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## **Development and performance evaluation of a novel** (I) CrossMark knowledge guided artificial neural network (KGANN) model for exchange rate prediction



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Artificial neural network; Exchange rate forecasting; Functional link artificial neural network (FLANN); Knowledge guided ANN model

**Abstract** This paper presents a new adaptive forecasting model using a knowledge guided artificial neural network (KGANN) structure for efficient prediction of exchange rate. The new structure has two parallel systems. The first system is a least mean square (LMS) trained adaptive linear combiner, whereas the second system employs an adaptive FLANN model to supplement the knowledge base with an objective to improve its performance value. The output of a trained LMS model is added to an adaptive FLANN model to provide a more accurate exchange rate compared to that predicted by either a simple LMS or a FLANN model. This finding has been demonstrated through an exhausting computer simulation study and using real life data. Thus the proposed KGANN is an efficient forecasting model for exchange rate prediction.

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#### 1. Introduction

Forecasting exchange rates is of prime importance for financial institutions as well as companies with exposure to foreign currencies. Corporate with such an exposure must necessarily

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hedge their foreign currency cash flows in order to protect their profit from change in currency rates. However, hedging is costly and can be avoided if it will be possible to protect currency rate accurately. Hence developing such an efficient prediction based research methodology would be invaluable for Banks and Companies. To achieve this an objective attempt has been made by researchers to develop different models for prediction of various exchange rates. The initial models suggested in the literature are based on statistical methods (Brillinger, 1975; Hannan, 1979) which assume that the data are correlated and linear in nature. However, in practice it is observed that the financial time series, particularly the foreign exchange rates, do not satisfy such assumptions. As a result the prediction of exchange rates by the conventional statistical

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methods is not satisfactory. To improve the prediction capability the neural network based approach (Ziurilli, 1997) was suggested which is basically adaptive in nature and required training data constituting the past exchange rates to develop the models. Amongst the various neural networks, the multilayer perceptron (MLP) (Haykin, 2004), the functional link artificial neural network (FLANN) (Pao, 1989), the cascaded functional link neural network (CFLANN) (Majhi et al., 2009) and the radial basis function (RBF) (Haykin, 2002) have been used for this purpose. In all these networks the learning algorithms that are used are mostly derivative based algorithms. In recent past evolutionary computing tools such as genetic algorithm (GA) (Bhattacharya and Meheta, 1998), genetic programming (GP) (Neely et al., 1997), particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), bacterial foraging optimization (BFO) (Passino, 2002) have been also employed to train the weights associated with the architectures of different models. In Bansal et al. (2010), a framework for intelligent interaction of automatic trading algorithms with the user was presented. In Chang et al. (2009), a back propagation neural network was employed to predict the buy/sell points for a stock and then applied a case based dynamic window to further improve the forecast accuracy. In Atsalakis and Valavanis (2009), a survey of more than hundred articles which used neural networks and neuro-fuzzy models for predicting stock markets was presented. It was observed that soft computing techniques outperform conventional models in most cases. Defining the structure of the model is however, a major issue and is a matter of trial and error. In Venugopal Setty et al. (2010), review of data mining applications in stock markets was presented. Huang and Jane (2009) presented a hybrid model for stock market forecasting and portfolio selection. Simon and Raoot (2012) explored the possible research strategies in the accuracy driven ANN models. In Xu et al. (2008), trend following (TF) degrades in performance in proportion to the amount of fluctuation of the market trend. This finding is important to the design of technical trading systems. It implies that the fluctuation of market trend should be monitored; when it exceeds a certain threshold the TF trading should be paused to prevent loss. In Kumaran Kumar and Kailas (2012), the prediction of future stock close price of SENSEX and NSE stock exchange is found using the proposed hybrid ANN model of functional link fuzzy logic neural model. In Sheikhan and Movaghar (2009), a rich evolutionary connectionist model is proposed, in which GA is used to determine the optimum number of input and hidden nodes of a feedforward neural network, the optimum slope of nodes' activation function and the optimum values of learning rates and momentum coefficients. Empirical results on foreign exchange rate prediction indicate that the proposed hybrid model exhibits effectively improved accuracy, when compared with some other time series forecasting models. These new models have been reported to offer improved prediction performance particularly for high range of prediction. The drawback of evolutionary computing approaches is high computational time as these are population based algorithms.

In recent years many publications have appeared in the literature in the area of exchange rate forecasting. In Tsai and Wu (2000), the higher order fuzzy time series is used to forecast exchange rates. In another publication the authors (Minghui et al., 2003) have proposed a sequential learning, neural network named as minimal resource allocating network (MRAN)

to forecast various monthly exchange rates. They have shown that this model predicts exchange rates better than the MLP model. Kamruzzaman and Sarkar have recently applied (Kamruzzaman and Sarkar, 2003) three ANN models for predicting exchange rates using historical data and moving average technical indicators. The Kullback information criterion (KIC) has been tested (Seghouane and Bekara, 2004) on real data to forecast foreign currency exchange rate with interesting results compared to the classical techniques. The support vector machine (SVM) has also been proposed (Cao et al., 2005) for exchange rate prediction with promising results. Recently efficient prediction of various exchange rates has been suggested by us (Majhi et al., 2006, 2007, 2009) using a novel low complexity artificial neural network model. The authors have demonstrated that this new model is computationally simple but provides excellent exchange rate prediction performance.

These foreign exchange rate forecasting models are essentially adaptive in nature and are obtained by training them with known time series data and using some standard learning algorithms. Such type of models has limitations such as more training time and less accurate prediction capability particularly for high range. To improve the prediction performance such as less training time and better accuracy alternative models can be developed. Keeping this objective in view the present investigation has been made and a new knowledge guided ANN (KGANN) forecasting model for efficient prediction of various exchange rates has been proposed. A similar idea has already been applied by us in estimating the path loss in mobile communication (Panda et al., 2005). In the approach a crude model using an adaptive linear combiner (Widrow and Stearns, 2002) is first developed using past exchange rates as input. This approximate model serves as a knowledge guide to the overall model. To further improve the prediction performance a low complexity single layer FLANN structure (Pao, 1989) is added parallel to the linear combiner model. The weights of the FLANN model are trained using the same known input data and combining the outputs of the two structures. It is expected that the hybrid structure would provide superior prediction performance compared to the crude model alone. It may be noted that in the first phase the weights of the linear combiner are trained using standard least mean square (LMS) algorithm whereas in the second phase the weights of the FLANN are updated. During actual operation the KGANN functions as a fixed model and the FLANN is used as an adaptive model.

#### 2. Development of knowledge guided ANN (KGANN) model

The KGANN hybrid adaptive model for the purpose of financial forecasting is shown in Fig. 1.

In the first stage an LMS model which is simple and robust is generated using a linear combiner and the LMS learning rule. To design this model, training patterns generated from exchange rate series are applied sequentially and for each pattern the output of the model is computed. This output is compared with the corresponding target value and the error is obtained. Using this error and the input the LMS algorithm computes the change in weights of the model. The training of the model continues with new input patterns until the squared error diminishes progressively and settles at a Download English Version:

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