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METAHEURISTIC ALGORITHM BASED FRACTIONAL ORDER PI CONTROLLER FOR AUTO REGULATION OF PO_2 SYSTEM

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ABSTRACT

The auto-regulation of Partial Oxygen Pressure (PO_2) in a perfusion system is crucial for maintaining the viability of cells and tissues in various medical and biotechnological applications. Traditional Proportional Integral (PI) controllers may struggle to provide optimal control due to the complex dynamics and nonlinearities of the perfusion system. In this study, we propose Fractional order PI controller and a novel approach using the Grey Wolf Optimizer (GWO) to tune a Fractional Order PI (FOPI) controller for the auto-regulation of PO_2. The FOPI controller offers advantages over traditional integer-order PI controllers by providing additional degrees of freedom for tuning, allowing for more flexibility in controlling system dynamics. The GWO algorithm is utilized to optimize the parameters of the FOPI controller, including the proportional gain (Kp), integral gain (Ki), and fractional order (α). Simulation results demonstrate that the proposed GWO-based FOPI controller achieves superior performance compared to conventional PI controllers in terms of setpoint tracking, disturbance rejection, and robustness to system uncertainties. The proposed approach shows promising results for the auto-regulation of PO_2 in perfusion systems, offering a viable solution for improving control performance and ensuring the viability of cells and tissues in various biomedical applications.

Keywords: Optimization, Grey Wolf, fractional order and Auto regulation.

1. INTRODUCTION

Metaheuristic algorithms have become powerful tools in modern modeling and control. The term "meta-" implies going beyond or operating at a higher level than ordinary heuristics. Metaheuristics are significantly more effective than typical heuristics. They often utilize randomization to explore a variety of solutions. Despite their popularity, there is no universally agreed-upon definition of heuristics and metaheuristics in the literature, leading to some researchers using these terms interchangeably [1]. However, the general consensus is to categorize all stochastic algorithms that employ randomization and global exploration as metaheuristics. Randomization plays a crucial role in shifting the search from local to global spaces. This characteristic makes almost all metaheuristic algorithms highly suitable for nonlinear modeling and control. These algorithms efficiently find acceptable solutions through trial and error, without guaranteeing the best possible solution within a reasonable time frame. The goal is to find a feasible solution within an acceptable time limit, rather than exhaustively exploring every possible solution in the search space.

The Grey Wolf Optimizer (GWO) algorithm, inspired by the hunting behavior of grey wolves, has emerged as a promising method for optimizing controller parameters. Its simplicity and efficiency make it particularly effective in this regard.The Grey Wolf Optimizer (GWO) is a metaheuristic algorithm inspired by the social hierarchy and hunting behavior of grey wolves. Grey wolves are apex predators that live in groups, typically consisting of 5 to 12 members. Within the group, there is a strict social hierarchy, with the alpha wolf being the dominant leader. The beta and delta wolves are subordinate to the alpha and assist in maintaining control over the omega wolves [2].

In the Grey Wolf Optimizer (GWO) algorithm, hunting behavior is simulated by the alpha, beta, and delta wolves, with the omega wolves following their lead. During hunting, grey wolves typically encircle their prey, with the alpha wolf providing leadership. The beta and delta wolves also participate in the hunt, though less frequently. It is assumed that the alpha, beta, and delta wolves have better awareness of the potential location of prey. As a result, the first three best solutions found are recorded, and other search agents adjust their positions based on these leaders. The hunting concludes when the prey stops moving, and the grey wolves attack. GWO has gained popularity among researchers and is widely used in various fields. However, while several new algorithms have emerged, pure algorithms may not always provide optimal solutions and are often outperformed by hybrid approaches [3].

Several studies have investigated the application of optimization algorithms for tuning controllers in various systems. The use of Fractional Order Proportional Integral (FOPI) controllers has gained attention due to their ability to handle complex system dynamics more effectively than traditional integer-order controllers [4]. In the field of perfusion systems, auto-regulation of Partial Oxygen Pressure (PO_2) is crucial for maintaining cell viability. Traditional Proportional Integral (PI) controllers often struggle to provide optimal control due to the nonlinearities and uncertainties in the system [5]. Optimization algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have been applied to tune controllers in perfusion systems [6].

However, the application of GWO for tuning FOPI controllers in perfusion systems is relatively unexplored. This study aims to fill this gap by proposing a novel approach using GWO to optimize the parameters of a FOPI controller for the auto-regulation of PO_2 in perfusion systems. The effectiveness of the proposed approach is evaluated through simulations and compared with traditional PI controllers and other optimization techniques. Overall, the literature suggests that the combination of FOPI controllers and GWO optimization has the potential to improve the control performance of perfusion systems, ensuring the viability of cells and tissues in biomedical applications.

2 PROPOSED MODEL FOR AUTO REGULATION OF PO_2

The proposed model for auto-regulation of PO_2 includes an actual Heart-Lung Machine (HLM) setup with an Automatic FiO_2 controller instead of manual control. Additionally, the setup includes a Blood Gas Analyzer (BGA), a temperature sensor, and a mode selector switch. In this setup, the atrial blood sample undergoes complete blood analysis in the Blood Gas Analyzer (BGA) [7,8,9,10]. The BGA measures the PO_2 value of the atrial blood sample, which is then used as an input to the automatic FiO_2 controller through a mode selector switch. The mode selector switch is controlled by a temperature sensor, which determines the operating mode based on the temperature of the atrial blood sample [11,12]. The mode selector switch has four modes: Mild, Moderate, Deep, and Profound temperature conditions [13.14,15]. It selects the Mild temperature condition mode when the atrial blood sample temperature is between 37°C and 32°C, the Moderate temperature condition when the temperature is between 32°C and 28°C, the Deep temperature condition when the temperature is between 28°C and 18°C, and the Profound temperature condition when the temperature is below 18°C. Additionally, the set point PO_2 can be manually adjusted if needed. The block diagram of the proposed model for auto-regulation of PO_2 is shown in Figure 1.

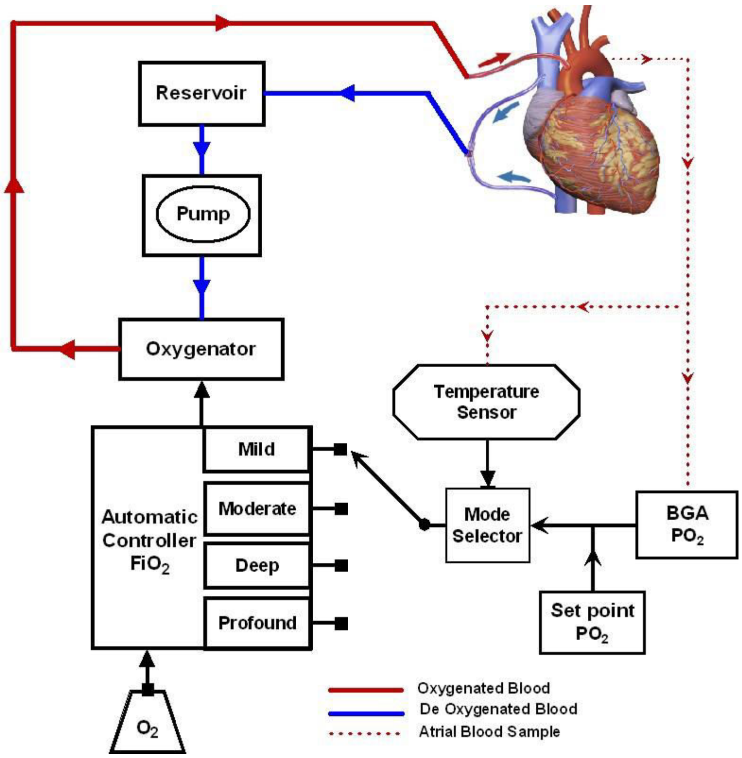

Fig. 1 The proposed model - Auto regulation of PO_2.

3 DESIGN OF PI CONTROLLER FOR AUTO REGULATION OF PO_2

In spite of the inherent nonlinearity present in the system, conventional controllers based on linear and nonlinear control theory have been used to control the processes owing to their simplistic nature. Here conventional controller namely PID controller is discussed [16]. A PID controller is widely used in feedback process control of industrial processes. PID controller can be understood as a controller that takes the present, the past, and the future of the error into consideration. It is the controller containing the linear combination of Proportional Integral, Derivative terms attempts to correct the error between a measured process variable and a desired setpoint. The Proportional value determines the reaction to the current error, the Integral value determines the reaction based on the sum of recent errors, and the Derivative value determines the reaction based on the rate at which the error has been changing. The weighted sum of these three actions is used to adjust the process via a control element.

The Process parameters are obtained using process reaction curve method and PI controller parameters are found using Z-N tuning method [17]. PID controller (PI Control mode) is constructed from various combinations to meet specific performance requirement functions.

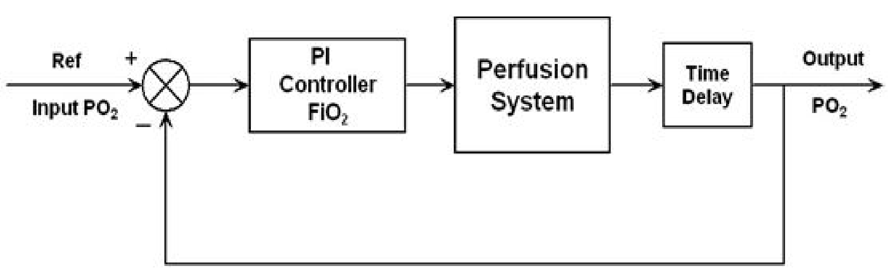

Fig. 2 : Perfusion System with PI controller

Table 1: Process and Controller Parameters of perfusion system

Temperature Condition (Region)	Process Parameters			Control Parameters	
	K_p	τ	t_d	K_c	T_i
Mild R1(40to45)	5.536	1.041	78.2	0.00216	260.48
Mild R2 (45to80)	4.90	1.041	78.22	0.00243	260.47
Mild R3 (80to85)	6.71	1.095	78.18	0.001878	260.5
Mild R4 (85to100)	9.363	1.038	78.22	0.001275	260.47
Moderate R5 (40to45)	6.8414	1.0425	88.2175	0.0015546	293.76
Moderate R6 (45to90)	4.799	1.029	78.23	0.002467	260.50
Moderate R7 (90to100)	6.482	1.071	78.193	0.001901	260.38
Deep R8 (40to45)	6.28	1.0575	78.217	0.001937	260.46
Deep R9 (45to100)	5.166	1.0425	78.225	0.002321	260.48
Profound R10 (40to45)	8.88	1.05	78.202	0.0013608	259.80
Profound R11 (45to100)	4.962	1.065	78.205	0.00247	260.422

4 FRACTIONAL ORDER PID CONTROLLER

The $PI^{\lambda}D^{\mu}$ controller involving an integrator of order λ and a differentiator of order μ where λ and μ can be any real numbers [18,19]. The transfer function of such a controller has the form

$$Gc(s) = \frac{U(S)}{E(S)} = k_p + k_I \frac{1}{S^{\lambda}} + k_D S^{\mu} \ , (\lambda , \mu > 0) \qquad (1)$$

Where *Gc(s)* is the transfer function of the controller, *E(s)* is an error, and *U(s)* is controller's output. The integrator term is 1 s^{λ}, that is to say, on a semi-logarithmic plane, there is a line having slope -20^{λ}dB/decade. The control signal u(t) can then be expressed in the time domain as

$$u(t) = k_p e(t) + k_I D^{-\lambda} e(t) + k_D D^{\mu} e(t) \qquad (2)$$

Clearly, selecting $\lambda = 1$ and $\mu = 1$, a classical PID controller can be recovered. The selections of $\lambda = 1$, $\mu = 0$, and $\lambda = 0$, $\mu = 1$ respectively corresponds conventional PI & PD controllers it can be expected that the $PI^{\lambda}D^{\mu}$ controller may enhance the systems control performance. one of the most important advantages of the $PI^{\lambda}D^{\mu}$ controller is that it provides very good control on dynamical systems and it is affected much lesser for variations in control system parameter.

5 Grey Wolf Optimization

Wolves, scientifically known as Canis lupus, are members of the Canidae family and are considered apex predators, occupying the top position in the food chain. They are highly social animals and typically live in packs. A wolf pack's size can range from 5 to 12 members on average. The pack adheres to a strict social hierarchy, as illustrated in Figure 3. At the pinnacle of this hierarchy is the alpha, which can be a male or a female. The alpha wolf is responsible for making all decisions for the pack, including hunting, sleep patterns, and travel routes. The rest of the pack follows the alpha's decisions, making the alpha the dominant member of the pack. Leadership is based on management skills rather than physical strength.

The beta wolf is the alpha's immediate subordinate and occupies the second position in the hierarchy. Like the alpha, the beta can be male or female. The beta wolf assists the alpha in decision-making and is crucial in maintaining discipline within the pack. In the event that the alpha becomes unable to lead, the beta is prepared to assume the alpha role. The beta also acts as a liaison between the alpha and the rest of the pack, conveying the alpha's commands and gathering feedback from the pack members to relay back to the alpha.

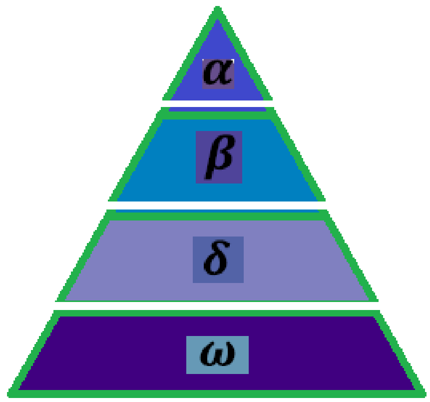

Fig.3. Hierarchy of Grey Wolf

The subordinate of alpha wolf and beta wolf is called as delta wolf. Delta wolf can be either a male or female. It is located in level three of grey wolf hierarchy. It needs to follow instructions given by both the alpha and beta wolves. Based upon the role these delta wolves are of five types. They are scouts, sentinels, elders, hunters, and caretakers. Scouts are those who look over the boundaries of the territory in search of a pray and they warn the rest of pack in case of any emergency. Sentinels are responsible for protection and safety of the pack. Experienced wolves termed as Elders, help alpha and beta in decision-making. Hunters are the one who helps the pack in hunting the prey and they provide food for entire pack. Lastly, caretakers are those who are responsible for taking care of the weak, wounded and ill wolves in the pack.

The least level of grey wolf is omega. Omega wolf need to obey the commands given by all the other three dominant wolves in the pack. They have the least priority in the pack and are the one allowed to eat at last.

5.1 Grey Wolf Optimization (GWO) Hunting Mechanism

The Grey Wolf Optimizer (GWO) algorithm is inspired by the hunting behavior of grey wolves in the wild. It begins by initializing a population of grey wolves with random positions in the parameter space. Each wolf's fitness is determined by evaluating the performance of the control system using its corresponding parameter values. The algorithm then identifies the alpha, beta, and delta wolves in the population based on their fitness, with the alpha wolf having the highest fitness, followed by the beta and delta wolves.

(a) Encircling prey

After identification of a prey, hunting mechanism starts by encircling the prey from all sides. Mathematically the encircling mechanism can be represented as follows.

$$\vec{D} = |\vec{C}.\vec{X}_p(t) - \vec{X}(t)| \qquad (3)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}\cdot\vec{D} \qquad (4)$$

In the equations (3) and (4), t represents the present iteration, $\vec{X}$ is grey wolf position vector, $\vec{X}_p$ is the position vector of the prey. $\vec{A}$ and $\vec{C}$ are the coefficient vectors which can be summarized by the following two equations.

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \qquad (5)$$

$$\vec{C} = 2\cdot\vec{r}_2 \qquad (6)$$

In the equations (5) and (6) vector $\vec{a}$ is a value that linearly decreases from 2 down to 0 during the iterative process. The vectors $\vec{r}_1$ and $\vec{r}_2$ are the random values in the range [0, 1].

(b) Hunting prey

The general hunting process is guided by alpha that are to be followed by beta and delta. Mathematically we initialize by assuming alpha, beta and delta have better knowledge about the position of a prey. Therefore, we save the first best three solutions as alpha, beta and delta. This process will be continued to update their next best positions based on the position of search agents. Mathematically this is given as follows:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \quad (7)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \quad (8)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (9)$$

(c) Attacking Prey

When the prey is unable to take a step (stops moving any further) the grey wolf stops hunting process by attacking the prey. In mathematical model, prey position can be analysed based on the value of $\vec{A}$which is a function of $\vec{a}$. As $\vec{a}$ value ranges from 1 to 0, $\vec{A}$varies from 2 to 0. In the iterative process if $|A| < 1$it means the prey position is stopped, this situation forces the grey wolves to attack the pray which means the most feasible solution has been obtained and the process may end by this.

(d) Search for Prey

The pack of grey wolf searches the prey based upon the positions of alpha, beta and delta. The members of the pack diverge each other in search of a prey and they converge in the process of attacking the prey. If prey is strong enough, then it will move against the pack. This means grey wolves cannot stop the prey. Mathematically this can be identified by vector $\vec{A}$. The condition $|A| > 1$ means the prey position cannot be stopped, and this situation forces the grey wolves to diverge from the prey and they begin to search for another prey. The GWO algorithm iteratively repeats the evaluation and update steps until a termination criterion is met, such as a maximum number of iterations or a minimum error threshold.

6 DESIGN OF FOPID CONTROLLER USING GWO ALGORITHM FOR AUTO REGULATION OF PO_2

Designing a Fractional Order Proportional Integral Derivative (FOPID) controller using the Grey Wolf Optimizer (GWO) algorithm for auto-regulation of PO_2 in a perfusion system is a multi-step process that requires careful consideration of the system dynamics and controller design. The first step is to clearly define the problem, including specifying the desired setpoint and acceptable ranges for PO_2 levels in the perfusion system. Next, a suitable fractional order model must be identified to accurately represent the dynamics of the system. This can be achieved using system identification techniques or experimental data to determine the parameters of the model. Once the model is identified, the structure of the FOPID controller must be chosen, taking into account the orders of the fractional components (proportional, integral, and derivative) based on the system dynamics and performance requirements.

After defining the controller structure, an objective function must be defined to quantify the performance of the controller. This objective function should consider metrics such as tracking error, rise time, settling time, overshoot, and robustness to disturbances. With the objective function in place, the GWO algorithm can be implemented to optimize the parameters of the FOPID controller. This involves initializing the parameters of the GWO algorithm, including the number of wolves, maximum number of iterations, and search space for controller parameters, and then using the algorithm to update the position of the wolves in the search space based on the objective function. The optimized controller parameters can then be fine-tuned to improve performance and validated using simulation studies. Design of a Fractional Order Proportional Integral Derivative (FOPID) controller using the Grey Wolf Optimizer (GWO) algorithm for auto-regulation of PO_2 in a perfusion system can help visualize the steps involved.

Step (1) Problem Definition

Define the objective of auto-regulation of PO_2 in the perfusion system.

Specify the desired setpoint and acceptable ranges for PO_2 levels.

Step (2) Fractional Order Model Identification

Identify a suitable fractional order model for the perfusion system.

Determine the parameters of the fractional order model using system identification techniques.

Step (3) FOPID Controller Structure

Choose the structure of the FOPID controller.

Determine the orders of the fractional components (proportional, integral, and derivative).

Step (4) Objective Function Definition

Define an objective function to quantify the performance of the controller.

Consider metrics such as tracking error, rise time, settling time, overshoot, and robustness.

Step (5) Grey Wolf Optimizer (GWO)

Implement the GWO algorithm for parameter optimization.

Initialize the algorithm with parameters such as the number of wolves, maximum iterations, and search space.

Step (6) Parameter Optimization

Use GWO to optimize the parameters of the FOPID controller.

Update the position of wolves based on the objective function.

Step (7) Controller Tuning and Validation

Fine-tune the optimized controller parameters for improved performance.

Validate the controller using simulation studies.

Step (8) Implementation

Implement the FOPID controller in the real perfusion system.

Integrate the controller with the existing control infrastructure.

7 RESULTS AND DISCUSSION

The performance of the Grey Wolf Optimizer (GWO) based Fractional Order Proportional Integral (FOPI) controller for the auto-regulation of PO_2 in a perfusion system was evaluated through extensive simulations and compared with traditional Proportional Integral (PI) controllers and FOPI controller. The GWO-based FOPI controller demonstrated superior setpoint tracking performance compared to conventional PI and FOPI controllers. It achieved faster response times, lesser Integral Square Error (ISE) and ensuring that the PO_2 level reached the desired setpoint more accurately and efficiently. The GWO-based FOPI controller exhibited robustness to system uncertainties and variations, ensuring consistent and reliable control performance over time. This is essential for maintaining the viability of cells and tissues in long-term perfusion applications.

The results demonstrate the effectiveness of the GWO-based FOPI controller for the auto-regulation of PO_2 in perfusion systems. It offers a promising solution for improving control performance and ensuring the viability of cells and tissues in various biomedical applications. The servo response of the auto regulation of PO_2 system are shown in Figures (4), (5), (6) and (7).

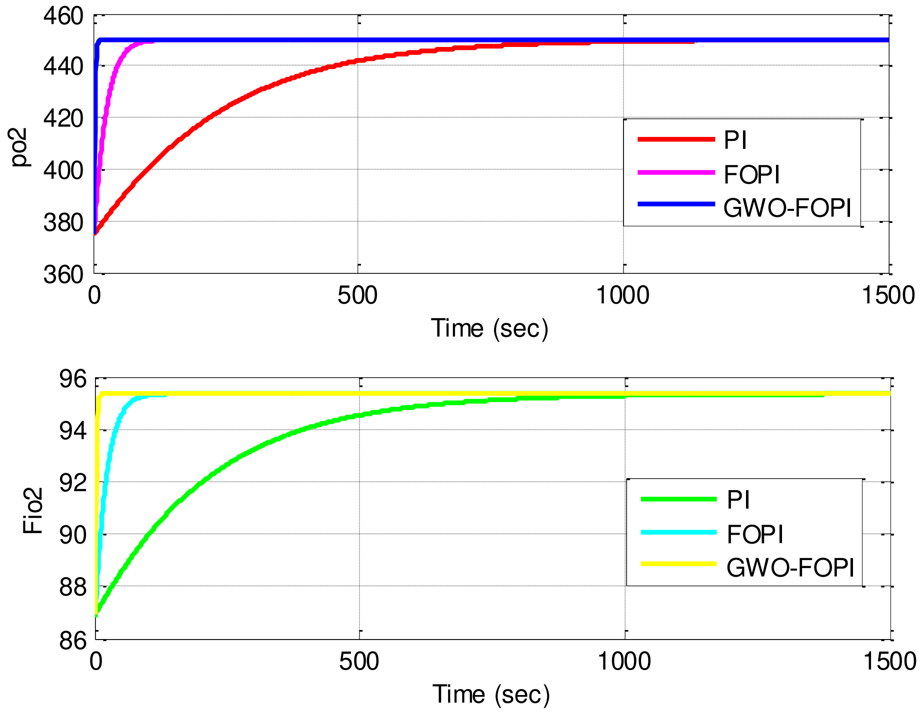

Fig.4: Servo response of Auto regulation of PO_2 system for the setpoint change of 380 to 450.

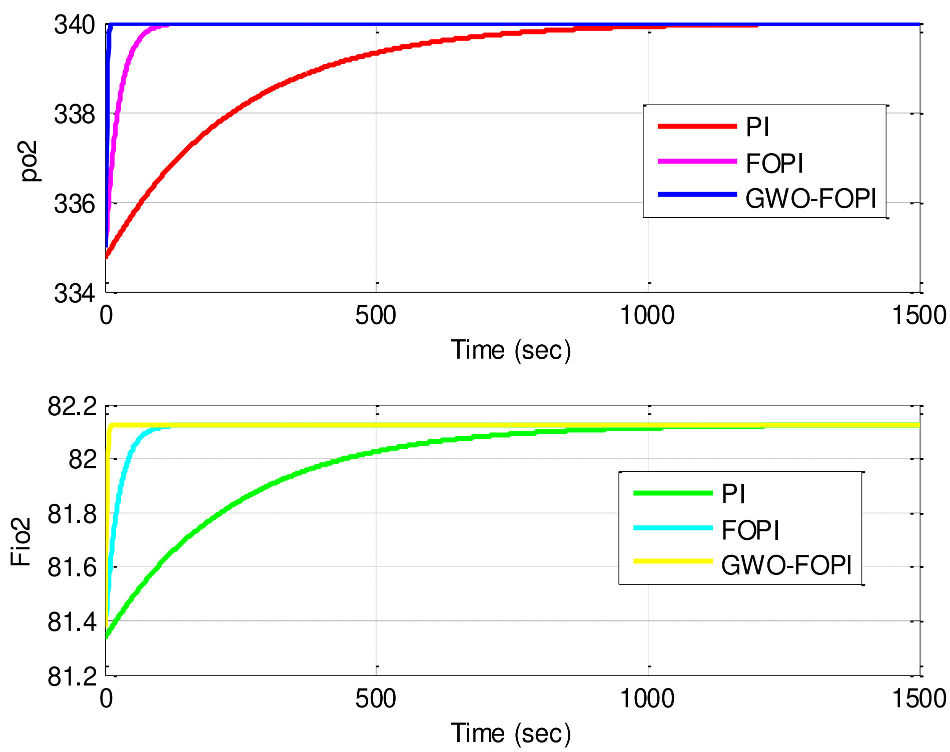

Fig.5: Servo response of Auto regulation of PO_2 system for the setpoint change of 335 to 340.

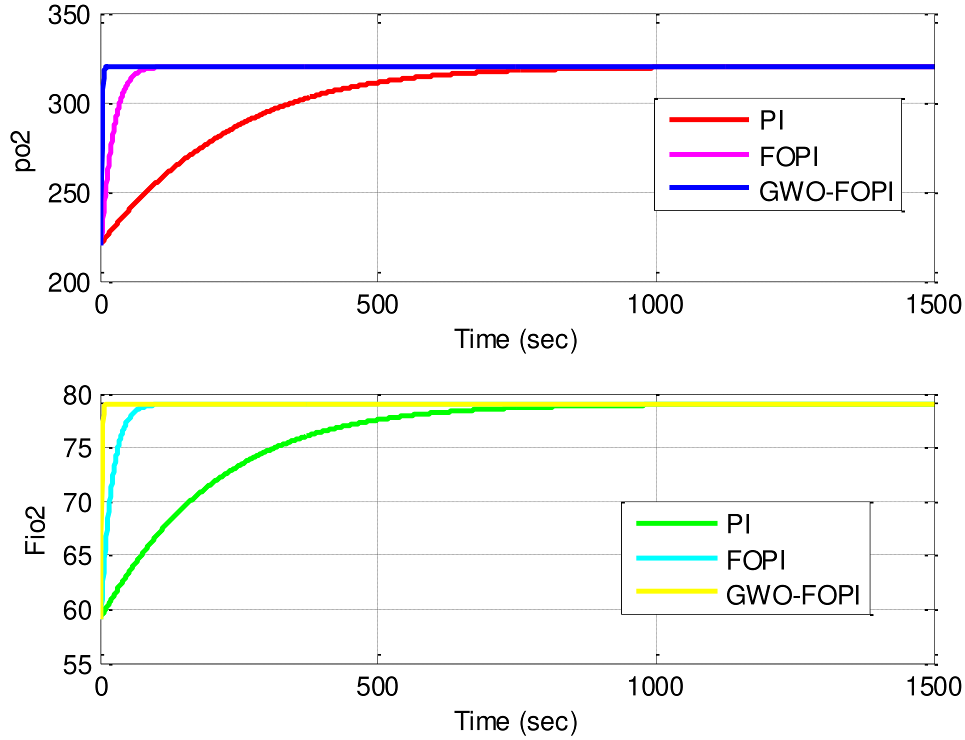

Fig.6: Servo response of Auto regulation of PO_2 system for the setpoint change of 225 to 320.

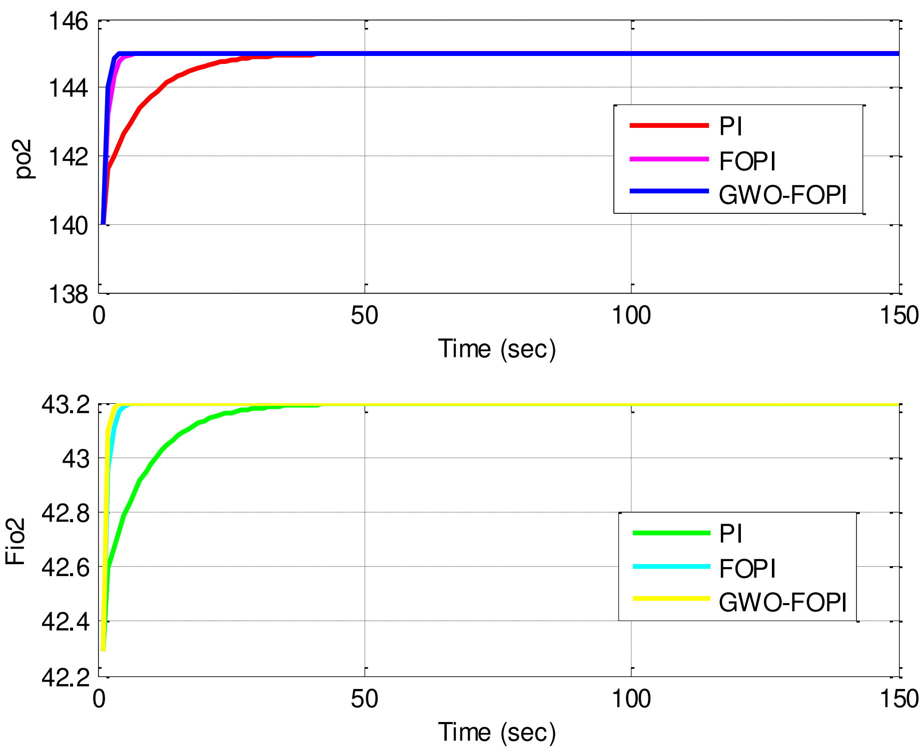

Fig.7: Servo response of Auto regulation of PO_2 system for the setpoint change of 140 to 145.

Table 2: Performance matrices for Auto regulation of PO_2 using PI, FOP I and GWO-FOPI controllers.

Controller	PI		FOPI		GWO-FOPI	
	ISE	Settling Time	ISE	Settling Time	ISE	Settling Time
Setpoint Change of 380 to 450	47872	1156	54.29	94	51.71	9
Setpoint change of 335 to 340	31694	1137	3197	89	34.93	7
Setpoint change of 225 to 320	13537	984	3374	87	16.09	7
Setpoint change of 140 to 145	1649	42	44.86	5	32.02	4

8 CONCLUSION

The Grey Wolf Optimization (GWO) based Fractional Order Proportional Integral (FOPI) controller shows significant promise for the auto-regulation of Partial Oxygen Pressure (PO_2) in perfusion systems. It outperforms traditional Proportional Integral (PI) and FOPI controllers in terms of setpoint tracking, disturbance rejection, and robustness to system uncertainties. The FOPI controller's ability to provide additional degrees of freedom for tuning, along with the GWO algorithm's efficiency in parameter optimization, makes it a valuable tool for improving control performance in biomedical applications.

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