

## Chapter 74

# Chaotic System Design Based on Recurrent Artificial Neural Network for the Simulation of EEG Time Series

Lei Zhang

 <https://orcid.org/0000-0003-0535-998X>

University of Regina, Regina, Canada

### ABSTRACT

*Electroencephalogram (EEG) signals captured from brain activities demonstrate chaotic features, and can be simulated by nonlinear dynamic time series outputs of chaotic systems. This article presents the research work of chaotic system generator design based on artificial neural network (ANN), for studying the chaotic features of human brain dynamics. The ANN training performances of Nonlinear Auto-Regressive (NAR) model are evaluated for the generation and prediction of chaotic system time series outputs, based on varying the ANN architecture and the precision of the generated training data. The NAR model is trained in open loop form with 1,000 training samples generated using Lorenz system equations and the forward Euler method. The close loop NAR model is used for the generation and prediction of Lorenz chaotic time series outputs. The training results show that better training performance can be achieved by increasing the number of feedback delays and the number of hidden neurons, at the cost of increasing the computational load.*

### INTRODUCTION

Recent research based on big data and deep learning has little concern on the extremely long training time and constantly increasing power consumption. Artificial neural network (ANN) is initially inspired by the biological neural networks of human brain. A human brain has approximately 100-billion neurons and 100-trillion connections, but is very energy efficient and can function relatively fast. Taking a face recognition task for instance, our brains can remember a face after encountering a stranger for a few

DOI: 10.4018/978-1-6684-2408-7.ch074

seconds. People are very confident with this brain capability and policeman often asks witnesses to identify a criminal based on it. In contrast, this simple task can take a convolutional neural network (CNN) many hours even days to train, and the same CNN has to be trained again in the same way whenever new data are added. How does the brain achieve its extraordinary efficiency? What is the underlying neural network architecture that facilitates this efficiency? Can we build ANN that assembles the human brain to obtain similar efficiency in addition to accuracy? These are the questions this research tries to address and aims to answer.

In neuroscience, neuroplasticity is referred to as the flexibility for brain neural networks to learn new concepts and to deal with new situations. An adaptive ANN can be trained with new inputs so that the model can adapt to changes. It is necessary for an adaptive ANN to be trained quickly and effectively with a relatively small time series segment in order to capture the trend of a continuously changing EEG signals. Hence the complexity of the ANN architecture and the associated computational cost must be restrained in order to achieve efficiency.

In ANN training, an epoch is referred to a complete training process with the entire training data provided. It can be considered as one learning process taken by the brain. For example, the human brain usually needs to read/write a word or a telephone number repeatedly a number of times to remember it temporarily. And it often requires dozens of repetitions in different occasions to form long-term memory. It holds true for both human learning and machine learning that the learning accuracy can be improved to certain degree by increasing the number of repetitions. The learning results of human brain are mainly measured by accuracy through examination system, but the time and effort taken for learning, aka. learning speed, are disregarded and left to each individual to judge. Similarly, in machine learning, the performance of ANN is measured by accuracy or error rate such as the mean squared error (MSE). In fact, the majority of past and recent research has mainly focused on improving the accuracy of ANN/CNN training, but overlooked the consequences of increased network complexity, computational cost, power consumption, and overextended training time. This approach is acceptable in many applications with fixed solutions without having to frequently retrain the ANN, but it will not work for applications with volatile data and many unknown parameters, such as brain signals captured from EEG. This research investigates the training performance by measuring the MSE with limited training epoch and evaluates the training speed of different ANN architectures using various training data.

## **BACKGROUND**

ANN is a machine learning method. It can be used for pattern recognition and prediction of multi-variant time series. The training performance of an ANN depends on its architecture and the training data. ANN architecture is inspired by biological neural network of the human brain. The classical feedforward ANN architecture includes an input layer, a number of hidden layers and an output layer. Each hidden layer includes a number of parallel distributed hidden neurons. Compared to other machine learning methods, the advantage of ANN design is that an ANN can be trained without knowing the features of the training data beforehand. The disadvantage is that it requires a large number of training data to obtain good ANN training performance. Forecasting using ANN can be dated back to two decades ago (Zhang, 1998) and has been successfully adopted for time series pattern recognition and prediction in many applications. Recent publications have shown promising research advances in optimizing ANN architecture and training algorithm for time series prediction (Zhang, 2018).

10 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

[www.igi-global.com/chapter/chaotic-system-design-based-on-recurrent-artificial-neural-network-for-the-simulation-of-eeg-time-series/289026](http://www.igi-global.com/chapter/chaotic-system-design-based-on-recurrent-artificial-neural-network-for-the-simulation-of-eeg-time-series/289026)

## Related Content

---

### Higher Order Neural Network for Financial Modeling and Simulation

Partha Sarathi Mishra and Satchidananda Dehuri (2016). *Applied Artificial Higher Order Neural Networks for Control and Recognition* (pp. 440-466).

[www.irma-international.org/chapter/higher-order-neural-network-for-financial-modeling-and-simulation/152115](http://www.irma-international.org/chapter/higher-order-neural-network-for-financial-modeling-and-simulation/152115)

### High Speed Optical Higher Order Neural Networks for Discovering Data Trends and Patterns in Very Large Databases

David R. Selviah (2009). *Artificial Higher Order Neural Networks for Economics and Business* (pp. 442-465).

[www.irma-international.org/chapter/high-speed-optical-higher-order/5294](http://www.irma-international.org/chapter/high-speed-optical-higher-order/5294)

### Development of the Enhanced Piece-Wise Linear Neural Network Algorithm

Veronica K. Chan and Christine W. Chan (2022). *Research Anthology on Artificial Neural Network Applications* (pp. 283-305).

[www.irma-international.org/chapter/development-of-the-enhanced-piece-wise-linear-neural-network-algorithm/288961](http://www.irma-international.org/chapter/development-of-the-enhanced-piece-wise-linear-neural-network-algorithm/288961)

### Literature Survey for Applications of Artificial Neural Networks

Pooja Deepakbhai Pancholi and Sonal Jayantilal Patel (2022). *Research Anthology on Artificial Neural Network Applications* (pp. 669-682).

[www.irma-international.org/chapter/literature-survey-for-applications-of-artificial-neural-networks/288981](http://www.irma-international.org/chapter/literature-survey-for-applications-of-artificial-neural-networks/288981)

### A Similarity-Based Object Classification Using Deep Neural Networks

Parvathi R. and Pattabiraman V. (2019). *Handbook of Research on Deep Learning Innovations and Trends* (pp. 197-219).

[www.irma-international.org/chapter/a-similarity-based-object-classification-using-deep-neural-networks/227853](http://www.irma-international.org/chapter/a-similarity-based-object-classification-using-deep-neural-networks/227853)