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AN IMPROVED WIENER MODEL FOR SYSTEM IDENTIFICATION

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ABSTRACT

Wiener block structure is formed by cascade of linear and nonlinear models. A novel and improved Wiener model structure for system identification area is proposed in this study. In proposed Wiener model, Finite Impulse Response (FIR) model is used as linear part and Soft Switching based Hybrid (SSH) model is used as nonlinear part. The SSH structure consists of a Second Order Volterra (SOV) nonlinear model, a Memoryless Polynomial (MP) nonlinear model, and a soft-switching part through a Neuro-Fuzzy (NF) network. In simulation studies, different types systems are identified by presented novel model. In addition to the mentioned identified systems, the performance of the improved model is also compared with Volterra model and Wiener models presented in the literature. Simulation results find out the success of the proposed model.

Keywords: System identification, Wiener, Hybrid model, Optimization.

SİSTEM KİMLİKLENDİRME İÇİN GELİŞTİRİLEN BİR WIENER MODEL

ÖZET

Wiener blok yapısı doğrusal ve doğrusal olmayan modellerin kaskad bağlanması ile oluşturulmaktadır. Bu çalışmada sistem kimliklendirme alanı için yeni ve geliştirilmiş bir Wiener model yapısı sunulmuştur. Önerilen yapıda, doğrusal kısım olarak Sonlu Darbe Cevaplı model, doğrusal olmayan kısım olarak Esnek Anahtarlama Temelli Hibrit (EATH) model kullanılmıştır. EATH yapısı, doğrusal olmayan ikinci derece bir Volterra model, doğrusal olmayan hafızasız bir polinom model ve bir bulanık sinir ağı temelli esnek anahtarlama mekanizmasından oluşmaktadır. Simülasyonlarda, önerilen model ile dört farklı sistem tipi kimliklendirilmiştir. İlave olarak, bu sistemleri kimliklendirmek için literatürde yeralan Volterra ve Wiener modellerde ayrıca kullanılarak önerilen modelin performansı ile karşılaştırılmıştır. Simülasyon sonuçları, önerilen modelin başarısını ortaya koymaktadır.

Anahtar kelimeler: Sistem kimliklendirme, Wiener, Hibrit model, Optimizasyon.

1. INTRODUCTION

System identification process begins with the selection of suitable input signals. So in our case one or several of coup, step, sinus or random signals are applied to system as input and output signal is recorded [1]. Since the main work of system identification is to obtain the best convenient and acceptable mathematical model to demonstrate the relations between the input, output and noise of a system. The behaviour of systems can be determined more clearly by using different models. It can be said that the performance of the model is detected by the convergence of the final solution and the real solution [2], and this mentioned model structure can be linear or nonlinear that shows the behaviour of most physical systems [3-12]. Many systems have nonlinear behaviours in real life. Since linear models are insufficient in the identification of such systems, nonlinear models are used [6-12]. The obtained parameters of the model are determined through some estimated or statistical methods. Another significant step of the identification procedure is estimation of the parameters correctly. In this step, the difference between the model's output and the system's output is determined. If the difference is wide another model structure is selected. If the difference is small, the obtained model can be used to identify and control the system [1].

Nonlinear block-oriented models are used to describe the nonlinear behaviour of the system over the entire range of operating conditions adequately, and the identified system is typically sectioned into linear and nonlinear blocks. Wiener model is a well-known block oriented model [13-19]. This model is obtained by cascade connecting of a linear block and nonlinear block, respectively [2]. The main motivation of using Wiener models is the computational effort related with the correct parameter

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estimation and the low suitability for control design. So, many studies have been presented on the parameters estimation of nonlinear systems [16,17]. Wiener model is used because of both its usefulness and its ability to effectively predict a wide nonlinear process [18-20]. Wiener model applied in a variety of fields, such as chemical studies [21], biological systems [22], control of electrical systems [23], biomedical engineering [24], wireless mobile communications [25], model predictive control (MPC) [26-32], pH processes [33], signal processing [34]. In addition, the Wiener structure is used frequently in control, particularly in advanced MPC. MPC studies based on Wiener models can be effectively applied to multivariable processes that have many inputs and outputs, and for processes that have difficult dynamic properties [26-32].

Generally, MP (Memoryless Polynomial) or SOV (Second Order Volterra) model as a nonlinear part and FIR or IIR (Infinite Impulse Response) linear model as a linear part is used in Wiener models [13-19, 35-40]. Most of the studies in literature, MP representation is preferred for nonlinear parts of block oriented structure because of its flexibility and simple usage [2, 16]. In addition to these advantages MP also decreases the number of parameters to be determined, therefore decreases computational complexity and convergence time of the Wiener block model. However once SOV model is used instead of MP model, identification performances of block models increases [38, 41].

In the last decade, many applications of soft computing techniques have been used to solve the problems in many areas like neural networks (NN) and fuzzy inference system (FIS) [42]. Neural network and FIS have robust learning and adaptation capabilities to solve linear or nonlinear problems. Neuro-Fuzzy (NF) system which integrates both NN and FIS has the potential to combine the advantages of NN and FIS in a single structure [43-45]. Thus, NF systems can be used as very powerful tools for identification areas. In literature there are various studies about NF based on Wiener [31, 40, 46-49] model types applied to system identification.

The main motivation of this study is to propose a robust and successful model structure. At this point authors designed an original Wiener model by combining linear FIR model and nonlinear Soft Switching Based Hybrid (SSH) model in which different types of memory and memoryless nonlinear models are used that previously proven Wiener block models in literature. The structure of the proposed Wiener model is shown in Figure 5. The SSH structure consists of a SOV nonlinear model, a MP nonlinear model, and a soft-switching mechanism through a NF network. Soft switching mechanism in SSH model increases the success of block model by selecting the best results of both nonlinear model outputs. This is due to enhanced features; the proposed Wiener model is a new block model different from the other models in literature.

2. WIENER MODEL TYPES

2.1. Wiener model with FIR and MP

In this Wiener model's structure, FIR model and MP model are used as a linear and nonlinear block, respectively. This block model is illustrated in figure 1 [13-19, 35, 36]

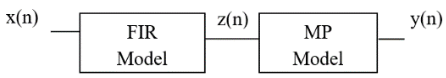

Figure 1. Wiener model with FIR-MP

FIR model [50,51] output;

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

m is model length, MP model output [52,53];

$$y(n) = \sum_{l=1}^{p} c_l z^l(n) \tag{2}$$

where *p* is MP model length [13-19, 35, 36].

2.2. Wiener model with FIR and SOV

In this Wiener model's structure, FIR model and SOV model are used as a linear and nonlinear block, respectively. This block model is illustrated in figure 2 [38].

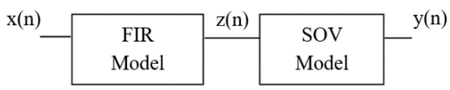

Figure 2. Wiener model with FIR-SOV

FIR model output;

$$z(n)=\sum_{k=0}^{m}a_k\,x(n-k) \tag{3}$$

m is model length. SOV model output [54,55];

$$y(n)=\sum_{i=0}^{r}h_i\,z(n-i)+\sum_{i=0}^{r}\sum_{j=0}^{r}q_{i,j}\,z(n-i)z(n-j) \tag{4}$$

r is SOV model length [38] .

3. NEURO-FUZZY (NF) NETWORK

Fuzzy logic is a popular computation system that is based on fuzzy IF-THEN rules, set theory and reasoning concepts. NF network is a fuzzy logic system that is developed by adaptable NF network framework. NF network is a combination of modelling uncertain features of fuzzy logic systems and learning ability of neural networks. Thus NF networks bring together the benefits of neural networks and fuzzy logic systems in one model. Fast and accurate learning, using data and expert knowledge together, and well generalization ability make the NF networks more popular in recent years [42-45, 56-58]

A typical NF network structure is shown in figure 3. In the above figure circle cells represent stable cells and square cells represent adaptive cells. For simplicity, the system has two inputs *x* and *y*, which can be considered as two canonical system. Sugeno's model is the first and most demanding model because of its well applicability, computational efficiency and optimization problems [59,60].

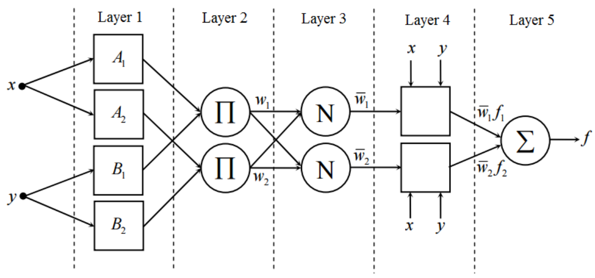

Figure 3. NF network structure

Since Sugeno's fuzzy model allows composing fuzzy rules based on input-output data couples, first degree of Sugeno model is used as NF network. According to this model, IF-THEN rules of the system can be written as follows [56];

Rule 1: If (x, A_1) and (y, B_1) then $f_1 = p_1x + q_1y + r_1$ (5)

Rule 1: If (x, A_2) and (y, B_2) then $f_2 = p_2x + q_2y + r_2$ (6)

Here A_i and B_i define fuzzy sets and p_i, q_i and r_i define designed parameters. As seen in figure 3 NF network consists of 5 layers.

Layer 1: Each cell in this layer defines the cell function as;

$$O_{n,i} = \begin{cases} \mu_{A_i}(x), & i = 1, 2 \\ \mu_{B_{i-2}}(y), & i = 3, 4 \end{cases} \tag{7}$$

Here $\mu_{A_i}(x)$ and $\mu_{B_{i-2}}(y)$ shows fuzzy membership functions, $O_{n,i}$, represents *i*. Output of *n*. layer. Data from this layer output is the blurred version of selected data of NF input through membership functions. These values define selected values' membership degree of the sets. The membership function of the NF network presented in this study is as follows;

generalized bell $$(x;a,b,c)=\frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \tag{8}$$

$\{a, b, c\}$ parameters that change the shape of membership function is named as rest parameters.

Layer 2: Each cell in this layer performs AND process in input signals (in fuzzy IF-THEN rules). So, trigger force of each rule can be calculated. Here fuzzy AND corresponds to multiplication process:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \qquad , i = 1, 2 \tag{9}$$

Layer 3: i cell in this layer finds the trigger rate of i rule to sum of all trigger forces. So the i rule of trigger force is normalized:

$$O_{3,i} = \tilde{w}_i = \frac{w_i}{\sum_{i=1}^{2} w_i} = \frac{w_i}{w_1 + w_2} \quad , \quad i = 1,2 \tag{10}$$

Here every $\tilde{w}_i$ is described as normalized trigger force of i rule.

Layer 4: Each cell in this layer has the following cell function:

$$O_{4,i} = \tilde{w}_i f_i = \tilde{w}_i (p_i x + q_i y + r_i) \ , i = 1, 2 \tag{11}$$

Here $\tilde{w}_i$ is the output of layer 3. Parameter set of this layer is named as $\{p_i , q_i , r_i\}$ result parameter.

Layer 5: The sole cell in this layer calculates the sum of all signals and sends to output. This can be described as [56];

$$O_5 = f = \sum_{i=1}^{2} \tilde{w}_i f_i = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{12}$$

During training, rest parameters in layer 1 and result parameters in layer 4 are adjusted until the NF network produce the desired response. In this study, in NF network training (parameter optimization) Levenberg-Marquardt algorithm [61, 62] is used [56].

4. PROPOSED WIENER MODEL

Proposed Wiener model is shown in figure 4. In inner structure of the model, FIR model and SSH model are used as linear and nonlinear part, respectively. The SSH structure consists of a SOV nonlinear model, a MP nonlinear model, and a NF network which uses output of the SOV model and the MP model to compute the Wiener model output.

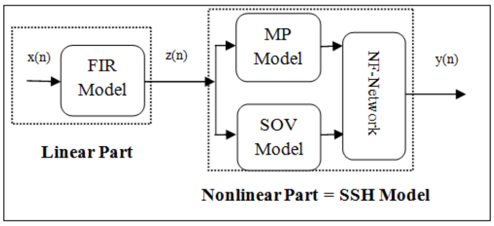

Figure 4. Proposed Wiener model

Soft switching mechanism of the system is a Sugeno typed NF network with first degree 2 input and 1 output. In each input of the network, there are 2 generalized bell typed membership function (13) and in output there is a linear membership function (14) [63-66].

$$\mu_{jk}(u) = \frac{1}{1 + \left| \frac{u - a_{jk}}{b_{jk}} \right|^{2c_{jk}}} \qquad , (j= 1,...., 10 ; k=1,2) \tag{13}$$

$$z_t(u_1, u_2) = d_{t1}u_1 + d_{t2}u_2 + d_{t3} , \quad (t= 1,......, 10) \tag{14}$$

In above equations a_{jk} is sigma of membership function, b_{jk} is dispersion of membership function, c_{jk} is center of membership function and d_t is the t th consequence of fuzzy rule. These parameters are used to adapt the type of membership functions. M_{jk} is the j th antecedent membership function of the k th input, and z_t is the consequent membership function of the t th rule. Rule base of the system consists of 10 rules that is the combination of inputs and the membership functions of these inputs. If x_1, x_2 represent 2 inputs of NF network and y represents output of NF network, the rule base of the NF network is as;

1) $If(x_1 \in M_{11})$ & $(x_2 \in M_{12})$ then (15)
$z_1 = d_{11}x_1 + d_{12}x_2 + d_{13}$

2) $If(x_1 \in M_{21})$ & $(x_2 \in M_{22})$ then (16)
$z_2 = d_{21}x_1 + d_{22}x_2 + d_{23}$

3) $If(x_1 \in M_{31})$ & $(x_2 \in M_{32})$ then (17)
$z_3 = d_{31}x_1 + d_{32}x_2 + d_{33}$
.
.

10) $If(x_1 \in M_{101})$ & $(x_2 \in M_{102})$ then (18)
$z_4 = d_{101}x_1 + d_{102}x_2 + d_{103}$

the NF network's parameters are optimized by using the hybrid learning optimization algorithm that combines the gradient method and the least squares estimate [63]. The NF network's output is the weighted average of rule outputs [63-66]. Weighted factor of each rule w_t is calculated through the past membership functions. For this process, first input values are converted to fuzzy membership and then *AND* operator is applied this membership values. *AND* operator is equal to multiplication of input membership values. So, weighted factors of rules are calculated as;

$$w_1 = M_{11}(x_1).\ M_{12}(x_2) \tag{19}$$

$$w_2 = M_{21}(x_1).\ M_{22}(x_2) \tag{20}$$

$$w_3 = M_{31}(x_1).\ M_{32}(x_2) \tag{21}$$

.
.

$$w_{10} = M_{101}(x_1).\ M_{102}(x_2) \tag{22}$$

NF network's output y can be obtained by calculating weighted average of rules when weighted factors are identified [63-66];

$$y = \frac{\sum_{t=1}^{10} w_t z_t}{\sum_{t=1}^{10} w_t} \tag{23}$$

5. SIMULATION STUDIES

The performance of Wiener model proposed in this paper is compared with known models in literature which are Wiener model with FIR-MP (in figure 1), Wiener model with FIR-SOV (in figure 2) and second order Volterra model. So, firstly, the optimization framework of known models are given in figure 5 for system identification. The identification processes for these known models are performed on unknown system. In simulations, white Gaussian noise and Chirp-type signals are used as x(n), input signal, separately. The white Gaussian noise is shown in figure 6. The Chirp-type signal is given as $x(n) = sin[(\pi/3)[L/(L-1)][n/L-1]^5]$, $n = 0,1,\ldots,L-1$, and as shown in figure 7. These models that are used for identification to unknown systems are optimized by Recursive Least Square (RLS) algorithm [41, 67].

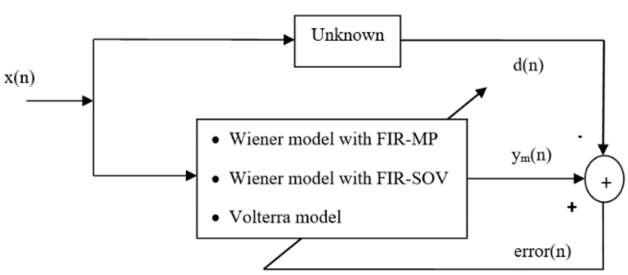

Figure 5. Optimization structure of system identification

Wiener model with FIR-MP (y_{m1}), Wiener model with FIR-SOV (y_{m2}) and second order Volterra model (y_{m3}) are given below in equation (24), (25), (27) respectively. Equation (24) is obtained from equation (2) with *p*=3, *m*=1, equation (25) is obtained from equation (4) with *r*=1, *m*=1 and equation (27) is obtained from equation (26) with *r*=1.

$$y_{m1}(n) = c_1[a_0x(n) + a_1x(n-1)] + c_2[a_0^2x^2(n) + a_0a_1x(n)x(n-1) + a_1a_0x(n-1)x(n) + a_1^2x(n-1)x(n-1)] + c_3[a_0^3x^3(n) + a_0^2a_1x^2(n)\,x(n-1) + a_1a_0^2x^2(n)\,x(n-1) + a_0a_1^2x(n)x^2(n-1) + a_1a_0^2x^2(n)\,x(n-1) + a_0a_1^2x(n)x^2(n-1) + a_0a_1^2x(n)x^2(n-1) + a_1^3x^3(n-1) \quad (24)$$

$$y_{m2}(n) = h_0[a_0x(n) + a_1x(n-1)] + h_1[a_0x(n-1) + a_1x(n-2)] + q_{00}[a_0^2x^2(n) + a_0a_1x(n)x(n-1) + a_1a_0x(n-1)x(n) + a_1^2x^2(n-1)] + q_{01}[a_0^2x(n)x(n-1) + a_0a_1x(n)x(n-2) + a_1a_0x(n-1)x(n-1) + a_1^2\,x(n-1)\,x(n-2)] + q_{10}[a_0^2x(n-1)\,x(n) + a_0a_1x(n-1)x(n-1) + a_1a_0x(n-2)\,x(n) + a_1^2x(n-2)x(n-1)] + q_{11}[a_0^2x(n-1)x(n-1) + a_0a_1x(n-1)x(n-2) + a_1a_0x(n-2)x(n-1) + a_1^2x(n-2)x(n-2)] \quad (25)$$

SOV model [54,55];

$$y(n) = \sum_{i=0}^{r} h_i x(n-i) + \sum_{i=0}^{r}\sum_{j=0}^{r} q_{i,j}\, x(n-i)x(n-j) \quad (26)$$

r is SOV model length [38].

$$y_{m3}(n) = h_0x(n) + h_1x(n-1) + q_{00}x(n)x(n) + q_{01}x(n)x(n-1) + q_{10}x(n-1)x(n) + q_{11}x(n-1)x(n-1) \quad (27)$$

Secondly, figure 6 infers the training and testing structure representing the optimization of the proposed Wiener model for system identification. The identification process for this model is performed on as unknown systems. In simulations, two different types of input signal are used; white Gaussian noise (in figure 7) and noiseless Chirp-type signal (in figure 8). The NF network uses the output of the SOV model and the MP model to compute the Wiener model output. This model is optimized with RLS and hybrid learning optimization algorithms.

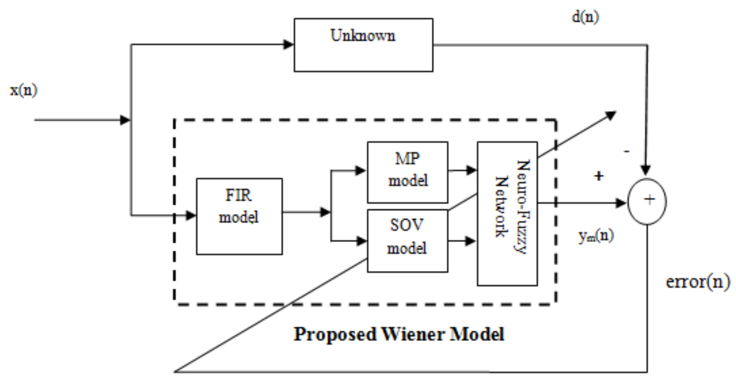

Figure 6. Training and testing of proposed Wiener model for adaptive optimization.

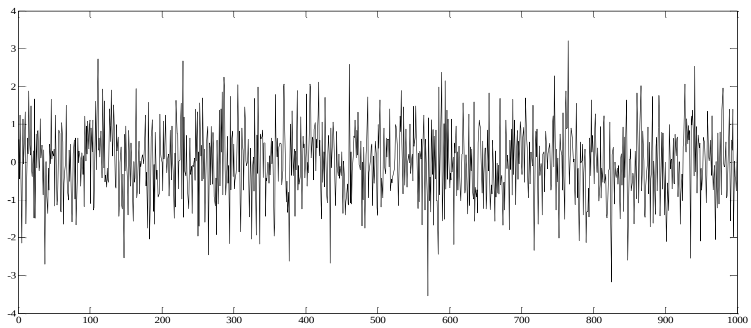

Figure 7. White Gaussian noise signal

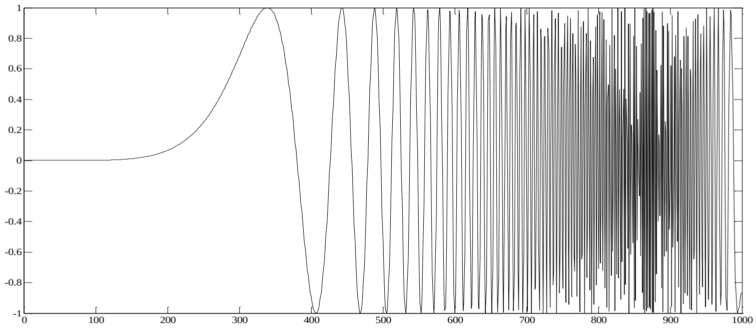

Figure 8. Noiseless Chirp-type signal

5.1. Example-I

A Wiener system (equation 29) is used as an unknown system in the structure of figure 5,6 [14]. The linear part,

$$z(n) = 0.75x(n) + 0.433x(n-1) + 0.5x(n-2) \tag{28}$$

and the memoryless nonlinearity of Wiener system,

$$d(n) = z(n) + z^2(n) \tag{29}$$

For White Gaussian noise input signal, MSE (Mean Square Error) and correlation results are given in table 1. Model outputs are shown in figure 9.

Table 1. MSE and correlation results

Model	MSE	Correlation
Volterra Model	0.98630	0.78526
Wiener Model with FIR-MP	0.98049	0.78541
Wiener Model with FIR-SOV	0.47824	0.91628
Proposed Wiener Model	**0.28106**	**0.94294**

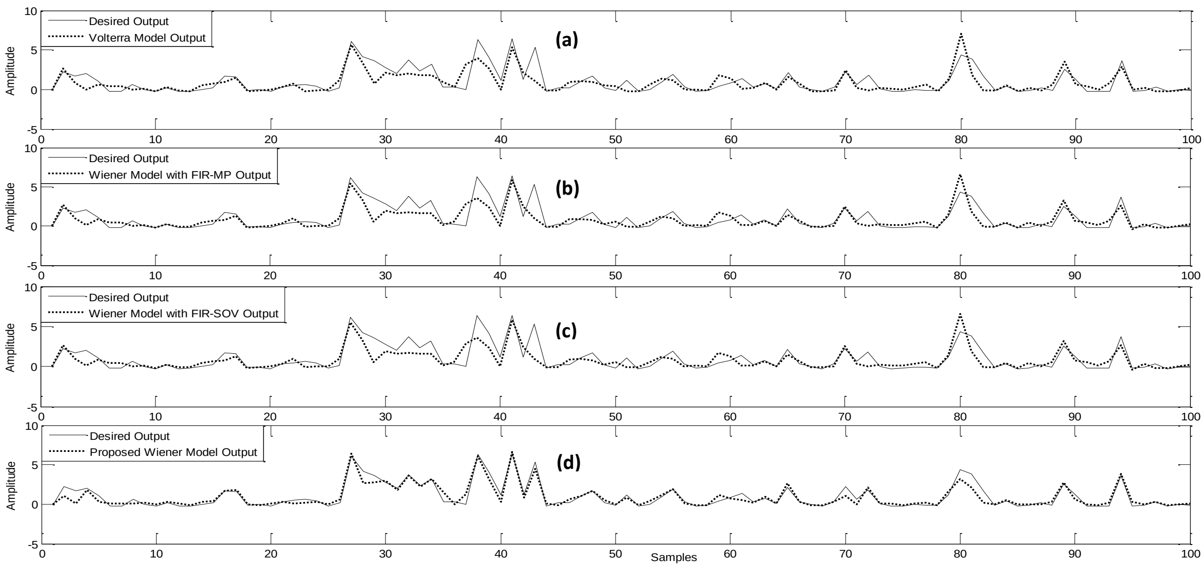

Figure 9. Simulation results [(a) Volterra model (b) Wiener model with FIR-MP (c) Wiener model with FIR-SOV (d) Proposed Wiener model]

For Chirp-type input signal, MSE and correlation results are given in table 2. Model outputs are shown in figure 10.

Table 2. MSE and correlation results

Model	MSE	Correlation
Wiener Model with FIR-MP	0.39486	0.83407
Volterra Model	0.22557	0.85223
Wiener Model with FIR-SOV	0.09758	0.93408
Proposed Wiener Model	**0.06176**	**0.95952**

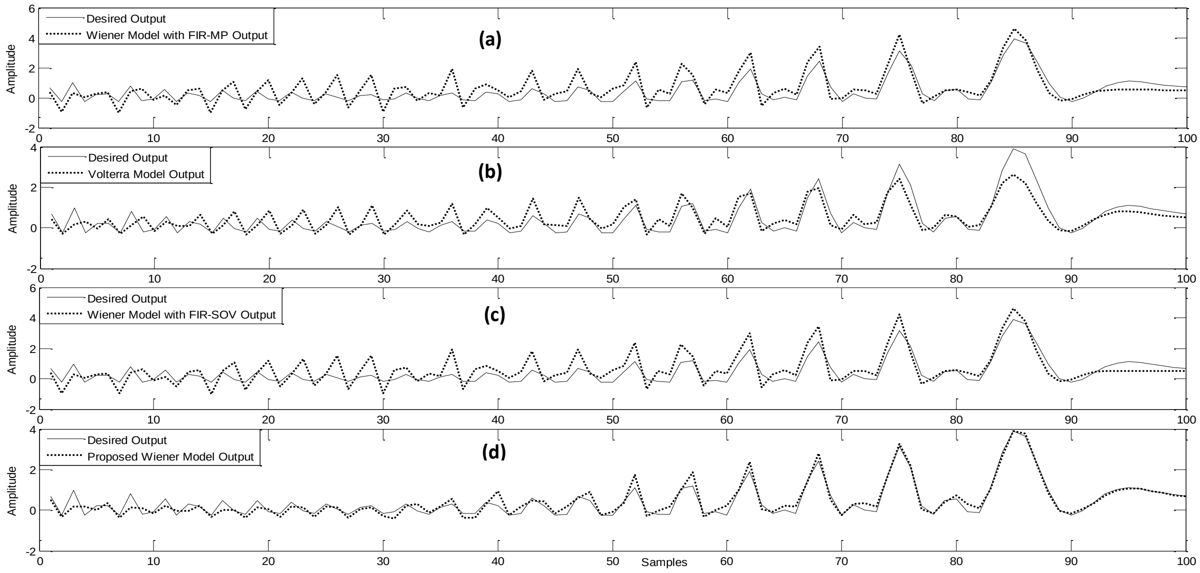

Figure 10. Simulation results [(a) Wiener model with FIR-MP (b) Volterra model (c) Wiener model with FIR-SOV (d) Proposed Wiener model]

5.2. Example-II

A Hammerstein system (equation 31) is used as an unknown system in the structure of figure 5,6 [68]. The memoryless nonlinearity of Hammerstein system,

$$z(n) = x(n) + 0.5x^3(n) \tag{30}$$

and a linear component with the transfer function

$$H(z) = \frac{0.4 + 0.2z^{-1}}{1 + 0.8z^{-1} + 0.6z^{-2}} \tag{31}$$

For White Gaussian noise input signal, MSE and correlation results are given in table 3. Model outputs are shown in figure 11.

Table 3. MSE and correlation results

Model	MSE	Correlation
Volterra Model	0.53478	0.77142
Wiener Model with FIR-MP	0.43585	0.82348
Wiener Model with FIR-SOV	0.42313	0.82510
Proposed Wiener Model	**0.32238**	**0.87221**

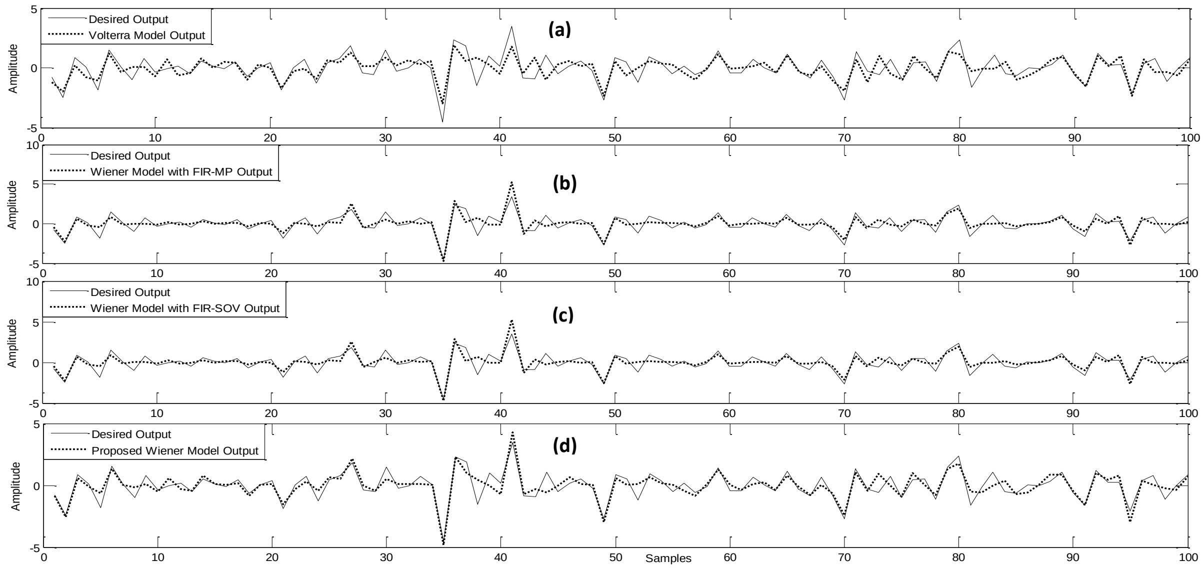

Figure 11. Simulation [(a) Volterra model (b) Wiener model with FIR-MP (c) Wiener model with FIR-SOV (d) Proposed Wiener model]

For Chirp-type input signal, MSE and correlation results are given in table 4. Model outputs are shown in figure 12.

Table 4. MSE and correlation results

Model	MSE	Correlation
Wiener Model with FIR-MP	0.12535	0.81874
Volterra Model	0.12427	0.82079
Wiener Model with FIR-SOV	0.08005	0.87279
Proposed Wiener Model	**0.07635**	**0.87860**

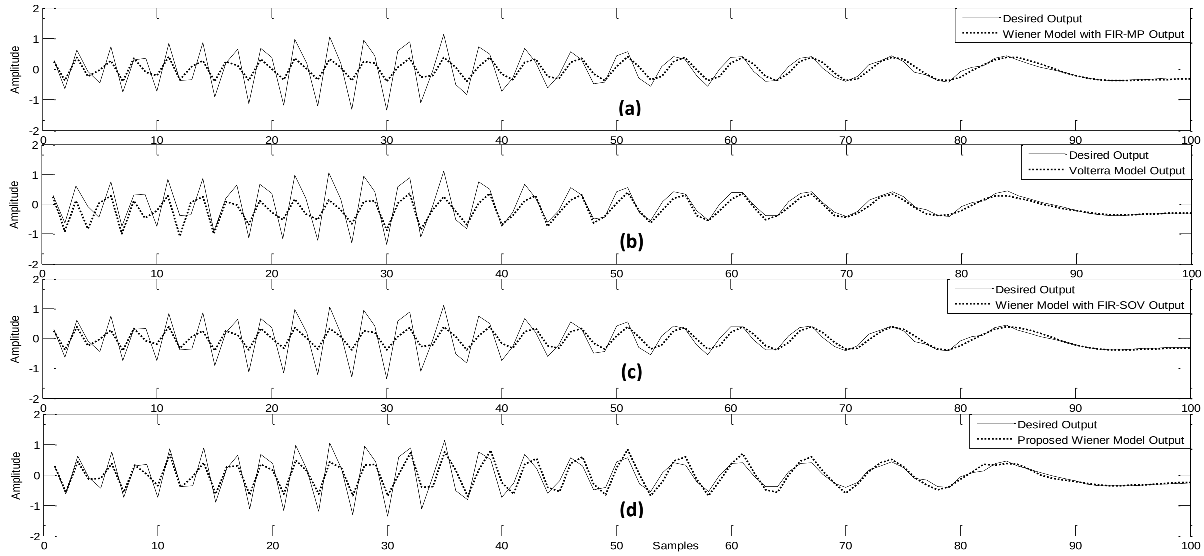

Figure 12. Simulation results [(a) Wiener model with FIR-MP (b) Volterra model (c) Wiener model with FIR-SOV (d) Proposed Wiener model]

5.3. Example-III

An ARMA system (equation 32) is used as an unknown system in the structure of figure 5,6 [69-73].

$$d(n)=0.7x(n)-0.4x(n-1)-0.1x(n-2)+0.25d(n-1)-0.1d(n-2)+0.4d(n-3) \quad (32)$$

For White Gaussian noise input signal, MSE and correlation results are given in table 5. Model outputs are shown in figure 13.

Table 5. MSE and correlation results

Model	MSE	Correlation
Wiener Model with FIR-MP	0.11292	0.89780
Volterra Model	0.10022	0.90236
Wiener Model with FIR-SOV	0.06813	0.93929
Proposed Wiener Model	**0.06218**	**0.94072**

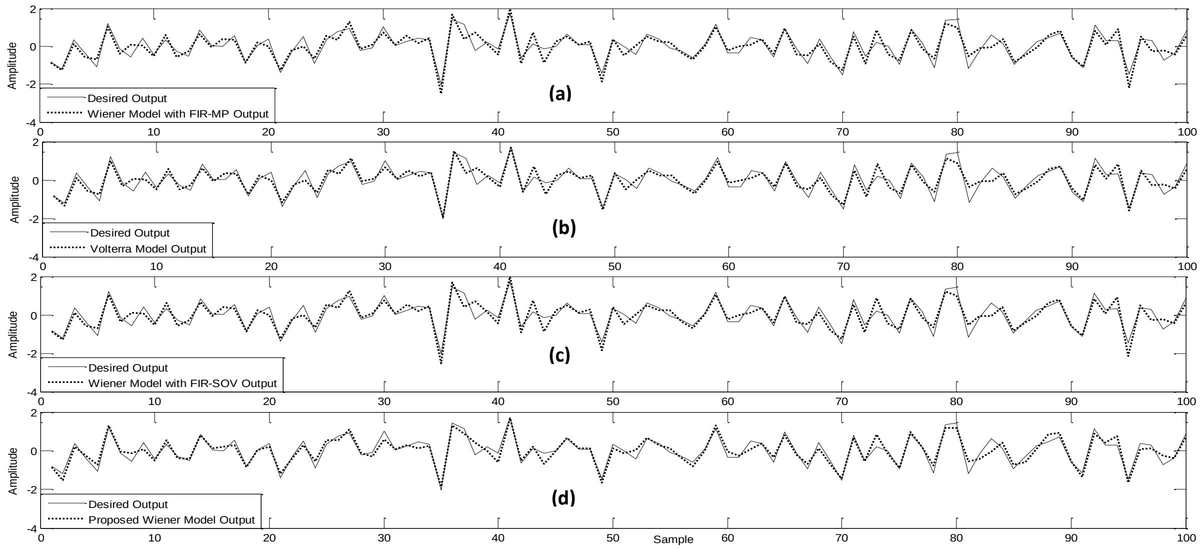

Figure 13. Simulation results [(a) Wiener model with FIR-MP (b) Volterra model (c) Wiener model with FIR-SOV (d) Proposed Wiener model]

For Chirp-type input signal, MSE and correlation results are given in table 6. Model outputs are shown in figure 14.

Table 6. MSE and correlation results

Model	MSE	Correlation
Wiener Model with FIR-MP	0.11444	0.89375
Volterra Model	0.08841	0.90354
Wiener Model with FIR-SOV	0.06520	0.91946
Proposed Wiener Model	**0.06201**	**0.92257**

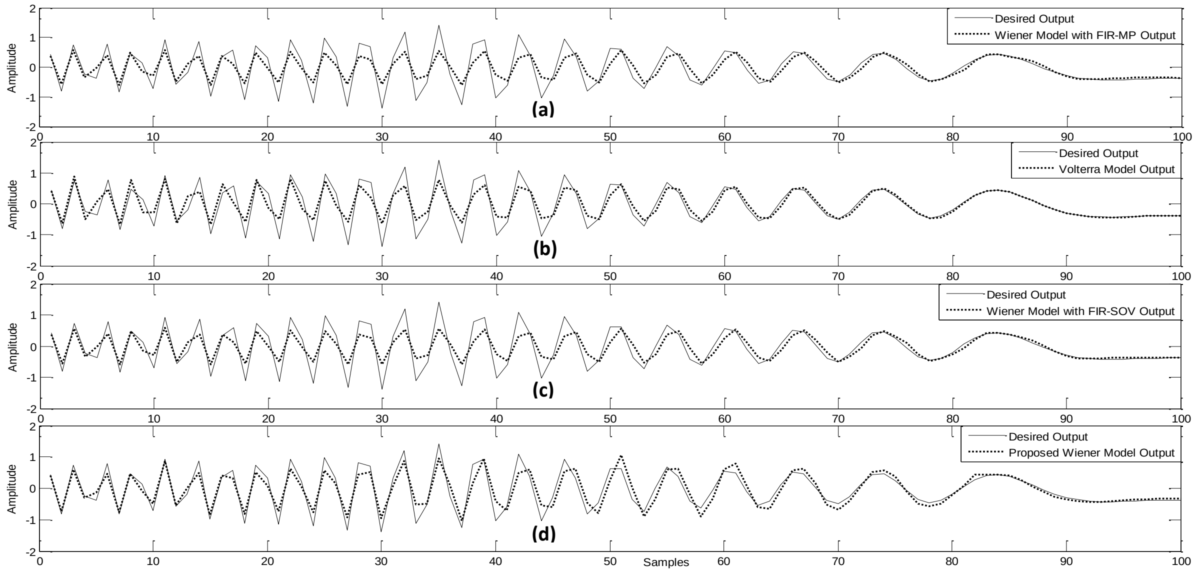

Figure 14. Simulation results [(a) Wiener model with FIR-MP (b) Volterra model (c) Wiener model with FIR-SOV (d) Proposed Wiener model]

5.4. Example-IV

A Bilinear system (equation 33) is used as an unknown system in the structure of figure 5,6 [41,70-73].

$$d(n)= 0.25d(n-1)- 0.5d(n-1)x(n) + 0.05d(n-1)x(n-1)- 0.5x(n) + 0.5x(n-1) \tag{33}$$

For White Gaussian noise input signal, MSE and correlation results are given in Table 7. Model outputs are shown in figure 15.

Table 7. MSE and correlation results

Model	MSE	Correlation
Wiener Model with FIR-MP	0.05451	0.93877
Volterra Model	0.04456	0.94861
Wiener Model with FIR-SOV	0.02647	0.97267
Proposed Wiener Model	**0.02099**	**0.97664**

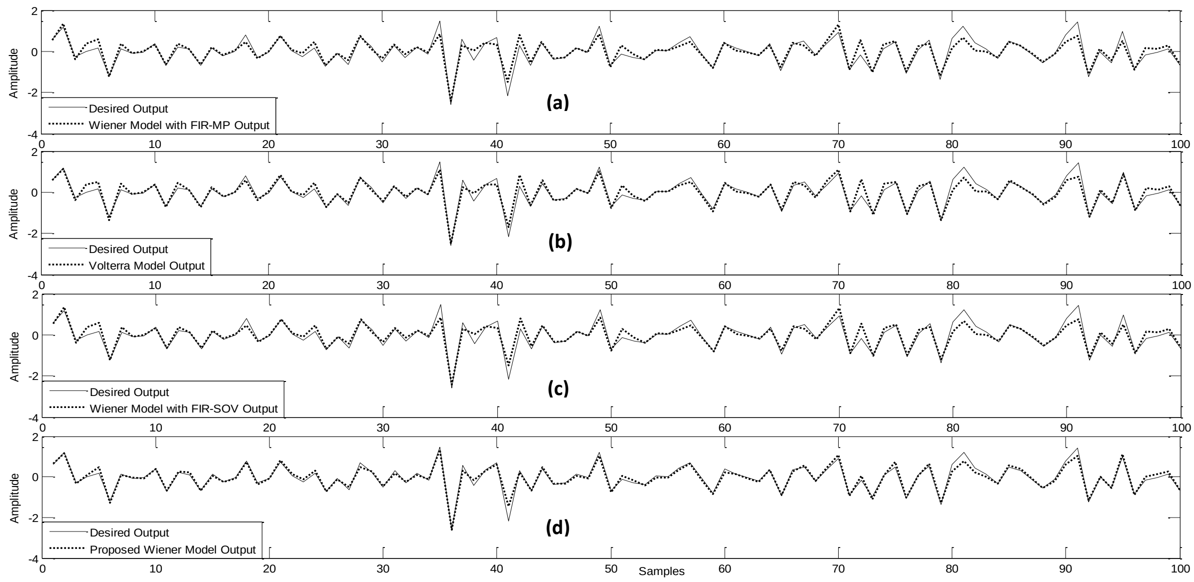

Figure 15. Simulation results [(a) Wiener model with FIR-MP (b) Volterra model (c) Wiener model with FIR-SOV (d) Proposed Wiener model]

For Chirp-type input signal, MSE and correlation results are given in Table 8. Model outputs are shown in figure 16.

Table 8. MSE and correlation results

Model	MSE	Correlation
Wiener Model with FIR-SOV	0.01971	0.96419
Wiener Model with FIR-MP	0.01908	0.96483
Volterra Model	0.01697	0.96742
Proposed Wiener Model	**0.00823**	**0.98365**

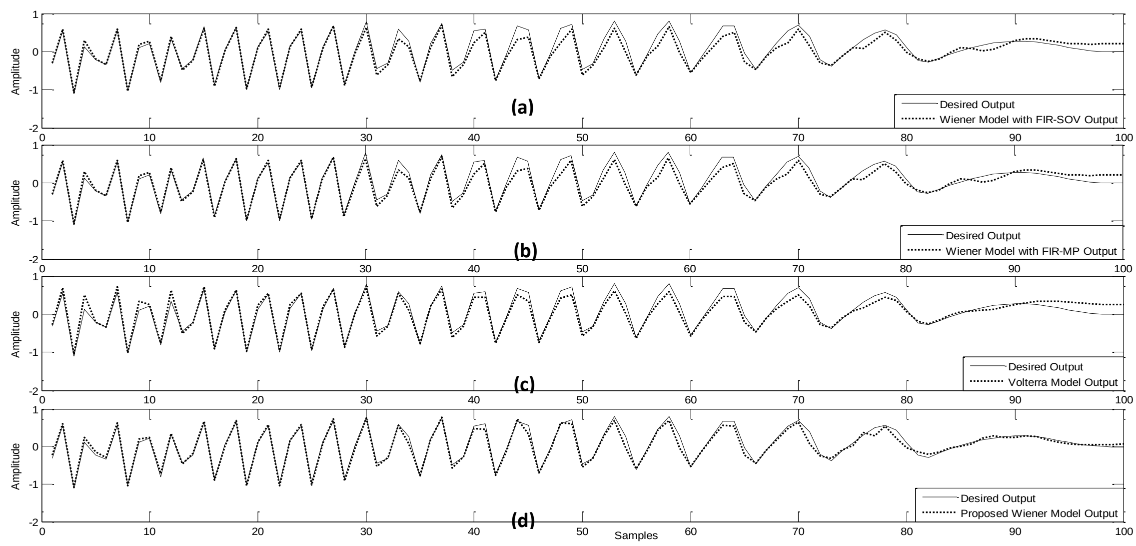

Figure 16. Simulation results [(a) Wiener model with FIR-SOV (b) Wiener model with FIR-MP (c) Volterra model (d) Proposed Wiener model]

According to results of all simulations, the proposed Wiener model is more successful in terms of MSE and correlation value compared to other models. In figures 9-16 and tables 1-8 the results are analysed.

6. CONCLUSIONS

This study aims to improve Wiener model for system identification area. Different from previous works in literature, in order to improve the Wiener model, FIR model is used as linear part, SSH model is used as nonlinear part. The SSH structure consists of a SOV nonlinear model, a MP nonlinear model, and a NF network. The NF network uses the information from the SOV model and the MP model to compute the Wiener model output.

System identification studies are carried out to determine the performance of proposed model. So, different structure unknown systems are identified with both proposed model and different type models. Proposed model has more complex structure compared to Volterra model, Wiener model with FIR-MP and Wiener model with FIR-SOV as disadvantage of the model but proposed model has a successful identification tool as advantage. According to MSE and correlation results, the systems can be identified with less error in proposed model compared to Volterra model, Wiener model with FIR-MP and Wiener model with FIR-SOV. In addition the author will try to identify real system problems in future studies.

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