RESEARCH PAPER

Hybrid Optimization based Controllers for Auto Respiration System for Patients

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Abstract— Artificial ventilation is frequently implemented to address a variety of respiratory conditions in humans. Smooth respiration necessitates the maintenance of the oxygen level in corona patients, a task that is exceedingly challenging. In order to achieve this state, the respiration system, which is powered by a motor and features a piston mechanism, must regulate air pressure. Hybrid optimization techniques are employed to optimize controller parameters and develop an automatic respiration system model. Hybrid Fminsearch Simulated Annealing-based PID controller and hybrid Ant Colony Optimization-Genetic Algorithm-based PID controller with ISE, IAE, and ITAE as objective functions were implemented to create a stable controller. The Ant Colony Optimization - Genetic Algorithm based PID controller with ITAE as the objective function achieves a superior outcome when the time domain and error indices are compared.

Keywords—Auto Respiration system, hybrid optimization, Ant Colony Optimization (ACO), Genetic Algorithm (GA), Fminsearch Algorithm, Simulated Annealing Algorithm

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I. INTRODUCTION

An automated respiratory system, or auto respiration system, is a medical device or system that is intended to assist or completely replace the breathing process for patients who are unable to breathe adequately on their own. These systems are essential in a variety of healthcare environments, including intensive care units (ICUs), surgery, and patients with chronic respiratory conditions. The fundamental component of mechanical ventilation is the ventilator, which delivers air (and frequently a combination of gases, including oxygen) to the patient's lungs. Ventilators can be configured to operate in a variety of modes to accommodate the patient's requirements, including volume control, pressure control, and spontaneous breathing modes. Numerous characteristics are tracked by sensors, including as oxygen levels (SpO2), tidal volume, respiratory rate, and airway pressure. Because of ongoing monitoring, the system can automatically modify parameters to ensure the best possible respiratory assistance [1]. Advanced control systems use feedback loops and algorithms to change the ventilator settings in real-time based on the patient's respiratory condition. This could entail adjustments to the volume of oxygen administered, the pressure, and the pace of breathing. Auto respiration systems have a crucial role in the treatment of patients suffering from neuromuscular disorders, acute respiratory distress syndrome (ARDS), chronic obstructive pulmonary disease (COPD), and during surgical operations involving anesthesia. Technological breakthroughs continuously improve these devices' operation, safety, and patient results [2].

By using positive pressure to get oxygen into the lungs, the device helps patients. The tidal volume (the amount of air provided with each inhalation) and the number of breaths per minute can both be adjusted to meet the specific needs of the patient. The patient's breathing characteristics are continuously monitored by the system, which allows it to make real-time modifications to the ventilation settings. This ensures that the patient gets the right amount of oxygen and that the concentration of carbon dioxide stays within a safe range.

A swarm-based optimization method is being used to optimize the complex response of the pressure-regulated artificial ventilation respiratory system. The swarm-based approach is verified with a simple lung device driven by a piston motor. In the future, nevertheless, this technique might be assessed on more intricate human lung auto respiratory systems [3].

The control approaches are implemented using a mechanical ventilator, which helps researchers find new patterns. It has been possible to create both conventional and intelligent control ventilators by utilizing flow, pressure, time, and volume [4].

The Genetic Algorithm (GA) and the Ant Colony Optimization Algorithm (ACO) are two popular approaches for tackling optimization problems. ACO is based on the process of natural evolution, while GA is based on the foraging habits of ant species. The Travelling Salesman Problem (TSP) is intended to be resolved using the composite GA-ACO algorithm known as Genetic Ant Colony Optimization (GACO). Using this method, GA will track and preserve the best ant in every cycle and generation, while ACO will assess just the cities that haven't been visited. According to the trial results, GACO performs better in terms of time complexity and efficacy than both GA and ACO [5].

A novel hybrid optimization method based on a blend of neural networks and genetic algorithms is described. The suggested approach makes use of a back-propagation neural network to improve the genetic algorithm's convergence while it searches for the global optimum. The use of the suggested computational methodology to a wide range of test scenarios demonstrates its effectiveness. The findings show that adding a neural network to the genetic algorithm approach can greatly speed up the genetic algorithm's convergence and improve the quality of the solution in the suggested hybrid strategy [6].

Hybrid Fminsearch Simulated Annealing-based PID controller and hybrid Ant Colony Optimization-Genetic Algorithm-based PID controller with ISE, IAE, and ITAE as objective functions were implemented to create a stable controller. The Ant Colony Optimization - Genetic Algorithm based PID controller with ITAE as the objective function achieves a superior outcome when the time domain and error indices are compared.

II. AUTO RESPIRATION SYSTEM

The patients are continuously monitored by the artificial respiration system, which comprises sensors, displaying apparatus, and a control mechanism [7]. Figure 1 illustrates the fundamental block diagram of the model. The input is the airway pressure that requires regulation, and the output is the desired or controlled pressure.

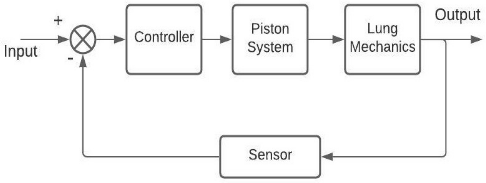

Fig. 1 Block diagram of the auto respiration model

An electric motor has already been installed to power the piston movement. Its primary function is to modulate the airway pressure within the oxygen compartment of the artificial respiration system. The controller modifies oxygen delivery to the alveoli in accordance with the necessary oxygen levels, with an emphasis on precise airway pressure control. Pneumatic resistance and lung capacity are factors that influence airway pressure (Pa). When the gain of the current control loop for the piston drive mechanism is taken into account, the system demonstrates first-order differential characteristics.

The piston system and pulmonary mechanics are the two primary components of the artificial respiration system. The respiratory dynamics are illustrated in Figure 2, which includes the input voltage (V), piston speed (Z), piston drive system output (X), airway pressure (Pa), and load torque (T). The control loop gain, control loop time, field flux, moment of inertia, piston area, friction coefficient, piston drive transmission, pneumatic resistance, and lung storage capacity are all incorporated into the system model [8]. The prototype model of the auto respiration system is depicted in Figure 3.

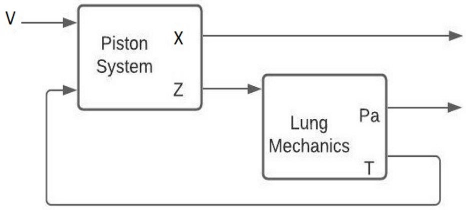

Fig. 2 The dynamics of respiratory mechanics as a system

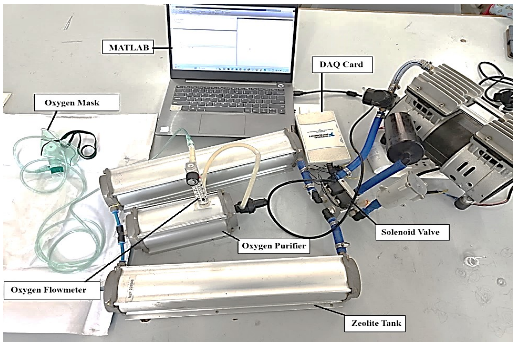

Fig. 3 Auto Respiration System Prototype Mode

The Table 1 represent the symbol used in the respiration system's open loop model.

TABLE I. THE RESPIRATORY SYSTEM'S OPEN LOOP TRANSFER FUNCTION MODEL'S SYMBOL AND VALUES

Symbol	Description	Values
ka	Current control loop Gain	0.368 A/V
Ta	Current control loop Time	9e-5
W	Field flux	2.79 Ncm/A
Jeff	Moment of inertia	0.0032 N cm s2
Apiston	Area of the Piston	1.62 dm2
kr	Coefficient of friction	0.005 N cm/ rad
kg	Transmission	0.4 mm/ rad
Rr	Pneumatic resistance	2 mbar s/l
Cr	Lung Storage capacity	70 ml /mbar
Km	Transfer ratio	0.0391 cm

A first-order differential equation can be employed to express the motor's time constant. Friction is presumed to have a linear relationship in the context of a piston-driven motor system. The applied motor voltage serves as the input variable for the piston-motor propulsion system. Additionally, the piston-motor drive system receives feedback regarding burden torque from the lung system. The torque balance equation is denoted by Equation 1.

$$j_{eff}.\omega = T + \frac{k_a}{1+T_a s}V - w^2\frac{k_a}{1+T_a s}\omega - k_r.\omega \tag{1}$$

where V represents the input voltage, T represents the load torque, ka represents the current control loop gain, Ta represents the current control time constant, kr represents the coefficient of friction, w represents the field flux, and jeff represents the moment of inertia. Equation 2 illustrates the Laplace domain.

$$T = K_m . A_{Piston}^2 . \left(R_r + \frac{1}{C_r . S}\right) . Z \tag{2}$$

The area of the piston is denoted by A_{piston}, the transfer ratio is represented by K_m, the lung storage capacity is represented by C_r, the pneumatic resistance of the lungs is represented by R_r, and the piston speed is represented by Z. When designing an artificial ventilator controller, a patient feedback control cycle is taken into account. The patient's interaction with the system may be regarded as a disturbance. The controller receives the reference signal, which is equivalent to the desired pressure. Figure 4 illustrates the closed-loop concept through the use of a controller in the block diagram.

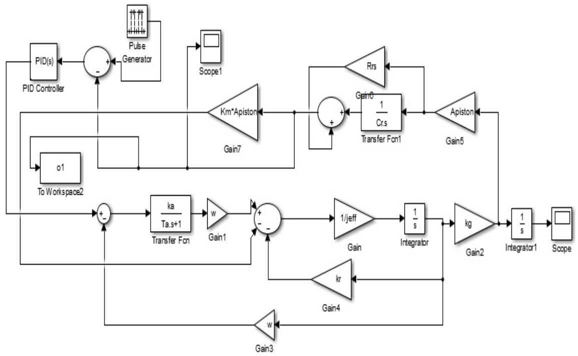

Fig. 4 The closed-loop transfer function model of the respiratory system

The lung parameters are compared to the age in Table 2. The lungs' storage capacity increases as they age, while pneumatic resistance decreases. Here, the Automatic Respiratory System is intended for adults.

TABLE II. THE PARAMETERS OF THE LUNG FOR VARIOUS AGE CATEGORIES

Age groups	Cr ml /mbar	Rr mbar s/l
New Born	3-5	30-50
Infant	10-15	20-30
Kids	20-40	10
Adults	70-100	2-4

III. HYBRID CONTROLLER DESIGN

By optimizing a variety of parameters, hybrid optimization techniques can substantially improve the performance of auto respiration systems, thereby ensuring that patient care is both efficient and effective [8]. The system can effectively adapt to changing patient conditions by dynamically adjusting the ventilator settings in real-time based on patient feedback, with hybrid optimization techniques. These techniques can improve patient outcomes by optimizing settings that are tailored to the unique requirements of each patient, thereby providing more precise and personalized respiratory support [9].

Better performance results from the algorithm being able to alter its behavior to the specific problem at hand due to this adaptive hybridization. ISE, ITAE, IAE are considered as objective function. The block diagram of the hybrid optimization process in shown in figure 5.

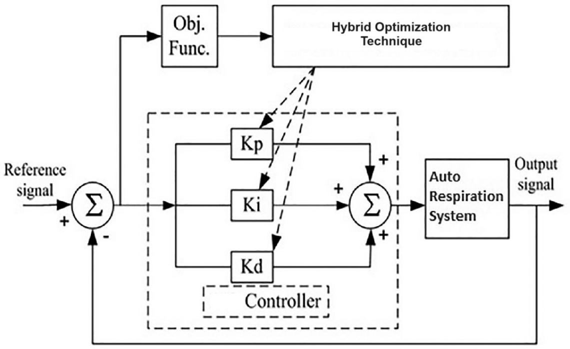

Fig. 5 Block diagram of hybrid optimization for auto respiration system

A. Hybrid Ant Colony Optimization – Genetic Algorithm based FOPID Controller

An auto respiration system can be made to function more effectively and adjust to the patient's respiratory needs by using the Ant Colony Optimization (ACO) to optimize its parameters. Every ant simulates its own auto respiration system with a different set of parameters. Evaluate the performance by taking into account variables including oxygenation levels, CO2 removal effectiveness, and patient comfort [10]. Pheromone concentrations on the insects' routes should be adjusted based on the caliber of the solutions. Pheromone levels are raised for high-performing solutions. Ants use a heuristic function that considers the patient's physiological requirements and pheromone levels to probabilistically determine parameter values. Investigate the parameter space and create new solutions by tracking the traces of pheromones. Proceed with the procedure until an appropriate resolution is achieved or until a pre-established quantity of iterations are finished. Because ACO can tolerate fluctuations and uncertainty in the patient's condition, it is a good fit for managing fluctuating respiratory requirements [11]. It is easy to adapt the algorithm to incorporate other restrictions or goals, including lowering energy usage or limiting patient suffering. To ensure optimal patient care, the auto respiration parameters should be regularly improved.

The output of ACO is sent to the Genetic Algorithm as input. In Figure 6, the flowchart is displayed.

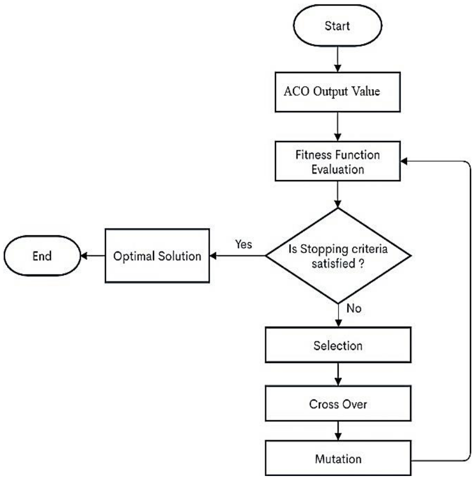

Fig. 6 Hybrid ACO-GA flowchart

Genetic algorithms (GAs) are robust optimization methods that are motivated by the principles of genetics and natural selection [12].

The following procedures are usually involved in developing a hybrid ACO-GA based FOPID controller [13]:

- Clearly state the control problem you're trying to solve. The control objective, performance criteria, constraints, and system dynamics are all identified during this procedure.
- Set the parameters: Type in the initial values for the fractional orders, time constants, and gains of the FOPID controller. These beginning points might be determined by preliminary computations or assumptions.
- Put the Control Algorithm to Use: Create a control algorithm based on GA and ACO. The FOPID controller parameters will be iteratively updated by this algorithm based on the optimization's outcomes.
- Determine an objective function that assesses the effectiveness of the control mechanism. Either this function must be minimized or optimized in order to meet the control objectives. Control system performance metrics like the Integral of Squared Error (ISE), Integral of Absolute Error (IAE), or other suitably chosen performance criteria may be included in the objective function.
- By applying ACO's technique for fractional order optimization, the FOPID controller's fractional orders can be improved. Define the heuristic data and pheromone trails in compliance with the performance requirements of the control system. The search for the best fractional orders will be guided by the ACO algorithm, which mimics the ant's depositing and following of pheromone trails.
- The gains and time constants of the FOPID controller, among other parameters, can be optimized using the GA approach. Create the mutation operators, crossover, selection, and GA population. In order to find the ideal or almost ideal values that minimize the objective function, the GA algorithm will iteratively update the parameter values and create a population of viable solutions.
- The FOPID controller's complete set of parameter values will be obtained by combining the results of the ACO and GA optimizations. Repeat the ACO and GA optimization procedure as required to refine the parameter values.
- Control Performance Assessment: Utilize the tuned FOPID controller settings to evaluate the control performance following the completion of optimization. Simulate the control system or conduct real-time experiments to assess the system's response to a variety of setpoints and disruptions. Compare the control performance metrics with the intended objectives to verify the effectiveness of the hybrid ACO-GA based FOPID controller.
- Iteration and fine-tuning: If the control performance is unsatisfactory, it may be necessary to review the control problem specification or modify the parameters. This iterative procedure can be employed to enhance the controller until the desired control objectives are achieved.

The response of the hybrid ACO-GA based FOPID controller for auto respiration system with objective functions as ISE, ITAE, IAE is shown in Figure 7, 8 and 9 respectively. Hybrid optimization techniques significantly enhance the performance of auto respiration systems by combining the strengths of multiple optimization methods [14]. The error indices are calculated to find which objective function gives better results for the ACO-GA based FOPID controller for the auto respiration system.

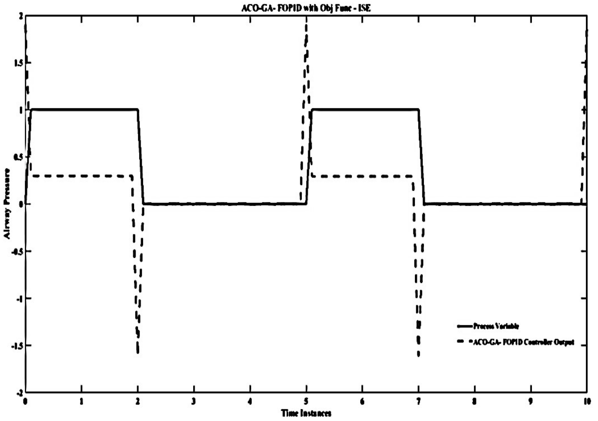

Fig. 7 Response of a hybrid ACO-GA-based FOPID controller for an auto-respiration system with ISE as an objective function

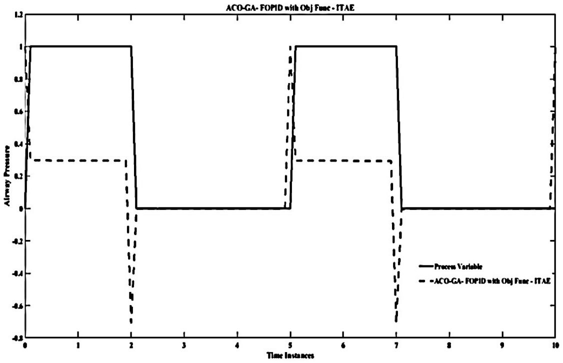

Fig.8 Response of a hybrid ACO-GA-based FOPID controller for an auto-respiration system with ITAE as an objective function

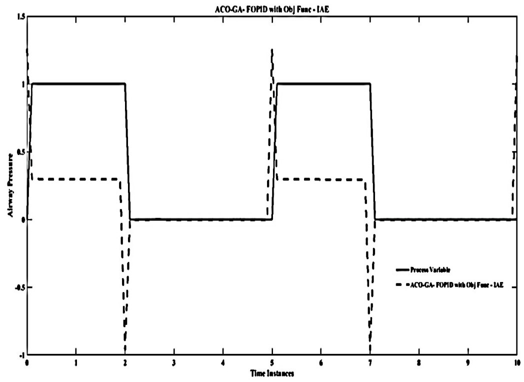

Figure 9 Response of a hybrid ACO-GA-based FOPID controller for an auto-respiration system with IAE as an objective function

B. *Hybrid Fminserach – Simmulated Annealing based PID Controller*

Fminsearch is a nonlinear optimization technique that is unconstrained and multidimensional. It commences with an estimate and endeavors to locate the local minimum of a multivariable scalar function [15]. Therefore, prior to selecting an appropriate objective function, it is necessary to establish the optimization parameters and provide an initial estimate when employing the fminsearch approach. Fminsearch is an optimization algorithm that does not necessitate derivatives. It is applicable to situations in which the objective function is not differentiable or when computing the derivatives is difficult due to its lack of dependence on gradient knowledge. Consequently, Fminsearch can be employed to resolve a diverse array of optimization challenges. Fminsearch stands out for its ability to handle objective functions that have noise or uncertainty in them. It can handle non-uniform, non-continuous, and atypically exhibiting objective functions. The Nelder-Mead simplex method in Fminsearch is especially useful for handling random or unstable objective functions.

When compared to using each method alone, the Fminsearch-Simulated Annealing-based PID controller can offer better control system performance by utilizing the advantages of both techniques.

The flowchart for the Hybrid Fminsearch-Simulated Annealing algorithm is shown in Figure 10.

When using Fminsearch-Simulated Annealing to create a PID controller, the following steps are usually taken:

- Clearly state the control problem you're trying to solve. The control objective, performance criteria, constraints, and system dynamics are all identified during this procedure.
- Set the Kp, Ki, and Kd PID controller parameters to their original values. These can be selected using informed guesswork or past experience.
- Put the Control Algorithm into Practice: Create a control algorithm that blends the methods of Simulated Annealing and Fminsearch. The PID settings will be iteratively changed using this strategy based on the optimization's outcomes.
- Establish an objective function that evaluates the control system's efficacy. Minimizing this function is necessary to achieve the necessary control objectives. Popular performance metrics include the Integral of Squared Error (ISE), the Integral of Absolute Error (IAE), and other suitable metrics.
- Optimization of Fminsearch: Utilize the Fminsearch algorithm to initiate the optimization process. Provide the objective function, the initial parameter values, and any applicable constraints. Fminsearch will seek the optimal PID values that deterministically minimize the objective function.

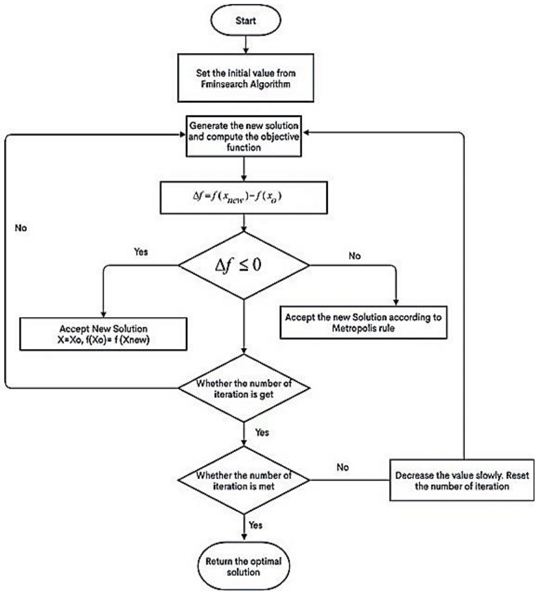

Fig. 10 Hybrid Fminsearch-Simulated Annealing algorithm flowchart

- Simulated Annealing Refinement: Utilize the results of the Fminsearch optimization as the initial solution of the Simulated Annealing algorithm. The PID parameters can be further enhanced by employing the Simulated Annealing process [16]. The method will arbitrarily perturb the parameter values and probabilistically accept both better and worse solutions in order to more thoroughly explore the solution space and potentially avoid local optimums.
- Develop a chilling schedule for the Simulated Annealing algorithm. The refrigeration schedule determines the gradual decrease of the temperature parameter over time [17]. It maintains the equilibrium between exploration and exploitation in the search process. A cooling timetable that is effective should prioritize exploitation toward the conclusion while also allowing for sufficient investigation at the outset.
- Determine the termination criteria that will determine the conclusion of the optimization process. These conditions may encompass a limit number of iterations, the attainment of a specific objective function value, or a specified degree of convergence.
- Control Performance Evaluation: Evaluate the control performance following the optimization procedure by utilizing the fine-tuned PID parameters. Simulate the

control system or conduct real-time experiments to assess the system's response to a variety of setpoints and disruptions. To determine the efficacy of the Fminsearch-Simulated Annealing-based PID controller, compare the control performance measures with the desired objectives.
- Iteration and fine-tuning: If the control performance is unsatisfactory, it may be necessary to review the control problem specification or modify the parameters. This iterative procedure can be employed to enhance the controller until the desired control objectives are achieved.

The Hybrid Fminsearch - Simulated Annealing-based PID controller is optimized for the auto respiration and vehicle suspension systems, with ISE, ITAE, and IAE serving as the objective functions and responses are shown in figure 11,12 and 13 respectively.

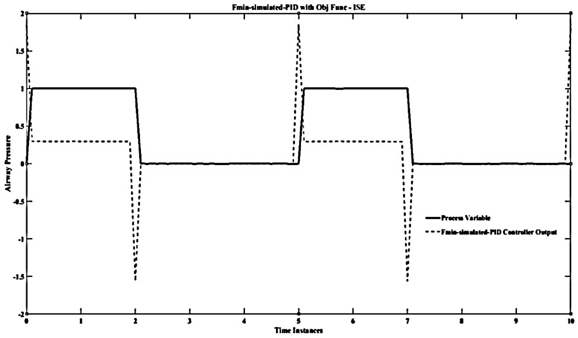

Fig. 11 Response of hybrid Fminsearch- simulated annealing-based PID controller for an auto respiration system with ISE as an objective function

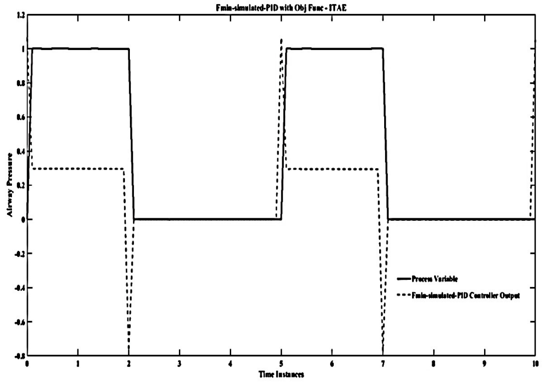

Fig. 12 Response of hybrid Fminsearch- simulated annealing-based PID controller for an auto respiration system with ITAE as an objective function

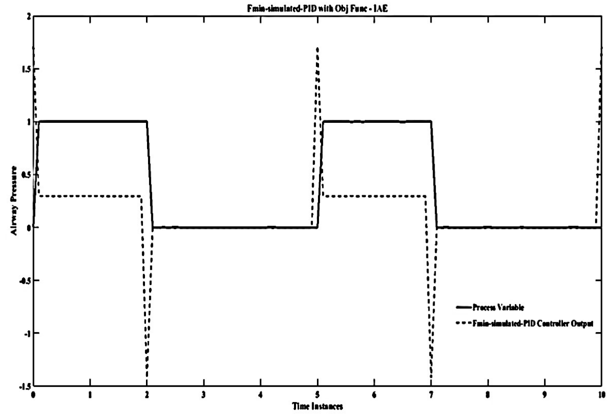

Fig. 13 Response of hybrid Fminsearch- simulated annealing-based PID controller for an auto respiration system with IAE as an objective function

IV. RESULTS AND DISCUSSION

The primary goal of the project is to ensure that the oxygen level is consistent with the patient's needs. The oxygen level that patients require will vary. The Fminsearch-Simulated Annealing Algorithm-based PID controllers and the Hybrid ACO - GA based FOPID controller are compared. MATLAB is employed to evaluate the response of the designed controllers to the pulse input.

The error indices of hybrid techniques are presented in Table 3.

TABLE III. ERROR INDICES

Controller	Objective Function	ISE	ITAE	IAE
Hybrid ACO-GA based FOPID Controller	ISE	0.08131	0.1035	0.03519
	ITAE	0.006428	0.03095	0.007701
	IAE	0.0954	0.08475	0.0458
Hybrid Fminserach-SA Controller	ISE	0.04892	0.03426	0.009473
	ITAE	0.00669	0.03167	0.008793
	IAE	0.04957	0.0398	0.01035

The selection of the appropriate optimization technique is contingent upon the intended solution quality, the type of problem, the availability of gradient information, and computational resources [18].

Combining ACO and GA mitigates each method's limitations. ACO's global exploration capability prevents premature convergence to local optima, while GA's local refinement improves solutions found by ACO. The hybrid ACO-GA-based FOPID controller with ITAE as the objective function exhibits a superior response when contrasted with the hybrid controller with ISE and IAE as the objective function, as evidenced by Table 3.

The hybrid approach can effectively optimize FOPID controller parameters and efficiently investigate large search spaces by utilizing parallelism and distributed computation strategies that are inherent in both ACO and GA. The hybrid approach is capable of adapting to changes in system dynamics over time, ensuring that control performance remains effective as conditions change [19].

V. CONCLUSION

The hybrid controller comparison shows that the hybrid Fminsearch-Simulated Annealing-based PID controller generates a less satisfying response than the ACO-genetic algorithm-based FOPID controller. Based on the ACO genetic algorithm, the FOPID controller improves the capability to monitor set points under a range of pressure conditions. Furthermore, compared to the GA-based FOPID approach, the hybrid Fminsearch-Simulated Annealing strategy converged much more slowly. The stability analysis of the FOPID controller based on evolutionary algorithms shows that the values are stable and fall within the required range. Thus, the goal of the genetic ACO-algorithm-based FOPID controller with ITAE is to guarantee that patients receive the required amount of oxygen in the Auto Respiration System within the allotted period. The proposed work's limitation is that the design criteria may be difficult to reach due to the imperfect model that may result from insufficient patient data. A model will be trained in the future to model the auto respiration system and obtain the necessary pressure value for corona patients by utilizing an artificial intelligence-based algorithm.

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