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RESEARCH PAPER

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Implementation of Bayesian Structural Time Series (BSTS) Method for Predicting Traditional Market Revenue Achievement in Surabaya

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ABSTRACT

Traditional markets play an important role in the regional economy, including in the city of Surabaya. However, the number of traditional markets in Surabaya has continued to decline in recent years due to competition with modern markets. In addition, the contribution of traditional markets to Regional Original Income (PAD) has fluctuated, for example 1.67% in 2013, 1.66% in 2014, and increased to 1.76% in 2015. This condition poses a challenge for the management of regional economic policies, so an accurate prediction method is needed to support strategic decision making. This study aims to predict the achievement of traditional market revenue in Surabaya using the Bayesian Structural Time Series (BSTS) method. The data used is the percentage of traditional market revenue achievement over the past fifteen years. The BSTS model is applied with various components, including Local Level, Local Linear Trend, and Seasonal, which allows flexibility in capturing trends, seasonal patterns, and structural changes in the data. Model evaluation is carried out using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) to assess prediction accuracy. The results of the study showed that the BSTS model with Local Level and Seasonal components and 1,000 MCMC iterations provided the best performance, with a MAPE value of 4.036% and an RMSE of 5.198. This model is able to capture trend and seasonal patterns well, making it effective in predicting traditional market revenue achievements. Based on these findings, the BSTS method has proven to be a reliable approach in predicting traditional market revenue achievements. The results of this study are expected to help market managers and policy makers in designing more adaptive strategies to maintain the competitiveness of traditional markets and increase their contribution to the regional economy.

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1. INTRODUCTION

Traditional markets are trading centers that play an important role in the local economy [1]. One of the areas that has a traditional market is the city of Surabaya. This city has a variety of traditional markets that play a role in meeting the daily needs of the community [2]. In Surabaya, traditional markets are managed by the Regional Company of Pasar Surya, which is tasked with managing and ensuring the sustainability of traditional markets so that they continue to contribute to the regional economy. However, the number of traditional markets in Surabaya has decreased, from 77 units in 2014 to 67 units in 2015 [3], Meanwhile, the number of modern markets experienced a significant increase from 437 units in 2013 to 729 units in 2017 [4]. This decline is thought to have occurred due to competition with supermarkets, convenience stores, and online stores that are increasingly squeezing the existence of traditional markets. Revenue from traditional markets also contributes to the Original Regional Income (PAD) of Surabaya City. The contribution of traditional markets to PAD also fluctuated, with figures of 1.67% in 2013, 1.66% in 2014, and increasing to 1.76% in 2015 [5]. The decline in the number of traditional markets and the fluctuation of their contributions pose challenges in the management and planning of regional economic policies. Therefore, a method is needed that can help predict the achievement of traditional market income in order to formulate a more effective strategy in maintaining the competitiveness of traditional markets.

Currently, the analysis of traditional market revenue achievement in Surabaya is not supported by an optimal predictive model. One approach that can be utilized time series analysis is used for making forecasts. [6]. Forecasting is a method for estimating future values by examining past and present data trends [7]. Most of the approaches used are still based on historical trends without considering seasonal factors and structural variations. In addition, traditional forecasting methods such as ARIMA have been widely used, but still have

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limitations in capturing complex patterns in time series data [8] [9]. ARIMA is also less flexible in capturing seasonal patterns and structural changes that may occur suddenly in the data [10]. Therefore, the Bayesian Structural Time Series (BSTS) model was chosen because it has the ability to accommodate trends and seasonality in one flexible modeling framework. BSTS also excels in handling model uncertainty and data dynamics that change over time, making it suitable for predicting traditional market revenue achievement data that tends to fluctuate.

The Bayesian Structural Time Series (BSTS) model is a method that can be applied to forecast time series data [11]. This method was chosen because it is able to identify trends, seasonal patterns, and other components with a high degree of accuracy [12]. Numerous studies have explored the implementation of the BSTS model across different domains. A study by [13] showed that air traffic demand in Colombia can be predicted to recover in the next few years using the BSTS model. The results showed low MAPE values (1-7%), indicating a high level of accuracy and the feasibility of this method for forecasting. Other studies by [14] Utilized the BSTS model to forecast sea surface temperature in the Red Se. The findings of this study demonstrated that the BSTS model can accurately forecast monthly sea temperatures. In addition, research by [15] compared the BSTS and ARIMA models in predicting syphilis trends in Jiangsu Province. The results showed that BSTS performed better with a MAPE value of 10.57%, compared to ARIMA which had a MAPE of 14.40%.

This research seeks to examine the pattern of traditional market revenue achievement in Surabaya using the BSTS model to help the Pasar Surya Regional Company in formulating strategic policies to maintain the existence of traditional markets amidst competition with modern markets. First, to develop a more accurate prediction model of traditional market revenue achievement in Surabaya with BSTS. Second, the results of the study can be a basis for the Pasar Surya Regional Company in designing strategies to maintain traditional markets. Third, to fill the research gap, because there has been no similar study on revenue achievement prediction. Fourth, to provide insight into the application of BSTS in regional economic forecasting, especially in the context of traditional market revenue achievement.

This study is organized as follows: Section II covers the materials, dataset, and research methodology. Section III outlines the processing results and evaluation of the BSTS model. Section IV provides an interpretation of the findings, a comparison with prior studies, and a discussion of the study's limitations. Lastly, Section V presents the conclusion, summarizing the objectives, key results, and potential directions for future research.

2. MATERIALS AND METHOD

A. Bayesian Structural Time Series (BSTS)

This The Bayesian Structural Time Series (BSTS) model is a state-space framework approach designed for analyzing time series data [16] [17] and A versatile framework for time series modeling, particularly effective in handling intricate patterns and significant uncertainty, as it is able to flexibly estimate time trends, seasonal patterns, and irregular deviations or dynamics through variable selection with shrinkage techniques on high-dimensional data [18]. The bsts package is available in R programming [19]. According to [20] [21], The application of the Bayesian approach to the BSTS model involves several main steps as follows:

1. Identify the prior distribution for each parameter in the model.
2. Estimating the posterior distribution. Due to the complexity of analytical calculations in Bayesian methods, a numerical approach is applied using MCMC simulations, such as Gibbs sampling. This technique draws samples from the posterior distribution to estimate parameters in the BSTS model.

The BSTS model divides time series data into several main components, such as trends, seasonal patterns, and other structures, so that it can provide more accurate and easy-to-analyze modeling. Here is the BSTS formula shown in Eq. (1) [20] and Eq. (2) [20].

$$y_t = Z_t^l \alpha_t + \epsilon_t \quad (1)$$
$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \quad (2)$$

The observation equation is expressed as the first equation (1), while the state equation is expressed as the second equation (2); both relate the observed data y_t to the state vector α_t. Where $\epsilon_t \sim N(0, \sigma_t^2)$ and $\eta_t \sim N(0, Q_t)$ are independent of each other and do not depend on other variables. ϵ_t represents the observation error, while η_t Represents the system error. The output vector, transition matrix, control matrix, and state-diffusion matrix are symbolized as Z_t, T_t, R_t, and Q_t [22]. The following are the components of the BSTS model used in this study.

1) Local Level.
Local level models are the simplest form of structural time series models. These models assume that trends are random and do not follow a particular pattern [22]. Therefore, this model is defined in Eq. (3) [20], and Eq. (4) [20].

$$y_t = \alpha_t + \epsilon_t \quad e_t \sim N\left(0, \sigma_\epsilon^2\right) \quad (3)$$
$$\alpha_{t+1} = \alpha_t + \eta_t \quad u_t \sim N\left(0, \sigma_\eta^2\right) \quad (4)$$

In the local level model, the Z_t, T_t, and R_t matrices in the equation are reduced to scalars with the value '1'. The parameters of this model are the variances of the error terms $(\sigma_\epsilon^2, \sigma_\eta^2)$ [20] [22] [23].

2) Local Linear Trend.
The local linear trend model is a valuable option for trend modeling due to its capability to respond directly to local changes, which plays a crucial role in

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short-term forecasting [19]. The following is the equation for the local linear trend component, as shown in Eq. (5) [17], Eq. (6) [17], and Eq. (7) [17].

$$y_t = \mu_t + e_t, \quad e_t \sim N\left(0, \sigma_\epsilon^2\right) \tag{5}$$

$$\mu_{t+1} = \mu_t + \beta_t + \omega_t, \quad \omega_t \sim N\left(0, \sigma_\omega^2\right) \tag{6}$$

$$\beta_{t+1} = \beta_t + \varphi_t \quad \varphi_t \sim N\left(0, \sigma_\varphi^2\right) \tag{7}$$

In this model, μ_t represents the trend, while β_t s the seasonal component. In addition, This model adapts more quickly within the state-space framework [17].

3) Seasonal.
The seasonal component in the time series model plays a role in capturing recurring fluctuations in a certain period [23]. Therefore, this model is defined in Eq. (8) [17] and Eq. (9) [17].

$$Y_t = \mu_t + \theta_t + e_t \quad e_t \sim N\left(0, \sigma_\epsilon^2\right) \tag{8}$$

$$\theta_{t+1} = -\sum_{s=0}^{s-2} \theta_{t-s} + y_{\theta,t} \tag{9}$$

In this case, S represents the number of seasons, while y_t represents the contribution to the response Y_t. This model has the most recent seasonal effect at $S-2$ and includes a scalar for the error term. In a state model with less than full equipment, the average The overall seasonal effect sums to zero across S seasons [17].

B. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a statistical measure utilized to assess the accuracy of a model [24]. A lower MAPE value indicates a higher level of accuracy in the prediction model [25]. MAPE is calculated by taking the absolute difference between the observed and predicted values, dividing it by the observed value, and representing the outcome as a percentage [26]. In this research, MAPE serves as a metric to assess the model's accuracy in forecasting traditional market revenue achievement. calculated using Eq. (10) [27].

$$MAPE = \frac{1}{n}\sum_{p=1}^{n}\left|\frac{Y_p - F_p}{Y_p}\right| x\ 100\% \tag{10}$$

Where Y_p is the actual data, F_p is the result data, n is the number of data [28]. The evaluation of accuracy is shown in the Table 1. below.

Table 1. Accuracy assessment [27] [29]

Nilai MAPE	Prediction Accuracy Assessment
< 10%	Highly accurate
11%-20%	Good prediction
21%-50%	Makes sense
>51%	Inaccurate

C. Root Mean Squared Error (RMSE)

RMSE (Root Mean Squared Error) is a commonly utilized metric to assess the accuracy and goodness of fit of a model [30]. The computation is done by taking the square of the difference between the actual and predicted values [31], taking the average, and then calculating the square root. A small RMSE value indicates that the prediction is close to the best method [32], while a large value indicates a higher error. In this study, RMSE serves as the primary indicator for assessing the performance of the BSTS model, aiming to minimize prediction errors and provide a reliable foundation for more accurate decision-making. The RMSE equation is shown in Eq. (11) [33].

$$RMSE \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \tag{11}$$

Where yi is the actual data, $\hat{y}i$ is the predicted data, n is the number of data [33].

D. Research Methodology

Fig. 1. is a research approach that includes multiple stages, namely data collection, data processing, BSTS modeling using local level components, local linear trends, and seasonality, and model evaluation using MAPE and RMSE. The following are the steps in the research process.

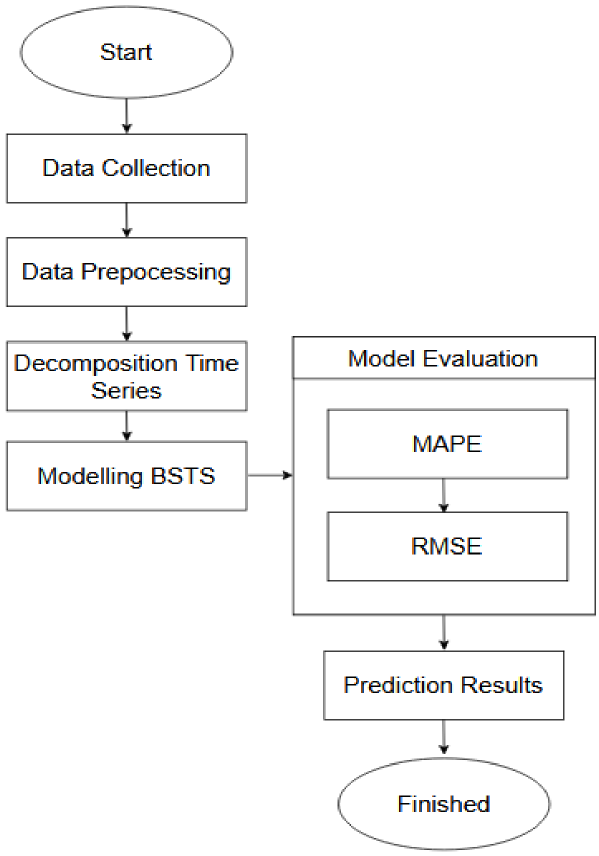

Fig. 1. Research flow

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1) Data Collection
This study uses monthly historical data from the Pasar Surya Surabaya Regional Company in the form of a percentage of traditional market revenue achievement over the past 15 years. The analyzed data spans from January 2009 to December 2023, consisting of a total of 180 records, which provides an overview of trends, fluctuations, and patterns of changes in traditional market revenue achievement over time.
2) Data Prepocessing
Data preprocessing includes different techniques to improve the quality of raw data, ensuring higher precision and dependability [34]. Data preprocessing aims to eliminate unwanted variations or disturbances in the signal, enabling optimal extraction of relevant information for more efficient modeling [35]. However, in this study, data processing is focused on handling outliers by replacing deviant values. So that the data used in analysis or forecasting has optimal quality and can produce more accurate results. Handling outliers is an important step before modeling, with the aim of identifying and addressing data that deviates significantly from the general pattern [36]. In revenue achievement data, outliers often arise due to recording errors or unexpected events that can disrupt the accuracy of the model. The outlier identification method with the Interquartile Range (IQR) was chosen because it is able to detect extreme values effectively without relying on a particular data distribution [37], with the criteria that data is considered an outlier if it is below $Q1 - 1{,}5xIQR$ or above $Q3 + 1{,}5xIQR$, where $Q1$ and $Q3$ are respectively the first and third quartiles of the data distribution. To maintain data quality. The detected outliers are then handled using linear interpolation [38], namely by replacing it based on the trend pattern of the values before and after. In this way, the data remains consistent and the forecasting model can work optimally.
3) Decomposition Time Series
Time series decomposition involves separating time series data into its fundamental components, including trend, seasonality, and residuals [39] [40]. The time series decomposition process helps understand patterns in revenue achievement data, including identifying long-term trends, seasonal patterns, and isolating seasonality and random variations that may affect analysis and predictions.
4) Modelling BSTS
Before modeling, The dataset is split into training and testing subsets to minimize overfitting. The training subset is utilized for model development, while the testing subset is used to assess its performance. In this study, the data was split using a 90:10 ratio for training and testing. The BSTS model will be constructed by testing each component individually and in combination to analyze its impact on prediction accuracy. Also, using three variations of the number of Markov Chain Monte Carlo (MCMC) iterations, namely 1,000, 5,000, and 10,000 iterations, to evaluate the stability and convergence of parameter estimates in the BSTS model. The selection of these variations aims to compare the estimation results and see whether increasing the number of iterations has a significant impact on the prediction accuracy and stability of the model. Although BSTS excels in modeling complex time series, it has limitations, such as potential bias if model components are not appropriate, and the risk of overfitting when the number of parameters is too large. In this study, the use of income achievement data also needs to be considered, because fluctuations or changes in achievement patterns can affect the accuracy of model predictions.
5) Evaluation Model
In this study, Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) are used as evaluation metrics because both provide a comprehensive picture of the model's accuracy. MAPE is chosen because it presents errors in percentage form, making it easy to understand and relevant for comparing model performance against data scales. RMSE is used because it calculates errors in squared form. The combination of the two reflects common practice in forecasting analysis. This study uses revenue achievement data without considering external variables that may affect the results, such as consumer visit rates, demographic changes, and consumer behavior trends. In the future, the BSTS model can be expanded by including these external factors to improve the model's robustness, enrich the analysis, and provide more accurate predictions of traditional market dynamics.

3. RESULTS

This result will discuss the collection of data obtained, the data preprocessing process to overcome outliers, time series decomposition to emit the existence of trends and seasonal patterns, modeling using BSTS, evaluation of model performance, and presentation of prediction results.

A. Data collection result

As a result of the data collection process, the following plots are presented that illustrate the patterns of the data that have been collected. Panel A displays the original time series, which represents the raw data without modification. Meanwhile, Panel B presents the seasonal time series, which shows the seasonal patterns that have been successfully identified from the data.

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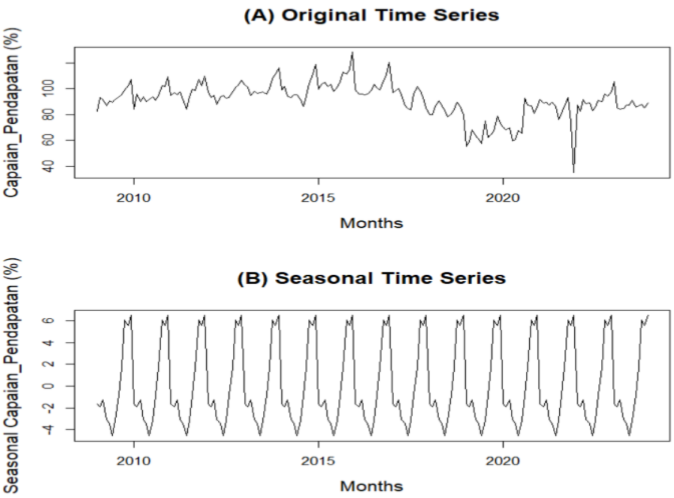

Fig. 2. Plot data collection results

Fig. 2. Above shows a time series analysis of traditional market revenue achievement. Panel (A) shows data from 2009 to 2023 which experienced a winter. Around 2018, there was a decline in revenue achievement which was estimated to be caused by increasing competition with modern markets. This decline continued until 2020, which was then exacerbated by the impact of the COVID-19 pandemic. After that, there was a gradual recovery, although data variability is still visible. Panel (B) displays the seasonal component that shows a recurring pattern every year, reflecting the presence of a consistent seasonal cycle. This pattern supports the use of the BSTS model, which is designed to capture trends and seasonality in time series data.

B. Data preprocessing result

The results of data processing include handling outliers by replacing values using linear interpolation. In addition, the data is also checked to ensure consistency and completeness before being used in modeling. he results of the data processing are presented below.

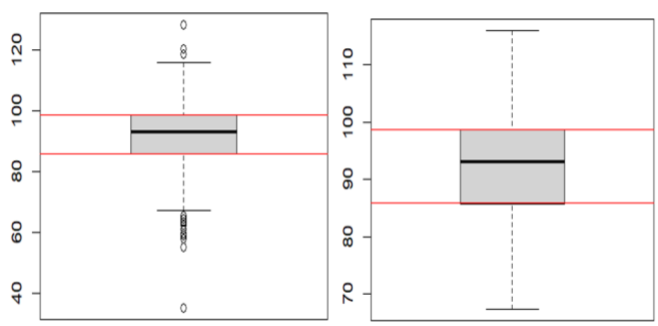

Fig. 3. Plot data prepocessing results.

Fig. 3. shows two boxplots comparing the data before and after outlier handling using linear interpolation. In the left boxplot, there are several outliers visible as points outside the whisker boundaries, indicating the presence of extreme values. After processing with linear interpolation, as seen in the right boxplot, the outliers have been removed, the data distribution is neater, and the median is more balanced. This process has successfully improved the quality of the data for further analysis.

C. Decomposition time series result

Time series data can be divided into several primary components, including trend, seasonal cycles, and irregular or random fluctuations. The decomposition results of traditional market revenue achievement data are presented in Fig. 4.

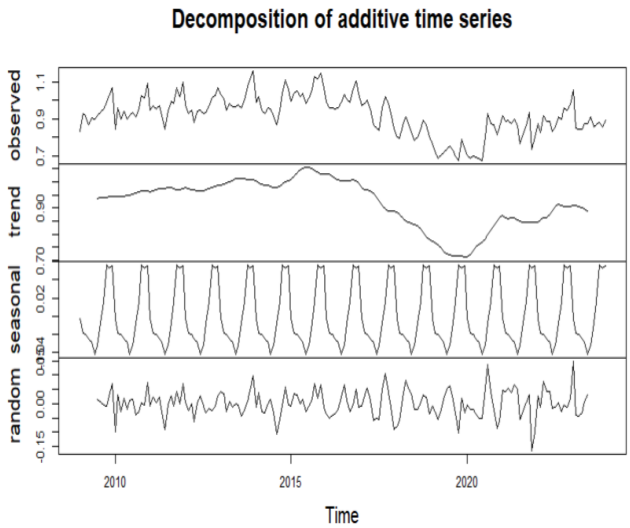

Fig. 4. Decomposition of revenue achievement data.

Fig. 4. The observation data pattern of traditional market revenue achievement can be separated into trend, seasonal, and random components. The trend pattern reflects the fluctuation of upward and downward movements over time. Seasonal effects are identified through time series decomposition analysis, which shows annual recurring patterns in the revenue achievement data. The seasonal pattern is additive with constant amplitude, reflecting repeated periodic fluctuations. Meanwhile, the random component is generally stable, but sometimes there are significant spikes reflecting unexpected variations. Based on the time series decomposition of the revenue achievement data, it is clear that the data exhibits trend and seasonal patterns.

D. BSTS Modelling

Based on the analysis of revenue achievement data, there are trends and seasonal patterns. Therefore, this study uses local level components, local linear trends, and seasonality. The following outlines a test scenario for BSTS modeling.

Table 2. Model parameters

States component	Iteration MCMC	burn-in samples
Local Level	n=1000	400
	n=5000	2000
	n=10000	4000

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Local Linear Trends	n=1000 n=5000 n=10000	400 2000 4000
Local Level and Seasonal	n=1000 n=5000 n=10000	400 2000 4000
Locar Linear Trends and Seasonal	n=1000 n=5000 n=10000	400 2000 4000

Table 2 Several BSTS models were developed, including those with a single state component local level and local linear trend and a model with two state components that encompass both local and seasonal levels, as well as their corresponding linear trends. The models were configured with 12 seasons (S=12), in accordance with the monthly data. In addition, the model will be tested with two numbers of MCMC iterations, namely 1,000, 5,000 and 10,000, with 40% of the iterations used as burn-in samples.

E. Evaluation modeling result

Each BSTS model's performance will be evaluated using MAPE and RMSE metrics. Thus, the best model for predicting traditional market revenue achievement in Surabaya can be determined. The MAPE and RMSE results for each model are displayed in Table 3 bellow.

Table 3. Results of bsts model evaluation.

States component	Iteration MCMC	MAPE	RMSE
Local Level	n=1000 n=5000 n=10000	6.005 6.161 5.979	7.824 7.923 7.790
Local Linear Trends	n=1000 n=5000 n=10000	7.153 6.327 6.347	8.483 8.015 8.029
Local Level and Seasonal	**n=1000** n=5000 n=10000	**4.036** 4.182 4.143	**5.198** 5.248 5.234
Locar Linear Trends and Seasonal	n=1000 n=5000 n=10000	8.565 4.343 4.259	9.512 5.297 5.300

The evaluation results in Table 3 of the Local Level and Seasonal models with 1,000 MCMC iterations show the best performance with a MAPE of 4.036% and an RMSE of 5.198, making it the most accurate in capturing revenue achievement data patterns. This model stands out due to its ability to identify seasonal trends and patterns within fluctuating data. The Local Level and Local Linear Trends models have higher MAPE and RMSE values, indicating less stable performance than other models. Meanwhile, the Local Linear Trends and Seasonal models have the highest MAPE at low iterations but improve at 10,000 iterations. Thus, the Local Level and Seasonal models with 1,000 MCMC iterations are the best choices for forecasting revenue achievement in traditional markets.

F. Prediction Result

After obtaining the best evaluation results on the Local Level and Seasonal components, the following is a comparison graph between the predicted values and actual values using the model with these components.

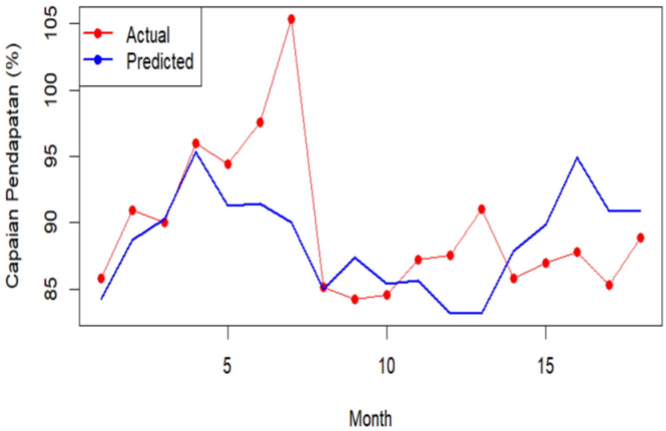

Fig. 5. Plot data actual vs predicted.

Fig. 5 above shows a comparison between the actual and predicted values of traditional market revenue achievement for 18 months. Overall, the prediction model is able to follow the general trend of the actual data, although there are some differences, especially in the sharp spike period around the 6th month. Nevertheless, the fluctuation pattern of revenue achievement is mostly successfully represented, indicating that the model has quite good predictive ability. After comparing the predicted data and the actual data, the researcher then made a prediction for the next six months.

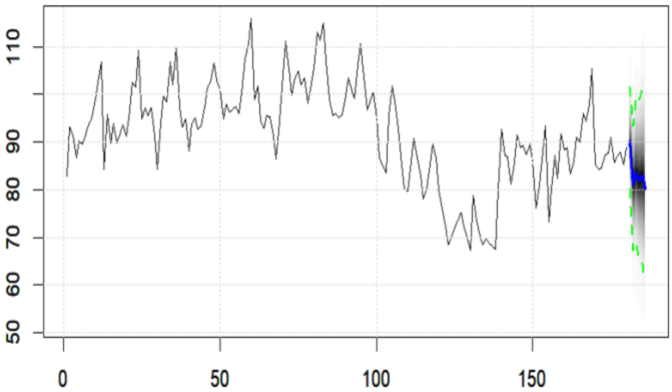

Fig. 6. Plot forecast results.

This Fig. 6. shows the forecast result plot for the next six months. From the graph, the model is able to capture historical patterns well. The predictions generated follow the trend of historical data, indicating that the model can accurately represent changes in revenue achievement. The fluctuations that appear in the prediction results reflect the natural variations found in historical data. For more details, the forecast value plot for the next six months is presented in the following figure.

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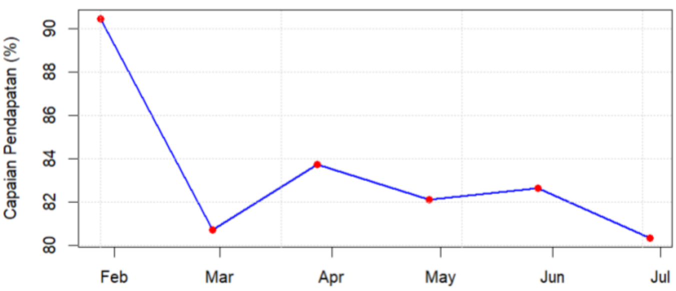

Fig. 7. Plot prediction results.

Fig. 7. shows the predicted revenue achievement graph from January to June. There is a sharp decline from January to February, followed by small fluctuations in the following months. In general, revenue achievement tends to be stable in the range of 80–85%, although there is a slight variation between months.

4. DISCUSSION

The results of the study show that the Bayesian Structural Time Series (BSTS) model that combines Local Level and Seasonal components with 1,000 MCMC iterations has the best performance in predicting traditional market revenue achievement, with a MAPE value of 4.036% and an RMSE of 5.198. The MAPE value is far below the 10% threshold as mentioned by [27], as well as the relatively low RMSE, indicating that this model is able to capture trend and seasonal patterns in the data effectively. These findings reflect the high prediction accuracy and relevance of BSTS as a forecasting method in the context of traditional markets. This accuracy also indicates that the model is successful in adjusting to the coordinates of revenue achievement data which are often influenced by seasonal factors and unstable market dynamics.

In particular, BSTS's ability to manage data uncertainty is one of its main advantages. This model is flexible in adjusting changes in data patterns over time, so it remains adaptive even in changing market conditions. This distinguishes BSTS from classical statistical models that tend to be rigid in dealing with complex data dynamics.

When compared to previous studies, this finding is in line with the study [20] which showed that BSTS outperforms ARIMA in predicting Flying Cement stock prices, with a MAPE of only 1.29% on a 15-day prediction horizon. The following is a comparative table between this research and previous research.

Table 4. Results of comparison of previous researchers.

Study	Prediction context	MAPE (%)
Almarashi et al. [20]	Stock price (Flying Cement)	1.29
This study	Traditional market revenue achievement	4.036

Although the MAPE value in that study was lower, the difference can be explained by the different context and characteristics of the data, namely stock data that has daily frequency and large volume. Meanwhile, in the context of traditional markets that tend to have seasonal variations and more limited historical data, BSTS still shows very good performance. Another advantage of this study is the application of more complete methodological stages, including data preprocessing and data sharing before modeling, which has not been widely carried out in similar studies.

However, these results are not without some limitations. First, the model only uses a single variable, namely market revenue achievement data, without considering external variables such as the number of traders, consumer activity, or government policies that can significantly affect revenue achievement. Second, the determination of the number of MCMC iterations and the proportion of training and testing data is determined subjectively, which has the potential to affect the analysis results. In addition, the performance of the model is highly dependent on the quality and completeness of historical data. If the data does not accurately represent market dynamics, the prediction results may be less reflective of real conditions.

The implications of this study are quite strategic, especially in the context of data-based decision-making in the traditional market sector. With an accurate forecasting method, stakeholders can be more proactive in responding to potential revenue declines, for example by allocating resources more efficiently, planning market infrastructure revitalization at the right time, or designing incentive policies during periods predicted to experience revenue declines. These findings can also be the basis for the development of further research that integrates external variables such as the number of traders, consumer activity, or government policies that can significantly affect revenue achievement, so that the model can capture more complex dynamics and provide deeper insights. In addition, alternative approaches using machine learning-based models such as Random Forest or XGBoost are also worth considering for comparison, in order to obtain the most effective modeling in describing the relationship between variables and market dynamics more comprehensively.

5. CONCLUSION

This research seeks to estimate the revenue achievement of traditional markets in Surabaya by utilizing the Bayesian Structural Time Series (BSTS) model, emphasizing the analysis of past patterns and the projection of future trends. The model is utilized to identify seasonal factors and trends influencing revenue achievement, providing more precise insights for strategic Strategic planning and policymaking in the traditional market industry.

According to the model evaluation results, the BSTS model incorporating Local Level and Seasonal components, using 1,000 MCMC iterations, demonstrated

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the best performance with a MAPE of 4.036% and an RMSE of 5.198. This model effectively captures the trend pattern of revenue achievement more accurately than other methods, making it a dependable choice for forecasting revenue achievement in traditional markets.

As future research, the model can be enhanced by incorporating external variables to improve prediction accuracy. Additionally, exploring other methods or integrating BSTS with machine learning approaches could serve as an alternative to generate more adaptive and precise forecasts in response to dynamic market changes.

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