metaheuristic optimization algorithms. Conventional tuning methods, such as trial-and-error or Ziegler-Nichols, generally fail to obtain globally optimal controller parameters for nonlinear systems. Therefore, population-based optimization techniques including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Artificial Hummingbird Algorithm (AHA), and many other nature-inspired optimization methods have been successfully employed for controller tuning according to various performance indices, including Integral Square Error (ISE), Integral Absolute Error (IAE), Integral Time-weighted Absolute Error (ITAE), and Integral Time-weighted Square Error (ITSE). Compared with conventional tuning approaches, these optimization algorithms generally provide faster transient responses, reduced overshoot, and lower steady-state errors. However, the controller parameters obtained by these algorithms are determined offline and remain fixed during system operation, which limits their ability to further improve the control performance of nonlinear glucose-insulin systems (Dagher and Haggege 2025; Çetkin 2013; Zhao *et al.* 2022; Çimen 2026; Sabzevar *et al.* 2023; Baldisseri *et al.* 2024).

Recently, Reinforcement Learning (RL) has attracted considerable attention as an effective data-driven framework for nonlinear control problems. Unlike conventional optimization techniques, RL enables an intelligent agent to learn an optimal control policy through continuous interaction with the environment by maximizing a cumulative reward function. Following the remarkable success of Q-learning, Deep Reinforcement Learning (DRL) algorithms, particularly the Deep Q-Network (DQN), have demonstrated significant potential in solving complex nonlinear control problems through the integration of reinforcement learning and deep neural networks. Recent studies have reported that RL-based controllers can successfully regulate blood glucose concentration while improving control performance compared with conventional approaches. Nevertheless, most existing RL-based methods either replace the entire controller structure or attempt to optimize all controller parameters simultaneously, which generally increases computational complexity, prolongs the training process, and reduces controller interpretability from a classical control engineering perspective (Sabzevar *et al.* 2023; Baldisseri *et al.* 2024; Mnih *et al.* 2015; Çimen 2025). Some studies comparing the findings in the literature are given in Table 1.

Motivated by these observations, this study proposes a hybrid control strategy that combines the advantages of offline metaheuristic optimization and online reinforcement learning. First, the parameters of a PID controller with derivative filter are optimally determined using the Artificial Hummingbird Algorithm (AHA) according to the Integral Square Error (ISE) performance criterion. Subsequently, rather than redesigning or retuning the entire controller, a Deep Q-Network (DQN) is incorporated to

Table 1 Comparison of representative studies on blood glucose regulation

Ref.	Model	Controller	Optimization	RL	Performance Index	Main Limitation
Farahmand *et al.* (2019)	Bergman	Fuzzy	LMI	–	H_∞	Complex controller design
Baldisseri *et al.* (2024)	Bergman	DDPG	–	DDPG	Reward	Long training time
Sabzevar *et al.* (2023)	Bergman	RL	–	RL	Reward	Slow convergence
Çimen (2024)	Bergman	PID	–	–	Fine tuning	Manual parameter tuning
Echajei *et al.* (2025)	Bergman	MPC	Bayesian Estimation	–	RMSE, Clarke Grid	High computational burden
This study	APMonitor	PID with derivative filter	AHA	DQN	ISE + Reward	–

determine an adaptive weighting factor for the derivative gain obtained through the AHA-based optimization. Consequently, the proposed approach preserves the simplicity, robustness, and stability of the optimally tuned PID controller while enhancing its control performance in regulating the nonlinear glucose-insulin system. Despite the significant progress achieved in blood glucose control during the last two decades, several challenges still remain. Conventional PID-based controllers offer simple implementation and satisfactory performance; however, their effectiveness strongly depends on appropriate controller tuning. Although metaheuristic optimization algorithms can successfully determine optimal controller parameters according to predefined performance criteria, the obtained gains remain fixed after the optimization process and cannot further improve the controller performance during operation.

On the other hand, reinforcement learning-based approaches provide adaptive decision-making capabilities through continuous interaction with the environment. Nevertheless, many existing studies employ reinforcement learning to completely replace conventional controllers or simultaneously learn all controller parameters, which generally increases computational complexity and training requirements while reducing the transparency of the controller design from a classical control perspective. Therefore, developing a control framework that preserves the simplicity of conventional controllers while exploiting the adaptive capability of reinforcement learning remains an attractive research topic (Zhao *et al.* 2022; Çimen 2026; Sabzevar *et al.* 2023; Baldisseri *et al.* 2024; Mnih *et al.* 2015; Çimen 2025; Hovorka *et al.* 2004).

To address this limitation, this paper proposes a hybrid control strategy for blood glucose regulation by combining the Artificial Hummingbird Algorithm (AHA) with a Deep Q-Network (DQN)-assisted PID controller with derivative filter. Initially, the controller parameters are optimally determined using AHA according to the Integral Square Error (ISE) performance criterion. Subsequently, instead of redesigning or re-optimizing the complete controller, the proposed DQN algorithm determines an adaptive weighting factor for the derivative gain obtained from the AHA-based optimization. Consequently, the proposed controller preserves the simplicity and stability of the optimally tuned PID controller while introducing an additional adaptive mechanism that improves the regulation performance of the nonlinear glucose-insulin system.

The main contributions of this study can be summarized as follows. First, an Artificial Hummingbird Algorithm-based optimization framework is developed to determine the optimal parameters of a PID controller with derivative filter using the ISE performance criterion. Second, a Deep Q-Network is integrated into the optimized controller to adaptively determine the weighting factor of the derivative gain without modifying the remaining controller parameters. Third, the proposed hybrid control strategy, conventional PID with AHA and MPC are implemented on the nonlinear blood glucose regulation model available in the APMonitor platform and its control performance is evaluated through numerical simulations. Finally, the proposed method is compared with the conventionally optimized PID controller and MPC, demonstrating that the integration of reinforcement learning improves blood glucose regulation while maintaining the simplicity and computational efficiency of the original controller structure.

MATERIALS AND METHODS

Nonlinear Blood Glucose Regulation Model

A mathematical model capable of accurately representing glucose-insulin dynamics is essential for the design and evaluation of automatic blood glucose regulation systems. Over the past decades, numerous mathematical models with different levels of physiological complexity have been proposed for artificial pancreas applications. Among these models, the Bergman Minimal Model has become one of the most frequently adopted control-oriented models owing to its simple mathematical formulation and its ability to describe the dominant glucose-insulin interactions using a limited number of state variables (Pompa *et al.* 2021; Friis-Jensen 2007; Hedengren 2008). Subsequently, more comprehensive models, such as the Hovorka model and the UVa/Padova simulator, were developed by incorporating additional physiological mechanisms including insulin pharmacokinetics, glucose absorption, meal disturbances, and patient-specific characteristics. Although these models provide a more detailed physiological representation, their increased complexity generally results in higher computational requirements for controller design and optimization (Friis-Jensen 2007; Dua *et al.* 2006).

In the present study, the nonlinear blood glucose regulation model available in the APMonitor platform was selected as the simulation environment for evaluating the proposed control strat-

egy (Mufti Azis *et al.* 2020). The APMonitor model is an extended nonlinear compartmental model derived from the classical Bergman glucose-insulin model. In addition to glucose concentration, plasma insulin concentration, and remote insulin action, the model explicitly represents gastrointestinal glucose transport and glucose absorption dynamics. Consequently, it provides a more realistic representation of postprandial glucose regulation while maintaining a computational complexity suitable for control design and numerical simulations (Mufti Azis *et al.* 2020).

The nonlinear model consists of six coupled state variables describing the physiological dynamics of blood glucose regulation. The state vector can be expressed as in Eq 1.

$$\mathbf{x}(t) = \begin{bmatrix} G(t) & X(t) & I(t) & q_1(t) & q_2(t) & G_{ut}(t) \end{bmatrix}^T \tag{1}$$

where $(G(t))$ denotes the blood glucose concentration (mg/dL), $(X(t))$ represents the remote insulin effect, (I(t)) is the plasma insulin concentration, $(q_1(t))$ and $(q_2(t))$ denote the glucose masses in the first and second gastrointestinal compartments, respectively, and $(G_a(t))$ represents the gut glucose absorption. The insulin infusion rate, $(u(t))$, generated by the controller is considered as the system control input, whereas meal intake enters the model as an external disturbance through the gastrointestinal subsystem (Mufti Azis *et al.* 2020).

The nonlinear state equations governing the glucose-insulin regulation process are expressed as in Equation 2.

$$\begin{aligned} \dot{G} &= -p_1(G - G_b) - s_i X G + \frac{f\,k_{\text{abs}}}{v_g} G_{gut} + \frac{fD}{v_g}, \\ \dot{X} &= p_2(I - X), \\ \dot{I} &= -k_e I + \frac{u_i}{V_I}, \\ \dot{q}_1 &= u_i - k_{\text{emp}} q_1, \\ \dot{q}_2 &= -k_{\text{emp}}(q_2 - q_1), \\ \dot{G}_{gut} &= k_{\text{emp}} q_2 - k_{\text{abs}} G_{gut}. \end{aligned} \tag{2}$$

The numerical values of system's parameters are presented in Table 2.

Table 2 Parameters of the nonlinear blood glucose model

Symbol	Parameter Value	Symbol	Parameter Value
G_b	291	k_{abs}	1.2×10^{-2}
p_1	3.17×10^{-2}	k_{emp}	1.8×10^{-1}
p_2	1.23×10^{-2}	f	0.8×10^{-1}
s_i	2.9×10^{-2}	v_g	12.0
k_e	9.0×10^{-2}	–	–

Unlike simplified linear benchmark models, the APMonitor model preserves the nonlinear coupling between glucose metabolism, insulin kinetics, remote insulin action, and gastrointestinal glucose absorption. This nonlinear interaction allows the controller to be evaluated under more realistic physiological conditions, making the model particularly suitable for investigating advanced control algorithms for blood glucose regulation (Mufti Azis *et al.* 2020).

Throughout this study, the physiological structure, parameter values, and initial conditions of the APMonitor model were preserved without modification. The primary objective of employing this nonlinear benchmark model is to provide a common simulation environment for comparing the conventionally optimized PID controller with derivative filter and the proposed DQN-assisted adaptive derivative gain weighting strategy. Therefore, all comparative simulations were performed under identical operating conditions to ensure a fair and objective performance evaluation.

PID Controller with Derivative Filter

The Proportional–Integral–Derivative (PID) controller is one of the most widely used control algorithms in engineering applications due to its simple structure, ease of implementation, and satisfactory control performance. In blood glucose regulation systems, PID controllers have been successfully employed to maintain glucose concentration around the desired reference value (Dagher and Haggege 2025; Çetkin 2013; Dua *et al.* 2006; Farahmand *et al.* 2019). However, the derivative term may amplify high-frequency measurement noise, resulting in undesirable fluctuations in the control signal. To overcome this drawback, a first-order derivative filter is incorporated into the derivative component of the controller (Çetkin 2013; Çimen 2026).

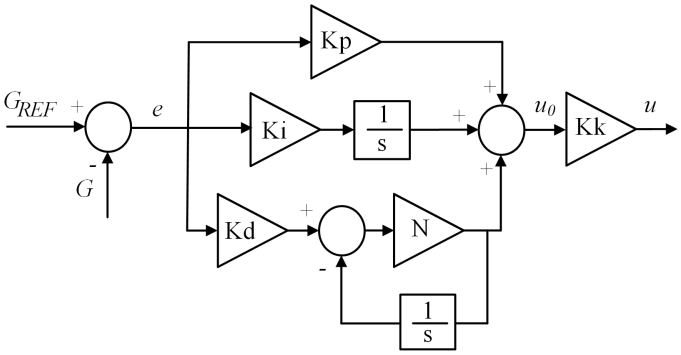

Figure 1 PID with derivative Filter

The transfer function of the PID controller with derivative filter used in this study is expressed as in Equation 3.

$$C(s) = \frac{u(s)}{e(s)} = K_K \left(K_p + \frac{K_i}{s} + \frac{K_d N s}{s + N} \right) \tag{3}$$

where (K_p), (K_i), (K_d) and (K_k) denote the proportional, integral, and derivative gains, scaling gain respectively, while (N) is the derivative filter coefficient.

The tracking error is defined as in Equation 4.

$$e(t) = G_{REF}(t) - G(t) \tag{4}$$

$G_ref(t)$ is the reference blood glucose concentration and $(G(t))$ is the measured blood glucose concentration. Based on this error signal, the controller generates the insulin infusion rate $(u(t))$.

The performance of the PID controller strongly depends on the appropriate selection of its parameters. Therefore, the controller parameters (K_p, K_i, K_d, Kk) were optimally determined using the Artificial Hummingbird Algorithm (AHA) while N parameter is set to 100. Objective function is Integral Square Error (ISE) criterion. The obtained optimal parameters constitute the baseline controller used throughout this study. The optimization procedure is presented in the following subsection.

Artificial Hummingbird Algorithm-Based Controller Parameter Optimization

The performance of a PID controller with derivative filter is highly dependent on the appropriate selection of its controller parameters. Inappropriate parameter values may lead to excessive overshoot, oscillatory responses, or slow convergence. Therefore, determining the optimal values of (K_p), (K_i), (K_d) and (K_k) can be formulated as a nonlinear optimization problem (Çimen 2026; Hovorka *et al.* 2004; Çimen *et al.* 2021).

In this study, the Artificial Hummingbird Algorithm (AHA) was employed to determine the optimal controller parameters. AHA is a population-based metaheuristic optimization algorithm inspired by the foraging behavior and flight characteristics of hummingbirds. Owing to its efficient balance between exploration and exploitation, AHA has demonstrated competitive performance in solving various engineering optimization problems (Zhao *et al.* 2022).

The optimization objective is to minimize the Integral Square Error (ISE), which is defined as in Equation 5.

$$\mathrm{ISE} = \int_0^{T_{\mathrm{final}}} e^2(t)\, dt \tag{5}$$

$e(t)$ denotes the blood glucose tracking error and T_{final} is the simulation time. The optimization variables are the controller parameters are given in Equation 6.

$$\left[K_p,\ K_i,\ K_d,\ K_k\right] \tag{6}$$

During the optimization process, each candidate solution generated by the AHA algorithm was implemented in the nonlinear APMonitor blood glucose regulation model. The corresponding ISE value was then calculated and used as the fitness value. This procedure was repeated until the stopping criterion of the optimization algorithm was satisfied. After completing the optimization process, the optimal controller parameters were obtained as $K_p = 0.2089$, $K_i = 0.2362$, $K_d = 0.7093$, $K_k = 0.1194$ and $N = 100$.

These parameters constitute the baseline PID controller with derivative filter used throughout the study. In the subsequent stage, the obtained optimal derivative gain is further enhanced using the proposed Deep Q-Network-based adaptive weighting strategy, while the remaining controller parameters remain unchanged.

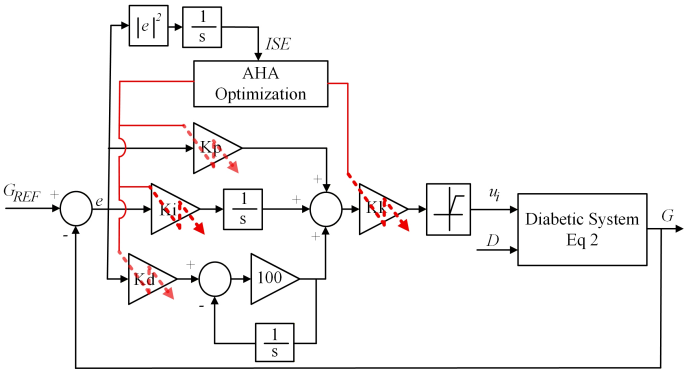

Figure 2 Flowchart of the AHA-based PID parameter optimization

DQN-Based Adaptive Derivative Gain Weighting

Although the Artificial Hummingbird Algorithm provides optimal controller parameters by minimizing the Integral Square Error (ISE), the obtained parameters remain fixed throughout the control process. To further improve the control performance of the nonlinear blood glucose regulation system, a Deep Q-Network (DQN) is integrated into the proposed control framework. Unlike conventional reinforcement learning-based controllers, the proposed DQN does not redesign the entire controller. Instead, it adaptively determines a weighting factor for the derivative gain obtained from the AHA-based optimization. At each sampling instant, the DQN agent observes the current state of the control system and selects an appropriate weighting factor according to the learned policy. The derivative gain used by the controller is then updated as in Equation 7.

Table 3 Optimization settings used in the Artificial Hummingbird Algorithm

Parameter	Value	Parameter	Value
Population size	10	Lower bounds	0
Maximum iterations	50	Upper bounds	1

$$K_d^* = \omega K_d \tag{7}$$

K_d denotes the optimal derivative gain determined by the AHA algorithm, (ω) represents the weighting factor generated by the DQN agent, and (K_d^*) is the adaptive derivative gain used by the controller.

The reinforcement learning agent interacts with the nonlinear blood glucose regulation model through the state-action-reward framework. The system state is constructed using the blood glucose control error as in Equation 8.

$$e(t) = G_{REF}(t) - G(t) \tag{8}$$

$e(t)$ represents the deviation between the desired and measured blood glucose concentrations. Based on the observed state, the agent selects an action corresponding to one of the predefined weighting factors for the derivative gain. Following the execution of the selected action, the blood glucose response of the system is evaluated and a reward is assigned according to the tracking performance. The reward function is designed to encourage accurate reference tracking while penalizing large glucose regulation errors. Consequently, the DQN agent gradually learns the weighting factor that maximizes the cumulative reward and improves the overall control performance. The DQN consists of an online neural network and a target network. During the training process, the online network estimates the state-action values, whereas the target network provides stable target values for updating the network parameters. Furthermore, an experience replay memory is employed to store previous interactions and randomly sample mini-batches during training. This strategy reduces the correlation between successive samples and improves the stability and convergence of the learning process (Çimen 2026; Mnih *et al.* 2015; Çimen 2025). By combining the globally optimized controller parameters obtained from the Artificial Hummingbird Algorithm with the adaptive learning capability of the Deep Q-Network, the proposed hybrid control framework preserves the simplicity of the PID controller while enhancing its ability to regulate the nonlinear blood glucose system. The overall architecture of the proposed AHA–DQN-assisted PID with derivative filter controller is illustrated in Figure 3.

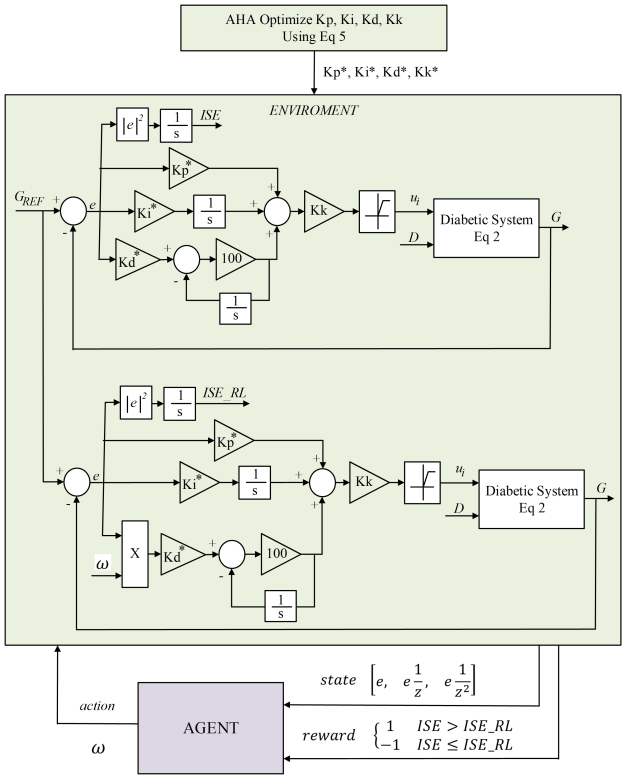

Figure 3 Proposed DQN-assisted PID with derivative controller

In Figure 3, the agent is presented with states and the reward function. The states used within DQN are given in Equation 9. The reward function used in training DQN is given in Equation 10. However, the action values that the agent will generate are discrete and these values are given in Table 4. DQN parameters for agent learning are presented at Table 5.

$$\textbf{state} = \left[e,\ ez^{-1},\ ez^{-2}\right] \tag{9}$$

$$\text{Reward} = \begin{cases} 1, & \text{ISE} > \text{ISE}_{\text{RL}}, \\ -1, & \text{ISE} \leq \text{ISE}_{\text{RL}}. \end{cases} \tag{10}$$

Table 4 Action and state parameters with ranges

Category	Parameter	Range
Action	ω	[0, 0.334, 0.667, 1.0, 1.334, 1.667, 2.0]
State	e	$[-\infty, +\infty]$
	ez^{-1}	$[-\infty, +\infty]$
	ez^{-2}	$[-\infty, +\infty]$

Overall Control Framework

The overall architecture of the proposed blood glucose regulation system is illustrated in Figure 3. The proposed framework combines the global optimization capability of the Artificial Hummingbird Algorithm (AHA) with the adaptive learning capability

Table 5 DQN parameters

Parameter	Value	Parameter	Value
Number of Layers	200	Epsilon Decay	0.99
Learning Rate	1×10^{-5}	Maximum Episodes	200
Mini Batch Size	32	Stopping Training Criteria	EpisodeCount
Replay Buffer Size	500		

of the Deep Q-Network (DQN) to improve the performance of a PID controller with derivative filter.

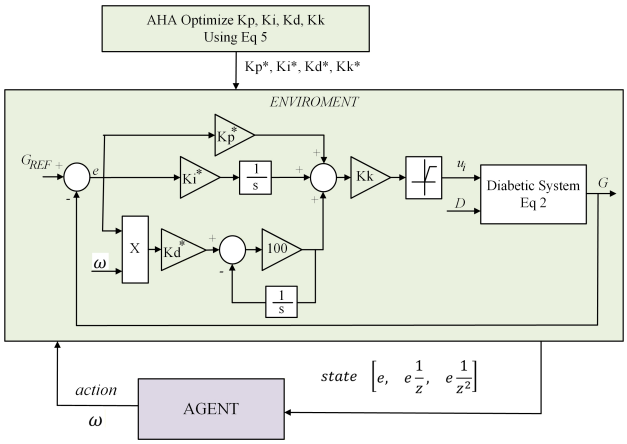

Figure 4 Overall architecture of the proposed AHA–DQN-assisted PID controller

Initially, the controller parameters (K_p), (K_i), (K_d) and (K_k) are optimally determined offline using AHA algorithm according to the Integral Square Error (ISE) performance criterion. These optimized parameters constitute the baseline controller employed throughout the control process. During online operation, the proportional, integral, and derivative filter parameters remain unchanged, while only the derivative gain is adaptively adjusted using the DQN agent. At each sampling instant, the blood glucose regulation model provides the current state information to the DQN agent. Based on the observed system state, the agent selects an appropriate weighting factor for the derivative gain.

The updated derivative gain is then incorporated into the PID controller with derivative filter, which generates the insulin infusion rate for regulating the blood glucose concentration. After applying the control action, the resulting glucose response is evaluated and a reward is calculated according to the tracking performance. The obtained reward and the next system state are subsequently used to update the DQN policy through the experience replay mechanism. By combining offline parameter optimization with online adaptive learning, the proposed control framework preserves the robustness and stability of the optimized PID controller while introducing an adaptive mechanism for improving the regulation performance of the nonlinear blood glucose system. The interaction among the nonlinear plant, the optimized PID controller, and the DQN agent forms a closed-loop control architecture

capable of achieving accurate blood glucose regulation.

RESULTS AND DISCUSSION

In this section, the simulation results obtained from the proposed AHA–DQN-assisted PID controller with derivative filter are presented and discussed. The performance of the proposed controller is evaluated in terms of DQN training behavior, blood glucose regulation response, insulin infusion signal, and quantitative error-based performance indices. The AHA-optimized PID controller with derivative filter and MPC are also implemented, and the proposed DQN-assisted controller is compared with these controller under the same simulation conditions. All simulations were carried out in MATLAB/Simulink environment on a computer equipped with an Intel Core i7-11800H 2.3 GHz processor, 32 GB RAM, and an NVIDIA GeForce RTX 3070 graphics card running Windows 11. The simulation duration was set to 50 s, while the sampling time of the DQN agent and MPC was selected as 0.5 s. During the simulations, the nonlinear APMonitor blood glucose regulation model, the AHA-optimized PID controller, MPC, and the DQN-assisted adaptive derivative gain weighting mechanism for PID were implemented within the same closed-loop control structure. Prediction horizon of MPC parameter is selected as 30 and control horizon of MPC parameter is 1. The results are presented in the following subsections. First, the training performance of the DQN agent is examined using reward, cumulative reward, and loss values. Then, the blood glucose regulation performance of the proposed method is compared with the AHA-optimized PID controller and MPC. Finally, quantitative performance indices are evaluated to demonstrate the improvement obtained by the proposed hybrid control strategy.

DQN Training Performance

The learning performance of the proposed Deep Q-Network (DQN) agent was evaluated over 200 training episodes. During the training process, the agent continuously interacted with the nonlinear blood glucose regulation model and updated the weighting factor of the derivative gain according to the received reward. The evolution of the instantaneous reward, cumulative reward, and network loss during the training process is illustrated in Fig. 5.

As shown in Figure 5(a), the reward values exhibit several fluctuations during the initial training episodes because the agent explores different actions to identify the most appropriate derivative gain weighting factor. As the training progresses, the reward rapidly converges to positive values and remains nearly constant for most of the remaining episodes. This behavior indicates that the DQN agent successfully learns an effective control policy capable of improving the blood glucose regulation performance.

The cumulative reward shown in Figure 5(b) presents a continuously increasing trend throughout the training process. Although temporary decreases are observed due to the exploration mechanism, the cumulative reward quickly recovers and reaches a stable value after approximately the first half of the training process. This result demonstrates that the proposed reward function effectively guides the learning process toward selecting more appropriate actions for derivative gain adaptation.

The training loss of the DQN is presented in Figure 5(c). Initially, relatively large loss values are observed because the neural network parameters are randomly initialized. As the training proceeds, the loss gradually decreases and remains close to zero with only minor oscillations. The reduction in the loss value indicates that the estimated Q-values become increasingly consistent with the target Q-values, demonstrating stable convergence of the learning algorithm.

Overall, the results presented in Figure 5 confirm that the proposed DQN agent successfully converges within 200 training episodes and learns an effective adaptive weighting strategy for the derivative gain. The stable reward evolution together with the decreasing loss values demonstrates that the proposed learning framework is capable of producing a reliable control policy before being employed in the blood glucose regulation system.

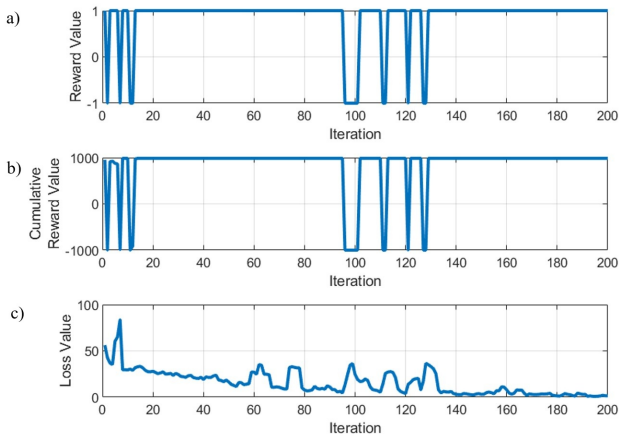

Figure 5 Reward during training

Blood Glucose Regulation Performance

The blood glucose regulation performance of the proposed control strategy was evaluated by comparing the AHA-optimized PID controller with derivative filter, MPC and the proposed DQN-assisted adaptive controller for PID. The corresponding blood glucose responses are presented in Figure 6.

As shown in Figure 6, all controllers successfully regulate the blood glucose concentration toward the desired reference value. However, noticeable differences are observed in their transient and steady-state responses. MPC and AHA-optimized PID controller provides satisfactory regulation performance. Especially AHA-optimized PID controller shows better performance than MPC owing to the optimal controller parameters obtained through the optimization process. Nevertheless, since these parameters remain fixed throughout the simulation, the controller exhibits relatively slower adaptation to the nonlinear dynamics of the glucose-insulin system.

In contrast, the proposed DQN-assisted controller demonstrates a faster and smoother tracking response. By adaptively adjusting the weighting factor of the derivative gain according to the current operating condition, the controller improves the transient response while maintaining closed-loop stability. Consequently, the blood glucose concentration approaches the desired reference value more rapidly with reduced oscillations compared with MPC and AHA-optimized PID controller. Another important observation is that the adaptive derivative gain weighting effectively suppresses fluctuations around the reference glucose level. As a result, the proposed controller provides a smoother blood glucose profile and improves the overall regulation quality without modifying the optimized proportional and integral gains determined by AHA algorithm.

The obtained results indicate that combining the global optimization capability of the Artificial Hummingbird Algorithm with the online learning capability of the Deep Q-Network enables the controller to adapt more effectively to the nonlinear behavior of the blood glucose regulation system. Therefore, the proposed hybrid control strategy achieves superior tracking performance while preserving the simplicity and robustness of the PID controller with derivative filter. In addition, Figure 8 shows ISE values calculated over time while the system was being controlled. This also shows that the proposed method is more successful.

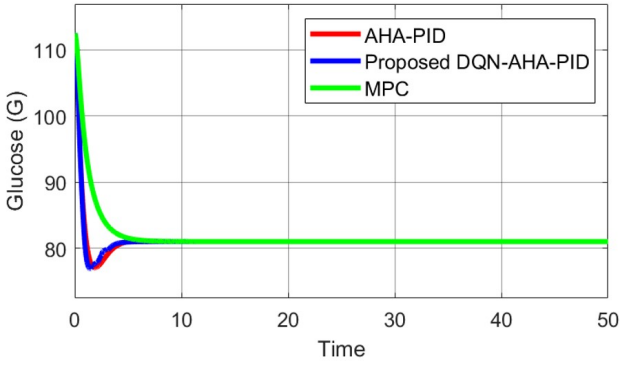

Figure 6 Blood glucose response

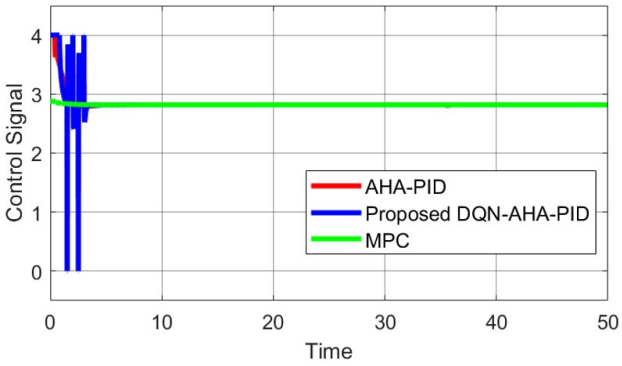

Figure 7 Insulin infusion rate

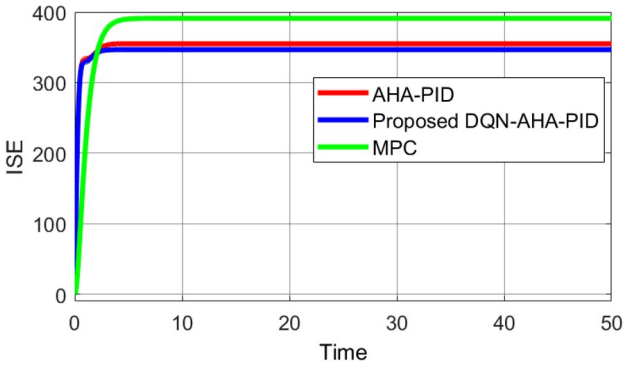

Figure 8 ISE Performance results for AHA-PID, Proposed DQN-AHA-PID and MPC

Figure 9 illustrates the blood glucose responses of the AHA-optimized PID controller, the proposed DQN-AHA-PID controller, and the nonlinear MPC controller under output disturbance conditions. The proposed DQN-AHA-PID controller achieved the smoothest glucose regulation throughout the simulation. Compared with both the conventionally optimized AHA-PID controller and the nonlinear MPC controller, it provided lower transient deviations, reduced oscillatory behavior, and faster recovery following disturbances. The MPC controller, although capable of maintaining closed-loop stability, exhibited inferior tracking performance under the considered disturbance scenario. These observations demonstrate that integrating offline AHA optimization with online DQN-based adaptation significantly enhances the robustness and control performance of the classical PID controller for nonlinear blood glucose regulation.

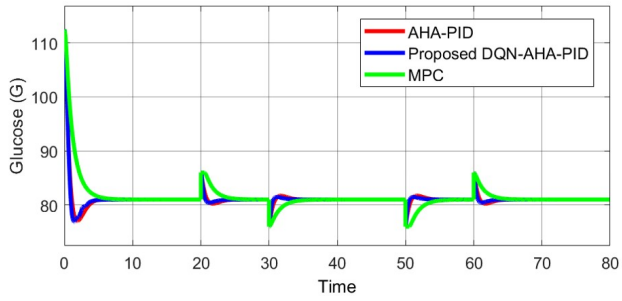

Figure 9 Blood glucose responses with output disturbance

Performance Comparison

To quantitatively evaluate the effectiveness of the proposed control strategy, several widely used performance indices were considered, including the Integral Square Error (ISE), Integral Absolute Error (IAE), Integral Time-weighted Absolute Error (ITAE). The comparative results obtained for the AHA-optimized PID controller with derivative filter, MPC and the proposed DQN-assisted controller for PID controller with derivative filter are summarized in Table 6.

As presented in Table 6, the proposed control strategy achieves superior performance in almost all evaluation criteria. The adaptive adjustment of the derivative gain enables the controller to reduce the tracking error while preserving the optimized controller structure obtained by the Artificial Hummingbird Algorithm. Consequently, lower error indices are obtained compared with AHA-optimized PID controller with derivative filter and MPC, indicating a more accurate regulation of the blood glucose concentration.

Furthermore, the proposed controller exhibits improved transient characteristics by reducing oscillations and accelerating the convergence toward the desired glucose level. Since only the derivative gain is adaptively updated during the online control process, the proportional and integral gains remain unchanged, preserving the stability and robustness of the optimally tuned PID controller. This hybrid strategy effectively combines the global optimization capability of the Artificial Hummingbird Algorithm with the adaptive decision-making capability of the Deep Q-Network.

Overall, both the graphical responses and the quantitative performance indices demonstrate that the proposed AHA–DQN-assisted PID controller provides a more accurate, stable, and adaptive blood glucose regulation performance than the conventional AHA-optimized PID controller with derivative filter and MPC. These results verify that the proposed reinforcement learning framework successfully enhances the control performance without increasing the structural complexity of the controller.

Table 6 Quantitative performance comparison

Method	ISE	IAE	ITAE	ITSE
AHA-PID	354.9	22.74	22.74	120.2
DQN-AHA-PID	346.6	21.20	18.09	103.2
MPC	680.3	39.72	47.77	391.1

Discussion

The simulation results demonstrate that integrating the Deep Q-Network with the AHA-optimized PID controller improves the blood glucose regulation performance without altering the overall controller structure. Although Artificial Hummingbird Algorithm provides an optimal set of controller parameters by minimizing the Integral Square Error, these parameters remain fixed throughout the control process. Consequently, the controller cannot adapt to variations in the nonlinear dynamics of the glucose-insulin system during operation. The proposed DQN-assisted control strategy overcomes this limitation by adaptively adjusting the derivative gain according to the current tracking performance. Instead of updating all controller parameters, only the derivative gain is modified online while the proportional and integral gains remain fixed at their optimized values. This design preserves the stability of the baseline controller and simultaneously provides additional flexibility for responding to changes in the system dynamics.

To further evaluate the effectiveness of the proposed method, its performance was also compared with a nonlinear Model Predictive Control (MPC) strategy under identical simulation conditions. Although MPC is widely recognized for handling constrained nonlinear systems through predictive optimization, the simulation results indicate that the proposed DQN-assisted controller achieved superior glucose regulation performance. In particular, the proposed controller exhibited smaller transient deviations, reduced oscillatory behavior, and faster recovery following output disturbances. These findings suggest that the adaptive derivative gain adjustment enabled by the DQN provides a more effective compensation mechanism for the considered nonlinear glucose-insulin dynamics than the prediction-based control strategy employed by MPC controller.

Another important advantage of the proposed approach is its relatively low computational complexity during online implementation. Since the Artificial Hummingbird Algorithm is executed only once during the offline optimization stage, the online controller requires only a forward pass through the trained DQN to determine the derivative gain weighting factor. In contrast, nonlinear MPC repeatedly solves an optimization problem at every sampling instant, resulting in a significantly higher computational burden. Therefore, the proposed method maintains the computational efficiency of a conventional PID controller while benefiting from the adaptive decision-making capability of reinforcement learning.

The obtained results are also consistent with previous studies reporting that reinforcement learning can improve the performance of nonlinear control systems by adapting the control policy according to the operating conditions (Tašić *et al.* 2022; Çimen 2024; Echajei *et al.* 2025; Mufti Azis *et al.* 2020). However, unlike many existing reinforcement learning-based blood glucose controllers, where the reinforcement learning algorithm directly generates the insulin infusion signal, the proposed method employs reinforcement learning only to adapt the derivative gain of an already optimized PID controller. This hybrid strategy significantly simplifies the learning problem while preserving the robustness and interpretability of the conventional controller.

Overall, the proposed AHA–DQN-assisted PID controller combines the advantages of offline global optimization and online adaptive learning within a unified framework. The comparative results against both the conventionally optimized PID controller and the nonlinear MPC controller confirm that the proposed strategy provides improved tracking accuracy, enhanced disturbance rejection, smoother glucose regulation, and lower computational complexity. These characteristics make the proposed approach a promising and computationally efficient alternative for intelligent nonlinear blood glucose regulation systems.

CONCLUSION

This paper presented a hybrid blood glucose regulation strategy combining the Artificial Hummingbird Algorithm (AHA) and a Deep Q-Network (DQN)-assisted PID controller with derivative filter. The controller parameters were first optimized offline using the AHA based on the Integral Square Error (ISE) criterion, after which the DQN was employed to adaptively adjust only the derivative gain during online operation. Simulation results obtained using the nonlinear APMonitor blood glucose model demonstrated that the proposed controller achieved improved blood glucose tracking performance compared with the conventionally optimized PID controller. Furthermore, comparison with a nonlinear Model Predictive Control (MPC) strategy showed that the proposed controller provided lower tracking error, reduced oscillatory behavior, and faster recovery under identical simulation conditions. The adaptive derivative gain weighting reduced the tracking error and oscillatory behavior while preserving the stability and simplicity of the optimized PID controller. The proposed hybrid framework combines the global optimization capability of the AHA with the adaptive learning capability of the DQN without increasing the structural complexity of the controller. Moreover, the proposed method offers a computationally efficient alternative to nonlinear MPC since it does not require solving an optimization problem at each sampling instant. This makes the proposed approach an effective and computationally efficient solution for nonlinear blood glucose regulation. Future studies will focus on evaluating the proposed method under different meal scenarios, patient-specific parameter variations, and more advanced deep reinforcement learning algorithms to further improve its robustness and adaptability.

Ethical standard

The author has no financial or non-financial interests to disclose.

Availability of data and material

Not applicable.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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