CHAPTER VIII

ANALYSIS OF RESULTS AND RECOMMENDATIONS

The various techniques of neural network employed to forecast new issued banknotes, as described in the previous chapter, yield vastly different results. This chapter will analyze and compare the results. It will then recommend the most suitable technique as well as the procedure for its usage.

8.1 Analysis of Results

1. Model Selection

There are several techniques of neural network. Only some are appropriate for forecasting new issued banknotes. Three major techniques are investigated in this study, i.e. perceptron, Widrow-Hoff algorithm, and backpropagation.

Perceptron is considered inappropriate in this case due to the fact that the form of the output from the network is limited to binary only. This form of output is not what is required in this case.

Widrow-Hoff and backpropagation techniques are applicable to forecast in this case. However the techniques are different in how they are applied. Widrow-Hoff algorithm, which its output can only be linear, relies on initial random weight, bias, learning rate, and epoch. These factors influence on the training period, the trend (divergence or convergence), and the accuracy of the result. The trend of the output can be observed from either weight or bias, or SSE of training data. The result with minimum SSE can be picked up from the trend. For backpropagation, learning rate, number of neurons, and error goal have a major impact on the result.

Widrow-Hoff algorithm can handle only situations where inputs and outputs are of linear relation while backpropagation can handle both linear and non-linear cases. The difference may contribute to the differences in the results obtained from them in forecasting the new issued banknotes.

2. Input and Output Data

Data selection is an important ingredient for the success of applying any neural network technique. Satisfying results may be obtained only if the network is well trained with appropriate data, both input and output. 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 out the best one.

For backpropagation, the study uses four set of parameters for input and output data while Widrow-Hoff algorithm (WidHof) uses the same data set as in one of those used for backpropagation which is described in Chapter 6 (Bckprop I) .

Both WidHof and Bckprop I use GDP growth rates and saving deposit rates as input data and use values of monthly issued banknotes as output data. Both input parameters are the ones being used by the BOT to forecast yearly value of new issued banknotes with some exceptions of an adjustment in using a dummy variable involving the existence of ATM during 1985-1986. The data available for the study are from the period of 1989-1996. They are divided into two independent groups for training and testing as shown in Table 8.1.

Table 8.1 - Training and Testing Data (Bckprop I)

Forecasting for	Training Data (Input and Output)	Testing Data (Input and Output)
1993-1996	1989-1992	1993-1996

The backpropagation model as described in 7.3.3 (Bckprop II) uses monthly values of admitted banknotes as input data and monthly values of issued banknotes as output data. The periods which the data are available and used in this model are from the period 1989-1996. All available data are divided into two independent groups for training and testing as shown in Table 8.2.

Table 8.2 - Training and Testing Data (Bckprop II)

Forecasting for	Training Data (Input and Output)	Testing Data (Input and Output)
1993-1996	1989-1992	1993-1996

The backpropagation model described in 7.3.4 (Bckprop III) uses monthly values of admitted banknotes as input data and monthly values of issued banknotes as output data. In the model, monthly data of the periods in Table 8.3 are available and used from the period 1989-1996. Different sets of data with overlapping periods are tested to see the effect of number of data periods to any improvements from Bckprop II. Highlighted are the data sets which results in minimum errors, and thus the appropriate ones to use.

Table 8.3 - Training and Testing Data (Bckprop III)

Forecasting for	Training Data (Input and Output)	Testing Data (Input and Output)
1996	**1992-1995**	**1993-1996**
1996	1991-1995	1992-1996
1996	1990-1995	1991-1996
1996	1989-1995	1990-1996
1995	**1991-1994**	**1992-1995**
1995	1990-1994	1991-1995
1995	1989-1994	1990-1995
1994	**1990-1993**	**1991-1994**
1994	1989-1993	1990-1994

The backpropagation model in 7.3.5 (Bckprop IV) uses GDP growth rates in the form of lnGDP, saving deposit rates, and dummy variables involving the existence of ATM during 1985-1986 as input data and values of new issued banknotes as the output. All data are yearly figures. The periods in which the data are available and used is shown in Table 8.4.

Table 8.4 - Training and Testing Data (Bckprop IV)

Forecasting for	Training Data		Testing Data	
	Input	Output	Input	Output
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

Each data set used in Bckprop I-III is composed of several data vectors while that of Bckprop IV has only one data vector. Each of the Bckprop I-III models can forecast the new issued banknotes several years in advance, while Bckprop IV can do only one year.

3. Forecasting Accuracy

The actual and the forecasted values of new issued banknotes in 1993 to 1996 are shown in Table 8.5.

Table 8.5 - Comparison the results from NN (Table C.1-C.4) and Regression

Year	Neural Network (Millions of Baht)	Actual (Millions of Baht)	Regression (Millions of Baht)
1993	234,200	235,221.00	240,990.35
1994	277,750	279,241.00	275,134.97
1995	328,370	323,147.50	317,050.22
1996	371,040	371,620.00	354,069.77

The minimum sum-squared error of testing data and percentages of error for each approach are compared as shown in Table 8.6 and 8.7 respectively.

Table 8.6 - Summary of SSE of Testing Data

Method	WidHoff	Bckprop I	Bckprop II	Bckprop III	Bckprop IV
SSE of Testing	2.4423	1.0098	0.5003	0.2444	3.35×10^{-7}

Table 8.7 - Comparison Percentages of Error (%)

between Neural Network and Regression Analysis

Year	Neural Network				Regression Analysis
	Bckprop I	Bckprop II	Bckprop III	Bckprop IV	
1993	19.10	8.63	NA	**0.43**	-2.45
1994	26.12	11.93	5.95	**0.53**	1.47
1995	60.35	20.92	**1.24**	-1.61	1.89
1996	49.16	28.11	9.69	**0.16**	4.72

SSE of testing data is a primary indicator for selecting forecasting model [6]. From Table 8.6, Widrow-Hoff approach does not perform better than any of the backpropagation models. Backpropagation from 7.3.5 does the best forecasting by giving the minimum SSE of testing data. Forecasting errors for individual periods are with the lowest ones highlighted.

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 the forecasted. In practice, the former case may result in additional stock of new banknotes and the latter case will require reissuing of more old banknotes in recycling process.

Bckprop IV gives minimum percentages of error in most periods. Though Bckprop III provides the minimum error for year 1995, Bckprop IV does not perform significantly worse. Hence it can be concluded that Bckprop IV is the best in terms of forecast accuracies.

From Table 8.7, comparing the results of Bckprop I and II, the latter is better since it uses selected input data obtained from preliminary tests (See Table 8.1 and 8.2). The input data for Bckprop II are values of admitted banknotes which are chosen after preliminary tests on all possible combination of relevant variables including GDP growth rates, saving deposit rates, and values of destroyed banknotes.

Comparing the results of Bckprop II and III, the latter is better since the latter uses input data for training with overlapping to input data for testing which ease the difficulties to reduce sum-squared errors (See Table 8.3).

Even there is an improvement on Bckprop III from Bckprop I and II, the model may not be practival. It requires forecasts of GDPs and saving deposit rates of the same periods as input data for testing. Also forecasting for many years in advance makes the job more difficult and are not accurate if there is a shift in demand pattern. In addition, the case of monthly data which requires many more data sets to deal with the yearly data makes Bckprop III even more difficult to use.

Bckprop IV results on year-to-year basis. It requires GDP growth rates and saving deposit rates as inputs (See Table 8.4).

4. Problems and Limitations

Like any other forecasting methods, neural network also has problems and limitations. Because this method is based on historical data, if there are events that shift data pattern from the past, this approach may not cover the real situation. Hence this approach is most suitable for steady-state situation.

Demand forecasts may not be used directly as 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 base on 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 experiences to adjust the forecasts.

For neural network, it is not necessary to check dependency of variables used in the forecast like regression technique. Some people often misunderstand that neural network is a way of statistics, but it is not. Neural network is very appropriate to situations where data have high correlation or high dependency which are very much in this case. It can detect the relationships among variables during training in both quantitative and qualitative. The two variables, i.e. the value of destroyed banknotes and the value of admitted banknotes, are clearly related to banknotes release. The dependencies of parameters in the model make the network complicated.

8.2 Recommendations

It is recommended that Bckprop IV be used due to its accuracy. The selected parameters to be in Bckprop IV 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}. Procedure for using this technique is described in Appendix D.

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Although Widrow-Hoff algorithm is simpler, its performance is much less satisfactory. Bckprop IV can handle complex situations. Other approaches use more than one data vector which make it very difficult to train and use in making forecasts. The BOT should extend the forecasting using this technique to individual denominations.

Further developments from this study may be done. The recommended technique may be extended to forecast individual denominations. Since neural network is parametric sensitive, as demonstrated in Chapter 7. In addition, a design of experiment should be applied in order to cover all appropriate experimentations and then gain better conclusion on the results. For the selected method here, if possible, some more experimentations to obtain the most suitable values of parameters. Smaller ranges of parameters will result in network stability.

When using this technique in forecasting the new issued banknotes, the users must be experienced. The technique requires the user's judgements to make adjustments to suit current conditions such as policies, 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 network or have no experience of forecasting new issued banknotes.

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