Prediction Farmer Exchange Rate Comparative Method of Analysis Holth-Winters Smoothing and Seasonal ARIMA

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Abstract. The purpose of this research was to predict seasonal time series data using the Holt-Winters exponential smoothing additive model and the Seasonal autoregressive integrated moving average (ARIMA). The data used in this study is data on farmer term of trade at Nort Sumatera in 2016–2020, the source of the data obtained from thes Social website of the Central Statistics Agency. The comparison of the Holt-Winters exponential smoothing method and SARIMA on farmer term of trade from 2016 to 2020 revealed trend patterns and seasonal patterns by first determining the initial values and smoothing parameters to minimize forecasting errors and obtain forecasting from the best model. The best model to prec farmer term of trade is SARIMA (2, 1, 1) 0, 1, 112 because the model fits the observed data well and shows no residual autocorrelation. The results of forecasting farmer term of trade at Nort Sumatera in 2016–2020 have increased continuously every month.

Keywords: Forecasting · Holt-Winters Exponential Smoothing · Seasonal Arima · Best Model

1 Introduction

Time series analysis and forecasting is an active area of research, so the accuracy of time series forecasting is very important for decision making [1]. All predictions, in general, are based on experience, but they can be formulated with varying degrees of mathematical accuracy, including varying degrees of probability or uncertainty. Forecasting does help in the planning and decision-making process, but forecasting results are not always accurate. The accuracy of the forecasting results depends on the accuracy of the data and the methods used.

There are several studies that have been done before to predict a situation in the future. The SARIMA technique is a univariate time collection technique that excels at making forecasts for short time periods [2] and rely on Box Jenkins autoregressive

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integrated moving average (ARIMA) or Seasonal ARIMA (SARIMA) [3]. ARIMA and seasonal ARIMA (SARIMA) models are popular methods for analyzing and forecasting time series data, respectively [4, 5]. The wave-based hybrid ARIMA-NNAR model is suitable for predicting the number cases of HFM [6]. To forecast production and air emissions, the aviation industry employs a hybrid SARIMA-SVR time series approach [7]. SARIMA model for forecasting influenza changes based on monthly data on influenza incidence in China from January 2005 to December 2018 [8]. HoltWinters' hybrid predictive model and support vector machine can be used to estimate shallot seed demand (SVM) [9]. The four comparison algorithms listed below can be used to assess early detection of an infectious disease's onset: Cumulative SUM (CUSUM), Aberration Reporting System (EARS), Autoregressive Integrated Movement (ARIMA), and the Holt-Winters algorithm are all examples of data analysis techniques [10]. This study presents eight statistical models for evaluating time series and comparing their ability to predict grain yield using Holt-Winters and dynamic linear models, which have the most consistent predictive results [11]. In the syndrome surveillance system, the Holt-Winters generalized exponential smoothing algorithm is used to detect time intervals [12–15] and Exponential Weighted Moving Average (EWMA) [16]. The results of the analysis show that by combining ARIMA and RBF models, the given model outperforms either the ARIMA or the RBF model [17]. While COVID19 case predictions are updated every 24 h, the Autoregressive Integrated Moving Average (ARIMA) model was developed to estimate these cases using the HoltWinters Expo Smoothing model in conjunction with the GARCH model [13].

The holt winter additive method's MAPE value is higher than the holt winter additive damped method, according to comparisons made by measuring the MAPE value [15]. The BoxJenkins solution of the autoregressive integrated moving average (ARIMA) and the HoltWinters exponential smoothing method are used in traditional statistical and mathematical techniques [12, 18]. Forecasting entails predicting future results based on historical and current evidence, as well as lowering decision risk by offering additional knowledge about possible outcomes. If a model's performance characteristics have been calculated, They should be validated or checked by comparing the model's forecasts to historical data for the method they are designed to forecast. The model is validated using calculation errors such as MAPE, RAE, and MSE [14, 18–20].

The advancement of the agricultural sector has significantly aided the advancement of national growth. The purchasing power of farmers to fund their household life is one of the measuring instruments used to assess the degree of agricultural welfare [21]. Farmer's Exchange Rate is one measure that shows how farmers' conditions are changing by measuring their capacity and purchasing power in rural areas. The strength of the exchange (terms of trade) between agricultural products and goods and services consumed, as well as production costs, can all be described by the Farmer's Exchange Rate [22]. In North Sumatra Province, the Farmer's Exchange Rate is influenced by inflation, interest rates, labor, GRDP, and the previous year's farmer exchange rate. We can see the evolution of the Farmer's Exchange Rate in North Sumatra Province over the last 30 years from 1989 to 2018 using the Autoregressive Ordinary Least Squares (OLS) method. The fact that the majority score is less than 100 indicates that the farmers of North Sumatra Province are not prosperous or in need [23], In order to assess the progress of development, data on the level of welfare of the population, especially farmers, is required in addition to data on economic growth. The Farmer Exchange Rate is one of the proxy measures that can be used to assess farmer welfare. In 2020, the exchange rate for farmers was 109.83 percent, The average index charged by farmers is 114.75 percent, and the average index earned by farmers is 114.75 percent. The percentage is 104.48 percent. The highest of farmer exchange rate was in December 2020, while the lowest was in May 2020 [22]. Factors influencing food crop farmers' well-being as calculated by Vector Error Correction Mode. Monthly data from 2011 to 2016 was used [24]. The aim of this analysis is to compare the Seasonal ARIMA (SARIMA) method with the Holt-Winters Exponential Smoothing method in a case study of farmer exchange rate data from 2016 to 2020 using the RMAE and RMSE values, as mentioned previously. It will be carried out in order to achieve the best results possible. From January to December 2021, we will forecast farmer exchange rates.

2 Method

In this research, SARIMA and Holt-Winters Exponential Smoothing were used. The procedures are as follows:

SARIMA

The SARIMA model expresses the additive interaction of seasonal and non-seasonal components in the model $\left((p, P), (d, D), (q, Q)_s\right)$ (Seasonal ARIMA), it's possible to write the X_t process like this:

$$\left(1 - \alpha_1 B - \cdots - \alpha_p B^0\right)(1 - B)^d \left(1 - B^s\right)^p D_t$$
$$= \left(1 + b_1 B + \cdots + b_q B^q + \theta_1 B^q + \cdots + \theta_q B^{sQ}\right)\varepsilon_i \tag{1}$$

where: B back operator (backward), is $\left(B^j Y\right) = Y_{t-j}$, p and q = the ARMA model's seasonal part, d = Non-seasonal elements are arranged in a different order, P = the number of autoregression coefficients, of the seasonal component, D = seasonal diferens order, Q = the sum of the moving average coefficients of the seasonal component.

Holt-Winters Exponential Smoothing

The Holth Winter's method is a method for dealing with seasonal and pattern elements that occur concurrently in time series data [14]. This method is based on three elements for each period: stationary elements, trend elements, and seasonality, and it provides three weightings in the prediction, namely α, β, and γ. Menurut Mulyana dalam [14] α, β, dan γ are Alpha (α) is a parameter that controls the relative refinement of the recently made observations, Beta (β) is a parameter that controls the relative refinement of observations made to estimate the appearance of a trend or trend element. Gamma (γ) is the parameter that controls relative generation of observations made to estimate the occurrence of seasonal elements. The amount of the coefficient α, β, and γ has a distance between 0 and 1 determined subjectively or by minimizing the error value of the estimate.

Suppose $X^{(0)} = \left\{x_1^{(0)}, x_2^{(0)}, \cdots, x_s^{(0)}\right\}$, classical Holt-Winter following the equation as:

$$S_t = \alpha \frac{x^{(0)}(t)}{I_{t-L}} + (1-\alpha)(S_{t-1} + b_{t-1}), 0 < \alpha < 1 \tag{2}$$

$$I_t = \beta \frac{x^{(0)}(t)}{S_t} + (1-\beta)I_{t-L}, 0 < \beta < 1 \tag{3}$$

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1}, 0 < \gamma < 1 \tag{4}$$

where L means the length of the season, like the month of the year and the day of the year. I_t is the coefficient of seasonal correction and b_t shows a trend. α, β, and γ is a weighting coefficient that varies from 0 and 1. Thus, the initial values can be initialized as follows:

Suppose the amount of data is as much s, so that the initial level value as a smooth:

$$L_s = \frac{1}{s}(x_1, x_2, \cdots, x_s) \tag{5}$$

Trend initial values:

$$b_s = \frac{1}{s}\left(\frac{x_{s+1} - x_1}{s} + \frac{x_{s+2} - x_2}{s} + \cdots + \frac{x_{s+s} - x_s}{s}\right) \tag{6}$$

Seasonal starting values:

$$S_1 = x_i - L_s; i = 1, 2, \cdots, s$$

The equation used to forecast the period m which will come:
where: L_s = the initial period exponential smoothing value, b_s = initial period trend estimation, x_s = actual value in period to –s, s = seasonal length, and m = the number of future periods to be predicted.

The author's research methodology is shown in Fig. 1.

Forecasting Error Measures

The best forecasting result is the value that has the smallest forecast error. The mean square error and mean absolute percentage error are the error measures used in this study.

The mean square error is a method that evaluates the forecasting method. Each error or bias is squared and then added or divided by the number of observations. This method manages large forecast errors by squaring the errors. Here is to calculate Mean Square Error (MSE).

$$MSE = \frac{\sum e_i^2}{n} = \frac{\sum (X_i - F_i)^2}{n} \tag{7}$$

Mean Absolute Percentage Error is calculated by dividing the absolute error for each period by the actual observed value for that period, and then multiplying the result by the mean absolute percentage error. This method is used to assess and measure the

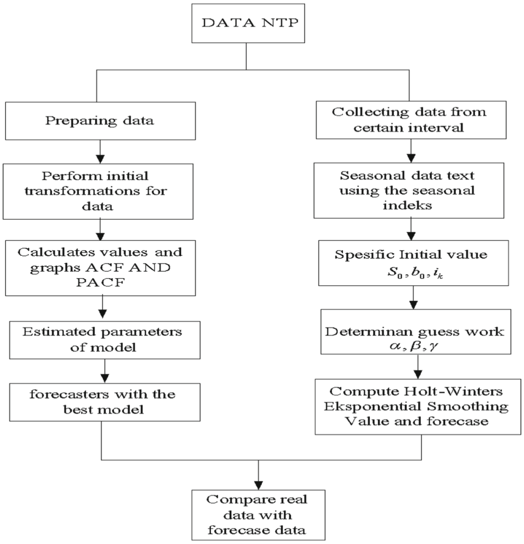

Fig. 1. The Comparing of SARIMA and Holt-Winters' Eskponential Smoothing

forecast's accuracy. MAPE measures the magnitude of the error in comparing the value of the forecast results to the actual value. The formula for calculating MAPE is as follows:

$$MAPE = \frac{\sum \frac{|e_i|}{X_i} \times 100\%}{n} = \frac{\sum \frac{|X_i - F_i|}{X_i} \times 100\%}{n} \tag{8}$$

where: n = the number of time periods in the data, e_i = error on a period of time to –i, X_i = data on time period to –i, F_i = the forecast for the time period to -i.

3 Result and Discussion

The research steps on forecasting farmer exchange rate (NTP) data were initiated with data preprocessing and continued with identifying the best model.

Best Performing SARIMA (Seasonal ARIMA).

Figure 2 shows that the above plot on the ACF/PACF function sig only on lag-1 and decays towards zero for another lag. Modeling is a good model with few parameters based on the principle of simplicity (parsimony). According to Fig. 2 the results of the NTP data plot are obtained by forecasting using Seasonal Autoregressive Integrated Moving Average (SARIMA):

Based on Fig. 3 forecast using exponential smoothing, the NTP data plotting results are obtained as follows: The overall smoothing parmater (alpha) = 0.9998, trend smoothing parameter (beta) = 0.0555 and seasonal smoothing parameter (gamma) = 1e-04. The initial values of level, trend and seasonality is interpreted (Fig. 4).

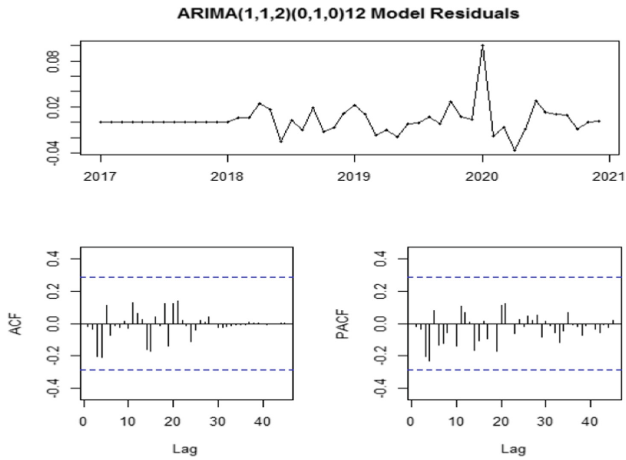

Fig. 2. Residual plot, corresponding ACF and PACF plot

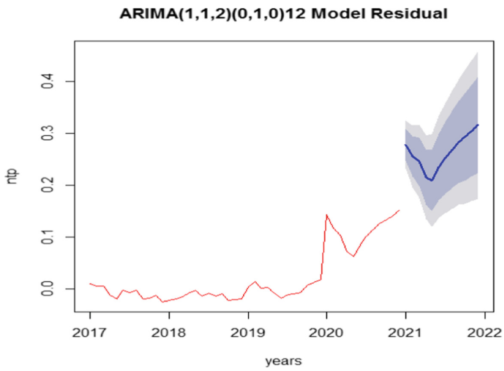

Fig. 3. Best Model ARIMA (1,1,2)0,1,012

The forecasted NTP values for the next two years, assuming they are for 2021 and 2022, are displayed. The values are calculated with a confidence interval of 80% and 95%. As a result, we can see that the above metric measures forecast accuracy. The plot above depicts estimates of the time series data's level, trend, and seasonal components (Fig. 5).

There is no pattern in the residual plot. As a result, we can conclude that the predicted values are correct.

The comparison results of SARIMA and Holt-Winters Exponential Smoothing are shown in Table 1. This can be seen especially in the RMSE and MAPE values which are overall smaller in value when compared to the RMSE and MAPE values of the other two models.

The forecasting results from the Seasonal ARIMA (SARIMA) method and the Holt-Winters Exponential Smoothing method are shown in Table 2.

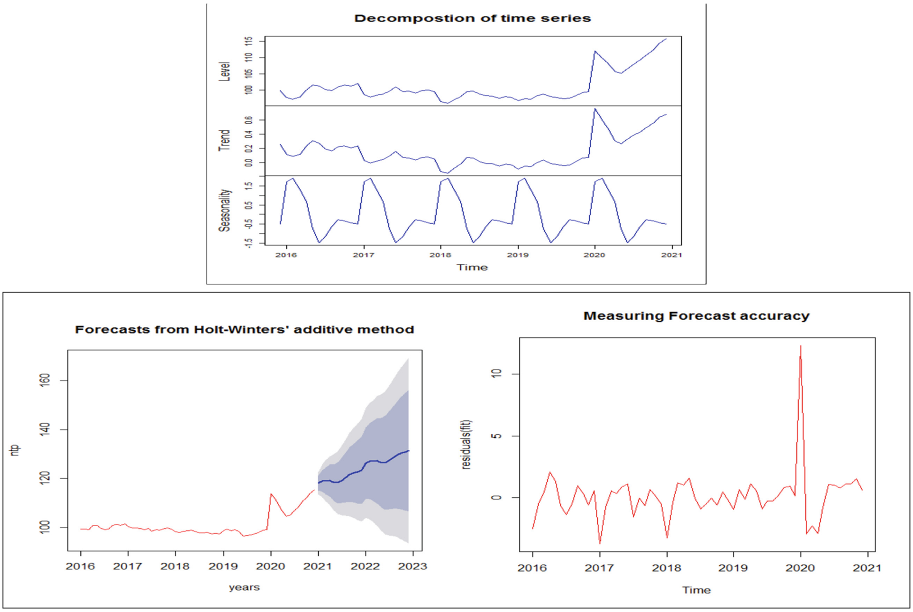

Fig. 4. Plot of estimates of leave, trend and seasonal component of the data time series measuring forecast accuracy

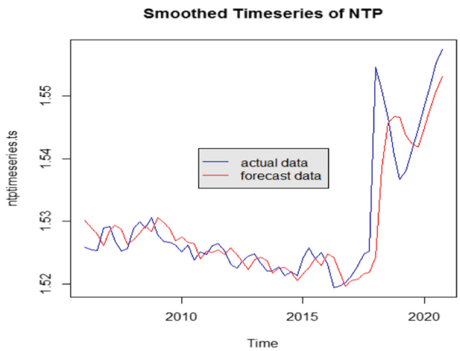

Fig. 5. The plot comparing actual and forecasted data

Table 1. Error Value Comparison of the Two Models Using RMSE and RMAE

Model	SARIMA	Holt-Winters Eksponential Smoothing
Best Parameter	p = 1, d = 1, q = 2	$\alpha = 0.9998$, $\beta = 0.0555$, $\gamma = 1e\text{-}04$
RMSE	0.01923946	2.163281
RMAE	0.01067915	1.036954

Table 2. Forecasting Farmer Term of Trade in 2021

Month	SARIMA	Holt-Winters Eksponential Smoothing
January	210,5071	118.1118
February	198,7070	118.9625
March	184,2608	119.0199
April	159,7961	119.1042
Mei	165,5294	118.3415
Juni	179,9622	118.2806
July	194,8129	119.2876
August	204,4553	120.4837
September	206,9268	121.5224
October	211,7031	122.1394
November	211,5970	122.7108
December	214,4630	123.3238

4 Conclusion

Based on the findings and discussion, it can be concluded that the comparison of Additive Holt-Winters Exponential Smoothing data and SARIMA data on farmer exchange rates from 2016 to 2020 contains trend patterns and seasonal patterns by determining the initial value and parameters in advance of smoothing, which can minimize forecasting error. The obtained additive Holt-Winters exponential smoothing parameters are = 0.9998, = 0.0555, = 1e-04 with RMSE = 2.163281 and RMAE = 1.036954 and also for SARIMA Methods parameters p = 1, d = 1, q = 2 with RMSE = 0.01923946 and RMAE = 0.01067915. The best model to prec farmer term of trade is SARIMA (2, 1, 1) 0, 1, 112 because the model accurately fits the observed data and exhibits no residual autocorrelation. The results of forecasting farmer term of trade at Nort Sumatera in 2016–2020 have increased continuously every month. Based on the results and discussions analyzed, the government and community of Nort Sumatera should pay attention to the increasing farmer term of trade to increase income of farmer in Nort Sumatera every month.

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References

1. Nurhamidah, N., Nusyirwan, N., and Faisol, A., Forecasting Seasonal Time Series Data Using the Holt-Winters Exponential Smoothing Method of Additive Models *J. Mat. Integr* **16** pp 151-157, (2020).
2. Phan, T. T. H., Poisson Caillault, É., and Bigand, A., Comparative study on univariate forecasting methods for meteorological time series *Eur. Signal Process. Conf* pp 2380–2384, (2018).
3. Đukec, D., Forecasting Tourism Demand in Croatia Using Box and Jenkins Methodology, **5** pp 263–273, (2019).
4. Farsi, M. *et al,* Parallel genetic algorithms for optimizing the SARIMA model for better forecasting of the NCDC weather data *Alexandria Eng. J* **60** pp 1299–1316, (2021).
5. ArunKumar, K. E. *et al*, Forecasting the dynamics of cumulative COVID-19 cases (confirmed, recovered and deaths) for top-16 countries using statistical machine learning models: Auto-Regressive Integrated Moving Average (ARIMA) and Seasonal Auto-Regressive Integrated Moving Average *Appl. Soft Comput.***103**, no. February, pp. 107-161, (2021).
6. Yu, G., Feng, H., Feng, S., Zhao, J., and Xu, J., Forecasting hand-foot-and-mouth disease cases using wavelet-based SARIMA-NNAR hybrid model *PLoS ONE* **16**, (2021).
7. Xu, S., Chan, H. K., and Zhang, T., Forecasting the demand of the aviation industry using hybrid time series SARIMA-SVR approach *Transp. Res. Part E Logist. Transp. Rev* **122** pp 169–180, (2019)
8. Cong, J., Ren, M., Xie, S., and Wang, P., Predicting seasonal influenza based on SARIMA model, in mainland China from 2005 to 2018 *Int. J. Environ. Res. Public Health* **16** pp 1–9, (2019).
9. Zhu, Y., Zhao, Y., Zhang, J., Geng, N., and Huang, D., Spring onion seed demand forecasting using a hybrid Holt-Winters and support vector machine model *PLoS ONE* **14** pp 1-18, (2020).
10. Yang, E., *et al,* A simulation-based study on the comparison of statistical and time series forecasting methods for early detection of infectious disease outbreaks *Int. J. Environ. Res. Public Health* **15** pp 1-18, (2018).
11. Rajendran, Han Shihand Suchithra, Comparison of Time Series Methods and Machine LearningAlgorithms for Forecasting Taiwan Blood Services Foundation'sBlood Supply l Of *Journal of Healtcare Engineering, Hindawi* pp 1- 6, (2019).
12. Adeyinka, D. A., and Muhajarine, N., Time series prediction of under-five mortality rates for Nigeria: comparative analysis of artificial neural networks, Holt-Winters exponential smoothing and autoregressive integrated moving average models *BMC Med. Res. Methodol.*, **20** pp 1–11, (2020).
13. Abdulmajeed, K. Adeleke, M., and Popoola, L., Online Forecasting of Covid-19 Cases in Nigeria Using Limited Data *Data in Brief* **30** pp 1–8, (2020)
14. Kalekar, P., Time series forecasting using Holt-Winters exponential smoothing *Kanwal Rekhi Sch. Inf. Technol* **04329008** pp 1–13, (2004)
15. Santosa, R. K. W. I .M.A. and Sarja, N.L.A. K.Y., Perbandingan Metode Holt Winter Additive dan Metode Holt Winter Additive Damped Dalam Peramalan Jumlah Pendaftaran Mahasiswa *J. Ilm. Rekayasa dan Manaj. Sist. Inf.* **5** pp 93–98, (2019).
16. Faverjon, C., Schärrer, S., Hadorn, D. C., and Berezowski, J., Simulation Based Evaluation of Time Series for Syndromic Surveillance of Cattle in Switzerland *Frontiers in Veterinary Science* **6** p 00389, (2019).
17. Wiyanti, D. T., RBF and ARIMA Combined for Time Series Forecasting RBF and ARIMA Combined for Time Series Forecasting *Seminar Nasional Aplikasi Teknologi Informasi (SNATI)* pp 22–27, (2016).

18. Dewi, E.A., Perbandingan metode Holth Winter's exponential smoothing dan extreme learning machine (ELM) pada reramalan penjalan semen pp. 6–13, (2018).
19. Wu, L., Gao, X., Xiao, Y., Liu, S., and Yang, Y., Using grey Holt–Winters model to predict the air quality index for cities in China *Nat. Hazards* **88** pp 1003–1012, (2017).
20. Liu, H. *et al,* Forecast of the trend in incidence of acute hemorrhagic conjunctivitis in China from 2011–2019 using the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Exponential Smoothing (ETS) models *J. Infect. Public Health* **13**, pp 287–294, (2020).
21. Riyadh, M. I., Analisis Nilai Tukar Petani Komoditas Tanaman Pangan Di Sumatera Utara *J. Ekon. dan Kebijak. Publik* **6** pp 17–32, (2015).
22. BPS (Badan Pusat Statistik) Provinsi Sumatera Utara, "Statistik Nilai Tukar Petani Provinsi Sumatera Utara 2020," in *Katalog*, Akhiru Miswar Me Nasution, Ed. Medan, Sumatera Utara: Badan Pusat Statistik Provinsi Sumatera Utara, (2021).
23. Ramadhanu, R., Analisis faktor-faktor yang mempengaruhi nilai tukar petani di provinsi Sumatera Utara *J. Chem. Inf. Model* **53** pp 1689–1699, (2013).
24. Murdy, S., Do Prices Affect Farmer's Term of Trade in Indonesia Jurnal Manajemen &Agribsinis **4** pp 264-272, (2017).