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Identification of Linear / Nonlinear Systems via the Coyote Optimization Algorithm (COA)

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Abstract

Classical techniques used in system identification, like the basic least mean square method (LMS) and its other forms; suffer from instability problems and convergence to a locally optimal solution instead of a global solution. These problems can be reduced by applying optimization techniques inspired by nature. This paper applies the Coyote optimization algorithm (COA) to identify linear or nonlinear systems. In the case of linear systems identification, the infinite impulse response (IIR) filter is used to constitute the plants. In this work, COA algorithm is applied to identify different plants, and its performance is investigated and compared to that based on particle swarm optimization algorithm (PSOA), which is considered as one of the simplest and most popular optimization algorithms. The performance is investigated for different cases including same order and reduced-order filter models. The acquired results illustrate the ability of the COA algorithm to obtain the lowest error between the proposed IIR filter and the actual system in most cases. Also, a statistical analysis is performed for the two algorithms. Also, the COA is used to optimize the identification process of nonlinear systems based on Hammerstein models. For this purpose, COA is used to determine the parameters of the Hammerstein models of two different examples, which were identified in the literature using other algorithms. For more investigation, the fulfillment of the COA is compared to that of some other competitive heuristic algorithms. Most of the results prove the effectiveness of COA in system identification problems.

Keywords: Least Mean Square Method, Coyote Optimization Algorithm, Particle Swarm Optimization, Adaptive Filter, FIR Filter, IIR Filter, System Identification, Hammerstein Models

1. Introduction

System identification is the process of constructing a model for a physical system, the constructed model type and its parameters depend on the properties of the actual system. Physical systems can be classified as linear systems and nonlinear systems [1]. The linear system model is based on adaptive digital filters, which can be regarded as one of the most important elements in many applications related to the fields of communication, speech processing, medical applications, image processing, control systems, etc. These filters can be used for noise cancellation, prediction, identification and equalization [2]-[6]. Two categories of filters are commonly used: finite impulse response (FIR) and infinite impulse response (IIR). IIR filters find a lot of attention due to their better performance than FIR filters. In addition, they can be implemented using a reduced number of digital elements. On the other hand, they need careful treatment in design to overcome the problems of multimodal error and instability [7]. In literature, the least mean square method (LMS) and its modified forms have been used to design adaptive filters for different applications. These classical techniques are not suitable for IIR design, as they usually converge to a locally optimal solution instead of a global solution, in addition to having instability problems [5], [7], [8], [9]. Several approaches were developed to enhance the performance of the LMS technique [10]-[12]. Recently, various optimization techniques inspired by nature have been used in determining IIR coefficients for different applications. Various optimization algorithms have been employed in IIR system identification like the particle swarm optimization algorithm (PSO) and some of its modified versions [13]-[19], the artificial bee colony algorithm (ABC) [20], the Seeker optimization algorithm [21], the cat swarm optimization algorithm [22], [23], the firefly algorithm [24] etc. In case of nonlinear system having low nonlinearities, the identification process can be carried out based on either FIR or IIR filters, whereas high nonlinearity needs more complex modelling. Due to their simple structure, Hammerstein and Wiener models were extensively used in literature to identify nonlinear systems; each of these models consists of a cascade connection of two blocks, one is linear and the other is nonlinear. The estimation of the parameters related to each block, is the goal of the identification problem. For this goal, both classical optimization techniques such as Recursive Least Squares (RLS) as well as recently developed optimization algorithms were used in literature as in the case of linear system identification [25]-[28].

The Coyote optimization algorithm (COA) [29] is one of the simplest and most recently used algorithms in the field of engineering [30]-[38] but we think that it has not been applied to the problem of system identification. COA has the advantage of making an adequate compromise between exploitation and exploration in addition to its competence of keeping higher divergence that helps obtain optimal solutions [39].

In this work, we investigate the effectiveness of COA in optimizing the parameters of different models constructed to resemble both linear and nonlinear plants. In the case of linear plants, the investigation is based on applying COA to the problem of identification of four different plants with different orders based on IIR filters. The results attained upon applying COA are compared to those obtained from PSO, which is extensively researched in the literature and considered one of the simplest algorithms. Whereas, in the nonlinear system case, the investigation is based on using COA to optimize the parameters of the Hammerstein models representing two different nonlinear systems. The results obtained in the case of nonlinear systems are compared to that found in the literature.

The rest of the paper begins with a description of the identification problem, then an overview of both the POS and COA algorithms is presented, followed by the results and discussion, and finally, the conclusions are drawn.

2. Methodology

2.1 System Identification Description

2.1.1. Linear System Identification

The essential problem in identifying linear systems is to find the tape weights of an adaptive filter, which results in a filter transfer function that is similar to that of the unknown system to be resembled. Hence, the role of any algorithm is to adjust these weights so as to minimize the error between the filter response y(n) and that of the unknown system d(n). the error can be written as e(n) = d(n) - y(n). A schematic diagram shown in Figure 1 represents this process.

A difference equation describing the response of the filter can be written as in (1):

$$y(n) = \sum_{m=0}^{N} a_m x(n-m) - \sum_{m=1}^{M} b_m y(n-m) \qquad (1)$$

Where x(n) is the filter input, y(n) is the filter response, N and M define the number of filter taps in both directions, a_m and b_m are filter weights, which are required to be estimated.

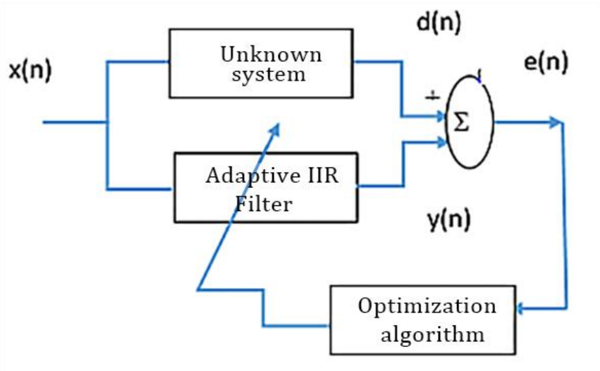


Figure 1. The graphical representation of the Identification Process

The mean-square error (MSE) in (2) can be regarded as the objective function for the optimization algorithm to find the optimum filter coefficients W= [a_m , b_m]:

$$MSE = \frac{1}{Ns} \sum_{n=1}^{Ns} e^2(n) \qquad (2)$$

Where Ns represents the sample number.

2.1.2. Non-Linear System Identification

The schematic shown in Figure 1 is also used to represent the nonlinear identification process, except that the Hammerstein model replaces the IIR filter. The graphical representation of Hammerstein model is shown in Figure 2. It consists of a memoryless polynomial nonlinear (MPN) block, representing the nonlinear part, followed by an FIR filter, representing the linear part.

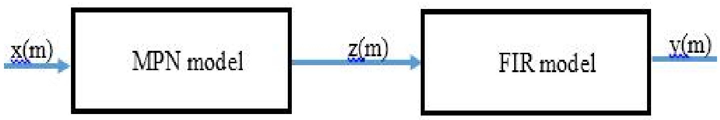


Figure 2. Schematic of Hammerstein Model with MPN-FIR

Where x(n) and y(n) represent the model input and output respectively and z(n) represents the internal signal described by (3):

$$z(n) = \sum_{l=1}^{p} c_l x^l(n) \qquad (3)$$

Where p is the polynomial order and the final output of the model is expressed as (4):

$$y(n) = \sum_{m=1}^{M} b_m z(n-m)$$

$$y(n) = \sum_{l=1}^{p} \sum_{m=0}^{M} b_m c_l x^l(n-m) \qquad (4)$$

Where c_l and b_m represent the weighting coefficients of the MPN model and FIR model, respectively, and M is FIR order.

2.2 Overview of Basic PSO Algorithm

PSO [40] is an optimization algorithm, which uses the basis of swarm ingenuity. It is one of the most recognized and most popular algorithms due to its simplicity, and hence, it is widely used in many industrial and scientific fields. It depends on communication between particles in the swarm, where each particle is considered a possible solution and hence, learning takes place based on some simple rules. In this algorithm, each particle is characterized by two parameters $ve_{i,k}$ and $po_{i,k}$, which are the i[th] particle velocity and position at instant *k*. The vector of particle position represents the solution of the problem. Each particle has a personal best, po_{best} and the whole swarm has a global best, $\mathrm{G_{best}}$. The updating values of position and velocity are given in Equation 5 and 6 respectively:

$$po_{i,k+1} = po_{i,k} + ve_{i,k} \tag{5}$$

$$\begin{aligned} ve_{i,k+1} = i_w\, ve_{i,k} + c_1.rand_1.(po_{best\,i,k} - po_{i,k}) + \\ c_2.rand_2.(G_{bestk} - po_{i,k}) \end{aligned} \tag{6}$$

Where i_w is a parameter known as inertia weight, which adjusts the rate of velocity change between iterations c_1 and c_2 are the rates of achievement of local and global optima, respectively. $\mathrm{rand_j} = \lfloor \mathrm{rand_{1,j}}, \mathrm{rand_{2,j}} \ldots\ldots\mathrm{rand_{l,j}} \rfloor$, j=1,2, l is the length of the solution vector. $rand_{l,j}$ represents a random number in [0*;* 1].

2.3 Coyote Optimization Algorithm (COA)

The COA can be regarded as one of the most recent population-based optimization algorithms. It was developed in 2018 [29] by Pierezan. The algorithm can be seen as an evolutionary heuristic algorithm as well as swarm intelligence. The COA focuses on both hunting prey and social composition. The total population in this algorithm consists of *Np* packs, each having *Nc* coyotes, and all have the same number of coyotes. In this algorithm, each coyote represents a possible solution based on its social conditions. The social conditions (SOCl) in (7) represent the *D* variables related to the optimization problem:

$$SOCl_c^{p,t} = (x_1, x_2, \ldots\ldots x_D) \tag{7}$$

The optimization based on COA can be carried out through the following steps:

Initializing both the coyotes' population and their corresponding social properties, which are assigned randomly for each coyote. The jth social condition variable for the Cth coyote belonging to the Pth pack is set randomly, as shown in Equation 6, and is listed below in (8):

$$SOCl_{c,j}^{p,t} = Lb_j + r_j.(ub_j - Lb_j) \tag{8}$$

Where r_j is a random number and ub_j, Lb_j are the upper and lower bounds of the variables.

Acclimation of coyotes to the environment with their current social status is determined by evaluating the objective function according to (9):

$$fit_c^{p,t} = f\,(SOCl_c^{p,t}) \tag{9}$$

Then, these results are ranked to determine the best-adapted coyote, which is called alpha and expressed as (10):

$$\begin{aligned} &alpha^{p,t} \\ &= \left\{ SOCl_c^{p,t} \,\middle|\, \mathrm{arg}_c = \{1, 2, \ldots., N_c\} \min f\,(SOCl_c^{p,t}) \right\} \end{aligned} \tag{10}$$

The COA takes into account the shared information between coyotes and computes the pack culture inclination for every social status, expressed as (11):

$$cult_j^{p,t} = \begin{cases} Or^{p,t}_{\frac{N_c+1}{2},j}, & \mathrm{N_c} \text{ is odd} \\ \dfrac{Or^{p,t}_{\frac{N_c}{2},j} + Or^{p,t}_{\frac{N_c+1}{2},j}}{2}, & \text{otherwise} \end{cases} \tag{11}$$

Where $Or^{p,t}$ is the ranked conditions in the pack.

Also, this algorithm takes into account birth and death in updating the population.To evaluate the culture interaction, first determine the culture difference between the alpha coyote and a random coyote denoted by cr_1, and the difference between another random coyote, cr_2, and the culture inclination of the pack.

$$\delta_1 = alpha^{p,t} - SOCl_{cr_1}^{p,t} \quad \text{and} \quad \delta_2 = cult^{p,t} - SOCl_{cr_2}^{p,t} \tag{12}$$

The social condition vector is updated as (13):

$$new\_SOCl_c^{p,t} = SOClp_c^{p,t} + r_1.\delta_1 + r_2\delta_2 \tag{13}$$

and the objective function is determined by (14) and (15):

$$new\_fit_c^{p,t} = f(new\_Socl_c^{p,t}) \tag{14}$$

$$SOCl_c^{p,t+1} = \begin{cases} new\_SOCl_c^{p,t}, & new\_fit_c^{p,t} \leq fit_c^{p,t} \\ SOCl_c^{p,t} & \text{otherwise} \end{cases} \tag{15}$$

The coyote with social conditions that leads to the best performance in terms of the objective function is considered as the optimal solution of the problem.

3. Results and Discussion

In this section, the efficiency of the COA is studied by making a comparison between the results attained up on using PSO to those obtained using the COA. Some standard transfer functions from the literature are used in this comparison. The steps of the experiments include defining the transfer function of the plant to be resembled, selecting the model to be used, estimating the parameters (unknown coefficients of the model) based on the optimization algorithm, and then estimating the mean square error (MSE) and convergence time. Figure 3. represents the architecture diagram for the proposed method.

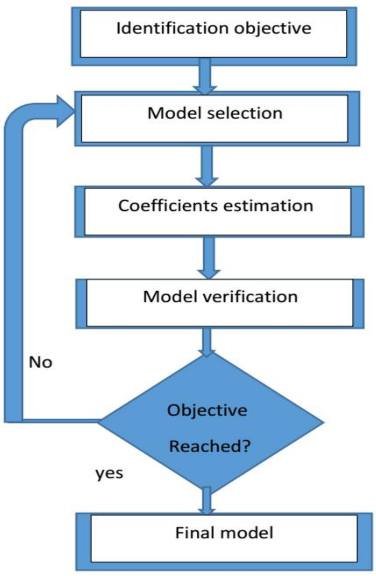


Figure 3. Architecture Diagram of System Identification

3.1 Linear System Identification

The identification process is carried out using the filter with the same order as well as in the case of reduced order.

Example 1:

The transfer function of the fourth-order system presented in [14], [15], [21], [41] is used here. Table 1 lists the weighting coefficients of the actual plant obtained from different algorithms in the case of a fourth-order system that represents the same order filter. In addition it contains convergence times and MSE. Also, convergence curves for both algorithms are shown in Figure 4. The convergence curves in Figure 4 can be compared to those in [15], which includes a comparison between variant swarm algorithms, showing that the maximum reduction in MSE obtained in [12] is about 50 dB, whereas that obtained by the COA in our work is about 90 dB in case of identification using a filter with the same order. Also, the results in the case of reduced order identification are shown in Figure 5. It is obvious from these results that using the COA results in a higher reduction in MSE as well as a rapid convergence.

Table 1. Coefficients of 4th-order Filter Representing 4th-order System

Coefficients	***Actual Values***	***PSO***	***COA***
a1	-0.9	-0.8784	-0.8999
a2	0.81	0.7687	0.8101
a3	-0.729	-0.7020	-0.7292
b1	-0.04	-0.0201	-0.0399
b2	-0.2775	-0.2958	-0.2773
b3	0.2101	0.2030	0.2100
b4	-0.14	-0.1185	-0.1401
MSE		2.2425e-05	1.3e-09
Convergence Time in Sec		43.1	14.43

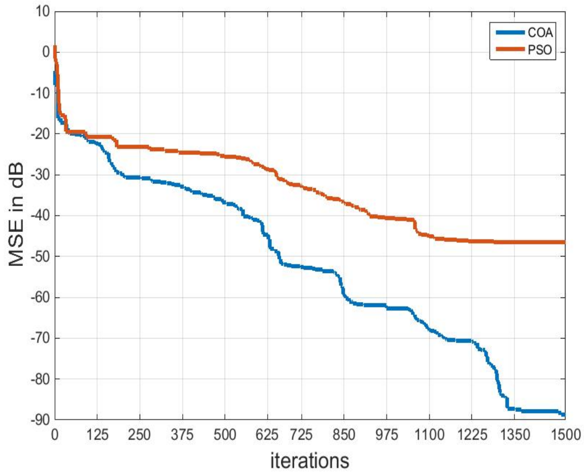


Figure 4. Convergence Curves for 4th-order Filter Representing 4th-order System

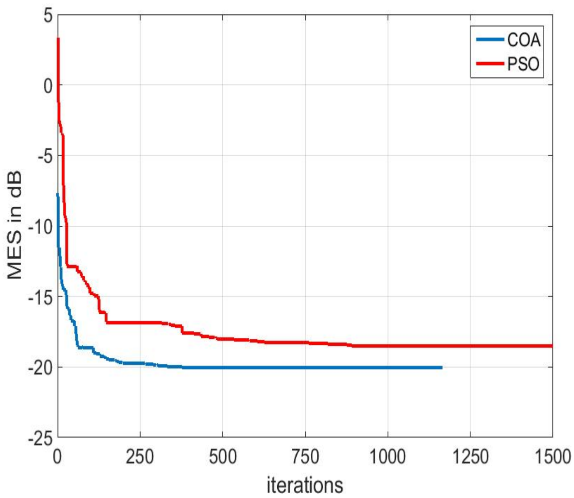


Figure 5. Convergence Curves for 3rd-order Filter Representing 4th-order System

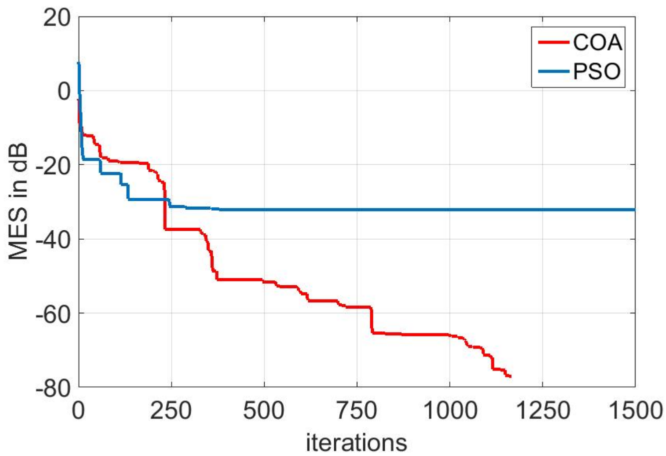
Example 2:
The transfer function of the considered plant is used in [20], [42], is :

$$A(z) = \frac{-0.3 + 0.4z^{-1} - 0.5z^{-2}}{1 - 1.2z^{-1} + 0.5z^{-2} - 0.1z^{-3}} \tag{16}$$

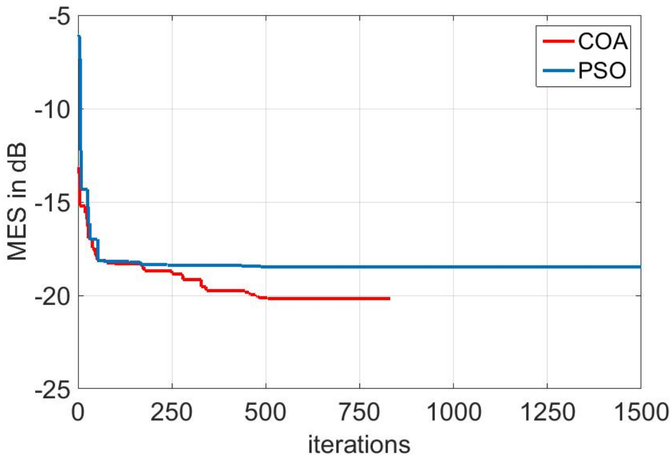
The MSE and convergence time values obtained from the two algorithms for filters with the same order and with reduced order are listed in Table 2. Also, the convergence curves for the two cases are shown in Figure 6.

Table 2. MSE Values and Convergence Time for Example 2

	The Same Order Case		**Reduced Order Case**	
	PSO	COA	PSO	COA
MSE	6.0e-4	1.97e-8	0.014	0.009577
Convergence Time in (s)	32.02	11.02	21	7.8



(a)



(b)

Figure 6. Convergence Curves for a 3rd-order System Identified by (a) 3rd-order Filter and (b) 2nd-order Filter

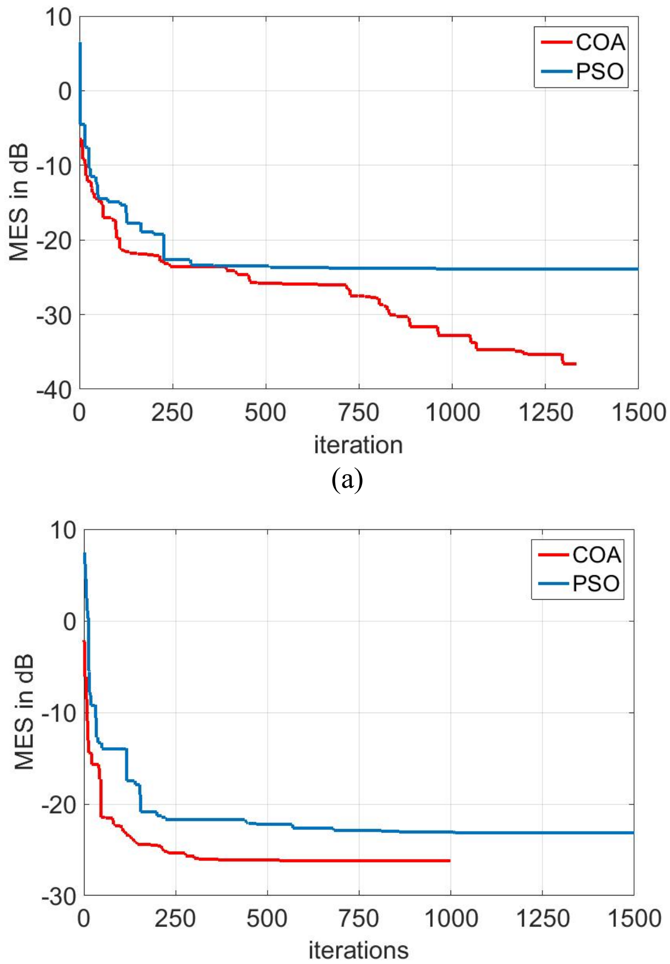
Example 3:
In this example, the considered system is characterized by:

$$A(z) = \frac{1-0.4z^{-1}-0.65z^{-2}+0.26z^{-3}}{1-0.77z^{-1}-0.8498z^{-2}+0.6486z^{-3}} \qquad (17)$$

This plant is modeled using a 3rd-order filter and a 2nd-order filter. The obtained results in both cases appear in Table 3. The corresponding convergence curves are illustrated in Figure 7.

Table 3. MSE Values and Convergence Time for Example 3

	The Same Order Case (3rd Order)		**Reduced Order Case (2nd Order)**	
	PSO	COA	PSO	COA
MSE	0.0041	0.000216	0.0049	0.00242
Convergence Time in (s)	37	12.45	25	9.13



(a)

(b)

Figure 7. Convergence Curves for 3rd-order System Identified by (a) 3rd-order Filter (b) 2nd-order Filter

Example 4:

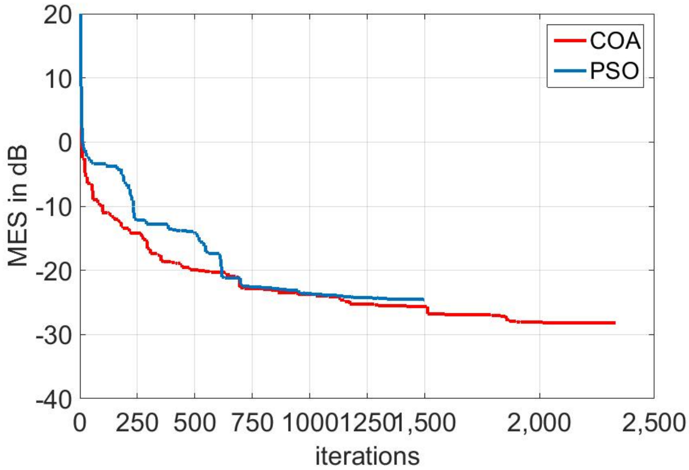
To investigate the performance of the COA in the case of high-order systems, the function is used as the plant to be identified.

$$A(z)=\frac{1-0.4z^{-2}-0.65z^{-4}+0.26z^{-6}}{1-0.77z^{-2}-0.8498z^{-4}+0.6486z^{-6}} \tag{18}$$

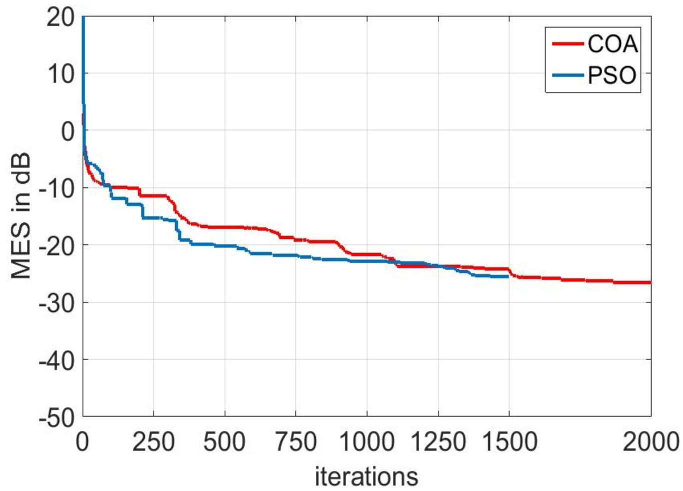
The results obtained using the COA and that of PSO are listed in Table 4. Moreover, the corresponding convergence curves are illustrated in Figure 8.

Table 4. MSE Values and Convergence Time for Example 4

	The Same Order Case (6th-order)		**Reduced Order Case(5th-order)**	
	PSO	COA	PSO	COA
MSE	0.0035	0.0015	0.0028	0.00223
Convergence Time in (s)	80	23.6	75.27	19



(a)



(b)

Figure 8. Convergence Curves for 6th-order System Identified by (a) 6th-order Filter and (b) 5th-order Filter

3.1.1. Statistical Analysis of MSE in the Case of Linear Systems

In this part, a statistical analysis is carried out for the results obtained by considering the results of a number of independent runs for each algorithm in various cases. The statistical analysis of the independent runs of Examples 1-4 are listed in Tables 5-8, respectively.

Regarding the obtained values of variance and standard deviation, it is obvious that the values in the case of COA are much smaller than PSO, which ensures the superiority of COA.

Table 5. MSE (dB) Statistics for Example 1

MSE Statistics	**Same Order Case**		**Reduced Order Case**	
	PSO	COA	PSO	COA
Best	-55.5	-92.842	-18.73	-20.1
Worst	-13.84	-66.668	-8.76	-18.9
Mean	-36.332	-83.934	-16.2	-19.4
Variance	230.3	87.9	12.64	0.12
Standard Deviation	15.17	9.4	3.56	0.3456

Table 6. MSE (dB) Statistics for Example 2

MES Statistics	**Same Order Case**		**Reduced Order Case**	
	PSO	COA	PSO	COA
Best	-39.1	-77	-18.8	-20.2
Worst	-20.86	-46.8	-17.8	-18.34
Mean	-30.3	-61.1	-18.125	-19.27
Variance	35.77	70.57	0.1046	0.34
S.D.	5.98	8.4	0.323	0.58

Table 7. MSE (dB) Statistics for Example 3

MES Statistics	**Same Order Case**		**Reduced Order Case**	
	PSO	COA	PSO	COA
Best	-28.86	-37.913	-24.32	-26.3
Worst	-21.8	-31.1	-11	-25.3
Mean	-24.127	-33.438	-21.24	-25.78
Variance	6.188	5.8363	27.45	0.09548
S.D.	2.488	2.416	5.24	0.31

Table 8. MSE (dB) Statistics for Example 4

MES Statistics	**Same Order Case**		**Reduced Order Case**	
	PSO	COA	PSO	COA
Best	-24.56	-28.2	-25.53	-26.52
Worst	-9.65	-21.221	-14.32	-20.8
Mean	-15.688	-24.71	-19.53	-23.86
Variance	37.536	4.9	16.006	5.46
S.D.	6.126	2.215	4.001	2.34

3.2. *Nonlinear System Identification*

Example 5:

In this example, a Bilinear system [23], [24] described by Equation 19 is modelled by the structure introduced in Figure 2.

$$\begin{aligned} y(n) &= 0.25y(n-1) - 0.5y(n-1).x(n) \\ &+ 0.05y(n-1)x(n-1) - 0.5x(n) + 0.5x(n-1) \end{aligned} \tag{19}$$

COA is used to obtain optimal parameters parameters of the MPN Hammerstein model to minimize the difference between its output and that of the bilinear plant described above. In this example, a Hammerstein MPN-FIR model with $p = 3$ and $M = 1$ is used.

The obtained results in terms of convergence time and MSE are compared to those obtained in literature [26], [27] using different optimization algorithms, as illustrated in Table 9.

The results listed in Table 9 indicate that COA is the most effective. The convergence curve of Example 5 is given in Figure 9.

Table 9. MSE and Convergence Time for Example 5

Algorithm	**MSE**	**Convergence Time(s)**
RLS	0.15384	0.1
CS	0.12724	150.5
ABC	0.12710	54.03
PSO	0.0431	18.18
COA	0.038761	37.6

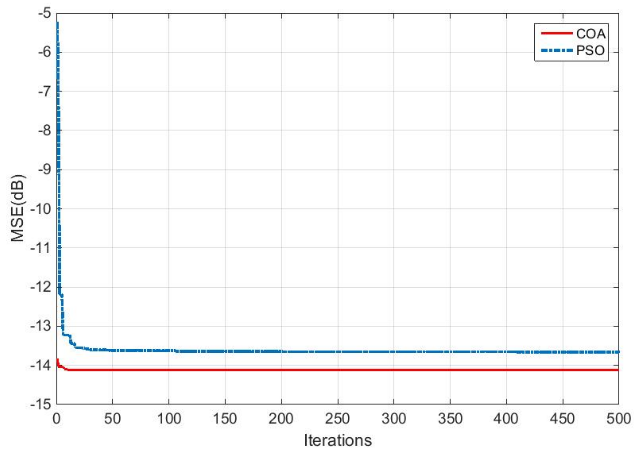


Figure 9. Convergence Curves of a Bilinear System Identification Given in Example 5

Example 6:

This example Identifies the Volterra system [28] given by Equation 20 using the structure introduced in Figure 2. Also, this example uses a Hammerstein MPN-FIR model with $p = 3$ and $M = 1$.

$$\begin{aligned} y(n) &= 0.8x(n-1) - 0.5x(n-2) + 0.7x^2(n-1) \\ &+ 0.1x^2(n-2) - 0.4x(n-1).x(n-2) \end{aligned} \tag{20}$$

Also, in this example, the comparison between our obtained results, upon applying the COA, and those obtained in [28] proves the effectiveness of COA because the identification based on COA resulted in smaller MSE, as shown in Table 10 and Figure 10.

Table 10. MSE Values for Example 6

Algorithm	**MSE**	**Convergence Time (s)**
RLS	0.3288	
PSO	0.1064	17.96
COA	0.092935	36

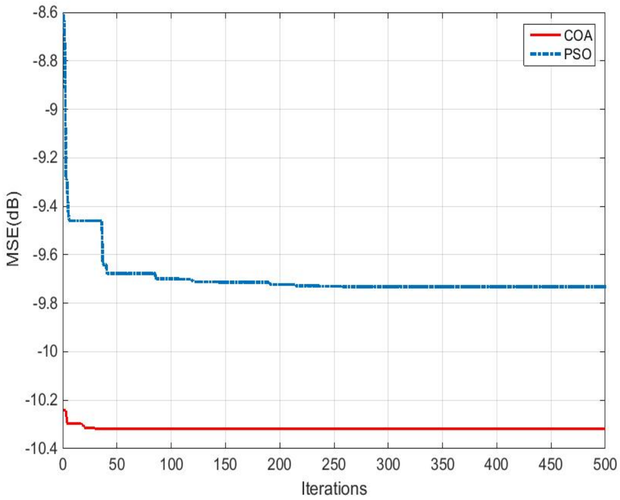


Figure 10. Convergence Curves of a Volterra System Identification Given in Example 6

Moreover, some other competitive heuristic algorithms, MFO [43], SSA [19], [44], SCA [45] and GWO [46], [47], have been executed to investigate the effectiveness of COA. The convergence curves of the implemented algorithms are compared with those of COA in Figures 10 and 11. Figure 11 represents the results related to linear case presented in Example 2, whereas Figure 12 presents the results related to the nonlinear case presented in Example 5.

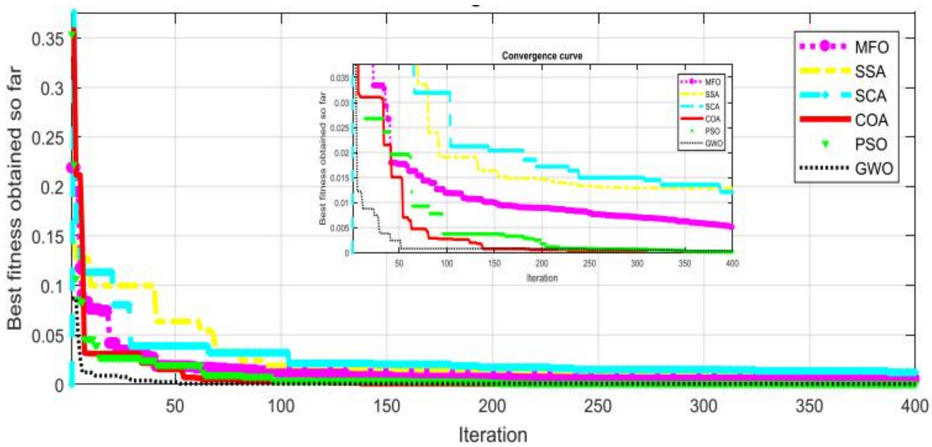


Figure 11. Convergence Curves of several Competitive Algorithms in Case of Linear System

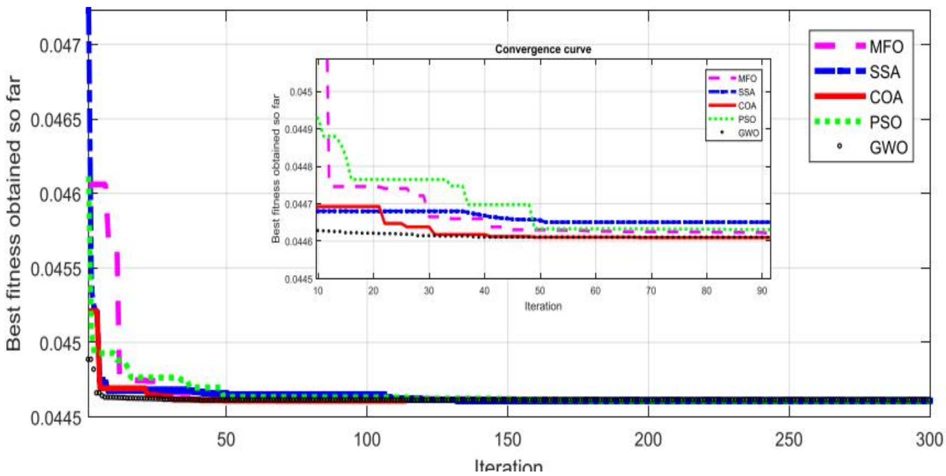


Figure 12. Convergence Curves of several Competitive Algorithms in Case of Nonlinear System

The results shown in Figures 11 and 12 indicate that COA competes well with other heuristic methods in terms of convergence speed and precision in addition to using a limited number of controlling parameters.

4. Conclusion

In this work, the COA, which is one of the recently used optimization algorithms in the field of engineering, is applied to the problem of system identification. The study included a number of plants that were used in the literature, considering both linear and nonlinear systems. The identification process in the case of linear systems was done for the case of same-order filters and reduced-order filters. To investigate the effectiveness of the COA, the results acquired by COA, in terms of mean square error and convergence time, were compared to those obtained from PSO, which is the most popular and most widely used algorithm. The obtained results show that the COA outperforms PSO in both MSE and convergence time, especially for lower-order filters. In the case of lower-order filters, the performance of COA in terms of MSE is approximately identical to that obtained by PSO, whereas in all cases, the convergence time of COA ranges between 25% and 30% of PSO convergence time. Also, a statistical analysis for the results of different independent runs from the two algorithms was done.

In the case of nonlinear system identification, two examples are considered; one of them identifies a Bilinear system, and the other identifies a Volterra system. The results of each of them have been compared to those obtained in the literature; the comparison in both two cases shows that COA gives smaller MSE than others. For more investigations, some other heuristic algorithms have been executed and compared to COA. In general, the results of both linear and nonlinear systems show that the COA is a promising algorithm in system identification processes.

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