Recent Metaheuristic-based Optimization for System Modeling and PID Controllers Tuning

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Abstract: Recently, several methods and techniques, including the metaheuristic algorithms, have been developed, to identify and control systems. In this paper, four recent algorithms, such as Ant Lion optimizer (ALO), Differential Evolution (DE), Bat Algorithm (BA), and Harmony Search (HS), are chosen and considered for a one-paper comparison for the first time and exclusively applied to four different types of behaviors. The present contribution concerns the systematic analysis and comparison between the mentioned algorithms for the two tasks of system modeling and for the tuning of proportional, integral, and derivative (PID) controllers. Comparisons with conventional methods, such as Least Squares (LS) for identification and Reference Model (RM) for control, are made with different instructions to highlight the efficiency of this methods Further, the details on their performance metrics in terms of premature convergence and dynamic searches are provided. Simulations results demonstrate how accurately they help to obtain optimal solutions and show the most reliable method for the two main tasks of control and identification. Moreover, the present results confirm that the Differential Evolution strategy has the best performance, stable convergence feature, robustness, and insensitivity to disturbance and signal excitation.

Keywords: Metaheuristic, Ant Lion optimizer, Differential Evolution, Bat Algorithm, Harmony Search, Identification, PID controller.

1. Introduction

Much research has recently focused on system modeling and control theories and applications on providing optimal solutions.

The very classical PID controller is the most used process for the control task and has also achieved progress in the field with considerable achievement as in (He et al., 2022; Shuaishuai et al., 2023). However, artificial intelligence has gained excellent attention with its suggested computation techniques in the field of metaheuristic algorithms. These are generally bio-inspired methods with computational and evolutionary features that drive their performances from nature and its own physical rules.

Particle swarm optimization (PSO) (Kennedy & Eberhart, 1995) and genetic algorithms (GA) (Yao, 1999) are two of the most used algorithms that successfully gained the optimal solution for several applications. For example, PSO has significantly been utilized and advanced for controlling four different types of systems (El Gmili et al., 2017). GA also provides an excellent performance for the optimal PID parameters to recognize and operate an unmanned quadcopter (Siti et al., 2017). The essential requirements of these algorithms are efficient exploration, rapid convergence, cheap computing effort, self-searching, and easy inclusion of constraints to optimization problems.

Ant Lion Optimization (ALO), Differential Evolution (DE), Bat Algorithms (BA), and Harmony Search (HS) are innovative random searches based on new structures imitations of hunting prey, natural selection, and genetic systems. They exhibit an enhanced mechanism of exploitation and exploration with crucial throws on the convergence speed to the best solutions. There have been previous works along these lines, starting with ALO, which is created based on swarm intelligence within the simulation of antlions seeking prey. It has been effectively exploited to optimize the PID gains for different applications. Moreover, it has high quality in terms of exploration rate in comparison to PSO. (Shaw & Nayak, 2017; Sahu & Shaw, 2018).

The DE algorithm has been used based on natural selection, and it was applied successfully to compute the optimal solution in order to meet the desired requirement with the PID controller. Otherwise, DE was preferable in terms of convergence for the given desired performance characteristics over GA (Saad et al., 2012; Ghadimi & Ghadimi, 2011).

Besides these algorithms, BA has also attracted increased attention for addressing the optimization field and emulating the bat mechanism, such as the optimal tuning of PID to increase the controlled system for attaining the best possible performances

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(Fister et al., 2016, Vijaya et al., 2019). The HS algorithm was also a successful metaheuristic algorithm suggested to solve optimization issues. It is a simple concept algorithm and easy to implement with a few parameters. It was inspired by the music improvisation process and applied in various fields, such as control engineering (Arulanand & Dhara, 2015), electrical engineering and power systems (Ambia et al., 2015; Sambariya & Shrangi, 2017).

In brief, in the various works cited above, the studied algorithms put forward that they are better at obtaining optimal solutions, which makes them ready for a comparison and analysis area to show the details of the most reliable one. Furthermore, these algorithms are so broad that some issues (dynamic convergence, the exploration and exploitation effect, etc.) need to be addressed and explained more.

The main contribution of this paper is related to the use of four recent algorithms and four different types of behaviors at the same time. This paper compares these algorithms when applied to get the optimal solution in identification and control tasks, considering different scenarios. Firstly, it evaluated the ability of the studied algorithms to obtain the optimally identified model parameters for four different types of behaviors in the case with two different excitation signals. In addition, PID controllers are tuned using these algorithms with enhanced objective function. The disturbance effect and the varying input signal are tested to examine their reliability against the existing difficulties. ALO, BA, DE, and HS and their dependability to retain the global optimum are then compared to conventional methods, as Least Squares technique (LS) for identification and Reference Model (RM) for the control.

This paper is structured as follows. In Section 2, an overview of the used algorithms is presented. Section 3 outlines the identification task. The design of optimal PID controllers is given in Section 4. The comparison of the proposed approaches is displayed in Section 5. The main conclusions are gathered in Section 6.

2. Metaheuristic Algorithms

In general, an optimization issue is described as a search for the best available solutions for a given fitness function with the goal of specifying whether the minimum or maximum of this function is optimal. Metaheuristic algorithms are one of the most used strategies for dealing with such issues. This section will consider four robust, reliable, faster algorithms.

2.1 Ant Lion Optimizer

The ALO algorithm is based on the antlion's survival strategy of becoming fitter while chasing ants as food. It also involves changing the antlion's position to a good ant's location; the process converges to an optimal solution (Mirjalili, 2015).

$$X(t)=[0, cumsum(2r(t_1)\text{-}1),\ldots,cumsum(2r(t_T)\text{-}1)] \quad (1)$$

$$r(t)=\begin{cases}1 & if \quad rand > 0.5\\ 0 & if \quad rand \le 0.5\end{cases} \quad (2)$$

where *cumsum* represents a cumulated sum.

The roulette wheel operator selects the current fitter antlion position at each computational iteration to affect random walk with the current elite, which has the best fitness value.

$$c_i^t = Antlion_i^t + c^t \quad (3)$$

$$d_i^t = Antlion_i^t + d^t \quad (4)$$

$$c^t = \frac{c^t}{I} \; ; \; d^t = \frac{d^t}{I} \quad (5)$$

$$I = 10^{\omega}\frac{t}{T} \quad (6)$$

Here c_i^t, d_i^t are the updated upper and, respectively, lower limits of variable i at t iteration and T is the maximum iteration. They should be calculated to normalize the created random walk X_i:

$$X_i^t = \frac{(X_i^t - a_i)(d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t \quad (7)$$

a_i, b_i are min and max values of random walk. Each optimal candidate path presents an antlion position randomly initialized in the first step. The update of each ant's position is done using the following equation:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (8)$$

where R_A^t and R_E^t are random walks around the selected antlion and around elite at iteration t. The used ALO algorithm is described in (Sahu & Shaw, 2018).

2.2. DE Algorithm

DE is a stochastic search-based strategy inspired by natural evolution. Its exploration and exploitation methods are based on reproduction (crossover and mutation) operators, where each individual from the original random population is developed to form a trial vector. Then it is compared with its corresponding parent to determine which should remain for the next generation (Price & Storn, 1997).

The mutation operator generates a mutant vector m_i for each target vector at generation G, according to equation (9). It is used to yield the trial vector with a crossover rate *CR,* which reminds the crossover step and a mutation constant F.

$$m_i^{G+1} = x_{i_1}^G + F(x_{i_2}^G - x_{i_3}^G),\ \ \mathrm{i}_1 \neq i_2 \neq i_3 \neq i \tag{9}$$

$$u_{ij}^{G+1} = \begin{cases} m_{ij}^{G+1} & if\ \ rand \leq CR\ \ or\ \ j = rand(i) \\ x_{ij}^{G} & if\ \ \ rand > CR\ \ and\ j \neq rand(i) \end{cases} \tag{10}$$

where $rand(i) \in \{1,...,D\}$ and D is the population size. The used DE algorithm is defined in (Saad et al., 2012).

2.3 Bat Algorithm

The BA method simulates changes in the rate of pulse production and speed of bats when looking for food. It utilizes a frequency regulation procedure to intensify the variety of solutions (Yang, 2010). Each bat represents a search agent for a possible solution. It is characterized by its speed v_i and position x_i in the search domain, updated in accordance to the calculated frequency.

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{11}$$

$$v_i^{t+1} = v_i^t + (x_{gbest} - x_i) f_i \tag{12}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{13}$$

f_{min}, f_{max} are minimal and maximal frequencies and x_{gbest} is the bat's global best position.

Here, a local search is carried by each bat through a random walk to enhance the variability of the potential solution.

$$x_{new} = x_{old} + \varepsilon \overline{A} \tag{14}$$

During the search process, the loudness A_i and the rate of the bat's launch pulse r_i depend on the location of the prey; then, it should be updated as follow:

$$A_i^{t\ \ 1} = \delta A_i^t\ ,\ 0 < \delta < 1 \tag{15}$$

$$r_i^{t+1} = r_i^t (1 - \exp^{-\lambda t})\ ,\ \lambda > 0 \tag{16}$$

The main steps of BA are presented thoroughly in (Fister et al, 2016).

2.4 Harmony Search

The HS is made more efficient by adopting an improvisation approach similar to that used in music creation (Geem et al., 2001).

The main concept of the HS algorithm begins with random initialization of harmony memory (HM). Then, harmony improvisation allows the generation of a new harmony vector x^*=[x_1^*.., x_D^*] from the HM stored values with a Harmony Memory Consideration Rate (HMCR). Wherefore, the pitch adjustment is performed with Pitch Adjustment Rate (PAR) probability and a Band weight constant *bw* as in equation (17).

$$x_i^* = x_i^* \pm rand().bw \tag{17}$$

The HM is then updated using the fitness function. If the new vector x^* outperforms the HM's worst harmony, it replaces it. The main HS algorithms steps are detailed in (Arulanand & Dhara, 2015).

3. Modeling

The system modeling procedure involves choosing an acceptable model and estimating its parameters by making the difference between the actual and the estimated response as small as possible. The topic addressed in this section is the estimation of the model parameters using the LS approach and the metaheuristic algorithms (ALO, DE, BA, and HS). For this study, four black boxes reflecting four typical behaviours were used: (G_1) underdamped system, (G_2) critically damped system, (G_3) oscillatory undamped system and (G_4) divergent system.

The used data was created using a fixed transfer function to a unit step response with noise added to the output signal.

Here, and as given in equation (18), an exclusive model $G_m(s)$ is selected for the different investigated systems.

$$G_m(s) = \frac{K\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} \tag{18}$$

The identification concept of the system needs the estimation of the three parameters *K*, ξ and ω_n, representing the gain, the damping ratio and the natural frequency of the model, respectively.

3.1 LS-based Modeling

Least squares is a statistical method for identifying systems. It is the most promoted and simplest conventional method. It is reliable to determine the model parameters by minimizing the squared deviation between the observed and the predicted values (Ding, 2010; Mjahed, 2016). The numerical expression equivalent to the predicted model is calculated for *N* available input/output as follows:

$$\hat{y}_i = a_0\, y_{i-1} + a_1\, y_{i-2} + b_0\, u_{i-1} + b_1\, u_{i-2} \tag{19}$$

Let consider θ as the list of the parameter to be estimated by minimizing the criterion *J*.

$$\theta = [a_0, a_1, b_0, b_1] \tag{20}$$

$$J = \sum_{i=n+1}^{N} (y_i - \hat{y}_i)^2 \tag{21}$$

where $\hat{y}$ is the estimated output calculated by equation (19).

The model parameters illustrated in equation (20) are calculated using the LS process described in (Mjahed, 2016). The estimated parameters of the model from equation (18) are expressed as follows:

$$\begin{cases} K = \dfrac{b_0 + b_1}{1 + a_0 + a_1} \\ \xi = \pm\sqrt{\dfrac{A^2}{1 + A^2}} \\ \omega_n = \dfrac{-\log(a_0)}{2\xi T_e} \end{cases} \tag{22}$$

where $A = \dfrac{-\log(a_1)}{2\cos^{-1}\left(\dfrac{-a_0}{2\sqrt{a_1}}\right)}\omega_p$

The values of the predicted model parameters for the displayed G_1-G_4 systems are summarized in Table 2.

3.2 Metaheuristic based Modeling

Each starting population matrix for ALO, DE, BA, and HS represents a set of vectors reduced to three elements:

$$P = \left[K \;,\; \xi \;,\; \omega_n\right] \tag{23}$$

The optimal solution is calculated by minimi-zing the error between the estimated and the actual outputs of the system. Accordingly, the objective function is equal to the quadratic error. The optimization is achieved with setting parameters exposed in Table 1. The model parameters values derived by metaheuristic algorithms are given in Table 2.

Table 1. Parameters tuning

Algorithm	Parameter	Signification	Value
ALO	NP	Population size	300
	T	Number of iterations	100
DE	F	Mutant constant	0.6
	CR	Crossover	0.9
BA	$[f_{\min}, f_{\max}]$	Frequency range	[0, 1.5]
	r_i^0	Initial pulse rate	0.5
	A_i^0	Initial loudness	0.5
HS	HMS	Harmony memory size	300
	N_Impro	Number of improvisations	2500
	HMCR	Harmony memory consideration rate	0.9
	PAR	Pitch adjustment rate	0.5
	bw	Band weight	0.7

Table 2. Estimated model parameters by using ALO, DE, BA, HS, and LS

	Estimated model's parameters											
	G_{1m}			G_{2m}			G_{3m}			G_{4m}		
	K	ξ	ω_n	*K*	ξ	ω_n	K	ξ	ω_n	*K* .e+7	ξ	ω_n
ALO	35.82	0.1898	0.3162	6.3311	1.7948	2.1025	0.5178	-0.0874	2.280	1.2898	-0.041	0.0016
DE	35.80	0.1897	0.3163	6.3310	1.7552	2.0567	0.4931	-0.0876	2.280	2.0596	-0.022	0.0024
BA	35.80	0.1898	0.3162	6.3310	1.7552	2.0567	0.6952	-0.0861	2.280	2.8356	-0.024	0.0011
HS	36.16	0.1944	0.3156	6.3315	1.7028	1.991	0.3060	-0.09	2.274	3.7795	-0.031	0.0009
LS	35.04	0.1904	0.3161	6.2523	1.7552	2.056	0.5186	-0.0877	2.280	3.92	-0.040	0.0021

4. PID Tuning

In this section, the PID controller parameters are set for the identified systems G_{mi}. The main purpose is to seek the optimal tuning of PID parameters according to desired performances for the closed loop by using the studied metaheuristic algorithms (ALO, DE, BA, and HS). In addition, these algorithms are compared to the Reference Model (RM) method.

The transfer function of the PID controller used is given in (24):

$$C(s) = K_p + \frac{K_i}{s} + K_d s \tag{24}$$

where K_p, K_i and K_d are proportional, integral and derivative gains, respectively.

4.1 RM-based PID Controller

Designing a PID controller using the reference model method mainly refers to defining the behaviors of the controlled system in accordance with some desired requirements (Mjahed, 2018).

In this work, the systems G_1 - G_4 modelled by G_{1m} - G_{4m} must behave without overshoot and with a desired settling time T_d of one second, and a desired time constant τ_d ($\tau_d = T_d/3$). Therefore, it should be an aperiodic system. The dominant pole should be located at ($-1/\tau_d$) and the other poles placed sufficiently on the left of ($-1/\tau_d$).

The desired characteristic polynomial $D_r(s)$ is set by considering the desired specifications for a system of order n (T_d, τ_d) (Mjahed, 2018).

$$D_r(s) = (s + \frac{1}{\tau_d})(s + \frac{a}{\tau_d})^{n-1} \tag{25}$$

where a is a chosen constant with a value greater than 1 to assure the dominance of the time constant pole.

By comparing the polynomial $D_r(s)$ and the characteristic polynomial of the closed loops, the parameters K_p, K_i and K_d are extracted. The obtained results of the conventional PID controller are illustrated in Table 3.

4.2. Metaheuristic-tuned PID controller

The proposed ALO-PID, DE-PID, BA-PID, and HS-PID are executed to improve the closed-loop step responses for the studied systems and obtain the optimal tuning for the used PID controller in order to reach the desired performances. Therefore, the starting population for each algorithm is a set of individual vectors, which define the three PID parameters as search agents.

$$P = [Kp, Ki, Kd] \tag{26}$$

An aperiodic behaviour for all the systems G_1-G_4 is desired. Consequently, it should be a behaviour without overshoot D_p, a squared error E set to zero with an adequate settling time T_s. Hence, the used fitness function combines all the desired specifications in one single optimization objective ff_0 as suggested in equation (27).

$$ff_o = aD_p + bT_s + cE \tag{27}$$

where a, b and c are positive weight coefficients.

It is required that, for all the steps responses, the overshoots and the squared errors tend to zero.

After several trials, the values for a, b, and c are chosen to be 1, 0.25, and 0.65, respectively. The search process works well and, therefore, it allows obtaining quality responses at different steps.

The optimization processes are done with the same settings parameters exposed in Table 1 except the population size, number of iterations, harmony memory size, and number of improvisations whose values are set to be 30, 40, 30, and 40

Table 3. PID gains for systems G_{m1}- G_{m4} calculated by ALO, DE, BA, HS, and RM

	Optimal PID gains											
	G_{m1}			G_{m2}			G_{m3}			G_{m4}		
	K_p	K_i	K_d	K_p	K_i	K_d	K_p	K_i	K_d	K_p	K_i	K_d
ALO	15.3	7.1	50.0	149.06	867.94	20.0	150.2	885.8	100.0	50.0	---	10.0
DE	15.4	1.8	50.0	144.63	0.01	20.0	150.0	1.1	100.0	49.99	---	10.0
BA	41.9	255.4	46.6	119.83	870.16	18.69	236.2	9.06.7	99.3	34.89	---	10.0
HS	22.9	125.4	43.9	35.97	28.67	18.61	170.1	1222.7	91.9	48.56	---	9.87
RM	647.4	1713.4	26.2	226.69	630.14	5.44	2397.7	6667.1	60.6	2.40	---	6.92

respectively. The main steps to get the optimal PID tuning are given in Algorithm 1.

Algorithm 1

Initialize the control parameters
Initialize the started population randomly
Calculate the fitness of each candidate vector
Find the best solution
***While** the end criterion is not satisfied*
***For** each vector P*
Update the vector using the algorithm equations
End for
Evaluation of the fitness value of all population vectors
Select the best ones for the next population
Update the best solution
End while
***Return** the optimal values*

The optimal gains values tuned by the studied metaheuristic algorithms are listed in Table 3.

5. Results and Discussions

Notice that, several MATLAB scripts are used to implement the recommended strategies on an Intel Core i5, 2.55 GHz. The results of the preliminary tests were used to set the control parameters for each algorithm.

5.1 System Modeling Results

The four investigated black boxes are utilized to illustrate the usefulness of the employed intelligent approaches used in obtaining optimal identification when compared to the least squares method as a conventional technique. Additionally, the employed metaheuristic techniques were compared with each other for one single plant, preserving the same key parameters: cost function, the maximum number of iterations, and the population size.

Figures 1-4 display the unit step responses of the systems and their expected models with the parameters obtained by ALO, DE, BA, and HS.

From the resulting plots, it is clearly demonstrated that the found systems based on the optimization techniques ALO, BA, DE, and HS and by LS as well, behave similarly to the real systems.

Furthermore, it is proved that metaheuristic algorithms outperform LS approaches for the different kinds of employed behaviours, which is supported by the information recorded in Figures 1-5 and Tables 2 and 4.

Table 4. The obtained minimum criterion *J* by using ALO, DE, BA, HS, and LS

	G_{m1}	G_{m2}	G_{m3}	G_{m4}
ALO	1.62e-10	6.89e-4	1.44e+10	1.14e+5
DE	1.98e-12	5.57e-15	5.35e+8	3.59e+2
BA	9.71e-28	3.85e-28	2.92e+7	5.78e+1
HS	2.09	1.193e-2	3.02e+13	1.01e+4
LS	3.32e3	1.12e-1	1.31e+22	4.56e+10

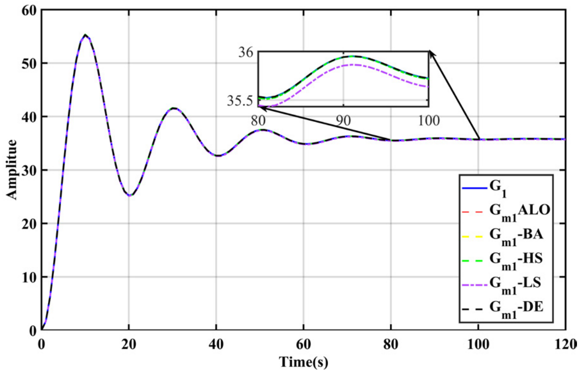

Figure 1. Response of system G_1 and its identified model G_{m1} by using ALO, DE, BA, HS, and LS

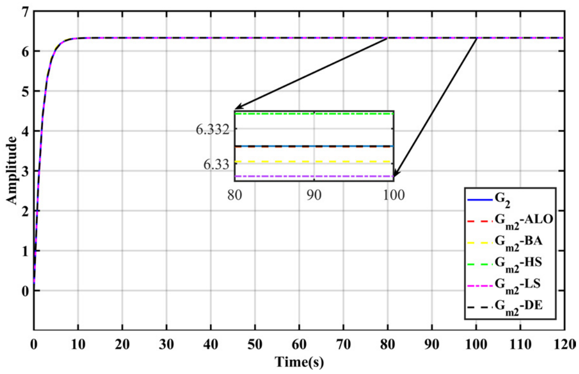

Figure 2. Response of system G_2 and its identified model G_{m2} by using ALO, DE, BA, HS, and LS

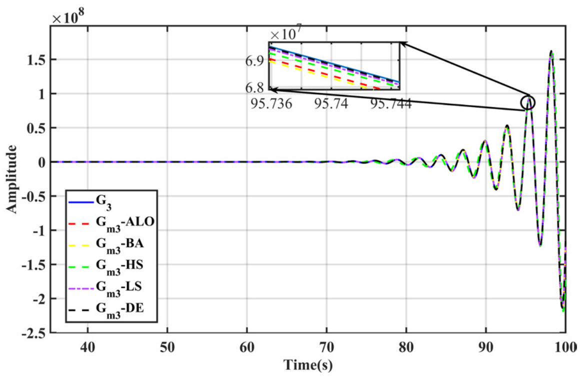

Figure 3. Response of system G_3 and its identified model G_{m3} by using ALO, DE, BA, HS, and LS

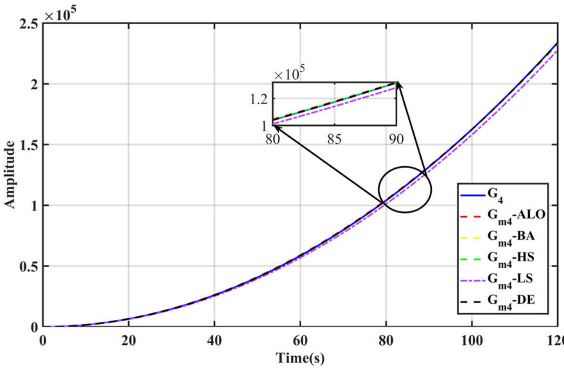

Figure 4. Response of system G_4 and its identified model G_{m4} by using ALO, DE, BA, HS, and LS

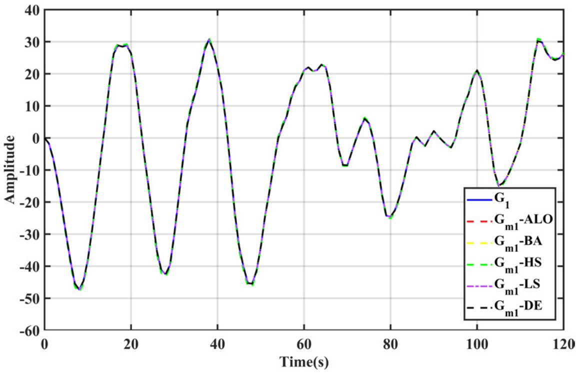

Figure 5. Response of the identified model G_{m1} excited by PRBS signal

The strength of variety and the dynamism of exploiting and exploring solutions through which these intelligent algorithms are embodied were favourably helpful in minimizing inaccuracy between the system and its predicted model in an actual length of time. Moreover, that was also a consequence of selecting the appropriate model for identifying the four investigated behaviors.

The excitation signal may also be a crucial aspect in validating the efficiency of the identification. For example, as illustrated in Figure 5, the pseudorandom binary signal (PRBS) is favourable as it activates all process modes with a high bonded frequency, making it profitable to capture data in the field. Consequently, good metaheuristic strategies may support a wider diversity of modeling behaviours, despite their complexity.

The employed intelligent identification techniques are compared to the unstable system G_3, preserving the same number of iterations that is set to 300 calculations, the same population size, and the same cost function, as illustrated in Figure 6.

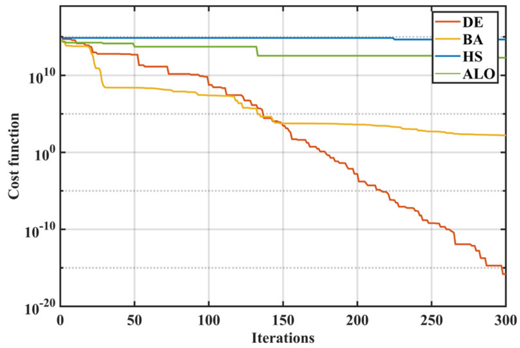

Figure 6. Convergence curve ALO, BA, DE, and HS for the oscillatory undamped identification model G_3

It is plainly evident that DE algorithm have higher performances compared to other used algorithms. Thus, the reproduction mechanism has an important influence on diversification in the search space for discovering alternative solution more suitable to the minimization. Moreover, the update frequency, speed, and positions in BA can also help in the exploration operation. However, the local search steps in BA do not serve the convergence speed properly, which explains the slowness of BA in obtaining the minimum value. Correspondingly, it appears that ALO and HS are impacted by the instability induced in the system. Consequently, the slow convergence speed can be observed, as well as a lot of local minimum influences. Based on the obtained results, DE algorithm actually proves its worthiness in the system-modelling task, and that through its simplicity of calculation, the convergence speed and the effectiveness of its own exploitation/exploration properties.

5.2 Control Results

Here, each PID gain can be optimally tuned to prove the identified unit step responses explored before using the studied intelligent tuning methods. Regarding this metaheuristic validity, the acquired findings have been compared to those produced using RM.

Thereafter, the selected cost function was compared to the Integral Absolut Error (IAE), Integral Squared Error (ISE), Integral Time Absolute Error (ITAE), and Integral Time Squared Error (ITSE) performance indexes to illustrate how it might aid in reaching the desired features.

Figures 7-10 show the controlled step responses using the metaheuristic strategies and RM as well. Table 5 summarizes the performance characteristics found using the intelligent tuning methods and RM.

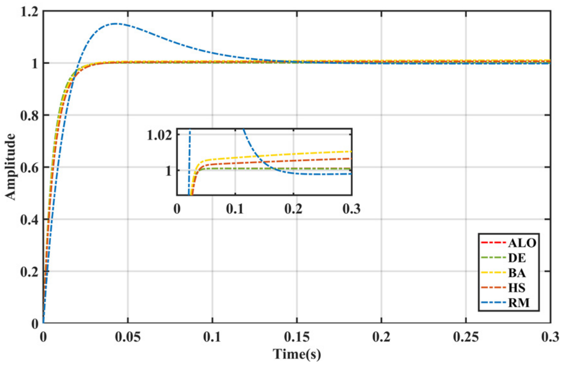

Figure 7. The closed-loop step response for different used algorithms for the controlled system G_{m1}

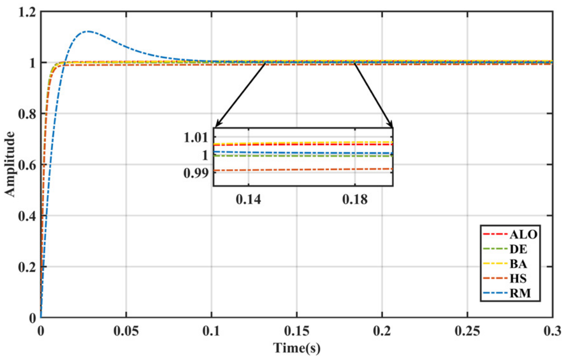

Figure 8. The closed-loop step response for different used algorithms for the controlled system G_{m2}

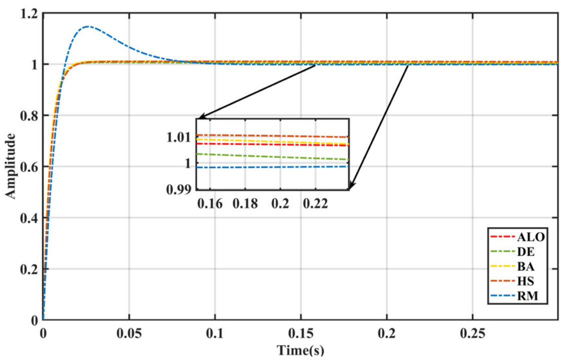

Figure 9. The closed-loop step response for different used algorithms for the controlled system G_{m3}

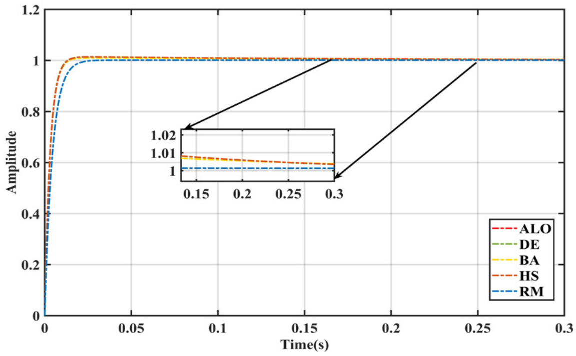

Figure 10. The closed-loop step response for different used algorithms for the controlled system G_{m4}

From the results gained for the closed-loop step responses for the four controlled systems, it is clear that the dynamics indicate that the presented methods meet the expected behaviours in terms of stability, low overshoot, and an appropriate amount of settling time.

Table 5 illustrates that metaheuristic techniques had the best results in reaching the desired performances.

Even though the classical controller RM is ideal for stabilization and gives a short settling time, it still has a non-significant overshoot, which needs to be reduced. For the situations of DE

and BA, the PID gains supply the answers to the steps that suit the required output with an important quality. This underlines once again the right of DE and BA algorithms to attain the desired qualities in a different and desirable manner compared to ALO and HS.

Employing the preset performance indexes ISE, IAE, ITSE, and ITAE for a comparison section with the enhanced fitness function ff_0 that relies on E, T_s, and D_p.

Figures 11-14 display the results for system G_1 controlled by ALO, DE, BA, and HS tuning methods to determine how well it performs, in order to attain the optimum performance.

Table 5. Overshoot (D_p) and settling time (T_s) of the controlled systems

	Performances							
	G_{m1}		G_{m2}		G_{m3}		G_{m4}	
	D_p (%)	T_s (s)	D_p (%)	T_s (s)	D_p (%)	T_s (s)	D_p (%)	T_s (s)
ALO	0	0.0218	0	0.0041	0.6554	0.0143	1.3890	0.0106
DE	0	0.0218	0	0.0041	0.5890	0.0144	1.3888	0.0105
BA	0.4491	0.0224	0	0.0044	0.9996	0.0140	0.9228	0.0109
HS	0.2048	0.0244	0	0.0046	0.9036	0.01535	1.3839	0.0106
RM	15.0576	0.1176	12.124	0.0718	14.6178	0.0709	0.0483	0.0171

Overall, it can be seen that the unit step responses achieved by ALO, BA, DE, and HS-based tuning controllers are optimally utilizing the enhanced fitness, and this becomes clear from the least exhibited overshoot and settling time for all utilized algorithms. Correspondingly, a one-target optimization enhancing the three desired performance characteristics had considerably better quality than the used performance criteria as a predefined fitness function. Table 6 summarizes the achieved performances discovered utilizing the functions ff_0 and ISE, IAE, ITSE, and ITAE.

The effectiveness of metaheuristic techniques was also evaluated in cases of the varied input signal. Figure 15 demonstrates that the controlled system G_{m1} followed the desired output with a significant settling time of 0.02s. Techniques used for intelligent correction have been shown to be highly successful in the tracking process.

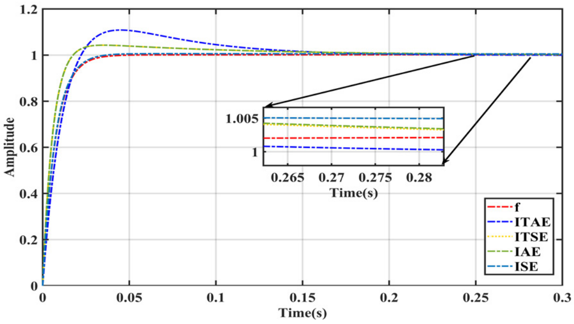

Figure 11. The closed-loop step response of system G_{m1} controlled by ALO using different cost functions

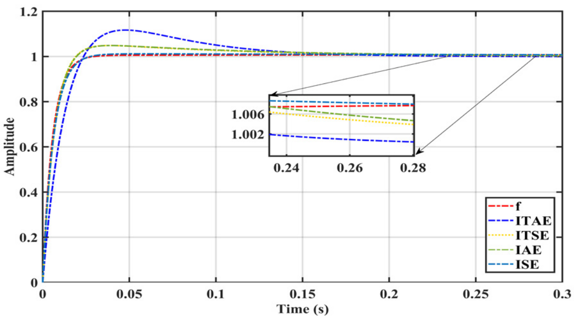

Figure 12. The closed-loop step response of system G_{m1} controlled by DE using different cost functions

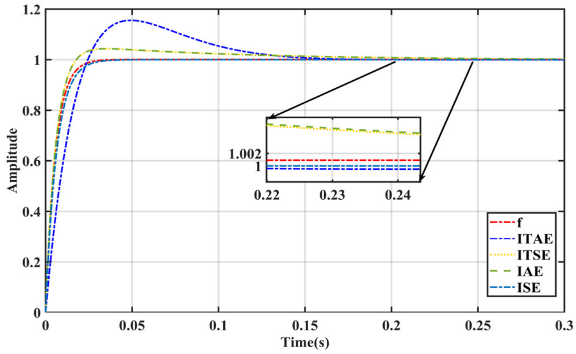

Figure 13. The closed-loop step response of system G_{m1} controlled by BA using different cost functions

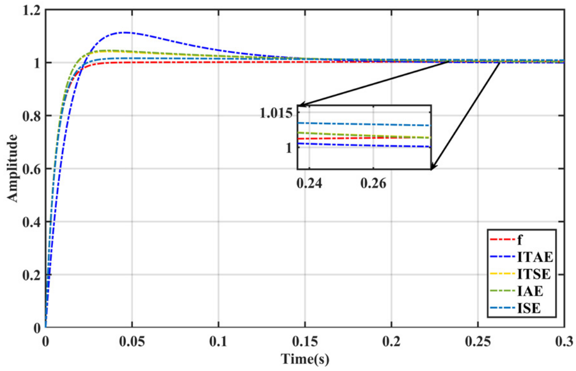

Figure. 14. The closed-loop step response of system G_{m1} controlled by HS using different cost functions

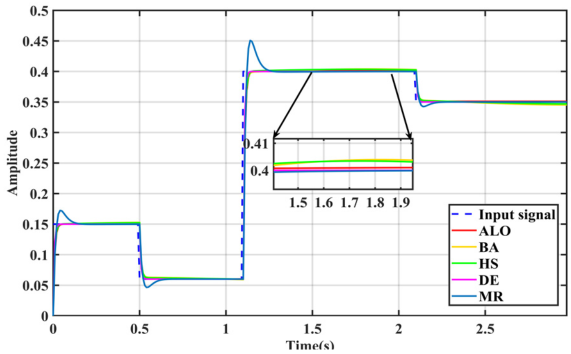

Figure 15. The closed-loop step response of G_{m1} with metaheuristic-based controller for a varied reference input

Table 6. Performance characteristics of the used algorithms by using different cost function ff_0, ITAE, ITSE, IAE, and ISE

Cost functions	Performances							
	ALO		DE		BA		HS	
	D_p (%)	T_s (s)	D_p (%)	T_s (s)	D_p (%)	T_s (s)	D_p (%)	T_s (s)
ff_0	0	0.0218	0	0.018	0.4491	0.0224	0.1437	0.0242
ITAE	10.8680	0.1353	15.5670	0.1276	11.7052	0.1406	10.10	0.1320
ITSE	4.3148	0.1150	4.3343	0.1143	4.8597	0.1284	4.1659	0.1388
IAE	4.3121	0.1147	4.4379	0.1158	4.8598	0.1366	6.5077	0.1330
ISE	0.5355	0.0264	0	0.0248	1.1690	0.0214	0.044	0.0272

To assess the robustness of the techniques, an external disturbance was added to the control law, a random signal of variable amplitude models it. Figures 16 and 17 illustrate that these intelligent tuning methods are considerably helpful to reject the undesirable impact of an added external disturbance.

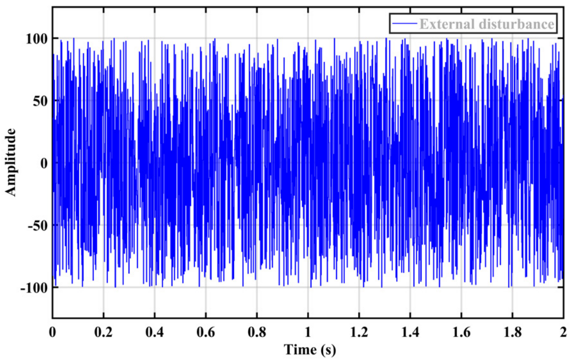

Figure 16. Disturbance signal

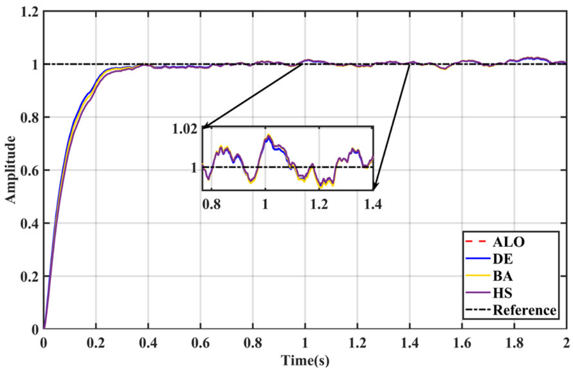

Figure 17. The unit step response of G_{m1} with metaheuristic-based controllers in the presence of the external disturbance

At the same time, we can also be noticed that DE- based tuning is the most robust and effective, providing the closest signal to the reference and the most significant settling time of 0.3 s.

6. Conclusion

Intending to compare four leader population-based approaches for the optimal system modeling and the PID controller tuning, attention was given to ALO, BA, DE, and HS. The conclusions of this paper are as follows:

The studied metaheuristic methods are excellent compared to the conventional approaches (LS and MR). The obtained rate in simulation results comes from the stochastic ability of each algorithm to cover all the search space. Moreover, the obtained results are represented by parameter setting and initialization dependence, which is a good reason to have several runs to achieve the expected performances.

The studied metaheuristic-based optimization methods have given good results. However, the difference between them is related to the exploitation/exploitation properties of each algorithm. Consequently, this directly affects the convergence speed which suggests that DE and BA significantly outperform the methods proposed in this paper, preserving the same optimization properties. Despite that, they are still quite sensitive to their regulatory settings; any change in these factors might substantially modify the dynamic convergence and disturb the power balance. Therefore, it should be carefully chosen. Regarding the ALO algorithm, it is quite evident that the lack of regulatory parameters is a specific benefit. Then the ALO improvement will depend on the initialization and boundary settings. With regard to the HS algorithm, the improved improvisation process and expansion of control settings will be crucial to investigate the dynamic adaption effect of the improvisation processor. In addition, a proposed hybridization may result in more productive outputs than the ones which have been attained previously.

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