Optimisation of Internal Model Control Performance Indices for Autonomous Vehicle Suspension

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Abstract- Autonomous vehicles (AVs) have grown in popularity and acceptability due to their unique capacity to reduce pollution, road accidents, human error, and traffic congestion. Vehicle suspension is an important component of a car chassis since it affects the performance of vehicle dynamics. As a result, enhancing suspension performance and stability is critical in order to achieve a more pleasant and safer car. Although there are several suspension control methods, they all suffer from fixed gain characteristics that are prone to nonlinearities, disturbances, and the inability to be tuned online. This research provides a comparison of Internal Model Control (IMC) performance metrics for vehicle suspension control. The IMC approach was tuned using the Genetic Algorithm and the Particle Swarm Optimisation algorithms. The performance of each of these schemes was analysed and compared in order to determine the approach with the best performance in terms of AV suspension control. The performance of the system response was compared to that of the traditional IMC. According to the comparison analysis, the optimized IMC systems had lower IAE, ITAE, ISE, rising time, and settling time values than the traditional IMC. Furthermore, there were no overshoots in any of the controllers.

Keywords- Autonomous Vehicles, Genetic Algorithm, Internal Model Control, Particle Swarm Optimisation, Vehicle Suspension

1 Introduction

The growth of robotics and intelligent systems has accelerated the development of autonomous and self-driving automobiles. The goal of these vehicles is to arrive at their destination safely and steadily (Park, Lee, & Han, 2015). Autonomous Vehicles (AVs) have gained widespread popularity and acceptance due to their unique ability to minimise pollution, road accidents, human errors, and traffic congestion. AVs also significantly contribute to saving energy, improving throughput, increasing efficiency, and enhancing safety (Bala, 2019).

Vehicle suspension is a vital component of a car chassis because of its influence on vehicle dynamics performance. The suspension is a collection of springs, linkages, and shock absorbers that connects the vehicle to the wheels and supports motion between the two sections (Dishant, Singh, & Sharma, 2017). The suspension establishes contact between the vehicle tyres and the road surface. This in turn has a direct implication on the ride, stability, handling, and comfort of the vehicle (Meng, Chen, Wang, Sun, & Li, 2021; Wang, 2018). Vehicles are complex and dynamic systems consisting of multiple inputs and multiple outputs. As such, improving suspension performance and stability is vital in achieving a more comfortable and safer vehicle.

Numerous control schemes have been proposed for suspension control (Djellal & Lakel (2018); Alexandru & Alexandru (2010); Alvarez (2013); Ghandhi & Ramaachandran (2017); Hanafi (2010)). However, the presence of uncertainties and nonlinearities affect the fixed gain characteristics of these techniques. The feedback gains of these controllers are obtained offline based on the system model, and once deployed, the gains cannot be changed (Fu, Li, Ning, & Xie, 2017). Thus, a more effective method for controller design is required for effective and efficient control performance.

This study presents a comparative evaluation of IMC performance indices for suspension control in AVs. The IMC technique was optimised using Genetic Algorithm and Particle Swarm Optimisation algorithms. The performance analysis of each of these schemes was carried out and compared to determine the technique with better performance with respect to AV suspension control. The rest of this paper is divided into four (4) sections. Section 2 presents a review of existing literature while the research methodology is presented in Section 3. The results and analysis are presented in Section 4 and the conclusion and future research directions are given in Section 5.

2 LITERATURE REVIEW

Proportional Integral Derivative (PID) control is widely used in control engineering due to its simplicity, low cost, and ability to guarantee satisfactory performance. In the work of Hanafi, (2010), a PID control scheme was developed for semi-active car suspension. The suspension model was obtained from an intelligent system identification process. The results showed good performance in shock absorber control and road surface disturbance rejection. Similarly, Ignatius, Obinabo, & Evbogbai, (2016) designed a PID controller for an active

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suspension system using an automated tuning technique. The PID tuner in MATLAB was utilised for the automated selection of PID gains and a performance meeting the design requirements specified was shown by the results. Papkollu, Singru, & Manajrekar, (2014) carried out a comparative analysis between the performance of the H-infinity controller and PID controller in a car suspension system. The PID was tuned using the root locus design technique and the results indicated that the PID outperformed the H-infinity control scheme in terms of passenger comfort although the H-infinity scheme provided better suspension deflection. A major limitation with these works is the employment of fixed gain parameters for PID controllers which limits performance in dynamic environments. Additionally, the utilisation of multiple gains in PID control leads to difficulty in tuning (selection of appropriate gains for effective performance) (Somefun, Akingbade &Dahunsi (2021)).

Internal Model Control (IMC) provides an easier design method than PID due to the need for tuning one parameter instead of three parameters as in the case of PID (Folorunso, Bala, Adedigba &Aibinu (2021)). In the work conducted by Qiu, Sun, Jankovic, & Santillo, (2016), a nonlinear IMC was designed for regulation of a wastegate in a turbocharged gasoline engine. When compared with a PI controller, the IMC exhibited faster reference tracking with less overshoot or oscillation. Prakash & Sohom, (2018) developed an IMC-based fractional order control scheme for specific non-minimum phase systems. The developed controller provides a good control performance in reference tracking, disturbance rejection, and error minimisation. In addition, Roslan, Abd Karim, & Hamzah, (2018) carried out a performance analysis of different tuning techniques for an isothermal CSTR reactor. Although, the IMC showed better results than Direct Synthesis (DS) and Ziegler Nichols (ZN) methods in the aspect of overshoot and undershoot, the other techniques outperformed the IMC in error minimisation and settling times.

IMC has also been implemented together with PID to provide an IMC-PID scheme or its variant. In the work of Cajo et al., (2018), an IMC-based PID technique was developed for a benchmark system. The suggested control scheme showed a better performance in disturbance rejection with lower control effort than the traditional PID scheme. Additionally, Babins & Pradeep, (2018) compared the performance of an IMC and an IMC-PID in a low control system for a conservation tank. The IMC-PID scheme exhibited better dynamic performance in terms of parameters such as set-point tracking, disturbance rejection, and robustness. An IMC-based PID controller was designed for a coupled tank system in the study conducted by Prakash, Yadav, & Kumar, (2016). The performance of the controller was compared with a traditional PID tuned with Ziegler-Nichols, Cohen Coon, and Tyreus-Luyben methods. The IMC-PID showed better robustness and performance. Pathiran, (2019) improved the regulatory response of a PID controller using IMC principles. The results showed the proposed scheme gives improved response and servo-regulatory performance than Ziegler Nichols PI/PID control techniques. Despite the improved performance of IMC and IMC-PID schemes in the literature, a major limitation with IMC techniques is the reliance on the accurate representation of the plant model. Because of this, the robustness and performance of the IMC may be reduced due to model inaccuracies and uncertainties. Therefore, the need arises for an adaptive and optimised IMC scheme for improved control performance (Zhu, Xiong, Liu, & Zhu, 2016).

3 Research Methodology

3.1 Problem Formulation

The suspension of the vehicle is modelled centred on a quarter car, passive suspension (Alvarez-Sanchez (2013), Bala, (2019)). The free body diagram is shown in Figure 1.

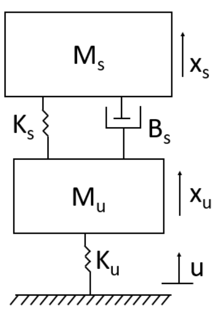

Fig. 1: Free Body Diagram of Car Suspension

Where:
Ms = Mass of Vehicle
Mu = Mass of Suspension
Ks = Spring Constant of Suspension
Ku = Spring Constant of Wheel
Bs = Damping Constant of Suspension

The variables xs, xu, and u represent the displacement of the vehicle, displacement of the suspension, and road profile change respectively.
Based on Figure 1, the following equations are obtained:

$$M_s\ddot{x}_s = -K_s(x_s - x_u) - B_s(\dot{x}_s - \dot{x}_u) \quad (1)$$

$$M_u x_u = K_s(x_s - x_u) + B_s(\dot{x}_s - \dot{x}_u) - K_u(x_u - u) \quad (2)$$

Converting equations 1 and 2 to Laplace transforms and substituting the parameters selected in Table 1, we obtain the representation in equation 3.

$$G(s) = \frac{x_s}{u} = \frac{4s+5}{0.06s^4 + 0.092s^3 + 20.01s^2 + 4s + 5} \quad (3)$$

Equation 3 serves as the vehicle model transfer function.

Table 1. Vehicle Suspension Parameters (Bala, 2019)

Parameter	Value
Mass of Vehicle	2000 kg
Mass of Suspension	300 kg
Spring Constant of Suspension	50,000 N/m
Spring Constant of Wheel	100,000 N/m
Damping Constant of Suspension	1200 Ns/m

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3.2 Internal Model Controller Design

The use of the Internal Model Controller in tuning the PID controllers has quickly gained popularity among researchers because of its simplicity, robustness, strong tracking performance, ease of disturbance abatement, and ease of tuning (due to single tuning parameter, λ) (Yu, Karimi, & Zhu, 2014; Payne, 2014). A traditional IMC architecture is shown in Figure 2 (Folorunso, Bello, Olaniyi & Abdulwahab, 2013).

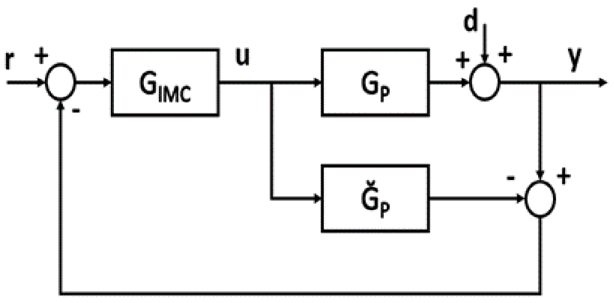

Fig. 2: Internal Model Controller Architecture

The variables r, u, d, and y respectively represent the input, control signal, disturbance, and output. Gp, and Ğp are the plant model, and process model respectively. G_{IMC} represents the IMC, and this is obtained using equation 4. F(s) is the filter, which is given by equation 5.

$$G_{IMC}(s) = \breve{G}p^{-1}(s)F(s) \tag{4}$$

$$F(s) = \frac{1}{(1+\lambda s)^n} \tag{5}$$

In equation 5, n represents the order of the plant model and λ is a tuning parameter responsible for speed of response and robustness. λ also deals with noise amplification and modelling errors. Thus, λ needs to be appropriately selected for effective control performance.

The IMC system is evaluated by taking the inverse of equation 3 and multiplying it by the filter in equation 5. Since the plant is a fourth order plant, the filter coefficient, n, will be equal to 4. Thus, we obtain the IMC equation as shown in equation 6.

$$G_{IMC}(s) = \frac{0.06s^4 + 0.092s^3 + 20.01s^2 + 4s + 5}{4s+5} \times \frac{1}{(1+\lambda s)^4} \tag{6}$$

$$G_{IMC}(s) = \frac{0.06s^4 + 0.092s^3 + 20.01s^2 + 4s + 5}{4\lambda^4 s^5 + (5\lambda^4 + 16\lambda^3)s^4 + (20\lambda^3 + 24\lambda^2)s^3 + (30\lambda^2 + 16\lambda)s^2 + (20\lambda + 4)s + 5} \tag{7}$$

The variable λ will be selected using the optimisation algorithms to provide the optimum control performance.

The IMC closed loop transfer function is given in equation 8.

$$G_c(s) = \frac{G_{IMC}(s)}{1 - G_{IMC}(s)\breve{G}_p(s)} \tag{8}$$

3.3 Particle Swarm Optimisation Algorithm

Particle Swarm Optimisation (PSO) is an algorithm developed from Swarm Intelligence in 1995 by Kenndey and Eberhart. It is a global optimisation algorithm developed based on the behaviour of birds and fish. Just like these animal groups that eventually converge at a food source through communication between themselves, the algorithm attempts to converge at an optimum solution through imitation of the behaviours of these animals (Olaniyi, Folorunso, Kolo, Arulogun, & Bala, 2016). The PSO algorithm is given in Figure 3.

```
function particleSwarm
define particlePositions, particleVelocities as double;
while (stopping criteria not met) {
For each particle i:
      Evaluate fitness yi at current position xi
      If yi is better than pbesti then update pbesti and pi
      If yi is better than gbesti then update gbesti and gi
For each particle i:
      Update velocity vi and position xi using:
      vi= vi + U(0,φ1)(pi – xi) + U(0,φ2)(gi – xi)
      xi = xi + vi
end function
```

Fig. 3: PSO Algorithm

From Figure 3, pbest and gbest respectively represent the particle's best position and the global best position. U(0, ϕ) is a random vector generated for each particle. Table 2 shows the PSO parameters used for this study.

Table 2. PSO Parameters

Parameter	Value
Swarm Size	100
Number of Iterations	200
Inertia Weight	0.7
Upper Bound	10
Lower Bound	1

3.4 Genetic Algorithm

Genetic Algorithm (GA) is an optimization algorithm introduced by John Holland in 1975 and solves problems using the principles of biological evolution (Haldurai, Madhubala, & Rajalakshmi, 2016; Obaid, Ahmad, Mostafa, & Mohammed, 2012). GA evaluates the problem space as a population of individuals and attempts to find the fittest individual by producing generations and applying concepts such as crossover, mutation and selection (Obaid et al., 2012). GA navigates a search area and attempts to find the optimum solution. Figure 4 shows a flowchart of the GA process.

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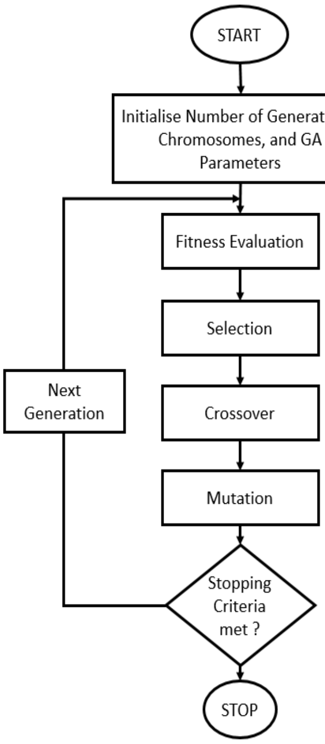

Fig. 4: GA Process

The GA parameters used for this study are presented in Table 3.

Table 3. GA Parameters

Parameter	Value
Number of Generations	100
Population	50
Crossover	Scattered (random)
Mutation	Gaussian
Selection Type	Stochastic
Upper Bound	10
Lower Bound	1

3.5 Objective Function Development

The objective functions implemented in this work are obtained based on common performance indices for control systems. These indices are the Integral Absolute Error (IAE), Integral Square Error (ISE), and the Integral of Time-weighted Absolute Error (ITAE). These are popular error performance indices with engineering practicality and selectivity (Li & Li, 2020). These indices will be adopted as the objective functions to be minimised by the optimisation algorithms. The functions are given in equations 9 to 11.

$$J_1 = ITAE = \int_0^{\infty} t|e(t)|dt \quad (9)$$

$$J_2 = ISE = \int_0^{\infty} e(t)^2 dt \quad (10)$$

$$J_3 = IAE = \int_0^{\infty} |e(t)|dt \quad (11)$$

4 Results and Analysis

The controller design and optimization algorithm were implemented using the MATLAB 2020 software. The iteration performance of the optimising algorithm is as presented in Table 4 and Table 5. In Table 4, the performance of the PSO is presented. The algorithm stops after 20 iterations due to the absence of any significant change in the objective function value. From Table 4 it is observed that the PSO algorithm ensures minimisation of the Best and Mean performance indices. However, in the instance of the mean ITAE, the minimisation value fluctuates around 3000. This can be attributed to the multiplication by the 'time' variable in the performance metric since the value increases as the algorithm progresses. Upon completion, the algorithm settles at the best objective value of 232.2, 168.8, and 2794 for the IAE, ISE and ITAE respectively.

Table 4. The Iteration Performance of the PSO

Iteration	Best f(x) - IAE	Mean f(x) - IAE	Best f(x) - ISE	Mean f(x) - ISE	Best f(x) - ITAE	Mean f(x) - ITAE
0	257.1	1362	172.3	1030	3488	120000
1	232.2	876.7	168.8	689.3	2802	103300
2	232.2	373.7	168.8	236.5	2796	26420
3	232.2	233.2	168.8	172.6	2796	4548
4	232.2	232.2	168.8	168.8	2795	2991
5	232.2	232.2	168.8	168.8	2795	3050
6	232.2	232.2	168.8	168.8	2795	3065
7	232.2	232.2	168.8	168.8	2795	3014
8	232.2	232.2	168.8	168.8	2794	3110
9	232.2	232.2	168.8	168.8	2794	2992
10	232.2	232.2	168.8	168.8	2794	3050

In Table 5, the results of the minimisation by GA are presented. Here, the algorithm ensure convergence to Best objective function values of 232.2, 168.8, and 4220 for the IAE, ISE, and ITAE respectively. Similar to the case of the PSO algorithm, the Mean ITAE hovers around 4500. However, this occurrence is also observed in the Mean ISE and Mean IAE values.

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Table 5. The Generational Performance of the GA

Generation	Best f(x) - IAE	Mean f(x) - IAE	Best f(x) - ISE	Mean f(x) - ISE	Best f(x) - ITAE	Mean f(x) - ITAE
1	232.2	1060	168.8	762.5	4323	75920
2	232.2	844.5	168.8	510.8	4323	45290
3	232.2	615.1	168.8	406.8	4323	21630
4	232.2	480.1	168.8	282.9	4323	13990
5	232.2	415.6	168.8	227.6	4323	6328
6	232.2	317.8	168.8	226.8	4220	5104
7	232.2	272	168.8	200.1	4220	5036
8	232.2	265.3	168.8	203.2	4220	4380
9	232.2	244	168.8	196.6	4220	4404
10	232.2	237.2	168.8	189.2	4220	4373

The optimisation algorithms' performance was also comparatively analysed in the aspect of the control system response of the performance metrics. Figures 4 to 6 show the step response of various controllers for the three performance indices.

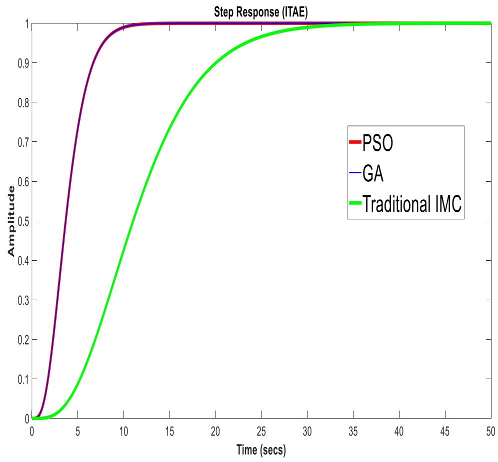

Fig. 4: Step Response of all Controllers (ITAE)

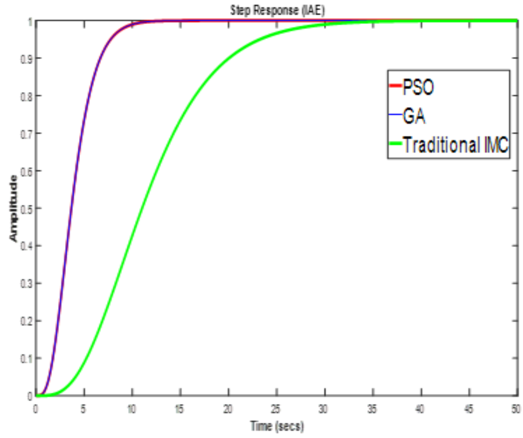

Fig. 5: Step Response of all Controllers (IAE)

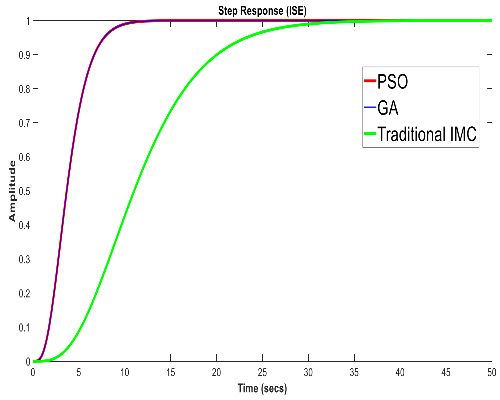

Fig. 6: Step Response of all Controllers (ISE)

In Table 6, the minimisation of the IAE resulted in a respective rise time and settling time of 4.94 seconds and 9.08 seconds for both the PSO and GA algorithms. The optimised IMC systems exhibited an IAE of 232.18 which is significantly lower than the value obtained by the traditional IMC which was 696.43. The λ parametric value of the traditional IMC was selected manually and was chosen to be 3, while the optimisation algorithms selected λ values of 1. All controllers exhibited an overshoot of 0% which is common with IMC systems. The results of the comparison of the various controllers with respect to the ITAE are presented in Table 7. The optimisation algorithms gave λ values of approximately 1 and 1 for the PSO and GA-based IMCs respectively. The ITAE, rise times, and settling times of the optimised controllers are also significantly lower than that of their traditional counterparts.

Table 8 shows the comparison of the various controllers with respect to the ISE. Similar to the IAE, the GA and PSO controllers exhibited similar response parameters and ISE values. The values gotten from the optimised controllers were significantly lower than the value gotten from the traditional controller. Similarly, all controllers gave no overshoots.

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Table 6. Controller Comparison (IAE & System Response)

Controller	λ	IAE	Rise Time (secs)	Settling Time (secs)	Overshoot (%)
Traditional IMC	3	696.43	14.8	27.3	0
PSO-IMC	1	232.18	4.94	9.08	0
GA-IMC	1	232.18	4.94	9.08	0

Table 7. Controller Comparison (ITAE & System Response)

Controller	λ	ITAE	Rise Time (secs)	Settling Time (secs)	Overshoot (%)
Traditional IMC	3	24675	14.8	27.3	0
PSO-IMC	1.0134	2794.3	5	9.21	0
GA-IMC	1.1924	4219.6	5.89	10.8	0

Table 8. Controller Comparison (ISE & System Response)

Controller	λ	ISE	Rise Time (secs)	Settling Time (secs)	Overshoot (%)
Traditional IMC	3	506.43	14.8	27.3	0
PSO-IMC	1	168.81	4.94	9.08	0
GA-IMC	1	168.81	4.94	9.08	0

The performance of the iteration performance of the PSO and GA algorithms, the optimal λ values of the have been selected based on tuning efficiency as depicted in Table 4 and Table 5. Based on this performance, an optimal λ value of 1 is selected. Hence, it is expected that the transient response of the IMC-PSO and IMC-GA would be the same. However, for the traditional IMC, a λ value of 3 was obtained based on the rule of thumb. Hence, it is expected that there would be a difference in the transient response and controller performance.

Observe from Table 6-8, showing the transient response and controller performance based on the IAE, ITSE, and ISE. It can be seen that all 3 approaches depict a zero overshoot, this is expected based on the inherent characteristic of the IMC algorithm. However, there exists a difference in the settling time and the rise time. It can be observed that the PSO and GA approach has the same rise time and settling time of 4.98 sec and 9.08 sec. This is a result of the same λ value obtained from the tuning of the PSO and GA algorithm. However, there is a difference in the performance metrics in comparison with the traditional approach due to the varying values of λ. The PSO and GA have a faster rise time and settling time as compared to the traditional approach, these can be observed in the performance plot as depicted in Figures 4-6. This evaluation places PSO and GA approaches as better controllers as compared to the traditional approach.

5 Conclusion

In this study, the optimisation of Internal Model Controller (IMC) performance indices was carried out for an Autonomous Vehicle (AV) suspension system. The suspension system was modelled based on a quarter car passive suspension. The IMC system was optimised using Particle Swarm Optimisation (PSO) and Genetic Algorithm (GA). These optimisation algorithms were designed to minimised error performance indices of control systems, namely: Integral Time-weighted Absolute Error (ITAE), Integral Absolute Error (IAE), and Integral Square Error (ISE).

The obtained results indicated that the optimisation algorithms ensured minimisation of all the performance indices considered. Additionally, the system response performance was compared with the conventional IMC. The comparative analysis showed that the optimised IMC systems exhibited lower IAE, ITAE, ISE, rise time, and settling time values than the traditional IMC. Furthermore, all the controllers exhibited no overshoots. The results gotten from the study indicate that PSO and GA can be successfully implemented in optimising IMC-based systems for AV suspension control. The PSO and GA based IMC systems minimise the errors values, reduce the rise and settling times, and produce no overshoots. These characteristics are desirable in control systems since they minimise damage, inaccuracy, and instability. Future research directions will focus on implementation of optimisation on nonlinear control techniques for performance evaluation.

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