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Comparing Accuracy Performance of ANN, MLR, and GARCH Model in Predicting Time Deposit Return of Islamic Bank

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***Abstract*—The utilization of artificial neural networks (ANN) in Islamic banking research is rarely reported. Therefore, this paper aims to examine the possibility of ANN utilization in case of predicting *mudharabah* time deposit return. This paper compares the accuracy performance of artificial neural networks (ANN), multiple linear regressions (MLR) and generalized autoregressive conditional heteroscedasticity (GARCH) model. Ten years monthly data of six macroeconomic variables are selected as independent variables. Meanwhile, the average rate of return of one month *mudharabah* time deposit of Indonesian Islamic banks (RR) is selected as dependent variable. For this purpose, the research employs Alyuda neuro intelligent software version 2.2 to develop ANN model and Eviews software version 5.0 to develop MLR and GARCH model. The performance is evaluated using visual methodology by analyzing predicted graph and statistical parameters such as R^2, Akaike's information criterion (AIC), mean absolute error (MAE) and mean absolute standard error (MASE). Accordingly, this research found that ANN outperforms MLR and GARCH model in explaining the volatility of RR. Even though GARCH model outperforms ANN in making out of sample data prediction, ANN achieves better accuracy performance in predicting one and two month ahead of out of sample data. All evidences demonstrate that ANN model provides more accurate prediction and is appropriate to be used in Islamic banking research.**

***Index Terms*—Islamic bank, rate of return, macroeconomic variables, artificial neural networks, multiple linear regression.**

I. Introduction

Forecasting technique has become very important in the literature of finance for performance analysis of the firm and assisting investor before making decisions. Particularly, when traditional statistic techniques perform low performance to deal with nonlinearities and non stationary of economic and financial data, the authors in this field have been encouraged to apply machine learning technique such as neural networks, genetic programming and support vector regression. The traditional statistic techniques commonly used in finance are multiple linear regressions (MLR) and generalized autoregressive conditional heteroscedasticity (GARCH). Both models are widely applied since their methodology has been established very well.

However, neural networks model has attracted many researchers to be applied as an alternative and becoming more popular in recent years since the ANN outperforms the traditional statistic model in terms of explained variance and out-of sample predictive accuracy [18]. Furthermore, the research motivation in bank's performance analysis and forecasting is mostly intended to provide information for management or policy maker. For example, [14] using regression technique to predict conventional bank failure using financial ratio variables. Additionally, [13] uses ANN to assess credit risk in Islamic bank. On the contrary, this research aims to examine the superiority of the ANN model in providing prediction information of one-month time deposit return for Islamic bank depositors by signaling the appropriate time to put monies in the bank when deposit return tends to rise or otherwise. To do so, the paper compares the forecasting performance of ANN, MLR and ARCH/GARCH model.

We justify the importance of this research according to the following reasons: First, the time deposit product of Islamic bank is developed using the profit and loss sharing principle. Second, prior studies suggested that Indonesian people in patronizing Islamic banks is expecting a better return rather than religion motives. Third, they freely put or withdraw their monies since the banks charge no penalty to break the time deposit account at any time. Therefore, applying the most appropriate technique for predicting one or two months ahead of time deposit return is very important to facilitate their profit motive.

According to our knowledge, this paper is considered to be the first experiment in Islamic banking research which compares neural networks and traditional statistic techniques in modeling depositor return prediction. For this purpose, this paper employs Eviews software version 5.0 to develop MLR and GARCH model and Alyuda neuro intelligent software version 2.2 to develop ANN model under Windows XP environment.

II. Literature Review

A. The role of macroeconomic variables in affecting bank's performance

This study follows the bank failure theory which issued by [9]. The theory said, "Extremely bad management may not prove fatal to a particular bank until economic condition leads to unexpected capital outflows or loan losses". Therefore, this research uses only macroeconomic variables to predict Islamic bank's performance which is reflected by time deposit return delivered to depositors.

Generally, the macroeconomic variables determine bank's profitability in the following ways: Reference [7] reports that market expansion would enable banks to increase profits as represented by a strong relationship between money supply and profit. Furthermore, stock indices may lead to a higher growth of the firm, industry and country level. Such conditions will give more profit to the banks from financing activities. Meanwhile, [5] informs that inflation positively affects the bank's profits if the revenue that accrues from business is larger than the arising of overhead cost due to inflation. Interest, on the other hand, affects the majority offunding and financing activities of a bank and later on the bank's profit.

Lastly, exchange rate does not affect profits of Islamic bank from foreign exchange trading, as it does to conventional bank, since it is prohibited. It benefits Islamic bank through its impact on the fluctuation of the price of goods that affect business trading and market.

B. *The uniqueness of Islamic bank time deposit*

One of the main sources of fund in Indonesian Islamic banks is called *mudharabah* time deposit. The banks use the fund to finance the business which is not prohibited by Islamic law and lately share the profit with depositors [10]. Unlike interest that provides fix regular revenue, the return of *mudharabah* time deposit which is represented by monthly rate of return is uncertain. Additionally, the rate is varied among Islamic banks since it depends on the bank's profitability and pre-agreed profit and loss sharing (PLS) ratio offered to depositors. Every month, the Islamic banks publish the RR report to assist depositors, comparing the current rate of return with current market interest rate.

Recently, the fund of *mudharabah* time deposit product contributes approximately 58 percent from the total depositor fund of Indonesian Islamic banks. Furthermore, the one-month mudharabah time deposit which offers the highest rate, contributes the largest portion of total time deposit fund for approximately 70 percent (Bank of Indonesia). Interestingly, the return of one-month time deposit is higher in some particular periods rather than the interest rate of one-month time deposit as depicted in figure 1.

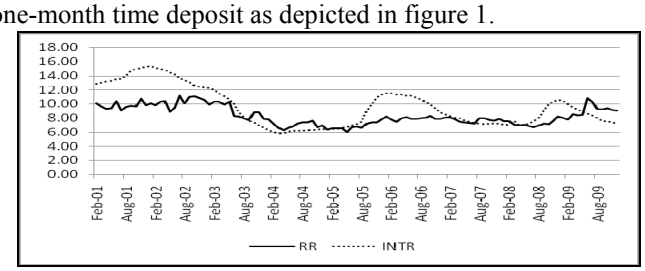

Fig.1. Comparison between *mudharabah* return (RR) and interest rate of one-month time deposit (INTR)

C. *Artificial Neural Networks (ANN) Model*

Accumulated studies have shown that ANN is better than traditional statistic model in making prediction. Reference [16] reported that ANN outperforms MLR in predicting housing value. Moreover, [17] reported the same evidence that ANN is the more powerful tool in predicting bank performance by comparing the mean square error (MSE) and mean square prediction error of both models.

Moreover, [2] confirmed the superiority of ANN against multi discriminant analysis model (MDA) in predicting bankruptcy of 128 firms. In detail, ANN achieves correct classification accuracy in the range of 77.8% to 81.5%, while MDA's accuracy is in the range of 59.3% to 70.4%. Additionally, [3] review 89 studies on corporate bankruptcy prediction. They found that ANN achieves 88% accuracy rate averagely while traditional statistical models achieve 84% accuracy rate. Although ANN model has demonstrated some successes in this area, there has been little work done on forecasting in Islamic banking and finance research using ANN model, as shown in table 1.

No	Authors	Title	Model (Year)
1	Al-Osaimy	A neural networks system for predicting Islamic bank performance.	Artificial neural networks. (1998)
2	Al-Osaimy & Bamakhramah	An early warning system for Islamic bank performance	Artificial neural networks. (2008)
3	Izhar & Asutay	Estimating the profitability of Islamic banking: Evidence from Bank Muamalat Indonesia	Artificial neural networks. (2010)

Actually, ANN is a part of machine learning technique which tries to simulate the way of learning of the human brain. Its function mimics biological neurons in which the structure consists of a group of artificial neurons which are interconnected, creating networks.

The main elements of neuron for learning or information processing are: Inputs, Weight, Summation Function, Transformation function and output. Similar to the human brain, the process of training the networks is needed to recognize patterns, develop generalization and learn to improve the performance. Accordingly, ANN is powerful to solve problem in areas of prediction and classification.

Technically, the process of ANN is briefly explained as follows. Initially, there is a neuron j which has a certain number of inputs (x_1,x_2, x_3,…x_j) and single output (y_j). Each input has a weight (w_{1j}, w_{2j}, w_{3j},...w_{ij}) as an indicator of importance of the incoming signal into neuron (j). The net value (u_j) of the neuron is then calculated with the sum of all the input value multiplied by their respective weight. Further, with reference to a threshold value (t_j) and activation function, the neuron (j) determines an output value (y_j) which will be sent as output to other neuron. Each neuron has its own unique threshold value (t_j). If the net value (u_j) is greater than the threshold (t_j), the neuron (j) will send output (y_j) to other neurons. In addition, the activation function is a function used to transform the activation level of a unit (neuron) to an output signal. Currently, sigmoid and logistic are the most popular activation functions used. All the processes are depicted in fig.2.

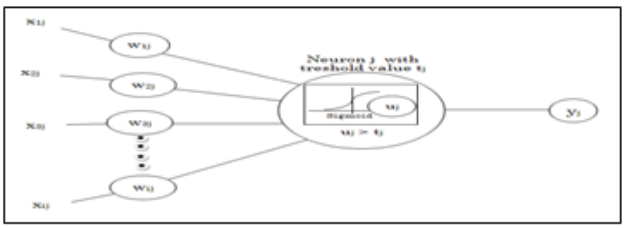

Fig. 2. A model of neuron

The typology of most neural networks generally involves a collection of neurons that are configured in two or more layers [18]. Therefore, the research combines some neurons into multilayer structures to have the power of pattern recognition and prediction. For this reason, this research employs a multi layer feed-forward networks which is the most common type of neural network currently in use. The multi layer feed-forward network comprises of input layer, hidden layer and output layer.

Specifically, the input layer is a layer that is directly connected to outside information. All data in the input layer will be feed-forwarded to the hidden layer as the next layer. Meanwhile, the hidden layer functions as feature detectors of input signals and releases them to the output layer. Finally, the output layer is considered as a collector of the features detected and as a producer of the response. In the networks, the output from output layer is the function of the linear combination of hidden unit's activation; whereas the hidden unit's activation function is in form of a non-linear function of the weighted sum of inputs. Mathematically, the ANN model can be written as in the following:

$$y = f(x,\theta) + \varepsilon \qquad \ldots \qquad (1)$$

Where x is the vector of explanatory variables, θ is weights vector (parameters) and ε is the random error component. Then, Equation (2) is the unknown function for estimation and prediction from the available data. As such, the model can be formulated as:

$$Y = f\left[v_0 + \sum_{j=1}^{m} h\left(\lambda_j + \sum_{i=1}^{n} x_i w_{ij} \right) v_j \right] \qquad (2)$$

Where:
Y = network output
f = output layer activation function
v_0= output bias
m= number of hidden units
h= hidden layer activation function
λ_j= hidden unit biases (j = 1,. . . ,m)
n= number of input units
x_i= inputs vector (i = 1,. . . ,n)
w_{ij}= weight from input unit i to hidden unit j
v_j= weights from hidden unit j to output (j = 1,. . . ,m)

D. Multiple linear regression (MLR) models

MLR is a technique used for modeling the relationship among more than two variables linearly. It is considered as the most common technique used in banking and finance area, especially for examining the financial performance in Islamic bank. For example [4] uses MLR model to measure profitability of two Sudanese Islamic bank. This model should be clear from autocorrelation, multicolinearity, and heteroscedasticity to produce Best Linear Unbiased Estimate (BLUE) model. The model is formulated as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \ldots + \beta_{p-1} X_{i,p-1} + \varepsilon_i \qquad (3)$$

Where:
Y_i = Dependent variable
X_i= Independent variables
β = Unknown coefficient
ε_i = Error term
i = 1,2,..n

E. GARCH model

Heteroscedasticity is a definition for unconstant size of expected error term of a particular time series data, wherein the expected error term depends on the size of independent variable. This condition violates the assumption of the least squares model which requires homoscedasticity in which the expected value of all error terms is the same at any given point and does not depend on the size of independent variable [8]. Accordingly, Engle in 1982, introduced the possibility of modeling the heteroscedasticity of mean error and the variance error of data series simultaneously by developing ARCH model. The essence of this model is to specify a stochastic process for the error terms and predict the average size of error terms when models are fitted to empirical data [8].

Later on, Bollerslev in1986 extended the ARCH model since the model usually needs many parameters to sufficiently describe the volatility of time series data namely Generalized Autoregressive Conditional Heteroscedasticity (GARCH). This model has only three parameters that allow for an infinite number of squared roots to influence the current conditional variance [12]. Bollerslev explained the GARCH(*p,q*) model mathematically as following:

$$Y_t = \sigma_t \epsilon_t; \quad \sigma_t^2 = \alpha + \sum_{i=1}^{p} \alpha_i e_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (4)$$

Where:
Y_t = dependent variable at current period t
σ_t = standard deviation at current period t
$\{\epsilon_t\}$= a sequence of independent and identically distributed data with mean is 0 and variance is 1.0.
α = mean value
e_{t-1}^2 = volatility of previous period t-1 (ARCH)
σ_{t-j}^2 = variance of previous period t-1 (GARCH)

III. Data And Methodology

A sample data set consisting six macroeconomic variables for the period of January 2000 – April 2010 are used as independent variables such as exchange rate of US dollar against Indonesian rupiah (EXCH), stock indices (STIN), money supply (represented by M1), inflation rate (INFR), market interest rate of one month time deposit (INTR), and central bank's interest rate (BIRT). Meanwhile, the data of average rate of return of one-month *mudharabah* time deposit of all Indonesian Islamic banks (RR) from the same period are used as dependent variable. Table 2 shows

descriptive statistics of data which used for in-sample data prediction. All data are collected from Indonesian central bank (Bank of Indonesia).

TABLE 2. DESCRIPTIVE STATISTICS

Parameters	RR	EXCH	STIN	M1	INTR	BIRT	INFR
Observations	108	108	108	108	108	108	108
Mean	7.845669	9275.611	1068.078	257351.3	9.821463	11.14417	0.686243
Median	7.69853	9178	760.5065	235892.5	10.032	10.905	0.57
Maximum	11.1475	12151	2745.83	491729	15.372	17.67	2.46
Minimum	0	7425	358.232	122160	5.852	7.32	-0.45306
Std. Dev.	1.694119	773.0911	720.4157	103588.3	2.812579	3.172921	0.584195

Initially, the relationship between independent variables and dependent variable for the period of January 2000 – December 2008 are examined separately using ANN, MLR and GARCH model. The result will indicate the significant variables among the six macroeconomic variables in determining RR fluctuation. Such information is important as preliminary understanding how those models doing their assignment by comparing the results with what theory said.

Moreover, the accuracy performance of each model is evaluated using following ways: 1. investigating actual vs. predicted graph using in-sample data. 2. Analyzing the statistical parameters. 3. Calculating accuracy rate of prediction using out of sample data

A. Working with ANN

In the beginning, all data are preprocessed to simply convert the input data into a new version for three reasons[6]. (1) To ensure the size of data reflect the importance level in determining the output. (2) To facilitate the random initialization of weights before training the networks. (3) To normalized all data to avoid different measurement due to different unit of input. Next, Alyuda provides an exhaustive search feature to design the neural networks architecture. As a result, this research use $N^{(8-6-1)}$ for learning and testing process which will be conducted later on. The configurations used for learning process are as following: (1) The logistic function is selected for all neuron. (2) The sum-of-squared errors are selected to minimize the output errors. These are summation of squared differences between the actual values and model's output. (3) The networks outputs are set up between 0 and 1 due to logistic activation function used.

Furthermore, the ANN is trained with specific condition to avoid over fitting such as using back propagation as learning algorithm, the learning and momentum rates are set at 0.1, and for completeness, the process should be stop when mean squared error reduces by less than 0.000001 or the model completes 20,000 iterations, whichever condition occur first. As a result, the process provides information about significant rate of each independent variable.

The quality of networks is investigated by using some criteria as shown in table 3. The value of correlation (r) and R^2 are the indicators of multiple correlations between independent variables and dependent variable. The coefficients of r can range from -100 to +100 percent. When the closer r is to 100 percent, the stronger the positive linear relationship between both variables. Meanwhile, mean of ARE (in absolute value) is error values that show the quality of in-sample prediction of the model. It means that the smaller the error is the better quality of the networks will be

TABLE 3. THE QUALITY OF NETWORKS

Data set	Correlation (r) in %	R^2 in %	Mean of ARE
Training data set	93.89	86.94	0.067
Validation data set	92.94	79.64	0.087
Testing data set	90.32	78.29	0.079
All data set	0.06	84.51	0.071

The ANN model shows that INTR, EXCH, STIN contribute 27.12%, 26.74%, and 22.15% in explaining RR volatility, respectively. Meanwhile, other variables such as BIRT, M1 and INFR give lesser contribution for about 13.73%, 9.76% and 0.47%, respectively.

B. Working with MLR

Initially, the research runs four times examinations to search the best MLR model which has no autocorrelation problem. However, the first three models are not sufficient to be chosen according to R^2, and Durbin-Watson (d) parameter. The prior is called a coefficient of determination which used to explain how well the independent variables determine the predicted variable which values varies from 0 to 1. In this case, the research needs a model with high value of R^2. Meanwhile, the later is a parameter to see the presence of autocorrelation whereas their values indicate the presence of autocorrelation problem. Furthermore, the research regress all independent variables using AR (1) and resulted a very good model as shown by model number 4. The model has a very high R^2 and indicates no autocorrelation as shown by Durbin Watson value (d) is 1.93 according the following formula: $4\text{-}d \geq 1.54$. Additionally, the heteroscedasticity issue from the proposed model has been accomplished using white method which is facilitated by Eviews software. This method is so-called heteroscedasticity-corrected variances. The detail parameters of each model can be found in table 4.

TABLE 4. PERFORMANCE OF REGRESSION MODELS

Model	Variables Used	Significant Variables	R2	Durbin-Watson
1	INTR, INFR, BIRT, M1, EXCH, STIN	INTR, M1 EXCH.	0.471056	0.442211
2	INTR, M1, EXCH	INTR, M1	0.434640	0.390432
3	INTR	INTR	0.373035	0.339401
4	INTR, INFR, BIRT, M1, EXCH, STIN, AR(1)	INTR, BIRT	0.851964	1.933205

Accordingly, the following MLR equation is proposed to examine the contribution of each independent variable in explaining the volatility of RR (equation 5).

$$RR = \beta_0 + \beta_1 EXCH_{i1} + \beta_2 STIN_{i2} + \beta_3 M1_{i3} + \beta_4 INFR_{i4} + \beta_5 INTR_{i5} + \beta_6 BIRT_{i6} + \varepsilon_i + AR(1) \quad (5)$$

Furthermore, the 124 data are collected. The first 108 data for period of January 2000 – December 2008 are used to

build the model. Meanwhile, the other 16 data for period of January 2009 – April 2010 are used to test the model as out of sample prediction. Actually, [11] recommended 30% of out of sample data to be used for testing the model. In this research, the out of sample testing uses 21% of total of initial sample size due to the limitation in collecting data.

Next, the least square method is used to do regression for the proposed MLR equation using AR(1). The results of least squares regression can be seen in table 5.

TABLE 5. LEAST SQUARES REGRESSION RESULTS

Dependent Variable: RR
Method: Least Squares
Date: 01/18/11 Time: 20:19
Sample (adjusted): 2000M02 2008M12
Included observations: 107 after adjustments
Convergence achieved after 7 iterations
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.283014	1.448768	3.646557	0.0004
INFR	0.004494	0.087653	0.051273	0.9592
INTR	0.824846	0.206605	3.992389	0.0001
EXCH	5.70E-05	0.000147	0.388708	0.6983
STIN	-0.000279	0.000324	-0.860529	0.3916
M1	-1.62E-06	2.36E-06	-0.686058	0.4943
BIRT	-0.460198	0.195746	-2.350994	0.0207
AR(1)	0.621213	0.108644	5.717872	0.0000

R-squared	0.851964	Mean dependent var	7.918993
Adjusted R-squared	0.841497	S.D. dependent var	1.520192
S.E. of regression	0.605226	Akaike info criterion	1.905393
Sum squared resid	36.26349	Schwarz criterion	2.105230
Log likelihood	-93.93850	F-statistic	81.39387
Durbin-Watson stat	1.933205	Prob(F-statistic)	0.000000

Inverted AR Roots .62

Accordingly, the regression formula can be written as following:

$$RR=5.28+0.000057EXCH-0.000027STIN-0.0000016M1$$
(t) (3.64) (0.388) (-0.86) (-0.68)

$$-0.0045INFR-0.82INTR-0.46BIRT+0.62 \quad (6)$$
(0.05) (3.99) (-2.35)

From the first order regression output, it was found that only two independent variables are significant in affecting RR volatility namely INTR, and BIRT. This is indicated by value of t-statistic which are 3.99, and -2.35 respectively. The value indicates should an independent variable be included in a model for 95% confident level. In other words, the research tolerates only a 5% chance that a particular independent variable does not belong in a model. Therefore, a value of t-statistic which is greater than 1.98 (if the coefficient is positive) or less than -1.98 (if the coefficient is negative) will be considered to be significant statistically. Moreover, all independent variables in the equation 5 are able to explain all variations of RR for about 85.19% as indicated by the R^2 value. Finally, the value of Akaike's information criterion (AIC) which is used to measure the goodness of fit of an estimated statistical model indicates the model is a good model (AIC value is 1.90).

C. Working with GARCH

Some trials have been conducted to find the best-fit model. Then, GARCH model combined with AR(1) sounds to be an appropriate model. This model is called as AR(1)-GARCH(1,1) which consists of the first lag of the squared RR or ARCH (1) and the first lag of the conditional variance or GARCH (1) combined with AR(1) process. The model is selected according to R^2, and AIC as shown in table 6 and normality test using Jarque-Bera statistic (see figure 3). Accordingly, the AR(1)-GARCH(1,1) model for predicting RR are formulated as it follows:

$$RR = 6.77+ 0.016INFR-8.28e-005EXCH+ 0.66INTR - 1.47e-004STIN -1.87e-006M1 - 0.35BIRT+0.62 \quad (7)$$

$$\sigma_t^2 = 0.0055 - 0.099\, e_{t-1}^2 + 1.02113512\, \sigma_{t-j}^2$$

TABLE 6. LEAST SQUARES REGRESSION RESULTS

Dependent Variable: RR
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/18/11 Time: 22:35
Sample (adjusted): 2000M02 2008M12
Included observations: 107 after adjustments
Convergence achieved after 30 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(9) + C(10)*RESID(-1)^2 + C(11)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	6.777023	0.505320	13.41135	0.0000
INFR	0.016803	0.051280	0.327665	0.7432
EXCH	-8.28E-05	3.93E-07	-210.6816	0.0000
INTR	0.669570	0.114668	5.839202	0.0000
STIN	-0.000147	0.000129	-1.147186	0.2513
M1	-1.87E-06	2.32E-07	-8.054470	0.0000
BIRT	-0.359507	0.116705	-3.080475	0.0021
AR(1)	0.626533	0.042496	14.74329	0.0000
Variance Equation				
C	0.005507	0.001937	2.843158	0.0045
RESID(-1)^2	-0.099398	0.062139	-1.599616	0.1097
GARCH(-1)	1.021135	0.043218	23.62762	0.0000

R-squared	0.845974	Mean dependent var	7.918993
Adjusted R-squared	0.829930	S.D. dependent var	1.520192
S.E. of regression	0.626921	Akaike info criterion	1.481429
Sum squared resid	37.73089	Schwarz criterion	1.756206
Log likelihood	-68.25646	F-statistic	52.72712
Durbin-Watson stat	1.924690	Prob(F-statistic)	0.000000

Inverted AR Roots .63

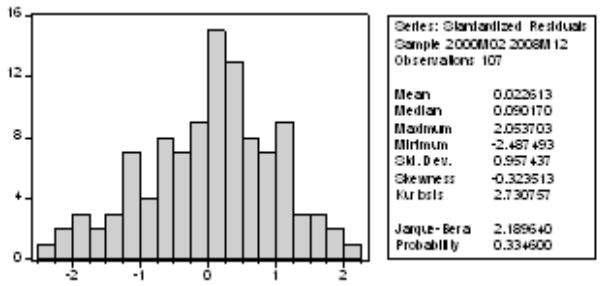

Fig 3. Jarque-Bera Statistic

Before goes to making prediction, this is necessary to do pre-estimation analysis by checking the presence of GARCH process in the selected GARCH model. This is to conform to homoscedasticity assumption which means the least square regression must have a constant variance. The analysis is conducted qualitatively and quantitatively. The former is carried out by creating plot of the sample autocorrelation function and the partial-auto correlation function to see the sign of correlation. Meanwhile, the later is carried out by calculating Ljung-Box-Pierce Q-Test. The indication of presence of GARCH process, qualitatively and quantitatively, is found as can be seen in table 7.

TABLE 7. THE PRESENCE OF GARCH PROCESS

Sample: 2000M02 2008M12
Included observations: 107
Q-statistic probabilities adjusted for 1 ARMA term(s)

Auto correlation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |* |	. |* |	1	0.069	0.069	0.5310	
. |. |	. |. |	2	0.040	0.035	0.7096	0.400
. |* |	. |* |	3	0.136	0.131	2.7721	0.250
. |* |	. |. |	4	0.073	0.056	3.3783	0.337
.*|. |	.*|. |	5	-0.068	-0.087	3.9099	0.418
. |* |	. |* |	6	0.114	0.105	5.4170	0.367
. |. |	. |. |	7	-0.009	-0.036	5.4262	0.490
. |. |	. |* |	8	0.064	0.080	5.9117	0.550
. |. |	. |. |	9	0.053	0.028	6.2402	0.620
. |* |	. |* |	10	0.157	0.140	9.1968	0.419
. |. |	.*|. |	11	-0.050	-0.075	9.5051	0.485
. |. |	.*|. |	12	-0.039	-0.076	9.6925	0.558
. |. |	. |. |	13	0.062	0.052	10.171	0.601

.*|	|	.*|	|	14	-0.094	-0.120	11.271	0.588
.*|	|	.*|	|	15	-0.115	-0.064	12.941	0.531
.*|	|	.*|	|	16	-0.078	-0.122	13.728	0.546
.*|	|	. |.	|	17	-0.065	-0.022	14.274	0.578
.*|	|	. |.	|	18	-0.063	-0.031	14.800	0.610
. |.	|	. |.	|	19	-0.014	-0.009	14.826	0.674
.*|	|	. |.	|	20	-0.068	-0.043	15.439	0.694
. |.	|	. |.	|	21	-0.034	-0.005	15.600	0.741
.*|	|	. |.	|	22	-0.077	-0.037	16.407	0.746
. |.	|	. |*	|	23	0.046	0.069	16.698	0.780
. |.	|	. |.	|	24	-0.035	0.035	16.874	0.815
.*|	|	.*|	|	25	-0.118	-0.086	18.852	0.760
.*|	|	. |.	|	26	-0.065	-0.037	19.455	0.775
. |.	|	. |*	|	27	0.058	0.072	19.950	0.794
.*|	|	.*|	|	28	-0.137	-0.103	22.739	0.699
. |.	|	. |.	|	29	-0.009	0.005	22.752	0.745
. |.	|	. |.	|	30	-0.023	-0.043	22.830	0.784
. |.	|	. |.	|	31	-0.015	-0.006	22.866	0.821
.*|	|	.*|	|	32	-0.083	-0.085	23.930	0.813
. |.	|	. |.	|	33	-0.012	-0.055	23.952	0.846
.*|	|	.*|	|	34	-0.173	-0.159	28.715	0.680
. |*	|	. |*	|	35	0.069	0.130	29.486	0.689
. |.	|	. |.	|	36	0.001	-0.009	29.486	0.731

It shows that there is a possible correlation between present and previous volatilities which indicates the fact that the variables are appropriate to be analyzed using GARCH model. Finally, according to table 6, the significant variables which influence the volatility of RR can be determined. It shows that EXCH, INTR, and BIRT are significant statistically for 95% confident level.

D. *Accuracy Performance Comparison*

The research uses three methods to compare the performance of each model as follow: (1) Comparing graph of actual and predicted RR using in sample data. (2) Comparing four statistical parameters such as R^2, AIC, mean absolute error (MAE) and normalized means squared error (NMSE). Actually, NMSE and MAE are parameters used to evaluate how close the prediction results are to the eventual outcomes MAE and NMSE parameter are calculated as follow:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|ActualRR_t - \Pr edictedRR_t\right| \qquad (8)$$

$$\text{NMSE} = \frac{1}{n}\sum_{t=1}^{n}\frac{\left(ActualRR_t - \Pr edictedRR_t\right)^2}{\sigma^2 \Pr edictedRR} \qquad (9)$$

(3) Investigate accurateness of models in making prediction using out of sample data according to equation 10, as follows:

$$Accuracy\ power = 100\% - \%\ Error\ of\ prediction \qquad (10)$$

IV. Result

As shown in figure 4, it suggests that ANN outperforms MLR and GARCH model since the predicted line of ANN locates closer to actual line rather than other model.

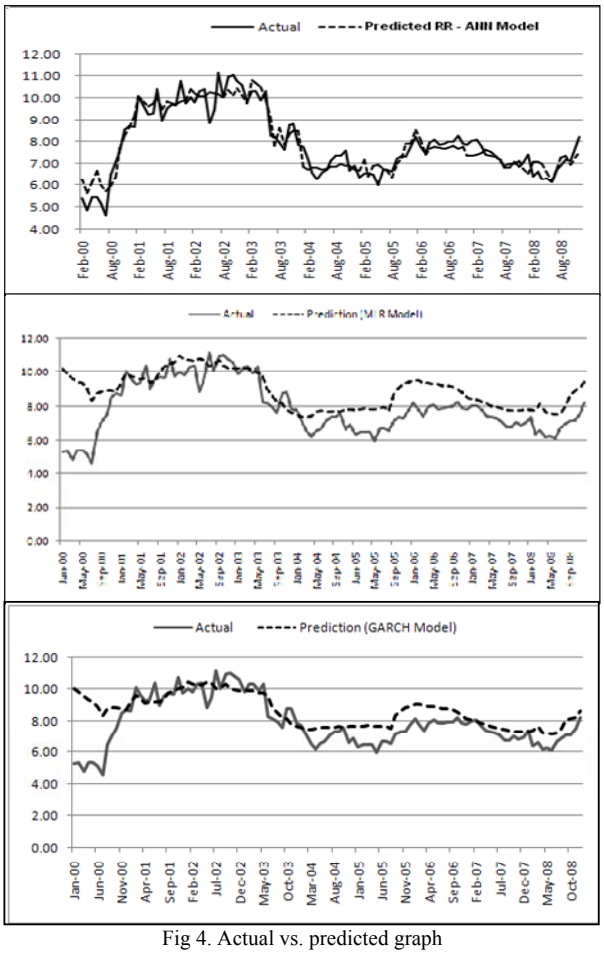

Fig 4. Actual vs. predicted graph

Furthermore, using statistical criteria as shown in table 8, it supports the graph finding that ANN's performance is better in which the value of R^2 is higher than such value of MLR and GARCH. On the other hand, the AIC, and MAE of ANN are lower than both models. Interestingly, the NMSE value of ANN is slightly higher than GARCH model which indicates the normalized mean squared error of prediction generated by ANN is larger. Thus, according to equation 9, the NMSE value of ANN has strengthened the previous finding in which the ANN's variance (σ^2) in making prediction is smaller than GARCH. Therefore, the ANN model is more appropriate to be used as prediction model rather than GARCH model due to its ability to reduce the volatility of error as needed when making prediction. The all conditions mentioned above demonstrate that ANN outperforms traditional technique in explaining RR volatility statistically.

TABLE 8. Performance Comparison Between ANN and MLR Model Using Statistical Criterion

Statistical Criterion	ANN	MLR	GARCH
R^2	**0.8786**	0.8519	0.8459
AIC	**-283.7863**	1.9053	1.4814
MAE	**0.4010**	1.1826	0.4050
NMSE	**0.2778**	1.9677	0.2298

Finally, the out of sample data prediction is carried out using formula 10 which the result is shown in table 9. It demonstrates that, in average, GARCH outperforms ANN and MLR model in this prediction which accuracy are 80.2%, 78.6% and 77.0% respectively. However, ANN provides better accuracy in predicting one and two months ahead of RR with 94.1% and 89.7%, respectively.

TABLE 9. ACCURACY RATE CALCULATION

Month	Actual	Prediction Results			Accuracy Performance		
		MLR	ANN	GARCH	*MLR*	ANN	GARCH
Jan-09	8.03	9.99	7.56	9.00	75.6%	94.1%	87.94%
Feb-09	7.73	10.02	6.93	8.94	70.3%	89.7%	84.34%
Mar-09	8.49	9.81	6.97	8.82	84.4%	82.1%	96.17%
Apr-09	8.32	9.78	7.67	8.86	82.4%	92.2%	93.47%
May-09	8.45	9.64	7.58	8.76	85.9%	89.7%	96.37%
Jun-09	10.77	9.55	7.53	8.65	88.7%	69.9%	80.35%
Jul-09	10.26	9.43	7.44	8.60	91.9%	72.5%	83.78%
Aug-09	9.24	9.10	7.14	8.25	98.4%	77.3%	89.33%
Sep-09	9.20	8.77	6.97	8.05	95.4%	75.8%	87.46%
Oct-09	9.38	8.79	7.36	8.05	93.7%	78.5%	85.81%
Nov-09	9.09	8.64	7.41	7.94	95.1%	81.5%	87.31%
Dec-09	9.06	8.50	7.25	7.82	93.8%	80.0%	86.36%
Jan-10	5.71	8.68	7.18	8.05	47.9%	74.3%	59.03%
Feb-10	5.39	8.55	7.39	7.92	41.4%	62.9%	52.99%
Mar-10	5.97	8.52	7.57	7.89	57.3%	73.2%	67.89%
Apr-10	5.86	9.96	7.97	9.07	30.0%	64.0%	45.25%
Accuracy performance in average					**77.0%**	**78.6%**	**80.2%**

V. CONCLUSION

From the study, we may conclude that ANN model can be used for predicting RR due to its better performance compared with traditional statistics model such as MLR and GARCH. Furthermore, the utilization of MLR and GARCH in modeling bank's performance based on macroeconomic variables is not as easy as ANN. The research needs extra effort to conform to the underlying assumption of regression model. It shows that developing regression model using macroeconomic variable is not an easy task since macroeconomic data are characterized as non linear time series data which violate the assumptions of linear regression [15]. On the contrary, with Alyuda neuro intelligent software, such task is quiet simple. The ANN's ability in self learning benefits the model which no needs preliminary assumptions. Additionally, the ANN, MLR and GARCH model provides information that market interest rate (INTR) is the leading indicator for predicting RR. Thus, the information will benefit depositor to simply concentrate on market interest rate to predict future RR.

Besides giving benefit for depositors and Islamic banks, the utilization of RR prediction model will also promote the expansion of Islamic bank industry. Because, the prediction information will provide more options for depositors to find other Islamic bank which probably provide better return. As a result, it will keep depositor funds stay longer in Islamic bank industry before shifting to conventional bank.

Somehow, this research has limitation that Alyuda software cannot provide the internal process of learning which describe the reasoning behind a prediction provided by neural networks. Therefore, the future research will be conducted by employing other software which is able to provide it.

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