A New Hybrid Model Based On Neuro Fuzzy Network Soft Switching Mechanism For System Identification

Araştırma Makalesi/Research Article

Selçuk METE*[1], Hasan ZORLU[2], Şaban ÖZER[3]

[1]Türk Telekom A.Ş., Kayseri Bölge Müdürlüğü, Servis Yönetim Merkezi, Kayseri, Türkiye
[2]Elektrik-Elektronik Mühendisliği, Mühendislik Fakültesi, Erciyes Üniversitesi, Kayseri, Türkiye
[3]Elektronik ve Otomasyon, Meslek Yüksekokulu, Kayseri Üniversitesi, Kayseri, Türkiye
selcuk.metes@gmail.com, hzorlu@erciyes.edu.tr, sozer@erciyes.edu.tr
(Geliş/Received:12.09.2018; Kabul/Accepted:14.11.2018)
DOI: 10.17671/gazibtd.459399

***Abstract*—** This paper aims to improve a new hybrid model for system identification area. The proposed hybrid model consists of an adaptive Hammerstein model, an adaptive Wiener model, and a Neuro-Fuzzy (NF) network based soft-switching mechanism (SSM). SSM structure in hybrid model increases the success of block model by selecting the best results of Hammerstein and Wiener model outputs. In literature, there are various studies about NF based on Hammerstein or Wiener model types applied to system identification. In the proposed model, Hammerstein and Wiener models with NF network are used together different from the literature. In simulation studies, five different type of systems are identified with different models (Hammerstein, Wiener and the proposed hybrid model) optimized by Recursive Least Square (RLS). Then the performances of these models are compared. Simulation results reveal the effectiveness and robustness of the proposed identification model.

***Keywords*—** fuzzy neural networks, hybrid intelligent systems, optimization, soft switching, system identification

Sistem Kimliklendirme İçin Bulanık Sinir Ağı Esnek Anahtarlama Mekanizması Temelli Yeni Bir Karma Model

***Özet*—** Bu çalışmanın amacı sistem kimliklendirme alanında yeni bir karma model geliştirmektir. Önerilen karma model uyarlanabilen bir Hammerstein model, bir Wiener model ve esnek anahtarlama mekanizmasına dayanan bulanık sinir ağını içermektedir. Karma modeldeki esnek anahtarlama mekanizması Hammerstein ve Wiener model çıkışlarının en iyi sonuçlarını seçerek blok model başarısını arttırmaktadır. Literatürde, sistem kimliklendirmede uygulanan bulanık sinir ağı temelli Hammerstein ya da Wiener modellerle ilgili birçok çalışma vardır. Önerilen modelde, bulanık sinir ağıyla birlikte Hammerstein ve Wiener modelleri literatürden farklı olarak bir arada kullanılmıştır. Simülasyon çalışmalarında, farklı tipteki beş sistem tekrarlayan en küçük kare ile optimize edilmiş olan farklı modeller (Hammerstein, Wiener ve önerilen model) ile kimliklendirilmiştir. Daha sonra bu modellerin performansları karşılaştırılmıştır. Simülasyon çalışmaları önerilen modelin etkinliğini ve sağlamlığını ortaya koymaktadır.

***Anahtar Kelimeler*—** bulanık sinir ağı, karma zeki sistemler, optimizasyon, esnek anahtarlama, sistem kimliklendirme

1. INTRODUCTION

System identification is the model of the system achieved by utilizing data obtained from experimental or mathematical way. The studies in literature show that system identification processes are successful in solving real life problems [1-3]. System identification is proceeded through linear and nonlinear models as to the linearity of the system [4-8]. 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 [4,5]. However, many systems in real life have nonlinear behaviours. Linear methods can be inadequate in identification of such systems and nonlinear methods are used [6-8]. In order to describe the nonlinear behaviour of the system over the entire range of operating conditions adequately, a nonlinear block-oriented model is often used and the identified system is generally subdivided into linear dynamic subsystems (or linear dynamic blocks) and nonlinear static subsystems (or nonlinear static blocks). The well-known Wiener model and Hammerstein model are nonlinear models that are used in many domains for their simplicity and physical meaning, where the system steady-state behaviour is determined completely by the static-nonlinearities, while the system dynamic behaviour is determined by both the nonlinearities and the linear dynamic model components. For example, a Wiener model consist of a linear dynamic block followed by a nonlinear static block. A Hammerstein model is just a Wiener model structurally reversed, that is, a nonlinear static block is followed by a linear dynamic block [9-11]. Moreover, 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 [10,11]. In this kind of cascade models, the polynomial representation has advantage of more flexibility and of a simpler use [9].

To improve Hammerstein [6,7,12-15] and Wiener models [16-18], various algorithms have been applied. In the last decade, various applications of soft computing techniques are used, such as Neural Networks and Fuzzy Inference System (FIS), for the problems in many ranges [19, 20]. Neural Network and FIS have robust learning and adaptation capabilities to solve linear or nonlinear problems. Neuro-Fuzzy (NF) system which integrates both neural networks and FIS has the potential to benefit from both in a single framework [21-23]. Therefore, NF systems may be used as more powerful tools for identification areas. In literature there are various studies about NF based on Hammerstein [24-26] or Wiener [27-30] model types applied to system identification.

The main motivation of this study is to suggest a simple and successful model structure. At this point authors designed a new hybrid model for system identification. The proposed hybrid model consists of an adaptive Hammerstein model, an adaptive Wiener model, and a NF network based soft-switching mechanism (SSM). The structure of proposed hybrid model is shown in Figure 3. SSM structure in proposed hybrid model increases the success of block model by selecting the best results of Hammerstein and Wiener model outputs. The advantage of the proposed model; It can make more successful and stable identification by using two different block models as Hammerstein and Wiener in a hybrid structure. The disadvantage of the proposed model; Because of its complex structure; it contains more mathematical operations and accordingly the duration of the identification is longer than other model types in literature. In simulation studies, five different type systems are identified with different Hammerstein, Wiener and the proposed hybrid models. Then the performances of these models are compared. Simulation results are showed that the proposed hybrid model has better result than the adaptive Hammerstein and Wiener models.

The paper is organized as follows: In section 2, model structures are detailed. In section 2.3, the proposed hybrid model is detailed. In section 3, Recursive Least Square (RLS) algorithm is explained. In section 4, simulations are made to verify the feasibility of the proposed method. Conclusions are offered in section 5.

2. BLOCK ORIENTED MODELS

Many nonlinear dynamic systems such as heat exchangers, electric drives, pH control, biological systems, and identification of linear systems with nonlinear sensors [31, 32] can be approximated by block oriented model such as Hammerstein or Wiener. Also in a Wiener and Hammerstein model, many different linear and nonlinear sub model structures have been considered.

2.1. Hammerstein Model

In Hammerstein model structure in Figure 1, Memoryless Polynomial (MP) model is used as a nonlinear part and Finite Impulse Response (FIR) model is used as a linear part. The nonlinear part is described by a polynomial function [33].

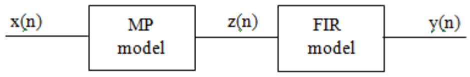

Figure 1. Hammerstein model

In Figure 1 $x(n)$ and $y(n)$ are the input and the output of the block model respectively. $z(n)$ represents the unavailable internal data. MP model output and intermediate variable $z(n)$;

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

FIR model output;

$$y(n) = \sum_{i=0}^{m} b_i z(n-i) \quad (2)$$

block model output;

$$y(n) = \sum_{l=1}^{p} \sum_{i=0}^{m} c_l b_i x^l(n-i) \quad (3)$$

where b_i and c_l are the coefficients of the MP and the FIR model. l is an integer and $l > 0$. m and p are lengths of the models [33].

2.2. Wiener Model

In Wiener model structure, FIR model is used as a linear block and MP model is used as a nonlinear block. Cascade structure is shown in Figure 2 [34-36].

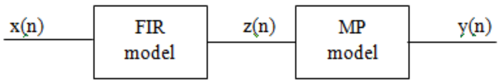

Figure 2. Wiener model

FIR model is defined as;

$$z(n) = \sum_{i=0}^{m} b_i x(n-i) \quad (4)$$

where m shows model length. MP and Wiener model output is defined as;

$$y(n) = \sum_{i=1}^{p} c_i z^i(n) \quad (5)$$

where p shows MP and Wiener model length. The disadvantage of Wiener compared to Hammerstein; is it can be formed with more complex mathematical substructure because of its structure.

2.3. Proposed Hybrid Model

Proposed hybrid model is shown in Figure 3. The model consists of a Hammerstein model, a Wiener model, input data and NF network based SSM. The NF network uses the information from the adaptive Hammerstein, the Wiener, and the input signal to compute the system output. The proposed model is different from the other hard switching models in literature in terms of soft switching feature.

SSM of the system is a first-order Sugeno typed NF network with 3 input and 1 output. In each input of the network, there are 2 Gaussian membership function and in output there is a linear membership function [37-39].

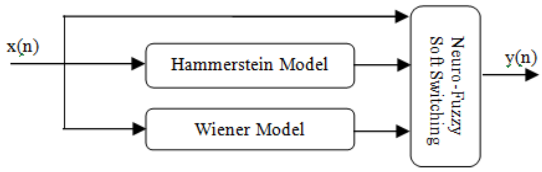

Figure 3. Proposed hybrid model

The parameters of the NF network are iteratively tuned by using the hybrid learning optimization algorithm which combines the gradient method and the least squares estimate to identify [37-39].

3. RLS ALGORITHM

RLS algorithm is used to optimization of model parameters. Studies in literature shows that RLS is popular optimization algorithm among derivative based algorithms [40]. 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 response by adjusting model parameters. The error is defined as Eq. (6).

$$e(n) = d(n) - w^H(n-1)x(n) \quad (6)$$

Here, e is error value, d is desired output, $x(n)$ is input signal for model and w is model parameters vector. Adjusting model parameter process is given by Eq. (7)

$$w(n) = w(n-1) - k(n)e(n) \quad (7)$$

Here, k is gain vector and defined by Eq. (8),

$$k(n) = \frac{\lambda^{-1}P(n-1)x(n)}{1+\lambda^{-1}x^H(n)P(n-1)x(n)} \quad (8)$$

Here, P is current covariance matrix and defined by Eq. (9)

$$P(n) = \lambda^{-1}P(n-1) - \lambda^{-1}k(n)x^H(n)P(n-1) \quad (9)$$

here, λ is forgetting factor for this algorithm [23, 40].

4. RESULTS AND DISCUSSION

Training and testing structures of a Hammerstein model, a Wiener model and the proposed hybrid model are given in Figure 4 and 5 for system identification. The input signal x(n) was preferred to be a Gaussian distributed white noise of 1000 data samples. Figure 4 shows the structure of the representing optimization of the adaptive Hammerstein and Wiener models. In these simulations, all models are optimized till the error $e(n)$ between the model $y_m(n)$ and system output $d(n)$ is minimized by RLS algorithm [40,41].

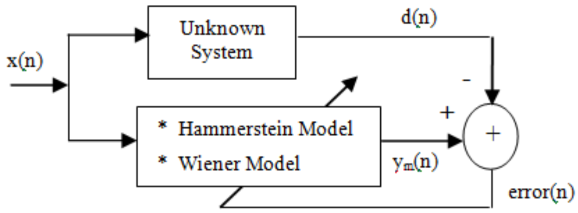

Figure 4. Training and testing structure of models for adaptive optimization.

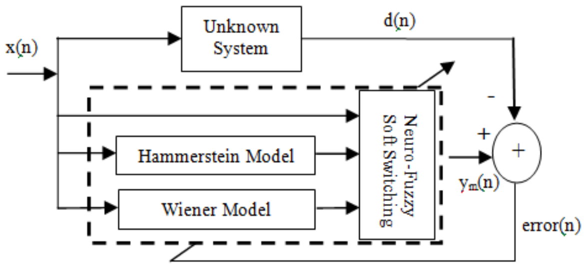

Figure 5. Training and testing structure of proposed hybrid model for adaptive optimization.

Figure 5 shows the structure of the representing optimization of the proposed hybrid model. All of these mentioned models were simulated using the noiseless input signal $x(n)$ and length L = 1000. The first 900 samples of the input signal were used for the model training and the remaining 100 sample data were used for model testing. Hammerstein and Wiener models are given Eq. (10) and (11).

Hammerstein model in Eq. (10) is obtained from Eq. (3) with p=3, m=1.

$$y_{m1}(n) = b_0c_1x(n) + b_0c_2x^2(n) + b_0c_3x^3(n) + b_1c_1x(n-1) + b_1c_2x^2(n-1) + b_1c_3x^3(n-1) \quad (10)$$

Wiener model in Eq. (11) is obtained from Eq. (5) with m=1, p=3.

$$y_{m2}(n) = c_1 b_0 x(n) + c_1 b_1 x(n-1) + c_2 b_0^2 x^2(n) + c_2 b_0 b_1 x(n) x(n-1) + c_2 b_1 b_0 x(n) x(n-1) + c_2 b_1^2 x^2(n-1) + c_3 b_0^3 x^3(n) + c_3 b_0^2 b_1 x^2(n)\, x(n-1) + c_3 b_1 b_0^2 x^2(n)\, x(n-1) + c_3 b_1^2 b_0 x(n) x^2(n-1) + c_3 b_1 b_0^2 x^2(n)\, x(n-1) + c_3 b_0 b_1^2 x(n) x^2(n-1) + c_3 b_0 b_1^2 x(n) x^2(n-1) + c_3 b_1^3 x^3(n-1) \quad (11)$$

4.1. Example-I

In this example, considering the structure given in Figure 4 and 5 unknown Hammerstein system [42] is chosen as in Eq. (12) and (13). The memoryless nonlinearity of Hammerstein system,

$$z_n(n) = x(n) + 0.5x^3(n) \quad (12)$$

and a linear component with the transfer function

$$H(z) = \frac{0.4 + 0.2z^{-1}}{1 + 0.8z^{-1} + 0.6z^{-2}} \quad (13)$$

The unknown system is identified with Hammerstein, Wiener and proposed hybrid models. Model successes for testing process were compared according to MSE [43], correlation and run time values, and the results are presented in Table 1. According to these comparisons proposed hybrid model identifies the unknown system with the lowest error. Also visual results for testing process are shown in Figure 6. Proposed hybrid model's performance of system identification in terms of membership function, number of membership and epoch number is presented in Table 2.

Table 1. MSE, correlation and run time values for example-I

Type of Model	MSE	Correlation	Run Time (sec)
Hammerstein	0.70642	0.78783	0.04
Wiener	0.43585	0.82348	0.03
Hybrid (Proposed)	**0.38710**	**0.84100**	79

Table 2. Proposed hybrid model performance

			NDS		HM		
MF	**NM**	**NE**	**TR**	**T**	**MSE**	**C**	**RTM**
gauss2mf	2	1000	900	100	0.38751	0.84076	8
gauss2mf	2	5000	900	100	0.38741	0.84080	40
gauss2mf	**2**	**10000**	**900**	**100**	**0.38710**	**0.84100**	**79**
gauss2mf	3	1000	900	100	0.43492	0.82962	18
gauss2mf	3	5000	900	100	0.43133	0.82401	91
gauss2mf	3	10000	900	100	0.42981	0.82460	186
gaussmf	2	1000	900	100	0.39329	0.83880	6
gaussmf	2	5000	900	100	0.40587	0.83528	28
gaussmf	2	10000	900	100	0.40568	0.83535	61
gaussmf	3	1000	900	100	0.44951	0.82001	15
gaussmf	3	5000	900	100	0.44971	0.81838	72
gaussmf	3	10000	900	100	0.45028	0.81839	143
gbellmf	2	1000	900	100	0.39926	0.83758	6
gbellmf	2	5000	900	100	0.41771	0.83013	30
gbellmf	2	10000	900	100	0.41788	0.83012	60
gbellmf	3	1000	900	100	0.44421	0.82180	15
gbellmf	3	5000	900	100	0.44788	0.82027	74
gbellmf	3	10000	900	100	0.45047	0.81917	149

MF=membership function, NM=number of membership, NE=number of epoch, TR= training, T= test, C=correlation, RTM=run time(sec), NDS= number of data samples, HM= hybrid model.

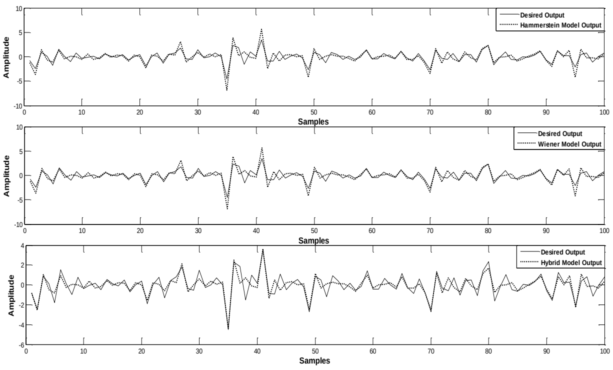

Figure 6. Simulated response comparisons of example-I

4.2. Example-II

In this example, considering the structure given in Figure 4 and 5 unknown Bilinear system [41,44] is chosen as in Eq. (14).

$$d(n) = 0.25y(n-1) - 0.5y(n-1)x(n) + 0.05y(n-1)x(n-1) - 0.5x(n) + 0.5x(n-1) \quad (14)$$

The unknown system is identified with Hammerstein, Wiener and proposed hybrid models. MSE, correlation and run time values of the tested models are given in Table 3. Proposed hybrid model identifies the unknown system with the lowest error. Proposed hybrid model performance is given in Table 4. Also visual results of the tested models are shown in Figure 7.

Table 3. MSE, correlation and run time values for example-II

Type of Model	MSE	Correlation	Run Time(sec)
Hammerstein	0.08602	0.90105	0.11
Wiener	0.05062	0.94425	0.03
Hybrid (Proposed)	**0.04013**	**0.95429**	21

Table 4. Proposed hybrid model performance

			NDS		HM		
MF	**NM**	**NE**	**TR**	**T**	**MSE**	**C**	**RTM**
gauss2mf	**2**	**1000**	**900**	**100**	**0.04013**	**0.95429**	**21**
gauss2mf	2	5000	900	100	0.04036	0.95401	106
gauss2mf	2	10000	900	100	0.04045	0.95390	212
gauss2mf	3	1000	900	100	0.13445	0.89624	128
gauss2mf	3	5000	900	100	0.19795	0.87445	636
gauss2mf	3	10000	900	100	0.18350	0.88110	1322
gaussmf	2	1000	900	100	0.04370	0.94995	17
gaussmf	2	5000	900	100	0.04331	0.95040	83
gaussmf	2	10000	900	100	0.04332	0.95039	167
gaussmf	3	1000	900	100	0.09719	0.90308	121
gaussmf	3	5000	900	100	0.15744	0.86162	604
gaussmf	3	10000	900	100	0.20771	0.82143	1214
gbellmf	2	1000	900	100	0.04229	0.95220	17
gbellmf	2	5000	900	100	0.04342	0.95070	86
gbellmf	2	10000	900	100	0.04467	0.94912	175
gbellmf	3	1000	900	100	0.09158	0.90805	124
gbellmf	3	5000	900	100	0.11851	0.89029	606
gbellmf	3	10000	900	100	0.12877	0.89635	1211

MF=membership function, NM=number of membership, NE=number of epoch, TR= training, T= test, C=correlation, RTM=run time(sec), NDS= number of data samples, HM= hybrid model.

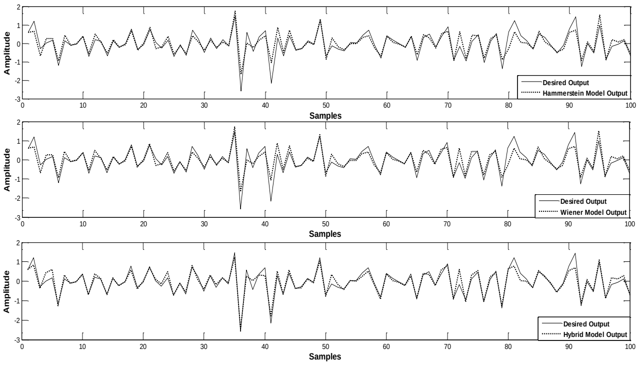

Figure 7. Simulated response comparisons of example-II

4.3. Example-III

In this example, considering the structure given in Figure 4 and 5 unknown ARMA system [45,46] is chosen as in Eq. (15). The unknown system is identified with Hammerstein, Wiener and proposed hybrid models.

$$d(n) = 0.7x(n) - 0.4x(n-1) - 0.1x(n-2) + 0.25y(n-1) - 0.1y(n-2) + 0.4y(n-3) \quad (15)$$

Model successes were compared according to MSE, correlation and run time values, and the results are presented in Table 5. According to these comparisons proposed hybrid model identifies the unknown system with the lowest error. Also visual results are shown in Figure 8.

Table 5. MSE, correlation and run time values for example-III

Type of Model	MSE	Correlation	Run Time(sec)
Hammerstein	0.11002	0.89874	0.09
Wiener	0.10737	0.89810	0.03
Hybrid (Proposed)	**0.10051**	**0.90206**	28

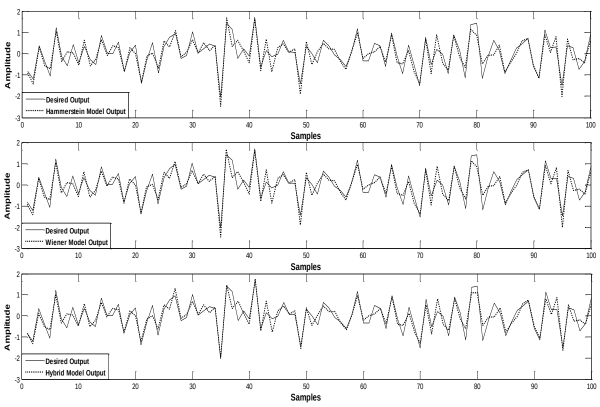

Figure 8. Simulated response comparisons of example-III

Proposed hybrid model's performance of system identification in terms of membership function, number of membership and epoch number is presented in Table 6.

Table 6. Proposed hybrid model performance

			NDS		HM		
MF	NM	NE	TR	T	MSE	C	RTM
gauss2mf	2	1000	900	100	0.10527	0.89734	8
gauss2mf	2	5000	900	100	0.10554	0.89712	42
gauss2mf	2	10000	900	100	0.10554	0.89712	84
gauss2mf	3	1000	900	100	0.10792	0.89461	18
gauss2mf	3	5000	900	100	0.10962	0.89288	88
gauss2mf	3	10000	900	100	0.10961	0.89289	174
gaussmf	2	1000	900	100	0.10056	0.90199	6
gaussmf	**2**	**5000**	**900**	**100**	**0.10051**	**0.90206**	**28**
gaussmf	2	10000	900	100	0.10054	0.90203	57
gaussmf	3	1000	900	100	0.10933	0.89314	15
gaussmf	3	5000	900	100	0.10929	0.89313	74
gaussmf	3	10000	900	100	0.10910	0.89329	143
gbellmf	2	1000	900	100	0.10249	0.90022	6
gbellmf	2	5000	900	100	0.10257	0.90010	30
gbellmf	2	10000	900	100	0.10250	0.90017	60
gbellmf	3	1000	900	100	0.10667	0.89577	14
gbellmf	3	5000	900	100	0.10830	0.89405	73
gbellmf	3	10000	900	100	0.11027	0.89199	147

MF=membership function, NM=number of membership, NE=number of epoch, TR= training, T= test, C=correlation, RTM=run time(sec), NDS= number of data samples, HM= hybrid model.

4.4. Example-IV

In this example, considering the structure given in Figure 4 and 5 unknown Hammerstein system [47] is chosen as in Eq. (16) and (17). The unknown system is identified with Hammerstein, Wiener and proposed hybrid models. The memoryless nonlinearity of Hammerstein,

$$z_n(n) = 0.1x(n) - 0.075x^2(n) + 0.05x^3(n) \quad (16)$$

and a linear component with the transfer function

$$H(z) = \frac{0.25}{1 - 0.4z^{-1} + 0.2z^{-2}} \quad (17)$$

MSE, correlation and run time values of the tested models are given in Table 7. Proposed hybrid model identifies the unknown system with the lowest error. Also visual results are shown in Figure 9.

Table 7. MSE, correlation and run time values for example-IV

Type of Model	MSE	Correlation	Run Time(sec)
Hammerstein	6.2794×10^{-5}	0.99460	0.07
Wiener	1.8446×10^{-4}	0.99192	0.04
Hybrid (Proposed)	$\mathbf{5.8115 \times 10^{-5}}$	**0.99490**	102

Proposed hybrid model's performance of system identification in terms of membership function, number of membership and epoch number is presented in Table 8.

Table 8. Proposed hybrid model performance

			NDS		HM		
MF	**NM**	**NE**	**TR**	**T**	**MSE**	**C**	**RTM**
gauss2mf	2	1000	900	100	5.9144×10^{-5}	0.99485	20
gauss2mf	**2**	**5000**	**900**	**100**	$\mathbf{5.8115 \times 10^{-5}}$	**0.99490**	**102**
gauss2mf	2	10000	900	100	5.8187×10^{-5}	0.99490	203
gauss2mf	3	1000	900	100	6.2953×10^{-5}	0.99455	128
gauss2mf	3	5000	900	100	6.2294×10^{-5}	0.99457	632
gauss2mf	3	10000	900	100	6.5483×10^{-5}	0.99431	1346
gaussmf	2	1000	900	100	5.9588×10^{-5}	0.99475	19
gaussmf	2	5000	900	100	5.9577×10^{-5}	0.99475	96
gaussmf	2	10000	900	100	5.9564×10^{-5}	0.99475	190
gaussmf	3	1000	900	100	6.3496×10^{-5}	0.99439	132
gaussmf	3	5000	900	100	6.4853×10^{-5}	0.99427	659
gaussmf	3	10000	900	100	6.6535×10^{-5}	0.99412	1237
gbellmf	2	1000	900	100	6.0544×10^{-5}	0.99466	22
gbellmf	2	5000	900	100	6.0417×10^{-5}	0.99468	94
gbellmf	2	10000	900	100	6.0468×10^{-5}	0.99467	15
gbellmf	3	1000	900	100	8.5860×10^{-5}	0.99267	18
gbellmf	3	5000	900	100	7.1000×10^{-5}	0.99380	643
gbellmf	3	10000	900	100	6.7246×10^{-5}	0.99410	1276

MF=membership function, NM=number of membership, NE=number of epoch, TR= training, T= test, C=correlation, RTM=run time(sec), NDS= number of data samples, HM= hybrid model.

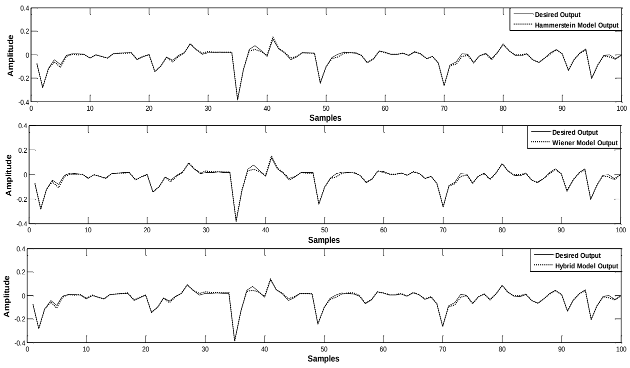

Figure 9. Simulated response comparisons of example-IV

4.5. Example-V

In this example, considering the structure given in Figure 4 and 5 unknown Volterra system [48,49], is chosen as in Eq. (18). The unknown system is identified with Hammerstein, Wiener and proposed hybrid models.

$$d(n) = -0.64x(n) + x(n-2) - 0.9x^2(n) + x^2(n-1) \quad (18)$$

Model successes were compared according to MSE, correlation and run time values, and the results are presented in Table 9. According to these comparisons proposed hybrid model identifies the unknown system with the lowest error. Also visual results are shown in Figure 10.

Table 9. MSE, correlation and run time values for example-V

Type of Model	MSE	Correlation	Run Time(sec)
Hammerstein	1.02608	0.87619	0.05
Wiener	0.90383	0.89176	0.03
Hybrid (Proposed)	**0.88671**	**0.89378**	18

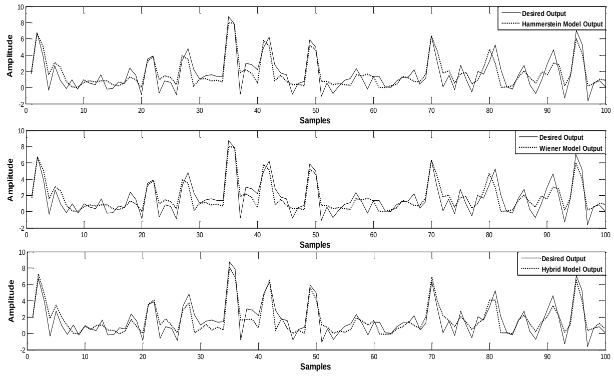

Figure 10. Simulated response comparisons of example-V

Proposed hybrid model's performance of system identification in terms of membership function, number of membership and epoch number is presented in Table 10.

Table 10. Proposed hybrid model performance

			NDS		HM		
MF	**NM**	**NE**	**TR**	**T**	**MSE**	**C**	**RTM**
gauss2mf	2	1000	900	100	0.90132	0.89189	7
gauss2mf	2	5000	900	100	0.90289	0.89169	36
gauss2mf	2	10000	900	100	0.90300	0.89168	71
gauss2mf	**3**	**1000**	**900**	**100**	**0.88671**	**0.89378**	**18**
gauss2mf	3	5000	900	100	0.88811	0.89357	93
gauss2mf	3	10000	900	100	0.88815	0.89359	196
gaussmf	2	1000	900	100	0.90511	0.89140	6
gaussmf	2	5000	900	100	0.90441	0.89149	29
gaussmf	2	10000	900	100	0.90443	0.89149	62
gaussmf	3	1000	900	100	0.90232	0.89176	16
gaussmf	3	5000	900	100	0.90339	0.89163	90
gaussmf	3	10000	900	100	0.90468	0.89147	163
gbellmf	2	1000	900	100	0.90039	0.89202	6
gbellmf	2	5000	900	100	0.89842	0.89227	33
gbellmf	2	10000	900	100	0.90493	0.89142	68
gbellmf	3	1000	900	100	0.91063	0.89074	18
gbellmf	3	5000	900	100	0.91071	0.89073	89
gbellmf	3	10000	900	100	0.91073	0.89072	155

MF=membership function, NM=number of membership, NE=number of epoch, TR= training, T= test, C=correlation, RTM=run time(sec), NDS= number of data samples, HM= hybrid model.

Simulation samples, linear ARMA, nonlinear Hammerstein, Bilinear and Volterra systems are identified through various studies. According to results of all simulation samples, the proposed Hybrid model is more successful in terms of MSE and correlation value compared to other models. In Figures 6-10 and Tables 1-10 the results are analysed. But the proposed model is unsuccessful in terms of run time, compared to other models. This is the disadvantage of the proposed model.

5. CONCLUSION

This study aims to improve a new hybrid model for system identification area. At this point authors designed a soft-switching hybrid model through a NF network to improve the performance of block-oriented models in system identification area. 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.

As disadvantage of the model, proposed model has more complex structure compared to Hammerstein and Wiener models. Also the proposed model requires a lot of parameter estimation. Thus, the run time is increasing. In order to decrease the run time in simulations, NF network based SSM forms are tested different membership functions, different membership numbers and different number of epoch. The details are presented in Table 2,4,6,8,10. According to these results, it is concluded that working time is prolonged due to the increase of membership number and number of epochs. Membership function, number of membership and number of epoch simulation example details are as follows; For Example-I in Table 2, the control parameters for hybrid model performance tests the least MSE (**0.38710**) and the ideal correlation relation (**0.84100**) are as follows; *membership function=* ***gauss2mf****, number of membership=****2*** *ve number of epoch=****10000*****.** For Example-II in Table 4, the control parameters for hybrid model performance tests the least MSE (**0.04013**) and the ideal correlation relation (**0.95429**) are as follows; *membership function=* ***gauss2mf****, number of membership=****2*** *ve number of epoch=****1000*****.** For Example-III in Table 6, the control parameters for hybrid model performance tests the least MSE (**0.10051**) and the ideal correlation relation (**0.90206**) are as follows; *membership function=* ***gaussmf****, number of membership=****2*** *ve number of epoch=****5000*****.** For Example-IV in Table 8, the control parameters for hybrid model performance tests the least MSE (**5.8115** $\mathbf{x10^{-5}}$) and the ideal correlation relation (**0.99490**) are as follows; *membership function=* ***gauss2mf****, number of membership=****2*** *ve number of epoch=****5000*****.** For Example-V in Table 10, the control parameters for hybrid model performance tests the least MSE (**0.88671**) and the ideal correlation relation (**0.89378**) are as follows; *membership function=* ***gauss2mf****, number of membership=****3*** *ve number of epoch=****1000*****.**

But as advantage has a successful identification tool. According to MSE and correlation results, the systems can be identified with less error in proposed model compared to simple Hammerstein or Wiener model. In addition the author will try to identify real system problems in future studies.

REFERENCES

[1] M. Peker, O. Özkaraca, B. Kesimal, “Enerji tasarruflu bina tasarımı için ısıtma ve soğutma yüklerini regresyon tabanlı makine öğrenmesi algoritmaları ile modelleme”, *Bilişim Teknolojileri Dergisi*, 10(4), 443-449, 2017.

[2] U. Köse, E. Ülker, “Pareto zarflama-temelli seçim algoritması (PESA) ile B-spline eğri tahmini”, *Bilişim Teknolojileri Dergisi*, 5(2), 25-31, 2012.

[3] S. Özden, A. Öztürk, “Yapay sinir ağları ve zaman serileri yöntemi ile bir endüstri alanının (ivedik OSB) elektrik enerjisi ihtiyaç tahmini”, *Bilişim Teknolojileri Dergisi*, 11(3), 255-261, 2018.

[4] T. Schweickhardt, F. Allgöwer, "On system gains, nonlinearity measures, and linear models for nonlinear systems", *IEEE Transactions on Automatic Control*, 54, 62-78, 2009.

[5] N.B. Hizir, M.Q. Phan, R. Betti, R.W. Longman, "Identification of discrete-time bilinear systems through equivalent linear models", *Nonlinear Dynamics*, 69, 2065-2078, 2012.

[6] Y. Mao, F. Ding, Y. Liu, "Parameter estimation algorithms for Hammerstein time-delay systems based on the orthogonal matching pursuit scheme", *IET Signal Processing*, 11, 265-274, 2017.

[7] F. Ding, X.P. Liu, G. Liu, "Identification methods for Hammerstein nonlinear systems", *Digital Sig. Proc.*, 21, 215-238, 2011.

[8] S. Ozer, H. Zorlu, "Identification of bilinear systems using differential evolution algorithm", *Sadhana Academy Proceedings in Engineering Sciences*, 36, 281-292, 2011.

[9] F. Guo, **A new identification method for wiener and hammerstein systems**, Doktora Tezi, Karlsruhe Universitesi, Angewandte Informatik Bölümü, 2004.

[10] L.A. Aguirre, M.C.S. Coelhoand, M.V. Correa, "On the interpretation and practice of dynamical differences between hammerstein and wiener models", *IEE P-Contr. Theor. Ap.*, 152, 349-356, 2005.

[11] J. Lee, W. Cho, T.F. Edgar, "Control system design based on a nonlinear first-order plus time delay model", *J Process Contr.*, 7, 65-73, 1997.

[12] H.X. Li, "Identification of hammerstein models using genetic algorithms", *IEE P-Contr. Theor. Ap.*, 146, 499-504, 1999.

[13] K.S. Narendra, P.G. Galman, "An iterative method for the identification of nonlinear systems using a hammerstein model", *IEEE T. Automat. Contr.*, 11, 546-550, 1966.

[14] L. Yu, J. Zhang, Y. Liao, J. Ding, "Parameter estimation error bounds for hammerstein nonlinear finite impulsive response models", *Appl. Math. Comput.*, 202, 472-480, 2008.

[15] A. Gotmare, R. Patidar, N.V. George, "Nonlinear system identification using a cuckoo search optimized adaptive hammerstein model", *Expert Syst. Appl.*, 42, 2538-2546, 2015.

[16] H.N. Al-Duwaish, "A genetic approach to the identification of linear dynamical systems with static nonlinearities", *International Journal of Systems Science*, 31, 307- 313, 2010.

[17] D.L. Zhang, Y.G. Tang, J.H. Ma, X.P. Guan, "Identification of Wiener model with discontinuous nonlinearities using differential evolution", *International Journal of Control, Automation and Systems*, 11, 511-518, 2013.

[18] H. Al-Duwaish, M.N. Karim, V. Chandrasekar, "Use of multilayer feedforward neural networks in identification and control of Wiener model", *IEE Proc., part D.*, 143, 255-258, 1996.

[19] S. Haykin, **Neural Networks: A Comprehensive Foundation**, Macmillan College Publishing Company, New York, 1994.

[20] J.T.R. Jang, C.T. Sun, E. Mizutani, **Neuro-Fuzzy and Soft Computing**, Prentice Hall, PTR, 1997.

[21] M.E. Yuksel, A. Basturk, "Efficient removal of impulse noise from highly corrupted digital images by a simple neuro-fuzzy operator", *Int. J. Electron. Commun. (AEU)*, 57, 214-219, 2003.

[22] M.E. Yuksel, E. Besdok, "A simple neuro-fuzzy impulse detector for efficient blur reduction of impulse noise removal operators for digital images", *IEEE Trans. Fuzzy Syst.*, 12, 854-865, 2004.

[23] H. Zorlu, **Identification of nonlinear systems with soft computing techniques**, Doktora Tezi, Erciyes Üniversitesi, Fen Bilimleri Enstitüsü, 2011.

[24] L. Jia, M.S. Chiu, S.S. Ge, "A noniterative neuro-fuzzy based identification method for Hammerstein processes", *Journal of Process Control.*, 15, 749-761, 2005.

[25] J.S. Wang, Y.P. Chen, "A Hammerstein recurrent neuro-fuzzy network with an online minimal realization learning algorithm", *IEEE Transactions on Fuzzy Systems*, 16, 1597-1612, 2008.

[26] J. Zhai, J. Zhou, L. Zhang, J. Zhao, W. Hong, "Dynamic behavioral modeling of power amplifiers using ANFIS based Hammerstein", *IEEE Microwave and Wireless Compo. Letters*, 18, 704-706, 2008.

[27] E. Mohammadi, M. Montazeri-Gh, "A new approach to the Gray-Box identification of Wiener models with the application of gas turbine engine modelling", *J. Eng. Gas Turbines Power*, 137, 1521-1533, 2015.

[28] C.L. Chen, C.Y. Chiu, "A fuzzy neural approach to design of a Wiener printer model incorporated into model-based digital half toning", *Applied Soft Computing*, 12, 1288-1302, 2012.

[29] L. Yong, T. Ying-Gan, "Chaotic system identification based on a fuzzy Wiener model with particle swarm optimization", *Chinese Physics Letters*, 27, 1-4, 2010.

[30] R. Sujendran, M. Arunachalam, "Hybrid fuzzy adaptive Wiener filtering with optimization for intrusion detection", *ETRI Journal*, 37, 1-10, 2015.

[31] J. Wang, Q. Zhang, L. Ljung, "Revisiting the two-stage algorithm for hammerstein system identification", **Chinese Control Conf. (CDC)**, Shanghai, 3620-3625, 2009.

[32] H.N. Al-Duwaish, "Identification of Wiener model using genetic algorithms", **IEEE GCC Conf. & Exhib.**, Kuwait City,1-4, 2009.

[33] F. Sbeity, J.M. Girault, S. Ménigot, J. Charara, "Sub and ultra harmonic extraction using several hammerstein models", **Int. Conf. Comp. Syst. (ICCS)**, Morocco, 1-5, 2012.

[34] N. Wiener, **Nonlinear Problems in Random Theory**, Wiley, New York, 1958.

[35] M. Schetzen, **The Volterra and Wiener Theories of Nonlinear Systems**, Krieger, Malabar, 1980.

[36] P. Celka, N.J. Bershad, J.M. Vesin, "Fluctuation analysis of stochastic gradient identification of polynomial Wiener systems", *IEEE Transactions on Signal Proc.*, 48, 1820-1825, 2000.

[37] S. Ozer, H. Zorlu, "Neuro-Fuzzy soft-switching hybrid filter for impulsive noisy environments", *Turk. J. Elec. Eng. & Comp.*, 19, 73-85, 2011.

[38] A. Basturk, M. E. Yuksel, "Neuro-Fuzzy soft switching hybrid filter for impulse noise removal from digital images", **Proc. of the IEEE Signal Proces. Com. Ap. Conf. (SIU)**, Kayseri, 13-16, 2005.

[39] M.A. Soyturk, A. Basturk, M. E. Yuksel, "A novel fuzzy filter for speckle noise removal", *Turk. J. Elec. Eng. & Comp.*, 22, 1367-1381, 2014.

[40] Z. Wang, Y. Shen, Z. Ji, F. Ding, "Filtering based recursive least squares algorithm for Hammerstein FIR-MA systems", *Nonlinear Dynamic*, 73, 1045-1054, 2013.

[41] S. Mete, S. Ozer, H. Zorlu, "System identification application using hammerstein model", *Sadhana-Academy Proceedings in Engineering Sciences*, 41, 597-605, 2016.

[42] S.J. Nanda, G. Panda, B. Majhi, "Development of immunized PSO algorithm and its application to Hammerstein model identification", **IEEE Congress on Evoluti. Comp.**, Trondheim, 3080-3086, 2009.

[43] M. H. Calp, "İşletmeler için Personel Yemek Talep Miktarının Yapay Sinir Ağları Kullanılarak Tahmin Edilmesi", Politeknik Dergisi, 2019. DOI: 10.2339/politeknik.444380. (Basımda)

[44] H. Zorlu, S. Mete, Ş. Özer, "System identification using hammerstein model optimized with artificial bee colony algorithm", *Omer Halisdemir University Journal of Engineering Sciences*, 7(1), 83-98, 2018.

[45] S. Mete, S. Ozer, H. Zorlu, "System identification using Hammerstein model optimized with differential evolution algorithm", *International Journal of Electronics and Communications (AEU)*, 70, 1667-1675, 2016.

[46] Ş. Özer, H. Zorlu, S. Mete, "A comparison study of system identification using hammerstein model", **IEEE 2015 11th International Conference on Innovations in Information Technology (IIT'15)**, Dubai, 367-372, 2015.

[47] J. Jeraj, V.J. Mathews, "Stochastic mean-square performance analysis of an adaptive hammerstein filter", *IEEE Transaction on Signal Proces.*, 54, 2168-2177, 2006.

[48] H. Zorlu, S. Ozer, "Identification of nonlinear volterra systems using differential evolution algorithm", **National Conf. on Electrical, Electronics and Computer Engineering**, Bursa, 630-633, 2010.

[49] S. Mete, Ş. Özer, H. Zorlu, "System identification using hammerstein model", **22nd IEEE Signal Processing and Communications Applications Conference**, Trabzon, 1303-1306, 2014.