

Simulation-Based Performance Optimization of a Respiratory System via PID and FOPID Controllers

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Abstract

Developing artificial breathing machines is crucial in respiratory care, especially for people whose lungs are working poorly. This paper looks at building a math model and computer simulation of a device that tries to mimic normal breathing. The model integrates important lung characteristics such as compliance and resistance to the dynamics of real patient breathing. The initial round of verification tests attempts to validate the system's response to an ideal input, which allows an assessment baseline for future evaluations. In an effort to improve set-point stability and minimize the effect of disturbances, a PID and FOPID controller were employed on the airflow and pressure control system. In addition, the parameters of PID and FOPID controllers are tuned using PSO and Genetic Algorithms. Results from the assessment indicate that PSO performs better with less error proportional to the power of the simpler PID controllers while explaining more of the system variance. On the other hand, the addition of fractional-order terms to FOPID controllers arms them with greater precision and flexibility, and that is where GA is the most effective. Under the considered operating conditions and evaluation metrics, the FOPID controllers achieve lower error than the PID controllers, indicating the potential of fractional-order control for modeling and regulating the respiratory system.

Keywords

Genetic algorithm, particle-Swarm optimization, respiratory system, FOPID, PID, MATLAB

1. Introduction

In order to understand human respiratory mechanics and support the design of safer, more effective ventilators, researchers commonly rely on mathematical modeling and simulation to reproduce key physiological behaviors such as lung compliance, airway resistance, and the resulting pressure–flow–volume dynamics (Živčák et al., 2021). These models provide a practical, low-risk environment to evaluate ventilator concepts, compare control strategies, and study how patient-specific variations and external disturbances can affect stability and performance an increasingly important need as ventilatory support is tailored to individual patients and scaled for emergency scenarios (Tishin et al., 2019). Prior studies have demonstrated the value of simulation-driven respiratory control, including fuzzy logic and adaptive approaches for oxygen-flow and pressure regulation, as well as neuro-fuzzy and variable-gain strategies that improve tracking accuracy and robustness under changing conditions (Jaber et al., 2020), while practical implementation considerations and adaptive compensation for nonlinearities and delays have also been highlighted (Sanpanich et al., 2019) (Elmaati et al., 2018). Building on this foundation, this work develops a simulation-based respiratory system model intended to emulate realistic breathing dynamics and then enhances closed-loop performance by applying PID and fractional-order PID (FOPID) control, with controller parameters tuned using Particle Swarm Optimization and Genetic Algorithms to reduce disturbance effects and improve set-point tracking (Hunnekens et al., 2018) (Naskar et al., 2023).

1.1 Research Objectives

- Analyze breathing dynamics (pressure, volume, flow) to characterize system performance.
- Simulate prototypes to evaluate performance before clinical trials.
- Validate clinical protocols using simulation to ensure safety and efficacy in practice.

2. Methods

2.1. Model Description

Figure 1 outlines the mechanics of the lung breaking it down into the main and side airways with their own resistances R_c and R_p . It shows how air that gets to the alveoli makes the chest space bigger by stretching the lung C_L , and the chest wall C_w , which have their own stretchiness and are aligned one after the other. Some air doesn't reach the alveoli due to the stretchiness of the main airways and how squishy the gas is., this side-route air is a tiny bit, but it gets bigger if you've got stuff like blocked pathways (that means more R_p) or if the lung or chest wall isn't as stretchy (lowered C_L or C_w). To handle this, they include a side-route stretchiness C_s along with C_L and C_w .

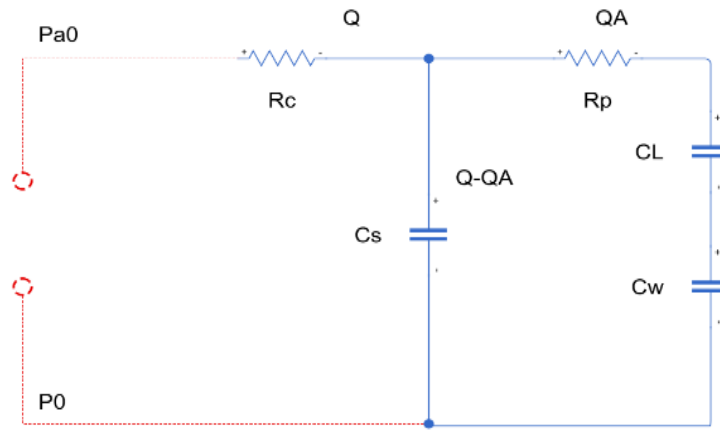


Figure 1. Equivalent electrical circuit of the physical system

2.2. Mathematical representation of the artificial respiratory system

Kirchhoff's laws help establish a mathematical relationship between P_{ao} and Q , with the shunted flow determined by compliance and resistances across the circuit.

$$R_p Q_A + \left(\frac{1}{C_L} + \frac{1}{C_W}\right) \int Q_A dt = \frac{1}{C_S} \int (Q - Q_A) dt \quad (1)$$

Applying Kirchhoff's First Law to the circuit containing R_c and C_s , we have,

$$P_{ao} = R_c Q + \frac{1}{C_s} \int (Q - Q_A) dt \quad (2)$$

Differentiating Equation (1) and Equation (2) with respect to time, and then combining the two equations to one by eliminating Q_A' we get the equation relates P_{ao} to Q :

$$\frac{d^2 P_{ao}}{dt^2} + \frac{1}{R_p C_T} \frac{dP_{ao}}{dt} = R_c \frac{d^2 Q}{dt^2} + \left(\frac{1}{C_S} + \frac{R_c}{R_p C_T}\right) \frac{dQ}{dt} + \frac{1}{R_p C_S} \left(\frac{1}{C_L} + \frac{1}{C_W}\right) Q \quad (3)$$

where C_T is defined by,

$$C_T = \left(\frac{1}{C_L} + \frac{1}{C_W} + \frac{1}{C_S}\right)^{-1} \quad (4)$$

The artificial breathing system was based on different work by (Sheltag & Kadhim, 2024) and (Al-Khalisy et al., 2024), with some modifications and extensions in order to build a closer model to our physical system. The model contains the parameters shown in the following Table 1:

Table 1. Parameters of the Respiratory System Model.

Parameters	
C _L	Lung Compliance
C _w	Chest-wall Compliance
C _s	Spring Compliance
R _p	Peripheral Airway
R _c	Central Airway
P _m	Pressure applied by the ventilator
Q	Airflow rate

P_{ao} and P_a represent, respectively, the pressure at the airway opening and atmospheric pressure. As described before, R is the lung resistance, and C is the lung compliance. The transfer function of this model is obtained from equation (5)

$$TF = \frac{s^2 + \frac{1}{R_p * \left(\frac{1}{C_T}\right)} s}{R_c s^2 + \left(\frac{1}{C_c} + \frac{R_c}{R_p * \left(\frac{1}{C_T}\right)}\right) s + \frac{1}{R_p * C_c} * \left(\frac{1}{C_c} + \frac{1}{C_w}\right)} \quad (5)$$

Let's assume this patient has typical mechanics. The pulmonary parameters are as follows: R_c = 1 cmH₂O sL⁻¹, R_p = 0.5 cmH₂O sL⁻¹, C_L = 0.2 L cmH₂O⁻¹, C_w = 0.2 L cmH₂O⁻¹, and C_s = 0.005 L cmH₂O⁻¹. We can tackle this problem in two ways. The first, and most direct, approach is to get the transfer function for the whole system and then use it as a single "block" in the SIMULINK program. With respect to the values for the variables mentioned above, after taking the Laplace transform of the differential equation, this is the expression we arrive at after rearranging some of the terms.:

$$TF = \frac{s^2 + 420 s}{s^2 + 620 s + 4000} \quad (6)$$

The respiratory system model's transfer function is converted to state-space form to aid system dynamic analysis and controller design.

$$\dot{X} = \begin{bmatrix} 0 & 1 \\ -4000 & -620 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} P_{ao}(t) \quad (7)$$

$$C = [0 \quad 420] \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} Q(t) \quad (8)$$

3. Lyapunov Stability

Lyapunov equation for a continuous system is given by:

$$A^T P + P A = -Q \quad (9)$$

- A is the state matrix of the system.
- P is the solution matrix that we need to determine.
- Q is a positive definite matrix (usually chosen as the identity matrix I for simplicity).

For stability, the solution P must also be **positive definite** (all eigenvalues of PPP must be positive). For the given problem:

$$A = \begin{bmatrix} 0 & 1 \\ -4000 & -620 \end{bmatrix} \quad (10)$$

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (11)$$

Expanding the Lyapunov equation for PPP, we assume:

$$\mathbf{P} = \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \quad (12)$$

And calculate:

$$\mathbf{A}^T = \begin{bmatrix} 0 & -4000 \\ 1 & -620 \end{bmatrix} \quad (13)$$

Now, substituting P, A, and Q into the Lyapunov equation

$$\begin{bmatrix} 0 & -4000 \\ 1 & -620 \end{bmatrix} \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} + \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \begin{bmatrix} 0 & 1 \\ -4000 & -620 \end{bmatrix} = - \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (14)$$

The solution for P is,

$$\mathbf{P} = \begin{bmatrix} 3.3041 & 0.000125 \\ 0.000125 & 0.0008067 \end{bmatrix} \quad (15)$$

Eigenvalues of P: Both are positive, confirming P is positive definite. The system is **stable** based on Lyapunov's stability criterion.

4. PID Controller

In lung mechanics, PID controllers are often implemented to keep airway pressure within a range for stable and healthy breathing. These controllers reduce error between the desired and actual pressure for precise airflow control, mitigating ventilator output. A Closed-Loop PID Control System is shown in Figure 2, where $r(t)$ is the set point, $e(t)$ is the error, $u(t)$ is the control action (PWM signal sent to the motor), and $y(t)$ is the output, which is measured. This system configuration enables both volume control and pressure control modes.

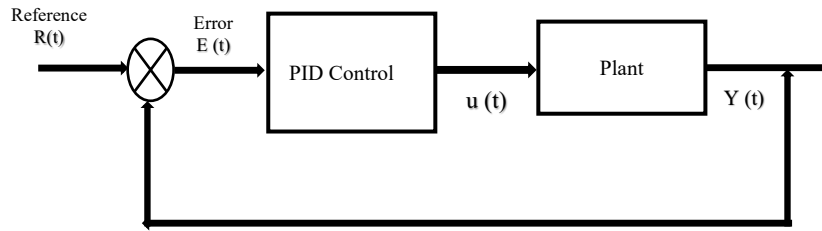


Figure 2. PID block diagram with respiratory system

The output of a PID controller, which is fed into the system as the manipulated variable input, is calculated in the time domain as follows:

$$U(t) = K_p e(t) + K_i \int_0^t e(t) dt + K_d \dot{e}(t) \quad (16)$$

The transfer function of the controller in the frequency domain is as follows:

$$C(s) = K_p + \frac{K_i}{s} + K_d s \quad (17)$$

5. FOPID Controller

A Fractional-Order PID (FOPID) controller, also known as a **PI^λD^μ** controller, generalizes the classical PID by introducing fractional powers for the integral and derivative terms. The FOPID controller provides more flexibility and robustness in system control. The FOPID control law is given as:

$$u(t) = K_p e(t) + K_i D_t^{-\lambda} e(t) + K_d D_t^{\mu} e(t) \quad (18)$$

The fractional orders λ and μ are typically non-integer values, giving the controller its flexibility (Figure 3).

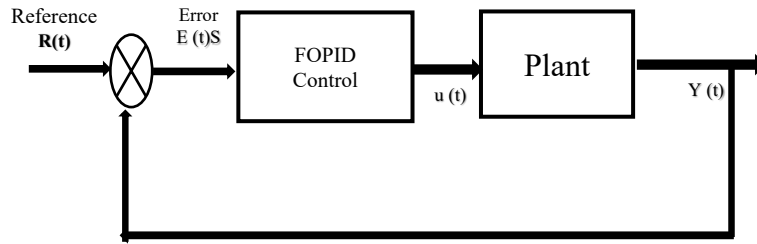


Figure 3. FOPID block diagram with respiratory system

6. Result

The experiments were performed in Matlab/Simulink. The Simulink model in Figure 4 captures the mechanics of a respiratory system under ventilatory support using contingent airway pressure, airflow, and lung volume. The ventilator's Paw signal influences Q and the volumetric activity of the system. R_c captures airway resistance and C_s , C_L , and C_w captures lung compliance together used to model the elastic and resistive components of the respiratory system. The pressure, flow, and volume models are derived system outputs 'captured and processed' for time-dependent respiratory analysis. The model serves in studying the patient condition, ventilatory settings and simulating pathological ventilatory conditions for clinical education and user training (Figure 4).

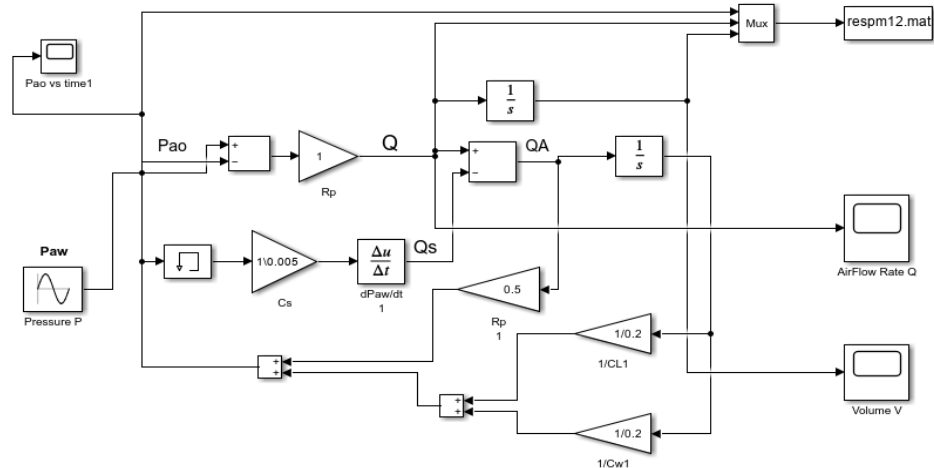


Figure 4. Simulink Model of Respiratory System

Now, introduce changes to the ideal lung model which will allow you to analyze the system more critically. These changes attempt to model variations in compliance, changes in resistance, or other factors extrinsic to the act of mechanical ventilation. With the inclusion of the disturbance signals, it may also be possible to study the system's stability and robustness so as to offer insights into the workings of this model under real-world, non-ideal configurations. This comparison with the ideal response will bring forward the limitations of the system and address the way to further improvements (Figure 5).

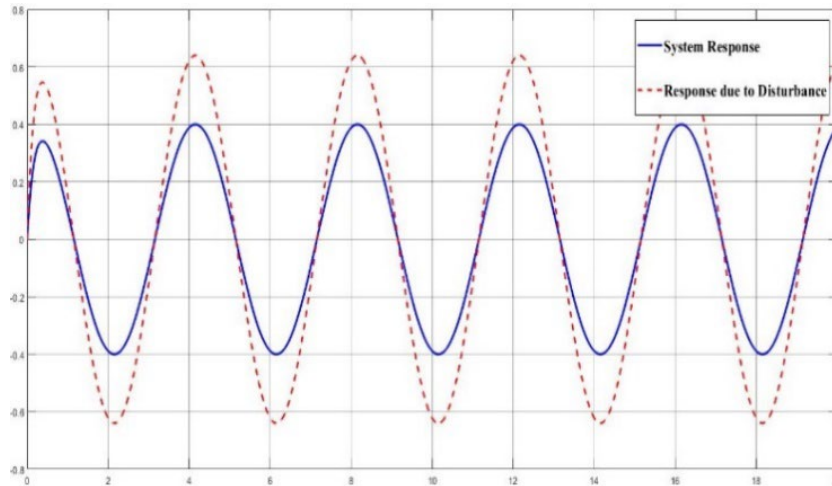


Figure 5. System Response with and without Disturbance

6.1. Implementation and Optimization of a FOPID and PID-Controller Parameters

To minimize disturbances and optimize airflow and pressure dynamics, a PID controller was installed. This approach specifically addresses the performance of a PID controller for strong and agile systems.

6.1.1. Optimizing the PID-Controller Parameters and Minimizing the error using GA and PSO

Methodologies such as GA and PSO derive their principles from nature, with the goal of optimizing the parameters of PID controller. GA applies evolutionary principles of selection, crossover, and mutation, while PSO model's social behavior and has particles modify their position based on individual and collective history. In both cases, a defined fitness function is utilized to optimize PID gains (K_p , K_i , K_d) and enhance control accuracy (Figure 6).

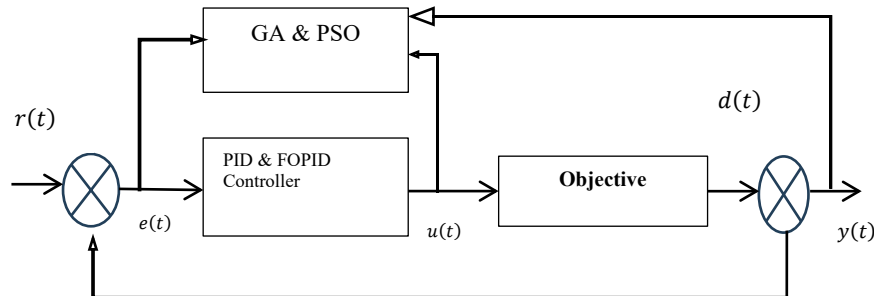


Figure 6. Block diagram of PID controller tuning using GA and PSO

In Figure 7 The model performs well as the predicted output (red dashed) is closely tracking the actual output (blue). The model predicted an MSE value of 0.00360, a MAE of 0.05390, and R^2 of 0.9547 which indicates high precision and low error. There are areas of slight overshoot during the top oscillation that can be improved upon further.

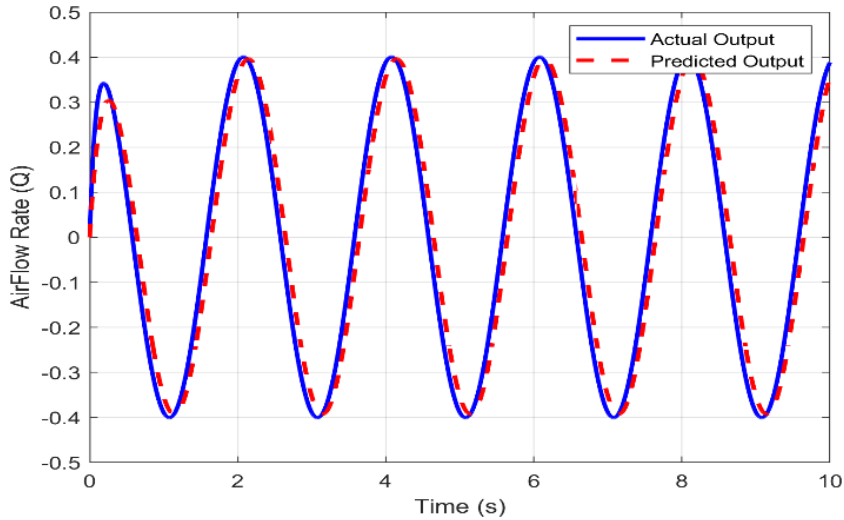


Figure 7. System Response due to GA Optimization of PID Parameter

Figure 8 shows that the PID parameters have been refined with Particle Swarm Optimization (PSO). Performance metrics MSE of 0.0002, MAE of 0.0051, and R^2 of 0.9777 confirm that PSO tuning improves tracking accuracy and better captures the system dynamics under the adopted fitness metrics.

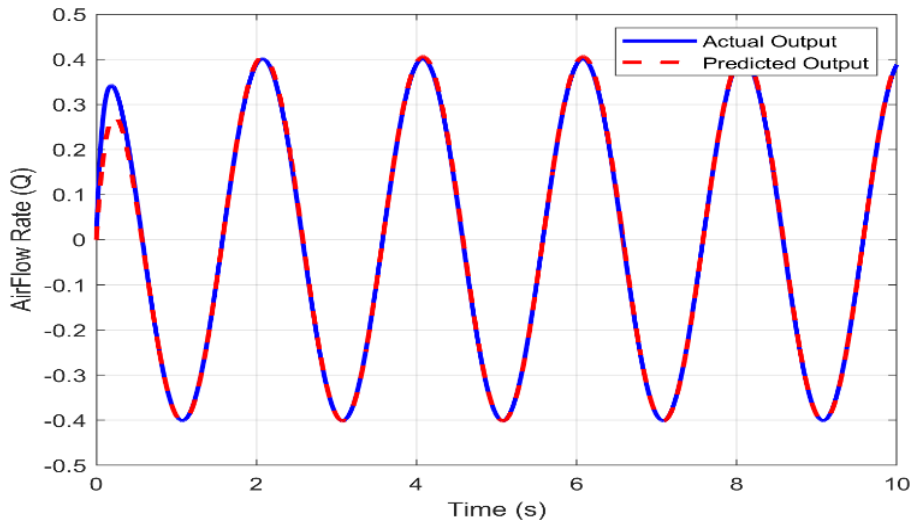


Figure 8. System Response due to PSO Optimization of PID Parameters

6.1.2. Optimizing the FOPID-Controller Parameters and Minimizing the error using GA and PSO

As seen in Figure 9, the application of Genetic Algorithm (GA) for FOPID controller tuning proves to be quite effective. High accuracy is achieved as the predicted output is almost perfectly matched with the actual output. The controller obtains a very low MSE of 0.0001789 alongside an impressive R^2 value of 0.99801. Also, GA performs approximately 99.77% of the output variance. These observations assert that GA optimally performed the FOPID parameter tuning needed for accurate and reliable control

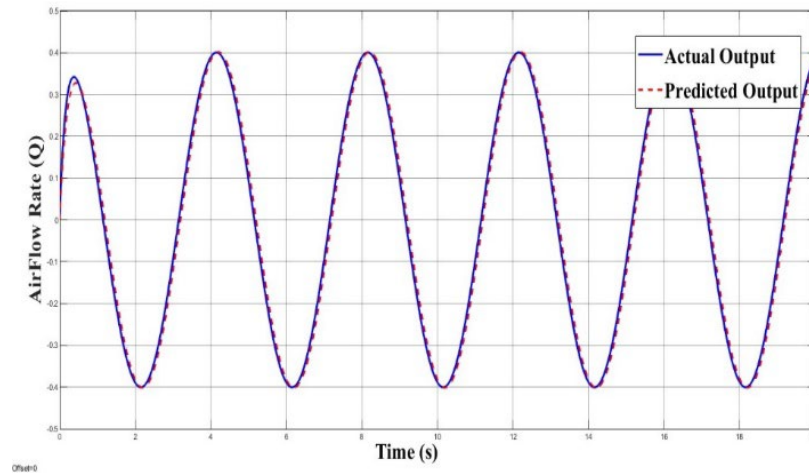


Figure 9. System Response due to GA Optimization of FOPID Parameters

As illustrated in Figure 10, the application of PSO in fine-tuning the FOPID controller has minimized the performance gap between the predicted red output and the actual blue output improving the overall system performance. As noted above, PSO performed with an MSE of 0.0004789 and R^2 of 0.9670 which is significantly accurate. Although PSO is not as precise as the genetic algorithm-based approach, it is still a well optimized and useful method in the problem domain of complex system FOPID controller tuning

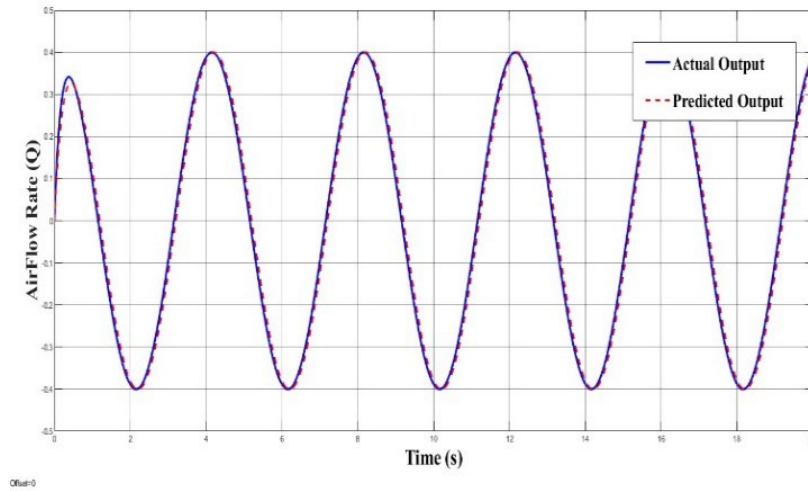


Figure 10. System Response due to PSO Optimization of FOPID Parameters

The two tables provide a comparative analysis of PID and FOPID controller parameter optimization using Genetic Algorithm (GA) in Table 2 and Particle Swarm Optimization (PSO) in Table 3. Both methods aim to optimize the controller parameters for achieving better control performance, and the differences in the results highlight the capabilities and characteristics of the two optimization techniques (Table 3).

Table 2. Comparative analysis between PID and FOPID parameters optimization using GA.

Controller	Kp	Kd	Ki	μ	λ
PID Controller	9.2557×10^{-6}	0.533860	0.022137	1	1
FOPID Controller	0.499	0.0095	0.003214	0.09876	0.0099

Table 3. Comparative analysis between PID and FOPID parameters optimization using PSO.

Controller	Kp	Kd	Ki	μ	λ
PID Controller	0.347030	0.534750	0.025114	1	1
FOPID Controller	0.5	0.009	0.022347	0.09877	0.0093

In Table 4, we compare GA and PSO for tuning PID and FOPID controllers using MSE and R². For the PID case, PSO achieved lower MSE and higher R² than GA (0.000200 vs 0.0036010 and 0.99770 vs 0.95471, respectively). For the FOPID case, GA achieved lower MSE and higher R² than PSO (0.0001789 vs 0.0004789 and 0.99801 vs 0.9670, respectively). These results indicate that, for the studied configuration and selected metrics, PSO is more effective for PID tuning, while GA is more effective for FOPID tuning. Because GA and PSO are stochastic metaheuristics, the reported values correspond to a representative run under fixed settings; a full robustness assessment based on multiple independent runs (e.g., mean \pm standard deviation) is left for future work.

Table 4. Performance of GA and PSO in optimizing the parameters of PID and FOPID controllers.

Controller	MSE (GA)	R ² (GA)	MSE (PSO)	R ² (PSO)
PID Controller	0.0036010	0.95471	0.000200	0.99770
FOPID Controller	0.0001789	0.99801	0.0004789	0.9670

7. Conclusion

This research focuses on modeling and control systems within respiratory systems, particularly when external factors interfere. Simulations of the perfect response to respiration showed a baseline, while disturbances demonstrated increased oscillation and sluggish recovery highlighting control needs. Assignment of PID and FOPID controllers made system responses converge to the ideal far better than previously possible; as with any self-regulating systems, proportional, integral, and derivative actions ensured a constant and even output. The Simulink model allowed to obtain the capture of the systems of pressure, volume, and flow, which illustrated how much control could aid in strengthening weak systems. Their approach is consistent with more recent work and justifies further advanced research on optimization and adaptive control strategies in biomedicine. Finally, since GA and PSO are stochastic, the comparative findings should be interpreted as configuration-dependent; future work will report statistical results over multiple runs and additional performance indices to quantify robustness.

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