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Unit Trust Forecasting using Adaptive Neural Fuzzy Inference System: A Performance Comparison

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Abstract

Unit trust market is equally important as stock market as both are contributed significantly to nation’s economic performance. Success in investing unit trust may also promises attractive benefits for investors. However, tasks to ensure successful prediction are highly complicated as many uncertainty and unpredictable factors involved. In this paper, the forecast ability of Net Asset Value (NAV) of three unit trust funds with Adaptive Neural Fuzzy Inference System (ANFIS) is examined. The objective of this study is to forecast NAV of three unit trust funds using ANFIS. Three unit trust funds were selected to model and forecast the NAV. One by four of input structure for each unit trust was defined prior to determining fuzzy rules in the fuzzy forecast. The experimental results indicate that the model successfully forecasts the NAV of the unit trust funds. The forecasting errors for the three funds were in the ranges of [-0.2461, 0.1], [-0.1384,0.08], and [-0.025,0.015]. The Pru Bond Fund recorded the least errors among the three funds. ANFIS offers a promising tool for economists and market players in dealing with forecasting NAV of unit trusts.

Keywords: Unit trust; Neural fuzzy; Error Analysis ; Forecasting

1. Introduction

Unit trust has been introduced in Malaysia relatively earlier than its Asian neighbors, when, in 1959, a unit trust was first established by a company called Malayan Unit Trust Ltd. The developments of unit trust industry in 1959 to 1979 were characterized by slow growth in the sales of units and a lack of public interest in the new investment product. Only five unit trust management companies were established, with a total of 18 funds introduced over that period. The 1980s witnessed the emergence of more unit trust management companies, which were subsidiaries of financial institutions. The period from 1991 to 1999 witnessed the fastest growth of the unit trust industry in terms of the number of new management companies established and funds under management. The period from year 2000 to current years shows a very promising future for the unit trust industry. A unit trust is a professionally managed investment fund, which pools together the money of investors having the similar objectives. Investors will invest their fund through purchase of units and the fund manager channels these funds into investment on behalf of unit holders who share in the proceeds of their investment according to the number of units held by them. The collected money will be invested by fund manager into portfolio security as share, money market bond and instrument or security to

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achieve the objective fund. The aggregate sum is then used by the fund to build a diversified investment portfolio which comprises stocks, bonds and other assets in accordance with the investment objective of the fund. The price of a unit reflects its total Net Asset Value, commonly referred to as NAV. The industry recorded double digit growth every year, growing from RM43 billion in NAV from Year 2000 to RM169 billion at 31 December 2007.

Development in financial analysis witnessing the importance of forecast modeling as successful forecasting may promise attractive benefits to investors. Adaptive Neural Fuzzy Inference System (ANFIS) is one the possible forecasting models in risk and uncertain financial forecasting environment. Jang [1] utters that ANFIS is a fuzzy inference system implemented in the framework of adaptive networks. According to Cheng et al. [2], ANFIS can overcome three major drawbacks in other time series investment forecasting models. ANFIS can be used with more than one variable and does not rely on assumptions. The rules mined from ANFIS are also easily understandable. This model is not new as it has been used in a number of fields such as engineering, education, medicine and financial investment successfully [3]. Chiang [4] points out neural networks are used by both academics and practitioners working in the area of financial analysis. The technology can be applied to finance and economies to solve complex problems. Chen and Huang [5], for example, have applied fuzzy in portfolio optimization of equity mutual fund by using fuzzy return rates and risk. Argawal et al. [6] presented an innovative approach for indicating stock market decisions that the investor should take for minimizing the risk involved in making investments. Jandaghi et al. [7] verified the capabilities of fuzzy-neural networks in a stock forecasting. Thammano [8] used the neural fuzzy model to predict the future value of bank which perform excellent in Thailand. Boyacioglu and Avci [9] investigated the predictability of stock market return with ANFIS. It seems that most the forecasting researches were concentrated on stock markets and forecasting to the investment in unit trust fund has been given very little attention. Very low return from unit trust investments is one of the possible reasons.

The contribution of unit trust fund to Malaysian economic development is enormous. It can be seen in the growth of unit trust in Malaysia. The rapid growth of asset in unit trust funds witnessing the importance of this type investment to Malaysian economics at large. However, selection of unit trust fund that can assure a good return is not always straight forward matters. The best performance of unit trust especially in uncertain and unpredictable environment requires an efficient forecasting tool. One of the possible forecasting tools that can excellently work in uncertain environment is ANFIS. Therefore, this study intends to predict performance of three selected unit trust funds in Malaysia. The performances of the unit trust fund based on NAVs is examined using ANFIS. Performance comparisons between actual NAV and ANFIS forecasting are also proposed using error analysis. Performance of unit trust may facilitate investors to make good decision in future investment.

1. A Framework of ANFIS

ANFIS is a fuzzy inference system implemented in the framework of adaptive networks. By using a hybrid learning procedure, the ANFIS can construct an input-output mapping based on both human knowledge in the form of fuzzy if-then rules and stipulated input-output data pairs and it can integrate the best features of fuzzy system and neural network.

Procedures of an ANFIS for simplicity can be illustrated by considering two inputs x, y and one output \( f_{out} \).

Layer 1: Every node i in this layer is a square node with a node function

\[
O_{1,i} = \mu_{A_i}(x), \text{ for } i = 1,2
\]

\[
O_{1,i} = \mu_{B_{i-2}}(y), \text{ for } i = 3,4
\]

Where \( x \) (or \( y \)) is the input of the node, \( A_i \) (or \( B_i \)) is the linguistic label, \( \mu(x) \) (or \( \mu(y) \)) is the membership function, usually adopting bell shape with maximum or minimum equal to 0 and 1, respectively as follows:

\[
\mu(x) = \frac{1}{1 + \left(\frac{x-c_i}{a_i}\right)2bi}
\]
or
\[
\mu(x) = \exp\left(-\left(\frac{x-c_i}{a_i}\right)^2\right)
\]  

(4)

Where \{a_i, b_i, c_i\} is the parameter set. As the values of these parameters change, the bell shaped functions vary accordingly.

Layer 2: Every node in this layer is a fixed node, marked by a circle and labelled \(\Pi\), with the node function to be multiplied by input signals to serve as output signal
\[
O_{2,i} = \mu_{A_j}(x) \cdot \mu_{B_j}(y) = \omega_j \quad \text{for } i = 1, 2
\]  

(5)

The output signal \(\omega_j\) represents in the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node, marked by a circled an labelled \(\mathcal{N}\), with the node function to normalize the firing strength by calculating the ratio of the i th node firing strength to the sum of all rules’ firing strength.
\[
O_{3,i} = \frac{\omega_j}{\sum \omega_j} = \frac{\omega_j}{\omega_1 + \omega_2} = \bar{\omega}_j \quad \text{for } i = 1, 2
\]  

(6)

Layer 4: Every node in this layer applied to the function
\[
O_{4,i} = \bar{\omega}_j \cdot f_i \quad \text{for } i = 1, 2
\]  

(7)

Where \(f_1\) and \(f_2\) are the fuzzy if-then rules as follows:

Rule 1 : if \(x\) is \(A_1\) and \(y\) is \(B_1\) then \(f_1 = p_1 x + q_1 y + r_1\)

Rule 2 : if \(x\) is \(A_2\) and \(y\) is \(B_2\) then \(f_2 = p_2 x + q_2 y + r_2\)

and where \(\{p_i, q_i, r_i\}\) is the parameter set.

Layer 5: Every node in this layer is a fixed node, marked by a circle and labelled \(\sum\), with node function to compute the overall output by
\[
O_{5,i} = \sum_i \bar{\omega}_j \cdot f_i = f_{\text{out}}
\]  

(8)

The overall error measure by:
\[
E = \sum_{i=1}^{n} E_i = \sum_{i=1}^{n} (T_i - f_{\text{out}})^2
\]  

(9)

where \(E_i\) is the error measure for the i th entry of the given training data set, \(T_i\) is the desired output of the i th entry and \(f_{\text{out}}\) is the output of the ANFIS using the i th entry. When the premise parameters \(\{a_i, b_i, c_i\}\) are fixed, the output \(f_{\text{out}}\) of the whole system will be a linear combination of the consequent parameters \(\{p_i, q_i, r_i\}\) as follows:
To calculate forecasting performance, Root Mean Square Error (RMSE) is used and the formula is shown as below:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (o_i - p_i)^2}
\]  

(11)

where \( o_i \) and \( p_i \) are the observed and predicted values on \( i \)th day, while \( N \) is the number of training data. Then, the equation can be expressed in matrix form as it shown as below.

\[
f = B^T \theta \]

(13)

Let \( \theta \) is an unknown matrix, whose elements consist of consequent parameters set. Thus, the least square estimator (LSE) \( \theta^* \) is represented by

\[
\theta^* = (B^T B)^{-1} B^T f
\]

(14)

The combination of the gradient method and the least square method in the hybrid learning algorithm is to update the parameters in an adaptive network. There are forward pass and backward pass for every epoch, which is the error tolerance in this algorithm. In forward pass, the corresponding node output is calculated by using the given input vector until the matrices in \( B \) and \( f \) in equation (12) are obtained. After using the equation (14) to identify the parameters in the consequent parameters set, the error measure is computed by using equation (9). While for the backward pass, the error rate \( \partial E_i / \partial O \) for the \( i \)th entry of the training data set and every node output \( O \) is calculated.

Let say \( \alpha \) is a parameter of the premise parameters set, then according to chain rule, the overall error measure \( E \) has the derivative with respect to \( \alpha \) which is:

\[
\frac{\partial E}{\partial \alpha} = \sum_{i=1}^{n} \frac{\partial E}{\partial \alpha}
\]
the outputs of V, the set of nodes depends on \( \alpha \), and \( \tilde{O} \) is a node output element of V. At last, by the gradient method the premise parameter has the updated formula in which \( \eta \) is a learning rate as below:

\[
\Delta \alpha = -\eta \frac{\partial E}{\partial \alpha}
\]

Figure 1 shows the framework of an ANFIS which gives a clearer picture about this study.

ANFIS as forecasting model can be used in investment and financial fields is that it plays a very important role in decision-making mechanisms.

2. Flow of the Experiment and Results

Three unit trusts were identified as Pru Growth Fund, Pru Asia Pacific Equity Fund and Pru Bond Fund. Data from the three unit trusts were gathered based on by daily base rate. Data were obtainable from prudential management fund [10] [11]. The experiment was summarized in the seven steps as shown below.

Step 1: Choose a unit trust for forecasting process
Step 2: Collect the data
Step 3: Define 1 x 4 input and 1 x 1 output structures
Step 4: Generate the membership function for input and output structures
Step 5: Train the data
Step 6: Compute the 1 x 1 output structure
Step 7: Generate and analyze forecasting errors.

As to accommodate with the purpose of this paper, the full computations are not shown but focus on performance measures instead. The final step in this experiment is error analyses. This step is essentially needed to determine the forecasting performances of the three unit trusts. The comparison between the actual data and the ANFIS forecasting provides the performances. The actual data and the ANFIS forecasting for Pru Growth Fund are shown in Figure 2.
For the Pru Growth Fund, the largest forecasting errors is in the range [-0.2461, 0.1]. Forecasting errors for Pru Asia Pacific Equity Fund and Pru Bond Fund are analysed with the similar fashion. Forecasting errors for Pru Asia Pacific Equity Fund are shown in Figure 3.

There is a huge forecasting errors on 750 days to 900 days and the largest forecasting errors for Pru Asia Pacific Equity Fund is in the range [-0.1384,0.08]. Performance of the Pru Bond Fund is shown in Fig 4.
The error on 1200 days to 1400 days and the largest forecasting error get from the ANFIS Forecasting for PRU Bond Fund is between the range of \([-0.025, 0.015]\).

From the three forecasting errors, it is apparent that Pru Bond recorded the least range of errors. Therefore, the present study concludes that investment in Pru Bond Fund is a worth.

3. Conclusions

ANFIS is a system where a relationship between inputs and outputs can be determined. ANFIS model was successfully used in scientific fields such as medicine and engineering and now can equally be extended to unit trusts forecasting. In this paper, ANFIS has been utilized as a forecasting tool to examine the performances of the three unit trust funds. ANFIS has shown the feasibility and performances of real data of NAV for the three unit trust funds. The prediction errors for the three funds were very marginal but suffice to make a comparison. Of the three funds, Pru Bond Fund is the most suitable fund to invest by using ANFIS model. It is shown by the smallest range of prediction errors. The results offer a new insight regarding the important decision in embarking fresh investment in unit trust funds. It should be cautioned that there are some limitations in financial forecasting due to the volatility in global market. Although ANFIS can be used to determine the performance of unit trust based on the daily price but still there are other factors need to consider such as market risk, single issuer risk, interest rate risk, credit risk and liquidity risk.

References


