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Araştırma / Research

SYSTEM IDENTIFICATION USING HAMMERSTEIN MODEL OPTIMIZED WITH ARTIFICIAL BEE COLONY ALGORITHM

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ABSTRACT

Hammerstein model is formed by cascade of linear and nonlinear parts. In literature, memoryless polynomial nonlinear (MPN) model for nonlinear part and finite impulse response (FIR) model or infinite impulse response (IIR) model for linear part are mostly preferred for Hammerstein models. This paper different from the studies in literature, focuses on the success of Hammerstein block model that Second Order Volterra (SOV) is preferred instead of MPN as nonlinear part. In this context, a new Hammerstein model is presented which is obtained by cascade form of a nonlinear SOV and a linear FIR model. In simulations, different types of system are identified by proposed Hammerstein model which is optimized with ABC (artificial bee colony) algorithm. The simulation results reveal effectiveness and robustness of the proposed model with ABC algorithm.

Keywords: System identification, Hammerstein model, artificial bee colony algorithm, clonal selection algorithm, recursive least square algorithm

YAPAY ARI KOLONİSİ ALGORİTMASI İLE OPTİMİZE EDİLEN HAMMERSTEIN MODEL KULLANARAK SİSTEMLERİN KİMLİKLENDİRİLMESİ

ÖZ

Hammerstein model, doğrusal olmayan alt model çıkışının doğrusal olan bir alt modelin girişine seri bağlanması ile oluşan bir blok model yapısıdır. Literatürde, Hammerstein modellerde çoğunlukla doğrusal olmayan bölümler için doğrusal olmayan hafızasız polinom (MPN - memoryless polynomial nonlinear) model ve doğrusal bölümler için sonlu darbe cevaplı (FIR- finite impulse response) ya da sonsuz darbe cevaplı (IIR- infinite impulse response) model tercih edilmektedir. Literatürden farklı olarak bu çalışmada doğrusal olmayan bölüm için MPN yerine ikinci derece volterra (SOV - Second Order Volterra) model tercih edilmiştir. Bu açıdan doğrusal olmayan SOV ve doğrusal FIR modelin kaskat bağlanmasından oluşan yeni bir Hammerstein model sunulmuştur. Simulasyonlarda, yapay arı kolonisi (ABC- artificial bee colony) algoritmasıyla optimize edilen Hammerstein model ile farklı sistemler kimliklendirilmiştir. Simulasyon sonuçlarında ABC algoritması ile önerilen modelin etkili ve güçlü olduğu görülmüştür.

Anahtar Kelimeler: Sistem kimliklendirme, Hammerstein model, yapay arı koloni algoritması, klonal seçim algoritması, yenilemeli en küçük kareler algoritması

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1. INTRODUCTION

In system identification, the model of the system is achieved by utilizing data obtained from experimental or mathematical way. System identification is preceded through linear and nonlinear models through the linearity of the system [1-13]. Linear system identification that the input and the output of the system are stated with linear equations is mostly used because of its advanced theoretical background [1-6]. However, many systems in real life have nonlinear behaviours. Linear methods can be inadequate in identification of such systems and nonlinear methods are used [6-13]. In nonlinear system identification, the input-output relation of the system is provided through nonlinear mathematical assertions as differential equations, exponential and logarithmic functions [14-18]. Autoregressive, Autoregressive Moving Average (ARMA) models or finite impulse response (FIR) and infinite impulse response (IIR) models are used for linear system identification in literature. Also Volterra, Bilinear and polynomial autoregressive (PAR) models are used for nonlinear system identification [15-25].

Also, many researchers preferred to use block-oriented models for system identification in literature. Hammerstein model is a class of block oriented model [13, 26-33]. This model consists of a series connection of a nonlinear sub model followed by a linear sub model. It's because this model is useful in simple effective control systems. Besides the usefulness in applications, this model is also preferred because of the effective predict of a wide nonlinear process [34, 35]. Hammerstein model is firstly suggested by Narendra and Gallman in 1966 and various models are tested to improve the model [36-39]. Generally, Memoryless Polynomial Nonlinear (MPN) model for nonlinear part and FIR or IIR model for linear part are preferred in Hammerstein models in literature [26-40]. In this kind of cascade models, the polynomial representation has advantage of more flexibility and of a simpler use. Naturally, the nonlinearity can be approximated by a single polynomial. Also the other benefit of these structures is to introduce less parameters to be estimated [39, 40]. To describe a polynomial nonlinear system with memory, the Volterra series expansion has been the most popular model in use for the last three decades. Although very comprehensive, this model involves a large number of parameters, which make it difficult to identify and use. For simplicity, the truncated Volterra series is most often considered in literature [19, 20, 41].

The Hammerstein model studies in literature shows; classical algorithms, such as Recursive Least Squares (RLS), are used to optimize Hammerstein models [42-45]. These algorithms present better solutions when the model structure and some statistical data (model degree, input and noise distribution etc.) are known. Classical techniques are mostly used because of their features such as lower hardware costs, convergent structure, and error analysis performance [18, 45]. The evolutionary and swarm intelligence based algorithms such as Clonal Selection (CS), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithm are recently become more popular and are mostly used in system identification. These algorithms are developed especially to solve parameter optimization problem. In literature, CS and PSO algorithms [36, 46] are used to optimize Hammerstein models. But the ABC wasn't used to optimize Hammerstein models for system identification in literature. The ABC [47-56] was proposed by Karaboga and it simulates the intelligent foraging behavior of honey bees [48]. This algorithm is simple to implement and also quite robust. Therefore, many tests were made to demonstrate the success of the algorithm [49-52]. The ABC has been applied to solve various problems such as adaptive filtering [53], system identification [54-56], noise cancellation [53], digital filter design [54].

The main motivation of this study is to suggest a successful model different from the structures in literature. In this paper, the performance of Hammerstein block model is focused in the case that Second Order Volterra (SOV) Model is preferred instead of MPN as nonlinear part. In this context a Hammerstein model consists of a series connection of a nonlinear SOV model followed by a linear FIR model is presented. In addition, the ABC algorithm is firstly used for Hammerstein model optimization. This proposed model is used to identify three different types of system. Also, its performances are compared with different models and different algorithms in simulations.

2. HAMMERSTEIN MODEL COMPONENTS

Hammerstein model structure in Figure 1 is formed by cascade of linear and nonlinear models [13, 26-33]. Hammerstein model structure can easily model practical applications such as heat exchangers, electric drives, thermal microsystems, sticky control valves, solid oxide fuel cells [27]. In Hammerstein model structure in Figure 1, $x(n)$ is nonlinear block input, $z(n)$ is linear block input and $y(n)$ is linear block output.

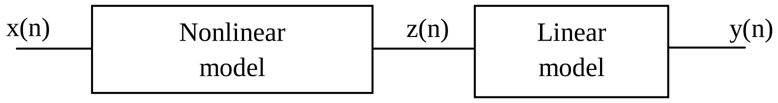

Figure 1. Hammerstein model structure

2.1. Linear Finite Impulse Response (FIR) Model

Linear FIR structure is a simple and practical model. Therefore, it is widely used for filtering, system identification [25]. In FIR model, output is dependent on the current and previous value of input, not dependent on the output value. This model is expressed as follows:

$$y(n) = \sum_{k=0}^{m} b_k x(n-k) \tag{1}$$

In above equation *x(n)* is input and *y(n)* is model output. Here m is the memory length and b_k is the parameter of FIR model [16]. Although a simple model structure is not preferred in the Hammerstein model [24-35].

2.2. Memoryless Polynomial Nonlinear (MPN) Model

MPN is a polynomial structure. It can be converged quickly since it has a memoryless structure. Therefore, it is frequently used in the block oriented model [26-40]. A polynomial of a known p order in the input, can be expressed as follows:

$$y(n) = \sum_{l=1}^{p} c_l x^l(n) = c_1 x(n) + c_2 x^2(n) + c_3 x^3(n) + \dots\dots\dots + c_p x^p(n) \tag{2}$$

where c_l is the coefficient of the polynomial, p is order of polynomial, and $p > 0$ [36]. The polynomial representation has advantage of more flexibility and of a simpler use. The nonlinearity can be defined by a single polynomial. Also the other benefit of these structures is their advantage of introducing less parameters to be estimated [39, 40]. Therefore, it is mostly preferred for filtering and system identification [26-40].

2.3. Second Order Volterra (SOV) Model

SOV model is mostly preferred in identification of the nonlinear system [16, 17, 19, 20].

$$y(n) = \sum_{i=0}^{r} h_i x(n-i) + \sum_{i=0}^{r} \sum_{j=0}^{r} q_{i,j} x(n-i) x(n-j) \tag{3}$$

Here *y(n)* represents output, *x(n)* represents input index, h_i represents linear and $q_{i,j}$ represents nonlinear parameters, *(n-i) (n-j)* represents delayed values of input, r represents model length. In literature, SOV structures, mostly only h_i and $q_{i,j}$ parameters are taken into consideration, are used in system identification [16, 17, 19, 20]. Because wider structure can be more complex, many researchers study on the block and adaptive applications of Volterra model [17].

2.4. Hammerstein Model with MPN-FIR

In this structure in Figure 2, MPN model is used as nonlinear part and FIR model is used as linear part. The nonlinear part is approximated by a polynomial function [32]. *x(n)*: block model input, $y(n)$: block model output and $z(n)$: unavailable internal data.

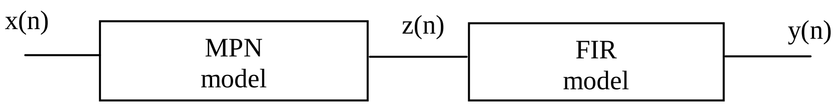

Figure 2. Hammerstein model with MPN-FIR

The internal signal $z(n)$ is expressed as follows:

$$z(n) = \sum_{l=1}^{p} c_l x^l(n) \tag{4}$$

Also $z(n)$ is the MPN model output and p is order of polynomial. The FIR model output is defined as;

$$y(n) = \sum_{k=0}^{m} b_k z(n-k) \tag{5}$$

Here m is the memory length and Hammerstein model output is defined as:

$$y(n) = \sum_{l=1}^{p} \sum_{k=0}^{m} c_l b_k x^l(n-k) \tag{6}$$

where b_k and c_l are the coefficients of the FIR and the MPN model respectively [32].

2.5. Hammerstein Model with SOV-FIR

In this structure, SOV model is used as nonlinear block and FIR model is used as linear block. Cascade structure is shown in Figure 3 [57].

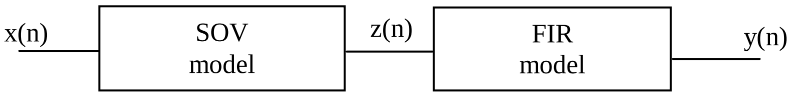

Figure 3. Hammerstein model with SOV-FIR

SOV model is defined as:

$$z(n) = \sum_{i=0}^{r} h_i x(n-i) + \sum_{i=0}^{r} \sum_{j=0}^{r} q_{i,j} x(n-i) x(n-j) \tag{7}$$

where r shows SOV model length and linear FIR model output is defined as:

$$y(n) = \sum_{k=0}^{m} b_k z(n-k) \tag{8}$$

where m shows FIR model length and Hammerstein model output is defined as [57]:

$$y(n) = \sum_{i=0}^{r} \sum_{j=0}^{m} b_i h_j x(n-i-j) + \sum_{t=0}^{r} \sum_{z=0}^{m} \sum_{w=0}^{m} b_t q_{z,w} x(n-t-z) x(n-t-w) \tag{9}$$

3. ARTIFICIAL BEE COLONY (ABC) ALGORITHM

ABC, swarm intelligence based algorithm, firstly suggested by Karaboga is a new algorithm based swarm intelligence that is developed through foraging behaviour of honey bees [58]. ABC algorithm is recently become more popular and is mostly used in optimization problems. This algorithm is simple to implement and also quite robust. Therefore, many tests were made to demonstrate the success of the algorithm [49-52]. To apply ABC, the considered optimization problem is first converted to the problem of finding the best parameter vector which minimizes an objective function. Then, the artificial bees randomly discover a population of initial solution vectors and then iteratively improve them by employing the strategies: moving towards better solutions by means of a neighbour search mechanism while abandoning poor solutions [48]. Flowchart of the ABC is presented in Figure 4 [53]. Three different bee types are foreseen in this algorithm: employed, onlooker and scout bees [48, 58]. There is an employed bee for each food source. Food amount in food source determines the quality degree of solution. Employed bees determine the food amount in each source. Scout bees randomly explore for new food sources [58].

Quantity of determined food source of the new one is higher than the previous one, the bee stores the new position and forgets the old one and its employed bee becomes a scout. So a new and more qualified source is researched even if low probability. In ABC algorithm each possible solution that determines each source is foreseen as a food source and defined as a vector with real valued and *n* dimensional [49].

In ABC algorithm w_i is the position of the i^{th} food source which is i^{th} solution to the problem and $f(w_i)$ represents its nectar amount that is the quality of solution. The population of food source is [54];

$$p(m) \ = \{w_i(m \mid i = 1,2,....,SN) \tag{10}$$

In equality *m* is cycle and *SN* is food source around the hive which is represent the employed or onlooker bees. P_i probability of food source which is chosen by onlooker bee is calculated through the following equality [58].

$$p_i = \frac{f(w_i)}{\sum_{k=1}^{SN} f(w_k)} \tag{11}$$

If a better food source is defined according to old one, the following equality is written for ABC algorithm:

$$w_i(m+1) = w_i(m) + \phi_i(w_i(m) - w_k(m)) \tag{12}$$

In equality, φ_i is a random number between [+1, -1], *k* is determined randomly but it has to be different from *i*. In this equality, solution defines a food source.This equality is developed till the limit [58, 59].

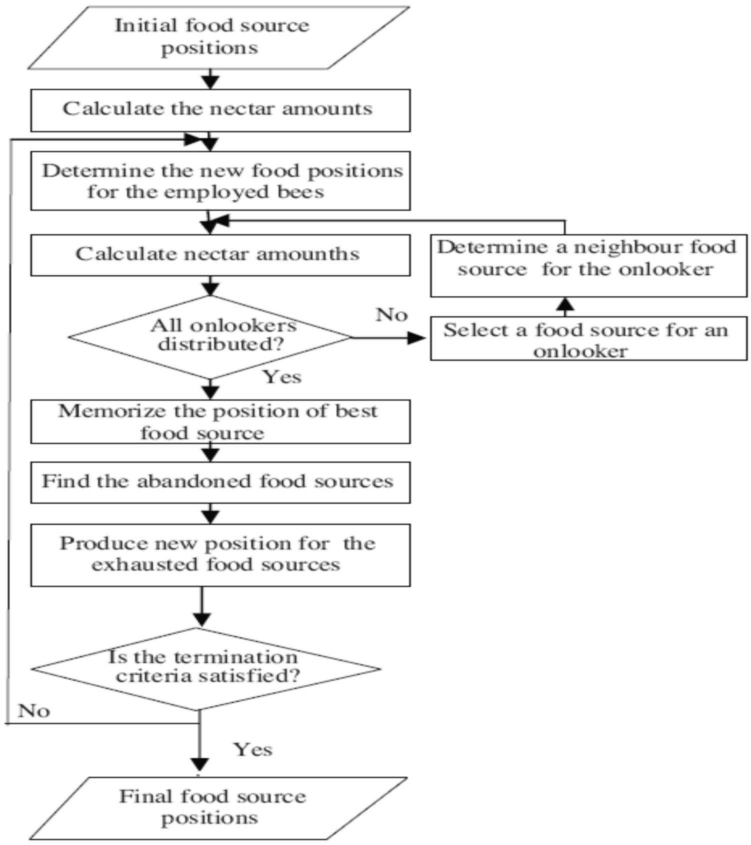

Figure 4. Flow chart of the ABC algorithm

The main steps of the ABC algorithm are given below [60]:

(1) Initialization
(2) Evaluate the population
Repeat
(3) Employed Bees Phase
(4) Onlooker Bees Phase
(5) Scout Bees Phase
(6) Memorize the best food source detected so far
Until Stopping criteria is satisfied

4. DEFINITION OF PROBLEM

In general identification process as seen in Figure 5, model parameters vector, *w*, are defined by minimizing the error value between adapted algorithm and desired output and model output with the help of a cost function [15, 61]. The cost function is defined as; (13) [15];

$$J(w) = \frac{1}{N}\sum_{n=1}^{N}(d(n) - y_m(n))^2 \tag{13}$$

Optimization problem is presented as cost function defined as $\min_{w \in W} J(w)$. In Equation (13), *d(n)* is desired response and $y_m(n)$ is model response. *N* is the length of the *J(w)* and the training set pattern number. The aim of the cost function J(w) is minimized by adjusting *w*. The cost function, called mean square error (Mean Squared Error, MSE), is usually expressed as the time averaged of function defined by Equation (13). MSE is a commonly used criterion of performance for model testing purposes.

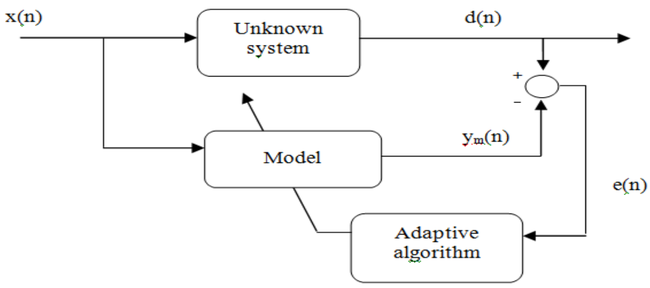

Figure 5. General structure of system identification

5. VARIOUS SYSTEM TYPES FOR COMPARING THE PERFORMANCE OF ABC

In this study, system identification structure using Hammerstein model is given in Figure 6. *d(n)* is desired system output, $y_m(n)$ is model output and *e(n)* is error value. In identification process, model parameters are defined by minimizing the error (MSE) value between adapted algorithm and system output and model output with the help of a cost function in Equation (13).

In simulation studies *x(n)* noiseless input data is used both system and model input. Input is White Gaussian sequence of 250 data samples and its variance is 0.9108. The identification process is performed on three different type of systems that are all unknown; linear (ARMA), nonlinear (Bilinear) and Wing Flutter (real data) systems. These systems are identified with four different types of models. These models are given in Equation (14), (15), (16), (17). Hammerstein model with SOV-FIR in Equation (14) is obtained from Equation (9) with *r*=1 and *m*=1. Hammerstein model with MPN-FIR in Equation (15) is obtained from Equation (6) with *p*=3 and *m*=1. SOV model in Equation (16) is obtained from Equation (3) with *r*=1. FIR model in Equation (17) is obtained from Equation (1) with *m*=1. The memory length of the used FIR and Volterra model memories are chosen same as the FIR and Volterra models in Hammerstein model block. In our studies, it is aimed to have better results in proposed Hammerstein structure than the sub models (FIR and SOV) that made up the block structure.

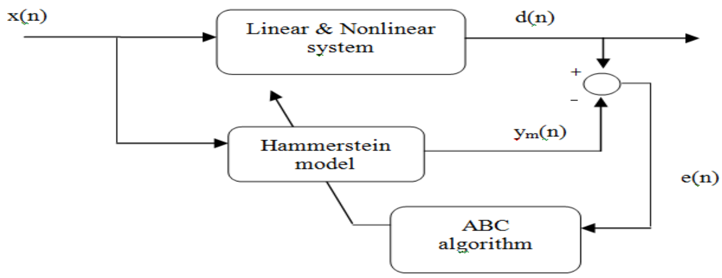

Figure 6. System identification structure using Hammerstein model

$$y_{m1}(n) = a_0h_0x(n)+ a_0h_1x(n-1)+a_0q_{0,0}\ x^2(n)\quad a_0q_{0,1}x(n)x(n-1) + a_0q_{1,0}x(n-1)x(n)+ a_0q_{1,1}x^2(n-1)+a_1h_0x(n-1)+a_1h_1x(n-2)+a_1q_{0,0}x^2(n-1)+ a_1q_{0,1}x(n-1)x(n-2) +a_1q_{1,0}x(n-2)x(n-1)+a_1q_{1,1}x^2(n-2) \tag{14}$$

$$y_{m2}(n) = b_0c_1x(n) + b_0c_2x^2(n)+ b_0c_3x^3(n)+ b_1c_1x(n-1) + b_1c_2x^2(n-1)+b_1c_3x^3(n-1) \tag{15}$$

$$y_{m3}(n)= h_0x(n) + h_1x(n-1)+q_{0,0}x^2(n) + q_{0,1}x(n)\ x(n-1)+ q_{1,0}x(n-1)\ x(n)+ q_{1,1}x^2(n-1) \tag{16}$$

$$y_{m4}(n)= a_0x(n) + a_1x(n-1) \tag{17}$$

In these studies, all models are optimized till the error between the model output and system output is minimized by ABC, CS and RLS algorithm. Simulation tests were performed in MATLAB platform. Also tests were performed on a computer with Intel Core i7 Q740 1.73 Ghz CPU and 4 GB RAM.

5.1. Example-I

In this example, considering the structure given in Figure 6, nonlinear system, which is a Bilinear [57, 62, 63], is chosen as in Equation (18). It is identified with four different types of model.

$$d(n)=0.25d(n-1)-0.5d(n-1)x(n)+0.05d(n-1)x(n-1)-0.5x(n)+0.5x(n-1) \tag{18}$$

It is identified with four different type models. All models are trained by ABC, CS, RLS algorithm and obtained MSE, correlation and time values are presented in Table 2. Control parameters of ABC, CS and RLS are given in Table 1 for this example. RLS algorithm has only one control parameter called forgetting factor (λ).

Table 1. Control parameters of ABC, CS and RLS for all models

Parameters	**Model Structure**				
	Algorithm	**Eq.(14)**	**Eq.(15)**	**Eq.(16)**	**Eq.(17)**
Population Size	CS/ ABC	80	50	60	20
Low-Upper Bound Range	CS	1.5	1.5	1.5	1.5
	ABC	20	20	20	20
Generation Number	CS/ ABC	500	500	500	500
Forgetting Factor	RLS	λ_1=0.1260 λ_2=0.7110	λ_1=0.063 λ_2=0.336	λ=1	λ=1

Table 2. MSE, correlation and time values for Example-I

	Algorithm	**Model Structure**			
		Hammerstein with SOV-FIR	**Hammerstein with MPN-FIR**	**Volterra**	**FIR**
MSE	RLS	0.06169	0.15384	**0.06615**	**0.13115**
	CS	0.05172	0.12724	0.06631	**0.13115**
	ABC	**0.05096**	**0.12710**	**0.06615**	**0.13115**
Correlation	RLS	0.9348	0.8257	**0.9232**	**0.8425**
	CS	0.9403	0.8476	0.9231	**0.8425**
	ABC	**0.9415**	**0.8477**	**0.9232**	**0.8425**
Run Time(s)	RLS	0.24	0.10	0.12	0.06
	CS	394.35	150.50	191.26	27.36
	ABC	86.36	54.03	64.69	22.39

The above results indicate that ABC is suitable for use in bilinear system identification problem. ABC produced better results than CS and RLS. However, other algorithms have not been successful in terms of run times. Also Hammerstein with SOV-FIR is the most successful in terms of model types.

The variation of MSE-Generation has also been presented in Figure 7 as graphically for 500 generation number. It is clearly seen from Figure 7 that ABC is faster than CS. Also Testing model outputs are shown for 30 data points in Figure 8.

Parameters of model are estimated with ABC, CS and RLS and these are given in Table 3 for this example.

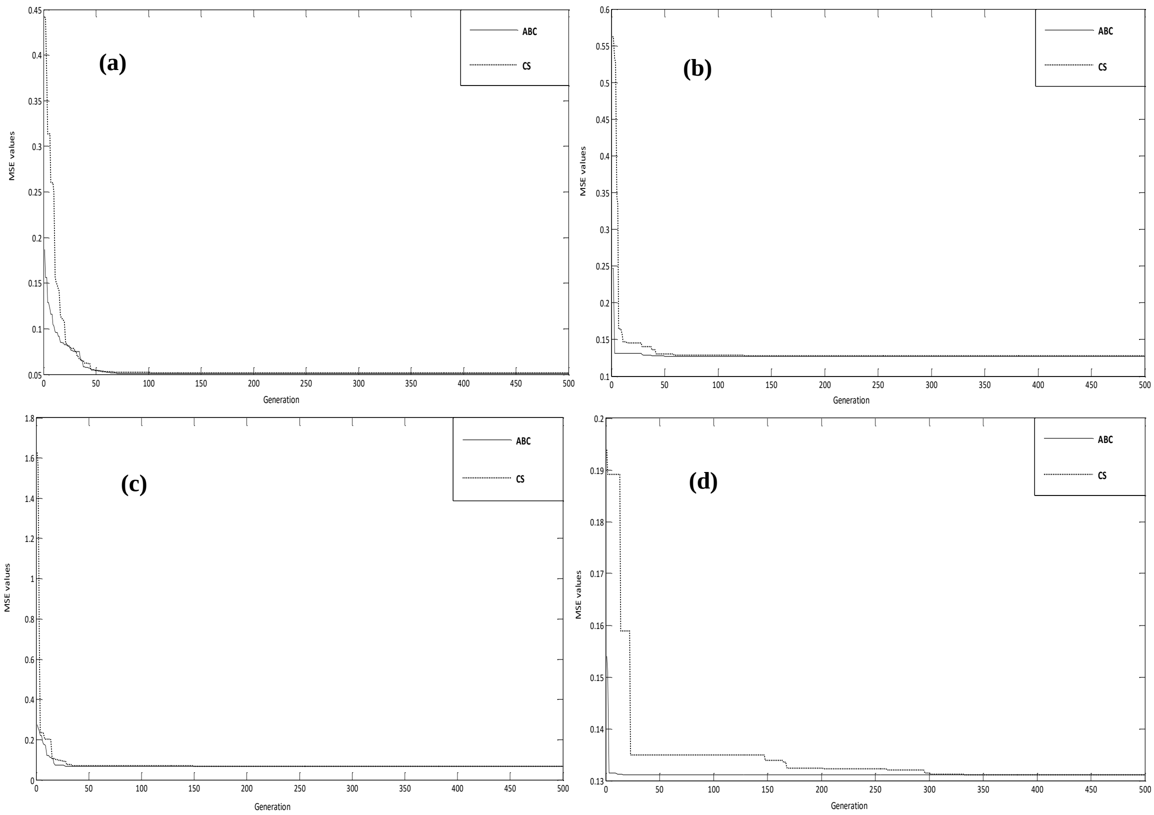

Figure 7. Evolution of the MSE values of example-I [(a) Hammerstein model with SOV-FIR, (b) Hammerstein model with MPN-FIR, (c) Volterra model, (d) FIR model]

Table 3. Parameters of model

Type of Algorithm	Type of Model	Parameters										
		a_0	a_1	c_1	c_2	c_3	h_0	h_1	q_{00}	q_{01}	q_{10}	q_{11}
ABC	Hammerstein with SOV-FIR	-0.989	-0.250	---	---	---	0.500	-0.477	0.019	-0.337	0.044	0.021
	Hammerstein with MPN-FIR	-0.842	0.575	0.660	0.009	-0.032	---	---	---	---	---	---
	Volterra	---	---	---	---	---	-0.490	0.341	-0.014	0.249	0.039	-0.037
	FIR	-0.488	0.328	---	---	---	---	---	---	---	---	---
CS	Hammerstein with SOV-FIR	0.351	0.082	---	---	---	-1.406	1.312	-0.046	-0.001	0.750	-0.075
	Hammerstein with MPN-FIR	-0.750	0.562	0.748	-0.001	-0.046	---	---	---	---	---	---
	Volterra	---	---	---	---	---	-0.468	0.347	-0.013	1.397	-1.109	-0.046
	FIR	-0.492	0.328	---	---	---	---	---	---	---	---	---
RLS	Hammerstein with SOV-FIR	-0.008	-0.001	---	---	---	63.625	-48.210	5.428	-17.831	-17.831	2.532
	Hammerstein with MPN-FIR	0.295	-0.172	-1.841	-0.075	0.210	---	---	---	---	---	---
	Volterra	---	---	---	---	---	-0.489	0.341	-0.014	0.144	0.144	-0.037
	FIR	-0.488	0.328	---	---	---	---	---	---	---	---	---

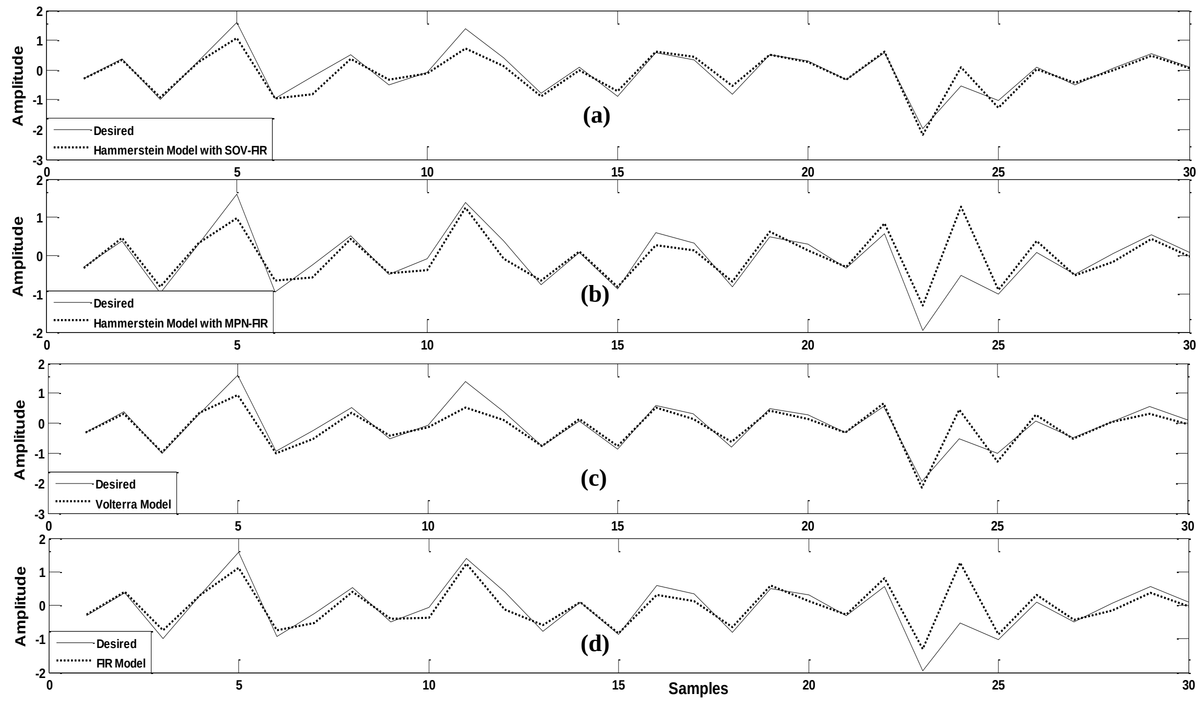

Figure 8. Simulated response comparisons of example-I [(a) Hammerstein model with SOV-FIR, Hammerstein model with MPN-FIR, (c) Volterra model, (d) FIR model

5.2. Example-II

In this example, considering the structure given in Figure 6, linear system, which is an ARMA [14, 62, 63], is chosen as in Equation (19). It is identified with four different types of model.

$$d(n)=0.7x(n)-0.4x(n-1)-0.1x(n-2)+0.25d(n-1)-0.1d(n-2)+0.4d(n-3) \quad (19)$$

The results achieved from simulations in the noiseless case have been presented in Table 4. It is clearly seen from Table 4 that ABC is more successful than CS and RLS. Also, better results are obtained from ABC based Hammerstein model with SOV-FIR. Control parameters of ABC, CS are given in Table 1 for this example.

Table 4. MSE, correlation and time values for Example-II

	Algorithm	Model Structure			
		Hammerstein with SOV-FIR	**Hammerstein with MPN-FIR**	**Volterra**	**FIR**
MSE	RLS	0.07612	0.11584	**0.11313**	**0.11386**
	CS	0.06646	0.11369	0.11320	**0.11386**
	ABC	**0.06637**	**0.11356**	**0.11313**	**0.11386**
Correlation	RLS	0.9344	0.8927	**0.8947**	**0.8940**
	CS	0.9396	0.8943	0.8948	**0.8940**
	ABC	**0.9397**	**0.8944**	**0.8947**	**0.8940**
RunTime(s)	RLS	0.23	0.09	0.11	0.06
	CS	443.18	142.20	232.71	29.07
	ABC	117.00	74.80	96.34	31.24

The variation of MSE-Generation has also been presented in Figure 9 as graphically for 500 generation number. It is clearly seen from Figure 9 that ABC is faster than CS. Parameters of model are estimated with ABC, CS and RLS and these are given in Table 5 for this example.

Table 5. Parameters of model

Type of Algorithm	Type of Model	Parameters										
		a_0	a_1	c_1	c_2	c_3	h_0	h_1	q_{00}	q_{01}	q_{10}	q_{11}
ABC	Hammerstein with SOV-FIR	-0,712	0,538	---	---	---	-0,972	-0,437	-0,009	0,535	-0,544	-0,024
	Hammerstein with MPN-FIR	0,671	-0,197	0,993	-0,013	0,008	---	---	---	---	---	---
	Volterra	---	---	---	---	---	0,682	-0,201	-0,008	0,177	-0,164	0,017
	FIR	0,681	-0,201	---	---	---	---	---	---	---	---	---
CS	Hammerstein with SOV-FIR	-0,539	0,421	---	---	---	-1,274	-0,585	-0,013	0,750	-0,761	-0,032
	Hammerstein with MPN-FIR	0,499	-0,146	1,303	-0,018	0,023	---	---	---	---	---	---
	Volterra	---	---	---	---	---	0,682	-0,201	-0,011	-0,750	0,750	0,023
	FIR	0,671	-0,199	---	---	---	---	---	---	---	---	---
RLS	Hammerstein with SOV-FIR	-0,558	0,404	---	---	---	-1,136	-0,487	-0,088	-0,020	-0,020	-0,101
	Hammerstein with MPN-FIR	0,343	-0,114	1,872	-0,108	0,017	---	---	---	---	---	---
	Volterra	---	---	---	---	---	0,682	-0,201	-0,008	0,006	0,006	0,017
	FIR	0,681	-0,201	---	---	---	---	---	---	---	---	---

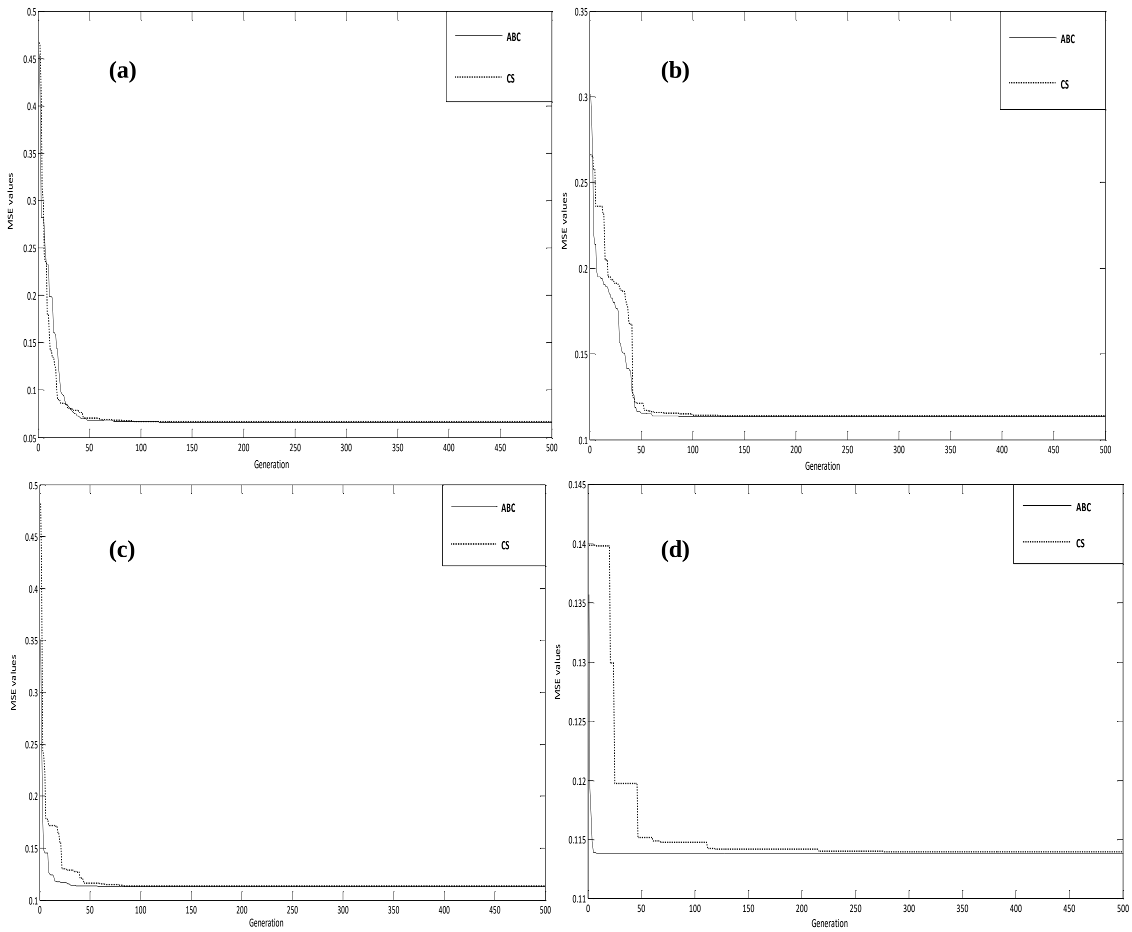

Figure 9. Evolution of the MSE values of example-II [(a) Hammerstein model with SOV-FIR, (b) Hammerstein model with MPN-FIR, (c) Volterra model (d), FIR model]

In addition, the results obtained from ABC and CS algorithms have been found after 20 trials for examples. Testing model outputs are shown for 30 data points in Figure 10.

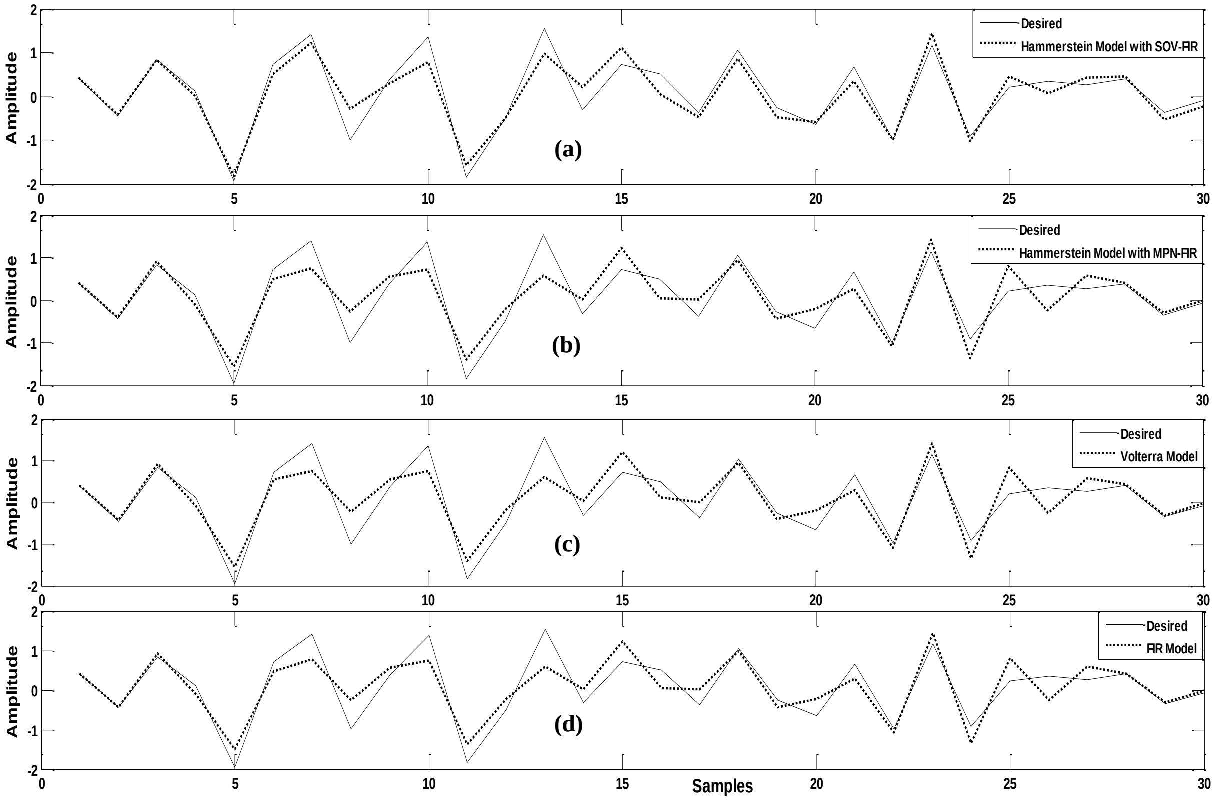

Figure 10. Simulated response comparisons of example-II [(a) Hammerstein model with SOV-FIR, (b) Hammerstein model with MPN-FIR, (c) Volterra model, (d) FIR model]

5.3. Example-III

In this example, considering the structure given in Figure 6, wing flutter data of Nasa's air research tool F-18 is applied as nonlinear system. It is identified with four different types of model. The data used in this sample is real data and taken from Katholieke Universiteit Lauven, Signals, Identification, System Theory and Automation's Identification Database [64, 65]. As seen in Table 7, ABC based Hammerstein model with SOV-FIR produced better results than other algorithms and other model types. Control parameters of ABC, CS and RLS are given in Table 6 for this example. RLS algorithm has only one control parameter called forgetting factor.

Table 6. Control parameters of ABC, CS and RLS for all models

Parameters	**Model Structure**				
	Algorithm	**Eq.(22)**	**Eq.(23)**	**Eq.(24)**	**Eq.(25)**
Population Size	CS/ ABC	80	50	60	20
Low-Upper Bound Range	CS	1.5	1.5	1.5	1.5
	ABC	50	50	50	50
Generation Number	CS/ ABC	500	500	500	500
Forgetting Factor	RLS	λ_1=0.9720 λ_2=0.0720	λ_1=0.9840 λ_2=0.6630	λ=1	λ=1

Table 7. MSE, correlation and time values for Example-III

	Algorithm	Model Structure			
		Hammerstein with SOV-FIR	Hammerstein with MPN-FIR	Volterra	FIR
MSE	RLS	0.00249	0.00362	0.00329	**0.00392**
	CS	0.00329	**0.00360**	0.00475	0.00587
	ABC	**0.00233**	**0.00360**	**0.00328**	**0.00392**
Correlation	RLS	0.9763	0.9642	**0.9674**	**0.9610**
	CS	0.9673	**0.9644**	0.9603	0.9511
	ABC	**0.9769**	**0.9644**	**0.9674**	**0.9610**
Run Time(s)	RLS	0.12	0.06	0.09	0.04
	CS	1067.28	423.50	624.61	85.83
	ABC	152.45	94.89	115.16	38.55

The above results indicate that in terms of run times by ABC other algorithms have not been very successful. Testing model outputs are shown for 30 data points in Figure 11. Parameters of model are estimated with ABC, CS and RLS and these are given in Table 8 for this example.

Table 8. Parameters of model

Type of Algorithm	Type of Model	Parameters										
		a_0	a_1	c_1	c_2	c_3	h_0	h_1	q_{00}	q_{01}	q_{10}	q_{11}
ABC	Hammerstein with SOV-FIR	0,488	-0,428	---	---	---	12,211	-10,666	0,836	0,657	-0,674	-0,543
	Hammerstein with MPN-FIR	-0,257	0,300	-6,001	-0,354	0,022	---	---	---	---	---	---
	Volterra	---	---	---	---	---	1,537	-1,787	0,613	-23,548	22,565	0,352
	FIR	1,508	-1,758	---	---	---	---	---	---	---	---	---
CS	Hammerstein with SOV-FIR	-1,451	0,023	---	---	---	-1,074	1,247	-0,492	0,778	0,001	-0,274
	Hammerstein with MPN-FIR	-1,043	1,217	-1,453	-0,093	-0,004	---	---	---	---	---	---
	Volterra	---	---	---	---	---	1,253	-1,500	-0,001	0,269	-0,202	-0,070
	FIR	1,124	-1,388	---	---	---	---	---	---	---	---	---
RLS	Hammerstein with SOV-FIR	-0,005	0,004	---	---	---	-1,087	0,982	-0,096	0,014	0,014	0,035
	Hammerstein with MPN-FIR	-0,002	0,002	-69,594	-33,840	2,302	---	---	---	---	---	---
	Volterra	---	---	---	---	---	1,528	-1,778	0,552	-0,432	-0,432	0,296
	FIR	1,497	-1,748	---	---	---	---	---	---	---	---	---

The variation of MSE-generation has also been presented in Figure 12 as graphically for 500 generation number. It is clearly seen from Figure 12 that ABC is faster than CS

In example I, II and III, it is aimed to model various type of linear (ARMA), nonlinear (Bilinear) and Wing Flutter (real data) system via proposed model. The MSE, correlation and time results obtained from simulations have been given in Table from 1 to 8 and Figure from 7 to 12. The results indicate that ABC, CS and RLS are suitable for use in Hammerstein model optimization problem. Terms of algorithms, ABC is faster than CS. Also, better results are obtained from ABC based Hammerstein model with SOV-FIR.

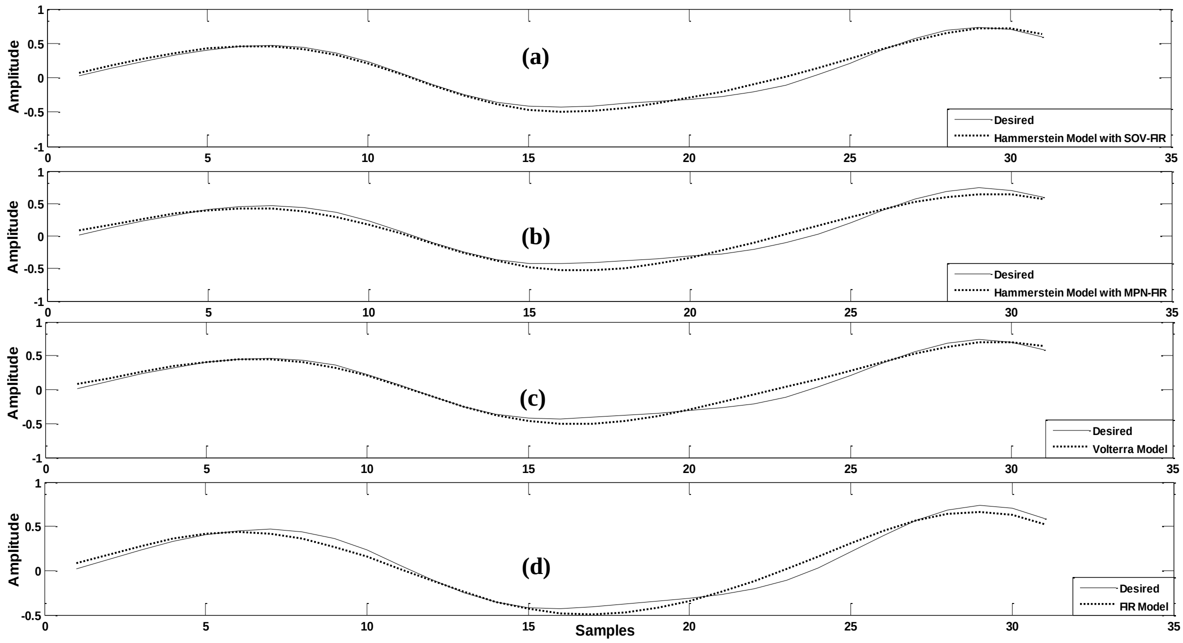

Figure 11 Simulated response comparisons of example-III [(a) Hammerstein model with SOV-FIR, (b) Hammerstein model with MPN-FIR, (c) Volterra model, (d) FIR model]

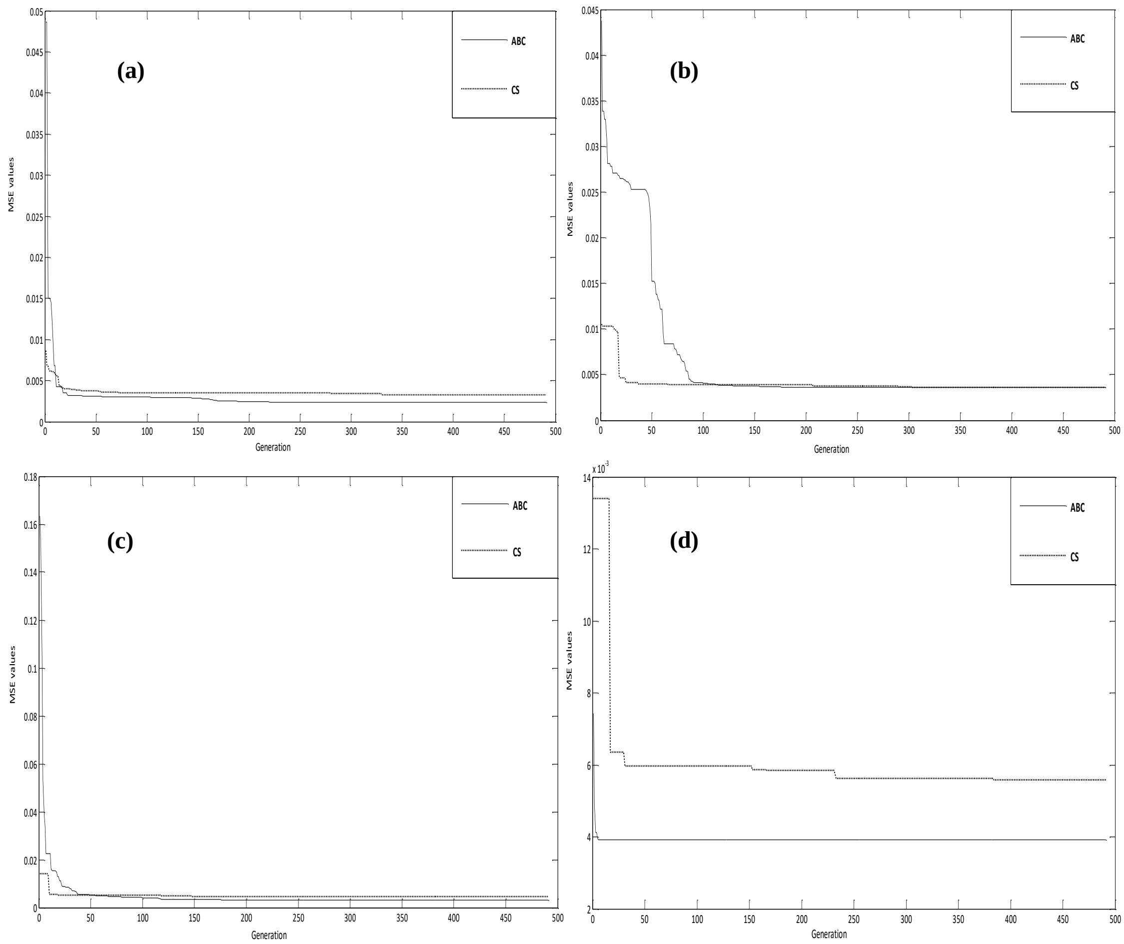

Figure 12. Evolution of the MSE values of example-III [(a) Hammerstein model with SOV-FIR, (b) Hammerstein model with MPN-FIR, (c) Volterra model (d), FIR model]

6. CONCLUSIONS

This study aims to improve Hammerstein model for system identification area. In this context, a Hammerstein model consists of a series connection of a nonlinear SOV model followed by a linear FIR model is presented. System identification studies are carried out to determine the prosperity of the proposed model which is optimized by ABC, CS and RLS algorithm. So, different structure systems are identified with both proposed model and different type models. Proposed model has a complex structure as a disadvantage but has a successful identification tool as an advantage. According to the results, the systems can be identified with less error in proposed Hammerstein model with SOV-FIR compared to other model types although this model contains more parameters and is mathematically more complex. The performance comparison of algorithms has been realized, as well. As a result of this performance comparison, ABC has produced better results than others. Also ABC algorithm based Hammerstein model with SOV-FIR can successfully be used for system identification areas.

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