Online PID Tuning of a 3-DoF Robotic Arm using a Metaheuristic Optimisation Algorithm: A Comparative Analysis*

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Abstract. This paper presents a metaheuristic algorithm-based proportional–integral–derivative (PID) controller tuning method for a 3 degrees of freedom (DoF) robotic manipulator. In particular, the War Strategy Optimisation Algorithm (WSO) is applied as a metaheuristic algorithm for PID tuning of the manipulator, and the performance of the controller is compared with Particle Swarm Optimisation (PSO) and Grey Wolf Optimisation (GWO) algorithms. According to the simulation outcomes, the WSO algorithm exhibits superior performance compared to the other two algorithms with respect to settling time, overshoot, and steady-state error. The proposed technique provides an effective approach for enhancing the performance of robotic manipulators and can be extended to other applications that require optimal PID controller tuning.

Keywords: Metaheuristic Algorithms · PID Controller · Robotic Manipulator.

1 Introduction

1.1 Literature Review

Proportional–integral–derivative (PID) control structures offer straightforward, reliable, and efficient solutions for the majority of control engineering applications. According to Ayala et al. [1], PID controllers account for a whopping 95% of all controller usage in industrial operations. Accurate tuning of the controller gains is necessary to maintain the beneficial properties of PID controllers. However, it was demonstrated by Desborough et al. [6] that approximately 80% of

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the existing PID controllers are not operating at peak efficiency, with improper controller tuning being one of the key contributing factors. Robotic manipulators, which are multi-input multi-output (MIMO) dynamic systems, are highly nonlinear and exhibit strong coupling. Although PID controllers are commonly used to control robotic manipulators, conventional tuning techniques that rely on manual or experimental approaches do not always yield satisfactory results for such complex systems, as noted in [8].

In situations where a robot's tasks change frequently or its configuration and shape are variable (such as in modular robots), traditional manual tuning and experimental approaches become more challenging. Therefore, an auto-tuning technique is essential in such scenarios. Auto-tuning techniques that utilise optimisation approaches have been increasingly applied to nonlinear systems in recent years to enhance their performance based on predetermined fitness functions that are relevant to the particular task being performed. This has been made possible by the significant advancement in computer power. Trajectory tracking tasks frequently use the integral of the absolute error (IAE) or the integral of the square error (ISE) as fitness functions.

Optimisation techniques like Particle Swarm Optimisation (PSO) [10] and Genetic Algorithms (GA) [11] have been utilised in the domain of robotic manipulators to automatically adjust PID controllers. Various studies have also been conducted to compare the efficacy of different algorithms. For example, in a study by Kapoor et al. [7], a GA algorithm was compared with a PSO approach and shown to produce superior tracking accuracy. On the other hand, in a comparative study by Ouyang et al. [15] involving GA, PSO, and Differential Evolution (DE), it was found that DE outperformed the other two algorithms across several performance-measuring functions. However, it should be noted that these findings were based on simplified simulations of serial robots. In addition to optimisation techniques, other methods such as fuzzy logic and neural networks have also been utilised in the design of PID tuning systems for robotic manipulators. This is because typical manual or experimental tuning methods may not yield satisfactory results for highly nonlinear and strongly coupled MIMO dynamic systems like robotic manipulators [8]. Several studies, including [3], [13], and [22], have developed such systems that transform traditional controllers into adaptive ones by allowing the PID gains to adjust their values dynamically based on real-time measurements of the robot joint positions.

Another method for optimising the PID's parameters is fuzzy logic. PIDs are commonly used to control rehabilitation robots, while fuzzy logic is used to optimise their parameters. Triangular membership functions and various sets of fuzzy rules are utilised to characterise each parameter of the PID controllers. When compared to conventional PID controllers, experimental results demonstrated that fuzzy PIDs deliver better and more effective trajectory-tracking capability. In [14], another strategy has been suggested: a hybrid PID regulator tuning method was created using both the GA methodology and fuzzy logic. This approach transformed the classic controller into an adaptive controller, which provided the PID gains with changing values based on real-time measurements of the robot joint positions. In [14], another strategy has been suggested. Here, a hybrid PID regulator tuning method was created using both the GA methodology and fuzzy logic. While these techniques have demonstrated improved performance over traditional methods, there is a clear research gap in terms of optimising PID controllers for increasingly complex robotic manipulators.

1.2 Contributions and Paper Organisation

The contribution of the paper are as follows:

1. A 3 degree of freedom (DoF) robotic manipulator is designed in MATLAB/Simulink;
2. a novel War Strategy Optimisation Algorithm (WSO) is used for optimal PID tuning of the considered robotic manipulator;
3. A comparison is made with PSO and GWO based PID tuners for the presented robotic manipulator;
4. WSO effectively tunes the PID controller by achieving less cost function value during tuning.

The remainder of the paper is structured as follows: Section 2 presents the proposed methodology, wherein first the robotic arm kinematic model is described, then the War strategy optimisation algorithm is presented with the PID controller for a 3 DoF robotic manipulator and WSO based PID tuning method is elaborated. Section 3 of the paper presents the results and discussion, while Section 4 summarises the conclusion of the study.

2 Proposed Methodology

2.1 Robotic Arm

A critical component of the robotic arm control system is the kinematic model describing the motion and position of the end effector (EE) of a robotic arm in three-dimensional space. The model typically consists of a set of equations that describe the relationship between the joint angles and positions of the end-effector.There are two main types of kinematic models: forward kinematics and inverse kinematics. To determine a generalized solution for the kinematic model for the Denavit-Hartenburg parameters are used as a numerical approach to the problem. The methodology of DH tables stipulate that any serial manipulator can be described as a kinematic model by specifying four parameters for each link: a_i length of the link, α_i twist of the link, d_i offset of the link, and θ_i angle of the joint. With the development of soft-computing methods, researchers have focused on alternative solutions of machine learning to devise approaches that bypass the traditional numerical approaches.

According to the study in [5], the neural network approach demonstrated superior performance in solving the forward kinematics problem of the HEXA parallel manipulator. Sanfillipo et al. [17] proposed a flexible control system architecture and a genetic algorithms that can automatically learn the inverse kinematic properties of different models. In [9], the authors proposed the use of neural networks and particle swarm optimization to develop a kinematic model for hybrid robots with parallel-serial structure, Figure 1 (a) shows a three revolute joint robotic manipulator on three linkages that will be used for the purposes of this study.

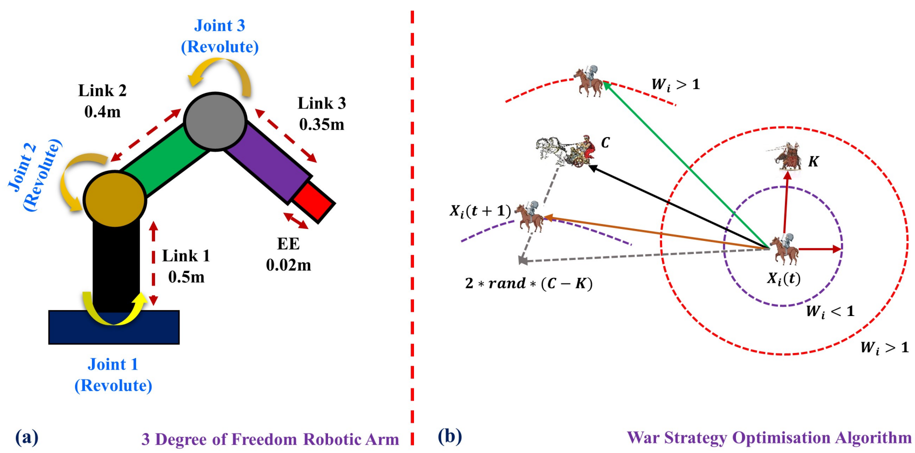

Fig. 1. (a) Robotic Manipulator Description (b) Operating Principle of WSO algorithm

2.2 War Strategy Optimisation Algorithm (WSO)

In this section, we develop the mathematical model of the WSO algorithm, as described in [2]. This is a swarm intelligence algorithm inspired by the strategy employed by military forces in battles. The Commander and the King both act as leader on the battlefield. The remainder of the army will follow the King and Commander's commands as they march around the battlefield. Based on their Combating Strength, all troops have an equal chance of becoming King or Commander at each iteration (Fitness Value). The enemy's soldier, who is strong enough to capture the Leaders, may put up a difficult fight against the King or the Commander. To avoid this, soldiers will follow the Commander and King's position in combat as well as their synchronised movement patterns. The working principle of WOS is shown in Figure 1 (b).

Attacking Policy: We have developed two plans for a potential war scenario. In the first plan, each soldier will adjust their position according to the locations of the King and Commander. The method of updating positions aims to position the monarch in the best possible location to launch a successful offensive against the enemy. The monarch is expected to have the highest level of fitness or assault force in this plan. When the conflict begins, all soldiers are assigned the same rank and weight. However, their respective ranks and weights will adjust as the plan is executed and its effectiveness is evaluated. Effective tactics will lead to a rise in rank and weight for soldiers, while ineffective strategies will cause their ranks and weights to decrease.

$$X_j(t+1) = X_j(t) + 2\rho(C-K) + (W_jK - X_j(t))rand, \tag{1}$$

where $X_j(t+1)$ denotes the next position, X_j the original position, ρ the commander position, K the king position, and W_j the weight. When $W_j > 1$, the new location of the agent that is the soldier will be away from the position of the agent that is the commander because $W_j \times K - X_j(t)$ lies outside the King's position. On the other hand, when $W_j \leq 1$, the updated location of the soldier will be between their current position and the King's position, and it will be determined by $W_j \times K - X_j(t)$.

When compared to the prior scenario, the soldier's revised position is closer. If W_j approaches zero, the soldier's new and better updated position moves nearer to the position of the commander. This indicates the final part of the war strategy.

Ranking Update Methodology: The positions of all agents are updated by taking into account the interplay of ranks of the three pieces in the war i.e., King, Commander, and and regular soldier. Each soldier's rank is determined by his record of success in battle, as determined by Eq. 4, which in turn influences the weighting factor W. Each soldier's rank represents how near the soldier is to the goal. It should be noticed that the weighting factors in other competing algorithms vary linearly, but the weight (W_i) in the present suggested WSO method exponentially using e as the growth factor. Provided that the new position of the assault force (F_n) is lesser than the strike force in its prior position, the soldier then assumes the former stance.

If the new position of the assault force (fitness) (F_n) is smaller from the strike force (fitness) in the prior position (F_p), the soldier assumes the former stance.

$$X_j(t+1) = X_j(t) \times F_n \geq F_p + R_j \times F_n \geq F_p \tag{2}$$

Provided the soldier agent successfully adjusts the location, the soldier's rank/weight R_j will be improved accordingly from the Equation provided as under:

$$R_j = (R_j + 1) \times F_n \geq F_p + R_j \times F_n \geq F_p \tag{3}$$

The current rank/weight determines the next rank/weight based on the following equation:

$$W_j = W_j(1 - R_j/Max_j)^{\alpha} \tag{4}$$

Defensive Strategy: Unlike the first plan, the second strategic position update considers the location of the key players in the war namely the King, Commander, and a random soldier chosen from the army, while maintaining a constant ranking and weighting of the soldiers.

$$X_j(t+1) = X_j(t) + 2\rho(K - X_j(t)rand) + randW_j(C - X_j(t)) \tag{5}$$

Since it includes the position of a random soldier, this combat strategy examines a larger search space than the preceding method. Soldiers take significant steps and update their position when W_j is high. W_j troops take modest moves while updating the position for small values of W_j.

Replacement of Weak Soldier: To identify weak soldiers in each iteration, various replacement strategies were attempted. One simple approach involved using a random soldier from the army population to replace the weakest soldier, as shown in Equation 6.

$$X_j(t+1) = Bound_{Lower} + rand \times (Bound_{Upper} - Bound_{Lower}) \tag{6}$$

The second technique involves moving the weak soldier to a location close to the middle of the army population in the conflict zone, using Equation 7 described below. This technique improves the convergence factor of the algorithm.

$$X_j(t+1) = -(1 - rand)(X_j(t) - median(X_j)) + K \tag{7}$$

2.3 PID Controller for Robotic Manipulator

A PID (Proportional-Integral-Derivative) controller is a common control algorithm used in many applications. A feedback controller uses the error between the desired setpoint and the actual process variable to adjust the control signal [12]. The PID controller comprises three components: the proportional term, the integral term, and the derivative term. The mathematical equation of a PID controller is given by:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt}, \tag{8}$$

where the control signal $u(t)$ in a feedback control system is calculated based on the error signal $e(t)$, which is the difference between the desired setpoint and the actual process variable. The values of the proportional gain K_p, integral gain K_i, and derivative gain K_d are used to determine the behaviour of the system.

The proportional term provides an immediate response to the error, while the integral term sums up the past errors to eliminate the steady-state error. The derivative term anticipates the future error by calculating the rate of change of the error. The PID controller combines these three terms to achieve a stable and accurate control of the system. The tuning of the PID gains is critical to achieve the desired performance, and various methods can be used to determine the optimal gains. The structure of PID control for Robotic manipulator is shown in Figure **??**.

PID controllers are widely used in robotic manipulators to achieve precise and stable control of the joint angles and velocities [21]. A PID controller can be designed to track the desired trajectory of the end-effector or to maintain a specific configuration of the manipulator [18], [19]. The proportional term of a PID controller provides the immediate response to the error in the joint position or velocity, while the integral term eliminates the steady-state error caused by external disturbances or system uncertainties. The derivative term in a PID controller can enhance the system's response speed and mitigate overshoot and oscillations. The tuning of the PID gains for robotic manipulators can be challenging due to the complex dynamics and nonlinearities of the system, and various optimization techniques can be used to determine the optimal gains.

2.4 WSO based PID Tuning

Metaheuristic optimisation algorithms are popular techniques for tuning the PID gains in robotic manipulators due to their ability to search the large parameter space and find the optimal solution efficiently [23]. These algorithms utilise a heuristic approach to search for the optimal solution by iteratively enhancing the candidate solutions based on the fitness function which is a measure towards the performance of the system, and in the case of PID tuning, it is typically defined as a combination of the tracking error and the control effort. One such cost function is the Integrated Time Error Absolute (ITEA) index, which is given by [16]:

$$ITEA = \int_0^T |e(t)|dt + \alpha \int_0^T |u(t)|dt, \tag{9}$$

where $e(t)$ is the tracking error, $u(t)$ is the control signal, T is the simulation time, and α is a weighting factor that balances the tracking error and the control effort. The ITEA index measures the cumulative error and control effort over the entire simulation time, and the optimisation algorithm seeks to minimise this index by adjusting the PID gains. The effectiveness of tuning the PID gains using metaheuristic optimisation algorithms has been demonstrated in various studies, and these techniques have been shown to provide improved performance compared to traditional methods of PID tuning. In this study, the WSO is used for tuning of PID gains for robotic manipulator. Figure 2 shows the detailed overview of proposed technique. Table 1 shows the parameters for tuning of PID using metaheuristic techniques.

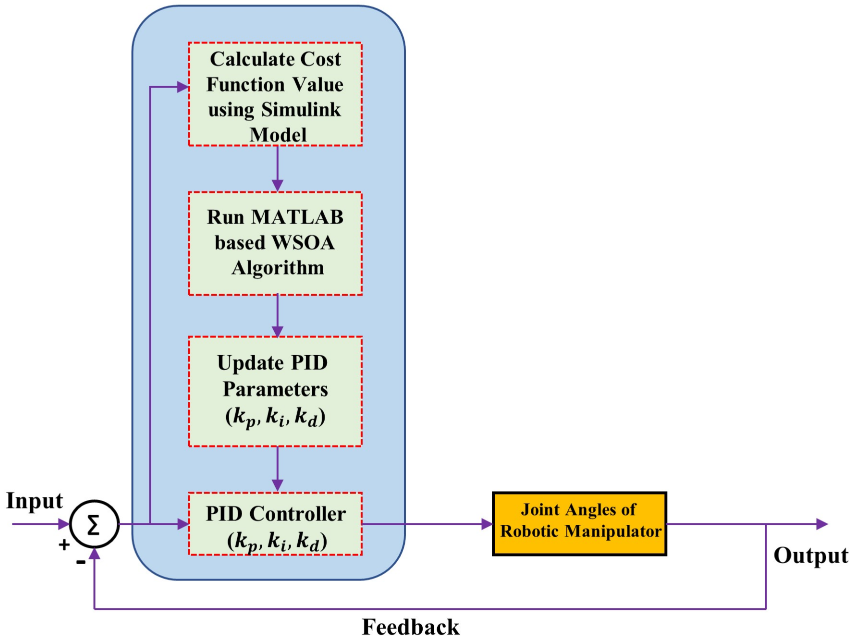

Fig. 2. WSO based PID tuning of Robotic manipulator in MATLAB/Simulink

Table 1. Simulation Parameters for Metaheuristic Algorithms based PID Tuning

Technique	Parameter	Values
PSO	Max Iterations	50
	Population Size	10
	$C1$	0.25
	$C2$ Text follows	0.1
	W	0.6
GWO	Max Iterations	50
	Population Size	10
	a	$2-0$
WSO	Max Iterations	50
	Population Size	10
	ϕ_r	0.5

Table 2. Comparative analysis of cost reduced during training by the proposed algorithms

Technique	Joint 1	Joint 2	Joint 3
PSO	0.0013	0.0027	0.3081
GWO	0.0012	0.0025	0.2667
WSO	0.00006	0.0007	0.1106

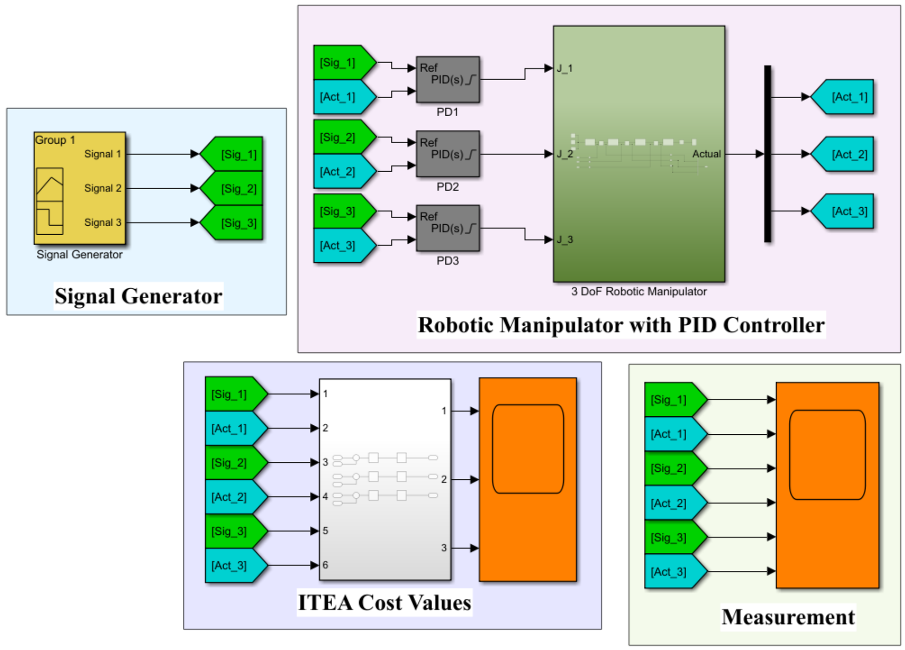

Fig. 3. 3-DoF Simulation model with PID control in MATLAB/Simulink

3 Results and Discussion

3.1 Simulation Model

The simulation setup consists of a 3 DoF robotic manipulator designed in MATLAB/Simulink, controlled by a PID controller tuned using a metaheuristic optimisation algorithm implemented in MATLAB. The cost function for the optimisation algorithm is the ITEA (Integrated Time Error Absolute) index, which measures the performance of the system in terms of the tracking error and the control effort. The simulation setup is shown in Figure 3. This simulation setup aims at achieving precise and efficient control of the robotic manipulator by optimising the PID controller gains through the metaheuristic algorithm. The results obtained from this simulation can be used to validate the proposed control strategy's effectiveness and provide insights for the design and optimisation of robotic manipulators in various applications.

3.2 PID Tuning Error Comparison

In this section of the paper, the authors have compared three different optimisation algorithms, namely PSO [20], GWO [4] and WSO for the purpose of tuning the PID control of a robotic manipulator. The aim of this study was to determine which of the three algorithms would result in the best performance in terms of the cost function and the number of iterations required to achieve a satisfactory result. The cost function used in this study was the Integral Time Absolute Error (ITAE) between the reference trajectory and the actual trajectory of the robotic manipulator. According to the findings of the research, the WSO algorithm demonstrated superior performance compared to the two algorithms namely; PSO and GWO in terms of achieving the best cost and the number of iterations necessary to attain that cost. The best cost versus iteration graphs presented in the paper clearly show that the WSO algorithm consistently outperforms the other two algorithms, with the PSO algorithm performing the worst. The minimisation of cost function by PSO, GWO and WSO is shown in Figure 4. As shown in Table 2 of the paper, the WSO algorithm attained the lowest cost values of 0.00006, 0.0007, and 0.1106 for joint 1, 2, 3, respectively. On the other hand, the GWO algorithm achieved cost values of 0.0012, 0.0025, and 0.2667 for joint 1, 2, 3, respectively. The PSO algorithm achieved a cost of 0.0013, 0.0027, and 0.3081 for joint 1, 2, 3 respectively. This indicates that the WSO algorithm is the most effective algorithm for tuning the PID controller of a robotic manipulator, in terms of both the cost and the number of iterations required to achieve that cost. The PID gains tunned by PSO, GWO and WSO are shown in Table 3.

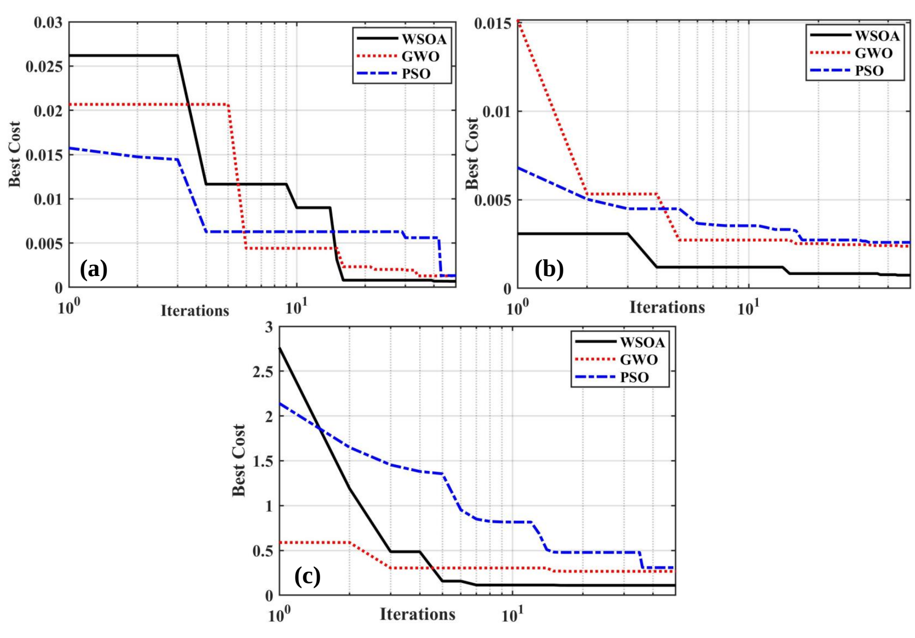

Fig. 4. Best Cost vs Iterations in Tuning of (a) Joint 1 (b) Joint 2 (c) Joint 3

Table 3. Optimised Values of PID Parameters by Algorithms

Technique	Joint	Kp	Ki	Kd
PSO	1	1.504	0.7577	0.0017
	2	2.411	0.3922	-0.0023
	3	1.868	0.6555	0.0039
GWO	1	1.725	0.1712	-0.0025
	2	2.473	0.7060	0.0070
	3	1.129	0.0318	0.0017
WSO	1	1.654	0.2769	-0.00063
	2	2.674	0.0462	0.0026
	3	0.485	0.0971	0.0016

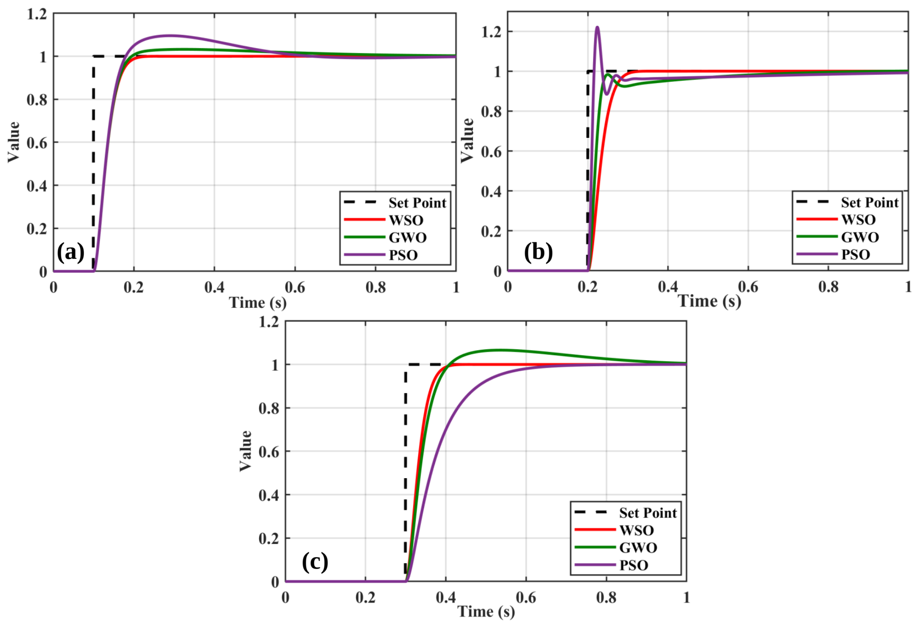

Fig. 5. Step Response Comparison of (a) Joint 1 (b) Joint 2 (c) Joint 3

3.3 Step Response Comparison

In this section of the paper, the authors have compared the step response of all three joints of a robotic manipulator controlled by PID controllers tuned using three different optimisation algorithms, PSO, GWO, and WSO. The step response refers to the duration it takes for a system to react to an abrupt change in input. In this study, the step response of all three joints of the robotic manipulator was measured and compared for each of the three algorithms. The comparison of the step response is shown in Figure 5.

The results of the study indicate that the WSO algorithm produces the best step response for all three joints of the robotic manipulator. The step response plots presented in the paper clearly show that the WSO-tuned PID controller produces a faster response with less overshoot compared to the PSO and GWO-tuned controllers. The PSO-tuned controller shows some oscillations and overshoots, especially in the second and third joints of the robotic manipulator. The GWO-tuned controller shows less overshoot compared to the PSO-tuned controller, but the response is slower. In contrast, the WSO-tuned PID controller produces a faster and smoother step response with minimal overshoot for all three joints of the robotic manipulator.

4 Conclusion

This paper presents a successful application of War Strategy Optimisation Algorithm (WSO) for tuning the PID controller of a three-degree-of-freedom robotic manipulator designed in MATLAB. The results demonstrate that WSO algorithm is more effective in optimising the PID controller parameters compared to Particle Swarm Optimisation (PSO) and Grey Wolf Optimisation (GWO) algorithms. The optimised controller demonstrated improved performance of the robotic manipulator, as evidenced by a faster settling time, reduced overshoot, and steady-state error. The proposed model provides an efficient and effective approach for enhancing the performance of robotic manipulators, and it can be extended to other applications that require optimal PID controller tuning.

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