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Does Holt-Winters Seasonality Fare Better Against Fuzzy Time Series in Forecasting Stock Index?

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Abtract

The purpose of this research is to compare the forecasting performance of Holt-Winter seasonality and Fuzzy Time Series Forecasting-Chen Model and to determine which method performs best. Holt-Winter seasonality was divided into additive and multiplicative Holt-Winters. The forecast object was IDXV30, that was the stock index of 30 lowest valued stocks with good liquidity and performance. The stock index was biweekly stock index beginning from August 2019 until September 2022. The result indicated that Holt-Winters Additive model has the best forecast accuracy, followed by Fuzzy Time Series-Chen Model and Holt-Winters Multiplicative model. The Mean Absolute Percentage Error (MAPE) of Holt-Winters additive model was 2.0982%, while Fuzzy Time Series-Chen model was 3.1471%. The MAPE for Holt-Winters multiplicative model was 10.47425. The implication of the research is that the time series econometrics model, in this case Holt-Winters Seasonality, is still a very powerful model for forecasting stock index in Indonesian Stock Exchange.

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1. Introduction

Forecasting events is a very important activity in business and economics. It can help improve company financial position (Krylov, 2018), plan better production activity (Chukwulozie, et al., 2015), prepare better strategic budget (Patty, 2019; Siregar & Susanti, 2018), and help investors assess better the risks and potential gains (Shen & Shafiq, 2020; Turcas, et al., 2020), among others. Regulators, such as central banks and stock market agency, need to know the trend of some indicators that portend to signal the macroeconomic well-being of a country (Hauzenberger, et al., 2023; Kumar, Sarangi, & Verma, 2022). Stock market in particular imposes its own risks to the investors (Mubarok & Fadhli, 2020; Kassi, et al., 2019). The movement of stock price incurs market risk to the parties involved. Volatility in stock price has the potential for capital gain as well as loss (Xiao & Su, 2022; Budiharto, 2021). One way to mitigate market risk is by forecasting (Gur, 2024; Yatigammana, et al., 2018). Anticipating the direction of price movement will enable investors to pursue or change their trading strategies. This can minimize the loss suffered or even increase the probability of obtaining some capital gain. Forecasting is also very instrumental in helping investors choose the stocks portfolios (Agustina, et al., 2021; Vijh et al., 2020; Mallikarjuna & Rao, 2019). Among the very popular methods of forecasting are Holt-Winters seasonality and Fuzzy Time Series. Holt-Winters model have the ability to map the trend and seasonality in the data. Many researchers have used Holt-Winters in regard to stock forecasting. Pongdatu & Putra (2018) compared the performance of SARI-

MA and Holt-Winters with multiplicative seasonality in forecasting. They found that while SARIMA is better than Holt-Winters, SARIMA is particularly better for short-term forecasting compared to the long-term one. On the other hand, Holt-Winters model is more versatile in that it can be used for long-term or short-term forecasting purpose. Agustina, et al. (2021) found that forecasting performance of Holt-Winters is very excellent. For a forecast lead of 90 days, Holt-Winters was able to generate MAPE (Mean Absolute Prediction Error) value of even less than 3%. Mgale, et al. (2021) compared the performance of ARIMA and Holt-Winters additive model for Tanzanian data. They found that both methods were neck and neck in terms of performance, although Holt-Winters model performs a little bit better. The MAPE of Holt-Winters was 5.3314%, compared to ARIMA's 5.7512%. They inferred that both methods are very appropriate for forecasting purpose. In addition to Holt-Winters model, Fuzzy Time Series forecasting is a progressive method used in computer science. It is very much useful to forecast stock index (Wu, et al., 2020; Majumder, et al., 2022) and rainfall (Arnita, et al., 2020; Susano & Anggraeni, 2021). In the realm of capital market, Fuzzy Time Series with all the variations has been employed to forecast results. Hansun (2012) utilized Fuzzy Time Series to forecast IDX composite index. The data extended from September 2011 to March 2012. The model accuracy was signified by the MAPE of 4.77%. This is a very good result since the MAPE is below 10%. However, the forecast results did not really show any seasonality. Firdaus, et al. (2020) endeavored to forecast the exchange rate of Dollar/Euro during 2020-2021 period. They found that Fuzzy Time Series scored a MAPE of below 1 percent, 0.790% to be exact. This showed the excellence of Fuzzy Time Series for exchange rate prediction. The above exposition of prior research ultimately dichotomizes the forecasting methods based on Econometrics and Computer Science. Methods like Holt-Winters and ARIMA belong to the classic Econometrics models while Fuzzy Time Series and SARIMA are more and more becoming the focus of forecasting in computer science. Franses & Welz (2022) contrasted forecasting methods employed in Econometrics and Computer Science. They stated that forecasting based on Machine Learning is very hard to replicate since the parameters are very obscure. This is in contrast with Babii, Ghysels, & Striukas (2023) that stated advances in computer science, like machine learning, has attracted more focus in forecasting techniques. Machine learning is also more flexible and versatile. Based on the contrasting arguments, this research is conducted to compare the performance of traditional time-series econometrics and advances in computers science. In this research, Holt-Winters model will be compared to Fuzzy Time Series in terms of their forecasting performance. Holt-Winters will be divided into Holt-Winters with additive seasonality and Holt-Winters with multiplicative seasonality. Fuzzy Time Series chosen will be the Chen Method. This research will shed light on which one is better between Holt-Winters and Fuzzy Time Series as the Holt-Winters will represent the traditional time-series econometrics, while Fuzzy Time Series with the Chen Method will represent development in computer science.

2. Literature Review

Forecasting stock market has been an interesting subject of interest since the early era of financial empirical research (Li et al., 2024).. Researchers are motivated to find the antesedents to the movement in stock price that give rise to the stock return. Some contend that mo-vement in price are resulted from the financial ratios or performance of the companies (Kipngetich et al., 2021; Abdurachman & Dewi, 2023). Therefore, we might forecast movement in stock price by heeding the magnitute of certain financial ratios or indicators. Others, however, contend that historical price itself can be functioned as the main determinants of future price (Pongdatu & Putra, 2018; (Kumar et al., 2020); and Majumder, et. al., 2022). There are certain patterns of trends, seasonalities, or cycles that could be identified and hence adding to the power of prediction. Observing hitorical price of stock for forecasting falls on the realm of technical analysis that has been shown to be efficient for forecasting purpose (Wong et al., 2003; Altarawneh et al., 2022; and Bouteska et al., 2023). Concerning forecasting purpose, it is a common methodology to compare two or more different methods (Ariqoh, et al., 2022; Waheed & Qingshan, 2023; Afrah, et al., 2024). There are two techniques that are frequently used in forecasting namely Holt-Winters (Pongdatu & Putra, 2018; Agustina, et al., 2021; Mgale, et al., 2021) and Fuzzy Time Series (Arnita, et al., 2020; Firdaus, et al., 2020; Wu, et al., 2020; Susano & Anggraeni, 2021; Majumder, et al., 2022). Holt-Winters represents the traditional time-series method, while Fuzzy Time Series represents a more current development in computer science. Comparing the contrasting methods will shed lights on the performance of each forecasting method in forecasting Indonesian stock index.

3. Data and Methods

The forecast object of this research is the IDXV30 index. IDXV30 index consists of 30 lowest valued stocks with good liquidity and performance. This stock index was first launch on 12 august 2019. The stock index data used in this research is biweekly data starting from 16 august 2019 and ending in 30 september 2022. The biweekly data are the data from week 2 and 4 every month. The data are divided into training data and test data. Training data extend from august 2019 until june 2022. Test data are from july 2022 until september 2022. The training data are used to derive the models and parameters for Holt-Winters seasonality (additive and multiplicative) and fuzzy time series. The models and parameters will subsequently be used to generate the forecast for july to september 2022. The forecast will then be compared with the actual data, namely test data, to obtain the forecasting performance. The first model used in this research is Holt-Winters seasonality adaptive model. The proxy for this model can be seen as follows (makridakis, et al., 1997).

Level: $l_t = \alpha (y_t - s_{t-s}) + (1 - \alpha) (l_{t-1} + b_{t-1})$
Trend: $b_t = \beta (l_t - l_{t-1}) + (1 - \beta) b_{t-1}$
Seasonal: $s_t = \gamma (y_t - l_t) + (1- \gamma) s_{t-s}$

For Holt-Winters additive model, the forecast at m period ahead equals $f_{t+1} = l_t + b_t m + s_{t-s+m}$. Therefore, we need to calculate the value of the level trend and seasonality before we can derive the forecast. The forecast is the sum of all the level, trend, and seasonality. This research uses biweekly data which will result in 24 periods per year. Therefore, seasonality will be calculated as the seasonal effect of 23 previous weeks. In contrast to the holt-winter multiplicative model, the level and seasonal component will be very different. In additive model the level and seasonality can be obtained by subtracting the s_{t-s} and l_t from y_t, while in multiplicative model we divided them from y_t. The following is the computation for the Holt-Winters multiplicative model:

Level: $l_t = \alpha (y_t/s_{t-s}) + (1 - \alpha) (l_{t-1} + b_{t-1})$
Trend: $b_t = \beta (l_t - l_{t-1}) + (1 - \beta) b_{t-1}$
Seasonal: $s_t = \gamma (y_t/l_t) + (1 - \gamma) s_{t-s}$

For Holt-Winters multiplicative model, the forecast for m periods ahead equals $f_{t+1} = (l_t + b_t m) s_{t-s+m}$. The other method used in this research is fuzzy time series-chen model. Fuzzy time series forecasting is a model in which it simplifies the calculation to derive the forecast so that no complicated method is necessary. The steps involved in conduction fuzzy time series forecasting-chen model (fauziah, et al., 2016):

Determine the universe of discourse.
Universe of discourse (u) is calculated using the equation $u = [d_{min} - d_1; d_{max} - d_2]$. The constant d_1 and d_2 is arbitrarily determined by the researcher.

Determine the interval
Universe of discourse is divided into several intervals. The range of interval (n) is calculated by using sturges formula of $n = 1 + 3.322\ log(n)$ where n is the number of observations.

Determine the fuzzy sets

Subsequent to determining the interval, we can create fuzzy sets that contain the aforementioned intervals. Each data will be included in each set if it satisfies the range determined for each set. This phase is also called by the step "determining the linguistic value." The defining of fuzzy sets of $a_1, a_2, \ldots, a_k$ in the universe of discourse is as follows:

$A_1 = 1/u_1 + 0.5/u_2 + 0/u_3 + 0/u_4 + \ldots + 0/u_p$
$A_2 = 0.5/u_1 + 1/u_2 + 0.5/u_3 + 0/u_4 + \ldots + 0/u_p$
$A_3 = 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + \ldots + 0/u_p$
.
.
.
$A_p = 0/u_1 + 0/u_2 + 0/u_3 + 0/u_4 + \ldots + 0.5/u_{p-1} + 1/u_p$

Determine the fuzzy logic relations (flr) and fuzzy logic relations group (flgr)
After having the fuzzy sets, we determine the flr and form groups of relations. For example, if $a_1 \rightarrow a_2$, $a_1 \rightarrow a_3$, and $a_1 \rightarrow a_4$, then the flgr is $a_1 \rightarrow a_2, a_3, a_4$.

Determine the weight
Each flrg should be assigned some weight. In this research we will assign equal weight to each flrg.

Forecasting

The forecasting is conducted by looking at the last real data from the observation. The last real data will be assigned its own linguistic value. Then from there, we can discern how each particular linguistic value will be proceeded by another linguistic value. If it is proceeded by more than one linguistic value, then we will find the middle value of each linguistic values and find the average of the total middle values from all linguistic values. This step is also called fuzzification.

Lastly, each forecasting method's performance will be compared. The comparison will be evaluated on the basis of the value of root mean squared error (rmse) and mean absolute percentage error (mape). Better forecasting performance will be indicated by lower rmse and mape. The calculation of rmse and mape is as follows:

$$RMSE = \sqrt{\frac{\Sigma(A(t)-F(t))^2}{n}}$$

$$MAPE = \sum \left| \frac{A(t)-F(t)}{A(t)} \right|$$

Where: *A(t)*= real observation at time t; *F(t)*= forecast result for time t; N= total observations

The method is the sufficient information for the reader to follow the research flow well, so that the reader who will examine or develop similar research obtains the description of the research steps. This section describes the types of research and data types, population and sample, operational research variables, the data used (types and sources), data collection technique, and data analysis technique (model analysis).

4. Result

The index used in this study is IDXV30 that consists of 30 stocks of lowest value with good liquidity and performance. The plot of the IDXV30 beginning from August 2019 until September 2022 is shown figure 1.

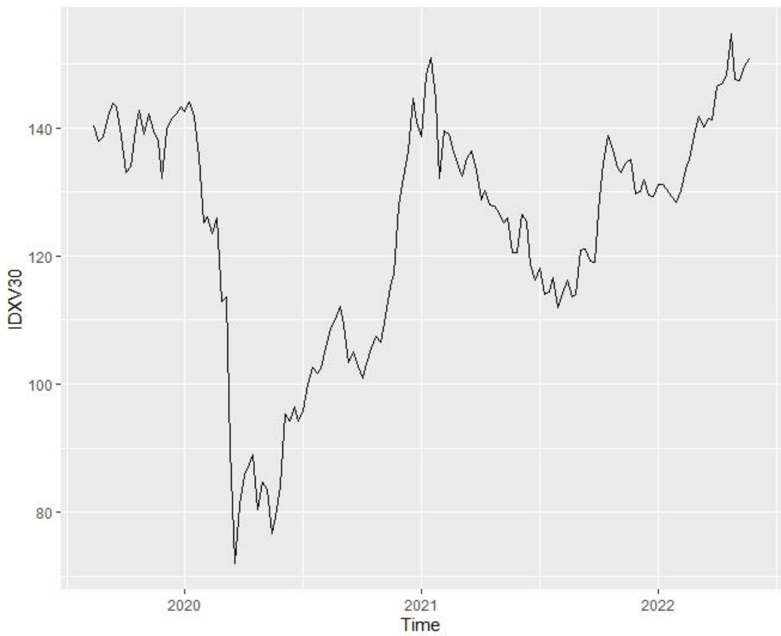

Figure 1 The Plot of IDXV30
Source: Processed Data, 2022

Figure 1 above shows the movement of IDXV30 beginning from 16 August 2022 until the end of September 2022. At the inception of the index establishment, the volatility is pretty high. This is typical for any stock index. The index hovered around 140 with occasional downturn to below 140 or a slight excess of 140. This went on until the end of 2019. Beginning from 2020, the index underwent a little increase to above 140. This could be attributed to January effect in which stocks and indices tend to increase during the first week of January due to the commencement of the stock trading at the beginning of the year (Hendrawaty & Huzaimah, 2019). After some mild volatility, the index started to plunge downward drastically. This signified the beginning of COVID-19 pandemic in Indonesia. The Indonesia government put some extraordinary measures in place to limit the spread of the highly contagious virus. The steps taken by the government had put tremendous pressure on the businesses run by individuals and companies. Stock indices declined sharply as a reflection of the pessimistic view by the investors.

At its lowest point, the IDXV30 fell to below 40 at the beginning of 2020. After some times, the index started its movement upward slowly despite some volatility. The index increased from July to September only to decrease again in October. However, IDXv30 managed to continue its path upward at the end of 2020. At the beginning of 2021, IDXV30 succeeded in reaching its peak at 150. This peak would only be beaten by the all-time high achieved at the first quarter of 2022. From 2021 to 2022, IDXV30 decline for the first half and surged again at the second half. In 2022, the trend of the stock index is positive up to the end of the research period. Next, we decompose the plot of IDXV30 so that we can observe the trend, seasonality and random components.

Figure 2 above shows the decomposition of IDXV30 index. The first subfigure shows the plot of the IDXv30 during the research period. Basically, this subfigure is identical to figure 1. We can see that, prior to 2020, IDXV30 tended to be stable with some volatilities. Beginning in 2020, IDXV30 suffered from a very steep drop that marked the beginning of the pandemic. From mid-2020 up to the end of the research period, there is an inclination for positive trend along with some volatilities. The second subfigure shows the smoothed trend. The obvious trend within the data shows the decline and then the move upward right after the pandemic started. Therefore, the threshold for the commencement of the upward trend is the start of pandemic at the beginning of 2020. Before that, the index slummed. The third subfigure shows whether seasonality exists. We can see that the data indeed have seasonality within it. Approaching the turn of the year, the index starts to go up. The move upward continues even after the new year has passed. After that, the index will decline somewhat drastically. This move upward followed by decline always occurs at the end and beginning of a year.

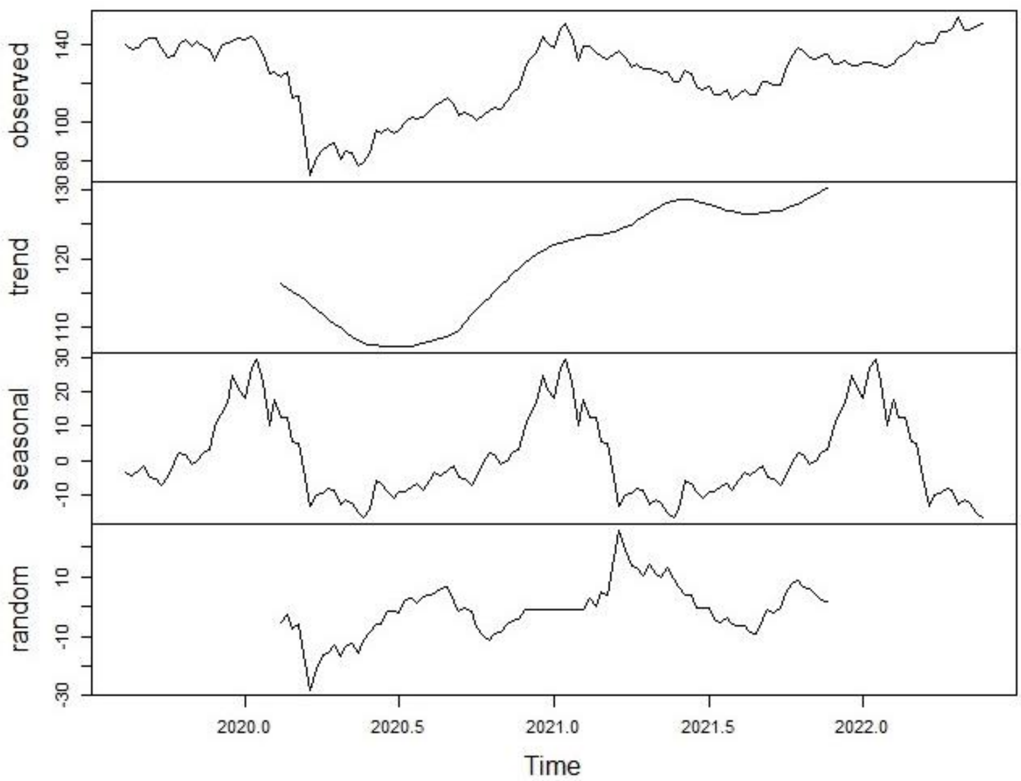

Figure 2 Decomposition of IDXV30

We can see that we have three peaks and troughs in the subfigure. This indicates that the seasonality is persistent in the data. The last component is the random component. This component is what is left after we capture the trend and seasonality in the data. The main point from the random subfigure is that it does not show any discernible or obvious pattern. From the subfigure, we can see that the random components do not have any particular pattern. This shows that time series econometrics method of Holt-Winters seasonality is appropriate for analyzing and forecasting using the

IDXV30 data. Next table shows the analysis of Holt-Winters (HW) Seasonality by additive and multiplicative method.

Table 1 Holt-Winters Seasonality

Parameters	HW-Additive	HW-Multiplicative
α	0.9253	0.7323
β	0.0002	0.0004
γ	0.0747	0.0019
RMSE	7.1754	7.0234
MAPE	4.5847	4.5509
AIC	649.6960	656.0753

Table 1 shows the results of Holt-Winters parameter estimation. The parameters resulted from the estimation is identical for both models in terms of β coefficient. The HW-additive scores a β of 0.0002 while HW-multiplicative is 0.0004. This is not a very marked difference. However, for α and γ, the parameters results are quite different. The α for HW-Additive is 0.9253, while HW-Multiplicative is 0.7323. This difference will account for the different forecasting results of both models. The γ parameter has also different parameters (0.0747 for HW additive and 0.0019 for HW Multiplicative). Applying both method to the training data results in different RMSE and MAPE. We can see that HW-Multiplicative has a good fitness to the training data better that HW-additive. However, this does not automatically mean that HW-Multiplicative will result in better forecasts. According to AIC, HW-additive has a better parameter for forecasting (lower AIC translates into better model estimators). AIC for HW additive is 649.6960 compared to 659.0753 for HW-Multiplicative. From the table 1, we can form the HW additive and multiplicative equations as shows in the followings (first shown is HW-additive followed by HW-multiplicative).

Level: $L_t = 0.9253\ (Y_t - S_{t-s}) + 0.0747\ (L_{t-1} + b_{t-1})$
Trend: $b_t = 0.0002(L_t - L_{t-1}) + 0.9998\ b_{t-1}$
Seasonal: $S_t = 0.0747\ (Y_t - L_t) + 0.9253\ S_{t-s}$
Forecast at 1 period ahead equals $F_{t+1} = L_t + b_t + S_{t-23}$
Level: $L_t = 0.7323\ (Y_t/S_{t-s}) + 0.2677\ (L_{t-1} + b_{t-1})$
Trend: $b_t = 0.0004(L_t - L_{t-1}) + 0.9996\ b_{t-1}$
Seasonal: $S_t = 0.019\ (Y_t/L_t) + 0.981\ S_{t-s}$
Forecast at 1 periode ahead equals $F_{t+1} = (L_t + b_t)\ S_{t-23}$

After succeeding in generating the parameters required for HW-Additive and multiplicative seasonality, we turn our attention to yielding the forecasts result by employing these parameters. The forecasts result will first be shown in graphical form. In subsequent section, the forecasts result will be in numerical table. The figure below shows the forecast by HW-additive seasonality.

Figure 3 above shows forecast results of HW-Additive model. This model generates results whose trend and seasonality is calculated using the parameters resulting from estimation with training data. The results contain trend and seasonality. The trend is positive. However, the trend is not very obvious if we rely on our sight manually. Some smoothing is required to see the obvious pattern. The seasonality component is virtually existent in the forecast results. At every beginning of the year, the inclination will be an upward move that later will halt itself and start downward movement. After that, the move upward will commence again, although in a less steep manner. Some volatility will always be present to indicate uncertainty or risk-taking by market players. The pattern of the forecast results is visibly obvious. This indicates the ability of HW-additive seasonality model in capturing the trend and seasonality existent in the historical data and project them into the future. The following figure is the forecast results generated by HW-Multiplicative model.

The figure 4 above shows the results of forecasting by HW-Multiplicative. Compared to HW-additive, the trend is slightly discernible in this method. It is a positive trend. The index will gradually increase in the long term. The HW-multiplicative model seems able to capture the trend and seasonality in the past data. Just line its counterpart, HW-multiplicative predicts that the index will move upward at the beginning of the year. However, the bull movement is very short-lived. It will start to go down just after the positive trend at the commencement of the year. The move downward is pretty drastic. However, after the move downward, the index will go up again toward the end of the year. Volatility will always be present despite the move upward or downward. In the long-term, the seasonality shows a very visible movement. We can infer that HW-multiplicative is very good at capturing the trend and seasonality of the past data and produce the forecast results that take these trend and seasonality into consideration.

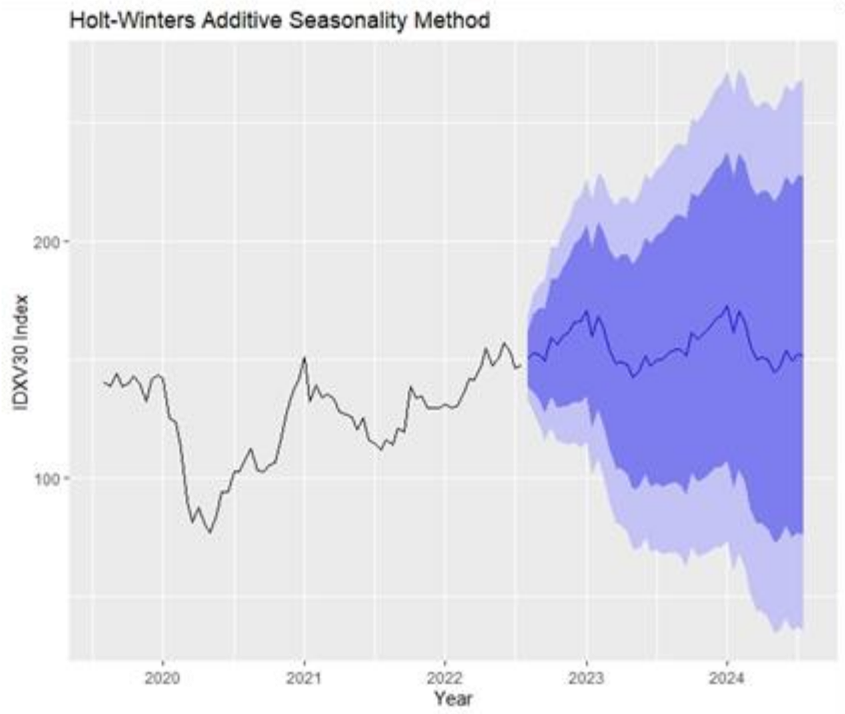

Figure 3 Forecast Results using HW-Additive

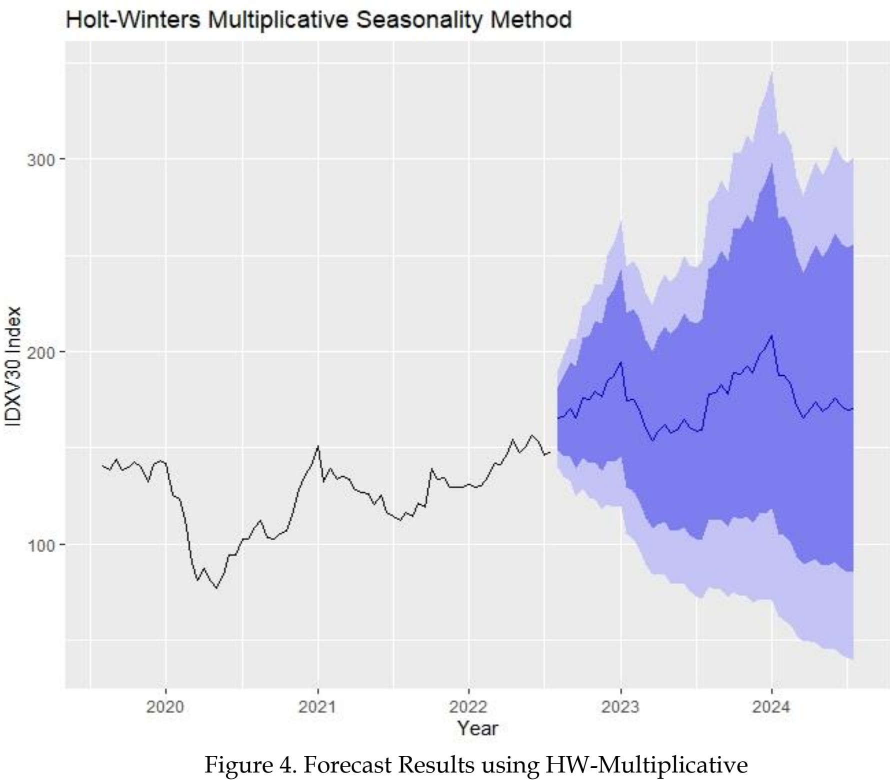

Figure 4. Forecast Results using HW-Multiplicative

The later section will discuss the forecasting by fuzzy time series.

The first step in Fuzzy Time Series-Chen method is to determine the range in which we allow the forecast results to extend from. In this case we set that the minimum value of index will be equal to the minimum value of index in the past data (the minimum value of IDXV30 is 76). Therefore, we set the increase in the minimum value to 0. Subsequently, we set the upper limit for the index value. We predict the upper limit to the forecast results is

161.84. The maximum value of the historical data is 156.84. Therefore, we allow the additional increase of 5 to the prediction. From the range set, we can establish the bins or classes. We have 9 classes each with its own interval. This step is also called fuzzification. The following table contains the parameters of fuzzification.

Table 2 Fuzzification Results

Fuzzification	Min	Max	Mid	Frequency
A1	76.26000	85.76889	81.01444	4
A2	85.76889	95.27778	90.52333	4
A3	95.27778	104.78667	100.03222	4
A4	104.78667	114.29556	109.54111	7
A5	114.29556	123.80444	119.05000	8
A6	123.80444	133.31333	128.55889	14
A7	133.31333	142.82222	138.06778	20
A8	142.82222	152.33111	147.57667	7
A9	152.33111	161.84000	157.08556	3

Table 2 shows the fuzzification of the data. The data are divided into 9 classes. The majority of the data belongs to the A7 bin. This bin contains 20 observations. After A7 bin, the next majority of the data is included in the A6 bin that contains 14 data. The third bin that contain most data is A5 with 8 observations. Now we know that the majority of the past data lies in the range of 114 to 142. We also determine the mid value of each bin. This mid value will represent the bin. Next, we determine the move of each data from one period to another period by presenting the movement in terms of the fuzzification.

A1->A1, A2
A2->A1, A2, A3
A3->A3, A4
A4->A3, A4, A5
A5->A2, A4, A5, A6, A7
A6->A5, A6, A7
A7->A6, A7, A8
A8->A6, A7, A8, A9
A9->A7, A8, A9

Based on the historical data, the observations that belong to A1 will stay in the A1 or move to A2. A2 observations will have more ramifications than A1. A2 observations will stay at A2 or move to A1 or A3. The data in A3 will either stay at A3 or move to A4. A5 has the most choices of movement. The data in A5 will either stay in A5 range or move to A2, A4, A6, and A7. The second range which has most ramifications in A8. Data in A8 either move to A6, A7, or A9, or remain at A8. From this movement map we can forecast the move of the data from our last observations and generate the forecast results. The following table shows the results of fitting the data using Fuzzy-Chen Method.

Table 3. The Performance of Fitting Chen Method to the Data

	ME	MAE	MPE	MSE	RMSE
Chen Method	2.087	6.163	1.159	5.023	63.25

The table 3 shows the performance of Chen method in fitting the model to the data. The MAE is 1.159%. Chen method generate a very small error percentage in fitting to the historical data. This means the bins and range chosen is very good for the historical data. The figure below shows the fitting of Chen method.

The figure 5 confirms the good performance of the Chen method in estimating past data. Therefore, the bins and range generated will be used to forecast future data. The forecasting method surprisingly comes up with only one generated forecast result that is 152.3311. This signifies the fact that the Chen method considers the data to resemble random walk. In random walk, the best prediction for a random walk series is the mean. So random walk will produce only one result of forecast. That is the case in the Chen method we are now employing. Table 4 below will show the performance comparison among the models employed.

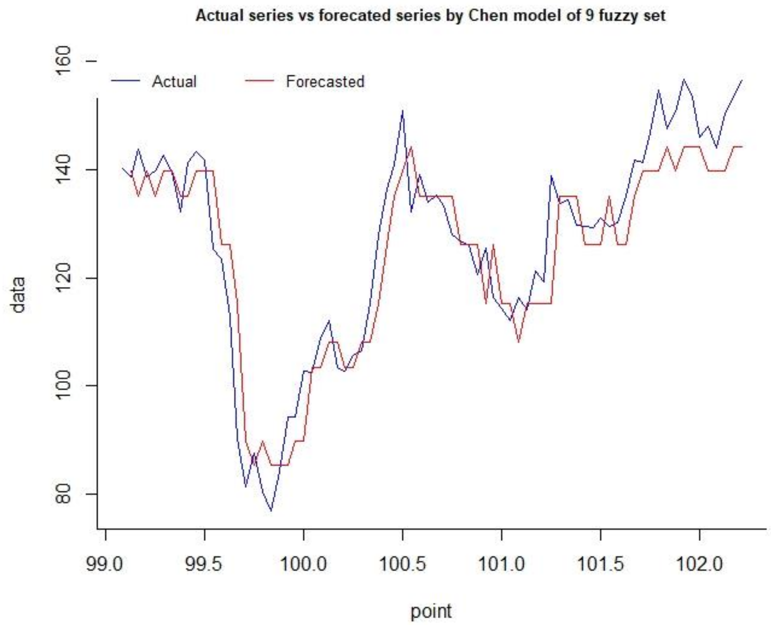

Figure 5. The fitting of Chen Method to the Past

Table 4. The Performance Comparisons

	IDXV30	HW-Additive	HW-Multiplicative	Fuzzy TS
July 2022-1	144.0685	150.5503	165.2462	152.3311
July 2022-2	150.2690	152.6357	166.4508	152.3311
August 2022-1	1523.3761	152.3250	170.0000	152.3311
August 2022-2	156.5620	149.4704	165.5348	152.3311
September 2022-1	161.3340	159.3552	175.9940	152.3311
September 2022-2	156.7370	156.6218	175.1068	152.3311
RMSE		4.1421	16.4296	5.656553
MAPE		2.0982	10.4742	3.1471

The table 4 shows that the RMSE for HW-additive is the lowest, followed by Fuzzy Time-Series Chen Method. The HW multiplicative has the most RMSE. The lowest the value, the better the performance.

5. Discusssion

We can conclude that HW-additive has the best performance among others. This is confirmed by the MAPE number. Again, HW-additive has the lowest value followed by Fuzzy Time-Series. HW-multiplicative comes last in this regard. HW additive has a mean error of 2.0982%. This is a low number for forecast error. Meanwhile, Fuzzy Time-Series also score MAPE way below 10%, namely 3.1471%. HW-multiplicative has a MAPE slightly above 10%. We should note, however, that Fuzzy Time-Series employs random walk model. The forecast result does not vary at all. Only a single value generated for forecast that is 152.3311. This is a little bit unsettling for investors. Fuzzy Time-Series fails to include the trend and seasonality contained in the past data. As a result, investors cannot use Fuzzy Time Series to capture the trend and seasonality since it will likely produce a stable number with little variations. Hence, Fuzzy Time Series is good to give us a general overview of the level of index in the future. Based on this explanation, Holt-Winter multiplicative is better for forecasting by investors since it can recognize any present trend and seasonality and the MAPE is just slightly above 10%. Based on the research results, we can infer that traditional time-series econometrics still excel at predicting forecasting objects that show clear trend and seasonality. The component of trend and seasonality in the econometrics model enable the recognition of upward and downward slope at certain times in a year. This contrasts with methods employed by advances in computer science in which they generate hyper parameters that make the recognition of trend and seasonality more complicated. Although the performance of Fuzzy Time Series is better than Multiplicative Holt-Winters, we do not recommend the use of it for investors or other parties due to the naïve results it generates.

6. Conclusion and Suggestion

Conclusion

The purpose of this research is to compare the forecasting performance of Holt-Winter seasonality and Fuzzy Time Series Forecasting-Chen Model and to determine which method performs best. The results showed that Holt-Winter with additive seasonality is the best method among all. Hence, Holt-Winters additive model is recommended for analysts and investors to yield prediction regarding stock market. The second-best model is Fuzzy Time Series-Chen model. This shows how this model can keep up with Holt-Winters additive model in generating accurate predictions. The main problem, however, is that Fuzzy Time Series-Chen model generates results of random walk properties. There is only one value of prediction, a kind of naïve prediction. This provides evidence of how Fuzzy Time Series-Chen model unable to capture trend and seasonality in the data. Based on this results, Fuzzy Time Series-Chen model is not really appropriate for investors in generating accurate predictions. The least accurate model is Holt-Winters multiplicative in which the percentage forecast result is within 10% range. This is the most errors among all. Despite the inaccuracy, Holt-Winters multiplicative method was able to capture the trend and seasonality and project them into the future. This is a feature that is needed by the investors and analysts because stock market will be more dynamic at a certain time in a year and less dynamic in the others. Analysts, investors, regulators, and other market players interested in making predictions can employ Holt-Winters additive and multiplicative model in this regard.

Suggestion

This research focuses on predicting the value of IDXV30 undex. There is no previous research that had focused on IDDXV30 as the research object. However, IDXV30 comes in biweekly frequency. There is no available data for daily IDXV30. Hence, the resulting forecasts are also biweekly. Future research should endeavour to forecast the daily data of stock index. Future research could still compare the performance of traditional econometrics methods with forecasting technique generated by recent advancement in computer science, like neural network or deep learning.

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