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Performance comparison of Genetic Algorithm and Artificial Bee Colony Algorithm in optimizing controller parameters of a flexible manipulator

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Abstract

Optimization is about finding the most suitable solution among all feasible solutions. For this purpose, many metaheuristic algorithms have been developed. Genetic Algorithm (GA) and Artificial Bee Colony (ABC) Algorithm are two popular algorithms developed for this purpose. Metaheuristic algorithms are also used in the optimization of controller parameters for flexible manipulators. In this study, parameter optimization was performed with GA and ABC Algorithms for a flexible manipulator controller. For the first comparison, the optimizations are repeated with different number of cycles, and for the second comparison, the simulations are repeated with different search space boundaries. Obtained results were compared over transient responses, maximum end point oscillations and required maximum torque values.

Keywords: Genetic Algorithm, Artificial Bee Colony, optimization, flexible manipulator, comparison.

1. Introduction

In scientific studies and technical problems, the search for optimum values is an important research area. For this purpose, many metaheuristic algorithms have been developed inspired by nature [1]. Genetic Algorithm (GA) and Artificial Bee Colony (ABC) Algorithm are common methods to find the optimum values of the parameters. In addition, determining the optimum value with low cost is an important criterion for optimization.

Studies have been carried out for many years on the design and control of manipulators [2, 3]. Metaheuristic algorithms are used for the dimensional design of the manipulators [4, 5]. In the literature, there are studies in which control parameters are determined by trial and error [6–8]. There are also studies in which metaheuristic algorithms are used in parameter optimization. A modified ABC Algorithm was used for the optimization of PD controller parameters for a single link manipulator [9]. For a double-link flexible manipulator, PID controller parameters were also optimized with Particle Swarm Optimization and ABC Algorithm, then the results were compared with Ziegler-Nichols method [10]. The Bees Algorithm was used in the optimization of LQR parameters [11]. GA, ABC and Vibrating Particles Algorithm were also used in the optimization of LQR parameters, then the performance of the optimization methods was compared [12]. In another study, LQR parameters for a single link manipulator were optimized by PSO, then the results were compared with pole replacement method [13]. PD-like fuzzy logic controller parameters were optimized with the Bacterial Foraging Algorithm, and the results were compared with the controllers referenced in the study [14]. A Fuzzy - Genetic Algorithm was used for the proposed controller for a flexible link manipulator [15]. In another study, the

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proposed controller was improved, and ABC based controller was used for the online optimization. Then, the results were compared with the reference controller [16].

This paper presents the results of the GA and ABC Algorithm optimizations based on the controller given by [16]. The performance of the algorithms is compared in two cases. In Case 1, a relatively large search space for parameter optimization is chosen compared to the given one by [16]. Different cycle numbers are chosen for performance comparison. In Case 2, a suitable cycle number is chosen from Case 1, then different search space dimensions are chosen for performance comparison. Results are compared for the transient response of the system, maximum end point oscillation and required maximum control torque value.

The rest of the paper is organized as follows: In Section 2, the dynamic model of the flexible manipulator and the control torque are described. In Section 3, the details of the performance analysis are presented, then performance comparisons are given. Finally, the conclusion of the paper is described in Section 4.

2. Dynamic Model of The Flexible Manipulator and Controller

Geometric model of the flexible manipulator is given in Figure 1.

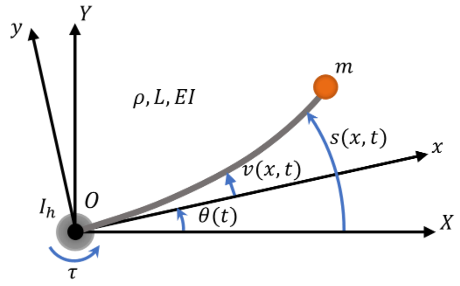

Fig. 1. Geometric model of the flexible manipulator

XOY is the fixed coordinates and xOy is the local coordinate. $\theta(t)$ is the angle of the hub respect to the fixed coordinates. $v(x,t)$ is the deformation of the link. $s(x,t)$ is the end point position of the link respect to the fixed coordinates. τ is the control torque. m is the end point mass and considered as a point mass. Thus, its rotational inertia is neglected. The manipulator is restricted to move only horizontal plane. It is also assumed that the manipulator is flexible in transverse direction, and rigid in other directions. Elongation between link and hub is small enough to be neglected. Definition and values of the other parameters are given by Table 1.

Table 1. Parameters of the flexible manipulator

Parameter	Definition	Value
I_h	Hub inertia	0,04 kgm^2
ρ	Mass of unit length	1 kgm^{-1}
L	Length of the link	1 m
EI	Flexural rigidity	3 Nm^2
m	Payload	0,2 kg

Dynamic model of the flexible manipulator is expressed in Equation 1 which has been derived by the authors in [16].

$$\boldsymbol{M\ddot{X}} + \boldsymbol{KX} = \boldsymbol{T} \tag{1}$$

Elements of the inertia matrix $\boldsymbol{M}$ are given by Equation 2-5. The number of assumed modes considered is represented with n.

$$M_{(1,\ 1)} = I_h + \rho \frac{L^3}{3} + mL^2 \tag{2}$$

$$M_{(1,\ i+1)} = \rho \int_0^L x\phi_i(x)dx + mL\phi_i(L) \quad i = 1,2,\dots,n \tag{3}$$

$$M_{(i+1,\ 1)} = M_{(1,\ i+1)} \quad i = 1,2,\dots,n \tag{4}$$

$$M_{(i+1,\ i+1)} = \rho \int_0^L \phi_i^2(x)dx + m\phi_i^2(L) \quad i = 1,2,\dots,n \tag{5}$$

Rigidity matrix $\boldsymbol{K}$ is a diagonal matrix and its elements are given by Equation 6 and 7.

$$K_{(1,\ 1)} = 0 \tag{6}$$

$$K_{(i+1,\ i+1)} = EI \int_0^L \phi_i''^2(x)dx \quad i = 1,2,\dots,n \tag{7}$$

System has only one controller as torque τ. Thus, $\boldsymbol{T}$ matrix is expressed as

$$\boldsymbol{T} = [\tau \quad 0 \quad \dots \quad 0]^T \tag{8}$$

The controller torque expression is chosen from the reference [16] for the system which is given as

$$\tau(t) = \frac{r_1}{1 + r_2 m_{11}}\big(\theta_d - \theta(t)\big) + \frac{r_2}{1 + r_2 m_{11}} k + \frac{-r_3}{1 + r_2 m_{11}} \dot{\theta}(t) \tag{9}$$

where

$$m_{11} = \boldsymbol{M}_{(1,1)} \tag{10}$$

$$k = (\boldsymbol{M}^{-1}\boldsymbol{K}\boldsymbol{X})_{(1,1)} \tag{11}$$

3. Performance Analysis

In this section, GA and ABC Algorithm are applied to optimize the control torque parameters of the flexible manipulator to analysis the performance of the algorithms. Two cases are chosen for comparison. In Case1, different cycle numbers and in Case 2, different search spaces are considered for optimization process.

As seen in Equation 9, control torque has three parameters as r_1, r_2 and r_3. In both cases, two different optimization sets are applied. In the first set, all three parameters are optimized simultaneously. Parameter r_2 effects all the coefficients in the torque expression as seen in Equation 9. Thus, in the second set, only parameter r_2 is optimized. Simulations are applied in MATLAB. Simulations are compared by 4 different results as: overshoot percentage of $s(L,t)$, settling time of $s(L,t)$ for transient response of the system. $v_{max}(L,t)$ as maximum end point oscillation and $\tau_{max}(t)$ as maximum torque value achieved during simulation. The desired position for flexible link is chosen as $\theta_d = 1\ rad$ in all simulations.

3.1. Case 1

Cycle number is one of the important parameters in optimization process. Higher cycle numbers result with higher costs for an optimization. Thus, simulations are repeated with different cycle numbers to examine the performance. Performed simulations in Case 1 is given by Table 2. First, simulations are performed for all three parameters optimization. Then, simulations are performed for parameter r_2 optimization. In these optimizations, constant parameters are selected as $r_1 = 4$ and $r_3 = 5$.

Table 2. Simulations for Case 1

Simulation No	Method	Optimization Parameters			
		Cycle Number	Population	Lower Bound	Upper Bound
1	ABC	5	20	1	100
2		20			
3		50			
4		100			
5	GA	5	20	1	100
6		20			
7		50			
8		100			

Simulation results are given by Figure 2 for three parameter optimization and Figure 3 for r_2 optimization.

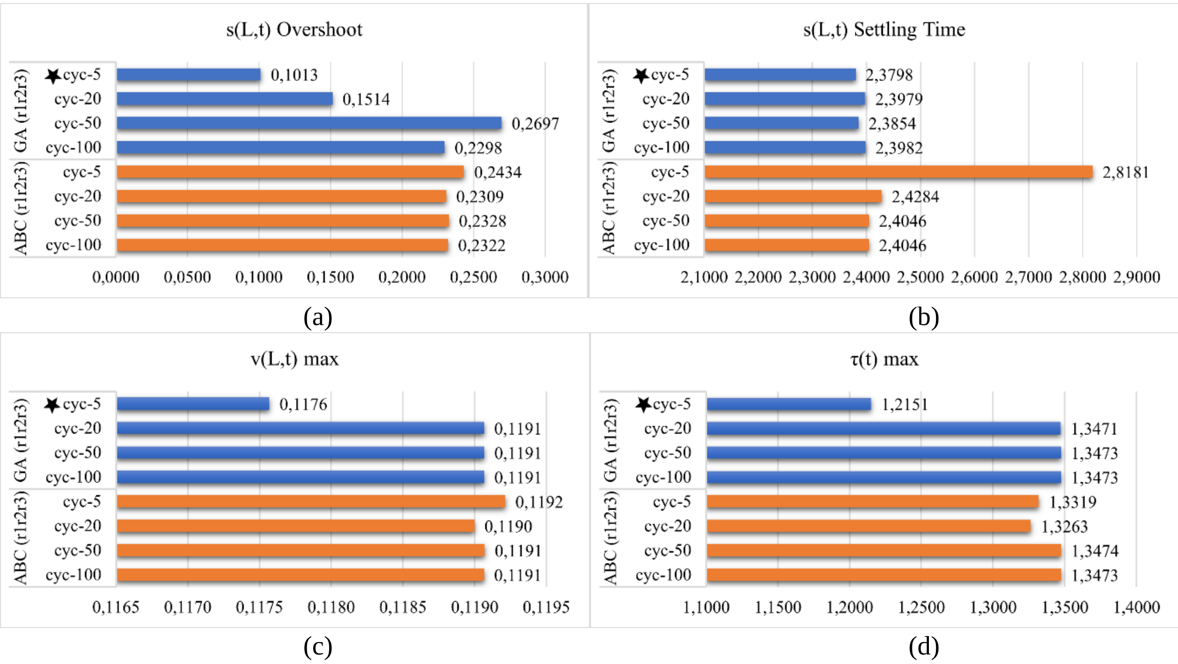

Fig. 2. Performance comparisons for all parameters optimization, (a) $s(L,t)$ overshoot, (b) $s(L,t)$ settling time, (c) maximum end point oscillation, (d) maximum torque value

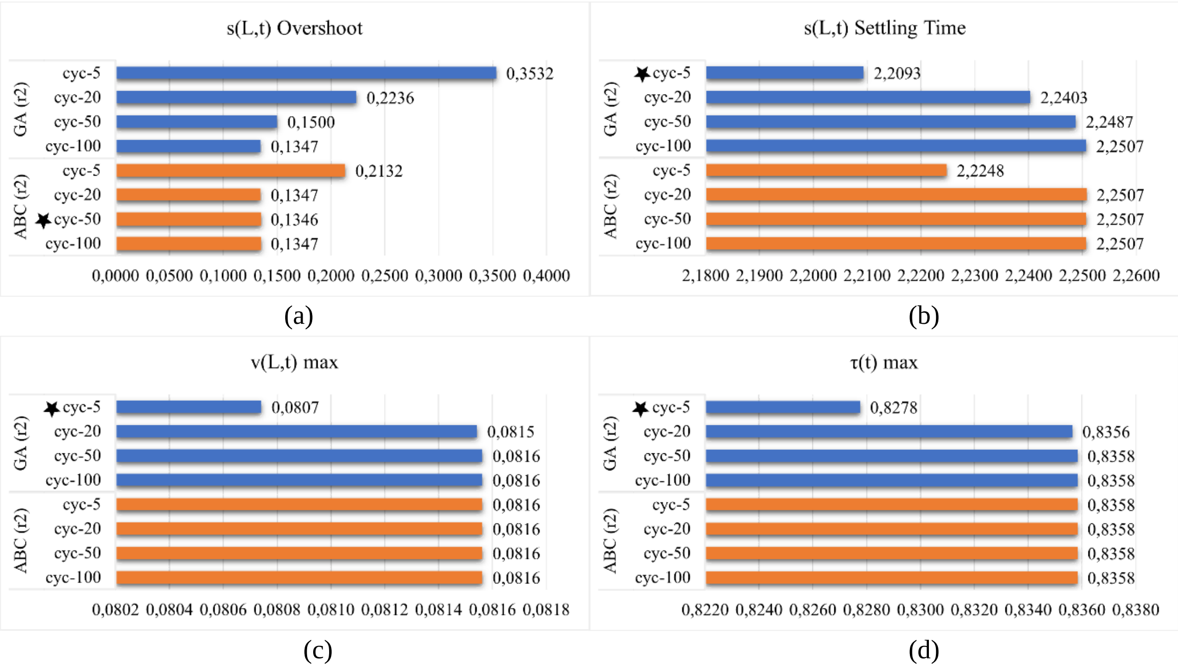

Fig. 3. Performance comparisons for r_2 optimization, (a) $s(L,t)$ overshoot, (b) $s(L,t)$ settling time, (c) maximum end point oscillation, (d) maximum torque value

Figure 2(a) shows the overshoot percentage of the end point for all parameters optimizations. For ABC Algorithm overshoot has closer values for all cycle numbers and smaller then 0,3% in all cases. However, GA gives better results with smaller cycle numbers. The best result for overshoot is achieved by GA with 5 cycles. Results for settling time of end point are given with Figure 2(b). All simulations give closer results except ABC Algorithm with 5 cycles. Although other simulations have closer results, the best settling time is achieved with GA with 5 cycles. Maximum oscillation values during simulations are given with Figure 2(c) and maximum torque values achieved during simulations are given with Figure 2(d). GA with 5 cycle gives the best results for these comparisons. Thus, for given conditions the best performance is achieved with GA with 5 cycles.

Overshoot of the end point for r_2 optimizations are given by Figure 3(a). Unlike the all parameters optimization smallest cycle number does not give the best performance. For ABC Algorithm, results are almost the same between 100 and 20 cycle numbers. But, significantly worst for 5 cycle number. However, it is seen that the number of cycle values for GA significantly affects the results. For 100 cycle GA gives the same overshoot percentage as ABC. The worst result is achieved by GA with 5 cycles. Figure 3(b) shows the settling time results for r_2 optimizations. Results are opposite of Figure 3(a) in terms of performance. The smallest cycles give the best result for both GA and ABC Algorithm. Once again, ABC Algorithm for simulations between 100 and 20 cycle numbers result with same performance. Performance of GA is also affected more clearly by changes of cycle number. Bu this time, smaller cycle numbers effect settling time in a positive way, unlike overshoot percentage. Figure 3(c) shows the maximum end point oscillations. All simulations give nearly the same oscillation, except GA with 5 cycles. Same performance is achieved for maximum torque values as seen in Figure 3(d).

As a result, for all parameters optimization GA with 5 cycles has the best performance for all comparisons. ABC Algorithm with 5 cycles has the closest performance to GA with 5 cycles. However, for r_2 optimizations, performances are dependent on the expectation. When smaller overshoot is the case, higher cycles give better results. But, when settling time is important, smallest cycles give the best performance for both algorithms.

3.2. Case 2

Search space is another important parameter in an optimization process. Chosen upper and lower bounds for parameters to be optimized identify the search space for an optimization. Applied simulations in Case 2 is given by Table 3. Simulations are applied for all three parameters optimization then applied for parameter r_2 optimization. In these optimizations, constant parameters are selected as $r_1 = 4$ and $r_3 = 5$ like Case 1.

Table 3. Simulations for Case 2

Simulation No	Method	Optimization Parameters			
		Cycle Number	Population	Lower Bound	Upper Bound
1	ABC	20	20	1	10
2					20
3					50
4					100
5	GA	20	20	1	10
6					20
7					50
8					100

Simulation results are given by Figure 4 for three parameter optimization and Figure 5 for r_2 optimization.

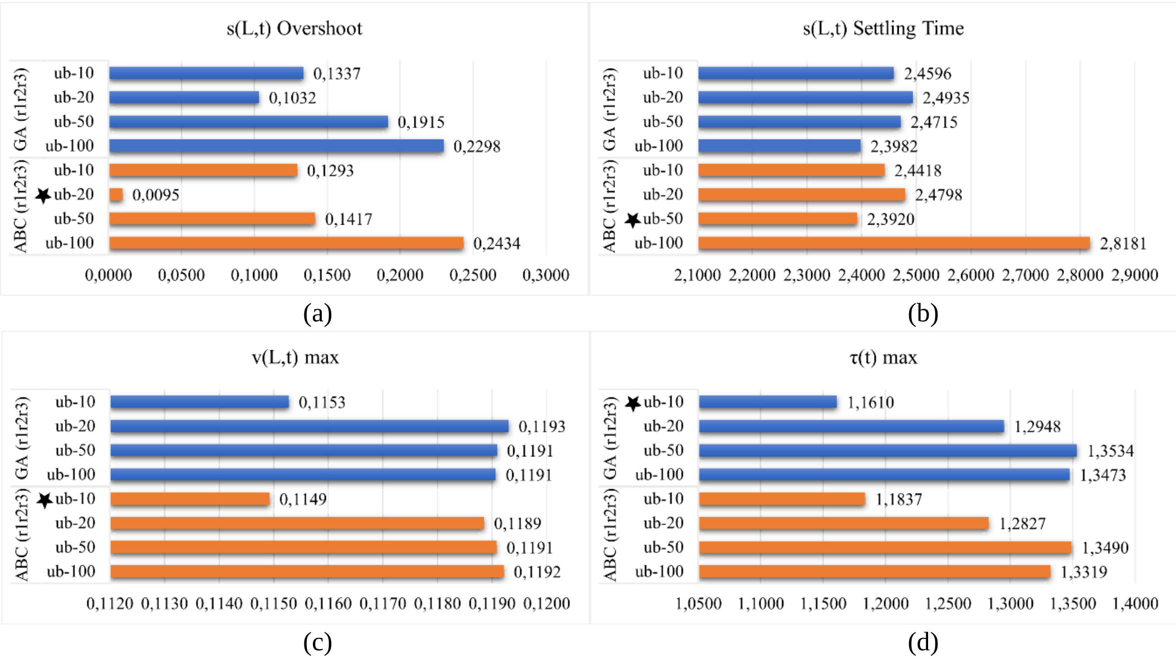

Fig. 4. Performance comparisons for different upper bounds, (a) $s(L,t)$ overshoot, (b) $s(L,t)$ settling time, (c) maximum end point oscillation, (d) maximum torque value

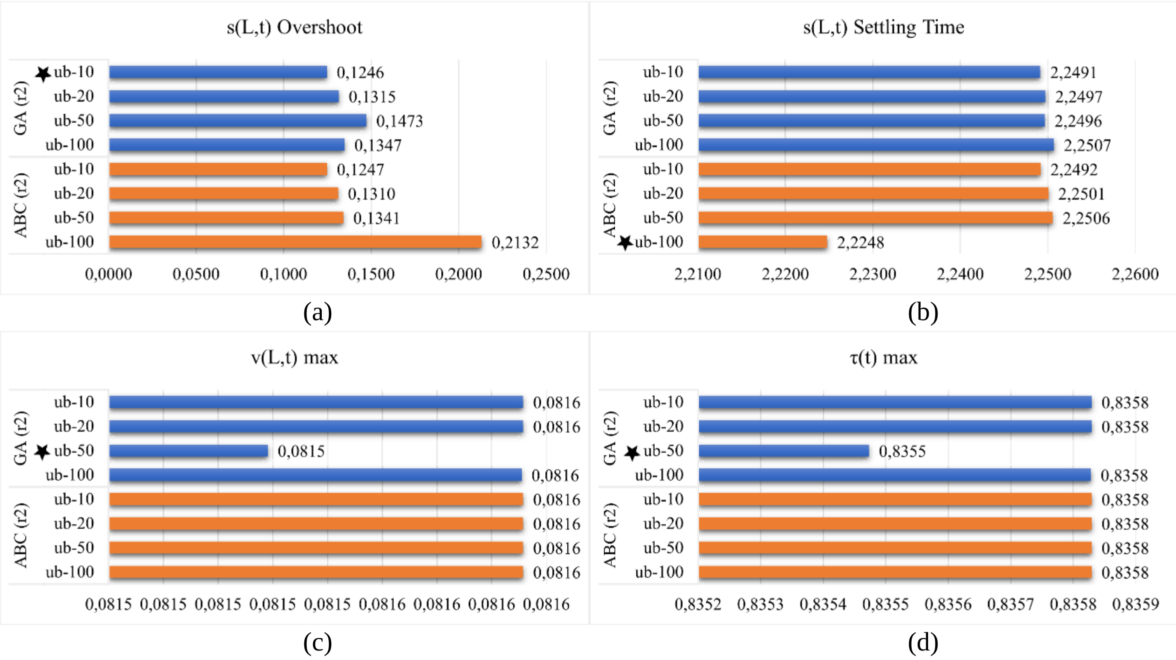

Fig. 5. Performance comparisons for different upper bounds, (a) $s(L,t)$ overshoot, (b) $s(L,t)$ settling time, (c) maximum end point oscillation, (d) maximum torque value

As seen in Figure 4(a), largest search spaces result with worse performances in terms of overshoot. Best results are achieved with optimizations by taking the upper bound value as 20 for both GA and ABC Algorithm. ABC Algorithm has the best performance with nearly no overshoot as 0,0095%. Figure 4(b) settling time performance of the optimizations. The worst settling time performance is achieved by ABC Algorithm with the largest search space. The best settling time is achieved by ABC Algorithm with upper bound value of 50. Also, the largest search space effect the performance of ABC more than GA in terms of settling time. Maximum oscillation values are given with Figure 4(c). Results are significantly close with all simulations except with upper bound value of 10 for both optimization methods. As seen in Figure 4(d), the biggest torque values are achieved with upper bound value of 50 and the smallest values are achieved with upper bound value of 10.

Figure 5(a) shows the overshoot percentage of the end point for r_2 optimizations. The biggest overshoot is seen with upper bound value of 100 for ABC Algorithm. This is also the worst performance for the overshoot. The best results are achieved both GA and ABC Algorithm with upper bound value of 10. Settling time performance is given by Figure 5(b). All simulations give closer result except ABC Algorithm with upper bound value of 100. Unlike overshoot performance, ABC Algorithm with largest search space gives the best result in all simulations in terms of settling time. Figure 5(c) and Figure 5(d) gives the maximum oscillation for end point and maximum torque values achieved during simulation, respectively. Results are almost the same for all optimizations as seen in these figures.

As a result, for all parameters optimization, the best performance is dependent on the expectation from the system. If smaller overshoot values are more important, then ABC Algorithm with upper bound value of 20 is the best option. When suppression of the end point oscillation is relatively more important than overshoot, then ABC Algorithm and GA with upper bound value of 10 are the best options. For r_2 optimizations, the performances of all optimizations are really close except ABC Algorithm with largest search space. This simulation is the best one only if the settling time is the most important performance parameter. But the smaller overshoot percentage is the case, upper bound value of 10 is the best options for both algorithms. There is no significant difference in terms of maximum oscillation for end point or maximum torque values.

4. Conclusion

In this study, GA and ABC Algorithms were applied to determine the optimum values of the flexible link manipulator controller parameters. Thus, optimization methods were compared over the optimum control of the system. Two cases applied for comparisons. In the Case 1, different cycle numbers are chosen for optimization. In the Case 2 different search spaces are applied by changing upper bounds of the optimization. Transient response of the system as overshoot percentage and settling time, maximum end point oscillation and maximum torque values achieved during simulations were used for performance comparisons. Because of the structure of the controller, optimizations both applied for all parameters optimization, also one parameters optimization that effect all coefficients in the controller.

In the Case 1, GA with smaller cycle value achieved optimum control for all parameter optimization condition. But, for the one parameter optimization results were depended on the expectation from the controller. Overshoot performance and the settling time performance were conflicted. A better overshoot performance resulted with worse settling time.

In the Case 2, optimum results were also depended on the expectation from the controller for all parameters optimizations. The smallest overshoot and the smallest end point oscillation achieved with different search spaces but the same optimization method which is ABC Algorithm. Performances of the optimizations for one parameter optimization were close enough for both GA and ABC Algorithm in terms of one parameter optimization with one exception that ABC Algorithm with the largest search space.

Author Contribution Statement

All authors have contributed equally.

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