# Chapter VII
# Ultra High Frequency Trigonometric Higher Order Neural Networks for Time Series Data Analysis

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## ABSTRACT

*This chapter develops a new nonlinear model, Ultra high frequency Trigonometric Higher Order Neural Networks (UTHONN), for time series data analysis. Results show that UTHONN models are 3 to 12% better than Equilibrium Real Exchange Rates (ERER) model, and 4 – 9% better than other Polynomial Higher Order Neural Network (PHONN) and Trigonometric Higher Order Neural Network (THONN) models. This study also uses UTHONN models to simulate foreign exchange rates and consumer price index with error approaching 0.0000%.*

## INTRODUCTION

Time series models are the most studied models in macroeconomics as well as in financial economics. Nobel Prize in Economic in 2003 rewards two contributions: nonstationarity and time-varying volatility. These contributions have greatly deepened our understanding of two central properties of many economic time series (Vetenskapsakademien, 2003). Nonstationarity is a property common to many macroeconomic and financial time series models. It means that a variable has no clear tendency to return to a constant value or a linear trend. Examples include the value of the US dollar expressed in Japanese yen and consumer price indices of the US and Japan. Granger (1981) changes the way of empirical models in macroeconomic relationships by introducing the concept of cointegrated variables. Granger and Bates (1969) research the combination of forecasts. Granger and Weiss (1983) show the importance of cointegration in the modeling of nonstationary economic series. Granger and Lee (1990) studied multicointegration. Granger and Swanson (1996) further develop multicointegration in studying of cointegrated variables. The first motivation of this chapter is to develop a new nonstationary data analysis system by using new generation computer techniques that will improve the accuracy of the analysis.

After Meese and Rogof's (1983A, and 1983B) pioneering study on exchange rate predictability, the goal of using economic models to beat naïve random walk forecasts still remains questionable (Taylor, 1995). One possibility is that the standard economic models of exchange rate determination are inadequate, which is a common response of many professional exchange rate forecasters (Kiliam and Taylor, 2003; Cheung and Chinn, 1999). Another possibility is that linear forecasting models fail to consider important nonlinear properties in the data. Recent studies document various nonlinearities in deviations of the spot exchange rate from economic fundamentals (Balke and Fomby, 1997; Taylor and Peel, 2000; Taylor et al., 2001). Gardeazabal and Regulez (1992) study monetary model of exchange rates and cointegration for estimating, testing and predicting long run and short run nominal exchange rates. MacDonald and Marsh (1999) provide a cointegration and VAR (Vector Autoregressive) modeling for high frequency exchange rates. Estimating the equilibrium exchange rates has been rigorously studied (Williamson 1994). Ibrahima A. Elbradawi (1994) provided a model for estimating long-run equilibrium real exchange rates. Based on Elbradawi's study, the average error percentage (error percentage = |error|/rate; average error percentage = total error percentage/n years) of long-run equilibrium real exchange rate is 14.22% for Chile (1968-1990), 20.06% for Ghana (1967-1990) and 4.73% for India (1967-1988). The second motivation for this chapter is to simulate actual exchange rate by developing new neural network models for improving prediction accuracy.

Barron, Gilstrap, and Shrier (1987) use polynomial neural networks for the analogies and engineering applications. Blum and Li (1991) and Hornik (1993) study approximation by feedforward networks. Chakraborty et al. (1992), and Gorr (1994) study the forecasting behavior of multivariate time series using neural networks. Azoff (1994) presents neural network time series forecasting of financial markets. Chen and Chen, (1993, 1995) provide the results of approximations of continuous functions by neural networks with application to dynamic systems. Chen and Chang (1996) study feedforward neural network with function shape auto-tuning. Scarselli and Tsoi (1998) conduct a survey of the existing methods for universal approximation using feed-forward neural networks. Granger (1995) studies modeling nonlinear relationships between extended-memory variables and briefly considered neural networks for building nonlinear models. Bierens and Ploberger (1997) derive the asymptotic distribution of the test statistic of a generalized version of the integrated conditional moment (ICM) test, which includes neural network tests. Chen and Shen (1998) give convergence rates for nonparametric regression via neural networks, splines, and wavelets. Hans and Draisma (1997) study a graphical method based on the artificial neural network model to investigate how and when seasonal patterns in macroeconomic time series change over time. Chang and Park (2003) use a simple neural network model to analyze index models with integrated time series. Shintani and Linton (2004) derive the asymptotic distribution of the nonparametric neural network estimation of Lyapunov exponents in a noisy system. However, all of the studies mentioned above use traditional artificial neural network models - black box models that do not provide users with a function that describes the relationship between the input and output. The third motivation of this chapter is to develop nonlinear "open box" neural network models that will provide rationale for network's decisions, also provide better results.

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