Media Statistika

p-ISSN 1979 – 3693 e-ISSN 2477 – 0647
MEDIA STATISTIKA 17(2) 2024: 197-208
http://ejournal.undip.ac.id/index.php/media_statistika

COMPARISON OF SARIMA AND HIGH-ORDER FUZZY TIME SERIES CHEN TO PREDICT KALLA KARS MOTORBIKE SALES

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DOI: 10.14710/medstat.17.2.197-208

Article Info:
Received: 25 May 2024
Accepted: 21 August 2025
Available Online: 10 October 2025

Keywords:
Forecasting; Fuzzy Logic; High Order; Model Accuracy; Seasonal Model; Time Series.

Abstract: Forecasting sales time series data is essential for companies to support effective planning and decision-making processes. This study evaluates the strengths of the Seasonal Autoregressive Integrated Moving Average (SARIMA) and High-Order Fuzzy Time Series Chen (FTS Chen) models in predicting motorbike sales at Kalla Kars Company, a prominent automotive dealer in Sulawesi, Indonesia. SARIMA is renowned for accurately capturing seasonal patterns, while the FTS Chen model excels in handling data uncertainties and incorporating complex relationships through high-order fuzzy logic. Weekly sales data from January 2020 to February 2024 were analyzed, with 205 weeks used for training and 13 weeks for testing. The results indicate that the third-order FTS Chen model outperforms SARIMA, achieving a Root Mean Square Error (RMSE) of 1.88 and a Mean Absolute Percentage Error (MAPE) of 4.64%. Forecasts for the next eight weeks using the third-order FTS Chen model suggest a decline in sales, contrasting with the SARIMA model, which predicts a slight increase. These results show that Chen's FTS model is more accurate and reliable, making it an effective choice for forecasting Kalla Kars motorbike sales.

1. INTRODUCTION

Time series forecasting is the process of predicting future values in a time series based on patterns and trends present in the data (Hyndman & Athanasopoulos, 2021). An important step in analyzing time series data is to find patterns in the time series data so that the proper method can be determined to model the data (Puspita et al., 2022). A forecasting method often used for data containing seasonal data patterns is the Seasonal Autoregressive Integrated Moving Average (SARIMA). The SARIMA model is an extension of the Autoregressive Integrated Moving Average (ARIMA) model, with the addition of a seasonal component (Ariyanti & Yusnitasari, 2023).

Another approach to time series forecasting introduced by Song & Chissom in 1993 is fuzzy time series (FTS) (Yuliyanto et al., 2023). This method uses the definition of fuzzy time series using fuzzy relational equations and forecasting reasoning presented in linguistic values. A method developed related to FTS is the Fuzzy Time Series Chen method (FTS Chen), introduced by Chen in 1996 (Chellai, 2022). The advantage of FTS Chen is its simplicity in calculations compared to genetic algorithms, including neural network models. This method also efficiently utilizes historical data by associating trend and cycle components through fuzzy logic relationships (Nasr, 2023). According to Yulianto et al. (2023), Chen introduced a high-order FTS in 2002 by developing the Fuzzy Logic Relations (FLR) determination step involving two or more historical data. High-order is used to obtain forecasting values with the greatest accuracy and capture variable data patterns.

Several studies have been conducted on the FTS and SARIMA methods in various case studies. Sugianto et al. (2017) conducted simulations to determine the performance of the combination of methods in Stevenson-Porter-Cheng FTS. Other research by Iswari et al. (2022) compared SARIMA and intervention models in forecasting the number of domestic passengers at Soekarno-Hatta International Airport. In addition, through simulation studies, Haji et al. (2018) compared the performance of ARIMA and FTS models for forecasting time series data. The simulation results show that the FTS Chen model performs well for modeling and forecasting time series data in all situations considered. This is an interesting result because the dataset is generated from the specified ARIMA model, and the FTS Chen model is a good fit for this simulation study, so the application of FTS Chen is recommended due to the method's accuracy.

Time series forecasting has been applied to many data, including sales data. Currently, the automotive industry is experiencing rapid development, and sales of premium motorbikes and electric motorbikes constitute a significant concern. As part of the Kalla Group, Kalla Kars Company is a company engaged in the dealership of four-wheeled and two-wheeled vehicles in the Sulawesi region, including premium motorbikes. The focus of research on Kalla Kars is based on its strategic role in the Sulawesi region's automotive market and the need to address specific challenges faced by the company, such as fluctuating market demand and inventory management. Sales analysis is crucial to help Kalla Kars company make effective marketing strategies, predict market demand, and manage inventory to make better decisions.

Previous studies in the automotive industry have highlighted the importance of accurate forecasting models. For example, Makatjane and Moroke (2016) compared SARIMA and Holt-Winters models to predict car sales in South Africa, finding that SARIMA effectively captured seasonal patterns and short-term trends. However, Holt-Winters performed slightly better in certain cases. Therefore, this research compares the high-order FTS Chen method and SARIMA in forecasting motorbike sales at Kalla Kars Company. The use of a high-order model is based on its ability to capture complex patterns and the inherent uncertainty often found in sales data, providing a more in-depth analysis. These two models are compared due to their distinct modeling approaches. By comparing these two methods, this study seeks to identify the most suitable strategy for capturing the characteristics of motorbike sales data at Kalla Kars. The analysis results are expected to be useful for Kalla Kars Company in improving forecasting accuracy, overcoming sales uncertainty, and increasing competitiveness.

2. LITERATURE REVIEW

2.1. Seasonal Autoregressive Integrated Moving Average

SARIMA is a development of the ARIMA model used for modeling time series data that has seasonal patterns and is denoted by SARIMA $(p, d, q)(P, D, Q)_s$ (Shumway & Stoffer, 2017). The automotive industry frequently exhibits significant seasonal patterns, such as higher sales towards the end of the year or a decline during a particular month. The

SARIMA model is designed to capture these seasonal patterns by adding seasonal components, resulting in more accurate predictions (Makatjane & Moroke, 2016). The general form of the SARIMA model is written as follows (Rochayati et al., 2019):

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D Y_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t \quad (1)$$

with (p, d, q) represents the respective orders of Autoregressive (AR), Moving Average (MA), and non-seasonal differencing models. (P, D, Q) s the seasonal part of the model with S as the number of seasonal periods and B is the backshift operator (Box et al., 2015). The steps of forming the SARIMA model are as follows:

1. Checking the stationarity of the variance and mean value of the data. If it is not stationary in variance, then the Box-Cox transformation is performed. Meanwhile, differencing is performed if it is not stationary in the mean value.
2. Identify the SARIMA model by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.
3. Estimate the model parameters using the maximum likelihood estimation (MLE) method and test their significance. A good model is indicated by all parameters being significant (Aziza et al., 2023).
4. Perform a model diagnostic test to assess the feasibility of the model
5. Overfitting by increasing the p, q, P, dan Q orders of the tentative model while still assessing the model that fulfills the parameter significance and model residual assumptions.
6. Select the best SARIMA model based on the smallest Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) values.

2.2. Fuzzy Time Series Chen Model

FTS is a time series forecasting method that uses fuzzy logic in time series forecasting problems, which can provide explanations for vague data and are presented in linguistic values. This model effectively handles data pattern uncertainty (Silva et al., 2020). Making it suitable for various predictive applications, including managing unpredictable demand fluctuations in the automotive industry. The FTS method developed by Chen in 1996 is one of the FTS forecasting methods, which developed fuzzy principles introduced by Song and Chissom in 1993 (Chellai, 2022; Yuliyanto et al., 2023). The following are the steps of fuzzy time series with the Chen algorithm:

1. Define the universum (U)

   $$U = [D_{min} - D_1, D_{max} + D_2] \quad (2)$$

   where D_1 dan D_2 are constants or arbitrary positive numbers determined by the researcher to define the universe of the historical data set.
2. Determine the interval length. Split the universe set into several equally spaced intervals. The average-based fuzzy time series forecasting method will be applied in this process.
3. Categories Y_t that is the actual data in the fuzzy set A_i based on the interval u_j. Suppose $A_1, A_2, \dots, A_k$ are fuzzy sets with linguistic values of linguistic variables, then fuzzy sets can be defined as follows:

   $$A_1 = \frac{a_{11}}{u_1} + \frac{a_{12}}{u_2} + \cdots + \frac{a_{1m}}{u_m} \quad (3)$$

   $$\vdots$$

   $$A_k = \frac{a_{k1}}{u_1} + \frac{a_{k2}}{u_2} + \cdots + \frac{a_{km}}{u_m}$$

with $1 \leq i \leq k$; $1 \leq j \leq m$, the value of a_{ij} indicates the degree of membership of A_i in u_j, equal to [0, 1]. After categorising Y_t and based on the definition, it is known that if the value of a_{ij} equal to 1 or maximum in u_j then $F(t)$ is the fuzzification of X_t into the fuzzy set A_i.

4. Form an FLR based on the data by examining the relationship between time series data and then grouping the data in a fuzzy logic relationship group (FLRG).
5. Perform forecasting, if $F(t-1) = A_i$, then the forecast value should be based on the following rules:
   a. If the FLR of A_i does not exist ($A_i \rightarrow \emptyset$) then $F(t) = A_i$
   b. If there is only one FLR $A_i \rightarrow A_j$, then $F(t) = A_j$
   c. If ($A_i \rightarrow A_{j1}, A_{j2}, \ldots, A_{jk}$) then $F(t) = A_{j1}, A_{j2}, \ldots, A_{jk}$

According to Yuliyanto et al. (2023), Chen introduced a high-order fuzzy time series in 2002 by developing FLR determination. The formation of FLR in high-order considers two or more historical data according to the order used.

2.3. Model Evaluation

Model evaluation is the step to evaluate the performance of the model. Model evaluation is performed by computing error metrics, such as Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The MAPE and RMSE formulas can be written as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{N} \left|\frac{Y_t - \hat{Y}_{(t)}}{Y_t}\right| \times 100\% \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{t-1}^{n}\left(Y_t - \hat{Y}_{(t)}\right)^2}{n}} \tag{5}$$

where Y_t is the actual data of period t, $\hat{Y}_{(t)}$ is the forecasting value of period t and n is the number of predicted data (Zha et al., 2022).

3. MATERIAL AND METHOD

3.1. Data

The data used in this research is secondary data, i.e. weekly motorbike sales data of Kalla Kars company from January 2020 to February 2024. Data obtained from Kalla Kars company, Makassar, South Sulawesi Province. The methods used in this research are SARIMA and high-order FTS Chen.

3.2. Analysis Method

The steps of data analysis using the SARIMA and high-order FTS Chen methods are as follows:

1. Explore Kalla Kars' motorbike sales data from January 2020 to February 2024 to understand the characteristics and patterns of the data.
2. Split the data into two parts: i.e. train and test data. 205 weeks of sales data are used as training data for modeling. Meanwhile, the remaining 13 weeks are used as test data to evaluate the model.
3. Perform analysis using the SARIMA and high-order FTS Chen method.

4. Perform forecasting using the SARIMA model and high-order FTS Chen according to the test data.
5. Evaluate high-order FTS Chen and SARIMA models based on MAPE and RMSE. The model with the smallest MAPE and RMSE values is selected as a good model for forecasting motorbike sales data of Kalla Kars company.

4. RESULTS AND DISCUSSION

4.1. Data Exploration

The results of data exploration of total motorbike sales at Kalla Kars company show that the average number of motorbike sales from January 2020 to February 2024 is 17.51 units with a standard deviation of 13.26. The highest total motorbike sales occurred in the second week of January 2021 as many as 75 units. The time series data plot on the total motorbike sales graph (Figure 1) shows that the data has a trend pattern and tends to fluctuate.

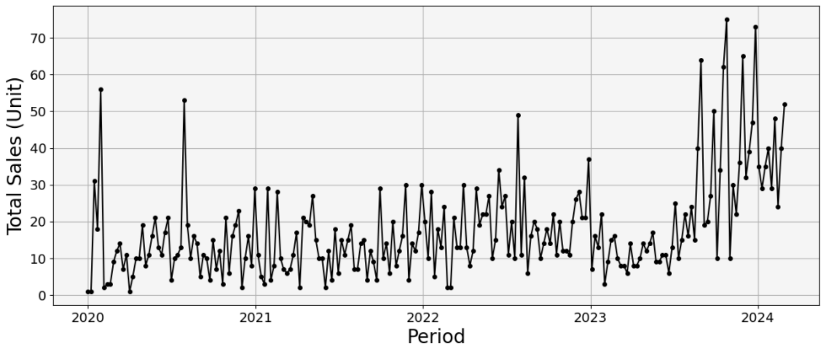


Figure 1. Plot of Kalla Kars' Motorbike Sales Data

The time series decomposition results also show that the identified time series data contains trend and seasonal components (Figure 2). Seasonal patterns are evident each week; the total motorbike sales will increase in the fourth week of each month and decrease in the first week. This happens because the company will pursue the motorbike sales target at the end of each month.

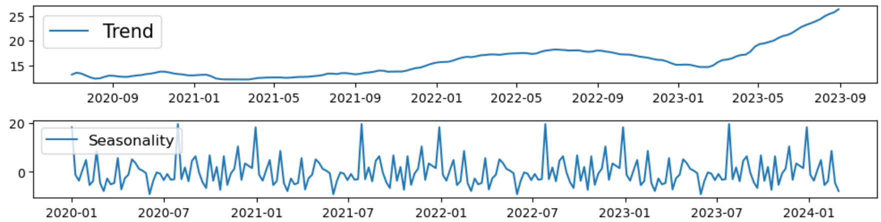
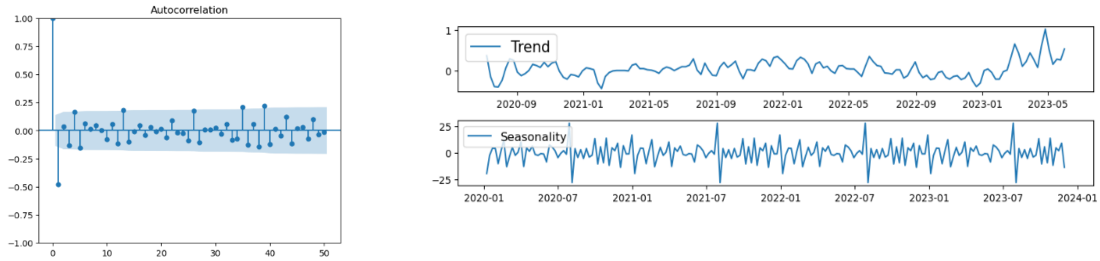


Figure 2. Decomposition Plot of Kalla Kars Motorbike Sales Data

4.2. Seasonal Autoregressive Integrated Moving Average Model

Data stationarity checks are performed by exploration and formal testing. Exploratively, stationarity in the mean was observed based on ACF and PACF plots (Box et al., 2015). The decomposition plot in Figure 2 shows a trend and seasonality in the data. The ACF plot also shows a slow decline and a sine wave, which indicates that the data has a seasonal pattern and is not stationary in the mean. The formal test used to check stationarity in the mean is the Augmented Dickey-Fuller (ADF) test (Hyndman & Athanasopoulos, 2021). The results of the ADF test show that the p-value of 0.717 is greater than the 5% significance level, meaning that the data is not stationary in the mean value, so it needs to be differentiated.

The ACF plot of the non-seasonally differenced data indicates that the data is stationary in mean value and variance as the ACF plot appears to decrease drastically at lag 1 (Figure 3). Checking stationarity with the ADF test on the differentiated data obtained a p-value of 0.00, which is smaller than the 5% significance level, which means that the data is stationary in the mean at the first differencing ($d = 1$).



(a) (b)

Figure 3. (a) ACF Plot (b) Time Series Decomposition Plot of Stationary Data

After the first differencing, the time series plot for Kalla Kars motorbike sales shows that the series is stationary, but there is still a seasonal trend. The ACF plot (Figure 3) shows that the data has a weekly seasonal period because the autocorrelation function value has a strong relationship at seasonal lags (lag 13, 26, 39, ...). Furthermore, to eliminate seasonal trends, seasonal differentiation is performed on the series of the first differentiation results ($D = 1$). After first differencing and seasonal differencing, it is shown in Figure 4 that the series no longer has any trend and has the same fluctuation width, so the data is also stationary in variance.

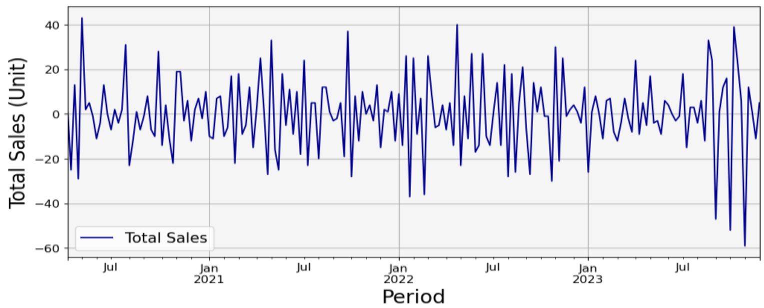


Figure 4. Time Series Plot of Motorbike Sales Data (Seasonal First Differencing)

The determination of the order p, q, and P, Q is performed using the ACF and PACF plots of the first differencing series. The identification results of the ACF and PACF plots of the stationary data obtained by the tentative SARIMA model based on Table 1, the SARIMA$(0, 1, 1)(0, 1, 1)^{13}$ model has the smallest AIC and BIC values compared to other tentative models.

Table 1. Comparison of Tentative Models

Model	AIC	BIC
SARIMA$(0, 1, 1)(0, 1, 1)^{13}$	1461.35	1471.11
SARIMA$(0, 1, 4)(0, 1, 5)^{13}$	1466.36	1498.88
SARIMA$(0, 1, 4)(0, 1, 4)^{13}$	1464.36	1493.64

The results of the homogeneity of variance test (p-value $= 0.048$) and the test of independence of errors (p-value $= 0.00$) of the SARIMA$(0, 1, 1)(0, 1, 1)^{13}$ model show a significant p-value with a significance level of 5%, which means that there is no violation of the assumption of homogeneity of variance and the assumption of independence of errors. It can also be observed from the residual plot and correlogram plot in Figure 5 that the autocorrelation values at all lags are within the interval.

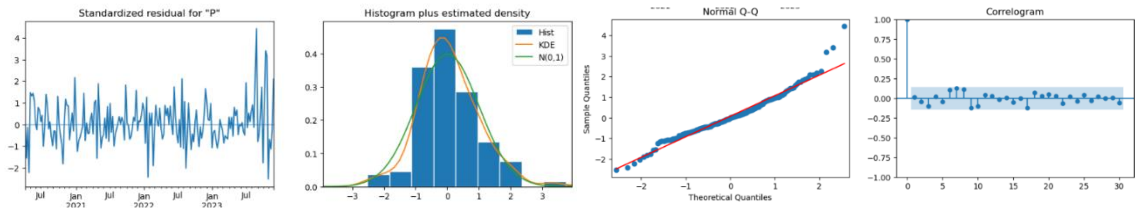


Figure 5. Diagnostics Plot of SARIMA(0, 1, 1)(0, 1, 1)^{13} Model

The Kolmogorov-Smirnov test results show that the residuals are not normally distributed with a p-value (0.00) smaller than the 5% significance level. However, this can be tolerated based on the central limit theorem. The central limit theorem states that a distribution can be approximated by a normal distribution when the sample size is large (Anderson et al., 2014). This research uses a sample of 218 so that it can be said that the assumption of normality of the residuals in the model is fulfilled because the sample size is relatively large. The normality test of the residuals with the QQ plot and histogram in Figure 5 also shows that the distribution of the residuals follows a normal distribution pattern.

Overfitting is performed by adding orders p, q, P, and Q alternately from the initial model to provide an opportunity for a better model than the selected initial model. The results of overfitting the SARIMA(0, 1, 1)(0, 1, 1)^{13} model are presented in Table 2. The parameter estimation results for the SARIMA(0, 1, 1)(0, 1, 1)^{13} model show that the SARIMA(0, 1, 1)(0, 1, 1)^{13} model is significant for each parameter estimation, this is indicated by the p-value which is smaller than the 5% significance level. Meanwhile, the model overfitting results based on Table 2 show that both models have parameter estimates that are not significant at the 5% significance level. The MA(2) parameter estimates in the SARIMA(0, 1, 2)(0, 1, 1)^{13} model and SMA(2) in the SARIMA(0, 1, 1)(0, 1, 2)^{13} model have p-values greater than the 5% significance level. Furthermore, the three models are also validated for their forecasting results with test data as shown in Figure 6, the forecasting results and MAPE values of the three models are not significantly different. This shows that overall, the best SARIMA model that will be used to predict the total motorbike sales of Kalla Kars for the next period is the SARIMA(0, 1, 1)(0, 1, 1)^{13} model.

Table 2. Overfitting Results of SARIMA(0, 1, 1)(0, 1, 1)^{13} Model

Model	Type	Coefficient	p-value	AIC	BIC	MAPE
SARIMA(0, 1, 1)(0, 1, 1)^{13}	MA(1)	-0.854	0.000	1461.35	1471.11	22.83
	SMA(1)	-0.722	0.000*			
SARIMA(0, 1, 2)(0, 1, 1)^{13}	MA(1)	-0.812	0.000*	1463.24	1476.25	22.81
	MA(2)	-0.024	0.763			
	SMA(1)	-0.723	0.000*			
SARIMA(0, 1, 1)(0, 1, 2)^{13}	MA(1)	-0.830	0.000*	1462.79	1475.80	22.66
	SMA(1)	-0.763	0.000*			
	SMA(2)	0.078	0.289			

*parameter estimator is significant at the 5% significance level

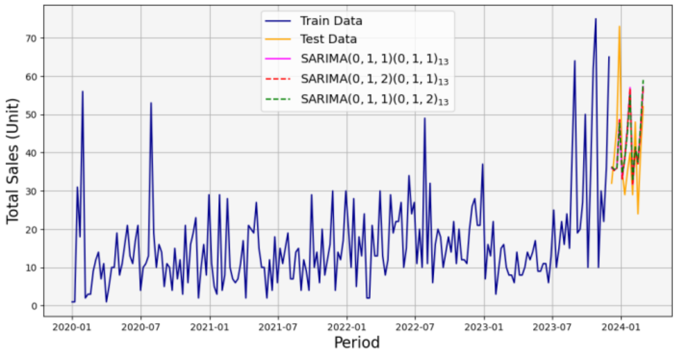


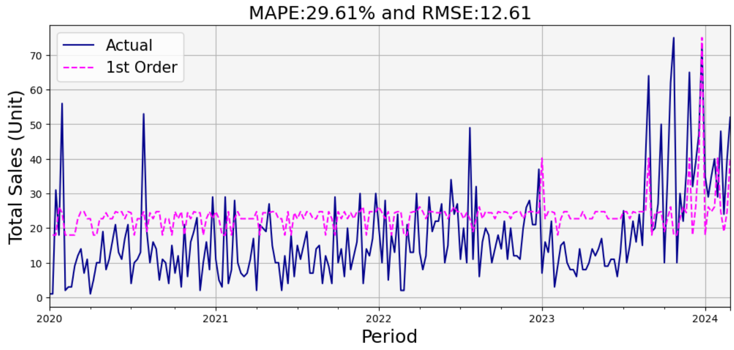
Figure 6. Comparison of SARIMA Model Forecasting Results

Kalla Kars motorbike sales data has the lowest value of 1 and the highest value of 75. The first step is the process of determining two values, D_1 and D_2 are set at 1 and 5, respectively, so that the universe (U) is defined as $U = [0; 80]$. The class segmentation process is carried out by applying an average-based algorithm, which results in an interval length of 6 with the number of interval classes is 13. So that the values u_1 to u_{13} are formed, which are the intervals of the universe (U). The next step is the fuzzification process to convert observed values into defined linguistic values. In this research, the FTS Chen method is applied using first-order, second-order, and third-order. The modeling is limited to third-order based on the consideration that higher-order models often face challenges such as inconsistent forecast rules and parameter sensitivity (Ortiz-Arroyo, 2023).

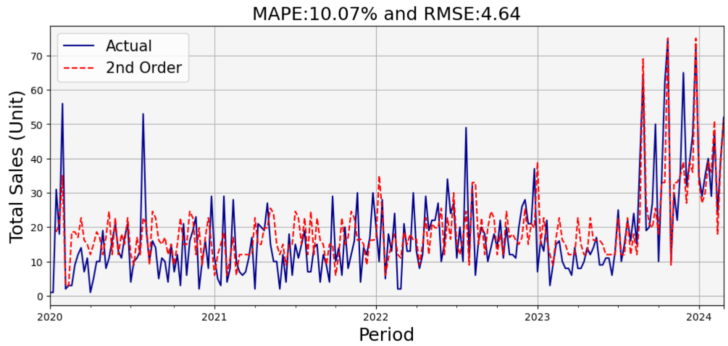
Table 3. High-Order FTS Chen Forecasting Results

Sales	Fuzzification	FLR			Forecasting		
		First-Order	Second-Order	Third-Order	First-Order	Second-Order	Third-Order
1	A_1						
1	A_1	$A_1 \to A_1$			18		
31	A_6	$A_1 \to A_6$	$A_1, A_1 \to A_6$		18	19	
18	A_4	$A_6 \to A_4$	$A_1, A_6 \to A_4$	$A_1, A_1, A_6 \to A_4$	26	21	21
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
24	A_5	$A_9 \to A_5$	$A_5, A_9 \to A_5$	$A_7, A_5, A_9 \to A_5$	19	18	27
40	A_7	$A_5 \to A_7$	$A_9, A_5 \to A_7$	$A_5, A_9, A_5 \to A_7$	25	39	39
52	A_9	$A_7 \to A_9$	$A_5, A_7 \to A_9$	$A_9, A_5, A_7 \to A_9$	40	51	51

Table 3 presents the results of Kalla Kars motorbike sales forecasting analysis using FTS Chen with first-order, second-order, and third-order. The difference between FTS Chen with high order lies in how the FLR is determined. The formation of FLR in high-order considers two or more historical data according to the order used. In this research, the determination of FLR for first-order involves one historical data, second-order involves two historical data, and third-order involves three historical data. The forecasting results on the overall data for each order with the actual data are presented in Figure 7. The figure compares between the actual data of Kalla Kars motorbike sales for the period January 2020 to February 2024 with the forecasting results using FTS Chen of first-order, second-order, and third-order. Based on the visualization, the third-order forecasting results tend to be closer to the actual data than the first-order and second-order forecasting results. Furthermore, the model evaluation uses two error metrics, MAPE and RMSE. The model was empirically validated by forecasting Kalla Kars' total motorbike sales for the next 13 periods, from December 2023 to February 2024.



(a)



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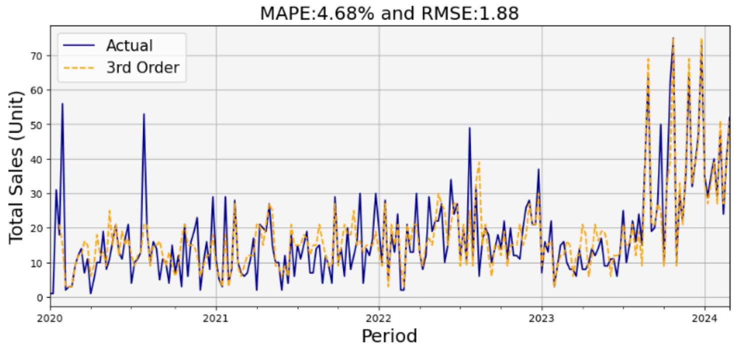

(c)

Figure 7. FTS Chen Forecasting Results (a) First-order, (b) Second-order, (c) Third-order

The forecasting results on the test data show that the first-order FTS Chen has MAPE and RMSE values of 29.61% and 12.61, respectively, the second-order FTS Chen has MAPE and RMSE values of 10.07% and 4.64, respectively, and the third-order FTS Chen has MAPE and RMSE values of 4.69% and 1.88, respectively. Based on these forecasting results, FTS Chen with third-order provides smaller MAPE and RMSE values than other orders for Kalla Kars motorcycle sales data. However, it cannot be definitively concluded that using higher orders always results in better predictions. Further research is needed to examine the limitations and trade-offs associated with higher-order models. Additionally, higher-order models are more complex and have a potential for overfitting.

Model evaluation on the test data is performed to compare the accuracy of the forecasting results of SARIMA and high-order FTS Chen models in forecasting the total motorbike sales of Kalla Kars company. Model evaluation is performed by forecasting the total motorbike sales of Kalla Kars based on test data using SARIMA and high-order FTS Chen models. The forecasting accuracy of the two models is calculated based on the MAPE and RMSE values. The third-order FTS Chen model has an RMSE value of 1.88 and MAPE of 4.64%, smaller than the SARIMA model, which has an RMSE of 10.95 and MAPE of 22.83%. This means that the accuracy of the third-order FTS Chen model is better than the SARIMA model in forecasting the total motorbike sales of Kalla Kars company based on the test data. The results of forecasting the total sales of motorbikes of Kalla Kars with SARIMA and third-order FTS Chen model show that the forecast value of third-order FTS Chen is almost close to the value in the test data (Figure 8).

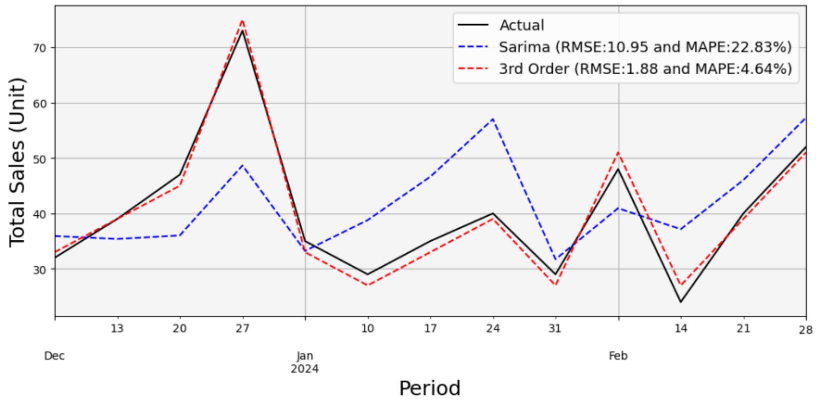

Figure 8. Third-order FTS Chen and SARIMA Forecasting Results with Test Data

Furthermore, SARIMA and third-order FTS Chen models are used to forecast the number of motorbike sales of Kalla Kars company for the next eight weeks. The forecasting results using third-order FTS Chen show a decrease in the total sales of Kalla Kars motorbikes during the next 8-week period. Meanwhile, the forecasting results using SARIMA show that the total sales of Kalla Kars motorbikes tend to increase. The findings of this study show that the third-order High-Order FTS Chen model provides better forecasting accuracy than the SARIMA model for motorcycle sales data at Kalla Kars Company.

Table 4. Forecasting Total Motorbike Sales Using Third-order FTS Chen and SARIMA

Weeks	Period	Forecasting	
		SARIMA	FTS Chen orde 3
1	06/03/2024	42	27
2	13/03/2024	41	33
3	20/03/2024	42	15
4	27/03/2024	54	21
5	03/04/2024	39	15
6	10/04/2024	44	19
7	17/04/2024	55	9
8	24/04/2024	63	15

The results of this study align with the previous research by Haji et al. (2018), which highlighted the advantages of the FTS Chen model. The research compares the performance of ARIMA and FTS models, specifically the Chen and Yu method, in forecasting time series data. The study was conducted through a simulation study using synthetically generated data from the ARIMA (1,0,1) model. The results show that the FTS Chen model has an acceptable performance for modeling and forecasting time series data in all of the situations considered. It is an interesting result because data sets are generated from the specified ARIMA model.

5. CONCLUSION

The analysis results show that the third-order Fuzzy Time Series Chen model is better for forecasting the total motorbike sales of Kalla Kars company. This is based on the validation results on the test data with a MAPE value of 4.69% and RMSE of 1.88 and the plot of forecasting results that are almost close to the test data. In addition, the forecasting results of Kalla Kars' motorbike sales with the third-order FTS Chen also show that there is a decrease in Kalla Kars' motorbike sales during the next 8-week period.

ACKNOWLEDGMENT

We express our deepest gratitude to Kalla Kars Company, which provides motorbike sales data access.

REFERENCES

Anderson, D. R., Sweeney, D. J., Williams, T. A., Camm, J. D., & Cochran, J. J. (2014). *Statistics for Business Economics*. South-Western: Cengage Learning ALL.

Ariyanti, V. P., & Yusnitasari, T. (2023). Comparison of ARIMA and SARIMA for Forecasting Crude Oil Prices. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, 7(2), 405–413. DOI: 10.29207/resti.v7i2.4895

Aziza, V. N., Moh'd, F. H., Maghfiroh, F. A., Notodiputro, K. A., & Angraini, Y. (2023). Performance Comparison of SARIMA Intervention and Prophet Models for Forecasting the Number of Airline Passenger at Soekarno-Hatta International Airport. *BAREKENG: Jurnal Ilmu Matematika Dan Terapan*, 17(4), 2107–2120. DOI: 10.30598/barekengvol17iss4pp2107-2120

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time Series Analysis Forecasting and Control* (5th ed.). Hoboken, New Jersey: Wiley.

Chellai, F. (2022). Forecasting using Fuzzy Time Series. *Munich Personal RePEc Archive Forecasting*. Retrieved from https://mpra.ub.uni-muenchen.de/113848/

Haji, H. A., Sadik, K., & Soleh, A. M. (2018). A Comparative Simulation Study of ARIMA and Fuzzy Time Series Model for Forecasting Time Series Data. *International Journal of Scientific Research in Science, Engineering and Technology*, 4(11), 49–56. DOI: 10.32628/ijsrset1184112

Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and Practice* (3rd ed.). Melbourne: OTexts.

Iswari, A., Angraini, Y., & Masjkur, M. (2022). Comparison of The SARIMA Model and Intervention in Forecasting The Number of Domestic Passengers at Soekarno-Hatta International Airport. *Indonesian Journal of Statistics and Its Applications*, 6(1), 132–146. DOI: 10.29244/ijsa.v6i1p132-146

Makatjane, K. D., & Moroke, N. D. (2016). Comparative Study of Holt-Winters Triple Exponential Smoothing and Seasonal ARIMA: Forecasting Short Term Seasonal car sales in South Africa. *Risk Governance & Control: Financial Markets & Institutions*, 6(1), 1–18.

Nasr, M. M. S. A. El. (2023). Fuzzy Time Series Forecasting: Chen, Markov Chain and Cheng Models. *Journal of Alexandria University for Administrative Sciences*, 60(2), 33–45. DOI: 10.21608/acj.2023.294123

Ortiz-Arroyo, D. (2023). A Fuzzy Time Series-Based Model Using Particle Swarm Optimization and Weighted Rules. *ArXiv*, 1–19. DOI: 10.48550/arXiv.2310.18825.

Puspita, N., Afendi, F. M., & Sartono, B. (2022). Comparison of SARIMA, SVR, and GA-SVR Methods for Forecasting the Number of Rainy Days in Bengkulu City. *BAREKENG: Jurnal Ilmu Matematika Dan Terapan*, 16(1), 355–362. DOI: 10.30598/barekengvol16iss1pp353-360

Rochayati, I., Syafitri, U. D., Sumertajaya, I. M., & IJSA, I. J. of S. and I. A. (2019). Kajian Model Peramalan Kunjungan Wisatawan Mancanegara Di Bandara Kualanamu Medan Tanpa Dan Dengan Kovariat. *Indonesian Journal of Statistics and Its Applications*, 3(1), 18–32. DOI: 10.29244/ijsa.v3i1.171

Shumway, R. H., & Stoffer, D. S. (2017). *Time Series Analysis and Its Applications: With R Examples*. Cham: Springer.

Silva, P. C. de L. e, Junior, C. A. S., Alves, M. A., Silva, R., Weiss Cohen, M., & Guimarães, F. G. (2020). Forecasting in Non-stationary Environments with Fuzzy Time Series. *Applied Soft Computing Journal*, Vol. 97. DOI: 10.1016/j.asoc.2020.106825

Sugianto, W. D., Soleh, A. M., & Afendi, F. M. (2017). Forecasting Simulation with ARIMA and Combination of Stevenson-Porter-Cheng Fuzzy Time Series. *International Journal of Computer Science and Network*, 6(6), 2277–5420.

Yuliyanto, M. R., Wuryandari, T., & Utami, I. T. (2023). Peramalan Pendapatan Bulanan Menggunakan Fuzzy Time Series Chen Orde Tinggi. *Jurnal Gaussian*, 12(1), 61–70. DOI: 10.14710/j.gauss.12.1.61-70

Zha, W., Liu, Y., Wan, Y., Luo, R., Li, D., Yang, S., & Xu, Y. (2022). Forecasting Monthly Gas Field Production Based on The CNN-LSTM Model. *Energy*, Vol. 260, 124889. DOI: 10.1016/j.energy.2022.124889