Chapter XII
Application of Pi-Sigma Neural Networks and Ridge Polynomial Neural Networks to Financial Time Series Prediction

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ABSTRACT

This chapter discusses the use of two artificial Higher Order Neural Networks (HONNs) models; the Pi-Sigma Neural Networks and the Ridge Polynomial Neural Networks, in financial time series forecasting. The networks were used to forecast the upcoming trends of three noisy financial signals; the exchange rate between the US Dollar and the Euro, the exchange rate between the Japanese Yen and the Euro, and the United States 10-year government bond. In particular, we systematically investigate a method of pre-processing the signals in order to reduce the trends in them. The performance of the networks is benchmarked against the performance of Multilayer Perceptrons. From the simulation results, the predictions clearly demonstrated that HONNs models, particularly Ridge Polynomial Neural Networks generate higher profit returns with fast convergence, therefore show considerable promise as a decision making tool. It is hoped that individual investor could benefit from the use of this forecasting tool.

INTRODUCTION

There are numerous research works being carried out in the area of neural networks, however not all of these research works can be used in real commercial applications. This is probably due to the size of the neural networks which can be large enough to prevent the problem solution from being used in real world problems. Furthermore, the large network size can slow down the training speed and its convergence.

The highly popularized Multilayer Perceptrons (MLPs) models have been successfully applied in financial time series forecasting. A review on existing literature reveals financial studies on a wide variety of subjects such as stock price forecasting (Castiglione, 2000; Chan, Wong, & Lam, 2000; Zekić, 1998), currency exchange rate forecasting (Chen & Leung, 2005; Gradojevic & Yang, 2000; Yao & Tan, 2000; Yao, Poh, & Jasic, 1996; Kuan & Liu, 1995), returns prediction (Dunis & Williams, 2002; Shachmurove & Witkowska, 2000; Franses, 1998), forecasting currency volatility (Yumlu, Gurgen, & Okay, 2005; Dunis & Huang, 2002), sign prediction (Fernandez-Rodriguez, Gonzalec-Martel, & Sosvilla-Rivero, 2000). Since MLPs structure is multilayered and the Backpropagation algorithm involves high computational complexity, this structure requires excessive training time for learning. Further, the number of weights and in turn the training time increases as the number of layers and the nodes in a layer increases (Patra & Pal, 1995; Chen & Leung, 2004).

Concerned with the slow learning problems of MLPs, this chapter investigates the use of artificial Higher Order Neural Networks (HONNs) which have a fast learning properties and powerful mapping of single layer **trainable weights** networks in financial time series prediction. Higher Order Neural Networks distinguish themselves from ordinary feedforward networks by the presence of **higher order terms** in the network. In a great variety of Neural Networks models, neural inputs are combined using the summing operation. HONNs in contrast contain not only summing unit, but also units that multiply their inputs which referred to **higher order terms** or product units.

Although most neural network models share a common goal in performing functional mapping, different network architectures may vary significantly in their ability to handle different types of problems. For some tasks, higher order combinations of some of the inputs or activations may be appropriate to help form good representation for input-output mapping. Two types of HONNs; the Pi-Sigma Neural Networks and the Ridge Polynomial Neural Networks were used as nonlinear predictor to capture the underlying movement in financial time series signals and to predict the future trend in the financial market.

ARTIFICIAL HIGHER ORDER NEURAL NETWORKS (HONNS)

Neurons in an ordinary feedforward network is just a first order neuron, also called a 'linear neuron' since it only uses a linear sum of its inputs for decision. This linearity, providing a hyperplane for decision limits the capability of the neuron to solve only linear discriminate problems (Guler & Sahin, 1994). Since Minsky and Papert's results (1969), it is well known that usual feedforward neural networks with first-order units can implement only linear separability mappings. One possibility to drop this limitation is to use multilayer networks where so-called hidden units can combine the outputs of previous units and so give rise to nonlinear mappings (Hornik, Stinchcombe, & White, 1989). MLP is of type 1st order neural network which can effectively carry out inner products which are then weighted and summed before passing through the non-linear threshold function. The other way to overcome the restriction to linear maps is to introduce higher order units to model nonlinear dependences (Giles & Maxwell¸1987; Giles, Griffin, & Maxwell, 1998).

HONNs are type of feedforward neural networks which provide nonlinear decision boundaries, therefore offering a better classification capability than the linear neuron (Guler & Sahin, 1994). The nonlinearity is introduced into the HONNs by having multi-linear interactions between their inputs or neurons which enable them to expand the