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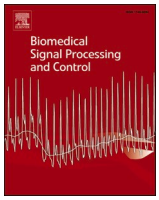

Fractional-order PID controller for blood pressure regulation using genetic algorithm

P. Siva Krishna [a,b,*], P.V. Gopi Krishna Rao [c,*]

[a] Jawaharlal Nehru Technological University Anantapur, Ananthapuramu, AP, India
[b] Rajiv Gandhi University of Knowledge Technologies-AP, R.K. Valley Campus, India
[c] Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal, Affiliated to Jawaharlal Nehru Technological University Anantapur, Ananthapuramu. AP, India

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ABSTRACT

In this paper, fractional order PID controller [FOPID] is designed for automatic blood pressure regulation. One of the most common problems faced by post-operative patients is abnormal blood pressure (BP). Infusion of sodium nitroprusside (SNP) into the patient reduces blood pressure by relaxing the peripheral vasculature's muscles. The patient's BP must be continuously monitored by an expert and the correct dose has to be given to the patient. It will be difficult to give the desired dosage to a patient manually because drug sensitivity is different for different patients. So, an appropriate controller must be designed to regulate blood pressure and minimize clinical expenses. A fractional-order PID controller is proposed in this paper to regulate mean arterial pressure, and FOPID parameters are optimized as a function of minimizing integral absolute error (IAE), integral squared error (ISE), and integral time absolute error (ITAE) using genetic algorithm. The performance of the proposed system is improved in terms of undershoot, settling time, and maximum peak overshoot. A MATLAB environment was used for the simulation of the system and the implementation of the algorithm.

1. Introduction

A blood pressure reading represents how much force the heart exerts when pumping blood to artery walls. An increase in blood pressure affects the workload on the heart. During surgery, there will be heavy blood loss and significant changes occur in the blood pressure. Excessive bleeding during the operation makes poor visibility for the surgeons and it will be difficult for the surgeon to carry out the operation hence it is essential in regulating the mean arterial blood pressure [1].

A person's blood pressure is determined by the amount of cardiac output and the amount of peripheral resistance. A vasodilating drug is infused into hypertensive patients to reduce their peripheral resistance, thereby lowering their blood pressure. The most common vasodilating drug is sodium nitroprusside (SNP). Sodium nitroprusside is a strong, rapid-acting agent when given intravenously to the patient, this infusion of the drug will decrease the peripheral resistance, maintaining the blood pressure within the limits. SNP enters the blood, combines with hemoglobin, and breaks down into nitric oxide, cyanide, and thiocyanate. Nitric oxide makes the walls of veins relax, thiocyanate is excreted in the urine whereas cyanide can accumulate if the infusion of the drug is higher or prolonged administration. Therefore, infusion rates of the drug have to be controlled and the infusion of the drug into the body has to be short to avoid toxicity. A serious problem for postoperative patients is the infusion of SNP and its effects on biological systems. It may reduce the blood pressure for hypertension patients, too much decrease in the blood pressure leads to low blood pressure causing dizziness, vomiting, headache, fatigue, restlessness, and hallucinations, points toward a serious heart attack, and it affects other important parts like a nervous system and may lead to shock. Therefore, the infusion rate of SNP must be properly maintained for the patient.

Clinically administering SNP to control blood pressure can be challenging due to patient variability and a controlled release of the drug over time. The state of mind of the patient may also affect the blood pressure. So, the clinical person should have awareness of patient sensitivity and he needs to spend more time monitoring the blood pressure of a patient. An automatic drug delivery system is required, which adjusts the infusion rate in order to ensure that overdosage does not occur and blood pressure remains within the desired level, regardless of patient sensitivity.

Automatic drug delivery was used by Bickford [2] to control

* Corresponding authors.
E-mail addresses: sivakrishna.polepalli@gmail.com (P. Siva Krishna), gopikrishnarao@gmail.com (P.V. Gopi Krishna Rao).

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anesthesia in patients in 1950. Later automatic drug delivery systems became popular and played an important role in the biomedical field. As the automatic controller for the regulation of blood pressure did not consider delays present in the patient response model, rabbits and dogs showed oscillatory responses during the study [3] Sheppard et al. developed a controller by studying the dynamics of the physiological responses of the post-operative patient to sodium nitroprusside with computer control methods to reduce oscillations but they have not taken patient sensitivity to the drug into account [4–5]. Initially, the automatic controllers were not adaptive. such controller performance will be good When the patient is ideal but in real-time there are a lot of disturbances, as the human body is a very complex system and the controller must handle it. A major disturbance in the regulation of MABP is surgical stimulus during operation [6–7]. To overcome all these issues, adaptive controllers were designed to achieve better results by using an online algorithm, the patient parameters will be estimated, and the controller will be adjusted accordingly [8–13]. Slate and Sheppard proposed a model-based adaptive controller that will take patient sensitivity into account for the drug [14]. Some other techniques and controllers have been satisfied for regulating the mean arterial blood pressure [15–21]. Jahn Proposed a control strategy based on internal model control and found the performance parameters in terms of steady state, settling time and peak overshoot is satisfactory [22]. In comparison to other Cohen-Coon and Chein, Hrones and Reswick (CHR) methods, Gopi Krishna Rao's implementation of IMC-tuning achieved higher performance and robustness [23]. The performance of the IMC filter has been proven to be robust and able to reject disturbances well [24]. The performance of optimal IMC is compared with the PID controllers and found settling time is less for the PID controller compared to the optimal IMC [25]. When compared to the IMC-based PID controller which gave a top response compared to the conventional Internal Model Controller [26]. Hammack [27] proposed an algorithm for controlling the mean arterial pressure which was represented by a fractional-order time-delay system with fractional-order PID controllers which are having a high disturbance ratio and their ability to perform in uncertain conditions with a high degree of freedom compared to the conventional PID controllers. Even though there are many methods for fine-tuning controllers, only a few delivers consistently effective outcomes. However, in recent years, optimization strategies have drawn greater attention. These heuristic and *meta*-heuristic-based optimization methods have shown promising results for setting the parameters of controllers, and with advances in computation, they are becoming more and more effective. Particle swarm optimization [28], multi-strategy modified INFO algorithm [29] Logarithmic spiral search-based arithmetic algorithm [30], novel hybrid algorithm [31], whale optimisation algorithm [32], human-inspired algorithm [33], and seeker optimization algorithm [34], are some of the most widely used optimization algorithms in this field. One of the popularly used algorithms in intelligent control systems is a genetic algorithm. A genetic algorithm is used to optimize PID parameters by minimizing the cost function. Using the genetic algorithm method, Gopi Krishna Rao achieved a faster response compared to Steepest Decent Gradient Method [35]. Zhang proposed a method for disturbance rejection by using a genetic algorithm for PID controllers [36]. Krohling and Kumar proposed a bioreactor system using the genetic algorithm-based controller that gave better results compared to the Ziegler-Nichols optimization algorithm in terms of setpoint tracking, peak shoot, and undershoot. [37–38]. These examples highlight the effectiveness of genetic algorithms in optimizing control parameters and enhancing control system performance across various applications. The paper aims to optimize the parameters of a Fractional Order Proportional-Integral-Derivative (FOPID) controller for regulating blood pressure using a genetic algorithm. The decision to employ a genetic algorithm is motivated by its resemblance to the process of natural selection and evolution found in biological organisms, including the human body. In this context, candidate solutions, representing various sets of controller parameters, are encoded in a manner like the representation of genes in biological organisms. This encoding allows the genetic algorithm to apply genetic operations such as crossover and mutation, generating new candidate solutions to efficiently search for the optimal controller parameters. By adopting this approach, the paper leverages the genetic algorithm's ability to explore the solution space effectively and identify the most suitable combination of FOPID controller parameters for regulating blood pressure efficiently. The analogy between genetic algorithms and biological evolution offers valuable insights into the optimization process and holds promise for innovative solutions in control engineering and medical applications.

Table 1
Parameter values of patients.

Parameter	Sensitive	Normal	Insensitive
K(mmHg/(ml/hr))	−9	−0.7143	−0.1786
α	0	0.4	0.4
T_{id} (sec)	20	30	60
T_{cd} (sec)	30	45	75
τ (sec)	30	40	60

2. Patient response model

Slate [1] explored the effects of the infusion of SNP on the patient by examining five parameters that show a large variation in the mean arterial blood pressure among patients to the SNP drug using correlation analysis and pseudo-random binary signals.

$$G_{plant}(s) = \frac{\Delta P_d(s)}{In(s)} = \frac{Ke^{-T_{id}s}(1 + e^{-T_{cd}s})}{\tau s + 1} \tag{1}$$

Where ΔP_d (s) is the change in MABP (mmHg), In(s) is the drug infusion rate (ml/hr), K is the drug sensitivity(mmHg/ml/hr), α is the recirculation constant, τ is the time constant (sec), T_{id} is the initial time delay (sec), and T_{cd} denotes the recirculation time delay (sec).

In this model, all time constants are expressed in seconds, and the patient model is classified into three categories based on patients' sensitivity to drugs as given in Table 1 [1].

In the patient model delay terms are present, the delay term $e^{-\theta s}$ can be approximated by Pade's second order as $e^{-\theta s} = \frac{\left(1-\frac{\theta}{2}s\right)^2}{\left(1+\frac{\theta}{2}s\right)^2}$ by producing the patient model given in the Table 2.

Biological systems are always affected by disturbances [39]. Due to the disturbances the blood pressure may increase or decrease at the time of clinical operations. The disturbances can occur due to respiratory effects, and reflex response due to relaxation due to infusion of the drug. These disturbances should include in the system model to have higher accuracy. Enbiya[25] created the simulink model of these disturbances as shown in Fig. 1.

2.1. Proposed controller

The FOPID controller has five adjustments particularly K_P, K_I, λ, K_D and μ. Compared to the classical PID it is having two more parameters to achieve a better result.

From Fig. 2, it can infer that the main aim of the work is to tune the FOPID parameters by minimizing the error between the setpoint value and output of the patient model value. $C_O(S)$ is the output of the FOPID controller which is given as input to the patient model. From the above figure we can write the following equations

$$G_{Controller}(s)G_{Plant}(s) = B(s) \tag{2}$$

$$\Delta P_d(s) = \frac{B(s)}{1 + B(s)}R(s) + \frac{1}{1 + B(s)}D(s) \tag{3}$$

Table 2
Mathematical model of patients.

Patient	Pade's second-order approximation
sensitive	$\frac{0.3(s^2-0.3s+0.03)}{(s+0.0333)(s^2+0.3s+0.033)}$
nominal	$\frac{0.02845(s+0.025)(s^2+0.08832s+0.003371)(s^2-0.1397s+0.008439)}{(s+0.0025)^2(s^2+0.08s+0.002133)(s^2+0.2s+0.0133)}$
insensitive	$\frac{0.0041767(s+0.01667)(s^2+0.04963s+0.0009068)(s^2-0.06487s+0.001549)}{(s+0.01667)^2(s^2+0.0444s+0.0006584)(s^2+0.08s+0.002133)}$

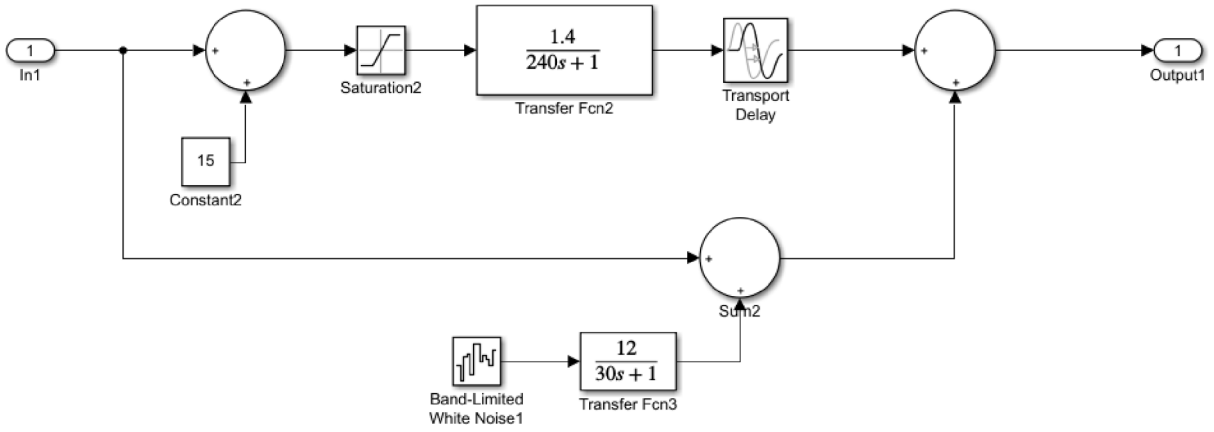

Fig. 1. Simulink model for the disturbances.

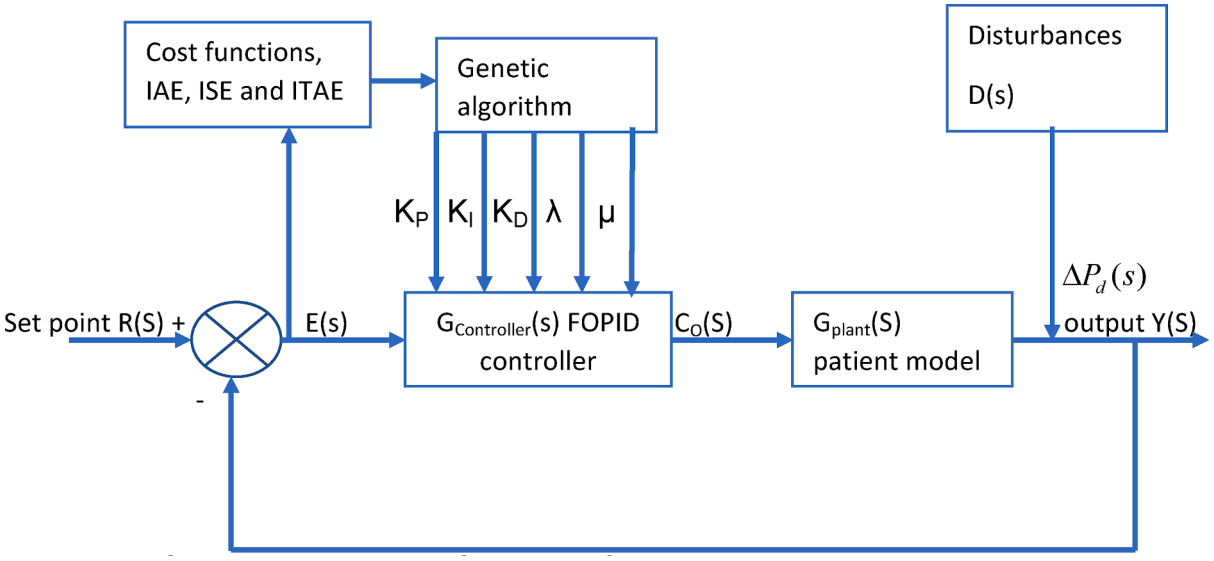

Fig. 2. FOPID controller with GA tuning for MABP regulation.

$$E(s) = \frac{R(s) - D(s)}{1 + B(s)} \tag{4}$$

The general criteria used to minimize the error value E(s) is by optimizing FOPID parameters are integral performance parameters ISE, IAE, and ITAE. From Fig. 2, it is evident that the ISE, IAE, and ITAE are used as cost functions for optimizing the FOPID parameters by using a Genetic Algorithm.

The main objectives of our FOPID controller are

(1) Settling time should be less than 800sec
(2) Setpoint is −30 mmHg
(3) Overshoot should be less than 5 mmHg
(4) Steady state error should be less than 5 mmHg

2.2. Fractional calculus

In fractional calculus, different possibilities of real numbers and complex numbers are analysed by differential and integral operators [40–41]. In fractional calculus, we use differintegral which is a combination of differentiation and integration and is denoted by ${}_a D_t^q$. The differintegral notation is used for taking fractional integration and fractional differentiation as a single expression as follows

$$\hat{a}D_t^q = \begin{cases} \frac{d^q}{dt^q} & q > 0 \\ 1 & q = 0 \\ \int_a^1 (dt)^{-q} & q < 0 \end{cases} \quad (5)$$

Where q is a fractional-order, a and t are limits of the operator. There are three definitions which are generally in the fractional order.

(1) The definition of Grunwald -Letnikov [39] is given based on the theory of backward difference as follows

$$\hat{a}D_t^q f(t) = \lim_{n\to\infty} \left(\frac{t-a}{N}\right)^{-q} \sum_{j=0}^{N-1} (-1)^j \left(\frac{q}{j}\right) f\left(t - j\left(\frac{t-a}{N}\right)\right) \quad (6)$$

where a and t are operator limits.

(2) The definition of Riemann-Liouville [39] for the fractional derivative of the order of q is simple and easy

$$\hat{a}D_t^q f(t) = \frac{1}{\Gamma(n-q)} \left(\frac{d}{dt}\right)^n \int_a^t (t-\tau)^{n-q-1} f(\tau) d\tau \quad (7)$$

where n is an integer, Γ () is an Euler's gamma function.

(3) f(t) function comprising n number of continuous derivatives for t ≥ 0 and n-1 ≤ q < n. an alternate definition for the fractional derivative is given by Caputo [42] as

$$\hat{a}D_t^q f(t) = \frac{1}{\Gamma(n-q)} \int_a^t (t-\tau)^{n-q-1} f^n(\tau) d\tau \quad (8)$$

Riemann-Liouville and Caputo's formulas coincide when the initial conditions are zero.

2.3. FOPID controller

The simplicity of PID controllers has made them popular in many industries and process control applications. All conventional PID controller has three tuning parameters in order to get better performance by reducing peak overshoot, enhancing the response time, and reducing settling time for slow process plants, but for handling dynamic systems or plants we need a higher degree of freedom compared to classical PID controllers, which motivates to choose FOPID controllers. FOPID controllers will enhance the dynamic system performance compared to the classical PID controllers. An advantage of FOPID controllers is their sensitivity to changes in system parameters. In addition, FOPID controllers have the advantage that if the order of the system increases, their performance will increase, unlike classical PID controllers.

The most common form of FOPID is $PI^{\lambda}D^{\mu}$ controller which is having differentiation of the order of μ and integration of the order of λ. The values of μ and λ lie in between '0′ and '1′. The transfer function of the FOPID controller is given by equation (9)

$$G_{Controller}(s) = \frac{C_o(s)}{E(s)} = K_P + K_I \frac{1}{s^{\lambda}} + K_D s^{\mu} \quad (\lambda, \mu > 0) \quad (9)$$

Where $G_{Controller}(s)$ is the controller transfer function, E(s) is the error between the setpoint value and output of the patient model value. $C_O(s)$ is the FOPID controller output. K_P is proportional constant gain, K_I is integration constant gain, K_D is derivative constant gain, λ is the order of integration and μ is the order of differentiation. All conventional types of PID controllers are unique cases of FOPID controllers. If we select λ and μ equal to one FOPID controller will become a conventional PID controller. If we select λ = 1and μ=0 then the FOPID controller will become the conventional PI controller. If we select λ = 0 and μ =1 then the FOPID controller will become a conventional PD controller. If we select λ = 0 and μ =0 then the FOPID controller will become a conventional P controller.

Simulation of the transfer function of the FOPID controller is more complex than that of the ordinary PID controller. This is because, in FOPID controllers, fractional order differentiation and integration are included. Finding the exact analytical solution is not possible in FOPID controller, when solving fractional order differentiation and integration, it is necessary to use approximation and numerical methods. The Oustaloup continuous integer order approximation is among the many approximate solutions and numerical methods available for the solution of fractional order equations [43]. In this approximation, poles and zeros are distributed recursively

$$\omega_k^{'} = \omega_l \left(\frac{\omega_h}{\omega_l}\right)^{\frac{k+N+\frac{1}{2}(1-\gamma)}{2N+1}} \quad s^q = A \prod_{n=1}^{N} \frac{1+\omega_k^{'}}{1+\omega_k} \qquad q > 0 \quad (10)$$

$$\omega_k^{'} = \omega_l \left(\frac{\omega_h}{\omega_l}\right)^{\frac{k+N+\frac{1}{2}(1-\gamma)}{2N+1}} \quad (11)$$

$$\omega_k = \omega_l \left(\frac{\omega_h}{\omega_l}\right)^{\frac{k+N+\frac{1}{2}(1+\gamma)}{2N+1}} \quad (12)$$

$$A = \omega_h^{\gamma} \quad (13)$$

Where N is the order of approximation, γ is fractional order derivative, $w_k^{'}$ and w_k are zeros and poles, (w_l, w_h) is the range of the frequency. In this paper we have taken N = 5, w_l is 0.001 rad/ sec and w_h is 10000 rad /sec.

2.4. Genetic algorithm

In recent years genetic algorithm is recognized as a powerful and potent algorithm in finding the effective solution to constrained and unconstrained equations. It is a random search engine for finding the optimum parameters in multidimensional space based on genetic and natural selection principles. Instead of deterministic transition rules, it uses probabilistic transition rules to handle a population of possible solutions. The solution evolves through iterations represented by a chromosome. Each iteration in the genetic algorithm is represented as a generation. At each generation, the genetic algorithm selects chromosome from the population and use them to generate off springs for the next generation and the process get repeated for multiple generations until the global solution occurs.

Genetic algorithm can be incorporated with the following steps

Step 1: Initialize the population of n chromosomes randomly.
Step 2: The fitness function gives the fitness score of each chromosome. The probability that a chromosome will be selected is based on the fitness score of chromosomes. Two chromosomes will be selected based on the principle of survival of the fittest.
Step 3: Offsprings are formed by exchanging the genes of chromosomes by themselves based on the crossover rules.
Step 4: New springs are formed by changing some of its genes from one to zero or from zero to one which are having low probability by mutation rules.
Step 5: Repeat step 2, till the optimum solution achieves.

Design of FOPID controller for blood pressure regulation using genetic algorithm: In the design of FOPID controller for blood pressure regulation by genetic algorithm the most challenging part is creation of objective function. In this objective function is required to evaluate FOPID controller for blood pressure regulation. An objective function is created in such a way that FOPID controller provides lesser settling time, minimum peak over shoot and faster response. An objective function is required to evaluate the fitness function of each chromosome. Authors [28,46] Uses mean squared error (MSE), Integral time absolute error

(ITAE), integral squared error (ISE) and integral absolute error (IAE) as performance indices.

$$IAE = \int_0^\tau |e(t)|\, dt \tag{14}$$

$$ISE = \int_0^\tau e^2(t)\ dt \tag{15}$$

$$ITAE = \int_0^\tau |e(t)|\, t\, dt \tag{16}$$

Here we use the above three performance indices for minimizing the error signal and to obtain the optimal FOPID controller parameters. The controller parameters K_P, K_I, and K_D are defined within the range of −100 to 100 by trial-and-error approach. To ensure control stability and minimize oscillations, the restricted the values of λ and μ to a range of 0 to 1. It is crucial to avoid using values greater than 1 for both λ and μ in a FOPID controller, as this may lead to intricate control behaviour, potentially causing instability and poor control performance. The following parameters are used in designing the FOPID controller by using genetic algorithm in MATLAB.

(1) Population size = 50
(2) Maximum number of Generations = 200
(3) Variable bounds (K_P, K_I,K_D,λ, and μ) = [(−100:100),(−100:100), (−100:100),(0:1) and (0:1)]
(4) Selection method = uniform
(5) Crossover fraction = 0.8
(6) Mutation method = uniform
(7) Crossover function = constraint dependent

By substituting the above parameters in GA by using MATLAB tool will provide the optimum parameters of FOPID controller.

3. Sensitivity assessment

The blood pressure regulating system faces major challenges as a result of uncertainty. A single model cannot accurately represent the dynamics for all patients due to the complex nature of this process. As a result, the behaviour of the blood pressure system varies significantly from patient to patient, making it difficult for a single controller to provide satisfactory results universally. Bequette [44] claims that blood pressure regulation has an average level of uncertainty between 33 % and 150 %. This uncertainty can be attributed to variations in the process parameters, which are influenced by the unique responses of each patient's body to drug infusions. These drug infusions can lead to varying behaviours in blood pressure. Given these challenges, it becomes crucial to design controllers that are insensitive to changes in dynamics. Therefore, it is obvious to perform the sensitivity analysis to determine whether the fractional-order controllers that were built for the study are effective Murray [45]. The following function can be used to calculate the absolute sensitivity numerically

$$S = \frac{1}{G_{Controller}(s)G_{Plant}(s)} \tag{17}$$

Where $G_{controller}$ (s) represent the FOPID controller, G_{plant} (s) corresponds to the transfer function of the patient model and S denotes the sensitivity function. The maximum value of S(jω) will provide the robustness and serve as a control system design criterion. The maximum sensitivity $M_s = max|S(j\omega)|$ provides insights into the potential amplification that can occur. Controllers with higher M_s values experience greater amplification. Conversely, lower M_s values indicate suggest higher robustness, ensuring a more stable system. For a satisfactory control system M_s should be in the range of 1.4 to 2.

Table 3
FOPID parameters for sensitive patient model using genetic algorithm for three different cost functions.

Cost functions	Tuned parameters of FOPID controller using genetic algorithm (Sensitive patient)				
	K_P	K_I	λ	K_D	μ
IAE	−0.0087	−0.0075	0.843	−0.8895	0.59
ISE	−0.12	−0.004	0.9637	−1.8578	0.9799
ITAE	−0.048	−0.0047	0.92	−0.9754	0.6695

Table 4
FOPID parameters for nominal patient model by using genetic algorithm for three different cost functions.

Cost functions	Tuned parameters of FOPID controller using genetic algorithm (Nominal patient)				
	K_P	K_I	λ	K_D	μ
IAE	−0.6	−0.02	0.965	−5.5	0.65
ISE	−0.1534	−0.054	0.8584	−9.266	0.4605
ITAE	−0.3968	−0.03	0.9345	−8.6733	0.53

Table 5
FOPID parameters for insensitive patient model by genetic algorithm for three different cost functions.

Cost functions	Tuned parameters of FOPID controller using genetic algorithm (Insensitive patient)				
	K_P	K_I	λ	K_D	μ
IAE	−0.15	−0.082	0.8522	−15.26	0.42
ISE	−0.28	−0.078	0.849	−11.62	0.38
ITAE	−3.25	−0.038	0.95	−87.83	0.97

3.1. Results

The FOPID controller was simulated in MATLAB on three different types of patient models. The response of each model is obtained in the presence of disturbances to the SNP drug. The FOPID controller parameters are tuned by Genetic algorithm by taking the cost functions for a sensitive patient, nominal and insensitive model and given in the Tables 3–5.

Fig. 3-5 show the simulation results of MABP response when the controller parameters are optimized by a genetic algorithm. From the figures, it is noticed that the controller satisfies the design requirement by making the reduction of mean arterial blood pressure with smaller settling time, and undershoot for three categories of patients by using integral error criteria. FOPID controllers using genetic algorithm reduce the integral error criterion values such as the integral squared error, the integral time weighted absolute error, and the integral absolute error when compared with IMC based ODF-PI and IMC based TDF-PID (the values are illustrated in Table 6). Reduced values of these parameters reflect FOPID controllers' better disturbance rejection capabilities.

From Table 6-9 it is noticed that by taking the IAE, ISE and ITAE as performance indices, FOPID controllers using genetic algorithms gave good results in terms of settling time and undershoot when compared with PID, IMC, MPC controllers (47) as well as SSA and BFO algorithms (48). Despite the results showing that the performance criteria are met with the cost function, the settling time was shorter for the sensitive patient when using the ISE cost function, while it was shorter for the nominal patient and insensitive patient when using the cost function (ITAE). In addition to settling time, undershoot is also evaluated compared to the previously evaluated controllers. As compared to nominal, insensitive, and sensitive patients, sensitive patients settle quicker.

Fig. 6-8 shows a graph between absolute sensitivity and frequency

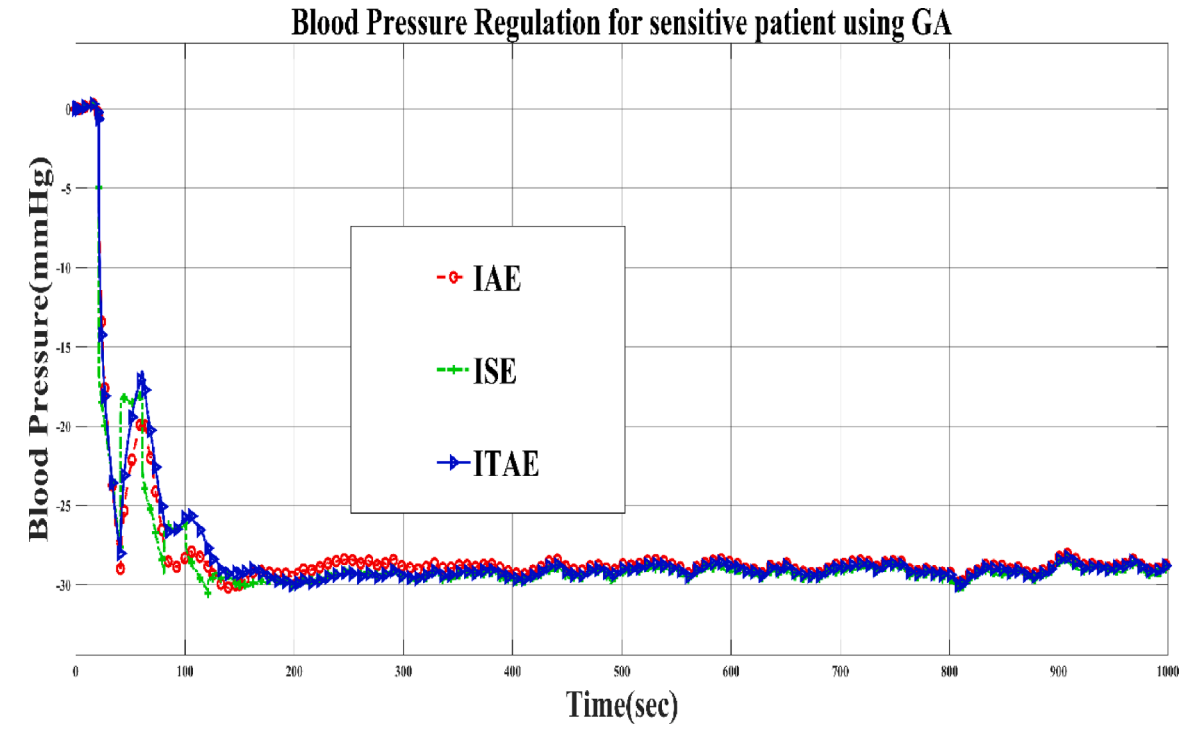

Fig. 3. Blood pressure regulation for sensitive patient using GA.

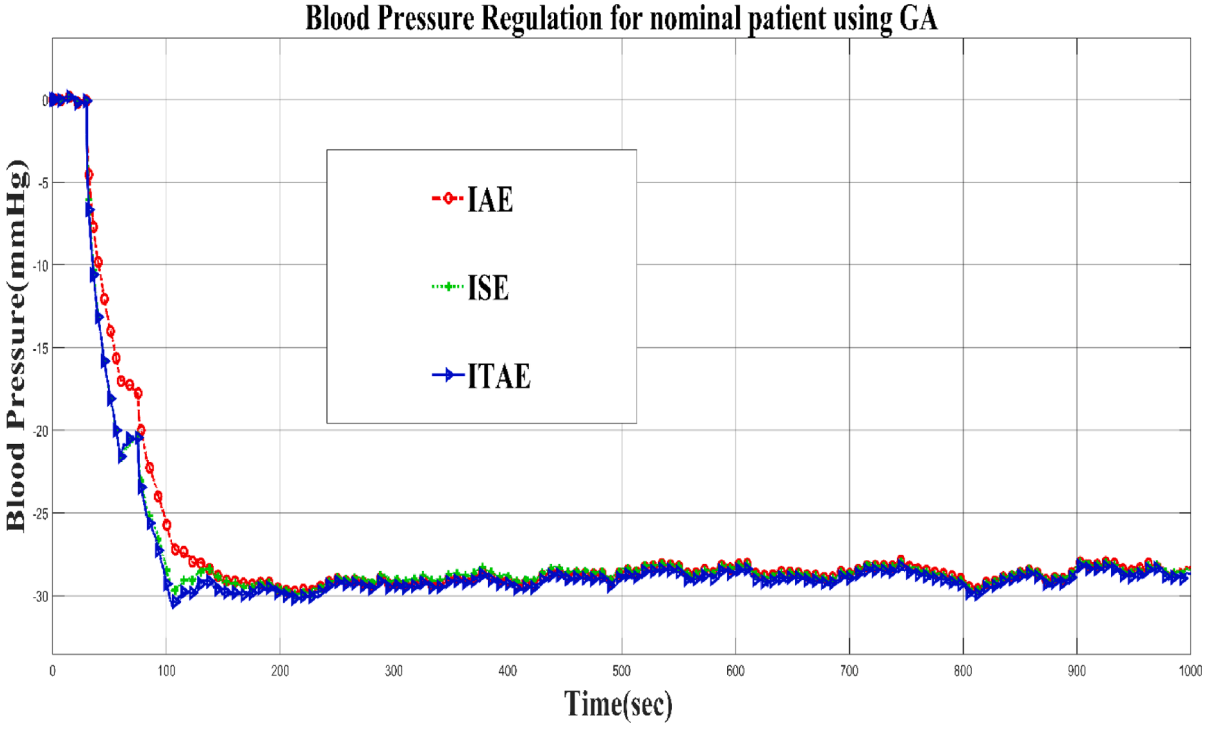

Fig. 4. Blood pressure regulation nominal patient using GA.

(rad/sec). The analysis of Fig. 6 reveals that the highest sensitivity is 2, achieved when optimizing the cost function for ITAE, while the least sensitivity of 1.48 occurs when utilizing the cost function for ISE. Similarly, Fig. 7 demonstrates a maximum sensitivity of 2.09 for the ISE cost function, and a minimum sensitivity of 1.42 for the cost function involving IAE. Observations from Fig. 8 highlight a maximum sensitivity of 1.48 for ITAE cost function, and a minimum sensitivity of 1.45 for ISE cost function. A higher value of "M_S" indicates that the system exhibits greater amplification of input disturbances and parameter uncertainties. Notably, when applying Genetic Algorithm (GA) to optimize the FOPID controller parameters across all cost functions, the maximum sensitivity falls within the range of 1.4 to 2. which indicates the system is more stable and robust in nature.

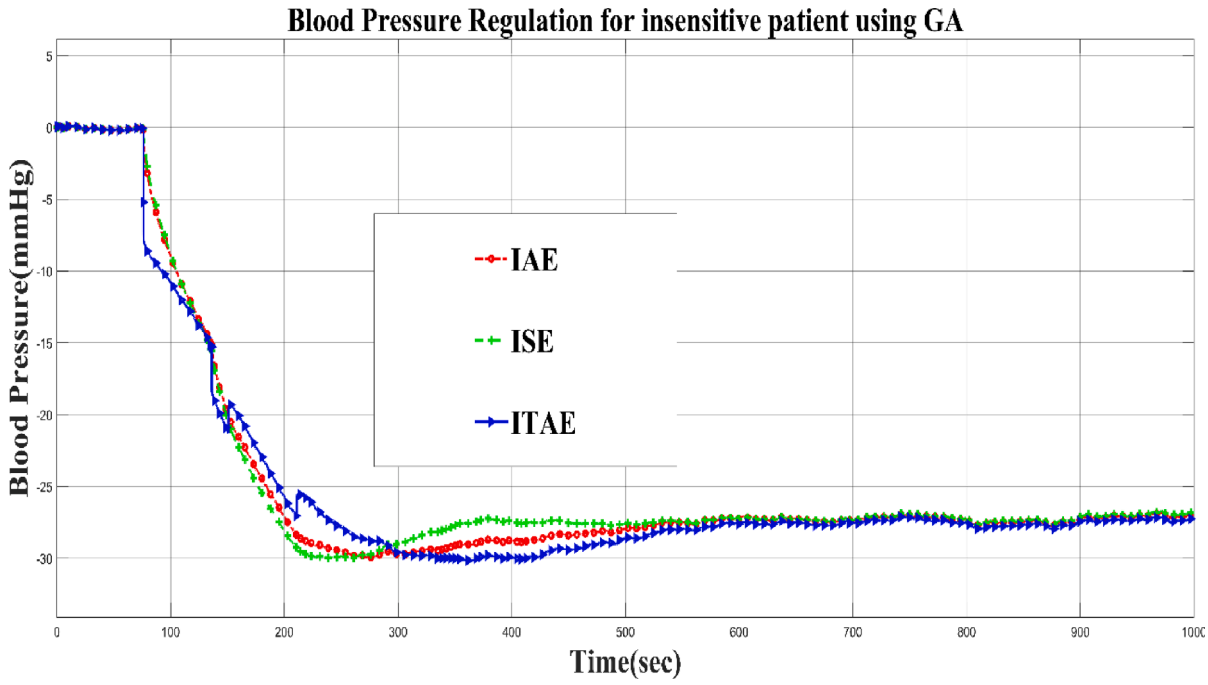

Fig. 5. Blood pressure regulation for insensitive patient using GA.

Table 6
Performance indices for patient model.

Controller	Sensitive patient			Nominal patient			Insensitive patient		
	IAE ($\times 10^3$)	ITAE ($\times 10^6$)	ISE ($\times 10^5$)	IAE ($\times 10^3$	ITAE ($\times 10^6$)	ISE ($\times 10^5$)	IAE ($\times 10^3$)	ITAE ($\times 10^6$)	ISE ($\times 10^5$)
IMC-based ODF-PI [27]	4.22	1.216	0.626	3.729	1.20	0.645	5.821	1.666	1.033
IMC-based TDF-PID [27]	7.26	1.959	1.23	6.16	1.55	1.183	9.3	2.893	1.707
PI-ID(SSA) [48]	3.9	0.692	0.768	6.6	1.14	1.34	11	2.95	2.4
PI-ID(BFO) [48]	3.7	0.473	0.717	6.98	1.38	1.34	11.3	2.96	2.43
FOPID (genetic algorithm)	2.1	0.5	0.238	2.9	0.0011	0.32	5.6	1.28	1.016

Table 7
Comparison of FOPID controller with other controllers for sensitive patient.

Controller	Settling time(sec)	Undershoot(mmHg)
PID [47]	1024	0.429
IMC [47]	738	0
MPC [47]	526	0
PI-ID(SSA) [48]	240	0
PI-ID(BFO) [48]	240	0
FOPID(GA)(IAE)	165	0
FOPID(GA)(ISE)	160	0
FOPID(GA)(ITAE)	190	0

Table 8
Comparison of FOPID controller with other controllers for nominal patient.

Controller	Settling time(sec)	Undershoot(mmHg)
PID [47]	948	0
IMC [47]	738	0
MPC [47]	716	0
PI-ID(SSA) [48]	450	0
PI-ID(BFO) [48]	448	0
FOPID(GA)(IAE)	235	0
FOPID(GA)(ISE)	250	0
FOPID(GA)(ITAE)	205	0

Table 9
Comparison of FOPID controller with other controllers for insensitive patient.

Controller	Settling time(sec)	Undershoot(mmHg)
PID [47]	858	0
IMC [47]	826	0
MPC [47]	816	0
PI-ID(SSA) [48]	770	0
PI-ID(BFO) [48]	850	0
FOPID(GA)(IAE)	492	0
FOPID(GA)(ISE)	450	0
FOPID(GA)(ITAE)	400	0

3.2. Performance analysis

In order to observe the controller's overall performance, the performance indices IAE, ITAE, and ISE, as well as the settling time and undershoot must be calculated. FOPID controller using genetic algorithm has a smaller settling time and undershoot over other controllers [47–48]. Table [6] shows the performance indices of the proposed FOPID controller using the Genetic algorithm, IMC-based ODF-PI, IMC-based TDF-PID, PI-ID(SSA), and PI-ID(BFO). Table 10 outlines the sensitive analysis of the FOPID controller using a Genetic Algorithm. Based on the observation of the different integral error criterion values between the proposed FOPID, IMC-PI, IMC-PID, PI-ID(SSA), and PI-ID (BFO) controllers found that the FOPID controller provides improved performance over the existing controller. Hence, a controller capable of delivering good disturbance rejection and optimum performance for

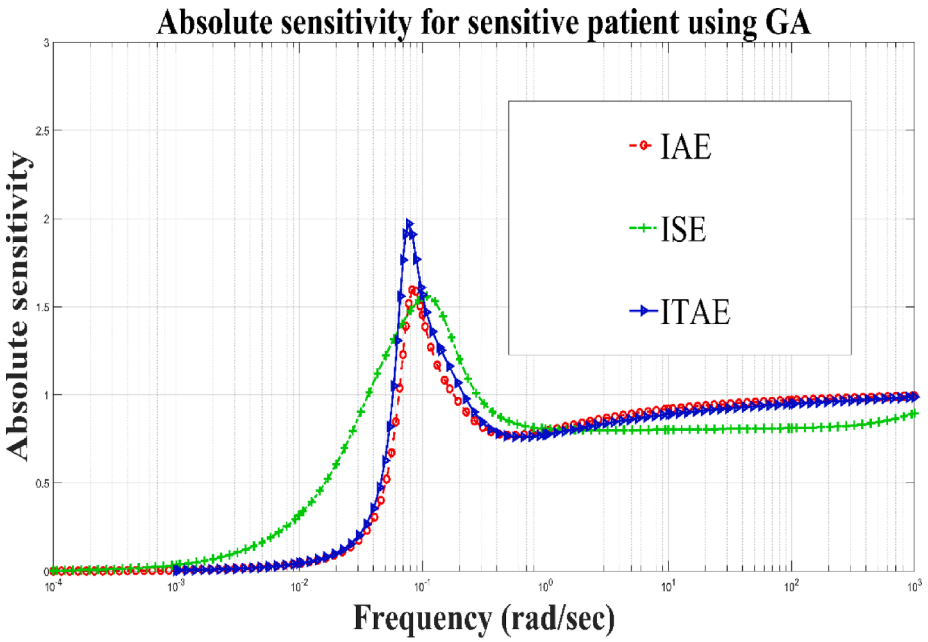

Fig. 6. Absolute sensitivity of sensitive patient using GA.

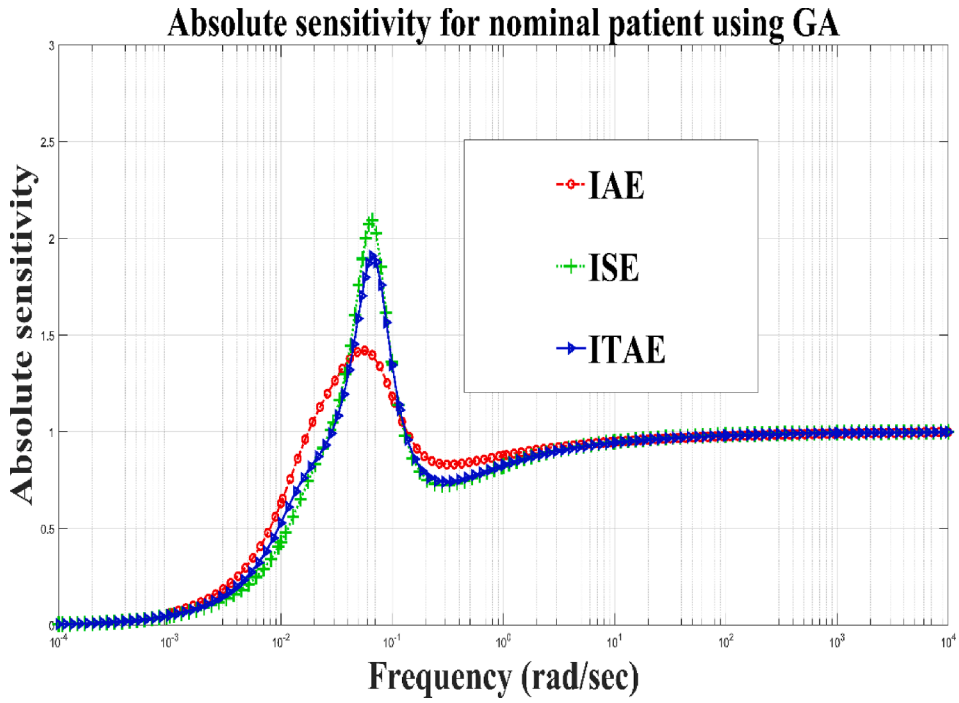

Fig. 7. Absolute sensitivity of nominal patient using GA.

three categories of patients has been successfully developed.

4. Conclusions

This paper uses a FOPID controller to control the blood pressure of three different patient models. In order to achieve the closed loop performance criteria, The FOPID controller with the genetic algorithm improves performance indices, settling time and undershoot when compared with other controllers and algorithms, In comparison to PID, IMC, MPC, SSA(PI-ID), and BFA(PI-ID) algorithms there is a reduction in the settling time by 540 %, 361 %, 220.4 %, 50 %, and 50 % for sensitive patients, a reduction in the settling time by 362 %, 261 %, 249.4 %, 119.5 %, and 118.5 % for nominal patients, and a reduction in the settling time by 114.5 %, 1065 %, 104.4 %, 92 %, and 112.5 % for insensitive patients. Additionally, the maximum sensitivity is within the range of 1.4 to 2 across all three patient categories indicates the FOPID controller's stability and robustness against patient model variations. This paper focus on SISO model to regulate blood pressure in hypertensive patients using SNP (Sodium Nitroprusside) infusion. However, it acknowledges the potential impact of SNP on other parameters, such as cardiac output. To address this limitation, future research aims to develop a MIMO (Multiple-Input Multiple-Output) model through experimental investigations under the guidance of expert doctors and hospital management based on the outcomes and results, aiming to

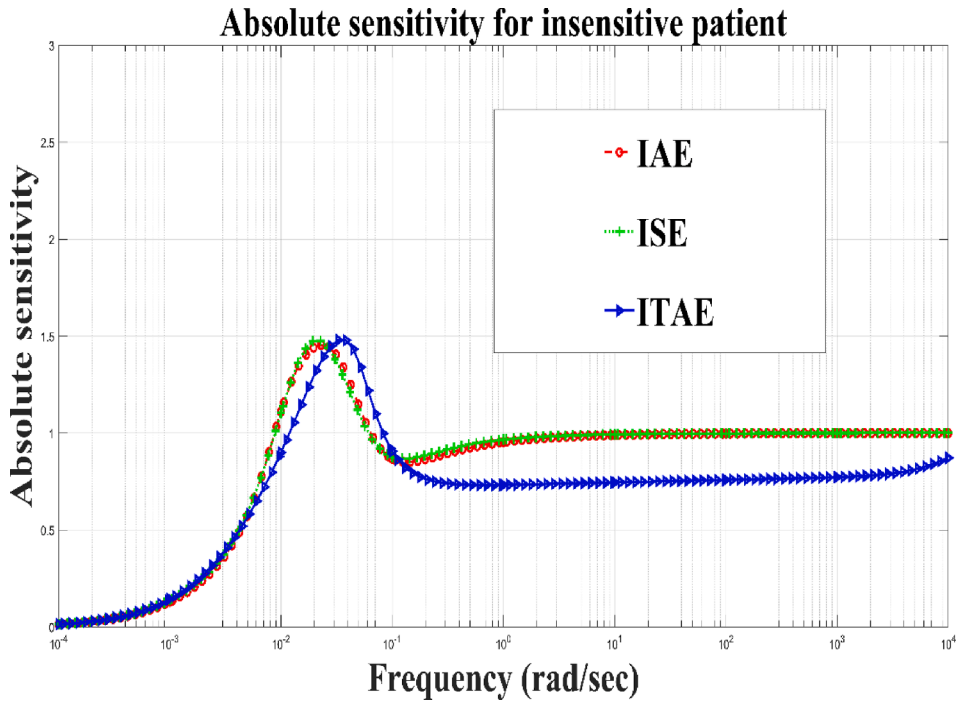

Fig. 8. Absolute sensitivity of insensitive patient using GA.

Table 10
Maximum sensitivity for three different types of patients using GA.

GA using cost functions	Maximum sensitivity in Blood Pressure Regulation		
	Sensitive patient	Nominal patient	Insensitive patient
IAE	1.5	1.42	1.46
ISE	1.48	2.09	1.45
ITAE	2	1.9	1.48

simultaneously regulate both blood pressure and cardiac output.

CRediT authorship contribution statement

P. Siva Krishna: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization, Project administration, Funding acquisition. **P.V. Gopi Krishna Rao:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Project administration, Visualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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