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The modelling and analysis of nonlinear systems using a new expert system approach

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Abstract

In the present study, a new modelling technique was developed for the modelling and analysis of hyperchaotic systems using an expert system based on wavelet decompositions and the Adaptive Neuro-Fuzzy Inference System (ANFIS). The success and superior properties of this new expert system were shown by applying the hyperchaotic Chen system which is a hyperchaotic system. The obtained expert system consists of two layers, including wavelet decomposition and ANFIS. Wavelet decomposition was used for extracting features in the first layer, and ANFIS was used for system modelling in second layer. Furthermore, HSPICE simulation of the hyperchaotic Chen system was carried out for comparison with the proposed expert system. The structure of the ANFIS was improved and trained in the MATLAB toolbox. Numerical simulations were used in this study. Five various data sets have been used to test the simulation speed of the proposed expert system and HSPICE. The obtained results show that the proposed expert system simulation has much higher speed and accuracy in comparison with HSPICE simulation. The proposed expert system can be simply used in software tools for the design and simulation of the hyperchaotic Chen system and other hyperchaotic systems.

Keywords*:* Expert system; wavelet decomposition; ANFIS; hyperchaotic Chen system

1. Introduction

Chaos is a very interesting nonlinear complex phenomenon and it is used in many application fields such as chemical and biological systems, signal generator design, secure communication, many other engineering systems, and so on.

Various chaotic systems have been introduced until now. For example, the nonlinear Chua circuit and nonlinear Duffing oscillators have been experimentally investigated (Fotsin and Woafo, 2005; Fotsin et al., 1999). One of these chaotic systems is the Chen system, which was first found by Chen and Ueta (1999). Rossler (1979) found another chaotic system. Lü and Chen (2002) found a new system representing the transition between the Lorenz and Chen attractors. Pehlivan and Uyaroglu (2010) achieved new three-dimensional systems.

Recently, hyperchaotic systems and related research have rapidly increased. In recent years, the modelling, control and synchronization of hyperchaotic systems have received more attention due to their potential applications to physics, neuro-fuzzy modelling and control theory, artificial neural networks, telecommunications and secure communication (Yan, 2005; Wang and Liu, 2006).

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There is a positive Lyapunov exponent in chaotic systems. However, a hyperchaotic system has multiple positive Lyapunov exponents, which indicates more complex behaviours and abundant dynamics than the chaotic system. Therefore, hyperchaotic systems can be better than chaotic systems for applications in secure communications. Wu and Lu (2009) presented the synchronization of fractional-order Chen hyperchaotic systems. Secure communications based on the synchronization of the hyperchaotic Chen and unified chaotic systems is proposed by Smaoui et al., (2011). A static output-feedback fuzzy controller for Chen's chaotic system with uncertainties is proposed by Chang et al., (2003).

Artificial neural networks (ANN) and fuzzy logic (FL) are used increasingly in various fields of engineering. ANFIS is commonly used in complex system studies for modelling, control or parameter prediction. Fuzzy modelling or fuzzy identification, first researched systematically by Takagi and Sugeno (1985) has found numerous practical applications in control estimations and inference. Functionality of the neural network of biological neurons can be described as simple processing elements based on an interconnection (Lu et al., 2006; Norgaord et al., 2002). There are simple rules of fuzzy systems which are useful for simplifying the learning process. Euro-fuzzy architectures have been developed with a combination of ANN and FL (Jang and Sun, 1995). Hayati et al., (2010) have applied modelling and simulation of combinational CMOS logic circuits by ANFIS. An expert system for the air flow control of HVAC systems based on ANFIS is presented (Soyguder and Alli, 2010). The modelling of a 1MBI 150NH-060 Typed IGBT Device with Fuzzy and Neural Network Approach is obtained by Tuntas (2005). ANNs have been used for the modelling and simulation of transistors and circuits (Andrejevic and Litovski, 2003; Djeffal and Chahdi, 2007). A fuzzy dynamic characteristic modelling and adaptive control method is proposed by Li et al., (2002).

Wavelet transform has found many applications areas in engineering. Daubechies, symlets, coiflets, and biorthogonals wavelet variants are used for automatic analogue modulation classification and the comparison of wavelet families (Avci, 2007). In addition, for forecasting oil price, trends are used with wavelet decomposition (Silva and Legey, 2010). Wavelet transform is also used for the analysis and simulation of integrated circuits with the potential to shorten the integrated circuit design cycle greatly (Dautbegovic et al., 2003). Previous work has reported an expert system based on wavelet decomposition and neural networks for the modelling and simulation of Chua's circuit which is used for chaos studies (Hanbay et al., 2008), and switched circuits are modelled based on wavelet decomposition and neural networks (Hanbay et al., 2010).

In this study, a new expert system is presented for the modelling and analysis of the hyperchaotic Chen system. For this purpose, firstly using the decomposition method, the original waveform reduced the signals to a lower dimension which contains most of the useful information from the original signals. Afterwards, the input signals of the ANFIS layer was obtained using the output signals of the wavelet layer, and the best ANFIS model was obtained by training and testing for different MFs. Finally, the proposed expert system was tested through the hyperchaotic Chen system by comparison with HSPICE simulation. The results are obtained and show that the proposed expert system simulation is much faster than HSPICE simulation.

The rest of the paper is organized as follows. Section 2 provides a brief overview on the description of the hyperchaotic Chen system. Section 3 presents three decomposed levels of wavelet transform. The structure of ANFIS is described in section 4. The procedure of the expert system is described in section 5. The case studies of application with the proposed methodology are demonstrated in section 6. Finally, section 7 reports the discussion and conclusion.

2. The hyperchaotic chen system

In 1999 Chen and Ueta (1999) created a new chaotic dynamical system called the Chen system. This Chen system is defined by the following set of ordinary differential equations:

$$\begin{cases} \dot{x} = a(y-x) \\ \dot{y} = (b-a)x - xz + by \\ \dot{z} = xy - cz \end{cases} \tag{1}$$

where x, y, z are the state variables and a, b and c are the positive parameters of the system. When a = 35, b = 28 and c = 3, the system (1) shows a chaotic behaviour. The hyperchaotic Chen system is created from the chaotic Chen system and is defined as follows:

$$\begin{cases} \dot{x} = a(y-x) + w \\ \dot{y} = dx - xz + cy \\ \dot{z} = xy - bz \\ \dot{w} = yz + rw \end{cases} \tag{2}$$

where x, y, z and w are the state variables, and a, b, c, d, and r are real constants. When a = 35, b = 3, c = 12, d = 7 and $0 \le r \le 0.085$, the system (2) is chaotic. When a = 35, b = 3, c = 12, d = 7,$0.085 \le r \le 0.798$, the system (2) is hyperchaotic. The Lyapunov exponents for the hyperchaotic Chen system when (a, b, c, d, r) = (35, 3,12,7, 0.5) are $\lambda_1 = 0.56$, $\lambda_2 = 0.11$, $\lambda_3 = 0$ and $\lambda_4 = -26.17$ and the Lyapunov dimension is equal to $D_L = 3.678$. When a = 35, b = 3, c = 12, d = 7,$0.798 \le r \le 0.9$, the system (2) is periodic.

3. Discrete wavelet transform

Discrete wavelet transform (DWT) which decomposes a signal into a number of frequency bands has been used in various fields such as computer vision, speech analysis, image coding and so on. The original signals are initially decomposed into two sub-units. This sub band is composed of a low-frequency (low-pass) sub band and high-frequency (high-pass) sub band. The forward decomposition of a signal is applied by a low-pass digital filter H and a high-pass digital filter G for the classical DWT. $X(t)$ is the original signal and passes through the multi-resolution analysis filter. The discrete wavelet algorithm used in this study is based on the results originally developed by (Wu and Liu, 2008; Gaing, 2004; Turkoglu et al., 2002). A novel self-organizing wavelet model articulation controller (CMAC) is proposed by Min and Yi (2013). A certain type of asymmetric sparse connection topology for networks of coupled chaotic systems is presented by Jonq and Lung (2013). The wavelet function $\varphi(t)$ and scaling function $\Phi(t)$ can be defined as follows (Wu and Liu, 2008).

$$\varphi_{j,k}\left[t\right] = 2^{\frac{1}{2}}\sum_{k} d_{j,k}\varphi[2^{j}t-k] \tag{3}$$

$$\Phi_{j,k}\left[t\right] = 2^{\frac{1}{2}}\sum_{k} c_{j,k}\Phi[2^{j}t-k] \tag{4}$$

where d_j and c_j are the wavelet and scaling coefficient at scale j. Assuming the signal by data extraction system $X(t) = (v_0, v_1 \ldots v_{N-1})$, the sampling number is $N = 2J$. J is an integer number. For $X_j(t)$, at scale j decomposed to scale $j-1$ of DWT mathematical model can be defined as:

$$DWT\left(X_j[t]\right) = \left(\sum_{k=0} cA_{j-1,k}\Phi\left[2^{j-1}t-k\right] + \sum_{k=0} cD_{j-1,k}\varphi\left[2^{j-1}t-k\right]\right)2^{\frac{t-1}{2}},$$

$$0 \le k \le \frac{N}{2^j} \tag{5}$$

$$cA_{j-1,k} = \sum_{h} c_{j,h}V_{j,h+2n}\ , \quad 0 \le h \le \frac{N}{2^j}-1 \tag{6}$$

$$cD_{j-1,k} = \sum_{h} d_{j,h}V_{j,h+2n}\ , \quad 0 \le h \le \frac{N}{2^j}-1 \tag{7}$$

$$d_h = (-1)^h c_{2p-1-h}\ , \qquad p = \frac{N}{2^j} \tag{8}$$

where a set of wavelet approximation coefficients, $cA_{j-1,n}$ and $cD_{j-1,n}$ are the approximated and detailed versions at scale $j-1$, and j is the translation coefficient. Multi resolution analysis leads to a hierarchical and rapid scheme. The decomposition can be realized on more resolution levels by successively splitting the low-pass channel. The framework of the DWT algorithm decomposed/ reconstructed to four levels is shown in Fig. 1 (Wu and Liu, 2008).

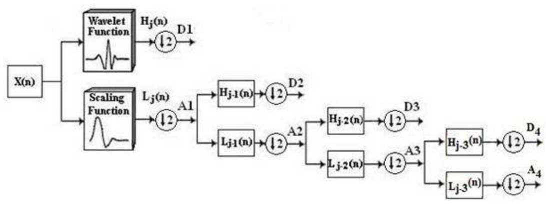

Fig. 1. Four decomposed levels of wavelet transform

4. ANFIS architecture

ANFIS is an adaptive network which allows the use of fuzzy logic together with a neural network (Turkmen and Guney, 2005; Culliere et al., 1995). ANFIS uses the learning capacity of ANN to determine the input–output relationship and build the fuzzy rules by defining the input structure. The non-linear and linear parameters are adjusted by ANFIS using back propagation gradient descent and the least squares method for a given input output data set (Jang, 1993; Nazari et al., 2012).

The five-layered characteristic ANFIS structures have m inputs (x1, xm) each with n membership functions (MFs), R rules and one output (f). If we suppose that the fuzzy inference system has two inputs (x, y) and one output (f), a first order Sugeno model can be described with two rules as follows:

Rule 1: *If x is A1 and y is B1, then f1 =p1x+q1y+r1,*

Rule 2: *If x is A2 and y is B2, then f2 =p2x+q2y+r2.*

The associated inference method is shown in Fig. 2. The output of each rule is a linear combination obtained by adding a constant term to the input variables. The final output of this inference system is the weighted average of each rule output. The structure of ANFIS is shown in Fig. 3 (Takagi and Sugeno, 1985).

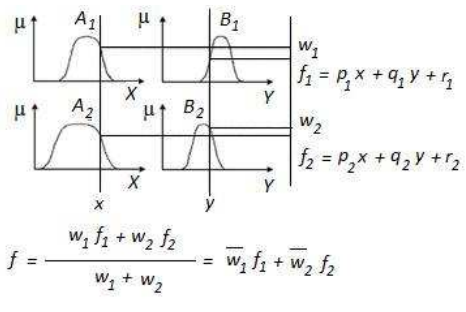

Fig. 2. The inference method of the Sugeno model

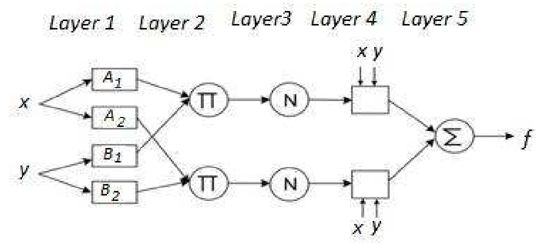

Fig. 3. The ANFIS architecture based on Takagi–Sugeno

Result parameters are identified by the least squares estimate, in the forward pass of the learning algorithm. In the backward pass, the error signals are propagated backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm (Qian, 1999; Shoorehdeli et al., 2009).

5. Methodology

The expert hyperchaotic Chen system model was obtained using the wavelet decomposition and ANFIS structure. In the analysis layer wavelet decomposition was used. Each stage of the modelling structure is described in Fig. 4. Feature extraction plays an important role in the intelligent modelling research because if distinctive features are not obtained using the input signals, the modelling structure used will produce poor results no matter how well designed. The size of the input signal can be reduced by using wavelet decomposition. The expert modelling structure given in Fig. 5 consists of two layers.

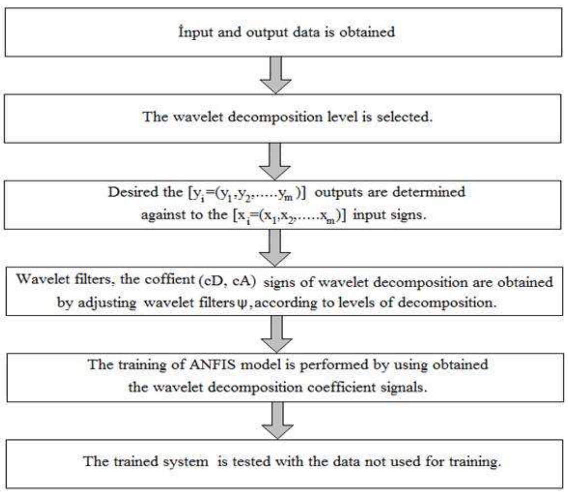

Fig. 4. Each stage of the modelling structure

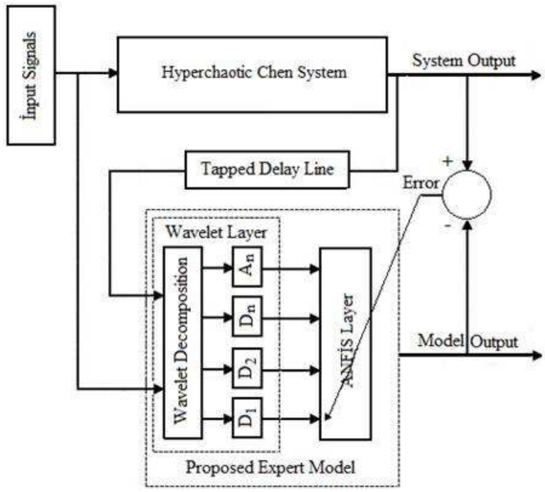

Fig. 5. Block diagram of the intelligent expert system

Wavelet layer: The wavelet layer is indisputably the most important component of designing an expert system based on ANFIS. In this layer, the original waveform can reduce the signals to a lower dimension, which contains most of the useful information from the original signals, using signal processing methods. The purpose of signal processing is to manufacture new signals which are used for safer intelligent modelling from input signals. The wavelet decompositions of input signals belonging to the hyperchaotic Chen system are carried out with this layer. The transformation filter used is daubechies-1. The four-detail wavelet coefficients and one- approximate wavelet coefficients are obtained as a result of the wavelet decomposed. The wavelet decomposition tree is shown in Fig. 6.

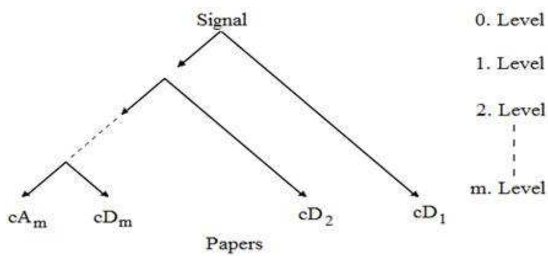

Fig. 6. The wavelet decomposition tree

ANFIS layer: Modelling is done in this layer using wavelet layer outputs. The input signals of the ANFIS layer are obtained using the output signals of the wavelet layer. This layer is responsible for the modelling of the hyperchaotic Chen system.

6. Modelling results

The proposed expert system was obtained with the use of wavelet decomposition and ANFIS respectively. The input signals which belong to the wavelet layer were acquired by numerical solution of the state variables of the hyperchaotic Chen system. After that, the input signals of the ANFIS layer were obtained using the output signals of the wavelet layer. This layer is responsible for the modelling of chaotic circuits. Using the structure of the proposed expert system, the hyperchaotic Chen system modelling obtained was tested and the performance of this model was presented graphically. In addition, the different input-output relations can be taught to model by re-training. In this way an adaptive hyperchaotic Chen system model is obtained.

In this study, the separate expert system models were performed and trained for each state variable (x, y, z, w). Each model structure has one input and one output. The inputs of the proposed expert system models were determined as the state variables of the hyperchaotic Chen system, and outputs were determined as the next state of these state variables. In this study, 2200 simulated signals of the hyperchaotic Chen system were generated using the numerical solution of differential equation systems (2) in MATLAB Toolbox.1500 of these 2200 signals were used for the training phase and the other 700 signals were used for the testing phase of the expert system.

The fourth-order Runge-Kutta method was used to solve the systems of differential equations (2). In addition, a time step of size 0.001 was employed. The parameters were chosen as a = 35, b = 3, c = 12, d = 7, r = 0.5, the initial states of the chaotic system were x(0) = 1, y (0) = 2, z (0) = 3, w (0) = 4**.**

The decomposition structure at level 4 was realized. Thus, each wavelet layer has one input and five outputs, and each ANFIS layer has five inputs, one output and three membership functions for this proposed expert system. Each state variable signal was used as the input, and the four -detail wavelet coefficients and one- approximate wavelet coefficients were used as the outputs for each wavelet layer. The four -detail wavelet coefficients and one- approximate wavelet coefficients were used as the inputs, and the next state of state variable was used as the output for each ANFIS layer.

According to the above parameter values and initial conditions, the chaotic attractor curves of the hyperchaotic Chen system obtained with the proposed expert system are given in Fig. 7.

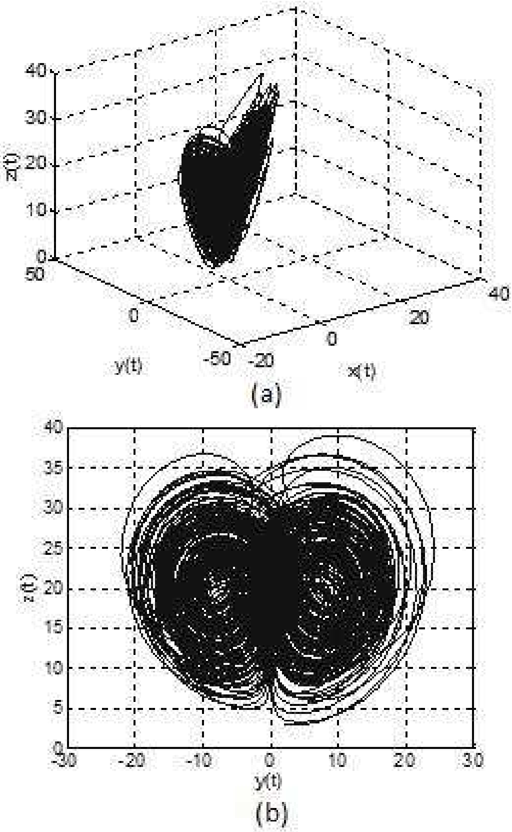

Fig. 7. Phase portraits of system (2) with parameters a = 35, b = 3, c = 12, d = 7, r= 0.5 and x(0) = 1, y (0) = 2, z (0) = 3, w (0) = 4, **(a)** 3D view in the x-y-z space, **(b)** Projection on the y-z plane

The proposed expert system was trained using different MFs, given in Table 1for 20 epochs. Their performances were compared in terms of the RMSE and R^2 values for the training and testing data sets of the proposed expert system in Table 2.

Table 1. Membership functions

Type of MF	Descriptions
GAUSSMF	Gaussian curve membership function.
GAUSS2MF	Two-sided Gaussian membership function
PIMF	Pi-shaped curve membership function.
TRIMF	Triangular membership function.
GBELLMF	Generalized bell curve membership function

Table 2. Performance comparison for different MFs

Membership functions	For the training data sets		For the testing data sets	
	RMS	R2	RMS	R2
Gaussmf	5.7549e-5	0.999999	0.000098	0.999999
Gauss2mf	6.7141e-5	0.999999	0.002047	0.999963
Pimf	2.3836e-5	0.999999	0.000512	0.999987
Trimf	4.3938e-5	0.999999	0.000153	0.999997
Gbellmf	3.0371e-5	0.999999	0.000295	0.999996

The best performance was obtained using the Gaussian curve membership function. The RMSE value is 0.000098 and the R^2 value is 0.999999. The structure, architecture and training parameters of ANFIS models are presented in Table 3 for

Gaussian curve membership function and the x state variable signal of the proposed hyperchaotic Chen system.

Table 3. The structure, architecture and training parameters of ANFIS models for Gaussian curve membership function and the x state variable signal

Architecture, training and ANFIS parameters	Values
The number of layers	5
The number of input	5
The number of output	1
The number of MFs	3
Type of input MFs	Gaussian
Activation functions	Log-sigmoid
Learning rule	Hybrid learning algorithm
Number of nodes	524
Number of linear parameters	1458
Number of nonlinear parameters	30
Total number of parameters	1488
Number of training data pairs	1500
Number of fuzzy rules	243

Then, HSPICE was used as a general simulator for comparing and testing the ability of the simulation method belonging to the proposed expert system. The five various data sets that were shown in Table 4were used for testing the simulation speed of the expert system model and HSPICE.

The proposed expert system simulation method is much faster than HSPICE simulation, as shown in Table 4. The better and faster results are obtained with an increasing number of data.

Table 4. The comparison between HSPICE and expert system model simulation time for ALU

Number of data	Simulation time (s)		Speed improvement
	HSPICE	Expert System	
250	14	0.32	43.75 times
600	34	0.51	66.67 times
1000	53	0.76	69.74 times
1500	78	1.08	72.22 times
2000	87	1.17	74.36 times

Furthermore, only the ANFIS models of the hyperchaotic Chen system were obtained for each state variable. Each ANFIS model structure has one input and one output. The inputs of the ANFIS models were determined as the state variables of the hyperchaotic Chen system, and outputs were determined as the next state of these state variables. Then, both the ANFIS model and proposed expert system model were trained with the 1500 training data set and 20 training epoch numbers for the different number membership function of daubechies-1. To show the performance of these models, the obtained results were compared as shown in Table 5 for the 700 test data set. Likewise, in the testing stage the proposed expert system values with the numeric values of the state variables were shown by comparing them on the same curve as shown in Fig. 8.

Table 5. Performance comparison between ANFIS and the expert system for db1 wavelet filter

The number of MFs	ANFIS Model for the testing data sets				Expert System Model for the testing data sets			
	Training Epoch Numbers	MSE	(R^2)	(RMS)	Training Epoch Numbers	MSE	(R^2)	(RMS)
4	20	0.00215347	0.9992	0.0183	20	0.00018326	0.9998	0.0104
7	20	0.0010372	0.9993	0.0176	20	0.00003682	0.9998	0.0083
9	20	0.00096568	0.9993	0.0168	20	0.00000874	0.9999	0.0073
12	20	0.00079625	0.9996	0.0162	20	0.00000851	0.9999	0.0058

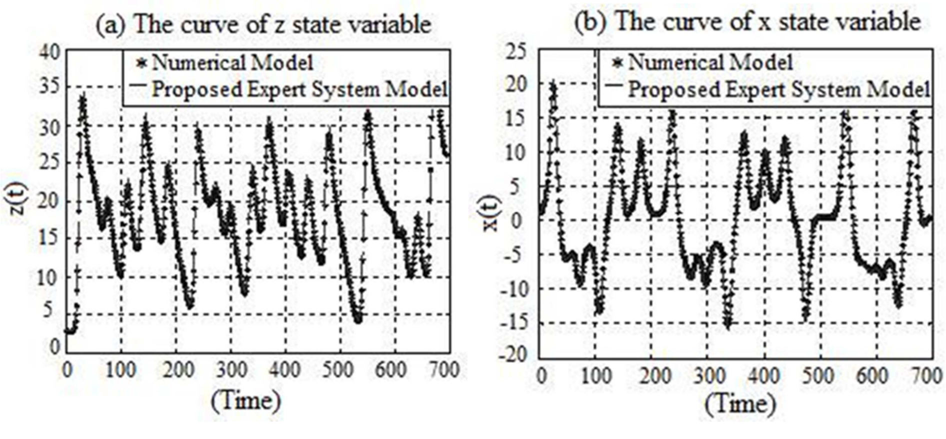

Fig. 8. The nonlinear waveforms of the numerical model and expert system model of the hyperchaotic Chen system on the same graphics. (a) Curve of x state variable, (b) curve of z state variable

7. Discussion and conclusions

In this study, an expert system based on wavelet decompositions and ANFIS was developed. This DWT-ANFIS algorithm has the capability of successfully modelling hyperchaotic systems. The tasks of feature extraction and modelling were performed using the DWT-ANFIS algorithm. The performance of the proposed expert system is given in Table 4 and Table 5. To assess the effectiveness of the proposed expert system, five various data sets were used for testing the simulation speed of the expert system model and the simulation speed of the general simulator HSPICE. The proposed expert system simulation method is much faster than HSPICE simulation as shown in Table 4.Furthermore, both the performance of the proposed expert system model and the ANFIS model were compared as shown in Table 5. The obtained results show that the proposed method can make an effective interpretation as an alternative prediction and modelling method for the hyperchaotic Chen system. In this study, the statistical values obtained for the proposed expert system were that the RMS value is 0.000098 and the R2 value is 0.999999.

For this method, the state equations of hyperchaotic Chen system and initial values of state variables were used. Wavelet decomposition was demonstrated to be an effective tool for processing the signals obtained from the state variables of the hyperchaotic Chen system. An analysis method different from the traditional analysis was carried out with the use of the new information obtained, by extracting the features of information from the hyperchaotic Chen system variables with the signal processing method.

This model can be used in any other nonlinear dynamic system analysis and chaos studies. The obtained results in this study show that the proposed expert system has a number of superior features such as higher speed, accuracy, efficiency of operation and its simple structure. Also, the proposed expert system modelling can be used in the field of chaos synchronization, chaotic communication and especially in secure communication.

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