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A New Hybrid Approach For Forecasting Interest Rates

David Enke*, Nijat Mehdiyev

David Enke
Department of Engineering Management and Systems Engineering
Missouri University of Science and Technology
Rolla, MO 65409-0370, USA
Email: enke@mst.edu

Nijat Mehdiyev
Department of Finance and Information Management
Technical University of Munich & The University of Augsburg
86159, Augsburg, Germany
Email: nijat.mehdiyev@student.uni-augsburg.de

Abstract

The dynamic, non-linear, volatile and complex nature of interest rates makes it hard to predict their future movements. In order to deal with these complexities, the authors propose a two-stage neuro-hybrid forecasting model. In the initial data preprocessing stage, multiple regression analysis is implemented to determine the variables that have the strongest prediction ability. The selected variables are then provided as inputs to a Fuzzy Inference Neural Network to forecast future interest rate values. The proposed hybrid model is implemented using data from the U.S. interest rate market.

Keywords: Regression Analysis, Neural Networks, Interest Rate Forecasting, Hybird Model

1. Introduction

1.1. Motivation

In addition to stock market prediction, one of the more challenging problems in the finance area involves forecasting the future movements of interest rates. The nonlinear and dynamic nature of interest rates, as well as the discontinuities and high frequency multi-polynomial time series components complicate the environment for

* Corresponding author. Tel.: 573-341-4749
E-mail address: enke@mst.edu.

predicting future returns. The nonlinear nature implies that the future interest rates are related to their past prices and have a very complicated relationship which makes it hard, but not impossible, to forecast the future returns. The Random Walk Hypothesis implies that the past interest rate values follow a martingale process, providing no information about the future, allowing one at best to only predict no change in the returns. LeRoy (1) considers that if the T-bill rates play some role for predicting future T-bill returns, whether small or large, then their movement cannot be considered random and the random walk hypothesis fails. Following this, the results of Larrain (2) indicate that past returns can determine the future interest rates. Furthermore, the relationship of the lagged interest rates and future returns are nonlinear, but these lagged interest rates are not the only determinants. The empirical results of his study reveal that fundamental factors also have to be considered when developing interest rate forecasting models.

1.2. Modeling Approaches

There are numerous research frameworks, methodologies, and models that have been implemented to predict future interest rates, including using predictions from the futures market, forecasts using surveys, no-change forecasts, and prediction with traditional statistical tools such as regression analysis, ARIMA, GARCH, VAR, and Bayesian VAR (BVAR). Dorfman and McIntosh (3) suggest that "structural econometrics may not be superior to time series techniques even when the structural modelers are given the elusive true model." The noisy and complicated structure of historical interest rates, the errors in data collection, time lags, the reciprocal dependency of the input variables, and the need for the expression of linguistic variables decrease the prediction ability of traditional statistical models. Most of these traditional models have difficulties dealing with non-linearity, non-stationary, and the dynamic environment of interest rate markets. With the increasing demand for more sophisticated models to overcome these phenomena, the use of Artificial Neural Networks (ANN) has increased rapidly in part due to their ability to deal with non-linear problems. The use of ANN for modeling time series is also not impacted by irregular sampling and shortness of the time series and has been widely accepted as a powerful tool for modeling complex nonlinear and dynamic systems. Kang (4) found that ANN forecasting models perform quite well even with sample sizes smaller than 50, while the Box–Jenkins models (ARIMA) typically require at least 50 data points in order to forecast successfully. This data-driven approach is suitable for many empirical data sets where no theoretical guidance is available to suggest an appropriate data generating process (5). ANNs, particularly Fuzzy Inference Neural Networks (FINN), are considered very strong techniques for environments that cannot be easily modeled, even when historical input-output numerical data exist. Due to its multidimensional and non-stationary environment, interest rate prediction is very sophisticated and difficult to model with mathematical expressions.

Although ANNs offer many advantages over conventional statistical tools, there are important problems that need to be considered. The first limitation of ANN modeling is the uncertainty as to which type of neural network should be chosen. Researchers have conducted numerous studies on neural network modeling for stock and interest rate prediction, but there is no consensus about which topology and data model to use. Another limitation is related to decreasing reliability, as more complicated networks require numerous experiments to overcome this problem. The difficulty of their learning - to produce an adequate model for complex, multidimensional, and dynamic systems - is one of the biggest disadvantages of artificial neural networks. Complex networks with multiple inputs, output, and hidden neurons with forward and backward links can have very complex parametric error function spaces. There can also be a limitation related to the required data structure. In general, the more data that is available, the more precise the results that are provided to and are delivered by the neural network. This can be a problem when there is not enough data to properly train the network, as might be the case for a new stock or new interest rate product. Another limitation of neural network modeling concerns data design. Different users tend to use diverse modeling approaches without following the benchmark. Buried noise, and the complex dimensionality of the interest rate market, can also make it difficult to learn or re-estimate the ANN parameters (6). Finally, ANNs tend to suffer over-fitting problems, reducing their generalization ability when they have been trained too long on the same dataset.

Existing gradient descent-based local search techniques (e.g. error back-propagation and modifications) are not efficient in finding an adequate solution in highly multi-parametric and multi-extreme search space of the network error function. However, with recent developments in the area of evolutionary computation, new search/optimization algorithms, such as Differential Evolution (DE) (7) and Particle Swarm Optimization (PSO) (8), have been made available and are perfectly suitable to utilize as learning tools for speeding up solution of search

problems in continuous numerical spaces. Aliev, et al, (9) have suggested a Fuzzy Neural Network (FNN) with a Differential Evolution-based learning algorithm for outperforming many existing models and for solving such problems as identification and control of dynamic systems and forecasting. The FNN can accept both crisp and fuzzy values as its input. Neuro-Fuzzy models allow researchers to use both quantitative and qualitative factors as input variables.

1.3. Research Purpose

The purpose of this research is to develop a model to predict future interest rates, in particularly 3-month T-bill rates. The Root Mean Square Error (RMSE) is reported to measure model performance. In order to model the interest rate markets, a Differential Evolution-based Fuzzy Inference Neural Network is utilized to eliminate the drawbacks of traditional artificial neural networks and subsequently offer a superior prediction system to previously mentioned conventional statistical techniques. All existing research in the interest rate prediction area is based either on technical factors that refer to the past values of the interest rates, or fundamental factors that imply that the various economic and financial variables are determinants of the future returns. As distinguished from the majority of the work done in this area, the authors also consider the conjunction of the fundamental factors with the historical returns of the interest rates (technical factor) to get more precise results. The volatility present in both the technical and fundamental factors that influence the interest rate markets and their dynamic environment requires a good grasp of which variables have a stronger ability to describe the tendencies in interest rates. Therefore, the proposed model is extended to include data preprocessing with regression analysis.

2. Proposed Model and Empirical Results

As mentioned in the introduction, this paper introduces a new hybrid artificial neural network model that integrates a Differential Evolution Optimization-based (DE) Fuzzy Inference System with Multiple Regression Analysis for predicting 3-month T-bill rates. As illustrated in Figure 1, there are two stages of the proposed hybrid model. The first stage reduces the variable size by using Multiple Regression Analysis (MRA) to select variables that are highly correlated with interest rate returns and therefore should have strong prediction ability. In the second stage of the proposed model, a Fuzzy Inference Neural Network, is utilized for predicting future interest rate returns using the variables chosen from the first stage.
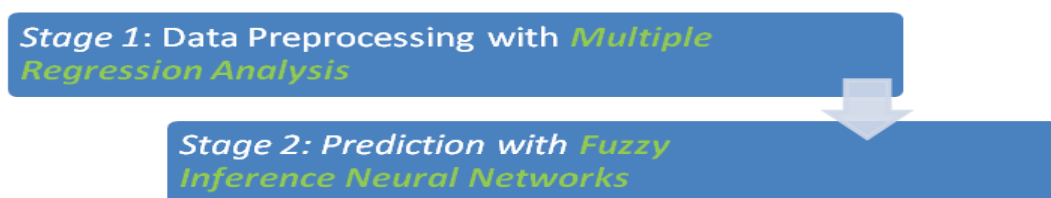

Figure 1. Proposed Model

2.1. Multiple Regression Analysis

Retaining high information content, variable selection is one of the most important issues in stock market prediction. Stage 1 of the proposed model involves reducing the dimensionality of the input variable dataset by eliminating variables with weaker forecasting ability. In the first stage of the interest rate prediction model, numerous variables can be chosen as input to the hybrid model. For the proposed model, 20 different financial and economic variables, including leading economic indicators as well as non-linear variants of historical interest rate returns, were included to the regression analysis. The quarterly data cover the period from June 1960 to January 2011, for a total of 208 data points.

The results of the regression analysis have kept the following variables for the second stage:

- $M2_{(t-2)}$ (Money Supply)
- $GNP_{(t)}$ (Gross National Product)
- $CPI_{(t-1)}$ (Consumer Price Index)
- $FFR_{(t)}$ (Federal Funds Rate)
- SP $500_{(t-1)}$ (Standard and Poor 500 Market Index)
- $r^2_{(t)}$ (Squared 3-month T-bill rate of the current month)
- $r^3_{(t)}$ (Cubed 3-month T-bill rate of the current month)

The combination of these variables indicates high correlation with the 3-month T-bill rate of the next quarter, $r_{(t+1)}$. The significance level is much less than 0.05 (5% false-positive rate), while $R^2 = 0.9377$, implying that the model provides a good fit (R = 0.9683, adjusted $R^2 = 0.9351$).

2.2. Fuzzy Inference Neural Network

The Fuzzy Inference Neural Network that was implemented in Stage 2 has five layers, in addition to the various inputs and the defuzzified output (see Figure 2). The first layer of the model consists of membership functions that map inputs to the fuzzy terms used in the rules. The second layer comprises nodes representing these rules. Each rule node performs the Min operation on the outputs of the incoming links from the previous layer. The third layer consists of output membership functions. The fourth layer computes the fuzzy output signal for the output variables. Finally, the fifth layer provides an output using the Center-of-Gravity (COG) defuzzification technique.
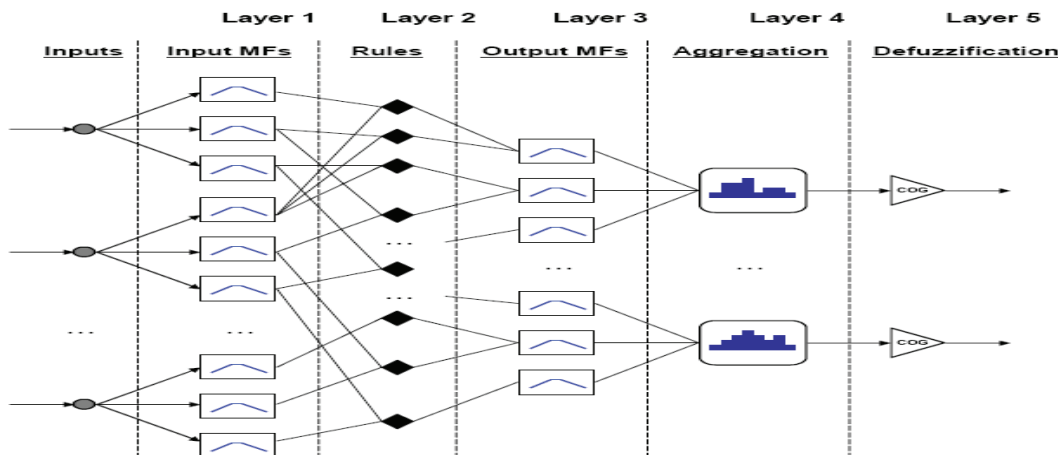

Figure 2. Fuzzy Inference Neural Network

The fuzzy inference process can be described using the following steps:

1. For each rule level of validity, define the preconditions
$$\alpha_i = \min_{j=1}^{n}[\max_{X_j}(A_j^{'}(x_j) \wedge A_{ij}(x_j))$$
   where $A_j^{'}(x_j)$ are new independent values of input variables

2. For each rule calculate the individual outputs
$$B^{'}(y) = \max(B_1^{'}(y), B_2^{'}(y),...., B_m^{'}(y))$$

3. Calculate the aggregative output:

$$B_i^{'}(y) = \min(\alpha_i, B_i(y))$$

The network was trained using a data holdout procedure. A total of 138 of the available 208 data points were used for training the network. The remaining 70 data points were used for testing. The experimental results indicate that the Fuzzy Inference Neural Network model with Multiple Regression Analysis achieves a good performance with RMSE = 0.3877. Figure 3 illustrates both the real and predicted values of the 3-month T-bill rates.
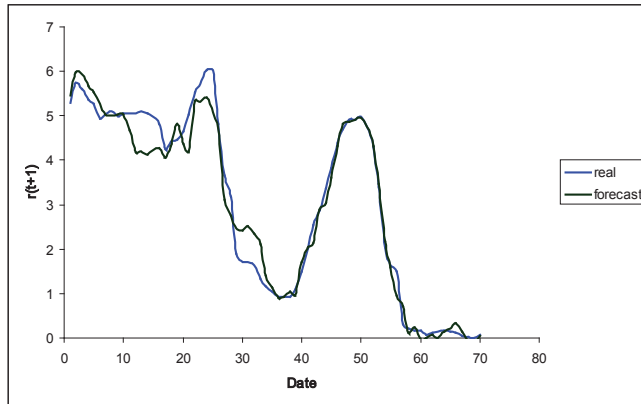

Figure 3. Real Versus Predicted Values of the 3-month T-bill Rates

3. Conclusion and Future Work

For this research, a hybrid Multiple Regression and Fuzzy Inference Neural Network model for interest rate forecasting was proposed and developed. During the first stage of the model, the number of the variables is reduced using multiple regression analysis, keeping only those variables that have strong prediction ability. One of the main differences to the existing models is the combination of the technical and fundamental factors. The following five fundamental and two technical factors were selected as input to the Fuzzy Inference Neural Network in order to predict the interest rate returns for the following period:

- $M2_{(t-2)}$ (Money Supply)
- $GNP_{(t)}$ (Gross National Product)
- $CPI_{(t-1)}$ (Consumer Price Index)
- $FFR_{(t)}$ (Federal Funds Rate)
- $SP\ 500_{(t-1)}$ (Standard and Poor 500 Market Index)
- $r^2_{(t)}$ (Squared 3-month T-bill rate of the current month)
- $r^3_{(t)}$ (Cubed 3-month T-bill rate of the current month)

The model achieves a good performance with an RMSE value of 0.3877.

To extend the current research, different data preprocessing techniques other than regression analysis can be selected and empirically analyzed to determine which model and/or technique may improve the results. In addition, before predicting future interest rate returns, the variable data from Stage 1 of the model can be clustered and the extracted rules from the clusters can be provided as input to Stage 2. Implementation of diverse types of neural networks, such as fuzzy type 2 neural networks, can also be tested in order to determine their effect on improving the results of the model.

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