

Article

Optimization of the Controller Settings for the Mean Arterial Blood Pressure Regulation Using Pelican Optimization Approach

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Abstract

This paper presents a unified comparative study of various controllers, including proportional–integral–derivative (PID), Fractional-Order PID (FOPID), Internal Model Control (IMC) controllers, and Tilt–Integral–Derivative (TID) controllers, for the regulation of mean arterial blood pressure (MABP). The controllers are optimally tuned by using a single metaheuristic approach, namely the Pelican Optimization Algorithm (POA), ensuring a fair and consistent comparison. The POA optimizes the objective function using standard error indices (ITAE, IAE, and ISE) along with transient characteristics. The aforementioned controllers are then evaluated under varying patient conditions for different patient categories, including sensitive, nominal, and insensitive, and their performance is systematically compared with one another and with the reported methods from the existing literature. The simulation results demonstrate that IMC offers fast settling with minimal overshoot, FOPID improves robustness through fractional dynamics, and the TID controller provides the smoothest transient response and disturbance rejection across all patient categories. The results confirm the effectiveness of advanced control strategies over conventional PID and highlight the potential of POA-tuned TID control for reliable and patient-specific MABP regulation in critical care applications.

Keywords: mean arterial blood pressure; optimal controllers tuning; Pelican optimization algorithm; dynamics states

1. Introduction

Mean arterial blood pressure (MABP) is one of the most important physiological variables for maintaining adequate tissue perfusion and ensuring the proper functioning of vital organs. Abnormal fluctuations in MABP can lead to severe cardiovascular complications, organ damage, and increased clinical risk, particularly during surgical procedures and critical care treatments. In many clinical situations, sodium nitroprusside (SNP) is administered intravenously to reduce elevated MABP. However, the response of patients to SNP infusion varies considerably due to differences in physiological characteristics, drug sensitivity, and cardiovascular dynamics. These variations make manual regulation difficult and motivate the development of automated closed-loop control systems capable of maintaining MABP within a desired range while minimizing the risk of over- or under-medication.

Several studies have specifically focused on automated drug infusion systems for regulating MABP using SNP drug. Fox et al. [1] investigated the physiological mechanisms



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associated with blood pressure variations during cardiovascular interventions, highlighting the need for reliable control strategies. Koivo et al. [2] further demonstrated the feasibility of automated blood pressure regulation through computer-controlled drug administration systems. These pioneering studies established the foundation for modern intelligent control techniques used in physiological regulation.

Early investigations primarily employed adaptive and model-based control approaches to handle patient variability and changing physiological conditions. He et al. [3] and Martin et al. [4] proposed multiple-model adaptive control schemes capable of accommodating variations in patient dynamics during drug infusion. These methods improved blood pressure regulation under uncertain conditions; however, their practical implementation often required accurate model identification and substantial computational effort. Gao and Er [5] later introduced intelligent adaptive control strategies that enhanced adaptability and tracking performance, while Yu et al. [6] incorporated predictive control concepts for simultaneous regulation of mean arterial pressure and cardiac output. Although these approaches demonstrated improved control performance, their complexity and dependence on accurate patient models limited their broader clinical applicability.

Among conventional control techniques, the proportional–integral–derivative (PID) controller remains one of the most widely used approaches due to its simple structure, ease of implementation, and satisfactory performance in a variety of industrial and biomedical applications. Kumar et al. [7] demonstrated the effectiveness of optimization-based PID tuning for blood pressure regulation. Nevertheless, physiological systems exhibit nonlinear behavior, significant transport delays, and considerable patient-to-patient variability, which can adversely affect the performance of conventional PID controllers. Consequently, PID-based systems may experience larger overshoot, prolonged settling times, and reduced disturbance rejection capability under varying patient conditions. Behbehani and Cross [8] developed a first-order time-delay mathematical model of MABP and proposed an optimal closed-loop controller for automatic blood pressure regulation.

To overcome these limitations, researchers have increasingly explored fractional-order control techniques. Fractional-order proportional–integral–derivative (FOPID) controllers extend the conventional PID structure by introducing fractional integral and derivative orders, thereby providing additional tuning flexibility and enhanced control performance. Sondhi and Hote [9] demonstrated that fractional-order controllers can achieve improved gain and phase margins while maintaining robustness against model uncertainties. Recently, Krishna and Rao [10] employed a genetic algorithm for tuning FOPID controllers in blood pressure regulation and demonstrated improved dynamic performance compared with conventional PID-based approaches. Similarly, Paiva et al. [11] and Bhardwaj et al. [12] reported that FOPID controllers offer superior disturbance rejection and improved adaptability for nonlinear physiological systems.

Internal Model Control (IMC) has also emerged as a promising framework for physiological regulation due to its ability to explicitly incorporate process dynamics into controller design. IMC-based controllers facilitate systematic tuning and provide an effective balance between tracking performance and disturbance rejection. Saxena and Hote [13] investigated IMC-based control for MABP regulation and demonstrated improvements in transient response and closed-loop stability. Enbiya et al. [14] further highlighted the capability of IMC strategies to maintain robust performance under uncertain operating conditions. Owing to its model-based structure, IMC [15] is particularly attractive for physiological systems characterized by significant time delays and process uncertainties.

In recent years, the Tilt–Integral–Derivative (TID) controller has gained attention as an alternative to conventional PID and FOPID structures. By replacing the proportional action with a tilt component, the TID controller offers additional flexibility for shaping the

frequency response and improving transient characteristics. Several studies are available on MABP control using the TID controller. Karahan and Karci [16] demonstrated the effectiveness of TID control in automated drug infusion systems and reported superior disturbance rejection and smoother control action compared with conventional approaches. Likewise, Shukla et al. [17] and Tabak [18] showed that TID controllers can achieve enhanced robustness, improved damping characteristics, and reduced oscillatory behavior in nonlinear dynamic systems.

Alongside controller development, optimization algorithms have played a crucial role in determining optimal controller parameters. Metaheuristic optimization algorithms such as genetic algorithms (GA), Particle Swarm Optimization (PSO), Gray Wolf Optimization (GWO), Grasshopper Optimization Algorithm (GOA), and Dragonfly Algorithm (DA) have been successfully employed for controller tuning in biomedical applications. These techniques improve controller performance by minimizing error-based objective functions and enhancing convergence toward optimal solutions. Recently, the POA, inspired by the hunting behavior of pelicans, has demonstrated strong exploration and exploitation capabilities, rapid convergence, and reduced computational complexity. However, despite its promising characteristics, the application of POA to MABP regulation has received limited attention in the existing literature.

Despite the significant progress achieved in automated blood pressure regulation, several challenges remain unresolved. Most reported studies focus on single controller architecture or employ different optimization methods, making direct performance comparisons difficult. Furthermore, the performance of PID, FOPID, IMC, and TID controllers has not been comprehensively evaluated under a unified optimization framework for different patient categories. In addition, the application of the POA for tuning multiple controller structures in MABP regulation remains relatively unexplored. Consequently, a systematic comparative investigation is necessary to identify the most effective controller for handling patient variability, transport delays, and external disturbances.

To address these challenges, this study presents a comprehensive comparative analysis of PID, FOPID, IMC, and TID controllers for MABP regulation under nominal, sensitive, and insensitive patient conditions. The controller parameters are optimized using the Pelican Optimization Algorithm based on three widely adopted performance indices, namely the Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and Integral of Time-weighted Absolute Error (ITAE). The proposed framework enables a fair comparison of different controller structures under identical operating conditions and disturbance scenarios. The performance of each controller is evaluated in terms of setpoint tracking, disturbance rejection, transient response characteristics, and robustness against patient variability. The results provide valuable insights into the suitability of advanced controller designs for reliable and patient-specific blood pressure regulation.

A comparative summary of existing studies on MABP regulation is listed in Table 1. The comparison indicates that most previous studies focused on single-controller architecture and employed different optimization methodologies, making direct performance evaluation difficult. In contrast, the present work provides a unified comparison of PID, FOPID, IMC, and TID controllers under identical operating conditions using a common optimization framework based on the POA.

Main contributions of this work are as follows:

- A unified comparative framework is developed for evaluating PID, FOPID, IMC, and TID controllers for MABP regulation under identical conditions, where all the controllers are tuned using the same POA-based optimization framework, ensuring unbiased performance comparison. Unlike most existing studies that focus on a

single controller architecture, the proposed framework enables a fair and systematic comparison of multiple advanced control strategies.

- The effectiveness of the recently introduced literature on biomedical control, the TID controller for MABP regulation, is demonstrated under varying patient sensitivities and external disturbances.
- A detailed disturbance rejection analysis is performed to emulate real physiological perturbations, emphasizing controller robustness and clinical safety.
- The obtained results indicate that the tuned controllers using the POA approach demonstrate stabilize and satisfactory performance under nominal as well as in perturbed situations.

Table 1. Comparative summary of existing studies on MABP regulation.

Reference No.	Controller/Method	Optimization Algorithm	Patient Variability Considered	Comparative Study	Limitation
[3]	Multiple model adaptive control	Adaptive mechanism	Yes	No	High computational complexity
[4]	Adaptive control	Adaptive mechanism	Yes	No	Model identification required
[7]	PID controller	Conventional tuning	Limited	No	Reduced robustness under uncertainty
[10]	FOPID controller	Genetic algorithm	Yes	No	Focused on a single controller
[14]	IMC controller	IMC-Based design	Yes	No	Limited comparison with advanced controllers
[16]	TID controller	Conventional optimization	Limited	No	Evaluated for specific operating conditions
[17]	TID controller	Metaheuristic optimization	Yes	No	No comparison with IMC and FOPID
Present Work	PID, FOPID, IMC, and TID	Pelican Optimization Algorithm	Nominal, Sensitive, and Insensitive Patients	Yes	Comprehensive comparative analysis

The POA has not been applied previously for controlling the MABP. A systematic comparison of multiple controllers was optimized under an identical optimization algorithm to determine the most effective control strategy.

The remainder of this paper is organized as follows. Section 2 describes the system dynamics. Section 3 presents the controller design, Section 4 presents POA-based tuning methodology, Section 5 discusses the stability and robustness analysis, Section 6 discusses the simulation setup and comparative results, Section 7 presents the discussion, and Section 8 concludes the paper with key findings and future research directions.

2. System Dynamics

The model of the patient's response to the SNP drug referenced by [17,18] is represented as

$$G_{\text{plant}}(s) = \frac{\Delta P}{I(s)} = \frac{Be^{-T_{\text{in}}s}(1 + Ce^{-T_{\text{re}}s})}{(As + 1)}. \quad (1)$$

Here, ΔP denotes the change in blood pressure (BP) in mmHg, $I(s)$ is the SNP drug infusion rate in ml/h, B is the drug sensitivity in mmHg/(ml/h), A is the time constant, T_{in} is the initial transport delay in seconds, C is the recirculation constant, and T_{re} is the recirculation time delay in seconds. The patient model expressed in Equation (1) is categorized into three groups based on the patient's sensitivity to the SNP drug, as summarized in Table 2 [8,18].

Table 2. Parameters of patients depending upon category.

Control Parameters	Values for Sensitive Patients	Values for Nominal Patients	Values for Insensitive Patients
B	-9 mmHg/mL/h	-0.714 mmHg/mL/h	-0.178 mmHg/mL/h
A	30	40	60
T_{in}	20 s	30 s	60 s
C	0	0.4	0.4
T_{re}	30 s	45 s	75 s

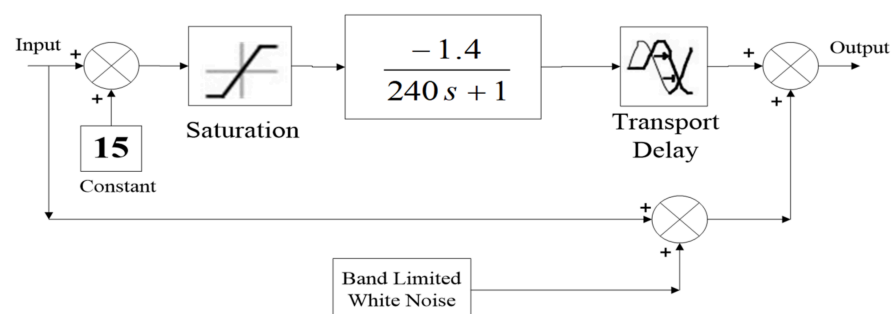
The patient category varies depending on the individual's medical condition and physiological response to SNP drug infusion. For simulation purposes, three categories are considered: sensitive, nominal, and insensitive patients. Sensitive patients exhibit a rapid and pronounced decrease in MABP for a small infusion of SNP, while insensitive patients require a relatively higher infusion rate to achieve the same level of BP reduction. Nominal patients lie in between these two extremes, showing an average drug response that is typically considered representative of the general population.

The patient model is influenced by disturbances arising within the human body. These disturbances reflect the complex dynamics of cardiovascular physiology and may include the following:

- (1) Physiological response after SNP drug infusion,
- (2) Effects due to respiration,
- (3) Auto-regulatory response of the patient due to an increase or decrease in BP.

These categories and disturbances are critical considerations in the design of automated BP regulation systems. Since the patient response to SNP infusion is highly nonlinear and varies significantly across individuals, the control strategy must be robust enough to ensure stable performance under all patient categories. The controller designed should effectively reject physiological disturbances while accurately tracking the desired BP setpoint.

The disturbance model considered for the present work is shown in Figure 1. The disturbance introduced into the simulation model represents unexpected variations commonly encountered during clinical blood pressure management. In practical scenarios, MABP may be affected by several external and physiological factors, including surgical stimulation, acute blood loss, fluid administration, changes in anesthetic depth, patient repositioning, stress responses, and variations in vascular resistance. Such events may cause sudden deviations in MABP and therefore constitute realistic disturbances for evaluating controller performance.

**Figure 1.** Block diagram of disturbance model.

The disturbance is applied after the system has reached its nominal operating condition to assess the disturbance rejection capability of the controllers independently of the setpoint-tracking phase. The selected disturbance timing allows the transient response as-

sociated with the initial setpoint change to settle before the disturbance signal is introduced. Consequently, the controller's ability to restore MABP to the desired reference value can be evaluated without interference from the initial tracking dynamics.

The magnitude of the disturbance was selected to produce a noticeable deviation from the reference pressure while maintaining physiologically realistic operating conditions. The disturbance level is sufficiently large to challenge the controller and reveal differences in robustness among the investigated control strategies, yet small enough to avoid unrealistic cardiovascular responses. Therefore, the disturbance model provides a practical representation of clinically relevant hemodynamic perturbations encountered during automated MABP regulation.

At specific time instants, sudden disturbances are introduced into the system to evaluate its ability to maintain stability and accurately track the setpoint within the desired response time. The mathematical representation of the applied disturbance is given by

$$G_{\text{disturb}}(s) = \frac{-1.4}{(240s + 1)}. \quad (2)$$

Physiologically, this disturbance can correspond to several real-world factors such as fluctuations in blood volume, variations in drug metabolism, or external stress responses. By applying such disturbances during simulation, the robustness of the controller can be assessed, ensuring that the system not only tracks the desired MABP set point but also effectively rejects sudden load changes and maintains stability under varying patient conditions.

3. Controller Design

In this work, different types of controllers are employed to compare their performance in regulating the MABP. This study specifically focuses on the PID, FOPID, IMC, and TID controllers. These controllers are selected to provide a comprehensive comparison: PID represents the conventional control approach, FOPID extends its flexibility through fractional-order dynamics, IMC incorporates model-based design principles for improved robustness, and TID offers enhanced performance in handling disturbances and system nonlinearities. The corresponding controller parameters are tuned using the POA [19]. The overall block diagram of the proposed system is illustrated in Figure 2. In Figure 2, the controller used is of different types for the proposed system such as PID, FOPID, IMC and TID.

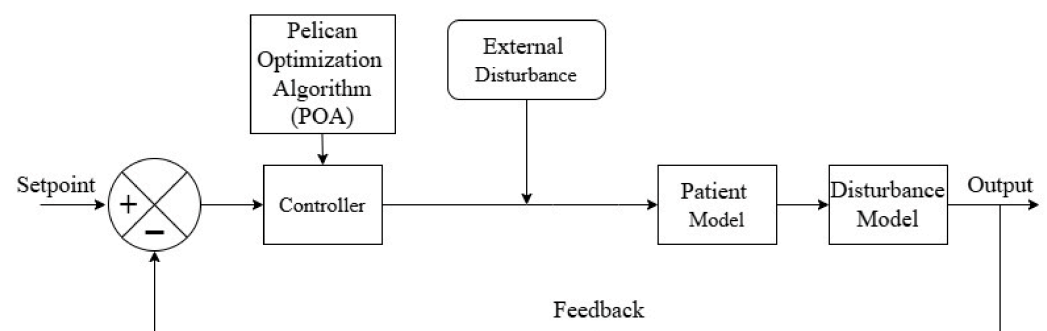


Figure 2. Block diagram of the proposed system.

The POA is a swarm-based metaheuristic inspired by pelican hunting strategies. It is increasingly being used in control system optimization because of its strong balance between exploration and exploitation [20]. Pelicans hunt by diving into water to catch fish,

and they cooperate to increase success. POA models this in two phases: exploration (search for prey) and exploitation (attack prey).

In control system applications, POA is particularly useful for parameter tuning since it avoids local minima and provides near-optimal solutions in complex, nonlinear search spaces [21]. In this work, POA is employed to determine the optimal parameter values of the PID, FOPID, IMC, and TID controllers by minimizing standard performance indices, including ITAE, IAE, and ISE.

A PID controller regulates MABP by continuously calculating the error between the desired set point and the actual MABP, then adjusting the control input accordingly. The equation for the PID controller [22,23] is given as

$$G_{c1}(s) = K_P + \frac{K_I}{s} + K_D s. \quad (3)$$

Here, K_P is the proportional gain, K_I is the integral gain and K_D is the derivative gain.

A FOPID controller plays a vital role in controlling MABP, especially in scenarios like anesthesia, critical care, or drug infusion control, where physiological systems are nonlinear, time-varying, and subject to disturbances. FOPID provides robust stability margins, maintaining effective control despite patient-to-patient variability and nonlinear drug effects. The equation for the FOPID controller is given as

$$G_{c2}(s) = K_P + K_I \frac{1}{s^\lambda} + K_D s^\mu. \quad (4)$$

The fractional orders λ and μ allow fine-tuning of integral and derivative actions, leading to better robustness against patient variability and improved disturbance rejection. The values of λ and μ are always kept greater than 0.

The IMC controller is often preferred for physiological regulation problems like MABP control because it directly incorporates system dynamics into the controller design. Since patients have different sensitivities to vasoactive drugs (nominal, sensitive, and insensitive cases), IMC [24] offers robust stability by balancing tracking and disturbance rejection through the filter parameter. The block diagram for the IMC structure is shown in Figure 3.

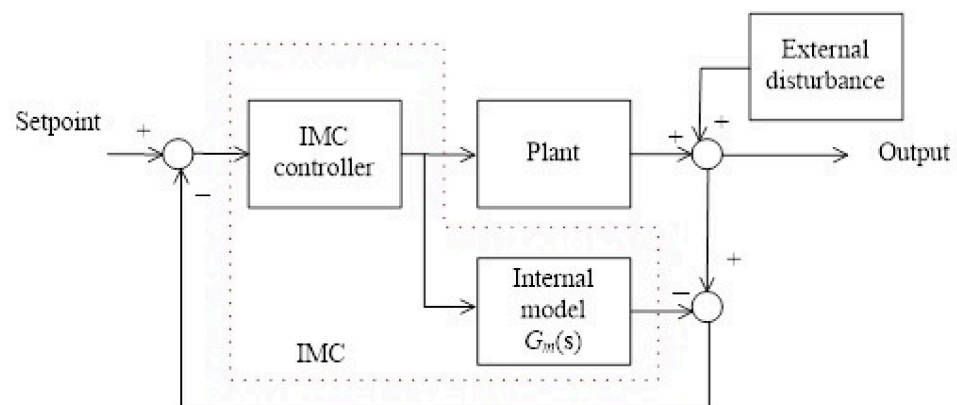


Figure 3. Block diagram for IMC structure.

By minimizing error metrics such as ISE, IAE, and ITAE, the IMC controller ensures smooth regulation of MABP and effective recovery to the desired level even under external disturbances. This approach achieves minimal overshoot, reduced settling time, and robust stability margins that are critical for maintaining patient safety. Figure 4 represents the block diagram of the proposed system using the IMC technique. The transfer function

shown in the figure is the same as that used for modeling. The values of K are calculated by the POA.

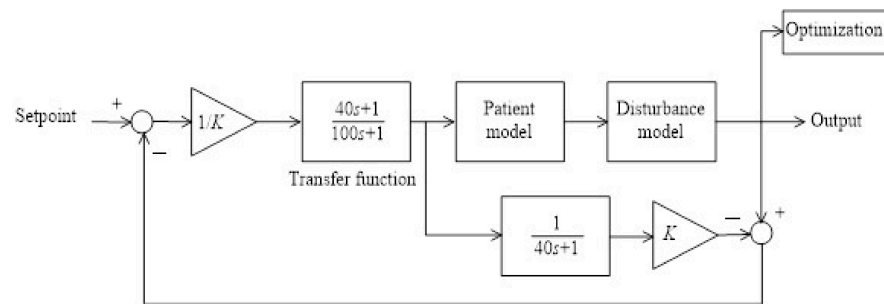


Figure 4. Block diagram for the proposed system using the IMC approach.

The equation for the IMC filter is given as

$$F(s) = \frac{1}{Ts + 1}, \quad (5)$$

where T is the user-chosen closed-loop time constant, and it is greater than 0.

IMC controller design is obtained by taking $G_m(s)$ into $G_m^+(s)$ and $G_m^-(s)$. Here, $G_m^+(s)$ is the non-minimum phase of the process model, and $G_m^-(s)$ is the minimum phase of the process model.

$$G_{IMC}(s) = \frac{F(s)}{G_m^-(s)} \quad (6)$$

The controller value is calculated by

$$G_{c3}(s) = \frac{G_{IMC}(s)}{1 - G_{IMC}(s)G_m(s)} \quad (7)$$

A TID controller [17] is implemented for regulating the MABP because it provides advantages over conventional PID in handling nonlinear and highly sensitive dynamics of physiological systems. The “Tilt” term introduces a fractional order behavior for proportional and integral control. This enhances flexibility in shaping the frequency response, which is often nonlinear and time-varying. A TID controller [19] offers flexibility to tune its parameters for different physiological profiles, ensuring more reliable control.

The controller equation for the TID controller is given as

$$G_{c4}(s) = K_t s^{-\frac{1}{n}} + \frac{K_I}{s} + K_D s. \quad (8)$$

Here, K_t is the tilt gain, $-\frac{1}{n}$ is the fractional integral, where n is the greater than 1, $\frac{K_I}{s}$ is the integer gain, and $K_D s$ is the derivative gain.

4. Optimization Algorithm and Optimization Problem Formulation

The POA is selected to design the PID, FOPID, IMC, and TID due to its balanced exploration–exploitation mechanism, simple implementation, and reported effectiveness in solving nonlinear optimization problems. The adaptive coefficient F present in POA enables a gradual transition from global exploration to local exploitation, which facilitates convergence toward high-quality solutions [25]. Before the start of optimization computations, this coefficient must be carefully tuned to the solved optimization problem [26]. Previous studies have demonstrated the successful application of POA in various engineering optimization problems. The primary objective of this study is to provide a fair comparison of PID, FOPID, IMC, and TID controllers under a common optimization framework.

The values of all the controllers are determined by using a metaheuristic approach POA [20,27], which was introduced in 2022 based on the hunting and foraging behavior of pelicans in nature. POA is designed for solving nonlinear optimization problems by mimicking natural behavior. A set of pelicans is randomly distributed in the search space given by Equation (9):

$$X_i = [x_{i1} + x_{i2} + x_{i3} + \dots + x_{iD}], \quad i = 1, 2, 3, \dots, N, \quad (9)$$

where N is the population size, and D is the problem dimension size.

Pelicans update their position in $t + 1$ iteration while scanning for the food source as follows:

$$X_i^{t+1} = X_i^t + r_1(X_{best}^t - X_i^t) + r_2(X_j^t - X_k^t), \quad (10)$$

where X_{best}^t is the best solution found, r_1 and r_2 are the random numbers ranging from $[0, 1]$, and X_j^t and X_k^t are two randomly chosen pelicans, which encourages global search and exploration of new areas for better results.

When a pelican dives to attack the prey, its movement is modeled by the following equation:

$$X_i^{t+1} = X_{best}^t + F(X_i^t - X_{best}^t) \quad (11)$$

where F is the adaptive coefficient used for controlling convergence of PAO; it brings the pelicans closer to the best solution. The algorithm is repeated until the maximum number of iterations are met.

The values of different controllers' settings are obtained for three different objective functions that are ITAE, IAE, and ISE, which are defined as follows:

The equation for the ITAE is given as

$$ITAE = \int_0^{\infty} t |e(t)| dt \quad (12)$$

The equation for the IAE function is defined as

$$IAE = \int_0^{\infty} |e(t)| dt \quad (13)$$

The equation for the ISE function is given as

$$ISE = \int_0^{\infty} (e(t))^2 dt. \quad (14)$$

Here, t is the time and $e(t)$ is the difference between the setpoint and the controlled variable.

The controller parameters are tuned using the POA, where different objective functions are employed to evaluate system performance. These objective functions ensure an optimal balance between setpoint tracking, disturbance rejection, and stability under varying physiological conditions.

The population size in the POA is represented by the pelican flock size that determines the number of search agents exploring the solution space. In this study, the flock size is set to 30 pelicans, as it provides an effective balance between exploration capability and total computational time of the optimization procedure. Furthermore, the maximum number of iterations is selected as 100, allowing sufficient opportunity for the pelicans to iteratively update their positions and gradually converge toward the optimal solution.

The adaptive coefficient, also referred to as the shrinking parameter, is defined as

$$F = 2 \left(1 + \frac{t}{t_{max}} \right) \quad (15)$$

where t represents the current iteration and t_{max} is the maximum number of iteration. This adaptive parameter gradually decreases from 2 to 0 during the optimization process. At the beginning of the optimization ($t = 0$), the value of the adaptive parameter is 2, which promotes exploration of the search space. As the iterations progress, the value decreases to 1 at the midpoint ($t = 50$) and finally approaches 0 at the final iteration ($t = 100$). The lower and upper bound obtained are listed in Table 3.

Table 3. POA values of lower and upper bound.

Parameter	Lower Bound	Upper Bound
K_p	0	10
K_i	0	10
K_d	0	10
λ	0.1	2
μ	0.1	2
K (IMC)	0.1	10
K_t	0	1
n	1	200
K_i (TID)	0	10
K_d (TID)	0	10

POA was executed independently 50 times to account for the stochastic nature of the optimization process. For each run, the controller parameters were optimized within predefined lower and upper bounds (Algorithm 1). The final controller settings reported in this study correspond to the best solution obtained among all independent runs. The use of multiple runs improves the reliability and robustness of the optimization results by reducing the influence of random initialization.

Algorithm 1. POA-Based Controller Parameter Optimization [27]

- Step 1: Define the objective function (ITAE, ISE, or IAE).
 - Step 2: Specify controller parameter bounds.
 - Step 3: Initialize the pelican population randomly within the search limits.
 - Step 4: Evaluate the fitness value of each pelican using the selected objective function.
 - Step 5: Determine the current best solution.
 - Step 6: Update pelican positions using the exploration phase to identify promising search regions.
 - Step 7: Apply the exploitation phase to improve local search around the best candidate solution.
 - Step 8: Enforce parameter boundary constraints.
 - Step 9: Recalculate fitness values for all updated solutions.
 - Step 10: Update the global best solution if a better fitness value is obtained.
 - Step 11: Check the stopping criterion (maximum iteration reached).
 - Step 12: If the stopping criterion is not satisfied, return to Step 6; otherwise, terminate the optimization process.
 - Step 13: Select the optimal controller parameters corresponding to the minimum objective function value.
-

Optimization Setup and Parameter Constraints

The POA was employed to determine the optimal controller parameters by minimizing the selected performance indices, namely ITAE, ISE, and IAE. A population size of 30 search agents and a maximum of 100 iterations were used throughout the optimization process. To reduce the influence of random initialization, the optimization was executed independently 50 times, and the best-performing solution was selected for controller implementation.

The initial population was generated randomly using a uniform distribution within the prescribed lower and upper bounds of each controller parameter. During optimization, all candidate solutions were constrained to remain within the specified search limits. Any solution violating the parameter bounds was projected back into the feasible search space.

For the PID controller, the proportional, integral, and derivative gains were restricted to $0 \leq K_p \leq 10$, $0 \leq K_i \leq 10$, and $0 \leq K_d \leq 10$. For the FOPID controller, the fractional integration and differentiation orders were additionally constrained within $0.1 \leq \lambda \leq 2$ and $0.1 \leq \mu \leq 2$. For the IMC controller, the filter parameter was restricted to $0.1 \leq K \leq 10$. For the TID controller, the tilt gain, tilt exponent, integral gain, and derivative gain were constrained as $0 \leq K_t \leq 1$, $1 \leq n \leq 200$, $0 \leq K_i \leq 10$, and $0 \leq K_d \leq 10$, respectively.

The optimization process was terminated when the maximum number of iterations was reached, and the optimization parameters obtained are listed in Table 4. The fitness function was evaluated for each iteration, and the controller parameters corresponding to the minimum objective function value were retained as the optimal solution. The convergence curve obtained is shown in Figure 5.

Table 4. Optimization parameters of POA.

Optimization Parameter	Value
Population size	30
Maximum iterations	100
Number of independent runs	50
Initialization method	Uniform random
Search strategy	POA with adaptive coefficient F
Objective functions	ITAE, ISE, IAE
Stopping criterion	Maximum iteration reached
Constraint handling	Boundary limitation

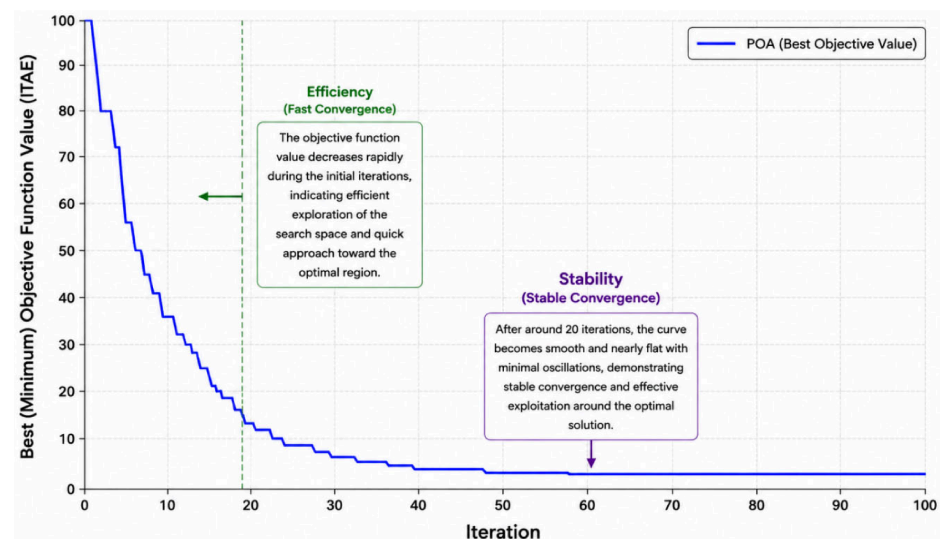


Figure 5. Convergence curve obtained for POA for 100 iterations.

The optimized values of the PID controller parameters obtained using POA are shown in Table 5 for three categories of patient sensitivities: nominal, sensitive, and insensitive. This categorization allows the controller to be assessed across diverse patient responses, ensuring robustness and adaptability of the proposed control strategy.

Table 5. Values of PID controller obtained by using POA for different patient categories.

	Insensitive			Sensitive			Nominal		
	K_p	K_i	K_d	K_p	K_i	K_d	K_p	K_i	K_d
ITAE	−0.6542	−0.0276	1.8932	−0.11	−0.0027	0.3652	−0.7235	−0.0181	2.4536
ISE	−0.7342	−0.0324	2.4562	−0.112	−0.0033	0.4231	−0.8235	−0.0199	3.8536
IAE	−0.8125	−0.0384	6.5289	−0.1128	−0.004	0.54	−0.9521	−0.0233	3.8654

The parameters of the FOPID controller are optimized by using the POA for different categories of patients, as shown in Table 6. These findings demonstrate the ability of the FOPID controller to accommodate different patient sensitivities, underscoring its enhanced flexibility relative to the conventional PID controller.

Table 6. Values of FOPID controller obtained by using POA.

		K_P	K_I	K_D	λ	μ
Insensitive	ITAE	−0.6542	−0.0157	1.8522	1.015	0.8
	ISE	−0.4255	−0.0141	4.8932	1.04	0.75
	IAE	−0.7532	−0.0171	3.1893	1.05	0.7
Sensitive	ITAE	−0.15	−0.0025	0.2653	1.05	0.8
	ISE	−0.1311	−0.0019	0.2652	1.105	0.8
	IAE	−0.1221	−0.0015	0.352	1.112	0.7
Nominal	ITAE	−0.8525	−0.0112	2.4521	1.02	0.8
	ISE	−0.6525	−0.0108	1.1252	1.06	0.85
	IAE	−0.7525	−0.0105	4.5654	1.03	0.9

The optimized parameter values of the IMC controller are presented in Table 7. In contrast to PID and FOPID controllers, the IMC structure is defined by a single tuning parameter K , which is directly related to the filter time constant and governs the trade-off between robustness and performance in the closed-loop system. In this study, the optimal value of K is obtained using POA, ensuring balanced setpoint tracking and disturbance rejection across different patient categories.

Table 7. Values of IMC controller obtained by using POA.

	Insensitive (K)	Sensitive (K)	Nominal (K)
ITAE	−0.5792	−9.5437	−1.8234
ISE	−0.4353	−8.6389	−1.0275
IAE	−0.6285	−7.9852	−1.1598

The parameters of the TID controller were optimized using POA, and the results are presented in Table 8. The TID controller extends the capabilities of the conventional PID controller by incorporating a tilt integral term. The inclusion of the tilt term provides a more versatile mechanism for shaping transient performance. It allows finer adjustment of overshoot, rise time, and settling characteristics while improving robustness against external disturbances and model uncertainties. Large values of n enhance low-frequency shaping, resulting in smoother transients without compromising closed-loop stability.

Table 8. Values of TID controller obtained by using POA.

		K_t	n	K_I	K_D
Insensitive	ITAE	−0.0112	195	−0.0123	−4.58
	ISE	−0.2125	200	−0.0111	−5.58
	IAE	−0.0111	100	−0.0122	2.45
Sensitive	ITAE	−0.0311	190	−0.0012	−0.00012
	ISE	−0.0123	150	−0.0011	−0.0011
	IAE	−0.0512	120	−0.0012	−0.0033
Nominal	ITAE	−0.0112	180	−0.005	3.851
	ISE	−0.0412	140	−0.006	5.85
	IAE	−0.0311	110	−0.005	−2.85

These values were subsequently implemented in simulations to facilitate a systematic comparison of the controllers under identical operating conditions. Simulations were then carried out using these values to enable a systematic comparison of the controllers in terms of their performance across different patient categories. Negative gain values arise due to the inverse relationship between SNP infusion rate and MABP, as increasing infusion causes a reduction in blood pressure.

Statistical performance metrics such as mean, standard deviation, and best/worst objective function values are evaluated as shown in Table 9. The values of the standard deviation for the other functions (ITAE, IAE and ISE) and for nominal, sensitive, and insensitive ranges from 0.15 to 0.01, which is satisfactory.

Table 9. Values of mean, standard deviation, best/worst values for sensitive ITAE function.

Statistic	Value
Best	4.86
Worst	4.94
Mean	4.88
Standard deviation	0.018

The relative computational complexity associated with each controller based on the number of tuning parameters and optimization search space is listed in Table 10.

Table 10. Comparative computational complexity of the investigated controllers.

Controller	Number of Tuned Parameters	Relative Optimization Complexity
PID	3	Low
IMC	1	Very Low
FOPID	5	High
TID	4	Moderate

5. Stability and Robustness Analysis

To verify the stability and robustness of the proposed control framework, additional analyses were performed under model uncertainty and external disturbances. The robustness study was conducted by applying the optimized controller parameters obtained using POA without any retuning.

The present study contains three cases, nominal, sensitive, and insensitive patient models, and for these cases, controllers are respectively designed. To show that the controller designed by POA can withstand the parametric variations, the controller designed for the nominal case has been used on both the nominal case and insensitive case, thereby

showing changes in patient parameters (B, A, T_{in} , C, and T_{re}). The simulations are performed as shown in Figure 6, and it is observed that the controller setting obtained by POA can satisfactorily withstand the parametric variations with sluggish response and more settling time as compared to the controller designed for the same case (nominal case and nominal plant).

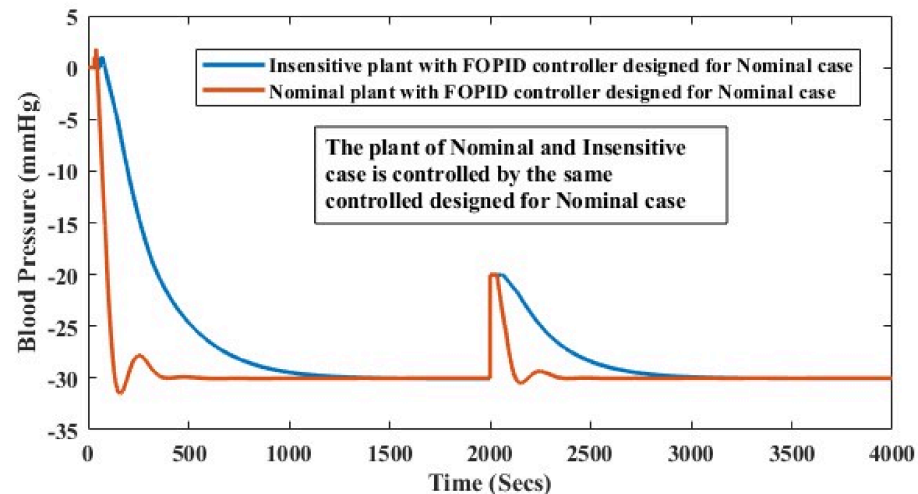


Figure 6. Response in perturbed conditions.

Further, an analysis is also carried out where the controller parameters are changed and the plant is kept constant. In this case, we performed the simulation considering the nominal case, where the controller designed using the nominal-case model is considered. To evaluate the effect of changes in controller parameters, the nominal-case controller is replaced with a controller designed using the insensitive-case model. The resulting response, presented in Figure 7, demonstrates that the insensitive-case controller can stabilize the nominal-case patient. Although the settling time is comparatively longer, the controller effectively tracks the setpoint and exhibits satisfactory disturbance rejection performance.

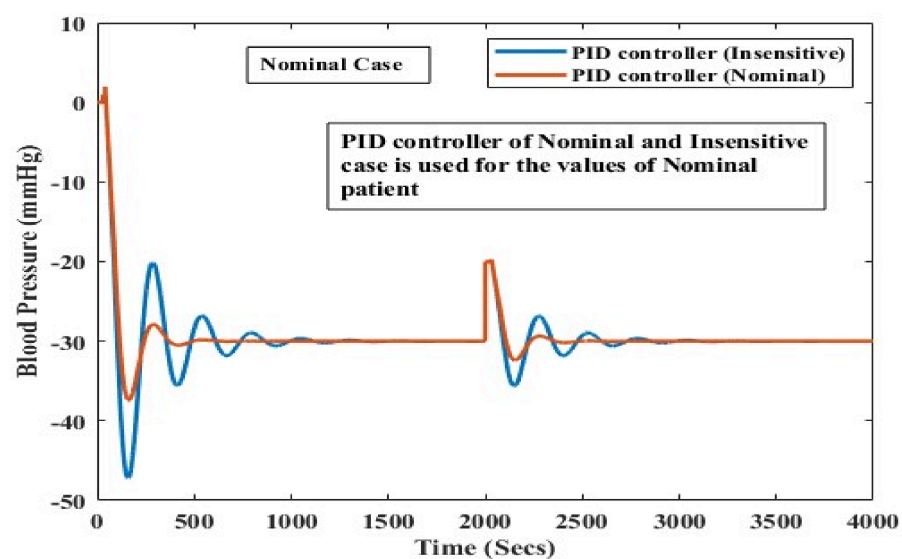


Figure 7. Response in varying controller setting for nominal case.

A qualitative assessment is also presented in Table 11 that shows the performance of the tuned controller using POA under plant model mismatch. All controllers maintained stable

closed-loop responses and successfully tracked the desired MABP setpoint. In disturbance case, the disturbance model was changed from $-1.4/(240s + 1)$ to $-1.4/(200s + 1)$, but no significant changes were observed.

Table 11. Qualitative stability and robustness assessment of different controllers.

Controller	Stability Under Different Patient Categories	Disturbance Rejection	Robustness	Overall Assessment
PID	Stable	Moderate	Moderate	Acceptable
FOPID	Stable	High	High	Very Good
IMC	Stable	High	Good	Excellent
TID	Stable	Very High	Very High	Very Good

The gain margin and phase margin are also calculated for gain margin (GM) and phase margin (PM) parameters for the insensitive case, reducing ITAE objective function for PID, IMC, TID and FOPID controllers, and are listed in Table 12. It can be observed from the table that the system tuned using the POA-based IMC controller exhibits the highest tolerance to significant parametric variations, outperforming the PID, TID, and FOPID controllers.

Table 12. Values of GM and PM for insensitive case, reducing ITAE objective function for PID, IMC, TID and FOPID controllers.

Insensitive ITAE	GM	PM
PID	27.58	45.69
IMC	249.03	Infinite
TID	13.1	Infinite
FOPID	26.36	59.88

6. Simulations and Results

The proposed control framework has been developed to regulate and stabilize MABP under varying physiological conditions. To evaluate the capability of the controllers, a simulation was done for each controller with different objective functions, i.e., ITAE, ISE and IAE. The values of the controllers are optimized by using POA for different plant functions, enabling a fair comparison between these controllers.

The simulation work is conducted for three different categories of patients, i.e., insensitive, sensitive, and nominal, to accommodate the variability in the patient responses. The comparative analysis includes the performance of the controller, including setpoint tracking, disturbance rejection capability, and peak overshoot with robustness parameter variation. The systematic analysis of each controller provides limitations of the control technique and identifies the best performing controller among these based upon physiological problems.

The simulation performed for different controllers was carried out for a time duration of 3000 s in the case of an insensitive patient, while the time duration was 2000 s for sensitive and nominal patients. To check the efficiency and robustness of the system, an external disturbance was applied to the system at 1500 s for the insensitive case and at 1000 s for the sensitive and nominal patient cases.

The simulation of the proposed system provides the ability of the controllers to reach the setpoint and maintain the stability of the system under diverse patient conditions. Figures 8–10 demonstrate the comparative analysis of different types of controllers using POA optimization for the objective functions ITAE, ISE, and IAE, respectively, for the

insensitive patient case. The performance of these controllers is also compared with that of Krishna and Rao [10] and Pachauri and Begum [28].

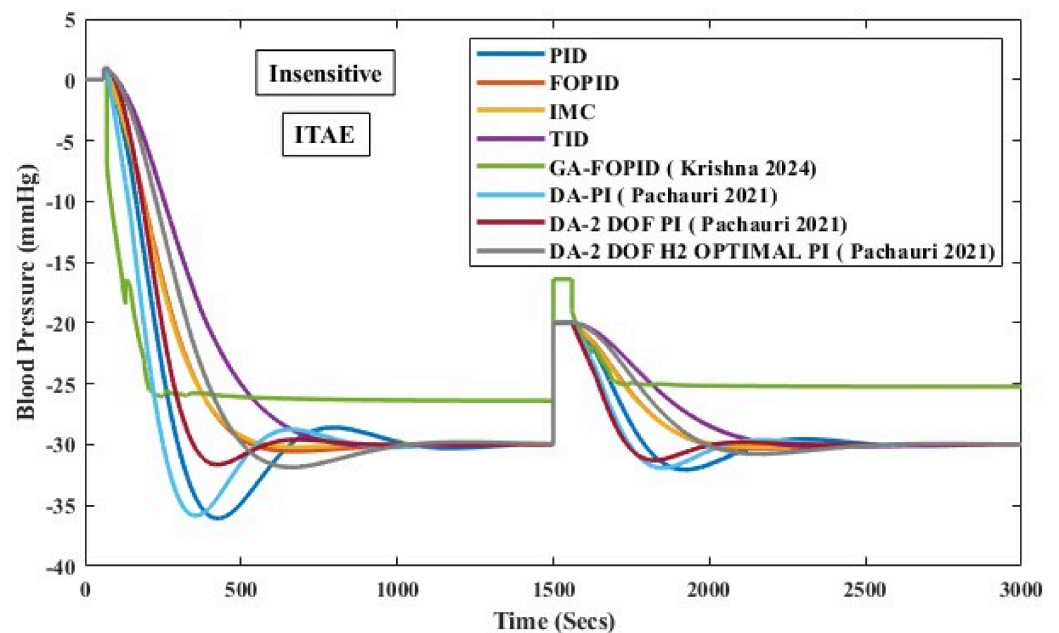


Figure 8. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28], DA-2 DOF H₂ optimal PI [28]) for an insensitive patient with ITAE.

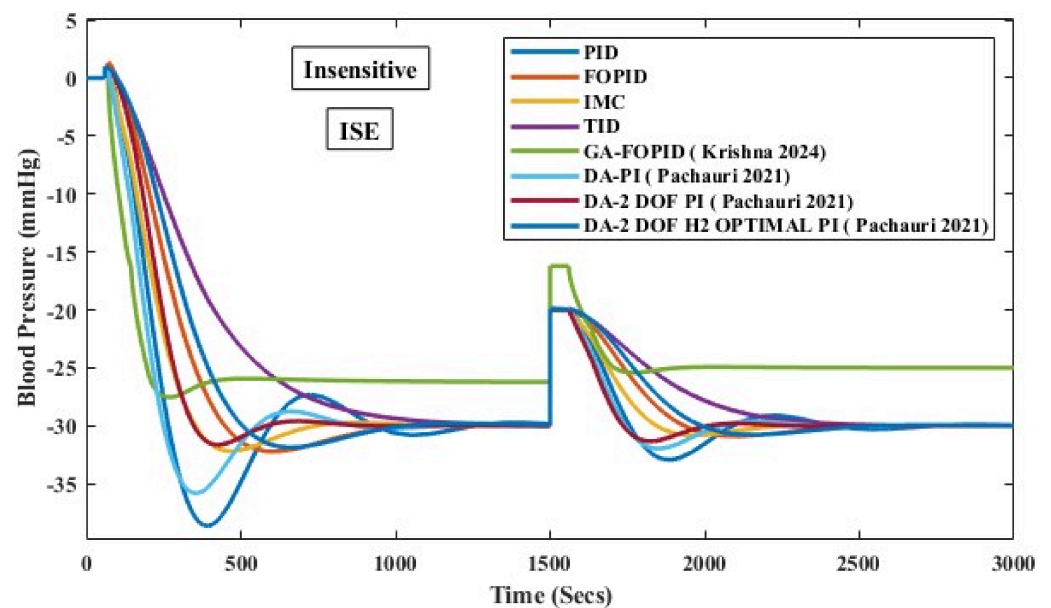


Figure 9. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28], DA-2 DOF H₂ optimal PI [28]) for an insensitive patient with ISE.

Figures 11–13 depict the performance comparison of various controllers for the sensitive patient, with optimization carried out using ITAE, ISE, and IAE as objective functions. The results underline how the controllers adapt to heightened sensitivity in patient dynamics, showcasing differences in transient response, disturbance handling, and steady-state accuracy. In this case, the TID controller exhibits a smooth transient response and effective disturbance rejection compared with the other controllers.

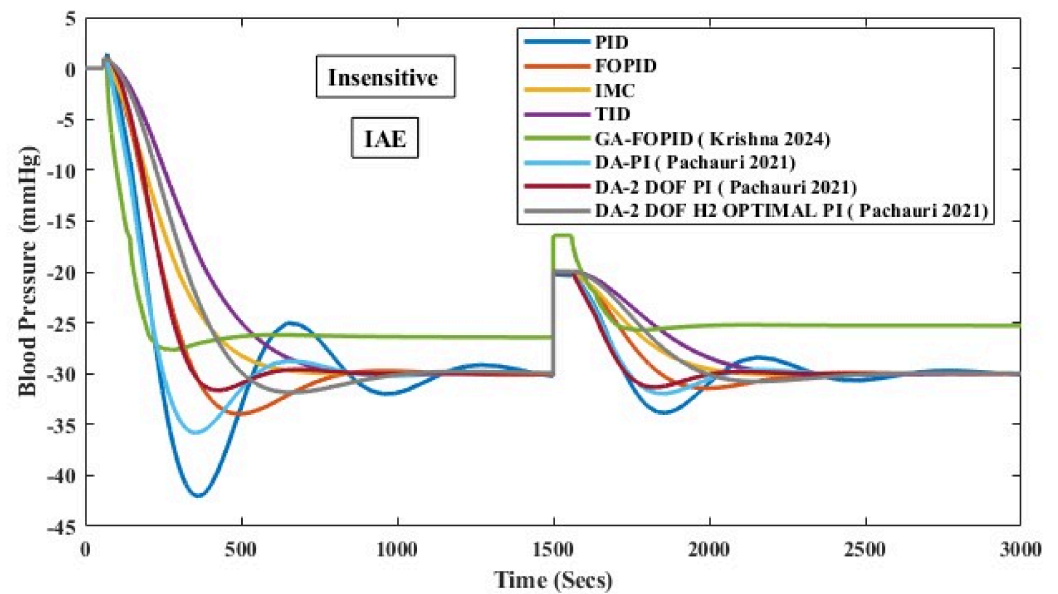


Figure 10. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28], DA-2 DOF H₂ optimal PI [28]) for an insensitive patient with IAE.

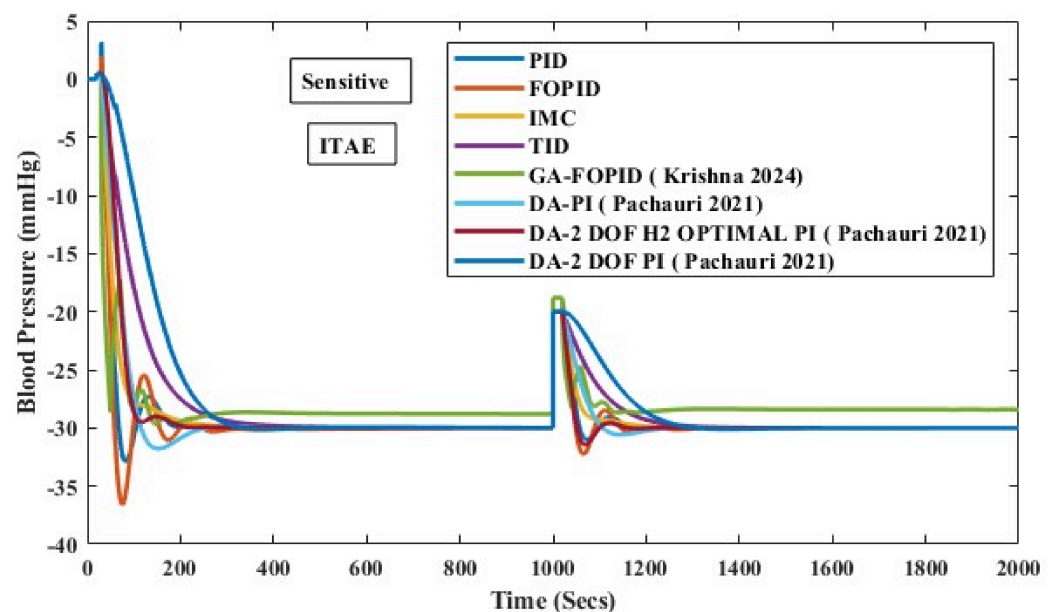


Figure 11. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28], DA-2 DOF H₂ optimal PI [28]) for a sensitive patient with ITAE.

Figures 14–16 illustrate the performance comparison of different controllers for the nominal patient. The analysis is carried out using ITAE, ISE, and IAE as objective functions, providing a balanced evaluation of controller behavior under standard physiological conditions. Although all advanced controllers improve the system performance compared to the classical PID controller, the TID controller provides the best overall trade-off between settling time, transient smoothness, and disturbance rejection.

These results reflect how each controller manages typical patient dynamics, highlighting differences in tracking precision, response speed, and resilience to external disturbances. The results show that the settling time of IMC and FOPID controllers is less, whereas TID gives a smooth response but its settling time is longer. A quantitative comparison between the designed PID, TID, IMC and FOPID controllers using the POA is listed in Table 13.

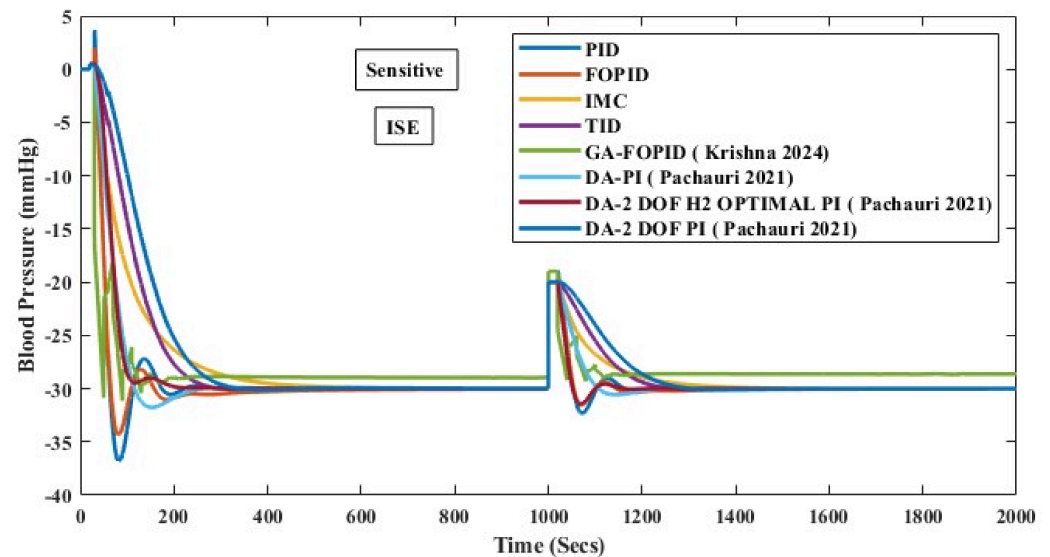


Figure 12. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28], DA-2 DOF H₂ optimal PI [28]) for a sensitive patient with ISE.

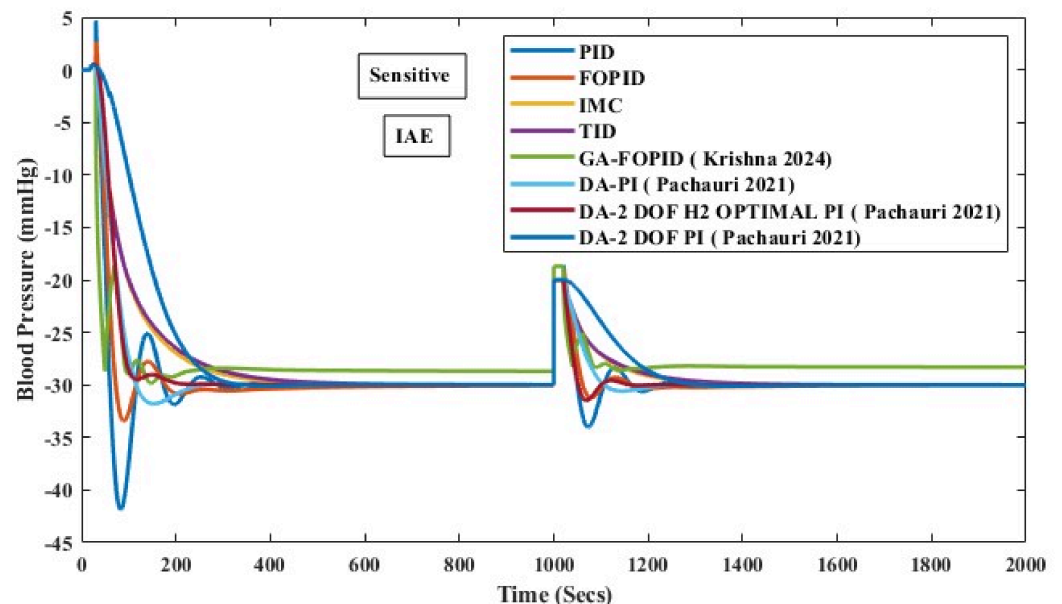


Figure 13. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28], DA-2 DOF H₂ optimal PI [28]) for a sensitive patient with IAE.

Furthermore, the simulation results of POA with DA and GA are shown in Figures 17 and 18, respectively, representing the effectiveness of POA over other optimization techniques. Also, POA is reported in the literature [29], which shows a comparison table for GA, PSO, GSA, TLBO, GWO, WOA, TSA and MPA and claims that the results from POA prove to be better than other optimization methods.

Table 13. Performance comparison of controllers.

Parameter	Controller	Settling Time	Peak Overshoot	Disturbance Recovery Time
ITAE Nominal	PID	900 s	42 mmHg	900 s
	FOPID	600 s	33 mmHg	600 s
	IMC	500 s	36 mmHg	500 s
	TID	580 s	31 mmHg	580 s

Table 13. Cont.

Parameter	Controller	Settling Time	Peak Overshoot	Disturbance Recovery Time
ITAE Sensitive	PID	400 s	34 mmHg	400 s
	FOPID	360 s	32 mmHg	360 s
	IMC	350 s	30 mmHg	350 s
	TID	390 s	30 mmHg	390 s
ITAE Insensitive	PID	1400 s	36 mmHg	1400 s
	FOPID	1000 s	32 mmHg	1000 s
	IMC	750 s	31 mmHg	750 s
	TID	800 s	30 mmHg	800 s

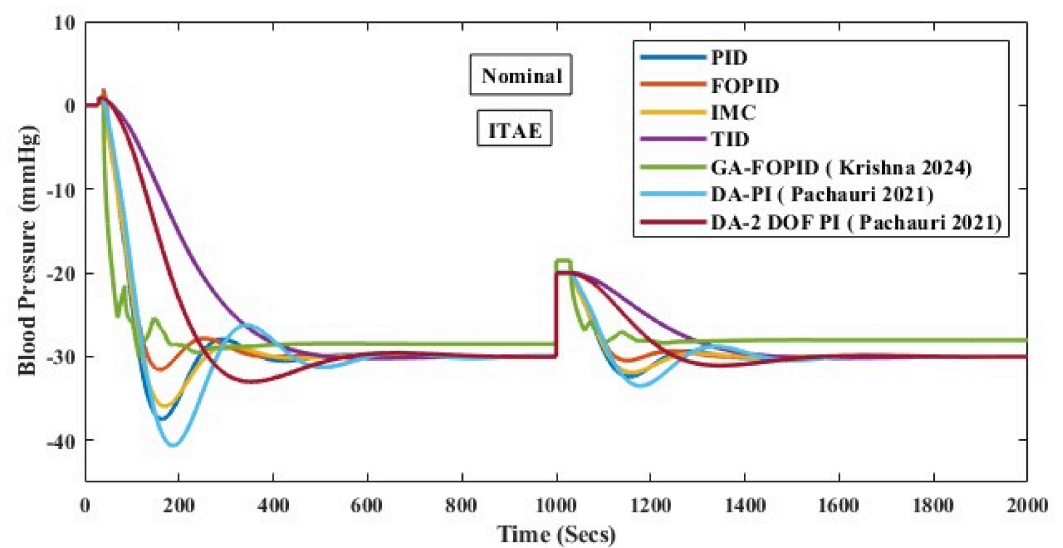


Figure 14. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28]) for a nominal patient with ITAE.

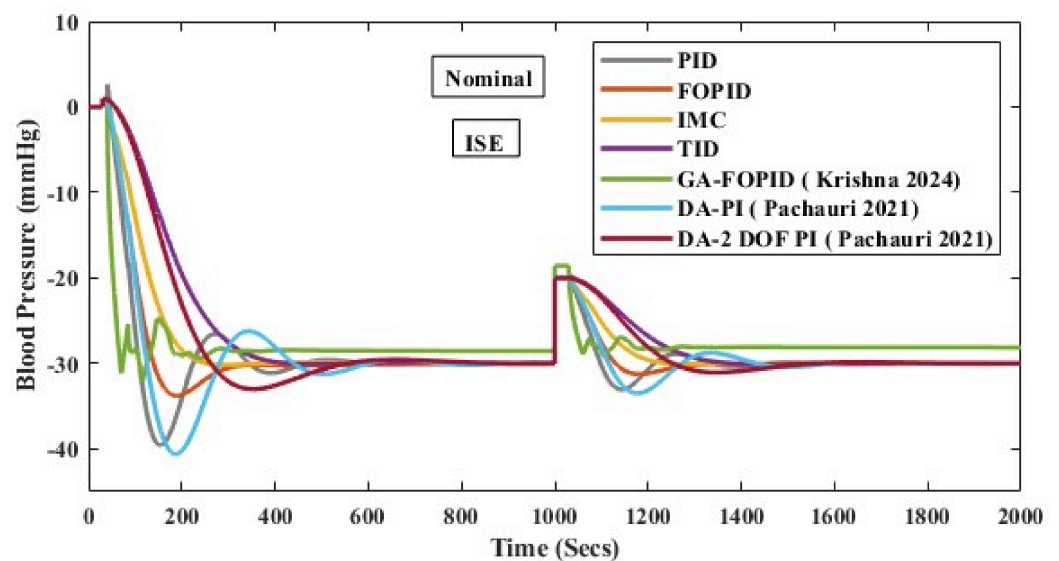


Figure 15. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28]) for a nominal patient with ISE.

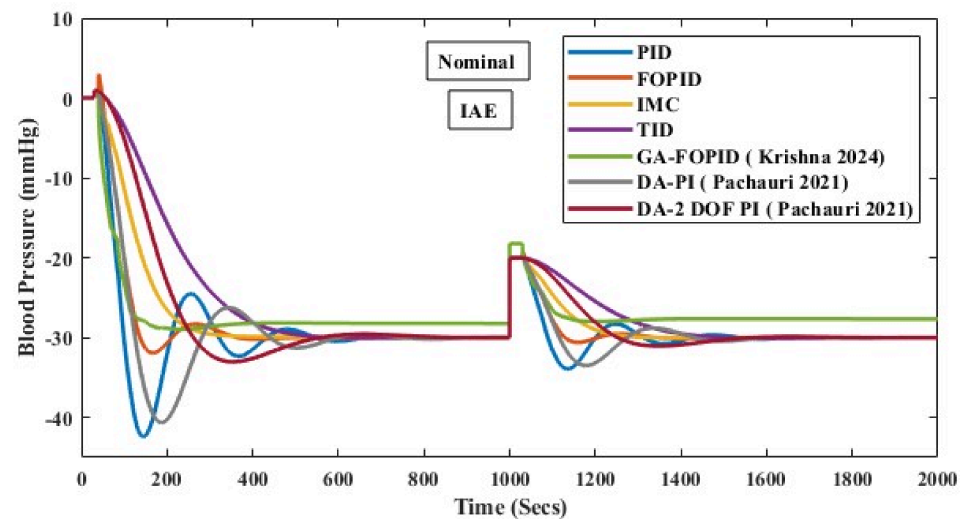


Figure 16. Comparative analysis of different controllers (PID, FOPID, IMC, TID, GA-FOPID [10], DA-PI [28], DA-2 DOF PI [28]) for a nominal patient with IAE.

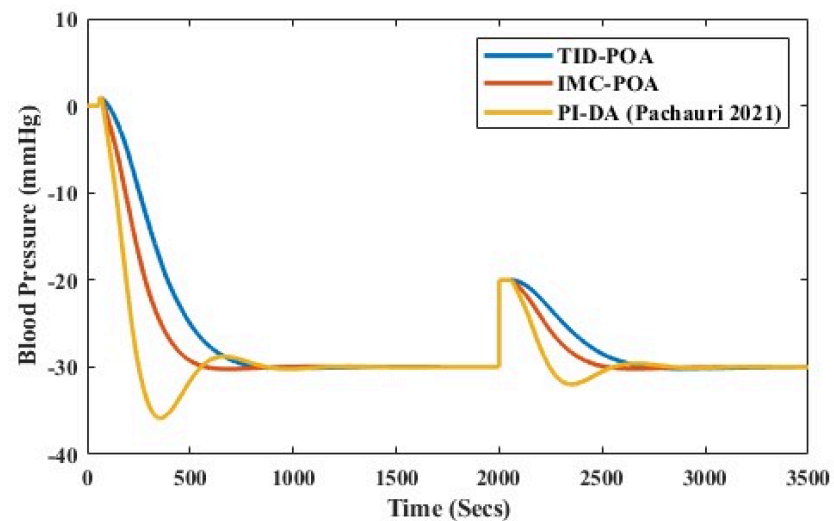


Figure 17. Comparison of POA and DA for different controllers (TID-POA, IMC-POA, PI-DA [28]).

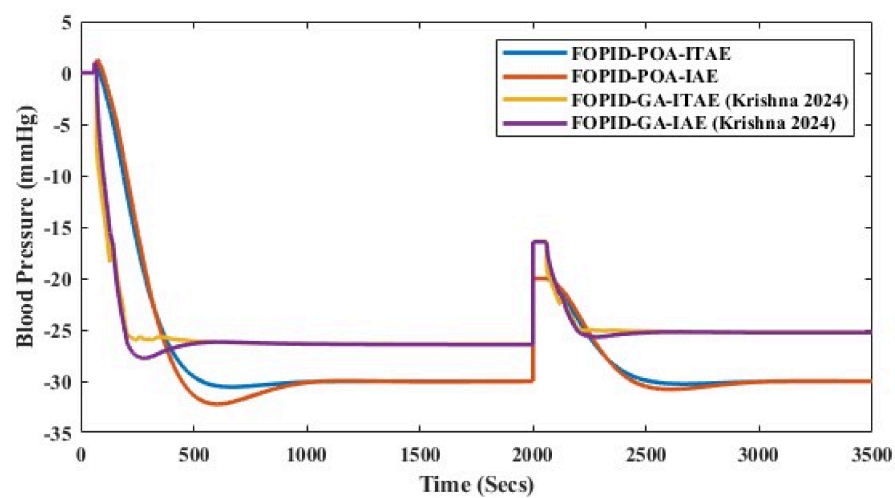


Figure 18. Comparison of POA and GA for different controllers (FOPID-POA-ITAE, FOPID-POA-IAE, FOPID-GA-ITAE [10], FOPID-GA-IAE [10]).

7. Discussion

7.1. Practical Implementation and Clinical Relevance

The proposed controllers are designed with practical real-time implementation in mind. In a clinical setting, continuous BP measurements can be obtained through invasive arterial catheters or advanced non-invasive monitoring systems. The measured MABP signal is fed to the controller, which computes the appropriate infusion rate of the vasoactive drug required to maintain the desired BP level. The optimization-based tuning approach employed in this study is performed to determine the optimal controller parameters.

From a clinical perspective, disturbances affecting MABP may arise from several physiological and external factors, including surgical stimulation, sudden blood loss, changes in patient positioning, fluid administration, and variations in anesthetic depth, stress responses, and alterations in vascular resistance. To evaluate the robustness of the proposed control schemes, a disturbance was introduced into the simulation model at a specified time instant. This disturbance represents unexpected hemodynamic changes commonly observed in intensive care units and operating rooms. The ability of the controller to rapidly reject such disturbances and restore MABP to the desired reference value demonstrates its potential suitability for automated MABP regulation. Therefore, the disturbance model serves as a clinically meaningful representation of real-world cardiovascular perturbations and provides a practical framework for assessing controller robustness and reliability.

7.2. Challenges in Clinical Implementation

Although the simulation results demonstrate the effectiveness of the proposed POA-tuned controllers for MABP regulation, several practical challenges must be considered before clinical deployment. The infusion pumps used for SNP administration possess physical flow-rate limitations and saturation constraints. Consequently, the control signal generated by the controller may need to be bound to ensure that the commanded infusion rates remain within clinically acceptable limits.

Patient safety is another critical consideration. Excessive SNP infusion may produce severe hypotension, whereas insufficient drug administration may result in uncontrolled hypertension. Therefore, practical implementations should incorporate safety constraints, infusion-rate limits, alarm mechanisms, supervisory control layers, and clinician override functionality to ensure safe operation under abnormal conditions.

The proposed controllers are suitable for real-time implementation because controller execution involves only simple arithmetic operations once the parameters have been optimized. The computationally intensive optimization process is performed prior to deployment and therefore does not impose a significant burden during real-time operation. Consequently, the proposed framework exhibits potential for implementation in computer-assisted drug infusion systems, provided that appropriate safety measures and clinical validation studies are performed.

7.3. Limitation of the Work

The patient models used in this study are based on established transfer-function representations and provide a suitable framework for comparative controller evaluation. However, real cardiovascular systems exhibit nonlinear behavior, parameter uncertainty, and significant patient-to-patient variability. Although nominal, sensitive, and insensitive patient models were considered, these models cannot fully capture the complexity of clinical conditions. Therefore, future work will focus on validating the proposed POA-based control strategy using nonlinear physiological models, uncertainty-based frameworks, and patient-specific models derived from clinical data to further assess robustness and clinical applicability.

7.4. Comparison with the Existing Literature

Several optimization algorithms, including GA, PSO, GWO, and DA, have previously been applied to controller tuning problems in physiological regulation systems. We agree that a direct claim regarding the superiority of POA over PSO, GWO, GA, Dragonfly Algorithm, or other metaheuristics would require dedicated comparative optimization studies under identical conditions.

Furthermore, the POA is also compared with DA and GA as shown in Figures 17 and 18. It is observed from the figures that the POA shows satisfactory performance over GA and DA for controlling MABP.

8. Conclusions

This paper presents a comparative investigation of the performance of PID, FOPID, IMC, and TID controllers for automatic regulation of MABP under varying patient categories using the same POA. The controllers were optimally tuned using the POA approach for minimizing the error in case of ITAE, ISE, and IAE to ensure a fair and consistent comparison. Simulations were conducted for sensitive, nominal, and insensitive patient models, considering external disturbances to emulate real physiological variations. From a clinical perspective, smoother transients and reduced oscillations are preferred over aggressive fast responses, as they minimize excessive drug infusion and reduce cardiovascular stress.

The simulation results indicate that the conventional PID controller ensures basic system regulation but exhibits limited robustness under different patient variability and disturbances. The advanced controller strategies, such as FOPID, IMC, and the TID control approach, demonstrate greater flexibility and precision. The FOPID controller demonstrates improved disturbance rejection capability and robustness due to its fractional-order dynamics. The IMC technique achieves faster settling time with minimal overshoot, owing to its model-based structure. The TID controller consistently produces non-oscillatory infusion behavior and smoother transient responses in the case of ITAE. The IMC and FOPID controllers demonstrated effective disturbance rejection and setpoint tracking across all patient categories, specifically in ISE and IAE, highlighting their effectiveness for nonlinear biomedical systems. Although IMC and FOPID achieve faster settling in certain scenarios, the TID controller consistently provides the smoothest transient response and the fastest disturbance recovery, which is clinically more desirable.

The overall results confirm that the advanced controllers significantly outperform the classical PID controller in handling nonlinear physiological systems. Among the evaluated methods, the POA-tuned TID controller demonstrated satisfactory overall performance regarding smoothness of response in the case of ITAE. This study highlights the potential of intelligent control strategies in ensuring safe, reliable, and patient-specific regulation of MABP. Future work will focus on real-time implementation, hardware-in-the-loop validation, and integration with patient-specific adaptive frameworks.

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References

1. Fox, S.; Pierce, W.S.; Waldhausen, J.A. Pathogenesis of paradoxical hypertension after coarctation repair. *Ann. Thorac. Surg.* **1980**, *29*, 135–141. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Koivo, A.J.; Smollen, V.F.; Barile, R.V. An automated drug administration system to control blood pressure in rabbits. *Math. Biosci.* **1978**, *38*, 45–56. [\[CrossRef\]](#)
3. He, W.G.; Kaufman, H.; Roy, R. Multiple-model adaptive control procedure for blood pressure control. *IEEE Trans. Biomed. Eng.* **1986**, *33*, 10–19. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Martin, J.F.; Schneider, A.M.; Smith, N.T. Multiple-model adaptive control of blood pressure using sodium nitroprusside. *IEEE Trans. Biomed. Eng.* **1987**, *34*, 603–610. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Gao, Y.; Er, M.J. An intelligent adaptive control scheme for postsurgical blood pressure regulation. *IEEE Trans. Neural Netw.* **2005**, *16*, 475–483. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Yu, C.; Roy, R.J.; Kaufman, H.; Bequette, B.W. Multiple-model adaptive predictive control of mean arterial pressure and cardiac output. *IEEE Trans. Biomed. Eng.* **1992**, *39*, 765–777. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Kumar, H.; Kumar, R.; Yadav, J.; Rani, A.; Singh, V. Genetic algorithm based PID controller for blood pressure and cardiac output regulation. In Proceedings of the 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India, 4–6 July 2016; pp. 1–6.
8. Behbehani, K.; Cross, R.R. A controller for regulation of mean arterial blood pressure using optimum nitroprusside infusion rate. *IEEE Trans. Biomed. Eng.* **1991**, *38*, 513–521. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Sondhi, S.; Hote, Y.V. Fractional-order PI controller with specific gain–phase margin for MABP control. *IETE J. Res.* **2015**, *61*, 142–153. [\[CrossRef\]](#)
10. Krishna, P.S.; Rao, P.G.K. Fractional-order PID controller for blood pressure regulation using genetic algorithm. *Biomed. Signal Process. Control* **2024**, *88*, 105564. [\[CrossRef\]](#)
11. Paiva, H.M.; Keller, W.S.; da Cunha, L.G.R. Blood-glucose regulation using fractional-order PID control. *J. Control Autom. Electr. Syst.* **2020**, *31*, 1–9. [\[CrossRef\]](#)
12. Bhardwaj, R.; Panigrahi, B.K.; Kumar, R. Fractional order control for blood pressure regulation in surgical patients. *Biomed. Signal Process. Control* **2020**, *59*, 101894.
13. Saxena, S.; Hote, Y.V. A simulation study on optimal IMC-based PI/PID controller for mean arterial blood pressure. *Biomed. Eng. Lett.* **2012**, *2*, 240–248. [\[CrossRef\]](#)
14. Enbiya, S.; Hossain, A.; Mahieddine, F. Performance of optimal IMC and PID controllers for blood pressure control. In *Proceedings of the 25th Southern Biomedical Engineering Conference, Miami, FL, USA, 15–17 May 2009*; Springer: Berlin/Heidelberg, Germany, 2009.
15. Nath, U.M.; Dey, C.; Mudi, R.K. Review on IMC-based PID controller design approach with experimental validations. *IETE J. Res.* **2023**, *69*, 1640–1660.
16. Karahan, O.; Karci, H. Closed-loop automated drug infusion regulation based on optimal 2-DOF TID control approach for the mean arterial blood pressure. *Med. Biol. Eng. Comput.* **2025**, *63*, 2069–2089. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Shukla, H.; Nikolovski, S.; Raju, M.; Rana, A.S.; Kumar, P. A particle swarm optimization technique tuned TID controller for frequency and voltage regulation with penetration of electric vehicles and distributed generations. *Energies* **2022**, *15*, 8225. [\[CrossRef\]](#)
18. Slate, J.B.; Sheppard, L.C.; Rideout, V.C.; Blackstone, E.H. Closed-loop nitroprusside infusion: Modeling and control theory for clinical application. In Proceedings of the IEEE International Symposium on Circuits and Systems, Houston, TX, USA, 28–30 April 1980; pp. 482–488.
19. Tabak, A. Modified and improved TID controller for automatic voltage regulator systems. *Fractal Fract.* **2024**, *8*, 654. [\[CrossRef\]](#)
20. SeyedGarmroudi, S.; Kayakutlu, G.; Kayalica, M.O.; Çolak, Ü. Improved pelican optimization algorithm for solving load dispatch problems. *Energy* **2024**, *289*, 129811. [\[CrossRef\]](#)
21. Trojovský, P.; Dehghani, M. Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications. *Sensors* **2022**, *22*, 855. [\[CrossRef\]](#) [\[PubMed\]](#)

22. Siddiqui, M.A.; Laskar, S.H.; Anwar, M.N.; Naseem, M. A model-free PI/PID controller based on direct synthesis approach to achieve disturbance rejection. *Proceedings of IECON 2019—45th Annual Conference of the IEEE Industrial Electronics Society*, Lisbon, Portugal, 14–17 October 2019; pp. 207–212.
23. Ishtiaq, A.; Siddiqui, M.A.; Asim, M.; Laskar, S.H. Load frequency control for single-area system using modified PSO and modified grasshopper optimization-based PID and PI controllers. In *International Conference on Signal, Machines, Automation, and Algorithm*; Springer: Singapore, 2023; pp. 687–695.
24. Somanshu, S.R.; Anwar, N.; Kumar, R. IMC-PI control-based solar PV output voltage regulation for battery charging. *Electr. Eng.* **2025**, *107*, 107–120.
25. Alamir, N.; Kamel, S.; Megahed, T.F.; Hori, M.; Abdelkader, S.M. Developing hybrid demand response technique for energy management in microgrid based on pelican optimization algorithm. *Electr. Power Syst. Res.* **2023**, *214*, 108905. [[CrossRef](#)]
26. Knypinski, Ł.; Kasprzak, K.; Joddumahanthi, V. Adaptation of the whale optimization algorithm to multi-objective and constrained optimization of the brushless DC motor. *Eksploat. I Niezawodn.—Maint. Reliab.* **2026**, *28*, 220513.
27. Sharma, S.; Singh, G. Design and analysis of novel chaotic pelican-optimization algorithm for feature selection of occupational stress. *Procedia Comput. Sci.* **2023**, *218*, 1497–1505. [[CrossRef](#)]
28. Pachauri, N.; Begum, G.K. Automatic drug infusion control based on metaheuristic H₂ optimal theory for regulating the mean arterial blood pressure. *Asia-Pac. J. Chem. Eng.* **2021**, *16*, e2654. [[CrossRef](#)]
29. Begum, K.G.; Verma, O.P.; Pachauri, N. Modified H₂ optimal PI tuning method for first order time delay systems. *Int. J. Syst. Assur. Eng. Manag.* **2021**, 1–17. [[CrossRef](#)]

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