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ARTICLE

Modified Elite Opposition-Based Artificial Hummingbird Algorithm for Designing FOPID Controlled Cruise Control System

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ABSTRACT

Efficient speed controllers for dynamic driving tasks in autonomous vehicles are crucial for ensuring safety and reliability. This study proposes a novel approach for designing a fractional order proportional-integral-derivative (FOPID) controller that utilizes a modified elite opposition-based artificial hummingbird algorithm (m-AHA) for optimal parameter tuning. Our approach outperforms existing optimization techniques on benchmark functions, and we demonstrate its effectiveness in controlling cruise control systems with increased flexibility and precision. Our study contributes to the advancement of autonomous vehicle technology by introducing a novel and efficient method for FOPID controller design that can enhance the driving experience while ensuring safety and reliability. We highlight the significance of our findings by demonstrating how our approach can improve the performance, safety, and reliability of autonomous vehicles. This study's contributions are particularly relevant in the context of the growing demand for autonomous vehicles and the need for advanced control techniques to ensure their safe operation. Our research provides a promising avenue for further research and development in this area.

KEYWORDS

Cruise control system; FOPID controller; artificial hummingbird algorithm; elite opposition-based learning

1 Introduction

Control engineering is a field that focuses on designing systems to maintain the desired performance of a process or a device. One of the most widely used systems in control engineering is the proportional-integral-derivative (PID) controller, which is used to control the output of a process based on its error signal. However, recent research has shown that fractional-order PID (FOPID) controllers offer improved performance over conventional PID controllers, especially in systems with nonlinear dynamics or time-varying parameters. The design of a FOPID controller involves the use of fractional calculus, which is an extension of classical calculus that deals with integrals and derivatives of non-integer orders. FOPID controllers offer greater flexibility in terms of tuning and can provide better control performance.

Control engineering is a field that deals with designing systems to regulate the behavior of a process or a device. One of the most commonly used systems in control engineering is the proportional-integral-derivative (PID) controller, which is used to maintain the desired output of a process based on its error signal. However, recent research has shown optimized FOPID (fractional-order PID) controllers, which offer improved control performance over conventional PID controllers. Optimized FOPID controllers involve the use of advanced algorithms and optimization techniques to tune the controller parameters and achieve desired control objectives. These controllers provide greater flexibility and can improve the control performance of complex systems with nonlinear dynamics or time-varying parameters.

Reducing fuel consumption and emissions, like carbon dioxide and air pollutants, is a pressing challenge for the transportation sector, particularly the automobile industry, which is grappling with oil scarcity and environmental concerns [1]. To address this, policymakers and car manufacturers are exploring a range of strategies and products, such as advanced engines, intelligent vehicles, and new energy technologies [2]. One technology that has gained attention is the cruise control system [3], a new technology with the potential to reduce fuel consumption (at both the local and global level), driver fatigue, risk of collisions, and traffic congestion [4].

The cruise control system aims to offer drivers a comfortable driving experience and improve fuel economy while meeting driving time and the desired speed limit [5]. Research on cruise control system has focused on controlling the vehicle speed at a desired velocity with more convenient control strategies in order to design a system that balances the fuel efficiency, driving safety and comfort [6]. Many control strategies have been proposed, including classic proportional-integral-derivative (PID) control [7] and its fractional counterpart (FOPID) [8], PID control with reference model [9], fuzzy logic control [10], and model predictive control [11]. Of the many controllers proposed, the PID framework has been favored for designing cruise control systems due to its simplicity [12]. On the other hand, the FOPID controllers can boast a greater capability as the use of fractional terms gives them more flexibility in design, making them a more suitable option for dynamic systems [13]. This has been confirmed by various applications that demonstrate the enhanced ability of FOPID controllers [14,15].

A proper tuning method is necessary to make the most of the benefits offered by FOPID controllers. In this regard, the metaheuristic algorithms have demonstrated significant capabilities as artificial intelligence optimization techniques [16–19]. Recently, researchers have utilized various artificial intelligence techniques to tune different controllers for cruise control systems, such as the enhanced reptile search algorithm [20], global neighborhood algorithm [21], modified version of Aquila optimizer [22], Harris hawks optimization [23], arithmetic optimization algorithm [24], antlion optimizer [25], genetic algorithm [17], and atom search optimization with Nelder-Mead method [3]. These methods have been shown to result in improved performance. Despite the advancements in optimization frameworks, there’s still ample room for improvement, as evidenced by the “no free lunch” theorem [26] as it highlights that there’s no one-size-fits-all solution, leaving the door wide open for further enhancement and development [27–29].

In this study, therefore, the authors aimed to apply a new intelligent optimization approach to design a FOPID controller in a cruise control system such that a more capable method can be developed. To this end, the artificial hummingbird algorithm [30] was adopted as a novel efficient optimization technique and its capability was further boosted with the aid of a modified version of the elite opposition-based learning scheme [31]. The modified elite opposition-based artificial hummingbird algorithm was initially tested on some of the widely used benchmark functions in order to show its superiority over the basic form of the artificial hummingbird algorithm. Then, it was utilized to appropriately tune the FOPID controller used in a cruise control system. The performance of the proposed method was tested against existing best and recent artificial intelligence-based methods used to tune FOPID controlled cruise control system. For this purpose, Harris hawks optimization [23] based FOPID, arithmetic optimization algorithm [24] and antlion optimizer [25] based integer order PID (IOPID) controllers were adopted alongside the basic and modified forms of the artificial hummingbird algorithms-based FOPID controllers. Transient response, frequency response and robustness analyses have shown that the proposed method based FOPID controller can perform more efficiently compared to the reported best approaches in the literature, making the proposed method in this study more favorable for the cruise control system.

The remainder of this paper is organized as follows: Section 2 shows the main procedure of the Artificial hummingbird algorithm. Section 3 shows the proposed modified elite opposition-based artificial hummingbird algorithm. Section 4 shows the experimental results on benchmark functions. This is followed by Section 5, which shows the simulation results on vehicle cruise control system. Finally, Section 6, the conclusion and future works directions.

2 Artificial Hummingbird Algorithm

Memory capacity, foraging strategies and flight skills of hummingbirds have inspired the construction of the artificial hummingbird algorithm (AHA) as an efficient optimization technique [30]. In this optimization technique, three models (guided foraging, territorial foraging, migrating foraging) are used for mimicking the foraging behaviors. A population of n hummingbirds is randomly initialized and located on n food sources using $x_i = L + r \cdot (U - L)$, where x_i is the position of the i^{th} food source, L and U are respectively the lower and upper limits of a d-dimensional problem, $i = 1, \ldots, n$, and r is a random vector within [0, 1]. The following definition is used to create a visit table:

$$VT_{i,j} = \begin{cases} 0, & i \neq j \\ null, & i = j \end{cases} \tag{1}$$

where $i = 1, \ldots, n$ and $j = 1, \ldots, n$. In the visit table defined by Eq. (1), *null* indicates a specific food source where a hummingbird takes the food whereas 0 means that the i^{th} hummingbird has just visited the j^{th} food source in the current iteration.

In guided foraging, the behavior of the hummingbird visiting the food source with the highest nectar refilling rate is modeled. A hummingbird flies towards the determined food source by performing omnidirectional, diagonal, and axial flight skills [30]. The mathematical model of the guided foraging is defined as:

$$v_i(t+1) = x_{i,trg}(t) + \alpha \cdot D \cdot \left(x_i(t) - x_{i,trg}(t)\right) \tag{2}$$

where $v_i(t+1)$ represents the candidate food source position, α is the guided factor subjecting to the normal distribution with mean 0 and deviation 1, $x_i(t)$ is the i^{th} food source position at time t, $x_{i,trg}(t)$ is the targeted food source that the i^{th} hummingbird aims to visit. The position of the i^{th} food source is updated as follows where f is the fitness function value.

$$x_i(t+1) = \begin{cases} x_i(t), & f(x_i(t)) \leq f(v_i(t+1)) \\ v_i(t+1), & f(x_i(t)) > f(v_i(t+1)) \end{cases} \tag{3}$$

A hummingbird is likely to look for a new food source after visiting the target food source. This is described as territorial foraging which is explained as:

$$v_i(t+1) = x_i(t) + b \cdot D \cdot x_i(t) \tag{4}$$

where b is a territorial factor which is subjected to the normal distribution with mean 0 and deviation 1. After performing the territorial foraging behavior, the visit table is updated. A hummingbird may also migrate to a food source, which is far away if a commonly visited region suffers from enough food supply. This behavior is described with the migration foraging behavior which is described as:

$$x_{wrst}(t+1) = L + r \cdot (U - L) \tag{5}$$

where x_{wrst} stands for the food source with the worst nectar refilling rate. The migration strategy helps the AHA to avoid local stagnation. More detailed explanation of the AHA can be found from [30].

3 Proposed Modified Elite Opposition-Based Artificial Hummingbird Algorithm

In the field of control engineering, the design of efficient and robust control systems is a critical task. One of the key challenges in this area is to develop controllers that can provide stable and accurate control of complex systems with nonlinear dynamics or time-varying parameters. One promising approach for addressing this challenge is the use of advanced optimization techniques to design controllers that can achieve optimal control performance.

One such optimization technique is the elite opposition-based artificial hummingbird algorithm, which is a metaheuristic algorithm inspired by the foraging behavior of hummingbirds. This algorithm has been modified and used in conjunction with fractional-order PID (FOPID) controllers to improve the control performance of cruise control systems.

The modified elite opposition-based artificial hummingbird algorithm for designing FOPID controlled cruise control systems involves the use of a population of hummingbirds that forage for food in an environment. The hummingbirds update their position based on their own experience and the experience of the best hummingbirds in the population. The algorithm also employs an opposition-based learning strategy to further enhance its performance.

The use of this modified algorithm has shown promising results in improving the control performance of cruise control systems by effectively tuning the parameters of the FOPID controller. This approach can potentially be extended to other control problems and applications, providing a novel and effective means of designing advanced control systems.

The proposed modified elite opposition-based AHA (m-AHA) optimization technique employs a novel modified version of the elite opposition-based learning technique to increase the performance of the original AHA optimization technique. The opposition-based learning (OBL) technique [32] has been a staple among researchers looking to enhance optimization algorithms [33]. Within the realm of OBL, the elite opposition-based learning (EOBL) is a unique approach that considers the best and current agents to generate opposite solutions of those agents [31]. Due to its promising capability, the EOBL has already been adopted for different applications as an aiding structure [34,35].

To define EOBL, $X^o = \langle x_1^o, x_2^o, \ldots, x_k^o \rangle$ can be used by considering $X = \langle x_1, x_2, \ldots, x_k \rangle$ to be an elite candidate solution with k decision variables where $x_i^o = \delta (da_i + db_i) - x_i$, δ is a parameter within (0, 1), da_i and db_i are the dynamic boundaries. In this study, three random variables of a, b and c, all of which within [0, 1], are adopted to redefine the the EOBL as $x_i^o = \delta (a \cdot da_i + b \cdot db_i) - c \cdot x_i$. The solution in basic EOBL is kept within boundaries (lower, Lb_i and upper, Ub_i) by using the definition of $x_i^o = rand (Lb_i, Ub_i)$. In here, $x_i^o < Lb_i$ or $x_i^o > Ub_i$ and $rand (Lb_i, Ub_i)$ is a random number within (Lb_i, Ub_i). In this study, however, the solution is set to the upper boundary when it exceeds the upper level; otherwise, it is set to the lower boundary. As illustrated in the detailed flowchart given in Fig. 1, the proposed m-AHA optimization technique firstly initializes its parameters, and then applies three foraging behaviors of the basic AHA. Simultaneously, it evaluates the current and elite candidate solutions and choses the best N solutions. This procedure continues for total iterations (T).

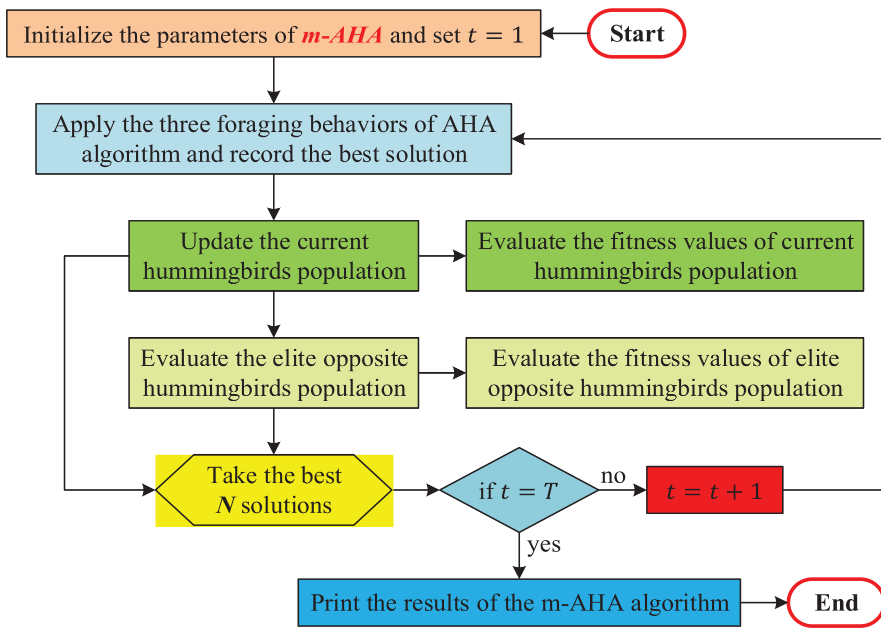

Figure 1: Flowchart of m-AHA

4 Experimental Results on Benchmark Functions

For an initial evaluation, the widely adopted test functions provided in Table 1 were used in this study. The definitions and other related details of the used benchmark functions are also provided in the respective table. For the fairness in the evaluation, the following parameters were used for the basic AHA and proposed m-AHA optimization techniques: Population size $n = 50$, maximum number of iterations $T = 1000$, migration coefficient $2 \times n$. The statistical and non-parametric statistical (Wilcoxon signed rank test) obtained from those test functions are presented in Table 2. As presented, the proposed m-AHA optimization technique reaches far better results for F1, F3 and F4 when compared to the basic AHA and it also achieves the optimal value for F2 indicating its superior performance. This is further supported via Wilcoxon's test as the m-AHA is the winner for all test functions.

Table 1: Review of used benchmark functions

Function ID	Name	Equation of function	Dimension (n)	Range	Optimum (f_{min})
F1	Sphere	$f(x) = \sum_{i=1}^{n} x_i^2$	30	$[-100,\ 100]$	0
F2	Rosenbrock	$f(x) = \sum_{i=1}^{n-1}\left(100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right)$	30	$[-30,\ 30]$	0
F3	Schwefel	$f(x) = \sum_{i=1}^{n}\left(-x_i \sin\left(\sqrt{\lvert x_i\rvert}\right)\right)$	30	$[-500,\ 500]$	$-1.2569\text{E}+04$
F4	Penalized	$f(x) = \frac{\pi}{n}\left\{10\sin^2(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2\left[1 + 10\sin^2(\pi y_{i+1})\right] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i,\ 10,\ 100,\ 4)$	30	$[-50,\ 50]$	0

Table 2: Statistical and non-parametric statistical test results

Function ID	Algorithm	Average	Standard deviation	Best	Worst	Time complexity (s)	Wilcoxon's test
F1	AHA	1.1784E − 294	0	2.9644E − 323	2.5685E − 293	3.4850	p-value: 1.7344E − 06
	m-AHA	0	0	0	0	3.5109	Winner: m-AHA
F2	AHA	2.5025E + 01	2.6857E − 01	2.4273E + 01	2.5474E + 01	2.5714	p-value: 1.7344E − 06
	m-AHA	2.7750E − 06	1.2813E − 05	1.7282E − 09	7.0495E − 05	2.6358	Winner: m-AHA
F3	AHA	−1.2288E + 04	3.1667E + 02	−1.2569E + 04	−1.1344E + 04	3.6451	p-value: 5.8505E − 05
	m-AHA	−1.2569E + 04	0	−1.2569E + 04	−1.2569E + 04	3.7883	Winner: m-AHA
F4	AHA	2.3351E − 07	1.3881E − 07	2.6905E − 08	5.1224E − 07	6.7099	p-value: 1.7344E − 06
	m-AHA	2.1912E − 11	2.3949E − 11	1.5466E − 13	9.3455E − 11	6.8402	Winner: m-AHA

5 Simulation Results on Vehicle Cruise Control System

In this section, the focus is on the cruise control system's linearized model and the steps involved in its implementation. The results obtained are compared and presented in order to showcase the proposed method's superiority for the cruise control system.

5.1 Linearized Model

The engine throttle angle (u) is adjusted by the cruise control system in order to maintain the actual speed (v) of a vehicle. This is performed based on the reference speed. The longitudinal dynamics of the vehicle can be represented as the combination of engine's climbing resistance (F_g), drive force (F_d) and aerodynamic drag (F_a) as well as the inertia force $M\,(dv/dt)$ using the following expression [36].

$$F_d = M\frac{dv}{dt} + F_a + F_g \tag{6}$$

The cruise control system's dynamic model is illustrated in Fig. 2 which represents the effects of the total mass (M), wind gust speed (v_w), road angle (θ) and aerodynamic drag coefficient (C_a).

Assuming the vehicle operates at a constant speed of 30 km/h without wind gust or climbing resistance, the state model of the system can be characterized as outlined in the following definitions [22]:

$$\dot{v} = \frac{1}{M}\left(F_d - C_a v^2\right) \tag{7}$$

$$\dot{F}_d = \frac{1}{T}\left(C_1 u(t - \tau) - F_d\right) \tag{8}$$

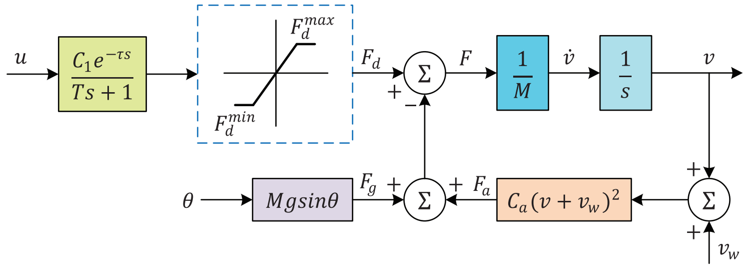

Figure 2: Cruise control system's dynamic model

A nominal drive force and throttle position are required to maintain an equilibrium state, which can be obtained via linearization around the set points using the following definitions:

$$\delta \dot{v} = -\frac{2C_a v_0}{M}\delta v + \frac{1}{M}\delta F_d \tag{9}$$

$$\delta \dot{F}_d = -\frac{1}{T}\delta F_d + \frac{C_1}{T}\delta u\,(t-\tau) \tag{10}$$

The transfer function of the linearized model can then be represented as a ratio of the following polynomials where $C = C_1/(MT\tau)$, $p_1 = -2\,(C_a v_0/M)$, $p_2 = -1/T$ and $p_3 = -1/\tau$:

$$G\,(s) = \frac{\Delta V\,(s)}{\Delta U\,(s)} = \frac{C}{(s-p_1)\,(s-p_2)\,(s-p_3)} \tag{11}$$

5.2 FOPID Controlled System

A more flexible controller is desirable for cruise control system like dynamic systems. To this end, the idea of using a fractional order controller for dynamic systems was proposed. Based on this idea, a generalized version of the PID controller named the FOPID controller was introduced as an improved version that incorporates fractional orders (λ and μ) [37]. FOPID controller's transfer function is defined as follows:

$$C_{FOPID}\,(s) = K_p + \frac{K_i}{s^{\lambda}} + K_d s^{\mu} \tag{12}$$

where K_p, K_i, and K_d are proportional, integral, and derivative gains, while λ and μ stand for fractional integral and derivative orders, respectively. Fig. 3 presents the block diagram of a cruise control system that is controlled with a FOPID controller.

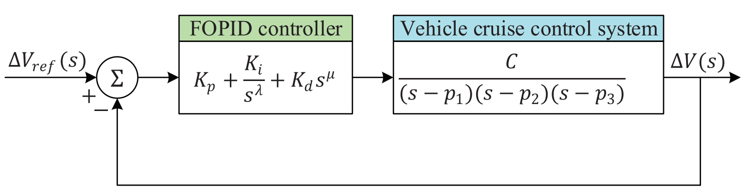

Figure 3: A cruise control system with FOPID controller

In this study, the following boundaries of $3 \le K_p \le 5$, $0.10 \le K_i \le 0.25$, $3 \le K_d \le 5$, $0 < \lambda < 2$ and $0 < \mu < 2$ are considered for the parameters of the FOPID controller [24].

5.3 Test System and Objective Function

For this study, we utilized comparable values found in previous research for the cruise control system in order to maintain fairness in comparison. The parameters given in Table 3 were used by setting the nominal operating speed to 30 km/h [9]. The performance of the cruise control system can be improved by minimizing its maximum overshoot percentage, steady-state error, settling time and rise time through the use of an objective function.

Table 3: The parameter values used for test system

Parameter	C_1	C_a	M	τ	T	F_d^{min}	F_d^{max}	g
Value	743	1.19	1500	0.2	1	−3500	3500	9.8
Unit (SI)	–	N/(m/s)^2	kg	s	s	N	N	m/s^2

In this study, we adopted the F objective function given in the following expression [38]:

$$F = \left(1 - e^{-\rho}\right)\left(\frac{\%OS}{100} + E_{ss}\right) + e^{-\rho}\left(T_s - T_r\right) \tag{13}$$

This function balances the maximum overshoot percentage ($\%OS$), steady-state error (E_{ss}), settling time (T_s), and rise time (T_r), with a weighting coefficient (ρ). Our simulations have determined that the best results are obtained when the weighting coefficient is set to $\rho = 1.5$.

5.4 Implementation Stage of Proposed m-AHA Algorithm

The procedure for implementing the m-AHA method to the cruise control system is outlined in Fig. 4. The m-AHA algorithm uses the F objective function to determine the optimal parameters for the FOPID controller. The study used the following parameters: population size $n = 30$, maximum number of iterations $T = 50$, migration coefficient $2 \times n$.

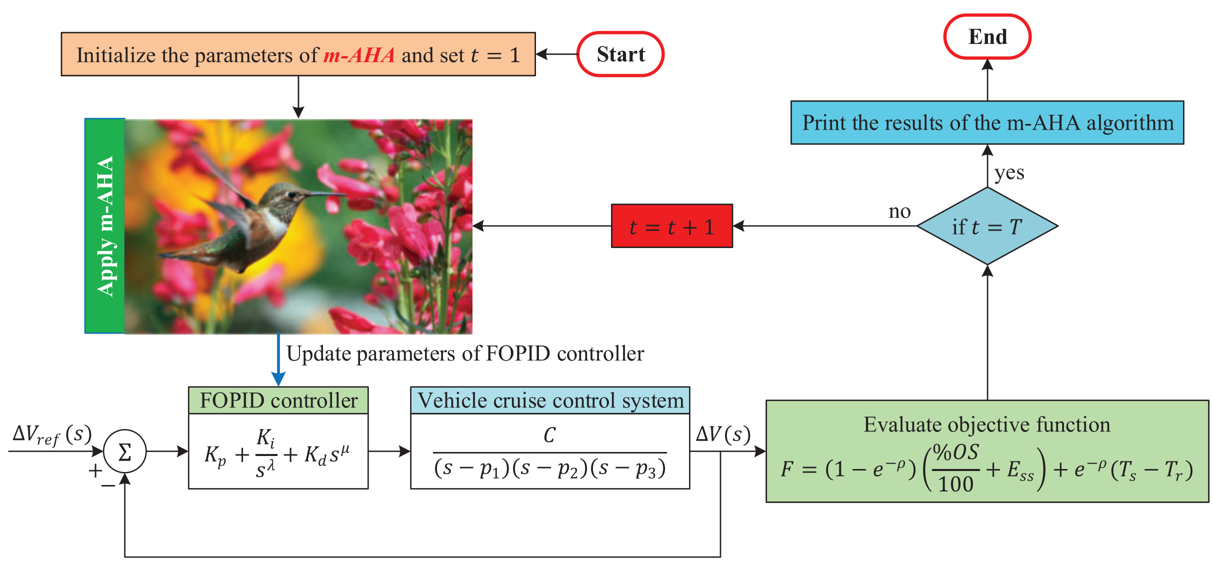

Figure 4: Block diagram detailing the implementation procedure of the proposed method to the cruise control system

The results of the objective function for each run of the AHA and m-AHA optimization techniques are displayed in Fig. 5. The figure clearly demonstrates that the proposed m-AHA optimization method consistently outperforms the original AHA technique, reaching the lowest values for each run. The more promising capacity of the m-AHA optimization technique is further validated with the statistical and non-parametric (Wilcoxon's test) tests presented in Table 4.

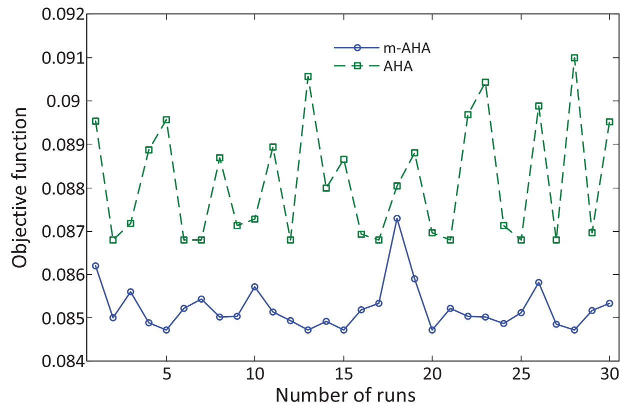

Figure 5: Objective function values for each run

Table 4: Statistical and no-parametric test results

Algorithm	Average	Standard deviation	Best	Worst	Time complexity (s)	Wilcoxon's test
AHA	8.8137E – 02	1.3786E – 03	8.6801E – 02	9.0993E – 02	70.4363	*p*-value: 1.7333E – 06
m-AHA	8.5231E – 02	5.4188E – 04	8.4730E – 02	8.7297E – 02	72.9833	Winner: m-AHA

5.5 Comparison with Existing Best and Recent Approaches

For this study, we adopted the existing best approaches reported in the literature in order to show the excellent capability of the proposed m-AHA optimization technique for the cruise control system. In that sense, we adopted the Harris hawks optimization (HHO) [23] based FOPID controllers, arithmetic optimization algorithm (AOA) [24] and antlion optimizer (ALO) [25] based IOPID controllers alongside the m-AHA and AHA optimization based FOPID controllers. Those approaches and the related best parameters obtained with each technique are listed in Table 5.

Table 5: Compared techniques and the best obtained parameter values

Algorithm/controller	K_p	K_i	K_d	λ	μ
m-AHA/FOPID (proposed)	4.9115	0.1754	4.9849	0.9603	1.0425
AHA/FOPID (proposed)	4.7183	0.2127	4.8352	0.9528	1.0280
HHO/FOPID [23]	4.4816	0.2261	4.6939	0.9523	1.0217
AOA/IOPID [24]	4.0407	0.2119	4.1548	1	1
ALO/IOPID [25]	3.8580	0.2089	3.8581	1	1

5.5.1 Transient Response Analysis

The velocity step responses for of the m-AHA/FOPID, AHA/FOPID, HHO/FOPID, AOA/-FOPID and ALO/FOPID approaches are illustrated in Fig. 6. One can easily observe the capability of the proposed m-AHA/FOPID approach in terms of reaching better transient response. This can also be further verified from the presented values in Table 6, which also shows zero overshoot, less rise and settling time values achieved via the proposed m-AHA algorithm.

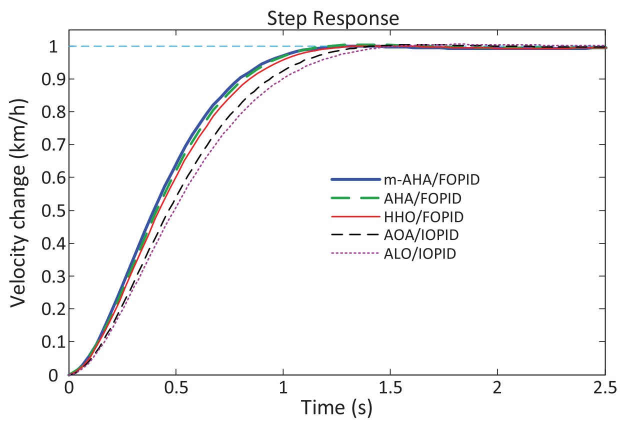

Figure 6: Velocity step responses

Table 6: Transient response metrics achieved via different approaches

Algorithm/controller	Overshoot (%)	Rise time (s)	Settling time (s)
m-AHA/FOPID (proposed)	0	0.6630	1.0427
AHA/FOPID (proposed)	0.4351	0.6760	1.0498
HHO/FOPID [23]	0.0640	0.7019	1.1034
AOA/IOPID [24]	0.3624	0.7797	1.2201
ALO/IOPID [25]	0.4792	0.8336	1.3093

5.5.2 Frequency Response Analysis

The importance of assessing the frequency response of the system cannot be overstated when it comes to determining the effectiveness of the FOPID controller that has been optimized using the proposed m-AHA technique in a cruise control system. To evaluate the system's performance, crucial parameters in the frequency domain such as bandwidth, gain and phase margins are employed. Fig. 7 displays the Bode plot of the cruise control system with the FOPID controller that has been optimized using the m-AHA technique.

Table 7 compares the performance of the basic AHA and the proposed m-AHA optimization techniques in terms of the frequency domain parameters, and it is evident that the proposed m-AHA/FOPID controlled cruise control system exhibits the most stability and is a testament to the superior capability of the proposed optimization approach.

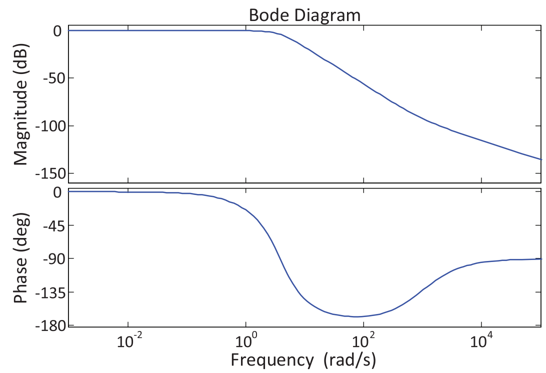

Figure 7: Bode diagram of m-AHA/FOPID-based system

Table 7: Frequency response metrics achieved via different approaches

Algorithm/controller	Gain margin (dB)	Phase margin (deg)	Bandwidth (Hz)
m-AHA/FOPID (proposed)	Infinite	180	3.3169
AHA/FOPID (proposed)	Infinite	180	3.2435
HHO/FOPID [23]	Infinite	180	3.1280
AOA/IOPID [24]	Infinite	173.1820	2.7921
ALO/IOPID [25]	Infinite	171.5498	2.5928

5.5.3 Robustness Analysis under Different Operating Speeds

The proposed m-AHA optimization technique was evaluated for its robustness in a FOPID-controlled cruise control system, considering two different scenarios that took into account changes in the reference speed. In that sense, velocity step responses for 20 km/h and 35 km/h were investigated. Figs. 8 and 9 respectively illustrate the velocity step responses for 20 km/h and 35 km/h reference speeds. The superiority and stability of the proposed method for various speeds is evident from the figures, showcasing its outstanding ability to regulate the cruise control system. This case is further numerically verified with the presented values in Table 8 as more desirable results (highlighted in bold) were achieved with the proposed m-AHA optimization technique.

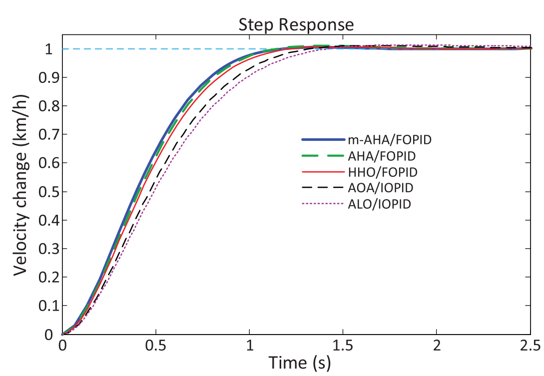

Figure 8: Velocity step responses for $\boldsymbol{v_0} = 20$ $\boldsymbol{km/h}$

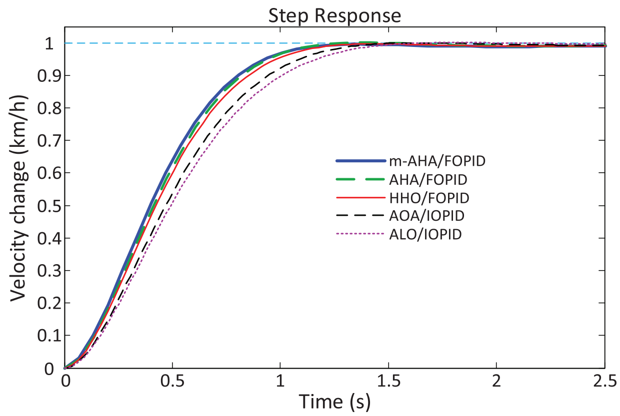

Figure 9: Velocity step responses for $\boldsymbol{v}_0 = 35\ \boldsymbol{km/h}$

Table 8: Comparison of transient response specifications under different operating speeds

Case	Algorithm/controller	Overshoot (%)	Rise time (s)	Settling time (s)
$v_0 = 20\ km/h$	m-AHA/FOPID (proposed)	**0.5874**	**0.6567**	**1.0139**
	AHA/FOPID (proposed)	1.0800	0.6682	1.0220
	HHO/FOPID [23]	0.7298	0.6939	1.0716
	AOA/IOPID [24]	1.1230	0.7691	1.1823
	ALO/IOPID [25]	1.2879	0.8213	1.2651
$v_0 = 35\ km/h$	m-AHA/FOPID (proposed)	**0**	**0.6669**	**1.0615**
	AHA/FOPID (proposed)	0.1186	0.6803	1.0641
	HHO/FOPID [23]	0	0.7065	1.1222
	AOA/IOPID [24]	0	0.7852	1.2426
	ALO/IOPID [25]	0.0797	0.8401	1.3357

6 Conclusion

The present study delves into exploring the potential of the m-AHA optimization technique in fine-tuning the parameters of a FOPID controller for regulating the speed of an autonomous vehicle that is equipped with a cruise control system. The m-AHA was constructed based on the convenient integration of the basic form of the AHA optimization technique and a newly modified EOBL mechanism. The more promising performance of the m-AHA optimization technique is shown on widely adopted and well-known benchmark functions through the evaluation of statistical and non-parametric statistical analyses. More excellent capability of the proposed m-AHA optimization technique for tuning the FOPID controller in a cruise control system is also comparatively demonstrated by using more recent and best performing approaches that employ the FOPID controller for the same purpose. The evaluations through transient, frequency and robustness characteristics have confirmed the proposed method's more effective capacity for the cruise control system that is controlled with a FOPID controller.

In conclusion, the use of FOPID controllers has shown promise for improving the performance of control systems, especially in systems with nonlinear dynamics or time-varying parameters. The design of FOPID controllers involves the use of fractional calculus, which provides greater flexibility in tuning the controller parameters. Future research in this area may focus on the development of novel optimization techniques for designing FOPID controllers that can achieve better control performance in various applications. Additionally, the application of FOPID controllers could be applied to other control problems beyond cruise control, such as robotics, renewable energy systems, and industrial processes. Overall, the use of FOPID controllers has the potential to significantly advance the field of control engineering and improve the performance of complex systems in various applications.

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