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Hybrid Neural Network and Decision Tree for Exchange Rates Forecasting

Soleh Ardiansyah[a], Mazlina Abdul Majid[b], Jasni Mohamad Zain[c]

[a,b,c]*Faculty of Computer System and Software Engineering (FSKKP), Universiti Malaysia Pahang (UMP), Kuantan, 26300, Malaysia.*

Abstract

As the largest financial market in the world, foreign exchange (Forex) is becoming a very profitable market with a daily transaction of more than 3.0 trillion U.S. dollars. Therefore, predicting about it has been a challenge for many years. Artificial Neural Network (ANN) provides better performance of forecasting but it tends to get stuck in local minima and there is no optimal way to determine the best classifier on it. Meanwhile, Decision Tree (DT) is able to generate classifier in the form of a tree. This paper proposes a hybrid prediction model by combining both ANN and DTalgorithm to predict exchange rates. The models are constructed by using the better of parameters and architectures based on related work such as filtering mechanism, number of hidden layers, number of hidden neurons, training algorithm, and error measurement, with the assumption that if the hybrid model is constructed by the better parameters and architectures, then the output of the model also produces better result.

Keywords: Hybrid system; Artificial Neural Network; Decision Tree; exchange rates; forecasting model.

1. Introduction

As the largest financial market in the world, Foreign Exchange (Forex) becomes very profitable market with a daily transaction of more than US$ 3.0 trillion. This situation attracts many people to trade Forex. However, many inexperienced traders and new traders that do not have enough information about trading knowledge keep trying their luck in Forex trading. This behavior may cause some losses. Although at risk, retail market is growing by leaps and bounds. Obviously, many traders have concluded that the opportunities outweigh the risk. Therefore, forecasting of Forex has become a challenge for many years and raised many theories and experiments. Over the years, linear techniques have been used by researchers and analysts since they are very simple and easy to apply. However, this linear indicator has always worked well on a linear movement but stops helplessly when dealing with nonlinear behavior of the market [2].Artificial neural network (ANN) is widely used in many applications as a prediction technique for its nonlinear structure which is able to deal with even the most complex problems, and that is the reason why ANN becomes a very promising prediction technique and it also provides better performance on forecasting [2-7, 31, 34]. However, ANN tends to get stuck in local minimum due to the stochastic gradient descent technique and there is no optimal way to determine the best classification [11]. On the other hand, Decision Trees (DT) which is one of the data mining techniques is able to generate classifier in the form of trees. Its learning algorithm is able to provide a solution that is always convergent to classify the training set of the data correctly [11].Recently, there is a very high interest among researchers in predicting the financial markets by combining several techniques, such as the classifier ensemble and hybrid techniques for their performance give better results than a single technique [1,8-11,16,18,22-23]. Therefore, the objective of this study is to develop a hybrid model based on experiment by using ANN and DT for exchange rate forecasting and to investigate the performance of the prediction models and prediction accuracy. This study also proposes an individual model of ANN and DT for forecasting. The filtering data mechanism is used to pre-process the raw data based on technical indicators of the exchange rate. The proposed model needs a benchmark as a performance measure in order to assess the feasibility and the effectiveness. The selection of an error measure as a benchmark depends on each situation. Therefore, this study uses *Mean Squared Error* (MSE), *Median Absolute Deviation* (MAD), and *Median Absolute Percentage Error* (MdAPE) to evaluate and compare the predictive performance of the forecasting model since they can provide the solution of an accurate prediction method by using a large number of time series data [29].This paper consists of five sections. In the section 2, the forecasting models of the related studies are summarized and compared. Section 3 presents the review of related literature. The methodology of the proposed model is described in section 4. Finally, conclusions are given in section 5.

2. Literature Review

2.1. Foreign exchange rates and technical indicators

The Forex market is one of the most interesting of all financial markets. Unlike other markets, this market is open 24 hours daily and has an estimated of 3.0 trillion U.S. dollars in foreign exchange transaction that takes place each business day, and the volume is increasing steadily. The currencies have their symbols and are always traded in pairs (between two currencies). The most popular currency pair is the EUR/USD. There are two important analyses of exchange rates. They are fundamental analysis which uses the macro economy such as inflation rate, employment, GDP, interest rate, non-farm payroll, etc. while technical analysis is based on the past trend to analyze the market movement [2].Technical analysis assumes that fundamental analysis is too varied and its use is difficult to count. In addition the information and news are just a cause and not the determinant of the direction of the price movement. Therefore, traders and participants assume that the most appropriate way of analysis is to study the behavior of market participants which is reflected in the price chart pattern. There are hundreds of technical indicators used in technical analysis in term of rise and fall to find patterns of market movement and trends. This study uses technical indicator to pre-process raw data before it is fed into the system as an inputs.

2.2. Artificial Neural Networks

Artificial neural networks are massively parallel adaptive networks of simple nonlinear computing element called neuron which is intended to abstract and model some of the functionality of the human nervous system in the attempt to partially capture some of its computational strengths. The basic unit in a neural network is a neuron. This can be of three layers: input, hidden, and output. Input neurons are designated to receive external stimuli presented to the network. Outputs from the network are generated as a signal of output neuron. Hidden neurons compute intermediate functions and their states are not accessible to the external environment. A layer is connected to the other weight through weight-labeled link. The output of the neuron is typically altered by a transfer function. The most common functions are binary threshold, linear threshold, and sigmoid function and they may differ from neuron to neuron within the network. Neural network is trained by using time series data in order to capture the nonlinear characteristic of the specific historical data [1].

2.3. Decision Tree

The Decision Tree (DT) is a popular technique in data mining which is usually used in prediction models and classifiers. Basically DT algorithm is to get the classification rules based on instance learning within the structure of a tree that depends on different situations to create a number of branches and nodes. Every branch presents a decision or process of classification and nodes present the target or output class. Pruning algorithm is used to calculate the error rate. It is also used to improve the forecasting and classification ability of DT and provide a more efficient decision [8].C4.5 is an evolution of ID3 which uses a gain ratio as splitting criteria. C4.5 algorithm is a decision tree technique that is commonly used for data classification due to certain advantages such as it can process numeric (continuous) and discrete data, it can handle missing attribute value, generate rules that are easily interpreted and it is the fastest among other algorithms. This study uses C4.5 algorithm due to predictive accuracy [38] and the numerous possibilities in term of pruning, nominal attribute, and numerical treatment [30].

2.4. Hybrid Systems

Hybridization in artificial intelligence usually involves two or more intelligent techniques that used simultaneously in order to handle the complex problems in the real world. It is frequently practiced in machine learning which is to make a classifier more powerful and reliable [6]. The combination of additional methodologies can be done in any form by modularly integrating two or more intelligent methodologies while maintaining the identity of each methodology; by fusing one methodology into another method; or by transforming the knowledge representation in one methodology into another form of characteristic representation to another [6].

2.5. Related Works

Basically, the machine learning technique aims to recognize patterns from large amounts of data and have the ability to learn automatically. There are so many techniques of machine learning in literature which makes classifications become difficult and confusing. This section tries to summarize and compare the forecasting model of the related studies. The literature is divided into a neural network, decision tree, hybrid/combination techniques and evolution and optimization techniques used for forecasting foreign exchange rates. Table 1 shows a summary and comparison of related studies on the forecasting of foreign exchange based on their forecasting models, datasets, data years, time-frame, evaluation methods, and findings. As shown in Table 1, there is a trend among researchers to use the ANN model and then optimizing it with another training algorithm or combining ANN into hybrid systems. The most commonly used variables are daily OHLC (open, high, low, close) price and also technical indicators. Therefore, this study proposes a combination of ANN and DT model into a hybrid system since there has been a lack of research in exchange rate forecasting by using the combination of both ANN and DT. Figure 1 shows the percentage of the number of paper publication to predict exchange rates in term of forecasting model based on the summary in Table 1.

Table 1. The summary and comparison of related studies in exchange rate forecasting

Years	Researchers	Forecasting model	Datasets	Data-years	Time-frame	Evaluation method	Findings
2010	S.-C. Huang, P.-J. Chuang, C.-F. Wu and H.-J. Lai [26]	Chaos-based SVR	EUR/USD GBP/USD NZD/USD AUD/USD JPY/USD RUB/USD	2005-2009	Daily	MSE, RMSE, MAE	The proposed model performs best, the RMSE forecasting error is significant.
2009	Y. Leu, C.-P. Lee and Y.-Z. Jou [24]	DBFTS; RW; RBFNN	NTD/USD JPY/USD CNY/USD KRW/USD	2006-2007	Daily	MSE	The proposed model outperforms the RW model and the ANN model in term of MSE
2009	R. Majhi, G. Panda and G. Sahoo [13]	FLANN; CFLANN	Conversion rates: INR/USD GBP/USD JPY/USD	-	-	MSE; APE	The CFLANN models perform the best for all cases of currency conversion.
2009	H. Ni and H. Yin [16]	RSOM; SVR; GA Trading Indicator;	USD/GBP	-	Daily	Virtual trading systems	The proposed method is improved over global models and other method but it depends on the specific fitness measure and quality/quantity of trading rules adopted.
2009	L. Anastasakis and N. Mort [23]	ANN Analog complexion	GBP/USD GBP/DEM	1996-2001	Daily	MSE; %sign; Profit	The combined method outperforms the individual methods.
2008	M.H. Eng, Y. Li, Q.-G. Wang and T.H. Lee [4]	ANN	GDP; CPI; Quarterly trade balance number	-	-	RMSE; DA	ANN fails to capture exchanged rate movements based on less updated input variable.
2008	L. Yu, K.K. Lai and S. Wang [14]	RBFNN ensemble	EUR/USD GBP/USD JPY/USD DEM/USD	1971-2000 2001-2006	Monthly	NMSE	The proposed RBFNN ensemble model can be used as a viable alternative ensemble solution for exchange rate forecasting.
2008	G. Jia, Y. Chen and Q. Wu [15]	MEPIP-FNT	EUR/USD GBP/USD JPY/USD	2000-2001	Monthly	NMSE	Simulation result from the Forex forecasting problems shows the feasibility and effectiveness of the proposed method
2007	Y.-Q. Zhang and X. Wan [25]	Fuzzy Interval Neural Learning Algorithm	USD/JPY	1998-2001	Weekly	Combining sample mean	The fuzzy interval neural network is able to construct predictive models and help user see future trends
2007	M. Khashei, S.R. Hejazi and M. Bijari [28]	Combining ANN & Fuzzy regression	USD/IRR	2005	Daily	MAE; MSE	The proposed model suitable for use in incomplete data situation, the performance is better than fuzzy and non fuzzy model.
2006	M.L. Seliem [2]	ANN	EUR/USD GBP/USD USD/CHF USD/JPY	-	Daily Weekly Monthly	MSE; Average pipes deviations	The daily prediction has given accurate result, the weekly prediction has given good result for some currencies, but the monthly prediction does not give satisfactory results
2006	H. Ince and T.B. Trafalis [10]	ANN; SVR; ARIMA; VAR	EUR/USD GBP/USD AUD/USD JPY/USD	2000-2004	Daily	MSE; MAE	SVR method outperforms MLP network. The best selection procedure depends on the training algorithm. (MLP-VAR/ARIMA-SVR)
2006	Y. Chen, L. Peng and A. Abraham [17]	FNT	EUR/USD GBP/USD JPY/USD	2000-2002	Daily	NMSE; D_{stat}	The proposed model is better than the conventional NN forecasting model.
2005	L. Yu, S. Wang and K.K. Lai [1]	Nonlinear ensemble (GLAR-ANN)	DEM/USD GBP/USD JPY/USD	1971-2000 2001-2003	Monthly	NMSE; D_{stat}; R	The nonlinear ensemble forecasting model can be used as a viable alternative solution for exchange rates prediction
2000	J. Yao and C.L. Tan [3]	ANN	DEM, GBP, JPY,UAD, CHF/USD	1984-1995	Weekly	NMSE	The forecasting results are very promising for most currencies.

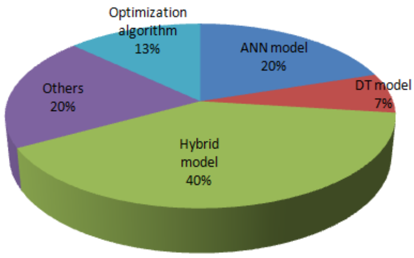

Figure 1 Forecasting models for exchange rates prediction

3. Research Methodology

3.1. Datasets descriptions

The data sets consist of the EUR/USD and USD/JPY and composed of daily rates from January 2000 to December 2010. The data sets are divided into two sets, training and testing datasets by 80/20 principle where 80% of the data are used as a training datasets and other 20% of the data are used as a testing datasets.Before datasets are fed into the systems, the data are pre-processed by using the filtering mechanism based on technical indicators. The technical indicators which are shown in Table 2 consist of four indicator types. They are a trend indicator to show market trends, momentum indicator to show trend strength/weakness, volatility indicator to show the magnitude of price fluctuations, and volume indicators show the level of trader's participation in the market. The market trends are market direction which are formally classified by the uptrend (rise) and the downtrend (fall).

Table 2. The type of technical indicators for filtering data mechanism

Trend indicator	**Momentum indicator**	**Volatility indicator**	**Volume Indicator**
Moving Average	Stochastic	Average True Range (AVR)	Money Flow Index
MACD	Relatives Strength Index	Bollinger Band	Volume
Parabolic SAR	Momentum	Bollinger Band Width	On Balance Value (OBV)
	Williams %R	Chaikin Volatility	
	Aroon indicator		

3.2. Artificial neural network prediction model

Multilayer feed forward neural network is the most common of neural network model and will be used in this study. The network model consists of an input layer and one or more hidden layer. Each layer consists of multiple node (neuron) that connects the neuron in adjacent layers. This type of neural network is known as a supervised network since it requires a desired output in order to learn the nonlinear characteristic of the data. The parameter such as connections weight and node bias will be adjusted iteratively by the process of minimizing the forecasting error.The parameters of creating the ANN model are described as follows:

- Hidden layer selection: In literature, if the accuracy of the result is a critical factor for an application then the multiple hidden layers should be used [12].
- Hidden neurons selection: Deciding the number of neurons in the hidden layer is a very important part of ANN architecture since there is no exact number of the hidden neuron [8]. Using too few neurons in the hidden layer will result in under-fitting and over-fitting will occur when using too many neurons in the hidden layer. Therefore, this problem depends on experimental method to find the optimal number of neuron [8].
- Training algorithm: This study uses Levenberg-Marquardt algorithm since this algorithm has been shown to be the fastest and the most efficient for training feed forward neural networks [32-33].
- All weights are initiated to sets of random numbers.The other parameter is set default value in MATLAB's NN Toolbox.

The steps of creating an ANN prediction model are shown in Figure 2. Before datasets are fed into the systems, the data are pre-processed by using the filtering mechanism based on technical indicators. 80% of the data are used for training ANN model in order to get the best architecture. After getting the best architectures of the model, that architectures are tested by using testing data to get the prediction result.

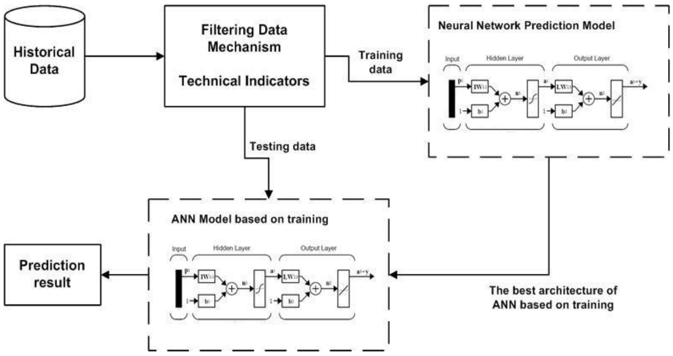

Figure 2. Neural network prediction model.

3.3. Decision tree prediction model

The decision tree is a supervised algorithm which recursively splits the data based on its attributes, until the stopping conditions are reached [37]. This recursive splitting gives the rise to a treelike structure. To construct a decision tree with C4.5 algorithm the first thing to do is select the attribute as the root, then make a branch for each value at the roots. The next step is split the case into a branch. Then repeat the process for each branch to branch until all cases have the same class. The selection of the attribute of the root is based on the high gain value of the existing attribute. The gain is one of the attribute selection measures used to select the test attribute of each node in the tree. The attributes with the highest information gain is selected as the test attribute of a node. The steps of creating DT prediction model are shown in Figure 3. Before datasets are fed into the systems, the data are pre-processed by using the filtering mechanism based on technical indicators. The classifications of the data set in the DT prediction model use C4.5 algorithm.

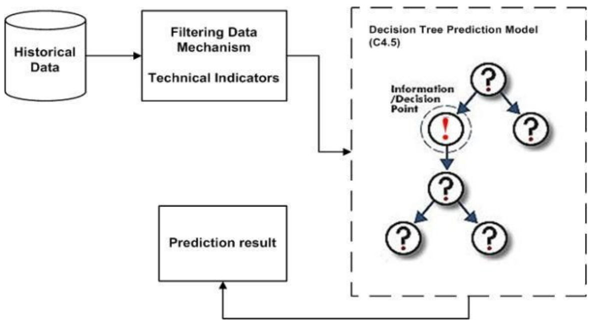

Figure 3 Decision tree prediction model

3.4. Hybrid prediction model

ANN becomes a very promising prediction technique and it also provides good performance of forecasting. However, ANN tends to get stuck in local minimum due to the stochastic gradient descent technique and there is no optimal way to determine the best classification [11]. On the other hand, Decision Trees (DT) which is one of the Data Mining techniques is able to generate classifier in the form of trees. Its learning algorithm is able to provide a solution that is always convergent to classify the training dataset correctly [11]. The basic idea of combining both technique ANN and DT is to handle the complex problem, with the expectation that each model can complement each other so that the model becomes more powerful and reliable. In this study, DT is used as an input selection.

Firstly raw data will be pre-processed by technical indicators and only the indicators which contain any relevant information will be selected by the DT. The output of the DT will be as an input of ANN. Assuming that the ANN is able to provide the best results if its input is good quality data. The steps of producing hybrid model of ANN and DT models are shown in Figure 4.

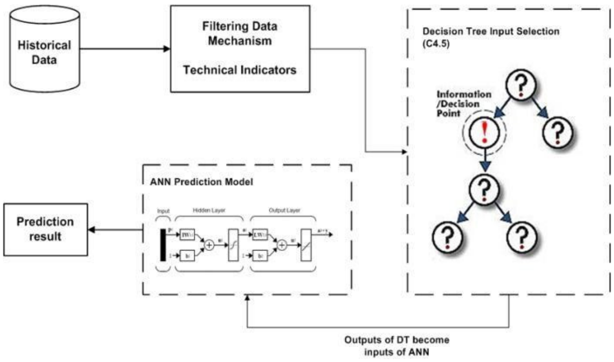

Figure 4 Hybrid prediction models of ANN and DT

3.5. Performance measure and comparison

To assess the feasibility and effectiveness of the proposed model, it needs a benchmark. The selection of an error measure as a benchmark depends on each situation. By only using one error measure for evaluating the prediction performance (e.g., RMSE), it does not show the behavior of the prediction in a clear way [21, 29]. Therefore, the use of more than one performance measure should be considered to provide robust evaluation of the prediction result and to achieve desirable goals [19-20].

This study has selected the following three standard criteria:

- *Mean Squared Error* (MSE). As seen in Table 1, this criterion is the most popular measure that is used to evaluate the prediction performance.
- *Median Absolute* Deviation (MAD). This criterion is the average of the absolute error value regardless of whether the error was under estimated or over estimated [27].
- *Median Absolute Percentage Error* (MdAPE). MdAPE is the middle value of all the percentage errors in a data set when the absolute values of the errors (negative signs are ignored) are ordered by size. This criterion is appropriate to compare models in numerous series and for selection among forecasting methods in term of reliability, construct validity, protection against outliner, and relationship to decision [29].

4. Conclusion

The Forex market is one of the most interesting of all financial markets and forecasting of it them has become a challenge for many years. There is a very high interest among researcher to predict Forex by using multiple techniques. This study attempt to develop a hybrid model based on experiment by using ANN and DT for exchange rate forecasting and to investigate the prediction performance of the models in term of the feasibility, effectiveness, and prediction accuracy. To achieve the objective, this study proposes a hybrid model by combining two machine learning technique. They are artificial neural network and decision tree C4.5 to predict exchange rate trends.

The historical data of Forex will be pre-processed into technical indicators trading signal which reflects the market behavior since neural networks have the ability to represent both linear and non-linear relationships and the ability to learn directly the relationships of the input data that are modeled. For combination methodology, after pre-processing raw data by using technical indicators, the outputs of filtering mechanism are fed into DT. DT will be an input selection for the appropriate input variable of neural networks and only the indicators which contain any relevant information will be selected by DT. This study uses C4.5 algorithm to build DT since this algorithm has been widely used and it can handle missing attribute value, generate rules that easily interpreted and the fastest among other algorithms.

The neural network is built by using Levenberg-Marquardt training algorithm since it has been shown to be the fastest method for training feed forward neural network [32-33], an efficient training algorithm for NN and it outperform resilient propagation in many cases [39]. The architectures of creating NN model are based on several parameters. For selection of the number of hidden layers, if the accuracy of the result is a critical factor for an application then the multiple hidden layers should be used [12]. To investigate the prediction performance of the models in term of the feasibility, effectiveness, and prediction accuracy, this study uses some error measure as an evaluation benchmark. They are MSE, MAD, and MdAPE. These error measures are chosen since they can give a selection of the most accurate model among the other forecasting models.

In addition, this study also individually constructs ANN model and DT model for exchange rate prediction. All models are constructed to be compared to each other in order to evaluate their predictive performance and to get the best model. This study develops the hybrid prediction models by using the better parameters and architectures of several related works such as filtering mechanism, number of hidden layers, number of hidden neurons, training algorithm, and error measurement. This is done with the assumption that if systems are constructed by using the better parameters, the output of the systems will be better too. Based on that assumption, this study expects to get a new model with better architectures and parameters in term of the feasibility, effectiveness, and a prediction accuracy of the prediction performance in order to predict forex rate trends.

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