

The Performance Analysis of Artificial Neural Network Based Shimizu-Morioka Chaotic System with Respect to Sample Numbers

M. Alçın, I. Pehlivan, and I. Koyuncu

Abstract— In this paper, Shimizu-Morioka Chaotic System (SMCS) is modelled using Feed Forward Artificial Neural Network. In the realized network model, Log-Sigmoid and Purelin transfer functions have been used for hidden and output layer, respectively. 3-10-3 network structure is created using MATLAB. The model inputs are the state variables of SMCS. Outputs represent not only the outputs of SMCS but also iterative versions of these inputs. For the equations' numeric solutions of describing SMCS, Runge Kutta 5 Butcher (RK-5-B) algorithm which is one of the differential equation solution methods, is used. Samples in the structure of described network, the created different numbers of samples using RK-5-B have been used as input data and performance analysis have been performed for these data. As a result, the paper shows that when the sample data numbers increase, network modeling performance gives more successful results.

Index Terms—Artificial Neural Networks, Chaotic System, Numerical Algorithm, Modeling.

I. INTRODUCTION

CHAOS has attracted the attention of scientists who work on nonlinear systems in recent years. Communication systems have become one of the most commonly used areas of chaos in engineering applications. Chaotic oscillators have frequently been used for the construction of such systems. There has been many researches exploiting chaotic oscillators in the areas of control, prediction, optimization, energy, cryptology and nanotechnology.

Artificial Neural Network (ANN) is a complex system in Artificial Intelligence (AI) that simulates human brain capabilities such as learning and generalization. It is possible to use ANN in function estimation, classification, pattern recognition, signal processing and system modeling.

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ANN have recently been used in many fields like prediction [1, 2], classification [3, 4], control [5, 6], optimization [7, 8], the analysis of complex problems and modeling of nonlinear systems [9, 10]. The usage of ANN in modeling of nonlinear systems has an important role in modeling chaotic oscillators using ANN. In the present work, the modeling of Shimizu-Morioka Chaotic System (SMCS) using Feed Forward Neural Network (FFNN) is presented [11-13]. For the numeric solution of the system, Runge Kutta 5 Butcher (RK-5-B) algorithm which is one of the differential equation solution methods is used [14]. A detailed analysis of the modeling related to sample number is carried out and obtained results have been explained.

II. BACKGROUND INFORMATION

A. Artificial Neural Networks

Nowadays, Fuzzy-Logic, Genetic Algorithms and ANN are among the AI technics that have been used in various areas [10, 15]. ANN can be used not only in system identification but also in modeling of system. Artificial Neuron system can be performed in modeling and analyzing of chaotic systems with a great success [9]. Model structure of feed-forward ANN for SMCS was shown in Fig. 1.

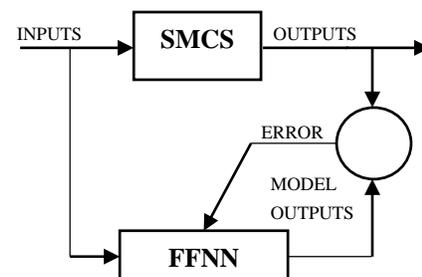


Fig. 1. Model structure of Feed-Forward ANN for SMCS.

ANN consists of inter-connected neurons which are organized in the form of layers [9]. The basic processing element of ANN is called artificial neuron (AN) as shown in Fig. 2. The ANN given in this figure has an input, denoted as p . The line connecting this input to the neuron is assigned a weight, denoted as w .

The neuron also includes an externally applied bias, denoted by b_k . The activation, f , determines whether the neuron is to be fired or not [16].

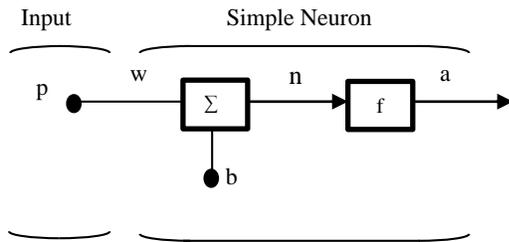


Fig. 2. Simple Neuron Structure [15].

This neuron has 3 functional operations. Firstly, p is multiplied with w to produce weighted input, denoted as wp in (1).

$$wp = w \cdot p \tag{1}$$

Then, weighted input is summed with bias, denoted by b to produce net input, denoted by n in (2).

$$n = w \cdot p + b \tag{2}$$

Finally, the net output, denoted by a is obtained by applying transfer function to n . These three steps are called weight function, net input function and transfer function [10, 17]. There are various transfer functions used in neuron structure in literature [18]. The neuron output, a is given in (3)

$$a = f(wp + b) \tag{3}$$

B. Shimizu-Morioka Chaotic System

Shimizu-Morioka Chaotic System is defined by the simple three-dimensional autonomous system in (4) [11]. T. Shimizu and N. Morioka have found out this system by computer simulations in 1980.

$$\begin{aligned} \dot{x} &= y \\ \dot{y} &= x - a \cdot y - x \cdot z \\ \dot{z} &= -b \cdot z + x^2 \end{aligned} \tag{4}$$

$a = 0.85$ and $b = 0.5$ are the system parameters of the SMCS. $x_0=0.1, y_0=0.1,$ and $z_0=0.1$ are the initial conditions of SMCS. The chaotic attractors obtained from these conditions using MATLAB software were given in Fig. 3.

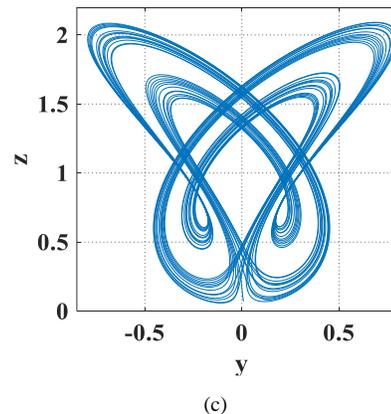
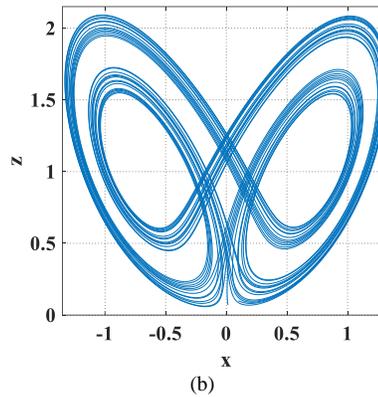
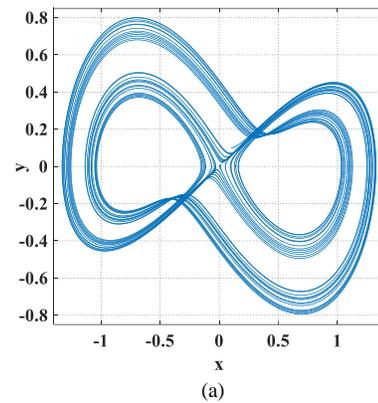


Fig. 3. The chaotic attractors of the Shimizu-Morioka Chaotic System for initial conditions $x_0=0.1, y_0=0.1, z_0=0.1$ and system parameters $a=0.85$ and $b=0.5$, a) x-y chaotic attractors, b) x-z chaotic attractors and c) y-z chaotic attractor.

III. MODELING OF THE SHIMIZU-MORIOKA CHAOTIC SYSTEM

In this paper, Shimizu-Morioka Chaotic System has been modeled using FFNN having different data sets of 100, 1000 and 10000 sample numbers. In the structure of modeled network, inputs represent the state variables and outputs represent the iterative versions of these inputs. As can be seen in Fig. 4, input layer has 3 inputs and output layer has 3 outputs. There are 10 neurons in hidden layer. LoSig (Logistic Sigmoid) transfer function has been used in hidden layer and Purelin transfer function has been used in output layer.

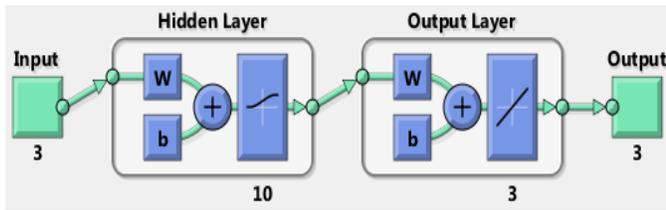


Fig. 4. View of ANN-based Shimizu-Morioka Chaotic System in MATLAB.

The parameters related to ANN-based Shimizu-Morioka Chaotic System has been given in Table I.

TABLE I
MODEL PARAMETERS

FFNN Model Structure	
Number of layers	3
Number of neurons in layers	Input: 3 Hidden:10 Output:3
Initial weights and bias values	Random
Transfer Function	Hidden:Log-Sigmoid Output:Linear
Learning Rule	Levenberg-Margquard Back Propogation

IV. PERFORMANCE RESULTS OF FFNN BASED SMCS

In this work, it is clear to see that the SMCS has been successfully modeled for three different data sets. The performance results related to training have been presented in Fig. 5, Fig. 6 and Fig. 7.

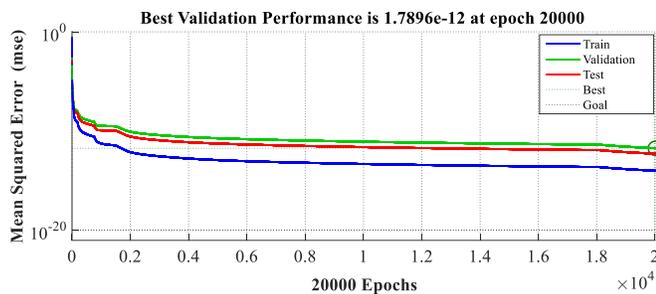


Fig. 5. Network performance results for data set of 100 samples.

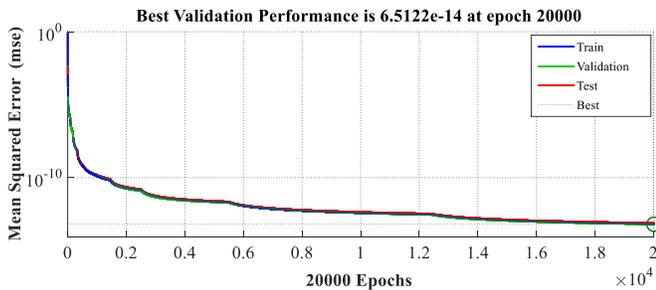


Fig. 6. Network performance results for data set of 1000 samples.

TABLE II
ANALYSIS OF MEAN SQUARE ERROR

	100 sample	1000 sample	10000 sample
Mean Square Error (MSE)	1.7896e-12	6.5122e-14	1.2622e-14

Mean Square Error (MSE) has been decreasing collaterally for each of training, validation and test data. Furthermore, the analysis results of MSE has been given in Table II.

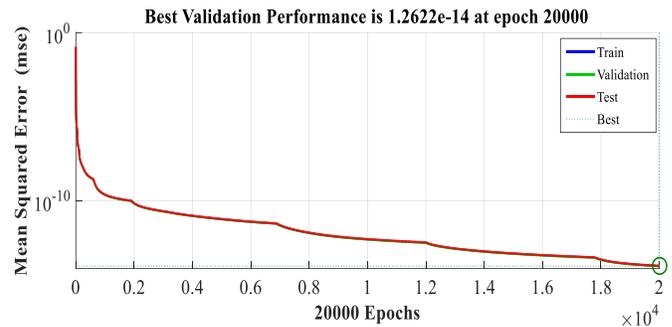


Fig. 7. Network performance results for data set of 10000 samples.

V. CONCLUSIONS

This paper presents the analysis of modeling performance effect of the network with respect to ANN model and sample data number to be used for modeling the dynamics of Shimizu-Morioka Chaotic System. The numeric solutions of the equations describing the SMCS have been performed with RK-5-B algorithm. The obtained data sets having sample numbers of 100, 1000 and 10000 have been modeled by FFNN separately for the network parameters. The performance results have been presented for each of the data sets. As a result, it is seen that the increment of sample number has a positive effect on the modelling performance. In other words, when the sample number increases, the Mean Square Error will decrease.

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