

Predicting Future Depositor's Rate of Return Applying Neural Network: A Case-study of Indonesian Islamic Bank

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Abstract

Islamic bank has to perform well in order to deliver better return in compensating depositor's money. This paper is conducted to identify the relative significance assigned to macroeconomics variables for maximizing depositor's opportunity. Furthermore, it becomes very necessary to have a prediction of future rate of return to get a clear picture in making deposit decision. This research uses some key macroeconomic variables such as; Jakarta Stock Indices (JSI), inflation rate (INFR), central bank's interest rate certificate (INTR), exchange rate (ER), and money in circulation (MIC). Since these variables are characterized as nonlinearities time series data, Artificial Neural Networks (ANN) is employed using back propagation algorithm as learning algorithm. From observation resulted that central bank's interest rate certificate (INTR) and Money In Circulation (MIC) could be used as leading indicators to face the problem with 94.95% accuracy.

Keywords: Islamic bank, Rate of return, Macroeconomic variables, Artificial neural networks

1. Introduction

Rate of return in Islamic bank defines as how much money will be received by depositor from their deposit in Islamic bank for one year. The rate is equivalent with conventional bank's interest rate. Furthermore, using profit and loss sharing principle, the Islamic bank must share the profit or loss to depositors based on predetermined profit and loss sharing ratio. Accordingly, the amount of return will be received by depositor depends on Islamic bank's profitability which performance is affected by macroeconomic condition. Figure 1 shows comparison between interest rate and rate of return of an Islamic bank in Indonesia namely PT Bank Syariah Mandiri for the period 2007 and 2008. This figure explains that rate of return of PT bank Syariah Mandiri is more stable than interest rate of Indonesian commercials and states bank. In fact, from July 2007 to June 2008, PT Bank Syariah Mandiri provides higher return to its depositor then conventional bank.

In addition, the expansion of Islamic bank industry has been the hallmark of the Islamic financial landscape in the 1980s and 1990s. Currently, with a network in more than 60 countries and asset more than \$166 billion; the Islamic bank plays an increasingly significant role in their respective economies (Hassan and Bashir, 2003). However, as the biggest Muslim country in the world, the Islamic banking industry in Indonesia is still far away behind other countries such as Malaysia and Turkey. Today, Indonesian Islamic bank's total asset accounted for USD 3.287 million. On the other hand, total asset of Islamic bank in Malaysia and turkey are amounted to USD 34.543 million and USD 12.902 million, respectively.

Lately, many researches about business cycle analysis in bank industry have been conducted. However, most of them focus on the implication of macroeconomic changes on bank's profitability. Moreover, they deliver the findings as recommendation to management or policy maker, especially in Islamic bank industry. [see for example, Meyer and Pifer (1970), al-Osaimy (1998), Cihak and Hesse (2008), Maximilian (2008)]. In contrast, this research, indeed, intends to help depositor to understand which macroeconomic variables will significantly affect volatility of depositor's rate of return in PT Bank Syariah Mandiri, the biggest Islamic bank in Indonesia and afterwards use the variables to predict future rate of return.

1.1 Research Objectives

The ability to predict future rate of return will enable depositors, especially individual depositors to take precautionary action to minimize their opportunity of loss. In this context, individual depositors may simply use the most significant macroeconomic variables as indicator to predict the rate of return will be received, whether increase, decrease, or constant compared with previous period.

2. Literature review

2.1 Prior Methods used to Predict Business Cycle

Actually, many methodologies have been developed on research related with business cycle analysis and prediction. For example, Mayer and Pifer (1970) used Linear Probability Model (LPM) to predict bank failure. Moreover, Al-Osaimy and Bamahramah (2004) and Cihak and Hesse (2008) used Multi Discriminant Analysis (MDA). In addition, Dewaelheyns and Hulle (2007) and Erdogan (2008) used Distributed Lag Model (DLM) and Logit. In the same view, Kiani, Khurshid and Kasten (2006) used macro-financial variables to forecast recession. Meanwhile, Hsieh, Liu and Hsieh (2006) used MDA assisted neural network to predict bankruptcy of Taiwan company.

However, only few such studies have been conducted using neural networks such as; Al-Osaimy (1998) and Maximilian (2008) who employed neural network in Islamic banking research. Therefore, we believe that conducting research in Islamic bank using artificial neural networks (ANN) model will be interesting. This research employs the model that is considered highly flexible functional forms of nonlinear models. Accordingly, the model is used to find predictability on return generation in Indonesian Islamic bank based on macroeconomic variables as independent variables. According to Maximilian (2008), complex unstructured relationship among macroeconomics variables are often encountered, therefore ANN model is better fitted in such condition.

2.2 Superiority of ANN method

Prudence (2002) states at least two benefits of using ANN method compared with other methods in doing prediction. First, the ANN is universal approximators of function in that they can approximate all types of functional form to characterize the time series data. That means, ANN is considered data-driven rather than model-driven (Argyrou, 2006). It is because they are best suited for problems, which data have no underlying theoretical model. (Zhang, Patuwo & Hu, 1998). As a result, it makes ANN superior than other statistical methods whereas ANN is able to deal with non-linear data and multi dimensional aspect. Second, ANN method has been proven better for long-term forecast horizons. In fact, the ANN is also as good as traditional statistical methods for shorter forecast horizons. This is supported by Atiya (2001) who summarizes paper of Odom and Sharda (1990) which compares forecasting power between ANN method and MDA method. As a result, ANN achieves correct classification accuracy in the range of 77.8% to 81.5% whereas MDA's accuracy were in the range of 59.3% to 70.4% in predicting bankruptcy of 128 firms using financial ratios.

3. Methodology

In constructing model to answer the problem, this research uses bankruptcy theory. The theory said that probability of default of the firm is a function of macroeconomic variables such as interest rate, foreign exchange rate, growth rate, government expenses, unemployment rate, and aggregate savings (Azis and Dar, 2004). It means that the ability of the firm in generating profit is highly influenced by changes in macroeconomic condition. Moreover, using profit and loss sharing principles, the ability of Islamic bank to generate and to share profit with depositor is also influenced by macroeconomic condition.

Since the variables used are characterized as nonlinearities time series data, ANN model will be constructed using back propagation algorithm as learning algorithm by employing Alyuda Neuro Intelligent software version 2.2 on a Pentium IV machine, under Windows XP Professional platform.

3.1 Artificial Neural Networks Model (ANN)

ANN is a branch of artificial intelligence, which is able to solve problem especially in pattern classification and recognition. Technically, ANN benchmarks their prediction with actual results and constantly revises the

predictions to improve forecasting capability (Wong, 2009). ANN modeling approach is useful for forecasters, and researchers who employ it especially in problems where data is available but the data generating process and the underlying theories are not known. Maximilian (2008) adopted this method to modeling Islamic bank credit risk in Indonesia. He found that ANN does overcome the problem of data sufficiency that limits many forecasting methods. In such case, ANN is treated as nonlinear and nonparametric statistical methods due to the independent distributions of the underlying data generating processes (White 1989). This research employs ANN model as used by Kiani et al (2006) which can be seen below in model [1]

$$f(x) = \text{sig} \left[\alpha_0 + \sum_{j=1}^n \alpha_j \text{sig} \left(\sum_{i=1}^n \beta_{ij} x_i + \beta_{0j} \right) \right] + \varepsilon \quad \dots [1]$$

where, n is the number of hidden nodes in neural networks and k is the number of explanatory variables in the networks, $\text{sig}(x) = 1/(1 + e^{-x})$, α_j represents a vector of parameters or weight that link the hidden node to output layers unit. β_{ij} ($i=1, \dots, k$; $j=1, \dots, n$) denotes a matrix of parameters from the input to the hidden layers units and ε is the error term. Additionally, the error term (ε) can be made arbitrary small in two conditions. First, if many explanatory variables are included sufficiently, and two, if n is chosen to be large enough. However, the model can be over fit when n is too large. In this case, in-sample errors can be made very small but out-of sample errors may be large or vice versa.

3.2 Data

Initially, this research attempts to use as much as possible of macroeconomic variables as input variables. However, considering availability of data and commonly used in Indonesian Islamic banking research area, this research uses some key macroeconomics variables as used by Maximilian (2008) such as; JSI which issued monthly by Indonesia Stock Exchange (ISE), INFR, INTR, ER and MIC which issued monthly by Indonesian Central Bank (BI). As output variables, the research uses general (not special) rate of return for 1-month time deposit, which issued by PT Bank Syariah Mandiri every month. These macroeconomic variables are incorporated in the model to be analyzed which variable will be the most determinant in pricing individual depositor's rate of return. Afterwards, this research uses the variables to predict the future return. For doing so, real monthly data for sixty months are collected from January 2004 to December 2008. This whole data set is then divided into three sets, which comprise of 59 accepted data, while 1 data as outlier. (September 2008 was removed from the sample, see table 1).

Specifically, the training set is a part of input dataset for training process as adjustment process to the network weights. Besides, the validation set is a part of dataset for tuning the network topology or network parameters rather than weights. The software uses validation set to calculate generalization of loss and keep the best network which is the network with the lowest error on validation set. Meanwhile, the test set is a part of input data set that used only to test how well the neural network will perform on new data. The test set is used after the network is ready (trained), to test what errors will occur during future network application.

3.3 Analysis and Prediction Process

The process of analysis and prediction can be seen in Figure 2. In the figure, Each arrow is connecting each node that represents the information (in terms of weight) in one particular node that might influence the other node. Technically, the network puts an initial weight on each arrow. This process is updated during the iteration (called epoch) to arrive at the lowest prediction error of default probability as the output variable in the iteration process. The level of complexity and predictive accuracy on the model depends upon the number of nodes in the architecture, Maximilian (2008).

Theoretically, the choice of the best neural network architecture is based on some criteria as mentioned in the literature in the case of prediction with neural networks. It simply puts the network with the best structure, which is the one that simultaneously fulfils all the following criteria: (1) It has the smallest training error; (2) It has the smallest test error; (3) It has the smallest difference between training and testing error and (4) It has the simplest structure. The background of using ANN in this research is that of allowing the network to map the relationships between macroeconomic variables in affecting rate of return given to depositor. Once the relationship is mapped, it gives the model needed to create rate of return prediction using macroeconomic data, which is out of sample period. In this case, the out of sample periods are January, February and March 2009. Furthermore, the accuracy will be evaluated on the basis of standard statistical measures like percentage errors, as following.

$$\text{Error (i)} = \frac{\text{Rate of Return Act (i)} - \text{Rate of Return Predict (i)}}{\text{Rate of Return Actual (i)}} \times 100\%$$

for $i=1,2,\dots,n$; where n is the number of testing data points. In this evaluation, the actual data of rate of return used are also out of sample period, which are January, February and March 2009. Finally, after calculating the forecast error, the forecasting accuracy will be calculated as;

Forecasting Accuracy = 100% - percentage of error in forecasting

3.4 Using Alyuda Neurointelligence

Argyrou, A. (2006) describes how to run Alyuda Neurointelligence to build the model's architecture, train and then test the models. In the first process, the input to the software is similar to spreadsheet. Furthermore, the rate of return column is initially set up as output or target variables while the respective variables are categorized as input variables, which configured as numerical data. Next, the data is partitioned into training, validation and testing sets (table 1). Additionally, the "date" column is included in the partition process to facilitate the data partitioning. Actually, the date column is not part of the input to the models. Therefore, the column plays no role in training or testing the neural networks. In the next step, the input data must be pre-processed (i.e. rate of return and macroeconomic variables) to remove data anomalies. It is because such anomalies can degrade the neural-network performance. According to Alyuda, data anomalies fall into the following two categories: (1) missing values and (2) outliers (Alyuda Neurointelligence v. 2.2 User Manual). In particular, missing values are values that are not known. It is resulting in blank cells in the input columns. Moreover, outliers are extreme values that differ from the majority of column data. In identifying outliers, the application uses the following formula for every column.

Outliers = (mean \pm standard deviation) \times 3.5.

Consequently, for a value that lies outside this range is considered an outlier and thereby is being removed.

In the second process, the research needs to normalize the input data to make it suitable for neural-network processing. The normalization essentially transforms the input data into a new representation before a neural network is trained. Bishop (1995) offers the following three reasons for input data normalization: (1) to ensure that the size of input data reflect their relative importance in determining the required output, (2) to enable the random initialization of weights before neural network training and (3) different variables may have different units of measurements, hence their typical values may differ significantly. All the input columns are normalized in the same way. It is because, they are in numerical values. In accordance with that, Alyuda provides only one method for data normalization as follows:

$$Y = SR_{min} + (X - X_{min}) \times SF$$

Where: $SF = (SR_{max} - SR_{min}) / (X_{max} - X_{min})$; Y = Normalized value; X = actual value of a numeric column; X_{min} = minimum actual value of the column; X_{max} = maximum actual value of the column; SF = scaling factor; Sr_{min} = lower scaling range limit; Sr_{max} = upper scaling range limit. In this method, the scaling range for input columns is [-1..1].

The third process is finding the best architecture for the network. We initially define the three properties before running the application. First, the logistic activation function is selected for all the neurodes regardless of the layer in which they are located. Second, the sum of squared errors is selected to minimize the output error function. This is the sum of the squared differences between the actual value and the model's output. For completeness, we restate that the neural network output falls in the range from 0 to 1 or from 0 to 100%, due to logistic activation function used. Next, we run the "exhaustive search" to select the best possible architecture for the models. This process is considered time consuming, because it explores all possible alternatives to find the best network architecture. As a result, Alyuda chooses 7-17-1 as the best architecture for the model, which consists of one hidden layer with seventeen neurodes. In addition, the model has 5 active neurons and 2 neurons as date, which plays no role in training or testing the neural networks. Meanwhile, the output layer (OI) has a single neurode representing the model's numeric output.

In the fourth process, the model is trained with some specific conditions as follow. (1) We use backpropagation algorithm as the learning law. (2) Both learning and momentum rates are set at 0.1. (3) The training stops when the model's mean squared error reduces by less than 0.000001 or the model completes 20,000 iterations, whichever condition occurs first. All network's parameters can be seen in the table 2.

In the fifth process, the model is tested against the testing set, resulting in the respective ex-ante prediction results. So that Alyuda Neurointelligence presents the results of training and testing processes are in the form of classification matrices. Finally, using out of sample data, we generate prediction of target variables whereas the results will be tested against actual rate of return of January, February and March 2009 to measure the model's accuracy.

4. Results and Discussion

The contribution factor resulted from the network shows that INTR and MIC ranked first and second on determination of depositor's rate of return in PT Bank Syariah Mandiri. Meanwhile, INFR, JSI and EXR ranked third, fourth, and fifth (table 3). The significant macroeconomics variables resulted (INTR and MIC) are similar with condition of Islamic bank in other countries such as Bahrain, Bangladesh, Iran, Jordan, Kuwait, Malaysia, Sudan, Tunisia, Turkey and United Arab Emirates. It is reported by Ahmad and Haron (1998) which explained that interest rate and money in circulation had a significant relationship with Islamic bank's return on capital. It means that both macroeconomic variables give significant impact on delivering return to Islamic bank's depositor.

The quality of applying neural network model to do prediction based on those five variables show in general are very good (table 4). Specifically, the trained network was applied to the training data set and showed that its quality is outperforming thorough value of Absolute Error (AE) and Absolute Relative Error (ARE).

The most common error used to measure the quality of continues values are RMSE (root mean squared error), AE and ARE. Additionally, RMSE and AE are absolute value (independent of the output value module). In contrast, ARE is relative value. All these values define the deviation of the predicted output value from the desired one. Specifically, ARE is an error value that indicates the quality in neural network training. This index is calculated by dividing the difference between actual and desired output values with the unit of the desired output value. As a result, the smaller the network error is, the better the network had been trained. Table 5 shows the actual values of out of sample period used to query prediction resulted from the ANN model. The network provides 99.17% accuracy in predicting RR of January 2009. Interestingly, the results are slightly increasing when predicting February 2009 and March 2009, which are 92.79% and 92.88%, respectively. The predictions resulted from actual variables using out of period sample can be found in table 6. Finally, this network gives satisfactory result for RR prediction of three upcoming periods with 94.95% accuracy in average.

5. Conclusion

In this paper, we have specified an empirical framework to investigate macroeconomic determinants of pricing individual depositor's rate of return in PT Bank Syariah Mandiri. Accordingly, interest rates certificate of central bank of Indonesia and money in circulation significantly determine pricing individual depositor's rate of return. By implication, these variables can be used by depositor as leading indicator to predict future rate of return. Therefore, in order to maximize their profit opportunity, depositor should pay considerable attention to these macroeconomic indicators. However, it should be considered that this paper is limited in one particular bank even though the bank is the biggest Islamic bank in Indonesia. Consequently, this result might be different when it is implemented in other Islamic bank. Moreover, through the continuous adoption and application of neural networks, this research will fulfill the primary aim. The aim will provide an indicator based to build depositor's understanding about the nature of Islamic banking operation that create investment relationship. This research also indicates that an Islamic bank is not stand-alone bank since economic condition strongly influences its profitability.

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Table 1. Classification of data

Training Set	From January 2004 to March 2008
Validation Set	From April 2008 to July 2008
Testing Set	August, October, November and December 2008 while September 2008 data is removed.

Table 2. Network’s parameters

Network Parameters	Optimal Value
Learning Rate	0.1
Momentum	0.1
Training tolerance (Sum squared error goal)	0.000001
Maximum Epoch (Iteration)	20,000

Table 3. Significance contribution of each variable in the model

Input column name	Importance (%)
Date/Period	0
INFR	20.072409
INTR	31.536034
EXR	6.049945
MIC	27.923971
JSI	14.417640

Table 4. Quality of trained network

	Target	Output	AE	ARE
Mean:	7.183922	7.246047	0.355332	0.050529
Std Dev:	0.467597	0.067808	0.264465	0.040582
Min:	5.78	7.148807	0.006062	0.000828
Max:	8.24	7.344634	1.373798	0.237681

Table 5. Accuracy level of prediction using out of period sample

Period	RR Actual	RR Predicted	Error	Accuracy
Jan-09	7.20	7.259707	0.83%	99.17%
Feb-09	7.80	7.237809	7.21%	92.79%
March-09	6.76	7.241615	7.12%	92.88%

Table 6. Out of period sample

Period	Actual Value of:					
	INFR	INTR	EXR	MIC	JSI	RR
Jan-09	9.17	8.75	11,355	1,859,891	1,332.7	7.20
Feb-09	8.60	8.25	11,980	1,890,430	1,285.5	7.80
March-09	7.92	7.75	11,575	1,909,681	1,434.1	6.76

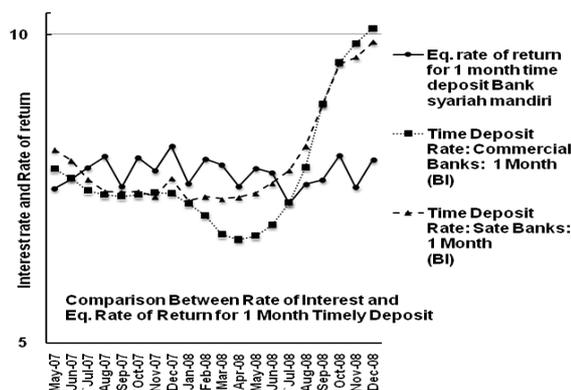


Figure 1. Comparison between rate of interest and rate of return for one-month time deposit

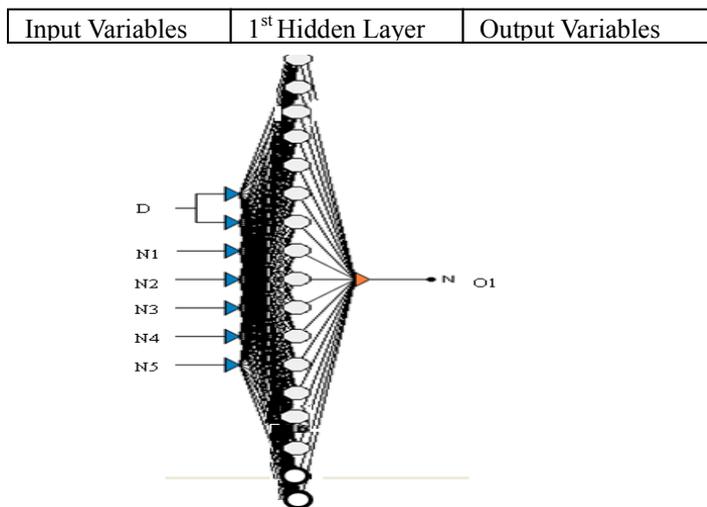


Figure 2. ANN architecture consists of 7 inputs, 1 hidden layer with 17 nodes and 1 output. D is date; N1 is JSI; N2 is INFR; N3 is INTR; N4 is ER; N5 is MIC; O1 is Islamic Bank's Rate of Return