Chapter 2.15
Applying a Fuzzy and Neural Approach for Forecasting the Foreign Exchange Rate

Toly Chen
Feng Chia University, Taiwan

ABSTRACT

Accurately forecasting the foreign exchange rate is important for export-oriented enterprises. For this purpose, a fuzzy and neural approach is applied in this study. In the fuzzy and neural approach, multiple experts construct fuzzy linear regression (FLR) equations from various viewpoints to forecast the foreign exchange rate. Each FLR equation can be converted into two equivalent nonlinear programming problems to be solved. To aggregate these fuzzy foreign exchange rate forecasts, a two-step aggregation mechanism is applied. At the first step, fuzzy intersection is applied to aggregate the fuzzy forecasts into a polygon-shaped fuzzy number to improve the precision. A back propagation network is then constructed to defuzzify the polygon-shaped fuzzy number and generate a representative/crisp value to enhance accuracy. To evaluate the effectiveness of the fuzzy and neural approach, a practical case of forecasting the foreign exchange rate in Taiwan is used. According to the experimental results, the fuzzy and neural approach improved both the precision and accuracy of the foreign exchange rate forecasting by 79% and 81%, respectively.

INTRODUCTION

The foreign-exchange rate between two currencies specifies how much one currency is worth in terms of the other. There are three types of exchange transactions: spot transaction, forward transaction, and swap transaction. Accurately forecasting the foreign exchange rate is very important for export-oriented enterprises in Taiwan. Unfavorable foreign exchange rates also result in the increase of raw material costs and the decrease of gross margin for these enterprises.

The fluctuation in the foreign exchange rate can be treated as a type of time series. Theoretically there are many approaches, e.g. moving average (MA), weighted moving average (WMA), exponential smoothing (ES), linear regression (LR), artificial neural network (ANN), auto-regressive integrated moving average (ARIMA), and others that can be applied to forecast the foreign exchange rate. Recently, Tseng et al. (2001) proposed fuzzy ARIMA for this purpose. In this study, Chen and Lin's hybrid fuzzy linear regression (FLR) and back propagation network (BPN) approach (Chen & Lin, 2008) is applied in this study. The FLR-BPN approach is a general approach like Mamdani's or Takagi-Sugeno's fuzzy inference systems, and can be applied to forecast any phenomena in various fields of research or applications, e.g. semiconductor yield forecasting (Chen & Lin, 2008), job cycle time estimation (Chen, 2009), the book-to-bill ratio forecasting (Chen & Wang, 2010), etc.

Theoretically, FLR problems can be classified into four categories, according to whether the inputs and outputs are fuzzy or not (D'Urso, 2003). Traditionally, there are two ways of solving an FLR problem: linear programming (LP) methods and fuzzy least-squares methods. The first one attempts to minimize the average fuzziness (Tanaka & Watada, 1988) or to maximize the average membership (Peters, 1994) given that the fuzzy forecast contains the actual value to a certain degree. Redden and Woodall (1994) compared various FLR methods and discussed the differences between fuzzy and traditional regression approaches. Some researchers (e.g. Chang & Lee, 1994; Donoso et al., 2006) pointed out the weakness of Tanaka's approach, which did not consider the optimization of the central tendency. In addition, Tanaka's approach usually derived a high number of crisp estimates. Bardossy (1990) used different fuzziness measures. The second way tries to minimize the sum of the square of residuals, which is quadratic in nature (Diamond, 1988; Tanaka & Lee, 1998). Recently, Donoso et al. (2006) constructed a quadratic non-possibilistic (QNP) model in which the quadratic error for both the central tendency and each one of the spreads is minimized.

On the other hand, a BPN (or a feed forward neural network) is a kind of artificial neural network with three types of layers – the input layer, the hidden layer, and the output layer. A BPN is frequently used to imitate the relationship among the inputs and outputs/responses of a complex system (Hsiao et al., 2008; Chen, 2009). Each layer in a BPN contains some neurons. Each neuron receives a signal from the neurons in the previous layer. These signals are multiplied by their weights. The weighted inputs are summed up, and then the result is scaled into a fixed interval before it is outputted to the neurons of the next layer. Finally, the network output can be compared with the actual response for which the deviation is calculated. Such a deviation is then passed backward throughout the network to adjust the weights/parameters. That's why it is called a back propagation network.

BPNs have been universally applied to forecast various phenomena in many research fields. For example, Piramuthu (1991) evaluated the financial credit risk with a BPN. Chang et al. (2005) and Chang and Hsieh (2003) both forecasted the cycle time of every job in a semiconductor manufacturing factory with the BPN approach. Li et al. (2006) constructed a BPN for network flow forecasting and diagnosis. Al-Deek (2007) combined a BPN and time series to forecast the inbound and outbound movements of heavy trucks at a seaport. The advantages of a BPN include the tolerance of noise, the speed of the application, and the capability of simulating complex systems (Piramuthu, 1991). FLRs and BPNs are linear and nonlinear in nature, respectively, and therefore their combination has the potential for dealing with data with hybrid or unclear patterns.

In the fuzzy and neural approach, multiple experts (or decision makers) construct their own FLR equations from various viewpoints to forecast

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