

# Chapter 29

## Cosine and Sigmoid Higher Order Neural Networks for Data Simulations

**Ming Zhang**

*Christopher Newport University, USA*

### ABSTRACT

*New open box and nonlinear model of Cosine and Sigmoid Higher Order Neural Network (CS-HONN) is presented in this paper. A new learning algorithm for CS-HONN is also developed from this study. A time series data simulation and analysis system, CS-HONN Simulator, is built based on the CS-HONN models too. Test results show that average error of CS-HONN models are from 2.3436% to 4.6857%, and the average error of Polynomial Higher Order Neural Network (PHONN), Trigonometric Higher Order Neural Network (THONN), and Sigmoid polynomial Higher Order Neural Network (SPHONN) models are from 2.8128% to 4.9077%. It means that CS-HONN models are 0.1174% to 0.4917% better than PHONN, THONN, and SPHONN models.*

### INTRODUCTION

This chapter introduces a new Higher Order Neural Network (HONN) model. This new model is tested in the data simulation areas. The contributions of this chapter are:

- Present a new model – CS-HONN.
- Based on the CS-HONN models, build a time series simulation system – CS-HONN simulator.
- Develop the CS-HONN learning algorithm and weight update formulae.
- Shows that CS-HONN can do better than Polynomial Higher Order Neural Network (PHONN), Trigonometric Higher Order Neural Network (THONN), and Sigmoid Polynomial Higher Order Neural Network (SPHONN) models in the data simulation examples.

DOI: 10.4018/978-1-5225-0788-8.ch029

## BACKGROUND

Many studies use traditional artificial neural network models. Blum and Li (1991) studied approximation by feed-forward networks. Gorr (1994) studied the forecasting behavior of multivariate time series using neural networks. Barron, Gilstrap, and Shrier (1987) used polynomial neural networks for the analogies and engineering applications. However, all of the studies above use traditional artificial neural network models - black box models that did not provide users with a function that describe the relationship between the input and output. The first motivation of this paper is to develop nonlinear “open box” neural network models that will provide rationale for network’s decisions, also provide better results.

Jiang, Gielen, and Wang (2010) investigated the combined effects of quantization and clipping on Higher Order function neural networks (HOFNN) and multilayer feedforward neural networks (MLFNN). Statistical models were used to analyze the effects of quantization in a digital implementation. This study established and analyzed the relationships for a true nonlinear neuron between inputs and outputs bit resolution, training and quantization methods, the number of network layers, network order and performance degradation, all based on statistical models, and for on-chip and off-chip training. The experimental simulation results verify the presented theoretical analysis.

Lu, Song, and Shieh (2010) studied the polynomial kernel higher order neural networks. As a general framework to represent data, the kernel method can be used if the interactions between elements of the domain occur only through inner product. As a major stride towards the nonlinear feature extraction and dimension reduction, two important kernel-based feature extraction algorithms, kernel principal component analysis and kernel Fisher discriminant, have been proposed. In an attempt to mitigate these drawbacks, this study focused on the application of the newly developed polynomial kernel higher order neural networks in improving the sparsity and thereby obtaining a succinct representation for kernel-based nonlinear feature extraction algorithms. Particularly, the learning algorithm is based on linear programming support vector regression, which outperforms the conventional quadratic programming support vector regression in model sparsity and computational efficiency.

Murata (2010) found that A Pi-Sigma higher order neural network (Pi-Sigma HONN) is a type of higher order neural network, where, as its name implies, weighted sums of inputs are calculated first and then the sums are multiplied by each other to produce higher order terms that constitute the network outputs. This type of higher order neural networks have good function approximation capabilities. In this study, the structural feature of Pi-Sigma HONNs is discussed in contrast to other types of neural networks. The reason for their good function approximation capabilities is given based on pseudo-theoretical analysis together with empirical illustrations.

Ghazali, Hussain, and Nawi (2010) proposed a novel Dynamic Ridge Polynomial Higher Order Neural Network (DRPHONN). The architecture of the new DRPHONN incorporates recurrent links into the structure of the ordinary Ridge Polynomial Higher Order Neural Network (RPHONN). RPHONN is a type of feed-forward Higher Order Neural Network (HONN) which implements a static mapping of the input vectors. In order to model dynamical functions of the brain, it is essential to utilize a system that is capable of storing internal states and can implement complex dynamic system. Neural networks with recurrent connections are dynamical systems with temporal state representations. The dynamic structure approach has been successfully used for solving varieties of problems, such as time series forecasting, approximating a dynamical system, forecasting a stream flow, and system control.

14 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/cosine-and-sigmoid-higher-order-neural-networks-for-data-simulations/161050](http://www.igi-global.com/chapter/cosine-and-sigmoid-higher-order-neural-networks-for-data-simulations/161050)

## Related Content

---

### Automatic Texture Based Classification of the Dynamics of One-Dimensional Binary Cellular Automata

Marcelo Arbori Nogueira and Pedro Paulo Balbi de Oliveira (2019). *International Journal of Natural Computing Research* (pp. 41-61).

[www.irma-international.org/article/automatic-texture-based-classification-of-the-dynamics-of-one-dimensional-binary-cellular-automata/237983](http://www.irma-international.org/article/automatic-texture-based-classification-of-the-dynamics-of-one-dimensional-binary-cellular-automata/237983)

### Detection of Diseases and Volatile Discrimination of Plants: An Electronic Nose and Self-Organizing Maps Approach

Reza Ghaffari, Fu Zhang, D. D. Iliescu, Evor L. Hines, Mark S. Leeson and Richard Napier (2011). *Intelligent Systems for Machine Olfaction: Tools and Methodologies* (pp. 214-230).

[www.irma-international.org/chapter/detection-diseases-volatile-discrimination-plants/52454](http://www.irma-international.org/chapter/detection-diseases-volatile-discrimination-plants/52454)

### Spiking Neural P Systems: An Overview

Gheorghe Paun and Mario J. Perez-Jimenez (2009). *Advancing Artificial Intelligence through Biological Process Applications* (pp. 60-73).

[www.irma-international.org/chapter/spiking-neural-systems/4972](http://www.irma-international.org/chapter/spiking-neural-systems/4972)

### Bio-Inspired Background Suppression Technique and its Implementation into Digital Circuit

Takao Yamanaka and Yuta Munakata (2013). *Human Olfactory Displays and Interfaces: Odor Sensing and Presentation* (pp. 340-358).

[www.irma-international.org/chapter/bio-inspired-background-suppression-technique/71932](http://www.irma-international.org/chapter/bio-inspired-background-suppression-technique/71932)

### Simulating Spiking Neural P Systems Without Delays Using GPUs

F. Cabarle, H. Adorna and M. A. Martínez-del-Amor (2011). *International Journal of Natural Computing Research* (pp. 19-31).

[www.irma-international.org/article/simulating-spiking-neural-systems-without/57968](http://www.irma-international.org/article/simulating-spiking-neural-systems-without/57968)