Chapter XVI
Forecasting Foreign Exchange Rates Using an SVR-Based Neural Network Ensemble

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ABSTRACT
In this study, a triple-stage support vector regression (SVR)-based neural network ensemble forecasting model is proposed for foreign exchange rates forecasting. In the first stage, multiple single neural predictors are generated in terms of diversification. In the second stage, an appropriate number of neural predictors are selected as ensemble members from the considerable number of candidate predictors generated by the previous phase. In the final stage, the selected neural predictors are combined into an aggregated output in a nonlinear way based on the support vector regression principle. For further illustration, four typical foreign exchange rate series are used for testing. Empirical results obtained reveal that the proposed nonlinear neural network ensemble model can improve the performance of foreign exchange rates forecasting.

INTRODUCTION
Foreign exchange rates are one of the most important indices in the international monetary and financial markets. With the collapse of the Bretton Woods system and the implementation of the floating exchange rate system in the 1970s, the fluctuation of foreign exchange rates becomes larger...
and larger. High volatility of foreign exchange rates also creates an opportunity to gain profit for traders. So far the foreign exchange market has become the largest and most liquid of the financial market, with an estimated $1 trillion traded everyday (Yao & Tan, 2000). Naturally to gain more profits, the traders must accurately predict the movement direction of foreign exchange rates. Driven by profits, foreign exchange rates modeling and forecasting has been a research focus in the last few decades (Yu, Wang, & Lai, 2005a). However, foreign exchange rates are affected by many highly correlated economic, political, and even psychological factors. The interaction of these factors is very complex (Yao & Tan, 2000). For these reasons, the foreign exchange rates have the characteristics of high volatility, irregularity, nonlinearity, and complexity. Therefore, foreign exchange rates forecasting is regarded as a rather challenging task.

Although predicting foreign exchange rates is very difficult, research challenge and profit inspiration still attracts much attention from researchers and practitioners. Accordingly, a great number of forecasting methods have been developed by many experts. Traditionally, statistical methods such as Box-Jenkins (1976) models dominate the time series forecasting. However, Refenes, Zapranis, and Francis (1994) indicated that traditional statistical techniques for forecasting have reached their limitation in practical applications with nonlinearities in the dataset such as stock indices. Similarly, for the highly volatile foreign exchange markets, traditional statistical modeling is also insufficient since it is hard to capture the nonlinearity hidden in the foreign exchange rates. As a result, many emerging artificial intelligent techniques, such as artificial neural networks (ANNs), were widely used in foreign exchange rates forecasting and obtained good prediction performance. For example, De Matos (1994) compared the strength of a multilayer feed-forward network (MLFN) with that of a recurrent network based on the forecasting of Japanese yen futures. Kuan and Liu (1995) provided a comparative evaluation of the performance of MLFN and a recurrent neural network (RNN) on the prediction of an array of commonly traded exchange rates. Tenti (1996) directly applied the RNN to exchange rates forecasting. Hsu, Hsu, and Tenorio (1995) developed a clustering neural network (CNN) model to predict the direction of movements in the USD/DEM exchange rate. Their experimental results suggested that their proposed model achieved better forecasting performance relative to other indicators. In a more recent study by Leung, Chen, and Daouk (2000), the forecasting accuracy of MLFN was compared with the general regression neural network (GRNN). The study showed that the GRNN possessed a greater forecasting strength relative to MLFN with respect to a variety of currency exchange rates. Similarly, Chen and Leung (2004) adopted an error correction neural network (ECNN) model to predict foreign exchange rates. Yu, Wang, and Lai (2005b) proposed an adaptive smoothing neural network (ASNN) model by adaptively adjusting error signals to predict foreign exchange rates and obtained good performance.

Recently, some hybrid forecasting models have been developed that integrate neural network techniques with many conventional forecasting methods such as econometrical models and some emerging intelligent models such as genetic algorithm to improve prediction accuracy. A few examples in the existing literature are presented. Yu et al. (2005a) also designed a hybrid model integrating neural network and generalized linear auto-regression (GLAR) to predict three main currencies: British pounds, German marks, and Japanese yen. Lai, Yu, Wang, and Huang (2006) hybridized neural network and exponential smoothing for foreign exchange rates forecasting. Empirical results with real data sets indicated that the hybrid model could provide an effective way to improve the forecasting accuracy achieved by either of the models used separately. Shazly and Shazly (1999) designed a hybrid model combining