Probability of trend prediction of exchange rate by ANFIS

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Abstract. Modelling the human behaviour in the market of the exchange rate was always an important challenge for the researchers. Financial markets are influenced by many economical, political and even psychological factors and so it is very difficult to forecast the movement of future values. Many traditional methods were used to help forecasting short-term foreign exchange rates. In their effort to achieve better results many researchers started to use soft computing techniques over the last years. In this paper a neuro-fuzzy model is presented. The model uses a time series data of daily quotes of the euro/dollar exchange rate in order to calculate the probability of the trend prediction as far as exchange rate. The data is divided into the training data, checking data and testing data. The model is trained using the training data and then the testing data is used for model validation.

Keywords: Neuro-fuzzy, exchange rate forecasting, time series forecasting.

1 Introduction

The difficulty in predicting the exchange rates has been a long-standing problem in the international financial sector. This is mainly because of the uncertainty and volatility that hinder the efforts for an informed prediction. The reason for this volatility is that the currency exchange markets are influenced by many economical, political and even psychological factors. But because of the great profits that someone can gain from investing in this field, many researchers have tried to solve this problem. As a result, many methods were used in order to predict the currency exchange rate.

At first heuristic methods were used such as moving averages [Brown, 1963] and exponential smoothing and adaptive exponential smoothing [Triggs, 1967]. Later on, many researchers started to use the autoregressive-integrated-moving-average (ARIMA) models [Box-Jenkins, 1970], which have been widely used since the early 1980’s. In the mid 1980’s, researchers focused on the volatility of foreign exchange rates. As a result, the Autoregressive Conditional Heteroskedasticity (ARCH) model was proposed by Engle (1982) in order to predict short-
Finally, Chien and Leung (2003) developed a Bayesian vector error correction model for forecasting exchange rates.

However, the traditional statistical techniques for forecasting currency exchange rates do not have satisfactory results. Yao and Tan (2000) argued that classical time series analysis, based on the theory of stationary stochastic processes, do not perform satisfactorily on economic time series. This is because economic data are not simple autoregressive-integrated-moving-average processes, they cannot be described by simple linear structural and they are not simple white noise or random walks.


Throughout this paper a neuro-fuzzy model is presented in order to calculate the probability of the trend prediction of the exchange rate. The paper is organized as follows: first of all, some general information about the ANFIS is being investigated, and then there is a description of the model. The results using the data are being presented. Finally a conclusion is being made after taking into account all the issues discussed and rose in this study.

2 Theoretical approach of ANFIS

A neuro-fuzzy system is being defined as a combination of Artificial Neural Networks (ANN) and Fuzzy Inference System (FIS) in such a way that neural network learning algorithm is used to determine the parameters of FIS [Jang, 1993]. Adaptive Neural Fuzzy Inference System (ANFIS) is a system that belongs to neuro-fuzzy category.

Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feedforward type. Due to this minimal restriction, the adaptive network's applications are immediate and immense in various areas. In this section, we proposed a class of adaptive networks, which are functionally equivalent to fuzzy inference systems.
The fuzzy reasoning mechanism that ANFIS uses is presented in the figure 1.

For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs \( x \) and \( y \) and one output \( z \). Presumably that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type:

- *Rule1:* If \( x \) is \( A_1 \) and \( y \) is \( B_1 \) then \( f_1 = p_1 \cdot x + q_1 \cdot y + r_1 \)
- *Rule2:* If \( x \) is \( A_2 \) and \( y \) is \( B_2 \) then \( f_2 = p_2 \cdot x + q_2 \cdot y + r_2 \)

The ANFIS architecture is shown in the Figure 2. The node functions in the same layer are of the same function family as described below:
Layer 1: Every node $i$ in this layer is a square node with a node function:

$$O_i^1(x) = \mu_{A_i}(x)$$

where $x$ - the input to node $i$ and $A_i$ - the linguistic label (small, large, etc.) associated with this node function.

In other words, $O_i^1$ is the membership function of $A_i$ and it specifies the degree to which the given $x$ satisfies the quantifier $A_i$. Usually the $\mu_{A_i}(x)$ is chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}}$$

or the Gaussian function:

$$\mu_{A_i}(x) = e^{-\left(\frac{x-c_i}{a_i}\right)^2}$$

where $a_i, b_i, c_i$ is the parameter set.

As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership function on linguistic label $A_i$. Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a circle node labelled $\pi$, which multiplies the incoming signal and sends the product out.

Layer 3: Every node in this layer is a circle node labelled $N$. The i-th node calculates the ratio of the i-th rules firing strength to the sum of all rules' firing strengths:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i=1, 2$$

For convenience, output of this layer will be called normalized firing strengths.

Layer 4: Every node $i$ in this layer is a square node with a node function

$$O_i^4(x) = \overline{w}_i \cdot f_i = \overline{w}_i (p_i \cdot x + q_i \cdot y + r_i)$$

where: $\overline{w}_i$ - the output of layer 3 \{ $p_i, q_i, r_i$ \} - the parameter set.

Parameters in this layer will be referred to as consequent parameters.
**Layer 5:** The single node in this layer is a circle node labelled Σ that computes the overall output as the summation of all incoming signals, i.e.,

\[
O^5_i(x) = \text{overall output}
\]

\[
O^5_i(x) = \sum_i \dfrac{\sum w_i \cdot f_i}{\sum w_i}
\]

Consider using all possible parameters which the number is a function of both, the number of inputs and the number of membership function then can be defined number of all rules as:

\[
\text{Rule}_{n} = \prod_{i=1}^{I_n} M \cdot f_i
\]

and if \( \text{premispara}_n \) is the number of all parameters which are necessary for membership functions then the number of all parameters is defined as

\[
\text{para}_q = \text{premispara} \sum_{i=1}^{I_n} M \cdot f_i + \text{Rule}_q (I_n + 1)
\]

Some papers that used ANFIS model for time series forecasting in finance, have been presented in the literature [Atsalakis, 2005a,b,c], [Ucenic, 2005].

### 3 Model description

In this study, an Adaptive Neural Fuzzy Inference (ANFIS) model is used to forecast the trend of the exchange rate of euro and dollar one-step ahead. Fuzzy inference systems using neural networks were proposed in order to avoid the weak points of fuzzy logic. The biggest advantage is that they can use the neural networks’ learning capability and can avoid rule matching time of an inference engine in the traditional fuzzy logic system. The model has three inputs and one output and the forecasting value is given by the following equation:

\[
y(t + 1) = f(y(t), y(t - 1), y(t - 2))
\]

The data used in this model concerns daily quotes of foreign exchange rates of euro/usd, which are displayed as time series. A number of 1355 daily observations are used, from which the first 1067 observations are used to train the model and the 269 to check the model.

As we can see in the figure below the model gives very low training and checking error and the step size, initially, was set in 0.1.
Three membership functions have been used. The membership functions used are of the triangular type. The formula of such function for training the model is:

$$\mu_{A_i}(x) = \begin{cases} 
0, & x \leq a \\
\frac{x - a}{b - a}, & a \leq x \leq b \\
\frac{c - x}{c - b}, & b \leq x \leq c \\
0, & c \leq x 
\end{cases}$$

where the parameters $a$ and $c$ locate the "feet" of the triangle and the parameter $c$ locates the peak.

The initial and final membership functions are presented in the Figures 4 and 5.
4 Results

This paragraph presents the results by using the model (ANFIS). The figure below shows the diagram of the model prediction trend of the currency exchange rate.
As can be seen in figure 6 the ANFIS model performs very well and it can successfully follow the direction of the change in the exchange rate movement. In order to see that more clearly, it is calculated how many times the actual close rate has positive and negative values and it is being done the same for the ANFIS close rate. Then, it calculates the percentage of accuracy that the ANFIS makes a correct prediction. By following this procedure, the ANFIS model has 62.79% possibility to predict the trend of currency exchange rate successfully.

5 Conclusion

ANFIS, when properly configured, provides pattern-matching capabilities that can be used for predicting the ups and downs fluctuation of exchange rate. The model demonstrates the potential of neuro-fuzzy modelling in the arena of financial prediction.

The results can be used by various trading strategies in order to verify the returns. Any system that can predict the trend more than 50% can be profitable. The approximate reliability of the neuro-fuzzy predictor being 63% is extremely important despite the fact that the correct direction of the price provides no evidence of the magnitude of the movement.

References

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