Comparative Study of Artificial Neural Network and Regression Analysis for Forecasting New Issued Banknotes

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Abstract

This study presents neural network techniques for forecasting the value of new issued banknotes. It employs a backpropagation technique to make forecasts during 1993-1996 using the data from the preceding 12-15 years. It is found that the backpropagation technique provides forecasted results closest to the actual figures with the following parameters: learning rates (10^{-1} to 1), error goals (10^{-2} to 10^{-1}), and sum of squared errors of training data (9.30×10^{-4} to 3.26×10^{-3}). When compared to the regression technique currently being used at the Bank of Thailand, the backpropagation technique gives more accurate results.

Introduction

At the Bank of Thailand (BOT), there are three departments involved in the printing of banknotes, i.e., the Economic Research Department, the Issue Department and the Note Printing Works. The printing planning can be described as follows.

Firstly the Economic Research Department forecasts all denominations of banknotes in circulation in overall value which is approximately equal to the value of issued banknotes. The forecasting technique used is the regression analysis and the forecasts are based on the Gross Domestic Product (GDP) and the savings deposit rate. The figures are brought to the Issue Department who divide the overall amount into each denomination of banknotes, namely, 10-baht, 20-baht, 50-baht, 100-baht, 500-baht, and 1000-baht notes. The division is done manually using past experience. Then the Issue Department gives the requirements of banknotes such as the amount to be printed and the safety stock to the Note Printing Works. After banknotes are printed and used by the public, old banknotes will be exchanged at the BOT. Their condition determines whether they are still fit to use. If they are not, they will be destroyed. Those that are still usable will be reissued into the system. Figure 1 shows a schematic diagram of note printing planning.

Currently the BOT uses a regression analysis technique to forecast the required value of new issued banknotes. This technique is ranked as the most popular among all quantitative methods used in business-and finance-related applications. However, the regression model may yield forecast errors which can be almost 5%, as shown in Table 1.

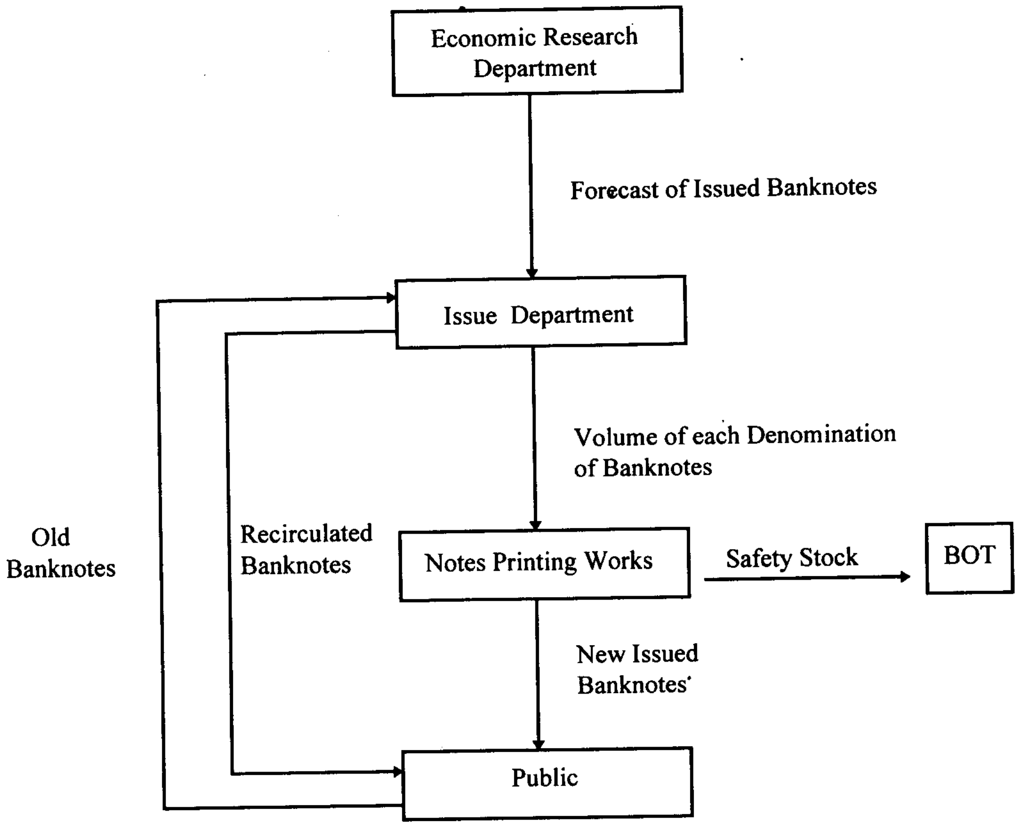

Figure 1 - The Plan of Banknotes Printing

TABLE 1
Comparison of Actual New Issued Banknotes with Forecasts by the BOT

Year	Forecast (Millions of Baht)	Actual (Millions of Baht)	Error (%)
1993	240,990.35	235,221.00	-2.45
1994	275,134.97	279,240.00	1.47
1995	317,050.22	323,148.00	1.89
1996	354,069.77	371,620.00	4.72

A neural network is introduced to a number of finance-related applications and satisfactory forecasts have been obtained. Dutta and Shekhar [2] compare regression analysis and neural network in bonding rating application and report that the regression analysis provides the parameters of a given functional form but not the correct functional form whereas neural network can determine the functional form as well as parameters by tuning both to fit the learning examples.This allows a more general framework for revealing relationships existing in the data.

Marquez et al. [6] state that Artificial Neural Network (ANN) models provide a viable alternative to classical regression models. ANN models can learn from experience, generalize and "see through" noise and distortion, and abstract essential characteristics in the presence of irrelevant data. In addition, ANN models can find the right transformations for variables, detect weak linear relationships, and deal with outliers.

The regression analysis is simple and straightforward whereas the neural network estimation is more complex. [6] found that ANN models possess considerable potential as an alternative to regression models. [2] apply ANN to predict bond ratings and show that ANN approaches consistently outperform regression methods. In case of chaotic time series, [5] finds that ANN approaches considerably outperform all existing techniques. Table 2 demonstrates the advantages and disadvantages of both regression and neural network approaches.

TABLE 2
Comparing Regression Analysis and Neural Network

Forecasting Technique	Advantages	Disadvantages
Regression Analysis	1. Easy to use 2. Easier to interpret the result	1. Limited number of variables 2. Not proper for high non-linear data 3. Only numerical data can be represented
Neural Network	1. Ability to handle more variables 2. Unlimited number of variables and more dimensions of data 3. Behaviour of data can be detected without identifying as inputs. 4. There is a trend that output will be more accurate. 5. Adaptability when parameters or data are changed.	1. Appropriate training period is unpredictable. 2. Different NN methodologies give different output which lead to uncertainty of the best solution. 3. It may lead to unstable condition. 4. More difficult and complicate to apply 5. It is difficult to get the reason why/how the network solves the problem.

The thrust of this paper is to compare the results of using regression analysis and ANN techniques in forecasting new issued banknotes. Initially, the background and the methodology currently used at the BOT are described. The neural network technique is then discussed, followed by banknote data used in this forecasting. Finally the forecasts of banknotes from both techniques are compared and discussed.

Forecasting Methodology used at the BOT

Money is a medium of exchange for goods and service. The most important form of money is banknotes. In Thailand, the BOT is the institution which is responsible for administrating banknote circulation. Some banknotes can be re-circulated. Others which are too old, soiled or damaged may have to be replaced with new issued notes. Note printing is done by the Note Printing Works of the BOT. The value of new issued banknotes is important information for planning note printing. Therefore, the accuracy of value forecasts of new issued banknotes is essential.

The equation which is obtained by executing the windows-based program called "Econometrics" and used for forecasting the value of new issued banknotes in 1996 using yearly data from 1980 to 1995 is demonstrated as follows. (see [4])

$$\ln[VN] = -2.33 + 0.99\ln[GDP] - 0.02[RS] - 0.05[D8586], \quad (1)$$

where:
- VN = value of notes in circulation,
- GDP = gross domestic product at the current price during 1980-1995 (millions of baht),
- RS = saving deposit rate during 1980-1995 (%) and
- D8586 = dummy variable involving the existence of Automated Teller Machine (ATM) during 1985-1986

It is noted that D8586 is a binary {0,1} variable of which the value is 1 during 1985-1986 otherwise it is 0.

All coefficients are changed every year and obtained by inputting all relevant historical data since 1980 into the Econometrics program. For historical data, the GDP at the current price is calculated by summing the value of goods and services produced within a country in a year. This data is collected by the BOT branches at Chiang-Mai, Khon-Kaen, and Hat-Yai. The saving deposit rate is set by the BOT according to the government's economic policies.

Substituting the model coefficients of Equation (1), i.e., GDP, RS, and D8586, by 4,689,600 millions of baht, 5%, and 0, respectively, the forecast of the 1996 new issued banknotes is 354,069.77 million baht.

Forecasting the New Issued Banknotes by a Neural Network Technique

To forecast the new issued banknotes using a neural network, two types of data, namely training data and testing data, are needed. Training data is the data used to determine the values of weight and bias from the designed network where the target outputs are known. Testing data is the data used to obtain the output where the obtained values of weight and bias are applied.

Structure of neural network models

A neural network is a computing system that imitates intelligent behavior of a human being [3]. It is made up of a number of simple, highly connected processing elements, and processes information by its dynamic state response to external inputs.

Neural networks are characterized in three ways: 1) architecture, 2) transfer function, and 3) learning paradigm used for training the network. A simple artificial neuron depicted in Figure 2 consists of a node (Y), called 'neurode', and its associated links. The value of the node, Y, is the sum of all the weighted input signals. This value is then compared with the node's threshold activation level. When its node value is equal to or greater than the threshold level, the node transmits a signal to its neighbors.

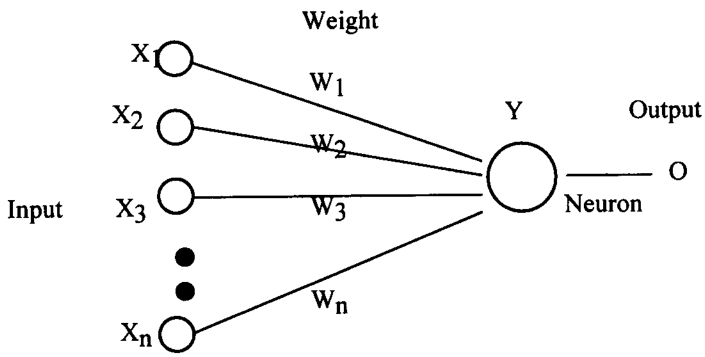

Figure 2 - A Single Artificial Neuron

Generally, a neural network can be tested using MATLAB to forecast the value of new issued banknotes [1]. Two layers of backpropagation network with tan-sigmoid and linear transfer functions in the first and second layer, respectively, are used. Several appropriate values of the parameters such as learning rate, error goal, and number of neurons are tested. Learning rate varies from 10^{-4} to 1.9, while error goal varies from 0 to 0.1 (where applicable) and number of neurons are from 1 to the number of input vectors.

Eighty percent of neural network applications utilize a backpropagation algorithm [9]. It is the most general purpose, and commonly used neural network paradigm [8].

The backpropagation approach requires a normalization process to transform data and represent them by values between 0 and 1. The available function for normalization from MATLAB is introduced to all input data which keeps data in proportion. The results are also normalized by dividing by 10^5 to make the figures less than 1.

Input Data and Results

Data selection is an important ingredient for the success of applying any neural network technique. Satisfactory results may be obtained only if the network is well trained with appropriate data. Therefore, various sets of data have been tested for the techniques used in this study. The results from each data set will be compared to find the best one.

For backpropagation, the study uses four set of parameters for input data and results. Method 1 uses GDP growth rates and saving deposit rates as input data and values of monthly issued banknotes as results. The data available for the study are from 1989-1996. They are divided into two independent groups for training and testing as shown in Table 3. Both input and results, for training data and testing data, are from 1989-1992, and 1993-1996 respectively.

The backpropagation model (Method 2) uses monthly values of admitted banknotes as input data and monthly values of issued banknotes as results. The periods for which the data are available and used in this model are from 1989-1996. All available data are divided into two independent groups for training and testing as shown in Table 3. Training data is from 1989-1992. Testing data is from 1993-1996.

The backpropagation model (Method 3) uses monthly values of admitted banknotes as input data and monthly values of issued banknotes as results. In the model, monthly data of the periods in Table 3 are available and used from 1989-1996. Different sets of data with overlapping periods are tested to see the effect of number of data periods to any improvements from Method 2. Highlighted are the data sets which result in minimum errors, and thus are the appropriate ones to use.

The backpropagation model (Method 4) uses GDP growth rates in the form of ln[GDP], saving deposit rates, and dummy variables involving the existence of ATM during 1985-1986 as input data and values of new issued banknotes as results. All data are yearly figures. The periods in which the data are available and used are shown in Table 3.

Each data set used in Method 3 is composed of several data vectors while that of Method 4 has only one data vector. Neural network models developed using Method 1-3 can forecast the new issued banknotes several years in advance, while the model using Method 4 can forecast only one year at a time.

The sum of squared errors (SSE) of testing data is a primary indicator for selecting appropriate forecasting model [3]. SSEs of testing data from Methods 1 to 4 are shown in Table 4. It is clearly seen that Method 4 provides the minimum SSE of testing data.

Discussions

The actual and the forecasted values of new issued banknotes during 1993-1996 are shown in Table 5. For a comparison of the results, forecast errors are calculated and shown in Table 6.

The negative errors indicate that the forecasted values are greater than the actual ones, while the positive errors indicate that the actual figures are greater than those forecasted. In practice, the former case results in an increase in the safety stock of new banknotes and the latter requires reissuing more old banknotes in the recycling process.

TABLE 3
Training Data and Testing Data for Neural Network Approach

Method	Forecasting Year	Training Data		Testing Data	
		Input	Output	Input	Output
1	1993-1996	1989-1992	1989-1992	1993-1996	1993-1996
2	1993-1996	1989-1992	1989-1992	1993-1996	1993-1996
3	1996	1992-1995	1992-1995	1993-1996	1993-1996
	1996	1991-1995	1991-1995	1992-1996	1992-1996
	1996	1990-1995	1990-1995	1991-1996	1991-1996
	1996	1989-1995	1989-1995	1990-1996	1990-1996
	1995	1991-1994	1991-1994	1992-1995	1992-1995
	1995	1990-1994	1990-1994	1991-1995	1991-1995
	1995	1989-1994	1989-1994	1990-1995	1990-1995
	1994	1990-1993	1990-1993	1991-1994	1991-1994
	1994	1989-1993	1989-1993	1990-1994	1990-1994
4	1993	1980-1991	1992	1981-1992	1993
	1994	1980-1992	1993	1981-1993	1994
	1995	1980-1993	1994	1981-1994	1995
	1996	1980-1994	1995	1981-1995	1996

TABLE 4
Summary of SSE of Testing Data

	Backpropagation Neural Network			
	Method 1	**Method 2**	**Method 3**	**Method 4**
SSE of Testing Data	1.0098	0.5003	0.2444	3.35×10^{-7}

TABLE 5
Comparison of the results from Neural Network and Regression (millions of baht)

Year	Actual	Regression Analysis	Backpropagation			
			Method 1	Method 2	Method 3	Method 4
1993	235,221.00	240,990.35	190,290.80	214,917.61	NA	234,200.00
1994	279,241.00	275,134.97	206,328.10	245,929.15	262,616.04	277,750.00
1995	323,147.50	317,050.22	128,124.10	267,242.47	319,127.26	328,370.00
1996	371,620.00	354,069.77	188,925.00	267,160.67	335,613.10	371,040.00

TABLE 6
Comparison of Forecast Errors (%) between Neural Network and Regression Analysis

Year	Regression Analysis	Backpropagation Neural Network			
		Method 1	Method 2	Method 3	Method 4
1993	-2.45	19.10	8.63	NA	0.43*
1994	1.47	26.12	11.93	5.95	0.53*
1995	1.89	60.35	20.92	1.24*	-1.61
1996	4.72	49.16	28.11	9.69	0.16*

*The minimum forecasting error for each period.

When comparing the results of Methods 1 and 2, the latter is found to be better. This is due to the fact that Method 2 uses values of admitted banknotes which are chosen after preliminary tests on all possible combinations of relevant variables including GDP growth rates, saving deposit rates, and values of destroyed banknotes as input data. However, the comparison between the results of Methods 2 and 3 shows that the latter is superior. This is attributed to the overlap between input data for training and testing. The overlap helps reduce the sum of squared errors.

Although there is an improvement in Method 3 from Methods 1 and 2, the model may not be practical due to the following three reasons: Firstly, it requires forecasts of GDP and saving deposit rate of the same periods as input data for testing. Secondly, forecasting for many years in advance makes the job more difficult and is not accurate if there is a shift in demand pattern. Thirdly, using monthly data requires more data sets to deal with and makes Method 3 even more difficult to use.

Method 4 forecasts on a year-to-year basis. It requires GDP growth rates and saving deposit rates as inputs. Additionally, the comparisons show that Method 4 gives minimum error for most periods. Although Method 3 provides the minimum error for year 1995, Method 4 still performs better than other methods including the regression analysis. Hence it can be concluded that Method 4 is the best in terms of forecast accuracy.

Conclusions

Similar to other forecasting methods, neural networks have problems and limitations. The accuracy of the forecasting greatly depends on historical data. If there are unforeseen events that alter data patterns from the past, neural networks may not cover the real situation. Hence this technique is most suitable for steady-state situations.

A problem may also arise when trying to directly use the demand forecast as the production volume. Users have to consider other factors, e.g., whether the BOT wants to release more old banknotes or to build up the new banknote inventory. Since the neural network approach used here is based on a time series which stipulates that the pattern in the past will repeat itself in the near future, it may not be applicable to some periods. Therefore, users should have skills and experience to adjust the forecasts.

To effectively use the backpropagation technique, users must have extensive experience in forecasting new issued banknotes. The technique requires the user's judgment to make adjustments to suit current conditions such as policies and economic situations. Besides, values of parameters that are selected in this study are expressed in terms of ranges which may be difficult to choose for users who are not familiar with neural networks or have no experience of forecasting new issued banknotes.

When using neural network, it is not necessary to check dependency of variables used in the forecast as in a regression technique. Some people misunderstand that neural network is a statistical method, but it is not. Neural network is very appropriate for situations where data have high correlation or high dependency such as the banknotes data. It can detect the relationships in both quantitative and qualitative variables during training. The two variables, i.e., the value of destroyed banknotes and the value of admitted banknotes, are clearly related to banknote release. The dependencies of parameters in the model make the forecasting complicated.

The result of this research study recommends that Method 4 be used due to its accuracy and its ability to handle complex situations. It also uses only one data vector which makes it relatively easy to train and use in making forecasts. The selected parameters and their ranges (shown in parentheses) to be used in Method 4 are learning rates (10^{-1} to 1), error goals (10^{-2} to 10^{-1}), and SSE training data (9.30×10^{-4} to 3.26×10^{-3}).

As a subject for further research, the recommended technique may be extended to forecast individual denominations since neural network is parametric sensitive (Rurkhamet, 1997). In addition, the design of the experiment may be applied to cover all appropriate experimentation and then gain better conclusions from the results.

Acknowledgements

The author are indebted to Mr.Karaket Kongkiat-Ngam, Ms.Pornpen Sodsrichai, and Dr.Anuchit Anuchitanukul of the BOT for their kind support.

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