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STOCK INDEX MODELLING USING ARIMA WITH STANDARD DEVIATION BASED TRIANGULAR FUZZY NUMBERS

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Abstract
Most stock price research focuses on model development rather than data preparation. Modeling stock indexes require meaningful data to obtain good accuracy in forecasting. Nevertheless, data gathered by multiple data collection methods mostly exposure to uncertainties that induce to the prediction model developed. It will lead to more errors being brought together into the predicted model, which results in less predictive model accuracy. Therefore, the data needs to be adequately processed, especially to handle the uncertainty inherent in the data.However, the standard procedure for data processing is minimal to follow to address uncertainties in the data using the fuzzy theory. In this paper, the procedure for preparing data that contains fuzzy information has presented by building Fuzzy Symmetry Triangular Fuzzy number data using the standard deviation method is presented for ARIMA.The study revealed that the proposed method to construct a fuzzy number for the ARIMA has a smaller error in the predictions. Improvements in the process of providing existing data sought from this study expected to benefit from achieving better prediction accuracy and addressing uncertainties in the analysis.

Keywords--Fuzzy Data, Data Preparation, ARIMA model, Stock index prediction

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INTRODUCTION

Stock index forecasts have always attracted researchers because it is highly unstable and vibrant (Schumaker and Chen 2009).A stock index can be defined as the public market that produces, buys, and sells trading on the stock exchange (Tillier 2017). It shows the ability, strengths, and weaknesses of an organization (Amin, Coval, and Seyhun 2004; Chen, Cheng, and Demirer 2017). Therefore, getting accurate predictions of a stock index is very important as it influences decision-making and profitability (Basak et al. 2019; Tae et al. 2019).

Among the challenges faced in making a stock index prediction is an uncertainty in the stock index (Ahn et al. 2019; Hoque and Zaidi 2019). Stock index uncertainty can be affected by several categories such as political uncertainty (Hillier and Loncan 2019), natural disasters uncertainty (Lee and Chen 2019), terrorism uncertainty (Moussa and Talbi 2019), and uncertainty in the data (Lah, Arbaiy, and Efendi 2019).

The results obtained help people, especially traders, to choose the best stock index to trade.The consequences to this are significant shocks, huge losses, many bankruptcies, and several trillion dollars of taxpayer money that spent in trying to resolve the problem(Makridakis, Hogarth, and Gaba 2009). Therefore, a high-accuracy forecasting model is essential to predict the stock index that affects decision making and contributes to the economy.

Data Input in the observation series should be processed beforehand because of many reasons, such as lost data, inconsistent data, and incomplete data that can lead to ambiguous results during the analysis phase.The data collected from multiple measurement methods usually contain uncertainties (Aubinet, Vesala, and Papale 2012), which creates data uncertainty. It is essential to represent the uncertainty in data to achievealifelikeoutcome from the data analysis phase. One of the hardest issues is interpreting observational evidence that has inherent measurement errors. Observation errors may derive from the measurement process(Clark and Bjørnstad, 2004). This error is a combination of the variations inherent in the observed phenomena and the other factors that interruptevaluation(Biemer et al. 2011; Coleman and Steele 2018). The error resulting from measured data can potentially lead to a bias in the calculation(Ferrero and Salicone 2003, 2007). Since eliminating all measurement error is impossible to obtain exact value. Thus, estimation or approximation technique has used with certain limits.

The uncertainties contained in the historical data used to build a prediction model can adversely affect the performance of prediction. The inherent uncertainty makes conventional analysis impossible to deal with(Arbaiy et al. 2018; Efendi, Arbaiy, and Deris 2018; Hussain et al., 2016; Efendi, Ismail, and Deris 2015). Time series records record single data values that are only consistent with existing conventional time series analysis.

However, most studies focus on model uncertainties regardless of data uncertainty. The data processing carried out may not always able to handle the uncertainty.The uncertainty in the input data not adequately addressed, resulting in more errors to include in the forecasts model.

Standard procedures are also minimal to follow to address uncertainties in the data.Because of this uncertainty may have significant implications for interpreting time series forecasts in ARIMA, a systematic technique for addressing uncertainty during data preparation are required(Chang, Wu, and Lin 2016; Ismail, Efendi, and Deris 2015; Hussain et al., 2015; Maciel, Gomide, and Ballini 2016; Singh 2017).

The uncertainty in stock index data exists and can be measured(Chuliá, Guillén, and Uribe 2017). In stock market forecasts, most professional traders use technical analysis to get patterns from the stock market. Therefore, these traders make predictions based on incomplete, blurred, incomplete, and uncertain information(Kabari and Asagba 2012). Conventional ARIMA methods have the limited ability to address uncertainties in data when modeling time-series predictions, which create uncertainties inherent in ignored data. It is common that during practical practice, data is changing rapidly, and the uncertainty exists. Some researches applied fuzzy theory in the ARIMA model to capture the uncertainty.

However, only a few researchers discuss fuzzy data treatment during data preparation, even though the process is essential to treat the data before the forecasts phase begins. Thus, a data preparation process for treating uncertainty contained in data is required to improve the accuracy in timeseries forecasting.

Therefore, the construction of fuzzy triangular fuzzy numbers (STFNs) from critical values involving fuzzy data transformations is crucial to obtaining fuzzy values that are sufficient for prediction. In this paper, a systematic procedure for fuzzy data preparationproposed to address uncertainty in measurement by constructing STFN.The STFN construction is based on the standard deviation value of the dataset and then used as the fuzzy triangle width.

The emphasis placed on the preparation of fuzzy data and model predictions is significant for improving the prediction results at the same time, achieving better prediction accuracy.The remaining of the paper consists of the following. Section 2 gives a brief review of the fundamental theories and the principal methodology of the study described in Section 3.

Section 4 presents an empirical study of stock price modeling using ARIMA, whereby the data which contain uncertainty preprocessed using standard deviation based STFN. Finally, the conclusions discussed in Section 5.

FUNDAMENTAL THEORIES

This section gives fundamental theories about the ARIMA model, Triangular Fuzzy Number, and Data Preparation in Sects. 2.1, 2.2, and 2.3, respectively.

ARIMA model

ARIMA divided into three parts: autoregressive (AR), differencing (I), and moving average (MA) that make up the ARMA and ARIMA. ARMA is a combined version of AR and MA, which includes both AR and MA functions. Meanwhile, ARIMA is the differencing sequence between AR and MA. It makes the ARIMA has a solution to the unstable non-stationary sequence.

There are three parameters in the ARIMA model: p, d, q corresponds to AR, I, MA, respectively. These three parameters affect the performance of ARIMA.

1) AR: In the autoregressive model, the current value of a variable is proportional to the sum of the values of the previously assigned value and the random variance of the previous process and shock values. The p^{th} order autoregressive model AR(p), representing the variable y_t is generally written as follows:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + e_t \qquad (1)$$

where$c$ is constant, e_t is white noise (error), and y_{t-1}, y_{t-2}, ..., y_{t-p} referring to the past series. The outcome variable in AR(1) is the process at some point in time, t is related only to line periods that are one period apart.

2) I: The number of times a sequence of sequences made to reach a stationary position. Stationery is a must for ARMA models.

3) MA: Moving average is a common approach for modeling univariate time series. The moving average model determines that the output variable depends linearly on the current and past values of the stochastic (unpredictable). The q^{th} order autoregressive model MA(q), representing the variable y_t is generally written as

$$x_t = ? + \emptyset_1 w_{t-1} + \emptyset_2 w_{t-2} + \cdots + \emptyset_p w_{t-p} + w_t \qquad (2)$$

where? is mean of the series and w_t, w_{t-1}, w_{t-2}, ..., w_{t-q} are white noise (error).

Time series modeling has a fundamental importance in various domains and has contributed to many types of current research work to date.Many related models have been proposed in the literature to improve the accuracy and efficiency of time series model predictions (Jenkins, 1970; Zhang, 2007; Tseng et al., 2001). ARIMA studies the variables by using autoregression, AR (p), and Moving Average (q) to investigate historical data and economic fluctuations (Jenkins, 1970).

Although the ARIMA model is successful in contributing to a variety of real-world problems (Singh, 2017; Tseng, 2001; Zhang, 2003; Volkan, 2007), its prediction accuracy remains a critical issue in the Autoregressive Moving Average (ARIMA) model.

Triangular Fuzzy Number

The imprecise numerical quantities on the practical level are manageable by using Fuzzy Number (FN)(Fortemps 1997; Pisz, Chwastyk, and Łapuńka 2019). Triangular Fuzzy Numbers (TFN) derived from FN and commonly used by researchers(Dutta and Goala 2019; Lah, Arbaiy, and Efendi 2019; Liu and Zhou 2019; Seikh, Nayak, and Pal 2012; Zhang et al. 2019). TFN represented with three points of $A = (a, b, c)$.

Definition 4: Let a, b, and c be real numbers with $(a < b < c)$. Then the Triangular Fuzzy Number (TFN) $A = (a, b, c)$ is the FN with membership function:

$$y = m(x) = \begin{cases} \frac{x-a}{b-a}, & x \in [a, b] \\ \frac{c-x}{c-b}, & x \in [b, c] \\ 0, & x < a \; and \; x > c \end{cases} \qquad (3)$$

From Eq. (3), we can define TFN as

$$TFN = y = [\alpha_l, c, \alpha_r] \qquad (4)$$

From Eq. (4), if TFN is symmetry, $\alpha_2 - \alpha_1 = \alpha_3 - \alpha_2$, then y can be written as follows:

$$y = [c, \alpha] \qquad (5)$$

Where αrepresent the spread of TFN and y is not a fuzzy number if $a = 0$.

PROPOSED METHOD: BUILDING SYMMETRIC TRIANGULAR FUZZY NUMBER (STFN) WITH STANDARD DEVIATION METHOD FOR ARIMA MODEL

This section discusses the procedure to build the STFN with the Standard Deviation method for developing the ARIMA forecasting model. A systematic step presented in the section. The Standard deviation used to determine the spread value of STFN, Δ_S. Fig. 1 shows the flow for the forecasting model based on ARIMA.

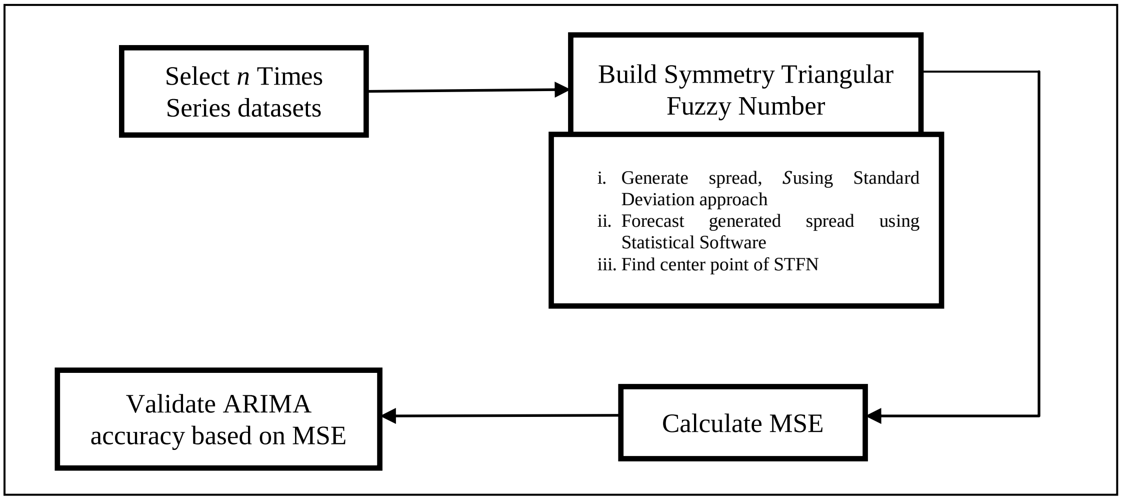

Figure 1. ARIMA forecasting workflow

The procedure for building ARIMA with standard deviation based STFN,Δ_S is explained as follows:

Step 1. Select n times series datasets in the form ofinput data. Table 1 shows the input data format.

Table 1. Input data format

Data	**1**	**2**	**...**	$\boldsymbol{n}$
Input	y_1	y_2	...	y_n

Step 2. Build STFN based on Standard Deviation method, Δ_S.

i. Generate spread, S.

The method is stimulated based onthestandard deviation concept, which measures the spread of data distribution.A fuzzy time-series data $\tilde{y}_t^S$at a time, t with STFN data written in Eq. (6).

$$\tilde{y}_t^S = [y_t - s, y_t, y_t + s] \tag{6}$$

where$y_t$is time-series data at a time, $t\ (t = 1,2,\dots,n)$ and Δ_S,is thetriangular spread based on the standard deviation of the dataset.

ii. Forecast generated spread using statistical software.

iii. Find center point for STFN,$\bar{\tilde{y}}_t^S$.

The center point for STFN value written as follows:

$$\bar{\tilde{y}}_t^S = \frac{\overleftarrow{y}_t^S + \overrightarrow{y}_t^S}{2} \tag{7}$$

where$\bar{\tilde{y}}_t^S$ representa center point for STFN.$\overleftarrow{y}_t^S$and$\overrightarrow{y}_t^S$represent left predicted value and right predicted value,respectively.$\Delta_S$representthe triangular spread based on the standard deviation of the dataset.

Table 2 shows the data format of the center point for STFN,$\bar{\tilde{y}}_t^S$.

Table 2. The data format for center point,$\bar{\tilde{y}}_t^S$

$\boldsymbol{y_t}$	$\boldsymbol{y_1}$	$\boldsymbol{y_2}$	...	$\boldsymbol{y_n}$
$\bar{\tilde{y}}_t^S$	$\bar{\tilde{y}}_1^S$	$\bar{\tilde{y}}_2^S$	...	$\bar{\tilde{y}}_n^S$

Step 3. Calculate the Mean Square of Error (MSE).

After all the datasets tested, the result is analyzed. Eq. 8 is used to obtain the total MSE for eachy_t^S.

$$MSE = \frac{\sum_{i=1}^{n}(y_t - \bar{\tilde{y}}_t^S)^2}{n} \tag{8}$$

wherey_t is a time-series data and $\bar{\tilde{y}}_t^S$are a predicted times series data at a time,$t\ (t = 1,2,\dots,n)$, and n is a sample size.

Step 4. Validate ARIMA with Δ_S accuracy based on MSE value. The model with the smallest MSE shows a better accuracy prediction.

The systematic steps presented in this section explain the ARIMA model building incorporated with fuzzy number construction from a single point value to address uncertainties co-exist. This step is vital during the data preparation phase(Efendi, Arbaiy, and Deris 2018; Lah, Othman, and Arbaiy 2019)since the crisp value is insufficient to interpret uncertainties inbuilt in the data.

EMPIRICAL STUDIES

The two stock indexes that were selected as benchmark data and used in this research are from the Nokia stock index and Zenith bank stock index (Ariyo, Adewumi, & Ayo, 2014). The ARIMA model for these two stock indexes has defined by Ariyo as Nokia - ARIMA (1,0,1) and Zenith Bank ARIMA (0,1,1). The timeframe for the data used is from March 1, 2010, to March 31, 2010, with a total of 23 data points for both stockindex.

Step 1. Select two time-series datasets. Table 3 shows two time-series datasets.

Table 3. Datasets from two stock indexes

Data	**1**	**2**	**...**	**22**	**23**
Nokia	50	52	...	40	37
Zenith Bank	57	59	...	52	50

Step 2. Build STFN based on Standard Deviation method, Δ_S.

i. Generate spread, S.

The spread ofSTFNis determined by using the standard deviationmethod (see Section 3 step 2) and is calculated based on Eq. 6. The STFNconstructed as ($\overleftarrow{y}_t^S, y_t, \overrightarrow{y}_t^S$). Table 4 shows the possibilities spread of STFN.

Table 4. The possibilities spread of STFN

$\boldsymbol{n}$	$\boldsymbol{y_1}$	$\boldsymbol{y_2}$	**...**	$\boldsymbol{y_{22}}$	$\boldsymbol{y_{23}}$
$\overleftarrow{y}_t^S$	12.6087	12.6087	...	13.8387	14.8387
$\overrightarrow{y}_t^S$	13.9513	14.1813	...	15.1813	16.2113

ii. Forecast generated spread using statistical software. The predicted result for the spread shown in Table 5.

Table 5. Predicted result for the spread of STFN

n	y_1	y_2	y_3	...	y_{23}
$\tilde{y}_t^S$	-	12.7987	12.9442	...	14.6047
$\vec{y}_t^S$	-	14.1413	14.2848	...	15.9473

iii. Find the center point of STFN, $\bar{\bar{y}}_t^S$ using Eq. (7). It is to transform the predicted values from STFN into a single point (defuzzification) to calculate the MSE. The center point of STFN shown in Table 6.

Table 6. Center point value for the spread of STFN

y_t	y_1	y_2	y_3	...	y_{23}
$\bar{\bar{y}}_t^S$	-	13.47	13.6135	...	15.2760

Step 3. The MSE for the Nokia stock index is calculated based on Eq. (8), and then presented in Table 7.

Table 7. MSE for Nokia stock index

Data	$ARIMA_{\Delta_S}$	$ARIMA_{Ariyo}$
Nokia	0.0853	* 0.131

Step 4. Validate ARIMA with Δ_S accuracy based on MSE

The accuracy of the prediction error is verified by comparison the MSE of each STFN. The STFN obtained from this study will be compared with the survey data from Ariyo (Ariyo et al., 2014). Table 8 shows the summary of MSEs for the two stock indices used.

Table 8. Summary of MSE

Data	$ARIMA_{\Delta_S}$	$ARIMA_{Ariyo}$
Nokia	0.0853	0.1310
Zenith Bank	0.3223	2.2289

Based on Table 8, the results are impressive when compared to benchmark data. This method has pushed the MSE from 0.1310 to 0.0853, for Nokia's stock index. Zenith Bank, MSE's stock index dropped from 2.2289 to 0.3223. The smaller the MSE, the better the results. It has proven that constructing STFNs using standard deviations is relevant. Of the two results, it also shows that the goal of obtaining MSE is smaller than the benchmark data achieved.

CONCLUSION

There are many ways to build an STFN, yet choosing the most appropriate one is crucial as it affects the outcome. In this study, the procedure for constructing STFN for ARIMA model predictions presented. The proposed procedure focuses on the input data in the data preparation phase. The proposed procedure emphasizes the process of handling the uncertainty contained within the information used for the prediction. It is crucial because uncertainties lead to more errors to include in the data, and subsequently affect the developed model. More errors will reduce the accuracy of prediction results. From this experiment, the proposed method shows a good result for both datasets as compare to Ariyo results. Additionally, the results can compete effectively with benchmarking data in terms of accuracy.

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