RESEARCH PAPER

Robust Sliding Mode Control Optimized via Pelican Optimization Algorithm for Mean Arterial Blood Pressure Regulation under Inter-Patient Variability

Abhishek Jain[1], Mohammad Atif Siddiqui[1] and Tirumalasetty Chiranjeevi[2]

[1]Department of Electrical Engineering, Integral University, Lucknow, Uttar Pradesh, India – 226026
[2] Department of Electrical Engineering, Shri Mata Vaishno Devi University, Katra, J&K, India – 182320
[1]abhishekjain.281988@gmail.com, [1]atifsiddiqui@iul.ac.in and [2]tirumalasetty.chiranjeevi@smvdu.ac.in

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ABSTRACT

Accurate regulation of Mean Arterial Blood Pressure (MABP) is essential in surgical and intensive care settings where sudden physiological variations may lead to severe complications. The cardiovascular system exhibits nonlinear dynamics, time delays, and inter-patient variability, which degrade the performance of conventional linear controllers. This paper proposes a robust Sliding Mode Controller (SMC) optimally tuned using the Pelican Optimization Algorithm (POA) for automated blood pressure regulation. The controller consists of an equivalent control component to maintain nominal dynamics and a nonlinear switching component to enhance robustness against disturbances and parameter uncertainties. A smooth sigmoid function is incorporated to mitigate chattering effects. Lyapunov-based stability analysis guarantees closed-loop convergence and satisfaction of the reaching condition. The proposed SMC–POA framework is validated on sensitive, nominal, and insensitive patient models under ±20% structured parameter variations and external disturbance injection. Comparative simulation results demonstrate reduced settling time, minimal overshoot, improved steady-state accuracy, and enhanced disturbance rejection compared with FOPID and H_2-optimal PI-based controllers. The results confirm that the proposed approach provides a reliable and robust solution for automated MABP regulation.

Keywords: Blood Pressure Regulation, Sliding Mode Control, Pelican Optimization Algorithm, and Robust Control.
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I. INTRODUCTION

Blood pressure (BP) regulation is a critical physiological control problem in intensive care, anesthesia, and surgical procedures, where rapid hemodynamic fluctuations can lead to organ hypoperfusion or cardiovascular complications [1], [2]. In response to these challenges, automated mean arterial blood pressure (MABP) regulation using vasodilator infusion has become a significant research area in biomedical control engineering [3]. As a result, the development of reliable automatic MABP control systems holds substantial clinical importance.

Building upon this need, several control strategies have been proposed for automated BP regulation, including conventional PID, fractional-order PID (FOPID), and optimal H_2-based controllers. Although these controllers provide satisfactory performance under nominal operating conditions, their effectiveness deteriorates in the presence of nonlinear dynamics, transport delays, and inter-patient variability. The human cardiovascular system exhibits parameter uncertainty due to variations in drug sensitivity, vascular resistance, and metabolic response. Since most linear controllers are designed around nominal models, their robustness against such uncertainties is limited.

SMC is a nonlinear control technique known for its robustness against matched disturbances and parametric uncertainties [4–6]. The design methodology of sliding surfaces and switching laws has been extensively studied in nonlinear control literature [7]. Moreover, SMC has demonstrated effectiveness in biomedical and physiological control applications, including systems subject to time delays and disturbances [8]. However, the performance of SMC strongly depends on the appropriate selection of sliding surface parameters and switching gains. Improper tuning may result in excessive chattering, which can degrade transient performance and lead to undesirable actuator oscillations [9].

Recently, metaheuristic optimization algorithms have been employed for controller tuning. Although SMC has been investigated for nonlinear biomedical systems, systematic tuning of sliding surface parameters and switching gains using the POA for unstable FOPDT models of MABP

**Author for Correspondence: abhishekjain.281988@gmail.com*

under structured ±20% parametric uncertainty has not been reported in the literature. Moreover, a unified performance comparison between POA-tuned SMC, FOPID, and H_2-optimal PI controllers under identical patient variability conditions remains unexplored. To enhance its performance, the parameters of the discontinuous control law are optimally tuned using the POA [10], ensuring faster convergence and reduced chattering effects. The controller is designed and tested for three categories of patients—sensitive, insensitive, and nominal—representing inter-patient variability in hemodynamic response to vasoactive drug infusion. The proposed control scheme is implemented in a simulated physiological environment, and its performance is evaluated through dynamic simulations. Furthermore, the obtained results are compared with those reported by Pachauri and Begam, providing a comparative assessment of the system's robustness, stability, and adaptability under varying patient conditions. The findings demonstrate that the POA-tuned SMC controller [11] achieves superior regulation of MABP, effectively rejecting disturbances and maintaining desired pressure levels across all patient categories.

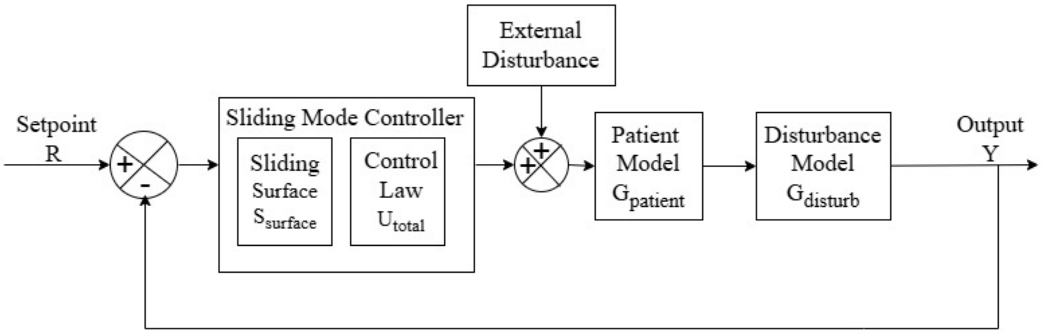

Figure 1: Block Diagram for closed-loop SMC system for regulating BP

The block diagram presented in Fig. 1 illustrates a closed-loop SMC system developed to regulate BP in patients [12]. The principal objective of this configuration is to ensure that the actual BP output closely tracks the desired setpoint despite the presence of external disturbances and physiological uncertainties. The control process begins with the reference signal, R(s), which represents the target mean arterial pressure that should remain within the normal physiological range. This signal is compared with the measured BP output, Y(s), at the summing junction to produce an error signal. The generated error is then processed by the SMC algorithm to determine the appropriate control action.

The SMC framework is generally divided into two fundamental components: the sliding surface and the control law [13]. The sliding surface, $S_{surface}(t)$, defines the desired dynamic response of the system and is typically formulated as a linear combination of the tracking error and its derivative. The control law, $U_{total}(t)$, consists of two distinct parts: an equivalent control that maintains system motion on the sliding surface, and a discontinuous control that enhances robustness against modeling errors and external disturbances. The discontinuous component enables switching actions that compensate for system deviations [14], thereby improving stability and overall performance.

The resulting control signal is applied to the patient model, $G_{patient}(s)$, which characterizes the dynamic relationship between the control input (e.g., the drug infusion rate) and the physiological output (mean arterial BP). To reflect realistic operating conditions, a disturbance model, $G_{disturb}$ (s), is incorporated to simulate external influences such as variations in vascular resistance, drug metabolism, and stress responses. This component enables the evaluation of the controller's ability to effectively reject disturbances. The BP output, Y(s), is continuously fed back to the controller to refine the control signal and minimize tracking error.

The main contributions of this work are:

- Development of a robust Sliding Mode Controller tailored for unstable first-order plus dead-time (FOPDT) blood pressure models.
- Integration of the Pelican Optimization Algorithm (POA) for multi-objective tuning of SMC parameters.
- Incorporation of a smooth sigmoid switching function to reduce chattering while preserving robustness.
- Lyapunov-based stability analysis ensuring satisfaction of the reaching condition and closed-loop convergence.
- Comprehensive validation across sensitive, nominal, and insensitive patient categories to address inter-patient variability.
- Robustness evaluation under ±20% parameter uncertainty and external disturbance injection.
- Quantitative comparison with recently reported FOPID and H_2-optimal PI controllers demonstrating improved transient and steady-state performance.

Unlike existing studies, where SMC parameters are manually tuned or optimized for nominal conditions, this work systematically integrates POA-based tuning for unstable FOPDT MABP models under structured ±20% parametric uncertainty, providing a unified comparison against FOPID and H_2 optimal PI controllers under identical patient conditions.

II. SLIDING MODE CONTROL

SMC is a nonlinear and robust control system that can provide better results in the presence of model uncertainties, parameter variations, and external disturbances [15]. SMC forces the state of the system to "slide" along a predefined surface called the "sliding surface" in state space. Once the system reaches the sliding surface, it slides to the desired equilibrium point.

The SMC control law is divided into two parts: the continuous control law, which drives the system towards the sliding surface, and the discontinuous control law, which maintains the system on the surface. The sliding surface is designed to obtain the desired response and stability characteristics of the system. By selecting an appropriate sliding surface, the controller ensures that the system tracks the reference signal and maintains stability even in the presence of uncertainties and external disturbances.

Initially, for designing the controller, the sliding surface is specified in [15] as in equation (1):

$$S_{surface}(t) = K_1 e(t) + K_2 \int_0^t e(t)dt + K_3 \frac{de(t)}{dt} + \frac{d^2 e(t)}{dt^2} \quad (1)$$

Here, K_1, K_2, and K_3 are constant gains, and $e(t)$ is the tracking error, given by e(t)=R(t)−Y(t).

The system should behave along the desired path; hence, the sliding surface should acquire a constant value that can be obtained by setting the value of the sliding surface and its derivative to zero. Hence, it is mathematically represented as:

$$S_{surface}(t) = 0 \quad (2)$$

And the derivative of the surface is represented as:

$$\frac{dS_{surface}(t)}{dt} = 0 \quad (3)$$

The objective of the controller is to design a control law $U_{total}(t)$ which comprises a continuous control law $U_{cont}(t)$ and a discontinuous control law $U_{discont}(t)$ [16, 17]. To satisfy the conditions of the control objective, the control law is stated as:

$$U_{total}(t) = U_{cont}(t) + U_{discont}(t) \quad (4)$$

Here, $U_{cont}(t)$ is the equivalent control that maintains the motion of the system along the sliding surface. $U_{cont}(t)$ is the function of system output Y(t), setpoint value R(t), and tracking value e(t), while $U_{discont}(t)$ is the discontinuous control that directs the system to reach the sliding surface.

$U_{discont}(t)$ results in undesirable oscillations due to high - frequency known as chattering. The control accuracy of the system is decreased if chattering increases; it also leads to instability or degradation in the performance of the system.

$$U_{discont}(t) = -K_F \, sign\,(S_{surface}) \quad (5)$$

Here, K_F is the switching gain. To eliminate chattering, the discontinuous law switching gain is dynamically adjusted based on system conditions to avoid excessive switching when the system is close to equilibrium. The solution for chattering is given as:

$$U_{discont}(t) = K_F \frac{S_{surface}(t)}{|S_{surface}(t) + \lambda|} \quad (6)$$

Here, K_F is an adjusting parameter that directs the system state trajectory to reach the sliding surface, and λ is the tuning parameter used for eliminating chattering, and λ>0.

The reaching condition is defined as:

$$S_{surface}(t). \frac{dS_{surface}(t)}{dt} < 0 \quad (7)$$

The reaching condition ensures that system trajectories converge to the sliding manifold in finite time.

III. System Dynamics

The modeling of biomedical systems is inherently dynamic and nonlinear, making their analysis and control a challenging task in biomedical engineering. A patient model is proposed by [18] for the drug infusion; the transfer of the model is given as:

$$G_{patient}(s) = \frac{H(1 + Ce^{-sTc})e^{-sTi}}{(Ts - 1)} \quad (8)$$

Here, H is the drug sensitivity of the patient in mmHg/(ml/h), T is the time constant, T_i is the initial transport delay in seconds, C is the recirculation constant, and T_c is the recirculation time delay in seconds.

The patient model expressed in equation (8) is categorized in 3 different categories, namely sensitive, insensitive, and nominal, based on the patient's sensitivity to Sodium Nitroprusside drug. Table 1 shows the parameters of the patient with categories [19].

Table 1: Parameters of the patient depending upon category

Control Parameters	Values for Sensitive patients	Values for Nominal patients	Values for Insensitive patients
H	-9 mmHg/ml/h	-0.714 mmHg/ml/h	-0.178 mmHg/ml/h
T	30	40	60
T_i	20 sec	30 sec	60 sec
C	0	0.4	0.4
T_c	30sec	45 sec	75sec

Patient categorization hinges on the specific medical status and the body's reactions to the drug infusion. Generally, for the purposes of both simulation and controller development, it's common to consider three patient types, namely sensitive, nominal, and insensitive. A sensitive patient will typically show a fast and strong drop in BP even with a relatively small dose of the drug. On the other hand, those who are insensitive need a larger dose to get about the same BP drop. Nominal patients, in most cases, show a response that's somewhere in the middle, normal drug sensitivity that can be observed in the wider population. Also, the patient model is made more complex by nonlinear disturbances; these arise because human cardiovascular systems are inherently complex. These disturbances include:

1. The physiological response following SNP infusion
2. Variations due to respiration
3. The body's auto-regulatory mechanisms that adjust BP in response to deviations from normal levels.

These considerations are critically important when designing systems that automatically control BP. The patient's response to SNP can be highly nonlinear, and it varies considerably from person to person. The control method needs to be robust to ensure reliable performance across all these different types of patient categories. Therefore, the controller needs to handle physiological disturbances effectively while also accurately keeping the BP at the desired target level.

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:

$$G_{\mathrm{disturb}}(s) = \frac{-1.4}{(240s+1)} \tag{9}$$

Physiologically, such disturbances may correspond to various real-world factors, including fluctuations in blood volume, variations in drug metabolism, or external stress responses. Introducing these disturbances in simulation enables the evaluation of the controller's robustness under realistic conditions. This ensures that the designed control system not only tracks the desired BP setpoint with high accuracy but also effectively rejects sudden load variations and maintains stability across different patient categories. Consequently, the control strategy must be capable of handling nonlinearities and inter-patient variability to ensure reliable and safe BP regulation in all physiological scenarios.

IV. CONTROLLER DESIGN

The design of SMC is based on variable structure control for linear and nonlinear processes. The design problem primarily involves determining the optimal set of controller parameters and establishing the switching logic that governs the operation of each control structure. This ensures that the system achieves the desired performance objectives under varying operating conditions. SMC technique offers several advantages, particularly its ability to maintain robust performance despite variations in system parameters. Due to its strong resistance to modeling uncertainties and external disturbances, SMC has been extensively utilized in the design of controllers for nonlinear and uncertain systems. The robustness of SMC is demonstrated in [20] for handling parameter variations, further validating its effectiveness in biomedical and industrial applications.

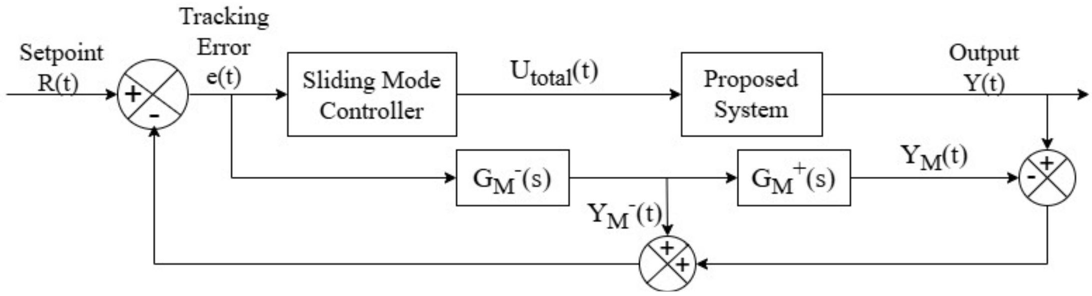

Figure 2: Proposed sliding mode control structure for the system

The block diagram shown in fig. 2 represents a closed-loop SMC system developed to achieve precise tracking of the desired setpoint while maintaining robustness against parameter variations and external disturbances. Here, R(t) is the reference signal or setpoint that defines the desired output of the process. This signal is compared with the actual system output Y(t) at the summing junction to generate the tracking error e(t)=R(t)−Y(t). The tracking error serves as the input to the SMC, which produces the total control signal $U_{total}(t)$.

The generated control signal $U_{total}(t)$ is applied to the proposed system, which gives the output response Y(t). In parallel, the system includes two model-based components, $G_M^-(s)$ and $G_M^+(s)$ that represent the nominal system dynamics and its inverse model, respectively. The block $G_M^-(s)$ processes the tracking error to produce an intermediate model output $Y_M^-(t)$, which is then passed through $G_M^+(s)$ to obtain the desired model output $Y_M(t)$. This model output acts as the reference trajectory that the actual system output is expected to follow. The feedback loops combine the model and actual outputs, continuously adjusting the control effort to minimize the tracking error e(t). As a result, the controller forces the actual output Y(t) to closely match the model output $Y_M(t)$, ensuring that the system output accurately tracks the reference signal R(t).

The reference model mode $G_M(s)$ is approximated to first order plus dead time delay [19]. The transfer function of the approximated model is given as:

$$G_M(s) = \frac{He^{-sTi}}{(1+Ts)} \tag{10}$$

This model is divided into two parts to design the SMC technique, given as:

$$G_M(s) = G_M^+(s)G_M^-(s) \tag{11}$$

The term $G_M^+(s)$ corresponds to the unstable portion of the model $G_M(s)$ that leads to a reliability problem, and $G_M^-(s)$ corresponds to the stable part of the model $G_M(s)$ that eliminates unstable dynamics of the system that generates an unreliable controller in the process model, ensuring the system remains stable and robust.

The transfer function for the equations $G_M^+(s)$ and $G_M^-(s)$ is given as:

$$G_M^+(s) = e^{-Ls} \tag{12}$$

$$G_M^-(s) = \frac{H}{(1+Ts)} \tag{13}$$

Designing the SMC for systems with time delays generally requires an approximation of the delay term, which can introduce modeling inaccuracies. The SMC involves defining a sliding surface $S_{surface}(t)$ that characterizes the system's behavior during transient response. Hence, a sliding surface is adopted as shown in equation (1), considering several guidelines from [9]. The error e(t) from equation (1) is defined as:

$$e(t) = R(t) - \left(Y(t) - Y_M(t)\right) - Y_M^-(t) \tag{14}$$

The equation that describes the control law is given by equation (4) as $U_{total}(t)$. It comprises of two functions, continuous function $U_{cont}(t)$ and discontinuous function $U_{discont}(t)$. The first component of the control law is responsible for maintaining the system dynamics on the sliding surface that represents the desired behavior of the closed-loop system. The second component typically acts as a switching function that drives the system state toward the sliding surface and compensates for uncertainties. The complete control law is derived by substituting the sliding condition into the system's dynamic equations. The main objective of this control process is to ensure that the controlled variable converges to its desired reference value, thereby achieving accurate tracking and stable performance.

Employing equations (2) and (3), and solving for the first derivative by considering $Y(t) - Y_M(t) = 0$ for the normal case, the equation for the first derivative is represented as:

$$\frac{d}{dt}Y_M^-(t) = \frac{dR(t)}{dt} + \lambda e(t) \tag{15}$$

Considering equation (15), we obtain:

$$\frac{Y_M^-(t)}{U_{cont}(t)} = G_M^-(s) = \frac{H}{(1+Ts)} \tag{16}$$

Substituting equation (14), we get:

$$T\frac{dY_M^-(t)}{dt} + Y_M^-(t) = H.U_{cont}(t) \tag{17}$$

Substituting the values obtained from equation (16) in equation (17), we obtain:

$$T\frac{dR(t)}{dt} + T\lambda e(t) + Y_M^-(t) = H.U_{cont}(t) \tag{18}$$

Solving equation (18) for the continuous control function, we get:

$$U_{cont}(t) = \frac{1}{H}\left(T\frac{dR(t)}{dt} + T\lambda e(t) + Y_M^-(t)\right) \tag{19}$$

If the setpoint is assumed to be constant, rather than a time-varying function, the expression $U_{cont}(t)$ can be simplified by eliminating the terms associated with the derivative of the reference signal. This simplification reduces computational complexity and facilitates easier implementation of the controller in real-time applications.

$$\frac{dR(t)}{dt} = 0 \tag{20}$$

In many controller applications, the derivative computation should be based on the value of the system variable itself rather than the reference signal. When the setpoint changes abruptly, taking its derivative results in an undesired control action known as the derivative kick [20]. To mitigate this effect and ensure smoother control performance, the derivative term is computed directly from the system output.

When selecting a switching function, practical implementation aspects must also be considered. To minimize chattering and improve robustness, a continuous approximation of the signum function is often preferred. In this work, a smooth nonlinear function is adopted as the switching function $U_{discont}(t)$. Accordingly, the sigmoid function is chosen to achieve a gradual transition between the control states, reducing discontinuities in the control signal. The sigmoid function is given as:

$$sign\left(S_{surface}(t)\right) = \frac{S_{surface}(t)}{S_{surface}(t)+\lambda}, \lambda > 0 \tag{21}$$

Here, λ represents a tunable parameter whose value can be adjusted to minimize or eliminate the chattering effect. By selecting an appropriate value of λ, a smooth control action can be achieved without compromising system robustness. Considering all the aforementioned conditions, the resulting control law can be expressed as follows:

$$U_{total}(t) = \frac{1}{H}\left(T\lambda e(t) + Y_M^-(t)\right) + K_F\frac{S_{surface}(t)}{|S_{surface}(t)+\lambda|} \tag{22}$$

For stability analysis, the Lyapunov stability criteria have been used, which are given by :

$$V = \frac{1}{2}S_{surface}^2 \tag{23}$$

The derivative of the Lyapunov is given as :

$$\frac{dV}{dt} = S_{surface}(t).\frac{dS_{surface}(t)}{dt} \tag{24}$$

By substituting the values of the obtained control law, we obtain

$$\frac{dV}{dt} \leq -\eta|S| \tag{25}$$

Here, $\eta>0$ and $\frac{dV}{dt}<0$ for global asymptotic stability

V. PELICAN OPTIMIZATION ALGORITHM (POA)

POA is a modern optimization technique inspired by the cooperative hunting behavior of pelicans. Introduced by [21] in 2022, the algorithm mimics how pelicans work together to locate and catch fish efficiently. In nature, pelicans often fly over the water to spot potential prey and then dive rapidly to capture it. POA uses this same concept to search for optimal solutions to complex mathematical and engineering problems. It operates in two main stages — exploration and exploitation. During the exploration stage, pelicans represent agents that move around the search space randomly, similar to how real pelicans scout for fish. This helps the algorithm explore a wide range of possible solutions and avoid getting stuck in local optima. Once promising regions are found, the algorithm moves to the exploitation stage, where pelicans dive toward the best solution found so far.

The algorithm begins by randomly generating a population of pelicans, each representing a potential solution to the problem. Pelicans adjust their positions based on this best solution, simulating cooperation and competition at the same time. The process repeats until a stopping condition is met, such as reaching a maximum number of iterations or finding a solution that meets the desired accuracy. POA has proven to be effective for a wide range of applications. It performs well on complex, nonlinear, and multidimensional optimization problems and is often compared favorably to other popular algorithms like the Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO). POA achieves faster convergence and better accuracy while maintaining a strong balance between global and local search.

The population of pelicans is initialized randomly within the search space:

$$X_i = X_{min} + rand()(X_{max} - X_{min}) \quad (26)$$

Here, X_i is the position of pelicans in the search space, and $rand()$ is a random number between 0 and 1.

Pelicans move to explore new areas in the search space:

$$X_i^{t+1} = X_i^t + A(X_{rand}^t - X_i^t) \quad (27)$$

Here, t is the current iteration, X_{rand} is a random pelican chosen from the population, and A is a random coefficient controlling the movement intensity.

Once prey is identified, the pelican dives to catch it as:

$$X_i^{t+1} = X_{best}^t + B(X_{best}^t - X_i^t) \quad (28)$$

Here, X_{best} is the best solution found so far, and B is a parameter that decreases with iterations, ensuring fine-tuning near the global optimum. Pelicans update their position closer to the best solution to enhance convergence. After each iteration, new positions are updated using objective functions, and the best solution is updated until the termination condition is met.

VI. CONTROL OBJECTIVES

The main objective of using SMC for blood pressure regulation is to keep a patient's BP close to the desired level in a reliable and consistent manner, even when conditions change. The controller is expected to track the target BP accurately while quickly counteracting common disturbances such as surgical stress, blood loss, or sudden physiological variations. One of the key strengths of SMC is its ability to remain effective despite uncertainties in the patient model and differences in drug sensitivity among patients. At the same time, the control strategy aims to provide a fast and well-damped response, avoiding excessive overshoot or oscillations that could be harmful in clinical settings. The system is designed to remain stable by guiding the BP dynamics toward a predefined sliding surface. In addition, the controller must generate safe and bounded drug infusion rates, ensuring smooth BP regulation while reducing undesirable chattering effects.

VII. SIMULATION RESULTS

The values of the SMC controller are represented in Table 2, which were obtained by using the POA technique.

Table 2: Values of the SMC controller obtained by using the POA technique

	K_F	λ	K_1	K_2	K_3
Insensitive	-28	5	6.8	-2	0.185
Sensitive	146.7	5	16.65	-1	0.185
Nominal	119.3	5	8.3	-1.8	3.02

The simulation work is conducted for three different categories of patients, namely insensitive, sensitive, and nominal, to accommodate the variability in the patient responses. The comparative analysis includes performance of the controller, including setpoint tracking, disturbance rejection capability, and peak overshoot with robustness parameter variation. The simulation performed for the SMC controller is taken for a time duration of 3000 seconds in the case of an insensitive patient, while the time duration is 2000 seconds for sensitive and nominal patients. To check the efficacy and robustness of the system, an external disturbance was applied to the system at 1500 seconds for the insensitive case and at 1000 seconds for the sensitive and nominal case of the patient.

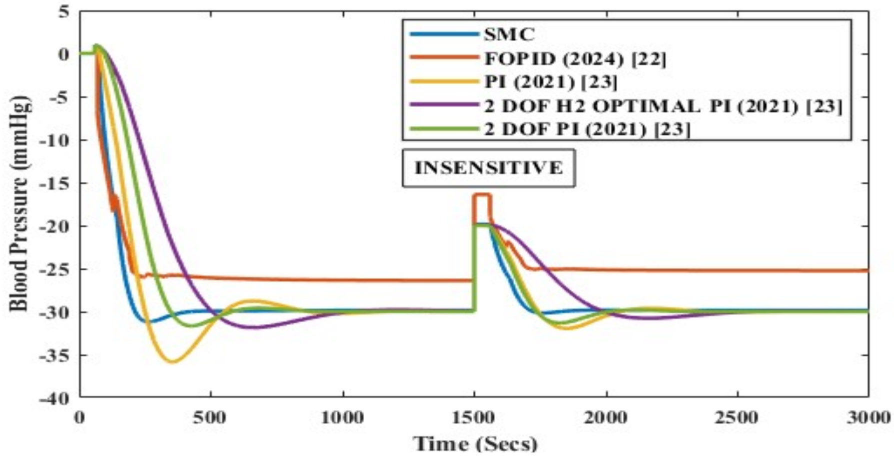

Figure 3: Result obtained for the SMC controller for an insensitive patient compared with recent literature

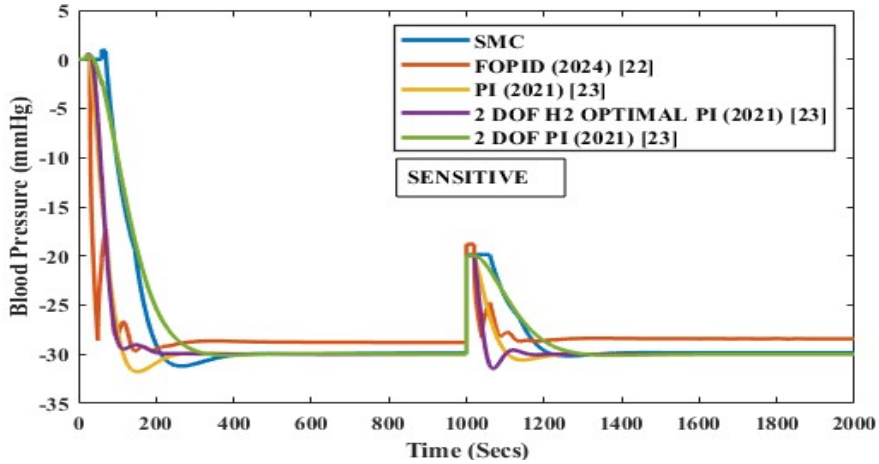

Figure 4: Result obtained for the SMC controller for a sensitive patient compared with recent literature

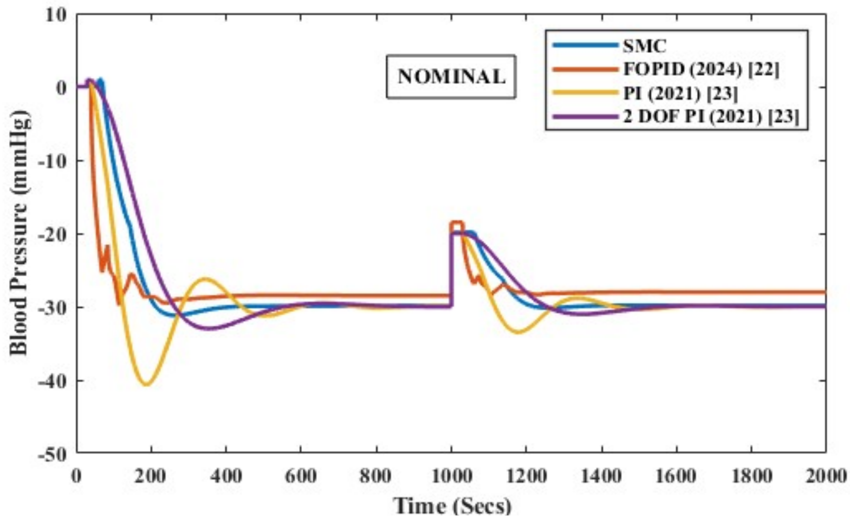

Figure 5: Result obtained for the SMC controller for the nominal patient compared with recent literature

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 3, 4, and 5 demonstrate the comparative analysis of the SMC controller using POA optimization. The performance of these controllers is also compared with that of Krishna and Rao [22] and Pachauri and Begum [23].

*Author for Correspondence: abhishekjain.281988@gmail.com

Robustness Analysis

The robustness of the proposed SMC–POA framework is evaluated under structured parameter variations and external disturbance conditions. Specifically, ±20% variations are introduced in drug sensitivity (H) and time constant (T) to emulate inter-patient variability and physiological uncertainty.

Due to the invariance property of sliding mode control, matched uncertainties do not affect the reduced-order dynamics once the system trajectory reaches the sliding surface. Simulation results demonstrate that the controller maintains stable closed-loop behavior with acceptable transient performance across all perturbation scenarios.

Additionally, sudden disturbance injection is applied during steady-state operation to represent abrupt physiological events such as blood loss or stress-induced vascular resistance changes. The controller effectively suppresses the disturbance and restores MABP to the desired setpoint within a short recovery time, confirming strong disturbance rejection capability.

The results verify that the proposed approach maintains stability, bounded control effort, and minimal performance degradation under significant parameter uncertainty, demonstrating superior robustness compared to conventional controllers.

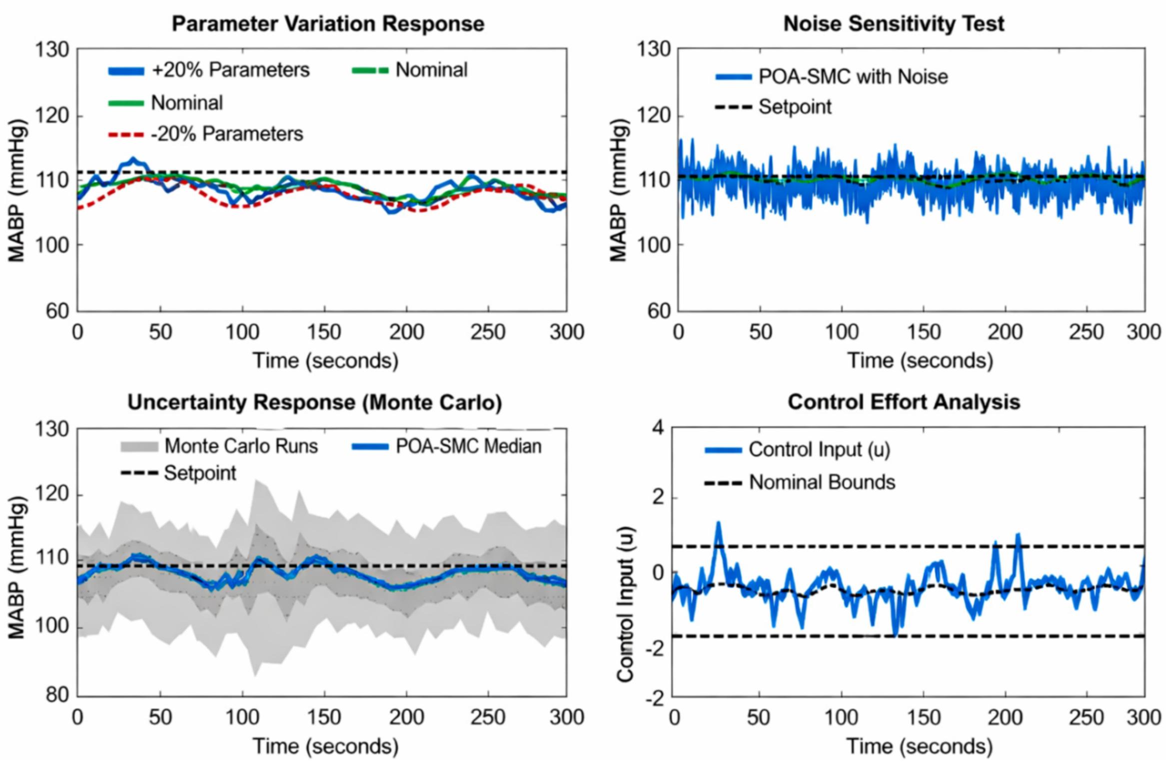

Figure 6: Robustness analysis for SMC-enabled BP using POA

Robustness is validated under:

1. ±20% variation in H (drug sensitivity)
2. ±20% variation in T (time constant)
3. External disturbance injection

The controller maintains stability and acceptable transient performance across all scenarios, confirming strong robustness against parameter uncertainty and physiological disturbances.

VIII. CONCLUSION

The results obtained from the simulations clearly show that the proposed SMC tuned using the POA optimization technique performs more effectively in regulating blood pressure compared to the FOPID controller [22] as well as the PI, 2-DOF PI, and 2-DOF H_2 optimal PI controllers reported in [23]. Simulation results across sensitive, nominal, and insensitive patient models demonstrate faster settling time, reduced overshoot, improved steady-state accuracy, and enhanced disturbance rejection compared to FOPID, PI, 2-DOF PI, and H_2-optimal PI controllers. Robustness analysis under ±20% parameter variations confirms the invariance and stability properties of the proposed approach.

The SMC-POA approach demonstrates a faster response, minimal overshoot, and improved steady-state accuracy across different patient conditions. In addition, it maintains stable performance even in the presence of disturbances and parameter variations, which are unavoidable in real physiological systems. Unlike conventional PI-based controllers, which may struggle under sudden changes, the SMC structure provides strong robustness and better disturbance rejection capability. The proposed controller integrates a Lyapunov-based design framework with a smooth switching mechanism to ensure closed-loop stability while mitigating chattering effects.

Another important advantage is that the POA optimization helps in selecting appropriate controller parameters, reducing undesirable chattering effects while preserving system stability. Overall, the comparative study confirms that the proposed controller offers more reliable and robust BP regulation than the previously reported methods, making it a promising solution for practical and clinical BP control applications.

A robust SMC optimized using POA has been developed for MABP regulation in patients with varying sensitivities. Lyapunov stability analysis guarantees closed-loop convergence. Comprehensive simulations demonstrate superior transient response, improved disturbance rejection, and enhanced robustness compared to recently reported controllers. The proposed framework offers a reliable and systematic approach for automated blood pressure regulation.

Future work includes hardware-in-the-loop validation, experimental implementation, and extension toward adaptive or higher-order sliding mode strategies.

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