Stock Price Prediction With Long Short-Term Memory Recurrent Neural Network

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***Abstract*— In this paper, we investigate the prediction of daily stock prices of the top five companies in the Thai SET50 index. A Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) is applied to forecast the next daily stock price (High, Low, Open, Close). Deep Belief Network (DBN) is applied to compare the result with LSTM. The test data are CPALL, SCB, SCC, KBANK, and PTT from the SET50 index. The purpose of selecting these five stocks is to compare how the model performs in different stocks with various volatility. There are two experiments of five stocks from the SET50 index. The first experiment compared the MAPE with different length of training data. The experiment is conducted by using training data for one, three, and five-year. PTT and SCC stock give the lowest median value of MAPE error for five-year training data. KBANK, SCB, and CPALL stock give the lowest median value of MAPE error for one-year training data. In the second experiment, the number of looks back and input are varied. The result with one look back and four inputs gives the best performance for stock price prediction. By comparing different technique, the result show that LSTM give the best performance with CPALL, SCB, and KTB with less than 2% error. DBN give the best performance with PTT and SCC with less than 2% error.**

Keywords— recurrent neural network; long short-term memory; stock price prediction.

I. INTRODUCTION

Many people have interested in stocks price prediction in hope for the best stock investment. There are many factors that affect the stock price movement such as inflation rates, economic environment, political issue, and so on [1]. These factors make stock price prediction to be a difficult task which is of interest in academic and business fields. Two main stock price prediction methodologies are soft computing analysis and non soft computing analysis [2]. In this paper, Soft computing analysis methodologies, especially deep learning is interested. The application of RNN with LSTM which is a new generation of deep learning is investigated.

Deep learning has a great advantage that can learn very complex function [3]. A recurrent neural network (RNN) is one of deep learning type. An RNN is a class of neural networks that add additional weights to the network. The purpose is to create cycles in the network graph to maintain an internal state. RNNs can store information while processing a new input because RNNs are the networks with loops that allow information to persist [4]. In addition, RNNs can learn and exploit context in sequence prediction problems but there is a problem of vanishing gradient in back-propagation through time. Long-Short Term Memory is proposed to solve this problem. An LSTM is a building block or unit for a layer of RNN. LSTM has a memory or gate cell, information can be stored in, written to, or read from a cell, much like data in a computer's memory [5]. Thus, an LSTM is an interesting technique for stock price prediction.

The purpose of this paper is to explore the prediction for the next day stock price. Top five Thai stock index is selected from the Stock Exchange of Thailand 50 (SET50) index. A Recurrent Neural Network (RNN) with Long-Short Term Memory (LSTM) is applied in this research.

The paper is organized as follows. In section II, literature review are introduced. Section III presents the architecture of recurrent neural network with long short-term memory and deep belief network. In section IV, data and Parameter set up are discussed as well as the input data and KPI measurement. In section V, the experiment result is shown. The comparison of top five companies from the SET50 index in different length of training data is displayed. Afterward, the comparison of one and two looks back with three different inputs is demonstrated. Section VI is regarded as the conclusion.

II. LITERATURE REVIEW

There are many research papers on stock price prediction.They used an Artificial Neural Network (ANN) [6][7][8][9], a Recurrent Neural Network (RNN) [10], RNN with hybrid model [4], and a Recurrent Neural Network with Long Short-Term Memory [11][12][13].

Adebiyi, Charles, and Marion apply an Artificial Neural Network to predict close price. A combination of technical and fundamental analysis variable is used as the inputs. In this paper is compared the model by testing with technical variables, fundamental analysis variables, and hybrid variables. The result of the hybrid model gives the best result [6]. Billah, Waheed, and Hanifa proposed the Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System (ANFIS) in MATLAB to predict close price [7]. As a result, ANFIS gives a better prediction result. Tsang and Kwok investigated buy and sell signal of stock price prediction. An Artificial Neural Network is proposed in this research. The model successfully predicts the stock price with 70% accuracy [9]. From the previous study, ANNs are an effectiveness and efficiency technique for stock price prediction. But ANNs is not applied on a time series prediction. As stock price change through the time period. A technique of Recurrent Neural Network is proposed as a time series prediction.

Hsieh, Hsiao, and Yeh (2011) integrated wavelet transforms and recurrent neural network based on artificial bee colony algorithm. The close price of the Dow Jones Industrial Average Index (DJIA), London FTSE-100 Index (FTSE), Tokyo Nikkei-225 Index(Nikkei), and Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) was predicted [10]. Another research of Akhter, Arun, and Sastry (2015) proposed a method of RNN and a hybrid model for prediction of stock returns [4]. All these studies provide the better result of stock price prediction. The development of RNN is more effective, to solve the problem of vanishing gradient was proposed as LSTM.

Zhuge, Xu, and Zhang proposed two models; emotional analysis model and long short-term memory (LSTM) time series learning model for stock price prediction [11]. The research of Kai Chen, Yi Zhou, and Fangyan Dai modeled and predicted China stock returns using LSTM. The input data of daily stock price are the feature to LSTM network. LSTM model returned the accuracy result from 14.3% to 27.2% [12]. Hengjian investigated the effectiveness of LSTM networks for stock price prediction. By applying the Google daily stock data include the open, high, low, close and volume to predict the next day of daily stock price. The result shows that LSTM predicts google stock price with less than 1% error of RMSE [13].

All above research paper was successfully predicting stock price by using various technique include ANN, RNN, and LSTM. For recently technique of RNN and LSTM was successfully applied on foreign stock price prediction. In this research, an analysis from Stock Exchange of Thailand (SET50) index with LSTM is done.

III. The Architecture of Neural Network

A neural network is highly structured and comes in layers. The first layer is the input layer. The final layer represents the output layer. All layers in between these two layers are referred as hidden layers. An input or output layer are independent of each other in a traditional neural network. A simple Neural Network structure is shown in “Fig. 1,”.

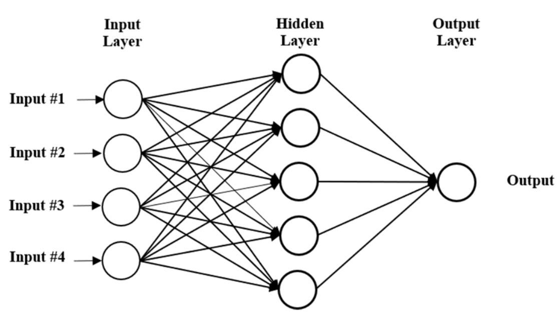

Fig. 1. Neural Network Structure

A. Long-Short Term Memory

A Recurrent Neural Network (RNN) was proposed by Jeff Elman [16]. A Recurrent Neural Network (RNN) is a variant of the deep neural network (DNN) which has an ability to handle the sequential data [11]. The idea behind RNNs is to make use of sequential information. RNNs are called recurrent because they perform the same task for every element of a sequence, with the output being depended on the previous computations [4].

In “Fig. 2,” x_t is an input at time step *t*, h_t is the hidden output at time step *t*, and y_t is an output at time step *t*. At time step *t* = 1, x_1 and h_0 are the inputs and the output is y_1. At time step *t* = 2, x_2 and h_1 are the inputs and the output is y_2. This shows that the RNN output of each time step is depend on the current input and the previous output from the hidden layer.

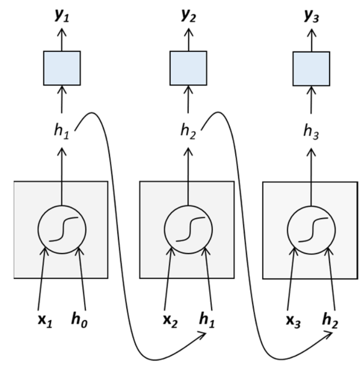

Fig. 2. Recurrent Neural Network Structure.

An important attribute of RNNs is the ability to map from the entire history of inputs x_t to each output y_t. Typically, an RNN is an extremely difficult network to train. The problem of the vanishing gradient is exponentially worse for an RNN. This leads to exponentially small gradients and a decay of information through time. Long-Short Term Memory (LSTM) is proposed to solve this problem.

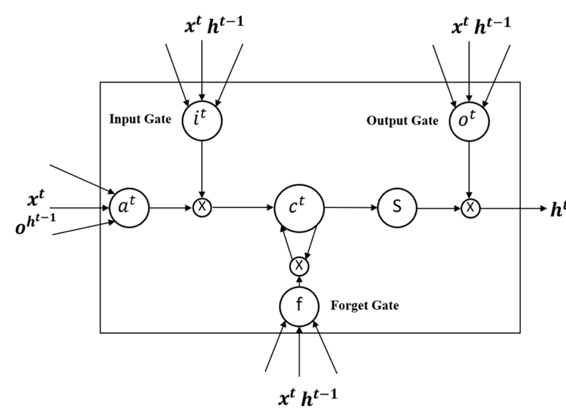

Fig. 3. LSTM memory block with a single cell

Long short-term memory (LSTM) networks were invented by Hochreiter and Schmidhuber in 1997 [17]. The basic unit of the LSTM architecture is a block memory with one or more different types of memory cells. These memory cells have three adaptive multiplications gates called input gate, forget gate and output gate [5]. The forget gate conditionally decides what information to throw away from the block. The input gate conditionally decides which values from the input to update the memory state. The output Gate conditionally decides what to output based on input and memory of the block. As in "Fig. 3," initially, at time *t*, the memory cells of the LSTM contain values from the previous iteration at the time (*t−1*). At time *t*, The LSTM receives a new input vector x^t (including the bias term), as well as a vector of its output at the previous timestep $o^{h^{t-1}}$. During this step, the values of the memory cells are updated with a combination of a^t , and the previous cell contents *c(t−1)*. The combination is based on the magnitudes of the input gate and the forget gate *ft*. The contents of the memory cells are updated to the latest values. Finally, the LSTM cell computes an output value by passing the updated (and current) cell value through a non-linearity. The output gate determines how much of this computed output is actually passed out of the cell as the final output h^t .

B. Deep Belief Network

Deep belief Networks were conceived by Geoff Hinton [14]. Deep belief network (DBN) is a class of deep neural network. DBN generally constructed by stacking of more than one Restrictive Boltman machine (RBM). [15] An RBM is two-layer stochastic network with input layer and visible layer. A DBN is trained as follows:

1. The first RBM is trained to re-construct its input as accurately as possible.
2. The hidden layer of the first RBM is treated as the visible layer for the second and the second RBM is trained using the outputs from the first RBM.
3. This process is repeated until every layer in the network is trained.

A greedy training approach is generally used to prepare the first stack of RBM. The input is mapped as visible layer. The output is mapped to the hidden layer. Contrastive Divergence is used to train RBM with positive phase and negative phase. A positive phase is updated all hidden units in parallel from visible unit. A negative phase is reconstructed the visible units from hidden units [15].

IV. DATA AND PARAMETER SET UP

The Stock Exchange of Thailand (SET) was officially established on April 30, 1975 [18]. The SET50 index and the SET 100 index are chosen based on large market capitalization, high liquidity and distribution of shares to minor shareholders [19].

In this research paper, five companies with different volatility from the SET50 list are selected for testing. The purpose of selecting these five stocks with various volatility is to compare how the model performs in different conditions. The five stocks are PTT public company limited (PTT), the Siam Cement Public company limited (SCC), the Siam Commercial Bank Public company (SCB), Kaksikorn Bank Public company limited (KBANK), and CPALL public company limited (CPALL).

The LSTM Recurrent Neural Network was applied in this study with varied input data. The network has a visible layer with four inputs, five inputs, and six inputs; a hidden layer with four LSTM blocks or neurons; and an output layer that makes daily stock price predictions. TABLE I indicates the input features for the network.

TABLE I INPUT FEATURES

Input Data		
Four Inputs	Five Inputs	Six Inputs
High Price (HP) Low Price (LP) Open Price (OP) Close Price (CP)	High Price (HP) Low Price (LP) Open Price (OP) Close Price (CP) Volume (V)	High Price (HP) Low Price (LP) Open Price (OP) Close Price (CP) Volume (V) 3days Simple Moving Average

The default sigmoid activation function is used for the LSTM blocks. The network is trained for 200 epochs with one look back and two lookbacks. One look back means training the model with one period back. As in the model, the LSTM model remembers the previous state. The input data of yesterday is used to predict the output data of today. All stocks are tested with a different length of training data. One-year training data is tested from 30th December 2015 to 30th December 2016. Three years of training data are tested from 30th December 2012 to 30th December 2016. Five years of training data are tested from 30th December 2011 to 30th December 2016.

The default relu activation function is used in Deep Belief Network (DBN). The network is trained for 200 epochs. All five stocks are tested in one-year training data with four inputs. High price, low price, open price, and close price are applied as the input data. The model is built by applying Long Short-Term Memory (LSTM) and DBN. It predicts high price, low price, open price, and close price. Ten-months data from 4th January 2017 to 30th October 2017 is tested. This research use Root Mean Squared Error (RMSE), Mean Absolute Percent Error (MAPE) and Mean Squared Error (MSE) to measure the error, which is the difference between the forecasted value and actual value. MAPE is a measure of prediction accuracy of a forecasting method in statistics [20]. The unit of MAPE is percentage. The MSE is a measure of the quality of an estimator. The value of MSE is always non-negative, and the closer to zero is better in term of accuracy [11]. Root Mean Square Error (RMSE) is the square root of the average of squared errors. RMSE represents the standard deviation of the differences between predicted values and observed values of a sample [9].

The functions of MSE, RMSE, and MAPE are shown as follows:

$$\text{MSE} = \frac{\sum_{t=1}^{n}(g_t - f_t)^2}{n} \tag{1}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(g_t - f_t)^2}{n}} \tag{2}$$

$$\text{MAPE} = \left[\frac{1}{n}\sum\frac{|g_t - f_t|}{g_t}\right] * 100 \tag{3}$$

where, g_t = actual value.
f_t = forecasted value.
n = number of data points.

Daily stock price is forecasted including HP, LP, OP, and CP. Moreover, the rolling technique is applied for training the model. For example, one year of data from 1st January 2015 to 30th December 2016 is used for training. The trained model is used to forecast 1st January 2017. After that, 1st January is added to update the model to forecast 2nd January 2017. This helps to reduce the error of forecasting.

V. Experiment Result

The results of the experiments are reported and discussed in this section. "Fig. 4,", "Fig. 5,", "Fig. 6,", and "Fig. 7," show the boxplots that compare five stocks in one-year, three years, and five years. The box plots are standardized display for the distribution of data based on five-number summaries: minimum, first quartile, median, third quartile, and maximum. The middle line is the median value of MAPE. The line outside the box is the outlier. "Fig. 4," is the boxplots that display MAPE of the close price. The result shows that CPALL gives the lowest median value of MAPE for one year and three-year. For five-year comparison, SCC gives the lowest median value of MAPE. "Fig. 5," is the boxplots that show MAPE of the high price. The result shows that SCC for one year and three-year give the lowest median value of MAPE. For five-year comparison, SCB gives the lowest median value of MAPE. "Fig. 6," is the boxplots that display by MAPE of the low price. The result shows that PTT and CPALL give the lowest median value of MAPE for one-year comparison. For three-year comparison, SCC and CPALL give the lowest median value of MAPE. For five-year comparison, SCC gives the lowest median value of MAPE. "Fig. 7," is the boxplot that shows MAPE of the open price. The result shows that SCC and CPALL give the lowest median value of MAPE for one-year comparison. For three-year and five-year comparison, SCC gives the lowest median value of MAPE.

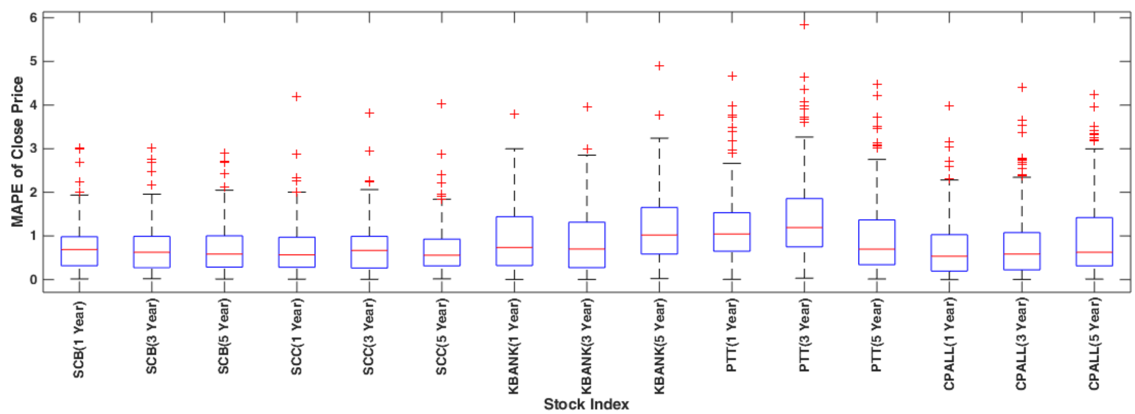

Fig. 4. Box plot comparisons for MAPE of testing data for close price prediction

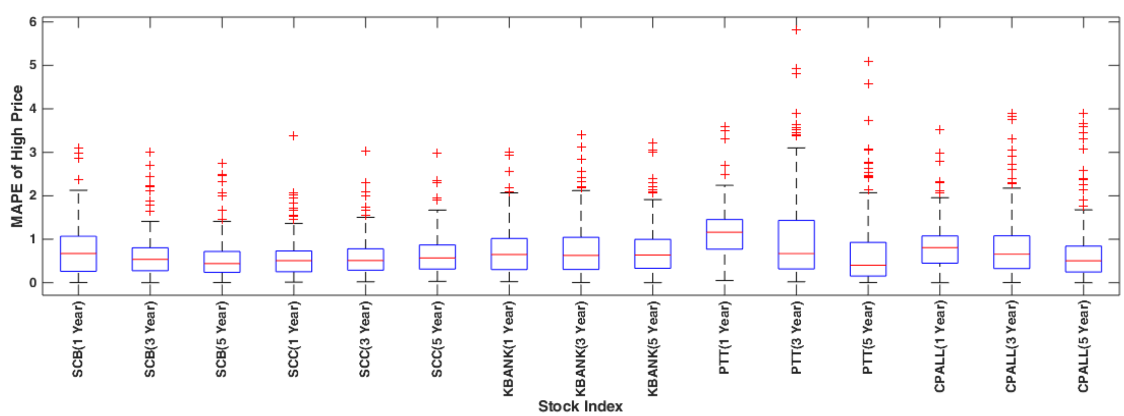

Fig. 5. Box plot comparisons for MAPE of testing data for high price prediction

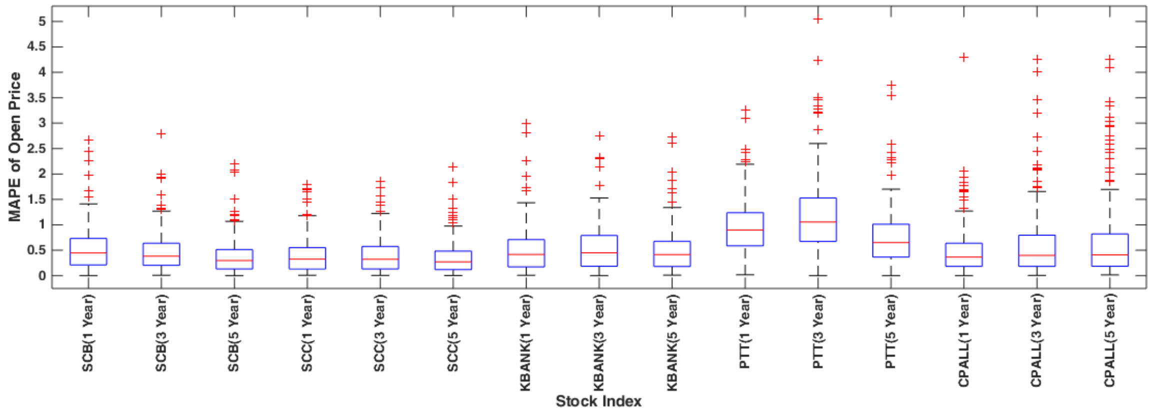

Fig. 6. Box plot comparisons for MAPE of testing data for open price prediction

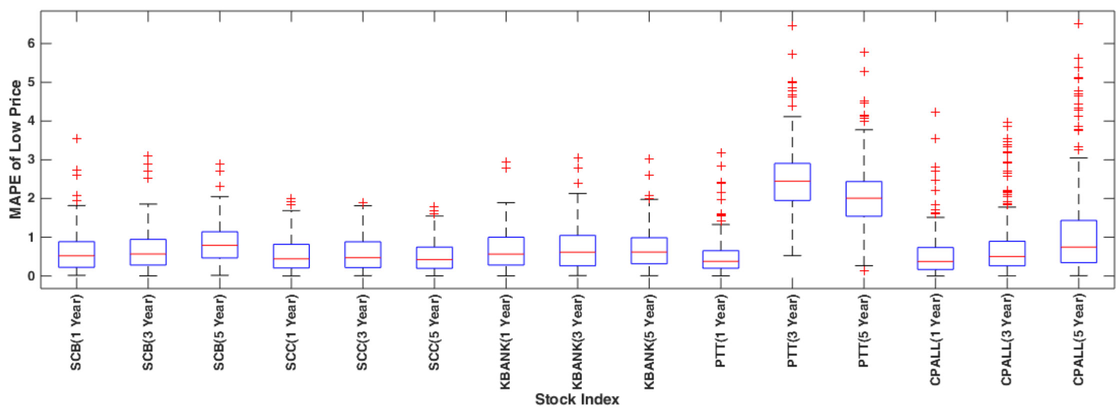

Fig. 7. Box plot comparisons for MAPE of testing data for low price prediction.

Table II shows the result of each stock by comparing LSTM with DBN. LSTM and DBN are applied to predict high, low, open, and close price. The network has a visible layer with four inputs and four outputs. For LSTM give a good result for CPALL, SCB, and KTB stock. For DBN give a good result for SCC and PTT stock. So, the performance of each technique is depended on each stock. An LSTM provide a good performance for low volatilities stock. A DBN give a better result for high volatilities stock such as PTT and SCC.

Table III shows the results with a different number of inputs and looks back with one-year training data. The lowest MAPE, RMSE, and MSE for CPALL, SCB, SCC, and KBANK come from four inputs with one look back. For PTT, the result of six inputs with one look back give the lowest error. According to Table IV, the performance of the forecasting model depends on the deviation of the price. High fluctuation in price leads to high forecasting error. This makes CPALL has the lowest MAPE error and PTT has the highest MAPE error among five stocks.

VI. Conclusion

This paper applies Recurrent Neural Networks with Long Short-Term Memory for Thai stock price prediction. Stock price prediction (open, high, low, close) are investigated in this research. The length of training data is varied in one, three, and five-year. The test data are SCB, SCC, KBANK, PTT, and CPALL.

By comparing the different length of training data, PTT and SCC stock give the lowest median value of MAPE by using five-year training data. KBANK, SCB, and CPALL stock give the lowest median value of MAPE by using one-year training data. By comparing the different number of inputs and look-backs, the result shows that RNN with LSTM successfully predicts the stock price of CPALL, SCB, SCC, and KTB with four inputs of one look back give less than two percent error. For PTT with six inputs give less than three percent error.

By comparing the different technique, the result shows that LSTM is better predicted CPALL, SCB, and KTB. LSTM is suitable for low volatilities stock. For DBN is better predicted with SCC and PTT. DBN is suitable for high volatilities stock.

For future study, more techniques will be investigated to compare the performance of stock price prediction. The number of look backs will be investigated in more detail. The critical impact factor that can affect to fundamental of Thai stock price analysis will be investigated, Moreover, the market condition will be investigated if it shows any relationship with the forecasting performance.

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TABLE II RESULTS OF EACH STOCK BY COMPARING LSTM AND DBN

Stock Index	**LSTM**				**DBN**			
MAPE (%)	Open	Close	High	Low	Open	Close	High	Low
CPALL	0.32	0.46	0.52	0.35	3.23	3.25	3.48	3.12
SCB	0.82	1.14	1.13	0.96	3.54	3.5	3.90	3.10
SCC	2.08	3.62	2.94	2.96	1.56	1.50	1.31	1.77
KTB	1.02	1.82	1.45	1.33	4.31	3.96	4.48	3.76
PTT	3.68	4.62	4.50	3.51	1.64	1.83	1.66	1.63

TABLE III RESULTS MEASURE BY MAPE, RMSE, AND MSE FOR FIVE STOCKS IN JANUARY 2017 WITH ONE-YEAR TRAINING DATA.

Stock Index	**Look Back**	**Input**	Open			Close			High			Low		
			MAPE	**RMSE**	**MSE**	**MAPE**	**RMSE**	**MSE**	**MAPE**	**RMSE**	**MSE**	**MAPE**	**RMSE**	**MSE**
CP ALL	**One Look Back**	4	0.32	0.41	0.26	0.46	0.63	0.40	0.52	0.62	0.39	0.35	0.52	0.27
		5	0.29	0.42	0.17	0.56	0.79	0.63	0.51	0.73	0.53	0.46	0.61	0.37
		6	0.46	0.72	0.52	0.64	0.94	0.87	0.53	0.76	0.58	0.42	0.57	0.32
	Two Look Backs	4	0.43	0.60	0.36	0.55	0.77	0.59	0.56	0.72	0.52	0.44	0.63	0.40
		5	0.48	0.69	0.48	0.69	0.98	0.97	0.64	0.95	0.90	0.54	0.75	0.56
		6	0.62	0.99	0.98	0.64	0.94	0.87	0.65	0.98	0.96	0.56	0.78	0.61
SCB	**One Look Back**	4	0.82	1.06	1.11	1.14	1.42	2.00	1.13	1.42	2.01	0.96	1.26	1.60
		5	0.93	1.17	1.37	1.25	1.57	2.46	0.10	1.29	1.67	1.28	1.55	2.40
		6	0.83	1.07	1.14	1.20	1.52	2.31	0.95	1.27	1.61	1.18	1.40	1.97
	Two Look Backs	4	0.92	1.21	1.47	1.23	1.55	2.41	1.21	1.55	2.41	1.20	1.55	2.42
		5	1.12	1.42	2.01	1.45	1.82	3.32	1.07	1.40	1.96	0.54	0.75	0.56
		6	1.12	1.40	1.95	1.20	1.52	2.32	1.16	1.50	2.24	1.47	1.73	2.99
SCC	**One Look Back**	4	2.08	2.75	7.57	3.62	4.71	22.16	2.94	3.74	14.01	2.96	3.86	14.90
		5	2.34	3.05	9.33	3.79	4.91	24.11	3.10	4.04	16.36	3.11	3.84	14.74
		6	2.20	3.01	9.08	3.85	5.00	24.95	3.00	3.98	15.85	3.05	3.69	13.61
	Two Look Backs	4	2.65	3.52	12.40	3.79	5.00	25.00	3.30	4.20	17.66	3.00	3.83	14.67
		5	3.21	4.06	16.44	4.27	5.45	29.70	3.59	4.73	22.34	3.67	4.60	21.21
		6	2.87	3.66	13.39	3.85	5.00	24.94	3.42	4.45	19.84	3.49	4.22	17.78
KBANK	**One Look Back**	4	1.02	1.36	1.85	1.82	2.34	5.49	1.45	1.83	3.35	1.33	1.67	2.80
		5	1.34	1.73	3.00	2.09	2.71	7.36	1.57	2.18	4.73	1.8	2.2	4.87
		6	1.16	1.50	2.25	2.06	2.64	7.00	1.47	2.00	4.00	1.56	1.89	3.57
	Two Look Backs	4	1.37	1.81	3.28	2.10	2.70	7.24	1.67	2.14	4.56	1.60	2.02	4.07
		5	1.57	2.00	4.01	2.27	2.90	8.40	1.84	2.47	6.07	2.05	2.50	6.24
		6	1.60	2.04	4.17	2.06	2.65	7.01	1.75	2.36	5.59	1.94	2.32	5.36
PTT	**One Look Back**	4	3.68	4.26	18.16	4.62	5.56	31.00	4.50	5.07	25.69	3.51	4.28	18.33
		5	3.38	4.26	18.23	3.99	5.16	26.66	3.75	5.05	25.49	3.53	4.26	18.16
		6	2.43	3.31	10.97	3.48	4.80	23.03	2.90	4.25	18.10	2.63	3.40	11.55
	Two Look Backs	4	2.75	3.65	13.34	3.57	4.77	22.79	3.43	4.27	18.22	2.53	3.58	12.80
		5	4.27	5.21	27.17	4.88	6.23	38.85	4.52	5.93	35.02	4.53	5.32	28.22
		6	6.75	7.58	57.44	3.48	4.80	23.03	6.94	8.24	67.87	6.72	7.40	54.74

TABLE IV STANDARD DEVIATION OF EACH STOCK COMPARE WITH MAPE ERROR OF CLOSE PRICE

	PTT	**SCC**	**KBANK**	**SCB**	**CPALL**
STDEV	54.21	30.67	15.28	10.89	7.85
MAPE of close price	4.62	3.36	1.82	1.14	0.46