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System identification application using Hammerstein model

SABAN OZER[1], HASAN ZORLU[1,*] and SELCUK METE[2]

[1]Department of Electrical and Electronic Engineering, Erciyes University, 38039 Kayseri, Turkey
[2]Kayseri Regional Office, Turk Telekom A.S., 38070 Kayseri, Turkey
e-mail: sozer@erciyes.edu.tr; hzorlu@erciyes.edu.tr; selcuk.metes@gmail.com

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Abstract. Generally, memoryless polynomial nonlinear model for nonlinear part and finite impulse response (FIR) model or infinite impulse response model for linear part are preferred in Hammerstein models in literature. In this paper, system identification applications of Hammerstein model that is cascade of nonlinear second order volterra and linear FIR model are studied. Recursive least square algorithm is used to identify the proposed Hammerstein model parameters. Furthermore, the results are compared to identify the success of proposed Hammerstein model and different types of models.

Keywords. System identification; nonlinear model; block-oriented model; Hammerstein model; RLS algorithm.

1. Introduction

System identification is proceeded through linear and nonlinear models as to the linearity of the system [1–10]. Linear system identification that the input and the output of the system stated with linear equations is mostly used because of its advanced theoretical background [3–5, 10]. However, many systems in real life have nonlinear behaviours. Linear methods can be inadequate in identification of such systems and nonlinear methods are used [1, 2, 5–9]. In nonlinear system identification, the input–output relation of the system is provided through nonlinear mathematical assertions as differential equations, exponential and logarithmic functions [11].

Autoregressive (AR), moving average (MA) and autoregressive moving average (ARMA) models or finite impulse response (FIR) and infinite impulse response (IIR) models derives of these models are used for linear system identification in literature. Also Volterra, bilinear and PAR models are used for nonlinear system identification [8, 11–19]. Moreover, recently the block oriented models to cascade of the linear and nonlinear models as Hammerstein, Wiener, Hammerstein–Wiener models are also popular [7, 20–33]. It is because these models are useful in simple effective control systems. Besides the usefulness in applications, these models are also preferred because of the effective predict of a wide nonlinear process [34]. Hammerstein model is firstly suggested by Narendra and Gallman in 1966 and various models are tested to improve the model [35]. Generally, memoryless polynomial nonlinear (MPN) model for nonlinear part and FIR model or IIR model for linear part are preferred in Hammerstein models in literature [20, 24, 26, 28, 36–38]. The main benefit of these structures is to introduce less parameter to be estimated. Also the polynomial representation has advantage of more flexibility and of a simpler use. Naturally, the nonlinearity can be approximated by a single polynomial. For these reasons, lots of block oriented applications are not considered the Volterra model for the nonlinear part [39]. To describe a polynomial non-linear system with memory, the Volterra series expansion has been the most popular model in use for the last three decades [16, 17, 40]. The Volterra theory was first applied with nonlinear resistor to a White Gaussian signal. In modern DSP fields, the truncated Volterra series model is widely used for nonlinear system representations. Also as the order of the polynomial increases, the number of Volterra parameters increases rapidly, thus making the computational complexity extremely high. For simplicity, the truncated Volterra series is most often considered in literature [16, 17, 40]. The number of parameters of the Volterra model quickly increases with order of nonlinearity and memory length. As a consequence, large data sets are required in order to obtain an estimation of the model parameters with reasonable accuracy.

In this paper, system identification applications using Hammerstein model that is cascade of nonlinear Volterra model and linear FIR model are presented. Recursive least square (RLS) algorithm is used to estimate the proposed Hammerstein model parameters. Also, the systems are identified with different models optimized by RLS such as a Hammerstein model cascade of nonlinear MPN model and linear FIR model, a Volterra model and an FIR model. The results of the Hammerstein model focused on this study

*For correspondence

compared with these different models. The rest of this paper is organized as follows. Section 2 provides a summary of FIR, Volterra, Hammerstein model structures. RLS algorithm is adapted to Hammerstein model in section 3. Problem is defined in section 4. Simulation results demonstrating the validity of the analysis in the paper are provided in section 5. Finally, section 6 contains the concluding remarks.

2. Model structures

2.1 *FIR model*

FIR structure is widely used for acoustic echo cancellation [41]. In FIR model, output is dependent on the current and previous values of input, not dependent on the output value. So the model is non-recursive. The input–output relation of FIR model is

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

$x(n)$ represents input signal and $y(n)$ represents model output. Here N is the memory length. FIR model's coefficient w weight vector is defined as [15]

$$w = [a_0 a_1 a_2 \ldots a_{N-1}]^T. \tag{2}$$

2.2 *Volterra model*

Volterra structure is mostly used model in identification of the nonlinear systems [15–17, 19] Volterra series are

$$\begin{aligned} y_n = {} & \sum_{i=0}^{N} h_i x_{n-i} + \sum_{i=0}^{N} \sum_{j=0}^{N} q_{i,j} x_{n-i} x_{n-j} \\ & + \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=0}^{N} q_{i,j,k} x_{n-i} x_{n-j} x_{n-k} + \cdots\cdots \end{aligned} \tag{3}$$

Here y_n shows output, x_n shows input index, h_i shows linear and $q_{i,j}$ shows nonlinear quadratic parameters, and N shows model length. In the literature, second order Volterra (SOV) structures, mostly only h_i and $q_{i,i}$ parameters are taken into consideration, are used in system identification [15–17, 19, 25], because wider structure can be more complex. Many researchers study on the block and adaptive applications of SOV model. SOV models are used in solving the problems in real life such as canal stabilization, echo suppression and adaptive noise suppression [19].

2.3 *Hammerstein model*

Many systems can be represented by linear and nonlinear structured models. Hammerstein model structure in figure 1 is formed by cascade of linear and nonlinear models [20, 24, 26, 28].

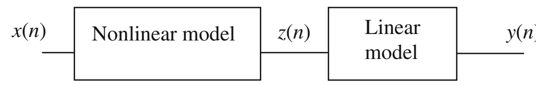

Figure 1. General Hammerstein model structure.

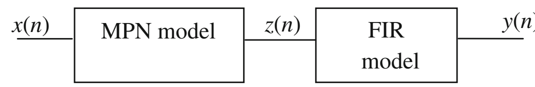

Figure 2. Hammerstein model with MPN–FIR.

Hammerstein model structure can easily model practical applications such as pH neutralization process, spark ignition engine torque, electrically stimulated muscle, continuous stirred tank rector, and fuel cell [28]. In Hammerstein model structure in figure 1, $x(n)$ is nonlinear model and Hammerstein structure input, $z(n)$ is linear model input and $y(n)$ is linear model and Hammerstein structure output.

2.3a *Hammerstein model with MPN–FIR:* In this structure, MPN model is used as nonlinear part and FIR model is used as linear part. The nonlinear part is approximated by a polynomial function. This structure is shown in figure 2 [38].

$x(n)$ and $y(n)$ are the input and the output data respectively of the Hammerstein model. $z(n)$ is the unavailable internal data. The Hammerstein model $H_H^{(p,m)}$ of order p and memory m can be described by the following equation:

$$y(n) = H_H^{(p,m)}[x(n)]. \tag{4}$$

Equation (4) could be expressed with an intermediate variable $z(n)$ as follows

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

with $z(n) = \sum_{l=1}^{p} c_l x^l(n)$ the internal signal $z(n)$ cannot be measured, but it can be eliminated from the equation, by substituting its value in (4). We got

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

where b_i and c_l are the coefficients of the FIR model and the MPN model respectively [38]. Schematic of this model is shown in figure 3.

2.3b *Proposed Hammerstein model with SOV–FIR:* In this proposed structure, SOV model is used as nonlinear part and FIR model is used as linear part. Cascade structure is shown in figure 4 [42].

Nonlinear SOV model is defined as

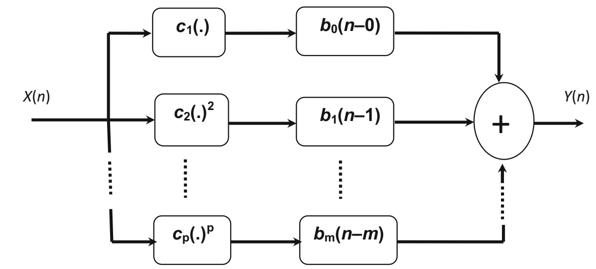

Figure 3. Schematic of Hammerstein model with MPN–FIR.

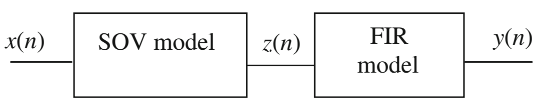

Figure 4. Hammerstein model with SOV–FIR.

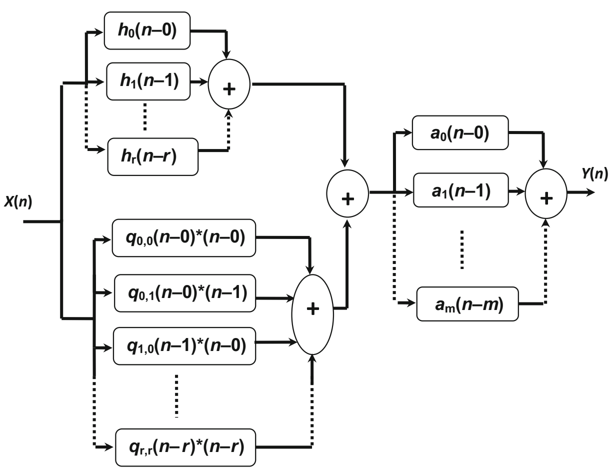

Figure 5. Schematic of Hammerstein model with SOV–FIR.

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

and linear FIR model output is defined as

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

Generalized Hammerstein model output with the combination of these two definitions is

$$\begin{aligned} y(n) &= \sum_{i=0}^{r}\sum_{j=0}^{m} a_i h_j x(n-i-j) \\ &\quad + \sum_{t=0}^{r}\sum_{z=0}^{m}\sum_{w=0}^{m} a_t q_{z,w} x(n-t-z)x(n-t-w) \end{aligned} \quad (9)$$

Schematic of this model is shown in figure 5 [42].

3. Recursive least square (RLS) algorithm

RLS algorithm is used for optimization of model parameters. Studies in literature show that RLS is popular optimization algorithm among derivative based algorithms [32, 43, 44]. The most important feature of RLS algorithm is that the algorithm uses all information in input data towards start moment. The aim of the RLS algorithm is minimized to error between desired and model responses by adjusting model parameters.

The error is defined as in the following equation

$$e(n) = d(n) - w^H(n-1)x(n). \quad (10)$$

Here, e is error value, d is desired output, x is input signal for model and w is model parameters vector. Adjusting model parameter process is given by the following equation

$$w(n) = w(n-1) + k(n)e(n). \quad (11)$$

Here, k is gain vector and defined by the following equation

$$k(n) = \frac{\lambda^{-1}P(n-1)x(n)}{1+\lambda^{-1}x^H(n)P(n-1)x(n)}. \quad (12)$$

Here, P is current covariance matrix and defined by the following equation

$$P(n) = \lambda^{-1}P(n-1) - \lambda^{-1}k(n)x^H(n)P(n-1). \quad (13)$$

Here, λ is forgetting factor for this algorithm. To adapt classical RLS algorithms to Hammerstein model first λ_1 is obtained by taking linear parameters partial derivative and λ_2 is obtained by taking nonlinear parameters partial derivative. In this method adapted gain is arranged for each iteration by the help of covariance matrix [19].

4. Definition of problem

Design of systems can be evaluated as an optimization problem of the cost function $J(w)$ indicated as follows

$$\min_{w \in W} j(w), \quad (14)$$

where w is the model coefficient vector. The aim of the cost function $J(w)$ is minimized by adjusting w. The cost function, called mean square error (MSE), is usually expressed as the time averaged of function defined by the following equation [8]:

$$J(w) = \frac{1}{N}\sum_{n=1}^{N}(d(n)-y(n))^2. \quad (15)$$

MSE is a commonly used criterion of performance for model testing purposes [45]. Where $d(n)$ and $y(n)$ are the desired and actual responses of the systems, respectively, and

N is the number of samples used for the calculation of the cost function [8]. The power of cost function will converge toward zero when the model coefficients are closer to optimal values [46]. The identification architecture is schematically given in figure 6 for systems by using the algorithm.

5. Simulation results

In this study, Hammerstein adapted identification structure, its block structure is given in figure 6, is studied. In identification process, model parameters are defined by minimizing the error (MSE) value between adapted RLS algorithm and system output and model output with the help of a cost function. In figure 6, $y(n)$ is unknown system output, $y_m(n)$ is model output and $e(n)$ is error value.

In simulation studies $x(n)$ input data is used as input of unknown system and model. Input sequence is Gaussian distributed white noise of 250 data samples. Its variance is 0.9108. Unknown systems are identified with four different types of models. These models are given in Eqs. (16), (17), (18), and (19). Hammerstein model with SOV–FIR in Eq. (16) is obtained from Eq. (9) with $r = 1$ and $m = 1$. Hammerstein model with MPN–FIR in Eq. (17) is obtained from Eq. (6) with $p = 3$ and $m = 1$. Volterra model in Eq. (18) is obtained from Eq. (3) with $N = 1$. FIR model in Eq. (19) is obtained from Eq. (1) with $N = 1$.

$$\begin{aligned} Y_{m_1}(n) = {} & a_0h_0x(n) + a_0h_1x(n-1) + a_0q_{0,0}x^2(n) \\ & + a_0q_{0,1}x(n)x(n-1) + a_0q_{1,0}x(n-1)x(n) \\ & + a_0q_{1,1}x^2(n-1) + a_1h_0x(n-1) \\ & + a_1h_1x(n-2) + a_1q_{0,0}x^2(n-1) \\ & + a_1q_{0,1}x(n-1)x(n-2) \\ & + a_1q_{1,0}x(n-2)x(n-1) + a_1q_{1,1}x^2(n-2) \end{aligned} \tag{16}$$

$$\begin{aligned} Y_{m_2}(n) = {} & b_0c_1x(n) + b_0c_2x^2(n) + b_0c_3x^3(n) \\ & + b_1c_1x(n-1) + b_1c_2x^2(n-1) + b_1c_3x^3(n-1) \end{aligned} \tag{17}$$

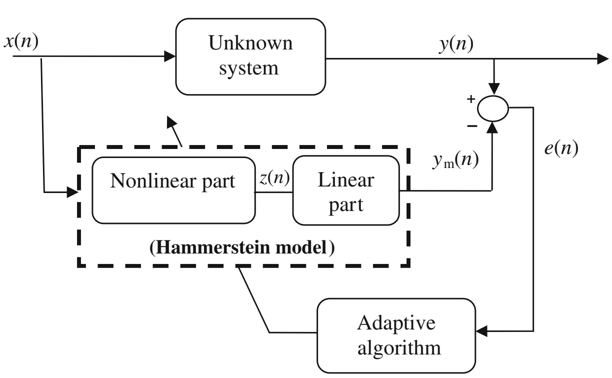

Figure 6. Hammerstein adaptive system identification.

$$\begin{aligned} Y_{m_3}(n) = {} & h_0x(n) + h_1x(n-1) + q_{0,0}x^2(n) \\ & + q_{0,1}x(n)x(n-1) + q_{1,0}x(n-1)x(n) \\ & + q_{1,1}x^2(n-1) \end{aligned} \tag{18}$$

$$Y_{m_4}(n) = a_0x(n) + a_1x(n-1). \tag{19}$$

Example 1: In this sample study, considering the block structure given in figure 6, Hammerstein system in Eq. (20) is chosen as unknown system and Hammerstein Model with SOV–FIR as in Eq. (16), Hammerstein model with MPN–FIR as in Eq. (17), Volterra model as in Eq. (18), FIR model as in Eq. (19) are used as models.

$$\begin{aligned} Y(n) = {} & 0.0089[-0.4898x(n) + 0.3411x(n-1) - 0.0139x^2(n) \\ & + 0.1147x(n)x(n-1) + 1447x(n-1)x(n) \\ & + 0.0379x^2(n-1)] + 0.0013[-0.4898x(n-1) \\ & + 0.3411x(n-2) - 0139x^2(n-1) \\ & + 0.1447x(n-1)x(n-2) + 0.1447x(n-2)x(n-1) \\ & + 0.0379x^2(n-2)]. \end{aligned} \tag{20}$$

The unknown system is identified with four different types of models. All models are trained by RLS algorithm and obtained MSE values are given in table 1. Also visual results are shown for 100 data points in figure 7.

Example 2: In this sample study, considering the block structure given in figure 6, Volterra System in Eq. (21) is chosen as unknown system [47] and Hammerstein Model with SOV–FIR as in Eq. (16), Hammerstein Model with MPN–FIR as in Eq. (17), Volterra model as in Eq. (18), FIR model as in Eq. (19) are used as models

$$\begin{aligned} Y(n) = {} & 0.8x(n-1) - 0.5x(n-2) + 0.7x^2(n-1) \\ & + 0.1x^2(n-2) - 0.4x(n-1)x(n-2). \end{aligned} \tag{21}$$

The unknown system is identified with four different types of models. All models are trained by RLS algorithm and obtained MSE values are given in table 2. Also visual results are shown for 100 data points in figure 8.

Example 3: In this sample study, considering the block structure given in figure 6, bilinear system in Eq. (22) is

Table 1. MSE values.

Type of model	MSE	λ_1	λ_2	The number of parameters
Hammerstein with SOV–FIR	5.983×10^{-10}	0.852	0.102	8
Hammerstein with MPN–FIR	6.122×10^{-6}	0.888	0.024	5
Volterra	2.498×10^{-7}	–	1	6
FIR	4.742×10^{-6}	1	–	2

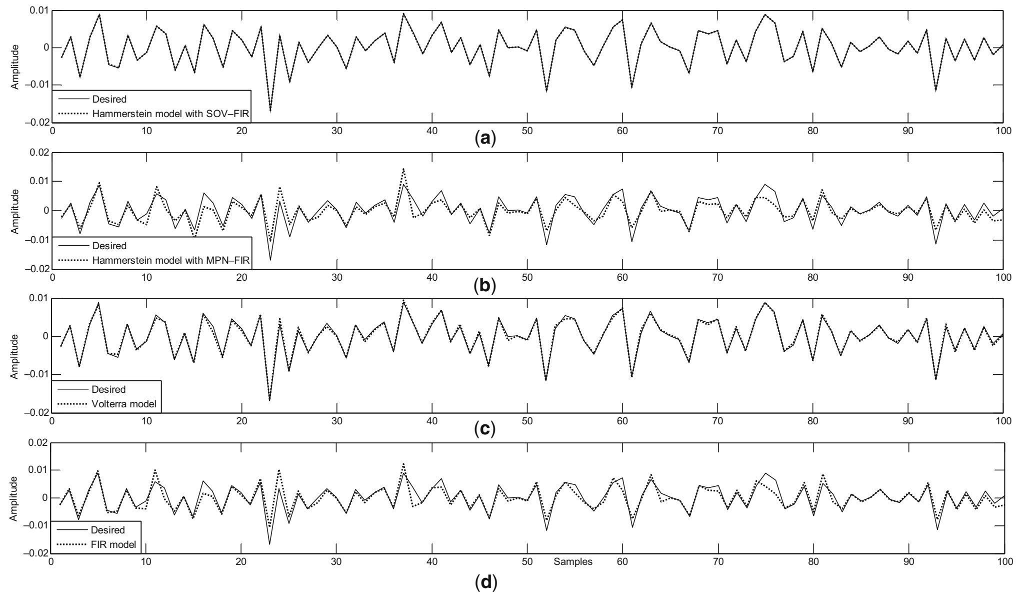

Figure 7. Simulation results of example 1: (**a**) Hammerstein model with SOV–FIR, (**b**) Hammerstein model with MPN–FIR, (**c**) Volterra model, and (**d**) FIR model.

Table 2. MSE values.

Type of model	MSE	λ_1	λ_2	The number of parameters
Hammerstein with SOV–FIR	1.3370×10^{-16}	0.8430	0.1470	8
Hammerstein with MPN–FIR	0.3288	0.9510	0.6270	5
Volterra	0.3278	–	1	6
FIR	1.5898	1	–	2

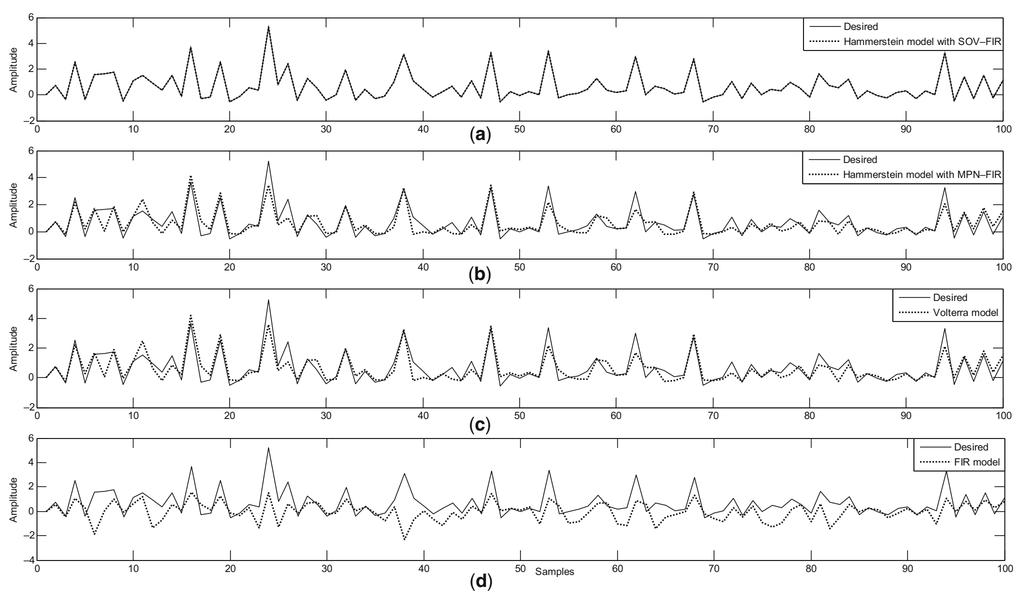

Figure 8. Simulation results of example 2: (**a**) Hammerstein model with SOV–FIR, (**b**) Hammerstein model with MPN–FIR, (**c**) Volterra model, and (**d**) FIR model.

chosen as unknown system [42] and Hammerstein model with SOV–FIR as in Eq. (16), Hammerstein model with MPN–FIR as in Eq. (17), Volterra model as in Eq. (18), FIR model as in Eq. (19) are used as models

$$Y(n) = 0.25y(n-1) - 0.5y(n-1)x(n) + 0.05y(n-1)x(n-1) - 0.5x(n) + 0.5x(n-1). \tag{22}$$

The unknown system is identified with four different types of models. All models are trained by RLS algorithm and obtained MSE values are given in table 3. Also visual results are shown for 100 data points in figure 9.

Example 4: In this sample study, considering the block structure given in figure 6, ARMA system in Eq. (23) is chosen as unknown system [48] and Hammerstein model with SOV–FIR as in Eq. (16), Hammerstein model with MPN–FIR as in Eq. (17), Volterra model as in Eq. (18), FIR model as in Eq. (19) are used as models

$$Y(n) = 0.7x(n) - 0.4x(n-1) - 0.1x(n-2) + 0.25y(n-1) - 0.1y(n-2) + 0.4y(n-3). \tag{23}$$

The unknown system is identified with four different types of models. All models are trained by RLS algorithm and obtained MSE values are given in table 4.

Table 3. MSE values.

Type of model	MSE	λ_1	λ_2	The number of parameters
Hammerstein with SOV–FIR	0.0617	0.1260	0.7110	8
Hammerstein with MPN–FIR	0.1538	0.0630	0.3360	5
Volterra	0.0661	–	1	6
FIR	0.1311	1	–	2

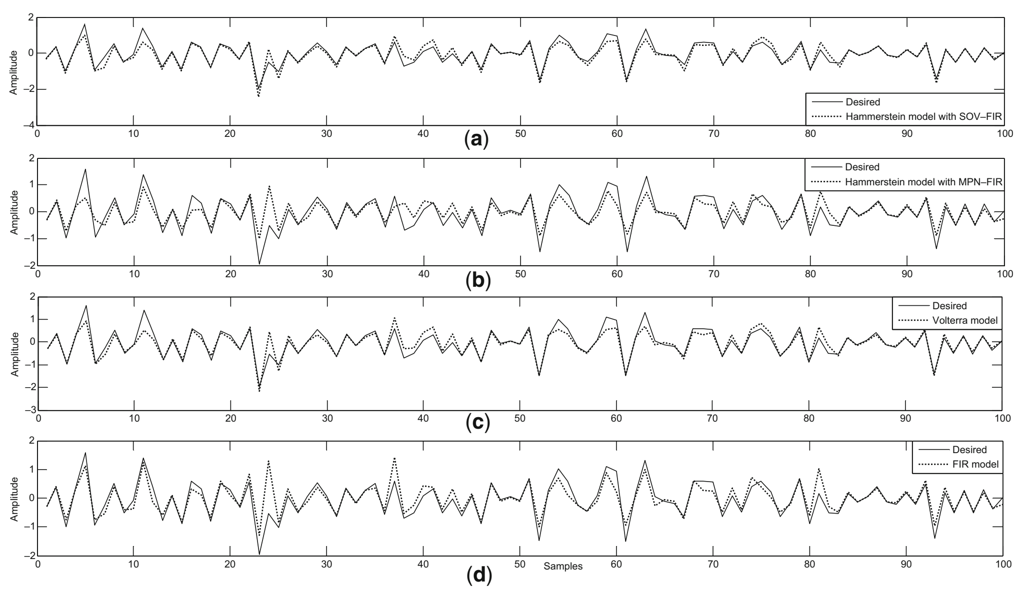

Figure 9. Simulation results of example 3: (**a**) Hammerstein model with SOV–FIR, (**b**) Hammerstein model with MPN–FIR, (**c**) Volterra model, and (**d**) FIR model.

Table 4. MSE values.

Type of model	MSE	λ_1	λ_2	The number of parameters
Hammerstein with SOV–FIR	0.0761	0.9120	0.7740	8
Hammerstein with MPN–FIR	0.1158	0.4410	0.1500	5
Volterra	0.1131	–	1	6
FIR	0.1139	1	–	2

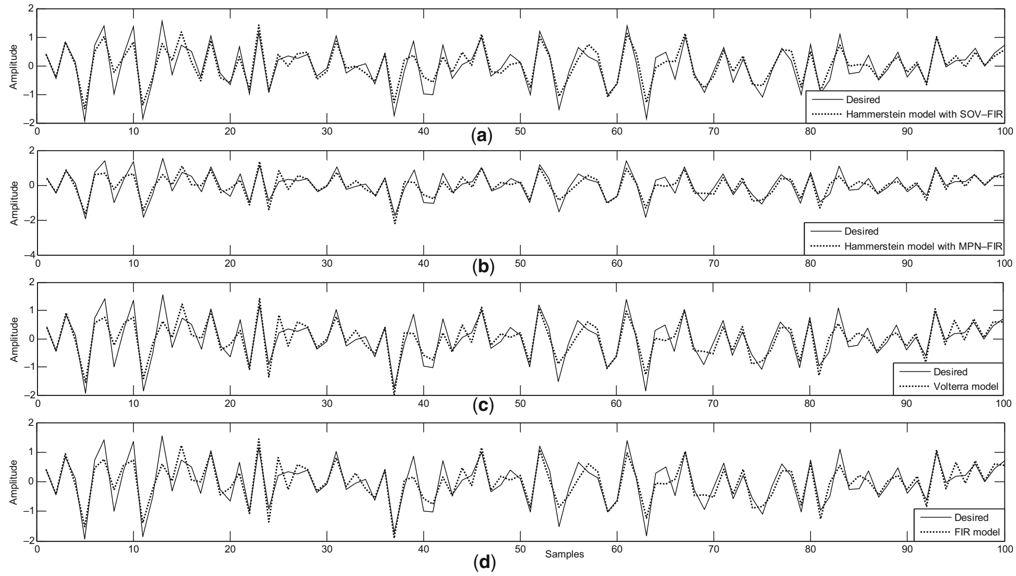

Figure 10. Simulation results of example 4: (a) Hammerstein model with SOV–FIR, (b) Hammerstein model with MPN–FIR, (c) Volterra model, and (d) FIR model.

Table 5. MSE values.

Type of model	MSE	λ_1	λ_2	The number of parameters
Hammerstein with SOV–FIR	0.1145	0.9120	0.9090	8
Hammerstein with MPN–FIR	0.3418	0.1050	0.3810	5
Volterra	0.3370	–	1	6
FIR	0.3385	1	–	2

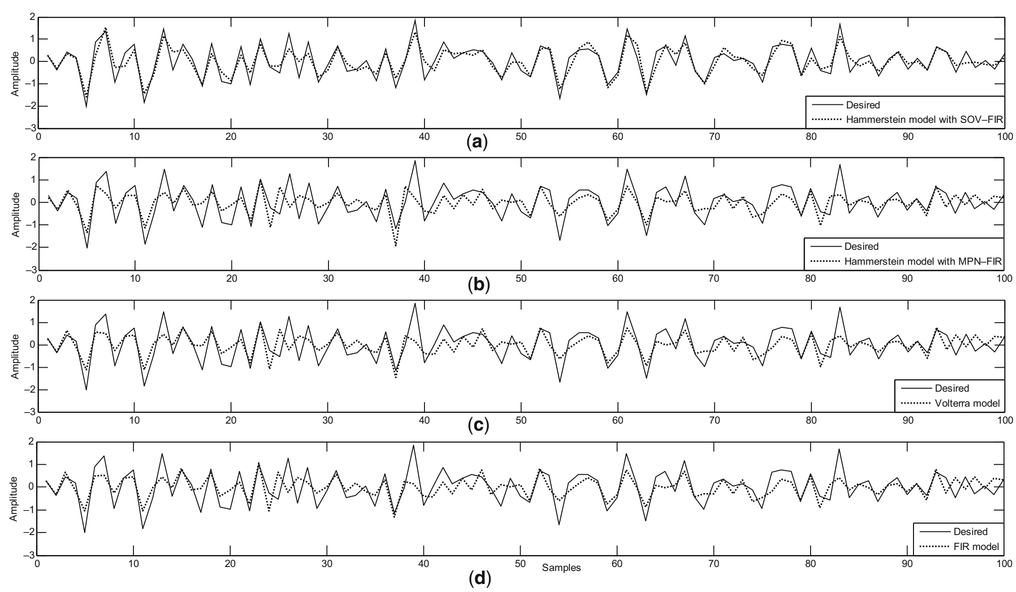

Figure 11. Simulation results of example 5: (a) Hammerstein model with SOV–FIR, (b) Hammerstein model with MPN–FIR, (c) Volterra model, and (d) FIR model.

Also visual results are shown for 100 data points in figure 10.

Example 5: In this sample study, considering the block structure given in figure 6, MA system in Eq. (24) is chosen as unknown system [49] and Hammerstein model with SOV–FIR as in Eq. (16), Hammerstein model with MPN–FIR as in Eq. (17), Volterra model as in Eq. (18), FIR model as in Eq. (19) are used as models.

$$\begin{aligned} Y(n) = 0.5x(n) - 0.25x(n-1) - 0.5x(n-2) \\ + 0.25x(n-3) - 0.25x(n-4). \end{aligned} \tag{24}$$

The unknown system is identified with four different types of models. All models are trained by RLS algorithm and obtained MSE values are given in table 5. Also visual results are shown for 100 data points in figure 11.

6. Conclusions

In this study, a Hammerstein model which is obtained by cascade form of the nonlinear SOV and a linear FIR model is presented. Identification studies of linear and nonlinear systems are carried out to determine the performance of proposed Hammerstein model optimized with RLS algorithm. So, different structure unknown systems are identified with both proposed model and different types of models. According to the results, in spite of Hammerstein model with SOV–FIR trained by RLS algorithms contain more parameters and are mathematically more complex, systems can be identified with less error compared to other model types.

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