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Aggregate Versus Disaggregate Data in Artificial Neural Network for Stock Market Forecasting

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Abstract: Stock market serves as a place for the public to earn profits in short period of time and hence, the idea of stock market forecasting was then surfaced as the reference for those traders to avoid losses and gain profits. There are many types of methods available for the forecasting, and this study aims to apply data disaggregation on the stock closing prices and utilize them to make forecast through artificial neural network. Specifically, it determines whether the application of disaggregate series can provide better forecast performance than using the traditional aggregate series. Historical stock closing prices from Malayan Banking Berhad was used for this study, and the forecast made from the neural network models by using aggregate and disaggregate series were measured by using mean forecast error, mean absolute percentage error and trend change error. According to the result, the aggregate forecast had outperformed the disaggregate forecast as it obtained lesser error in mean forecast error, mean absolute percentage error and trend change error, and can be concluded that the use of aggregate series for artificial neural network forecasting was the superior option.

Keywords: Data Disaggregation, Artificial Neural Network, Mean Forecast Error, Mean Absolute Percentage Error, Trend Change Error

1. Introduction

The stock market generally serves as a spot to attract the public to invest their resources on shares of company by offering the chances of financial gains [1]. The profits will be earned in the stock market by just a simple procedure which is to buy at the lower price, then sell them once the price has gone higher, in the shortest time possible [2]. Moreover, the stock market is not just a place for accumulating personal wealth but also to serve a crucial role in the growth of the economy. The contribution of stock market to the economy can be done by the activity of exercising in corporate and liquidity affects the economy from all around the world, and any alteration in stock prices will cause significant deviation

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in the economy [3]. However, the returns from stock trading does not come easily due to the prices of each stock are constantly in shifting movement and is volatile in nature that can be affected by many reasons [4]. Therefore, the idea of stock market forecasting had surfaced to predict the movement of prices for the purpose of guiding the traders to make better judgement calls, and avoid heavy losses.

There are various methods can be used to predict the stock prices. For instance, [5] utilized the regression approach to predict the stock market trend, and successfully acquired 95% prediction accuracy. Furthermore, the traditional time series approach especially the Box-Jenkins method were among the favorites of many researchers. Both [6] and [7] had applied the Box-Jenkins method to predict stock indices, and had obtained low MAPE for their predictions. Artificial Neural Network (ANN) sometimes considered to be the best method to forecast stock prices due to its ability to discover nonlinear functional relationship within the information [8]. Thus, many researchers often compared the ANN forecast with another method. The stock prices prediction through ANN was able to outperform the traditional method such as Box-Jenkins and regression, as per shown in [4] and [9] respectively, but was underperformed in predicting changes of direction of stock prices. Additionally, data disaggregation is a process used to break down an aggregate dataset into several different series in order to obtain extra information, where an aggregate data is generally the original raw dataset that is recorded in a one series format. The extra information produced from the data disaggregation can be incorporated with the forecasting process to increase the accuracy of prediction [10]. Besides, there are many error measurements available to be applied to evaluate the accuracy of the forecast performance, such as the widely used mean forecast error (MFE) and mean absolute percentage error (MAPE). Other than that, trend change error is another approach that can be considered in assessing the forecast made by measuring the correctly forecasted trend changes of the values [11].

Thereby, in the economic perspective, the fluctuations in the stock market have a close association with various economic indicators such as the gross domestic product, which hold direct influence to the economic growth [12]. However, the stock market is known to possess non-linear system due to its random fluctuations that can be presented through time series plot [13]. Hence, ANN is a rather suitable option to be applied for forecasting rather than other approaches since it has the advantage of interpreting the non-linear nature of stock prices. Furthermore, most of the stock market forecasting research were done by using the traditional original or aggregate series, and thus has constrained the potential of exploring better approaches on improving the accuracy of the stock prices prediction. Therefore, this study proposed to first apply data disaggregation on the aggregate series of historical stock closing prices of Malayan Banking Berhad, then two ANN forecasting models for the closing prices where each to be developed by using the aggregate and disaggregate series respectively. The forecast performances produced from the ANNs are then to be compared by using MFE, MAPE, and trend change error, in order to determine the most appropriate series to be used on the ANN forecasting for stock prices.

2. Methodology

The historical stock closing prices of Malayan Banking Berhad, which were extracted from Yahoo Finance, will be used as the dataset in this study. The period of the data was recorded in between 1st June 2016 and 31th May 2021. The dataset consists of 1234 observations where the final 30 observations is partitioned to become testing set, whereas the remaining observations prior to the final 30 is the training set. Every method in the following sections will be using this dataset for the analysis purposes.

2.1 Data Normalization

The purpose of implementing data normalization is to scale the observation from the dataset into an equal range, then be introduced the variables for the ANN model to reduce bias and fluctuation [14]. Min-Max Normalization is one of the techniques for this process where it scales the observation into a range of [0,1] or [-1,1]. The formula is shown in *Eq.1* in the following:

$$scaled\ price = \frac{price - Min_{price}}{Max_{price} - Min_{price}}\left[new\ Max_{price} - new\ Min_{price}\right] + new\ Min_{price} \qquad Eq. 1$$

2.2 Data Disaggregation

Data disaggregation is a process of breaking down the regular set of one series aggregate dataset into several disaggregate series based on certain categories, as [10] stated that by disaggregating a dataset can actually increase the information for the forecasting process, and hence better forecast accuracy. The application of pivot table from Microsoft Excel allows this process to take place by disaggregating the regular aggregate data into several different disaggregate series.

2.3 Box-Jenkins Analysis

The Box-Jenkins approach, commonly referred as ARIMA, is a technique involving three processes, which are autoregressive (AR), moving average (MA), and accompanied by differencing [15]. Aside from being a forecasting method, Box-Jenkins is always one of the best approaches to be applied for producing significant lagged variable, and to be used as the variables for the input layer of an ANN model [16]. The first phase of estimating ARIMA is model identification, which can be done by observing behavior autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, as per shown in Table 1. The second phase will be the parameter estimation for the selected model, where the *p*-value of each model should ideally be achieving less than 0.05. Lastly, the final phase is diagnostic checking that focuses on the autocorrelation within residuals, which can be done by using Ljung Box test. Ljung Box test capable of examining the lack of fit of any time series model by applying it to the residuals of a time series after being fitted in a model [17].

In terms of selecting the best ARIMA model after going through every stated phase, mean squared error (MSE) of each ARIMA model will be computed in order to determine its accuracy by using *Eq. 2*. The model with the lowest MSE will be selected as the best model.

Table 1: Behavior of ACF and PACF for Selecting ARIMA Model

Model	ACF	PACF
AR (*p*)	Quickly decay towards zero	Cut off after lag *p*
MA (*q*)	Cut off after lag *q*	Quickly decay towards zero
ARMA (*p*, *q*)	Quickly decay towards zero	Quickly decay towards zero

$$MSE = \frac{1}{n}\sum \quad y_t - \hat{y}_t \qquad Eq. 2$$

where:

n = number of observations

y_t = actual value at time *t*

$\hat{y}_t$ = predicted value at time *t*

2.4 Artificial Neural Network

ANN is an unusual forecasting method as it possesses the ability of classifying and distinguishing all forms of pattern which makes it perfect for stock market forecasting [8]. The ANN is developed based on the human brain, and thus it comprises countless processing nodes that are interconnected to each other in a rather complicate manner [18]. Moreover, multilayer perceptron (MLP) was used in numerous researches in the past to predict stock market prices as it is considered to be one of the simplest ANN to be constructed. MLP consists of three types of layers, which are an input layer, one or two hidden layers, and an output layer. Furthermore, backpropagation algorithm is an algorithm to be used along with the ANN process for the purpose of minimizing the error of the MLP by adjusting the weights through a reverse direction from the output layer to the input layer [19].

The formula of the processing unit transferred from the input layer to the hidden layer can be computed by using *Eq. 3*, whereas the formula for hidden layer to the output layer can be calculated by using *Eq. 4*.

$$a = \sum_{i} w_{ji} x_i + b \qquad Eq. 3$$

where x_i is the inputs, w_{ji} is the weights from input neuron *i* to hidden neuron *j*, *b* is the bias, and *a* is the net input to the hidden layer.

$$\hat{y_t} = b + \sum_{j=1}^{M} w_j h_j \qquad Eq. 4$$

where w_j is the weights from hidden neuron *j*, and h_j is hidden neuron *j*.

2.5 Accuracy Measurement

MFE and MAPE are some of the most applied error measurements to evaluate the forecast performance, where the model with least error obtained will be producing the most accurate forecast. MFE and MAPE can be computed based on the equations shown in *Eq. 5* and *Eq. 6* respectively.

$$MFE = \frac{\sum_{t-1}^{n} (y_t - \hat{y_t})}{n} \qquad Eq. 5$$

$$MAPE = \frac{1}{n} \sum_{t-1}^{n} \left| \frac{y_t - \hat{y_t}}{y_t} \right| (100) \qquad Eq. 6$$

where:

n = number of observations

y_t = actual value at time *t*

$\hat{y_t}$ = predicted value at time *t*

Furthermore, the application of trend change error can evaluate the trend change performance of the forecast. The changes of trend can be divided into two categories, which are downturns and upturns [20]. It is measured in terms of percentage regarding the correct prediction in changes of trend [21]. Trend change error can be computed according to the *Eq. 7* and *Eq. 8* in the following equations.

$$y_{t-2} < y_{t-1} < y_t \text{ and } Z < y_t = Downturn$$

$$Z \geq y_t = No\ Downturn \qquad Eq. 7$$

$$y_{t-2} > y_{t-1} > y_t \text{ and } Z > y_t = Upturn$$

$$Z \leq y_t = No\ Upturn \qquad Eq. 8$$

where y_1, y_2,…, y_t represent given past values of a variable, and Z is the future value starting y_{t+1}.

3. Results and Discussion

3.1 The Implementation of Data Disaggregation on Aggregate Data

The aggregate series was initially a single series dataset, arranged in a sequence according to date in an ascending order. Table 2 shows the first five observations of the result after the implementation of data disaggregation on the aggregate series. Five different series were formed with each representing the weekday, and the data recorded within each series was the closing prices, sorted according to their respective date. The number of observations of Monday until Friday was 236, 249, 247, 252, and 250 accordingly, and the sum of them was equivalent to 1234 data.

Furthermore, the final six observations of each of the five separate series were partitioned into becoming the testing sets for the forecasting in ANN, the forecast results obtained from each series were then combined and be compared to the result of the aggregate series, which would be presented in later section. Additionally, the remaining observations prior to the final six of each series were used as the training sets in order to fit the ANN models.

Table 2: Disaggregate Series of Daily Stock Closing Prices of Malayan Banking Berhad

Date/Weekday	Monday	Tuesday	Wednesday	Thursday	Friday
1/6/2016			8.23		
2/6/2016				8.27	
3/6/2016					8.27
6/6/2016	8.42				
7/6/2016		8.39			
…	…	…	…	…	…

3.2 Box-Jenkins Analysis Approach in Estimating Lagged Variable

The aggregate, and five other disaggregate series had undergone Box-Jenkins analysis in order to obtain the estimated lagged variable for each series, and those identified variables would later be fed into the input layer of ANN for further analysis.

3.2.1 Box-Jenkins Analysis for Aggregate Series

According to Table 3, ARIMA (1,1,0) has been selected as the best model as it has fulfilled all of the criteria. Firstly, the p-value obtained for its parameter was 0.000, which was statistically significant. Secondly, the *p*-value of Ljung Box test obtained by the model at both lag-12 and lag-24 were greater than 0.05, which indicates that the residuals were not correlated. Lastly, the error produced by ARIMA (1,1,0) was the least compared to others, as it was able to yield the smallest MSE values, suggesting that it was the best candidate among all of the alternatives.

Table 3: Tentative Model for ARIMA for Aggregate Series

Tentative Model	*P*-value of Parameter	*P*-value of Ljung Box Test		MSE
		Lag-12	Lag-24	
ARIMA (1,1,1)	AR (1) 0.393 MA (1) 0.686	0.088	0.087	0.0000216
ARIMA (0,1,1)	MA (1) 0.000	0.082	0.079	0.0000221

ARIMA (1,1,0)	**AR (1) 0.000**	**0.114**	**0.100**	**0.0000216**

Since ARIMA (1,1,0) was determined to be the best model, *Eq.9* was applied based on ARIMA (1,1,0) to identify the appropriate lagged observation. Based on the following derivation, y_{t-1} and y_{t-2} were estimated to be the lagged variable for ARIMA (1,1,0), and would be used in the input layer of ANN modelling with aggregate series as dataset.

$$\phi_p(B)(1-B)^d y_t = \theta_q(B)a_t$$

$$(1-\phi_1 B)(1-B)y_t = a_t$$

$$y_t - y_{t-1} - (-0.1106)y_{t-1} + (-0.1106)y_{t-2} = a_t$$

$$y_t = y_{t-1} - 0.1106y_{t-1} + 0.1106y_{t-2} - a_t \qquad Eq.9$$

3.2.2 Box-Jenkins Analysis for Disaggregate Series

The same process of Box-Jenkins analysis that was first applied on aggregate series, was also utilized on all of the five disaggregate series. The best ARIMA models and the estimated lagged variables for each of the disaggregate series were summarized into Table 4. According to Table 4, y_{t-1}, y_{t-2}, and y_{t-3} would be used as the lagged variables in the input layer of ANNs modeling with Monday, Tuesday, Wednesday and Thursday series. On the other hand, ANN modelling with Friday series would be using y_{t-1} and y_{t-2} as the lagged variables for its input layer.

Table 4: Best ARIMA Models and Lagged Variables for Every Disaggregate Series

Disaggregate Series	ARIMA Model	Lagged Variable(s)
Monday	ARIMA (2,1,2)	$y_{t-1}, y_{t-2}, y_{t-3}$
Tuesday	ARIMA (2,1,2)	$y_{t-1}, y_{t-2}, y_{t-3}$
Wednesday	ARIMA (2,1,2)	$y_{t-1}, y_{t-2}, y_{t-3}$
Thursday	ARIMA (2,1,2)	$y_{t-1}, y_{t-2}, y_{t-3}$
Friday	ARIMA (1,1,2)	y_{t-1}, y_{t-2}

3.3 Artificial Neural Network for Stock Market Forecasting

The ANN forecast estimated using disaggregate series has to first be grouped into a single data series prior to the comparison with ANN forecast made with aggregate series. Table 5 shows each ANN model developed with different disaggregate series had produced six weekdays ahead in respect to its weekday series. Since the 30-day of the actual closing prices was started on Wednesday, therefore for better comparison purposes, the Wednesday series was assigned to be the leading point, followed by Thursday, Friday, Monday and Tuesday in that particular order. Hence, the forecast from each row of the five different series were then grouped together to become one single series, with 30 observations in total.

Figure 1 shows the comparison between the 30-day forecast closing prices by using aggregate series and disaggregate series, against the actual closing prices. Based on Figure 1, both forecast closing prices were unable to entirely capture the direction of changes and movements of the actual closing prices. In the beginning of the period, both forecasts were struggled to produce values that were closer to the actual closing prices, and have over-magnified trend changes. By the middle of the period, the aggregate forecast was able to exhibit similar trend to the actual closing prices, and presented slightly better compared to disaggregate forecast.

In brief, stock market data poses a random and unpredictable pattern as it can easily be influenced, and hence, the forecasts produced via the application of ANN for prediction, along with the incorporation of data disaggregation could only go as close and accurate as this study can get as per shown in Figure 1. In addition, the more detailed comparison between the aggregate and disaggregate forecasts will be presented in Section 3.4, where the forecast accuracy was evaluated through different accuracy measures in order to determine the better approach in forecasting stock prices.

Table 5: Forecast Closing Prices Using Disaggregate Series

No.	ANN (Wednesday)	ANN (Thursday)	ANN (Friday)	ANN (Monday)	ANN (Tuesday)
1	8.25	8.00	8.20	8.38	7.99
2	8.11	8.16	8.08	8.15	8.21
3	8.09	8.19	8.21	8.18	8.18
4	8.10	8.19	8.16	8.19	8.10
5	8.23	8.19	8.25	8.16	8.20
6	8.19	8.00	8.21	8.19	8.15

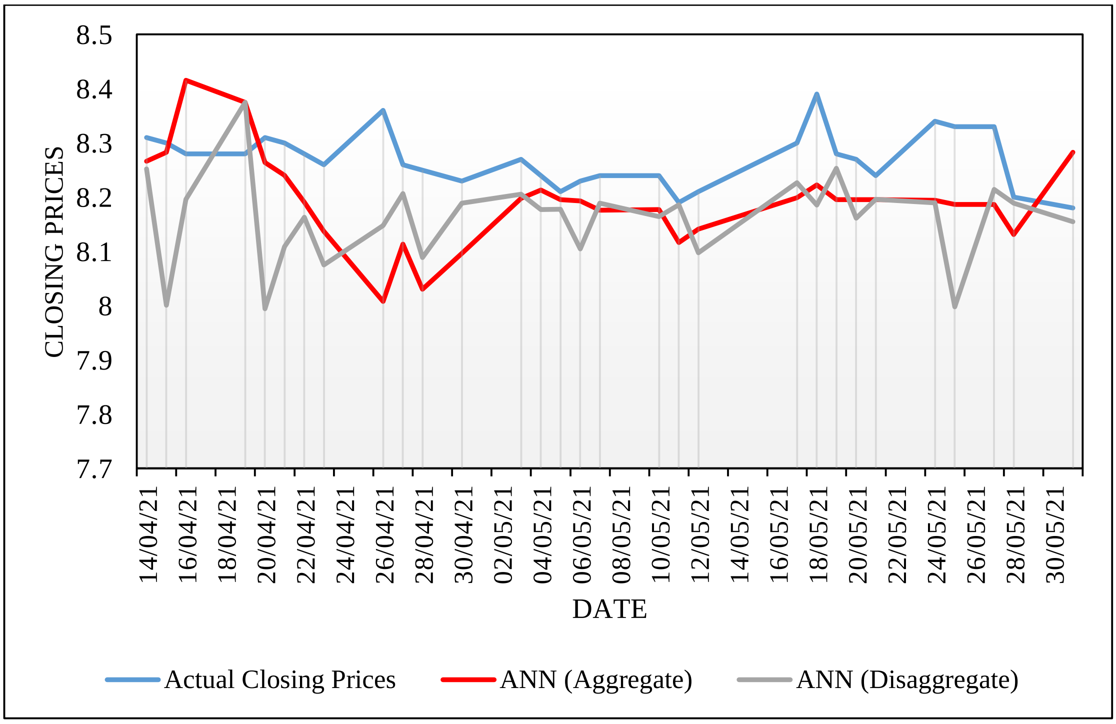

Figure 1: Actual Closing Prices Against Forecast Closing Prices with Aggregate and Disaggregate Series

3.4 Forecast Accuracy Measurement

According to Table 6, both ANN with aggregate and ANN with disaggregate forecasts obtained positive MFE values, which indicates that they were marginally under-forecasting where there were more actual values than forecast values. However, The MFE of ANN with aggregate series was closer to zero in comparison to its opponent, and hence, it can be stated the use of aggregate series in the ANN forecasting had slight edge advantage in producing more accurate forecast over the use of disaggregate series.

Moreover, MAPE values obtained from the ANNs with aggregate and disaggregate series were below 10, for which suggesting that they were fairly accurate. Nevertheless, the MAPE obtained from ANN forecast developed from aggregate series, which was 1.18%, was somewhat still lower than the one with disaggregate series, 1.37%. Therefore, MAPE has once again proved that the prediction of daily stock closing prices through ANN would be more accurate if the dataset used was an aggregate series.

Additionally, trend change error was another measure used to determine the accuracy of the forecasts. Based on Table 6, the error produced in changes of trend by the forecast of ANN with aggregate series was 54%, whereas the forecast with disaggregate series had significantly higher error percentage, 82%. Despite for the high trend change error from both of the ANN forecasts, the use of aggregate series for ANN forecasting was still considered to be replicating and producing more accurate trend changes of the actual closing prices.

Based on all of this, the ANN forecasting of daily stock closing prices was more superior in producing accurate result if the aggregate series was utilized as the dataset since it was proven to be performing better than the application of disaggregate series. In an idea scenario, the disaggregate series was assumed to be providing extra information to the ANN forecasting process, which would then end up becoming the superior option. However, in reality, the presence of stock market data which possess unpredictable behavior has hindered the disaggregate series to live up to the expectation.

Table 6: Accuracy Measurement

Model	Error Measurement		
	MFE	MAPE (%)	Trend Change Error (%)
ANN (Aggregate)	0.0763	1.18	54
ANN (Disaggregate)	0.1135	1.37	82

4. Conclusion

Two forecasting on stock closing prices were conducted by using the ANN method but with different approach in terms of the structure of the dataset. The first forecasting was carried out using the aggregate series of the historical closing prices of Malayan Banking Berhad. The result obtained through this attempt was fairly accurate, and hence the model can be recommended to be used as a reference opposing to the actual changes of closing prices. Therefore, this ANN with the utilization of aggregate series as dataset is a great combination in predicting future daily closing prices.

Furthermore, data disaggregation was implemented on the aggregate series to create a disaggregate series that contained five distinct datasets and were used on the second ANN forecasting. The result produced from each of the ANN by using disaggregate series were then grouped and compared to the one made by aggregate series. Based on the comparison using MFE, MAPE and trend change error between the two ANNs, the use of disaggregate series as dataset for ANN forecasting was found to be producing less accurate forecast than the ANN with aggregate series.

This study was proposed to determine the most appropriate series as dataset on the ANN forecasting, with the initial expected result of the disaggregate series would be able to produce the most accurate result. However, the outcome acquired according to the ANN models in this study proved to be otherwise, whereby the ANN forecasting constructed using aggregate series was able to obtain less error in MFE, MAPE, and trend change error, for which has indicated that it was the superior option as it was able to predict more accurate closing prices due to lesser forecast errors, and have better prediction in changes of trend of the stock closing prices due to the low trend change error.

In the nutshell, the application of data disaggregation on the dataset in theoretically speaking, was supposed to provide extra information that would allow the ANN forecasting to be more accurate. Nevertheless, this study has overturned that theory and proved that the use of aggregate series for stock market forecasting through ANN was the better option.

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