

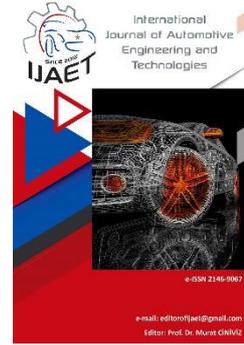


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Original Research Article

Grey wolf optimizer-based PID controller design for an automobile cruise control system



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ABSTRACT

The cruise control systems are designed to maintain a desired speed of the vehicle and they can contribute to the comfort and fuel economy of the vehicle. Although PID controllers are popular for controlling the speed of the vehicle, their performance is highly sensitive to the choice of parameters. This paper presents the application of the Grey Wolf Optimizer algorithm for the optimization of PID controllers of a widely used cruise control system of an automobile by optimizing the Integral of Time-Weighted Squared Error (ITSE). The performance of the derived PID controller is analyzed in the time and frequency domains and the results are compared with the metaheuristic approaches available in the literature for the same plant model. The results show that the GWO optimized controller provides a stable closed-loop response and comparable performance in the time and frequency domains which confirms the applicability of GWO for the optimization of PID controllers of the cruise control system of an automobile.

Keywords: Cruise control system, PID control, Optimization, Grey Wolf Optimizer.

1. Introduction

The automotive industry is shifting towards more intelligent transportation systems with a focus on safety, awareness and fuel economy. Cruise Control Systems (CCS) and Adaptive Cruise Control (ACC) systems, which were luxury features a decade ago, are now critical for road safety and a necessary feature in every car. At a conceptual level, CCS/ACC systems control a car's forward movement; however, it is marred by nonlinear effects like friction, rolling resistance and gravity on undulating roads. As Osman et al. state, for a model to

adequately represent a realistic system, it needs to model a nonlinear system along with a linear system [1]. Frank et al.'s classic work on longitudinal control and the challenge to automate it on cooperative highways is one of the pioneers in the field [2]. As stated by Rajamani, the ultimate benefit comes from high-performance dynamics inspired by high-performance control design, particularly in the presence of disturbances [3]. Furthermore, Musul and Cihan proposed a novel Intelligent Adaptive Cruise Control (IACC) architecture that integrates Traffic Sign and Limit

Recognition (TSLR) and GPS data to enhance safety, particularly on curved roads [4]. A wide variety of control approaches have arisen to tackle dynamics. One reason for the increased use of fuzzy controllers is that they can deal with model uncertainties and model the human decision-making process without explicitly knowing a mathematical model of a system. As an example of a control strategy, Asere et al. propose a CCS that dynamically changes along with the change in the car's weight by using a set of fuzzy control strategies [5]. Aligned with the trend, there is online learning based on fuzzy control by Onieva et al., which feeds back and dynamically changes along with road conditions to prove that soft computing can easily surpass others [6]. By developing a cascaded fuzzy logic architecture, which arranges fuzzy inference systems into a hierarchical tree to reduce computational complexity, Simic further advanced this field [7]. Other noteworthy contributions include Wu et al.'s application of variable universe fuzzy control based on Finite State Machine theory to increase tracking precision and Naranjo et al.'s successful implementation of fuzzy control for gap-keeping [8, 9]. Furthermore, Muller and Nocker showed early on that fuzzy logic could manage the nonlinearities in intelligent cruise control [10]. Because of its dependability and structural simplicity, the proportional-integral-derivative (PID) controller continues to be the industry standard despite the success of fuzzy systems. However, ideal parameter tuning is crucial to its performance. PID, Fuzzy, ANFIS and Model Predictive Control (MPC) were compared by Al-Saoudi et al., [11]. Ogata particularly highlighted that classical methods of tuning lack robustness against disturbances in nonlinear systems [12]. Moreover, according to a study conducted by Li et al., due to increased necessities of predictive control methods to achieve performance improvements based on road elevation data, there arose a requirement for modernization in conventional control methods [13]. Being a means to cope with challenges related to controller tuning, there arose a requirement for metaheuristic algorithms, as Genetic Algorithms proved very efficient in

determining global optima values for PI and PID gain parameters [14, 15]. Rout et al. illustrated that PID controllers based on GA resulted in superior transient performance as against state-space methods [16]. Subsequent authors, Chirantan et al., also evaluated stability where GA-based methods resulted in a decrease in settling time and overshoot as against Ziegler-Nichols methods [17]. This similarity study was further extended to Linear Quadratic Regulators (LQR) by Mahmood et al., [18]. They found that a greater compromise between safety and comfort can be gained using evolutionary algorithms. Another successful example of swarm intelligence can be seen in applications related to control engineering. Salem et al. successfully employed Particle Swarm Optimization (PSO) to optimize the Time Integral Absolute Error (TIAE) metric [19]. Their objective was to improve the speed of response of a control system. Chaturvedi and Kumar also demonstrated the success of a PSO-tuned PID controller in avoiding overshoot when compared with fuzzy PID and PD+I controllers [20]. Similarly, Abdulnabi successfully demonstrated the reliability of a PSO-based approach in searching the optimum PID gains for a cruise control system [21]. More recently, new approaches based on metaheuristics have emerged. Pradhan et al. introduced the Ant Lion Optimizer (ALO), proving its superiority over GA in maintaining stability under Bode ideal transfer function constraints [22]. Izci et al. further presented an improved Opposition-based Arithmetic Optimization Algorithm (ObAOANM) that succeeded in minimizing the integral time squared error [23]. Ekinci et al. designed the Modified Oppositional Chaotic Local Search-based Aquila Optimizer (CmOBL-AO) for PID2 controller parameter optimization [24]. This optimizer demonstrated exceptional robustness even in the presence of external disturbances. Hlangnamthip et al. used the Modified Bat Algorithm (MBA) for PID controller optimization [25]. The algorithm succeeded in reducing response time with fewer oscillations compared to the traditional PSO algorithm. Further, the recent work by Saravanan et al. has utilized the Red Panda Optimization (RPO)

algorithm that proved successful in improving the rise time and stability of ACC [26]. Finally, Jing referenced the usage of the genetic fuzzy immune PID algorithm [27]. The trend in this case is the hybridization of multiple intelligent methods to deal with the challenging scenario of downhill driving.

Despite these developments, there is still a need to further explore optimization techniques that can be effectively used for PID tuning problems. This paper investigates the application of the Grey Wolf Optimizer (GWO) for tuning the PID parameters of a widely adopted automobile cruise-control benchmark model by minimizing the Integral of Time-Weighted Squared Error (ITSE). GWO has been reported in prior studies as a usable alternative for similar tuning tasks; therefore, it is worth exploring within this framework. The obtained controller gains are evaluated using standard transient response indices and frequency-domain characteristics and the results are benchmarked against recent metaheuristic PID designs reported in the literature for the same plant model. The comparative analyses indicate that the proposed GWO-PID achieves stable closed-loop behavior and competitive performance across the considered criteria.

The contribution of this study is not in the application of GWO for the first time in the tuning of a PID controller. Rather, it is in the provision of a transparent workflow for the tuning of a popular automobile cruise control benchmark by a GWO approach and a comparison with some recent results on the application of various metaheuristic approaches for the tuning of a PID controller for the same model.

2. Cruise Control System Modeling

The purpose of the cruise control system is to bring the vehicle's speed close to and maintain the reference speed set by the driver. Using the reference speed signal (v_R) from the driver and feedback information measured from the speed sensor, the controller adjusts the throttle angle (u). The throttle angle changes the traction force (F_d) produced by the engine; thus, the vehicle speed (v) is increased or decreased.

The longitudinal motion of the vehicle shown in Figure 1 is modeled based on Newton's law.

$$F_d = M \frac{dv}{dt} + F_a + F_g \tag{1}$$

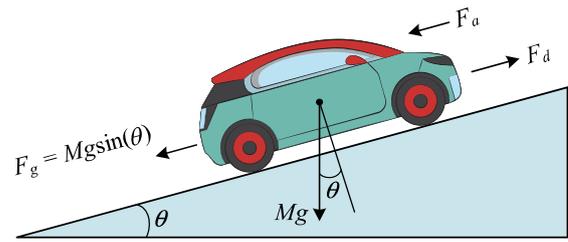


Figure 1 Longitudinal forces on a vehicle.

In this approach, the engine's traction force counteracts the inertial effect required for vehicle acceleration and the drag forces that slow down the motion. Two main effects are considered on the drag side: aerodynamic drag, which increases with speed and the climb/descent component caused by road gradient. The model scheme also includes parameters such as wind gust velocity (v_w), road gradient (θ), vehicle mass (M) and aerodynamic coefficient (C_a). Actuator and propulsion dynamics are not practically "instantaneous": the throttle command is converted into traction force with a time delay and first-order behavior; moreover, the traction force is limited by physical limits. The traction force is bounded in practice because the engine/drivetrain and the tire-road interface impose finite limits on the achievable longitudinal force. To avoid non-physical actuator demands in simulations, the traction force is therefore treated as saturated and is constrained to the nominal range reported in Table 1.

Table 1 System Parameters

Description	Value
F_d Drive force	± 3500 N
τ Driver reaction time	0.2 s
T Observation time	1s
M Mass of vehicle and passenger	1500 kg
C_l Actuator constant	743
C_a Aerodynamic drag coefficient	1.19 N/(m/s) ²
g Gravitational acceleration	9.8 m/s ²

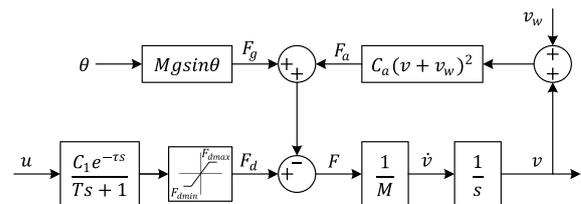


Figure 2 Dynamics of cruise control system.

To simplify controller design, the model shown in Figure 2 is simplified: initial conditions are assumed to be zero and

disturbances, wind and slope are eliminated. In this case, vehicle speed and drive force are selected as the system's state variables and nonlinear state equations giving the speed and force relationship are written.

$$\dot{v} = \frac{1}{M}(F_d - C_a v^2) \quad (2)$$

$$\dot{F}_d = \frac{1}{T}(C_1 u(t - T) - F_d) \quad (3)$$

$$y = v \quad (4)$$

The nonlinearity in these equations arises from the drag varying with the square of the speed. Overcoming this problem, one possible way is linearizing all state-equations by differentiating both left and right-hand sides of the equations when M , C_a , C_1 , T and v are held constant. The state-equations, after differentiation;

$$\frac{d}{dt} \dot{v} = \frac{1}{M}(-2C_a v \delta v + \delta F_d) \quad (5)$$

$$\frac{d}{dt} \dot{F}_d = \frac{1}{T}(-C_1 \delta u(t - T) - \delta F_d) \quad (6)$$

$$y = \delta v \quad (7)$$

δv indicates that the output is a delta function and δF_d indicates that drive force is also delta function whereas v indicates desired and $\delta u(t - \tau)$ indicates time delay of engine. Until now, both state and output equation are described in time domain. From linearized model, it has been understood that there is transfer function that could be solved to get the ratio of $\Delta V(s)/\Delta U(s)$.

$$\frac{\Delta V(s)}{\Delta U(s)} = \frac{\frac{C_1 e^{-\tau s}}{MT}}{\left(s + \frac{2C_a v}{M}\right)\left(s + \frac{1}{T}\right)} \quad (8)$$

Based on the approximation of power series expansion of time delays in the transfer function of the system, time delay could be approximated to be;

$$e^{-\tau s} \approx \frac{1}{1 + \tau s} \quad (9)$$

Insert this value into the plant transfer function of;

$$G_p(s) = \frac{\Delta V(s)}{\Delta U(s)} = \frac{\frac{C_1}{MT}}{\left(s + \frac{2C_a v}{M}\right)\left(s + \frac{1}{T}\right)\left(s + \frac{1}{\tau}\right)} \quad (10)$$

The upcoming calculation will be as difficult as the case when linearization has not been carried out yet. At least, it should reduce the

complexity of the calculations. Next, the transfer function of the system can be represented as in (11) with a nominal speed of 30 km/h based on the values in Table 1.

$$G_p(s) = \frac{\Delta V(s)}{\Delta U(s)} = \frac{2.4767}{(s+0.0476)(s+1)(s+5)} \quad (11)$$

To provide a fair and transparent benchmarking of the tuning approaches, the nominal linear cruise control plant model is used in this study and disturbance-free speed regulation is considered. In addition, wind gusts, road grades and mass variations are not considered in the current simulation studies. The current modeling approach decouples the impact of controller tuning and provides direct comparability with previous studies that have reported results on the same nominal plant. The robustness of the tuned controller against wind, grade and mass uncertainties is identified as an important extension and is recommended as future work.

3. PID Control

In this section, a traditional PID controller is described to decrease the speed error for the cruise control system. The controller's input is the error signal expressed as $e(t)$ and the output is $u(t)$, which is the sum of three parts: the proportional part provides instantaneous acceleration to the system to decrease the error, the integral part reduces the steady-state error to zero and the derivative part contributes to the elimination of overshoots by taking into consideration the change in the value of the error signal with time.

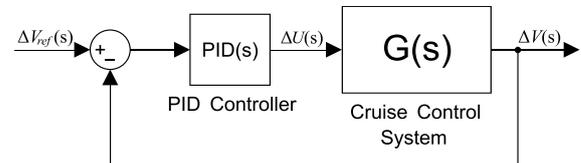


Figure 3 PID Control of CCS.

The general structure of the PID controller is presented as a block diagram in Figure 3. In addition, the general PID control equation, which expresses how the control signal is generated depending on the error signal, is given in Equation (12) [12].

$$PID(s) = K_p + \frac{K_i}{s} + K_d s \quad (12)$$

The overall closed-loop structure is realized by

combining the PID controller with the plant transfer function obtained in the previous section. The closed-loop transfer function from the reference input to the system output is given in Equation (13) when the controller and plant expressions are substituted into the

feedback structure.

$$CLTF_{PID}(s) = \frac{G_{PID}(s)G(s)}{1 + G_{PID}(s)G(s)} \tag{13}$$

$$= \frac{2.4767(K_d s^2 + K_p s + K_i)}{s(s + 0.0476)(s + 1)(s + 5) + 2.4767(K_d s^2 + K_p s + K_i)}$$

4. Grey Wolf Optimizer

In this research, Grey Wolf Optimizer (GWO) is used as a method for exploring solutions and finding optimal PID gain parameters for the cruise control system. GWO is a metaheuristic algorithm developed by Mirjalili et al. inspired with a grey wolf-prey hunting mechanism [28]. GWO is based on the social hierarchy of grey wolves shown in Figure 4. In the GWO algorithm, solutions are explored with the help of alpha, beta and delta grey wolves in the encircling-prey hunt.

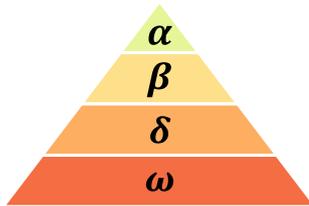


Figure 4 Hierarchy of grey wolves [28].

Grey wolves' hunting behavior is illustrated in Figure 5, highlighting how the wolves cooperatively encircle the prey during the search process. As shown in the figure, a grey wolf can update its position based on the current position of the prey.

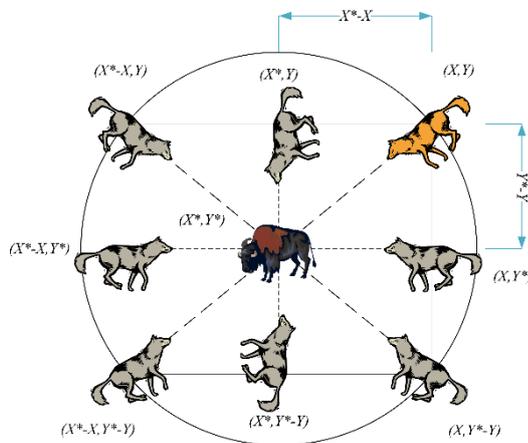


Figure 5 Grey wolves' hunting behavior [28].

The overall procedure for tuning K_p , K_i and K_d

using GWO is summarized in Figure 6. Further, the GWO algorithm uses the Integral of Time-weighted Squared Error (ITSE) shown in figure as the objective function.

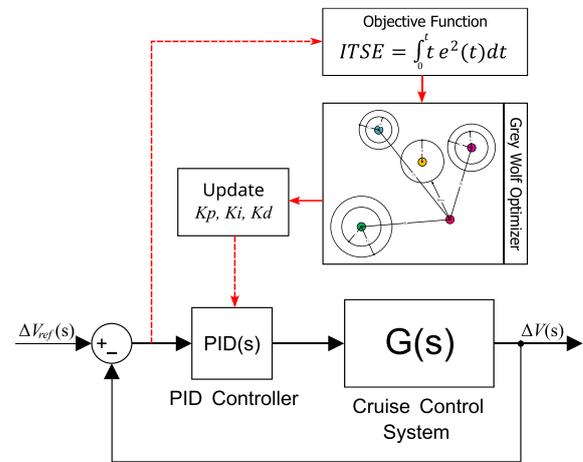


Figure 6 GWO procedure for tuning PID.

Finally, the search is constrained within predefined lower and upper bounds for each PID parameter, as reported in the min–max limits table. The min–max bounds in Table 2 is selected to constrain the search to practically reasonable PID magnitudes for the adopted benchmark plant and to avoid excessively aggressive gains that may lead to unrealistic control effort or poor numerical behavior during optimization. In addition, the bounded search space improves convergence reliability by focusing the exploration on gain ranges that yield feasible and stable closed-loop responses for the considered model.

Table 2 PID parameters search limits.

	K_p	K_i	K_d
Min	3	0.10	3
Max	5	0.25	5

5. Results and Discussion

This section presents the performance of the Grey Wolf Optimizer based PID tuning applied to the cruise control system. The GWO algorithm is executed with 30 search agents, 200 iterations and the Integral of Time-weighted Squared Error (ITSE) is used as the objective function to identify the PID gains for the best closed-loop response. Moreover, the obtained results are compared with alternative metaheuristic approaches reported in the literature, using the same plant model and evaluation criteria. The compared methods are the Genetic Algorithm (GA), the Arithmetic Optimization Algorithm (AOA) and the Ant

Lion Optimizer (ALO). Grey Wolf Optimizer and the compared metaheuristic algorithms are stochastic by construction. To reduce run to run variability, the GWO-based tuning is executed multiple times and the controller gains reported in this manuscript correspond to the most suitable run in terms of the predefined objective function and stable closed-loop response. The optimal PID parameters obtained by each optimization method are given in Table 3. This table shows the tuned parameters by GWO and the other optimization methods. This table provides a clear numerical view of how different optimization methods result in varying gain values for solving the same control problem.

Table 3 Optimized PID parameters.

	K_p	K_i	K_d
GWO	4.2360	0.1721	4.4986
AOA [23]	4.0407	0.2119	4.1548
ALO [22]	3.8580	0.2089	3.8581
GA [16]	3.5907	0.1630	3.3021

For a better understanding of the optimization process, Figure 7 shows the convergence curve of the objective function. From this figure, it can be observed how the ITSE value changes over the iterations.

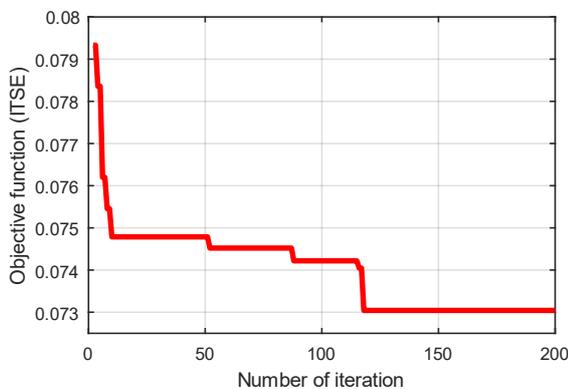


Figure 7 Convergence curve of the GWO.

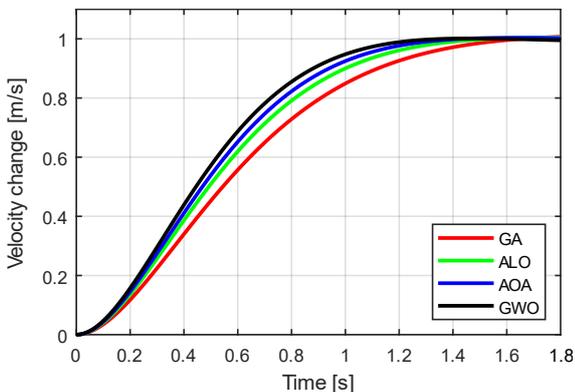


Figure 8 Step responses for PID tuned by proposed GWO, AOA [23], ALO [22] and GA [16].

The closed-loop step responses of the PID gains tuned by GWO and the other methods are compared in Figure 8. As seen in the figure, the responses are largely similar and the results indicate comparable behavior among the approaches considered.

In addition to time-domain analysis, frequency-domain characteristics are given by Bode plots. Figure 9 shows the Bode magnitude and phase responses for the controllers being compared for the closed loop systems obtained from each method. This comparison gives an interpretation of the dynamic behavior in the frequency domain that supports the general assessment of the tuned controllers.

In the AOA study of İzci et al., the peak closed-loop gain (P_g) and bandwidth (B_w) are computed from the closed-loop transfer function [23]. For the GWO-PID, P_g is approximately 0 dB and is slightly lower than the AOA-PID value, which is 0.0217 dB, indicating reduced closed-loop peaking. The bandwidth of the GWO-PID is 0.4820 Hz, which is about 8.3% higher than that of the AOA-PID at 0.4451 Hz, suggesting a slightly faster closed-loop dynamics.

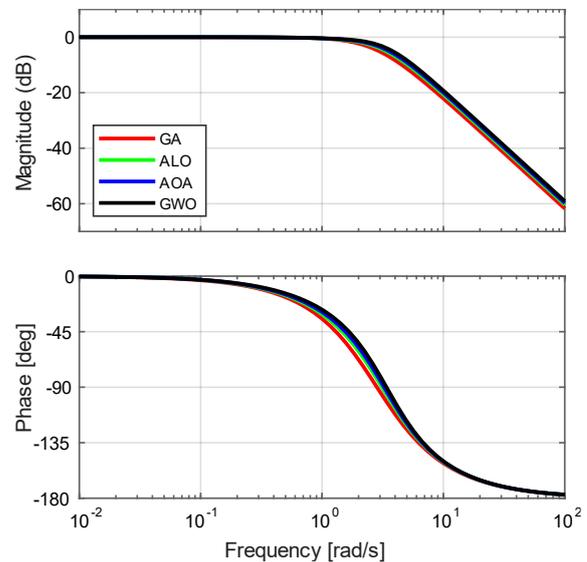


Figure 9 Frequency responses for PID tuned by GWO, AOA [23], ALO [22] and GA [16].

The main performance metrics derived from the step response of the system are shown in Table 4, these are maximum overshoot (M_p), rise time (t_r), settling time (t_s), peak time (t_p) and steady-state error (e_{ss}). Presenting these results together allows for a convenient comparison between the controllers based on

their tracking accuracy and transient response behavior. The percentage improvement of GWO over the reference algorithms is computed. Compared to AOA, ALO and GA, the proposed GWO reduces the maximum overshoot by 63.17%, 72.16% and 88.35%, respectively. Similarly, the rise time is reduced by 6.73% (vs AOA), 12.74% (vs ALO) and 22.57% (vs GA), while the settling time is reduced by 6.85%, 13.18% and 21.93%. For peak time, the corresponding improvements are 10.56%, 19.65% and 30.68%. The steady-state error remains zero for all compared methods.

Table 4 PID parameters tuned by proposed GWO, AOA [23], ALO [22] and GA [16].

	GWO	AOA	ALO	GA
M_p [%]	0.1335	0.3625	0.4795	1.1456
t_r [s]	0.7272	0.7797	0.8334	0.9392
t_s [s]	1.1365	1.2201	1.3091	1.4558
t_p [s]	1.4640	1.6369	1.8220	2.1120
e_{ss}	0	0	0	0

Overall, the results obtained with the tuned gains, the convergence behavior of the ITSE, the step responses, the frequency responses and the transient response specifications show that GWO provides an alternative which is feasible and applicable to the considered cruise control problem for PID tuning. The responses obtained are generally consistent with comparative methods, hence supporting the observation that GWO can easily be used in this type of controller parameter optimization task.

Although the differences in the metaheuristic structures may be insignificant when measured numerically, these differences have important implications for the operation of the cruise control system. For instance, a smaller overshoot indicates reduced deviations from the desired speed during the transient response, providing a smoother ride, while a reduced settling time indicates faster response to the steady-state condition and the desired point of operation. Therefore, any improvements to the transient response, although seemingly insignificant, can be noticeable during operation.

6. Conclusions

This study presents a Grey Wolf Optimizer based evaluation for tuning proportional

integral derivative controller parameters for a vehicle cruise control system by formulating the tuning task as the minimization of the Integral of time weighted Squared Error (ITSE). The resulting controller is assessed in closed loop simulations and its performance is compared against other metaheuristic tuning methods given in the literature using the same plant model. The convergence behavior of ITSE, together with the consistent step and frequency response support that GWO provides a feasible and applicable alternative for PID tuning in the considered cruise control problem and can be effectively used for controller parameter optimization tasks of this type.

External disturbances and parametric variations are not considered in the current benchmark setup. For future studies, wind gusts, road slopes and mass changes can be incorporated as disturbances. The controller design can be extended by reformulating the tuning task as a multi objective optimization problem. Robustness and uncertainty analyses can be performed to assess performance under modeling errors and parameter variations around the nominal operating point.

Conflict of Interest

There is no conflict of interest for the authors.

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