E-ISSN: 2615-5702, P-ISSN: 2620-5785
Vol. 7, No. 1, page 37-48

Forecasting Room Occupancy Rates in Batu City: Implications for Government Policy Using ARIMA Method

Clarissa Rexana Putri[1], Safandra Alifia Prabudhi[2], FX Gugus Febri Putranto[3*], Adina Astasia[4], Thomas Wunang Tjahjo[5]

[12]Departement of Statistic, Faculty of Science and Data Analysis, Institute Teknologi Sepuluh Nopember, Surabaya, Indonesia
[345]Badan Pusat Statistik Kota Batu, Kota Batu, Indonesia

Abstract

This study utilizes the Autoregressive Integrated Moving Average (ARIMA) to forecast the Room Occupancy Rate (ROR) for both Star Hotels and Non-Star Hotels in Batu City throughout 2024. Data from 2018 to 2023, sourced from the Central Statistics Agency, informs the analysis. The results indicate a gradual decline in room occupancy rates across both star and non-star hotels. These findings hold significant implications for decision-making within the tourism sector, offering insights to enhance tourist attraction and stimulate economic development in Batu City. By anticipating future trends in room occupancy, stakeholders can strategize effectively, potentially adjusting marketing approaches, infrastructure investments, or tourism policies to address the observed decline. This study contributes valuable information to guide policy interventions aimed at sustaining tourism vitality and fostering economic growth in Batu City.

Article Info

Keywords:
Tourism;
Room Occupancy Rate;
Forecasting;
ARIMA

Corresponding Author:
FX Gugus Febri Putranto
(gugusfebri@bps.go.id)

Received: 15-02-2024
Revised: 29-02-2024
Accepted: 08-03-2024
Published: 16-03-2024

Introduction

The tourism sector holds significant potential to drive economic growth within a region, given its substantial multiplier effect on the broader economy. One effective strategy to ensure the sustainability of this sector is through innovation in tourism-related infrastructure, such as hotels and restaurants. However, the COVID-19 pandemic has inflicted profound damages upon the tourism industry, surpassing the impact experienced by many other sectors. According to the World Travel & Tourism Council, approximately 100 million individuals worldwide employed in transportation and tourism face heightened risks as a consequence of the COVID-19 pandemic (World Bank, 2020). Moreover, both the tourism and transportation services sectors have carried the brunt of mobility restrictions imposed during the pandemic (Bank Indonesia, 2021).

In Indonesia, the pandemic's impact on the advancement of the tourism industry is notably pronounced, particularly in regions boasting tourism potential. Batu City, recognized as one of potential area in Indonesia, has likewise faced substantial repercussions from the pandemic, particularly affecting the accommodation and food and beverage sectors. Specifically regarding the tourism sector's progress in Batu City, Figure 1 illustrates a comparative analysis of the economic growth within the accommodation and food and beverage sectors at the national, East Java, and Batu City levels over the past five years.

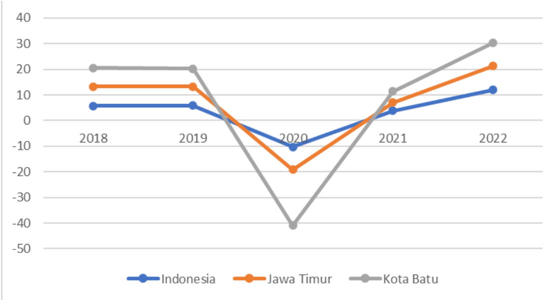


Figure 1. Economic Growth of Accomodation, Food, and Beverage Sector, 2018-2022
Sumber: BPS, 2023

Based on the depicted graph, it is evident that the growth rate within Batu City's accommodation and food and beverage provision sector surpasses that of both the national and East Java levels. This trend underscores Batu City's promising prospects within the tourism sector. However, amidst the peak of the 2020 pandemic, Batu City experienced the most significant contraction in economic growth within the accommodation sector when compared to East Java and the entirety of Indonesia.

The overall economic recovery of Batu City is further bolstered by its thriving tourism sector, recognized as one of its primary economic drivers. This potential is underscored by the presence of robust tourism-supporting infrastructure within Batu City. According to BPS data from 2023, projections indicate that by 2022, there will be a total of 1085 hotels and 60 tourist destinations within the area.

Fluctuations in hotel room occupancy rates often mirror the development of the tourism sector. These rates serve as primary indicators of tourism industry vitality, with a surge indicating increased tourist arrivals and demand for lodging, while a decline may signify obstacles or waning tourist interest. Analyzing hotel room occupancy trends provides invaluable insights into the tourism landscape dynamics, encompassing shifts in traveler preferences, global events like pandemics, and the efficacy of destination marketing endeavors. Hence, vigilant monitoring of hotel room occupancy rates emerges as a potent tool for stakeholders in steering and nurturing the tourism sector towards sustainable growth.

The development of the tourism sector is often mirrored by fluctuations in hotel room occupancy rates. These rates serve as primary indicators of the vitality of the tourism industry within a given destination. A surge in room occupancy rates signifies an uptick in tourist arrivals and a surge in demand for lodging, whereas a decline may signify obstacles or dwindling interest among tourists. Delving into the nuances of hotel room occupancy trends offers invaluable insights into the dynamics of the tourism landscape, encompassing shifts in traveler preferences, the ripple effects of global occurrences like pandemics, and the efficacy of destination marketing and promotional endeavors. Consequently, vigilantly monitoring hotel room occupancy rates emerges as a potent instrument for stakeholders vested in steering and nurturing the tourism sector towards sustainable growth. Graph 2 illustrates the visualization of data pertaining to Room Occupancy Rates derived from both star and non-star hotels across diverse regions, encompassing Indonesia in its entirety, East Java, and Batu City, spanning the past five years. This visual representation offers a comprehensive overview of the fluctuations in room occupancy rates across different geographical scales, ranging from the national scope down to the local level.

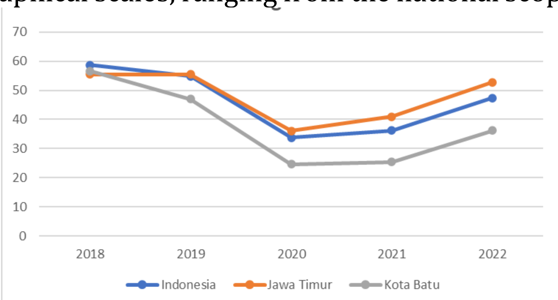


Figure 2. Star Hotel Room Occupancy Rate, 2018-2022

Sumber: BPS, 2023

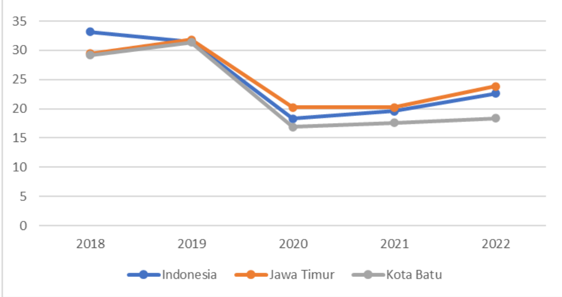


Figure 3. Non-Star Hotel Room Occupancy Rate, 2018-2022
Sumber: BPS, 2023

Based on Figure 2 and Figure 3, it is evident that the Room Occupancy Rates for both star and non-star hotels in Batu City consistently trend lower compared to those in Indonesia and East Java. Consequently, concerted efforts are imperative to bolster the occupancy rates of hotel rooms in Batu City, thereby maximizing the potential of the tourism sector as a key economic driver and fostering a beneficial multiplier effect on the overall economy of Batu City.

In order to achieve the optimization of room occupancy rates in Batu City, proactive measures are required, including the implementation of forecasting techniques to anticipate future trends. Accurate forecasting serves as a vital tool in strategic planning and decision-making within the hotel industry. By leveraging historical data pertaining to tourist arrivals, accommodation demand patterns, and external variables influencing the tourism sector, such as seasonal variations or global trends, forecasting enables more precise estimations of future room occupancy rates. Armed with enhanced foresight into future demand, hotels in Batu City can proactively respond to market fluctuations, optimize room capacity utilization, and devise more targeted marketing and promotional campaigns.

Furthermore, robust forecasting can facilitate long-term investment planning initiatives, such as the development of tourism infrastructure or the expansion of accommodation facilities. This, in turn, contributes to the sustained growth and resilience of the tourism industry in Batu City, ensuring its continued prosperity and competitiveness in the broader tourism landscape.

There are several definitions related to accommodation, namely as a means of providing lodging services, as well as being equipped with food and beverage services as a means of supporting tourism for tourists (Ismayanti, 2020). Salah satu jenis dari akomodasi yaitu hotel. According to American Hotel and Motel Associations (AHMA) in (Soewarno *et al*., 2021) A hotel is a place that provides accommodation, food and drink, and other services, for rent to people and guests who want to stay for a while. Hotels are closely related to the tourism sector. The higher the hotel room occupancy rate will result in a greater multiplier effect from tourist visits to Batu City.

There are several previous studies that used the ARIMA method to predict future conditions in the tourism sector. A study conducted by Ismail dan Sulistijanti (2018) forecasting the number of guests and hotel dinner visitors in Blora Regency using the ARIMA approach. Another study, conducted by Pramudita (2020) who estimated hotel occupancy levels using ARIMA analysis. Furthermore, research by Pratiwi (2019) also used the ARIMA method to predict the Bed Occupancy Rate (TPTT) of three-star hotels in the city of Surakarta. Apart from that, research conducted by Silalahi (2015) forecasted the Room Occupancy Rate (TPK) of star hotels using the ARIMA and Transfer Function methods. Other research relevant to this research was conducted by Indradewi, dkk. (2022) to predict room occupancy rates based on hotel class in Bali using the ARIMA method.

To optimize room occupancy rates in Batu City, proactive measures are essential, including the utilization of forecasting techniques to anticipate future trends. Accurate forecasting serves as a vital tool in strategic planning and decision-making within the hotel industry, enabling more precise estimations of future room occupancy rates by leveraging historical data and external variables influencing the tourism sector. Enhanced foresight into future demand empowers hotels in Batu City to proactively respond to market fluctuations, optimize room capacity utilization, and devise targeted marketing campaigns and promotional strategies. Furthermore, robust forecasting facilitates long-term investment planning initiatives, such as the development of tourism infrastructure or expansion of accommodation facilities. This contributes to the sustained growth and resilience of the tourism industry in Batu City, ensuring its continued prosperity and competitiveness in the broader tourism landscape.

Several previous studies have demonstrated the efficacy of employing the ARIMA method in forecasting hotel room occupancy rates in Batu City. Thus, the objective of this research is to predict the Room Occupancy Rates (ROR) for both star and non-star hotels in Batu City spanning the period from 2018 to 2022. The findings of this study will shed light on the extent of demand for accommodation services in Batu City, providing a foundational framework for formulating policies aimed at enhancing accommodation infrastructure within the Batu City vicinity.

2. Method

This research adopted a quantitative approach, utilizing Room Occupancy Rate (TPK) data sourced from both star-rated and non-star hotels in Batu City spanning the timeframe from 2018 to 2023. The data were procured from the Batu City Central Statistics Agency (BPS). A quantitative approach was deemed appropriate as it enables a systematic and objective analysis of trends in hotel room occupancy rates, thus facilitating a comprehensive understanding of the dynamics within the hotel industry in Batu City during the study period. By amalgamating data from star-rated and non-star hotels, the study aims to furnish an exhaustive depiction of the overall room occupancy rate in Batu City, while also undertaking an assessment of disparities in occupancy rates between the two hotel categories.

The ARIMA (AutoRegressive Integrated Moving Average) method stands out as a potent data analysis technique for predicting future values. This forecasting approach enables the projection of values in forthcoming periods by leveraging patterns and trends discerned from historical data. The outcomes of such forecasting serve as a cornerstone for decision-making processes pertaining to strategies to be adopted within the tourism industry. By grasping the trends and patterns unveiled through the ARIMA method, stakeholders within the tourism sector can devise more strategic initiatives aimed at enhancing the competitiveness of tourist destinations. Additionally, they can adeptly manage accommodation capacity, thereby optimizing marketing and promotional endeavors to allure a greater influx of tourists. The precision of forecasting yielded by the ARIMA method furnishes decision-makers with a valuable tool for navigating the complexities of the ever-evolving tourism market, enabling them to effectively address challenges and capitalize on emerging opportunities.

This research employs the Autoregressive Integrated Moving Average Model (ARIMA) method. ARIMA is a model that exclusively relies on time series data without considering independent variables for forecasting purposes. The ARIMA model comprises three key components: autoregressive (AR), moving average (MA), and integrated (I) models. These elements can be adjusted and combined to create alternative models, such as the autoregressive moving average (ARMA) model. The general formulation of the ARIMA model is denoted as ARIMA (p,d,q), where 'p' denotes the AR order, 'd' signifies the Integrated order, and 'q' represents the moving average order. In the case of an AR model, the general model simplifies to ARIMA (1,0,0) (Zulhamidi & Hardianto, 2017).

Based on Sirisha, et al. (2022), The ARIMA method unfolds through several key stages, commencing with a test for data stationarity, typically performed using the Augmented Dickey-Fuller (ADF) method. If the data fails the stationarity test, various transformations are applied to render it stationary. Subsequently, the AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) graphs are plotted, aiding in the determination of parameter values—p, d, and q—for the ARIMA model. These graphs offer insights into the correlation patterns between data values and their respective lags. By scrutinizing these patterns, significant lag counts affecting the data can be identified, enabling the selection of optimal parameter values for the ARIMA model. This process is critical to ensure the model effectively captures data patterns, thereby yielding accurate and relevant forecasts.

The subsequent phase entails evaluating model fit through three stages: constructing an AutoRegressive (AR) model, a Moving Average (MA) model, and subsequently merging them to formulate an AutoRegressive Integrated Moving Average (ARIMA) model. This iterative process facilitates the assessment of each component's contribution in modeling the data, culminating in the identification of the most suitable model aligning with the observed data characteristics.

Once the ARIMA model is established, the final step involves the forecasting process, alongside scrutinizing and evaluating the model's errors and accuracy. This evaluation enables an understanding of the model's efficacy in predicting future values and the identification of areas necessitating refinement or adjustment. By attentively assessing model errors and accuracy, essential enhancements can be pinpointed, thereby augmenting the forecasting quality and the applicability of analysis results within decision-making contexts.

3. Result and Discussion

1. Data Description

There are several seasonal patterns that can be seen from Figure 4, the room occupancy rate increases at the end of each year. Figure 4 shows a description of the data analyzed in this study. In the time span between 2018 to 2023, the percentage of Room Occupancy Rate for Star and Non-Star Hotels fluctuates relatively. The increase in hotel room occupancy rates in Batu City can be attributed to the school holiday season and year-end moments which cause a surge in tourist visits. The school holiday season is often a popular time for families to visit tourist destinations, while the end of the year, including the Christmas and New Year holidays, is a busy time for holidays and end-of-year celebrations. As such, hotels in Batu City tend to experience a surge in room bookings during this period, leading to an increase in overall occupancy rates. These findings provide a better understanding of the factors that influence hotel room occupancy rates in Batu City, and can be the basis for developing more effective marketing and capacity management strategies in dealing with the surge in tourist visits during the school holiday season and year-end moments

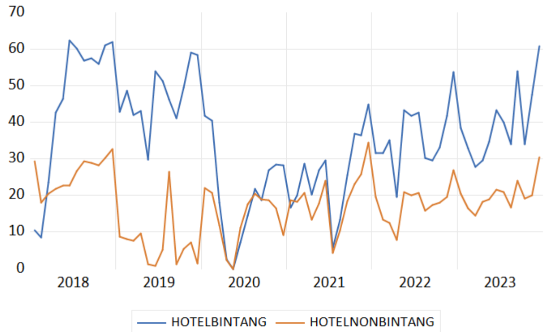


Figure 4. Room Occupancy Rate Star and Non-Star Hotel in Batu City, 2018-2023
Source: BPS, processed

In the last six years, the occupancy rate of star hotel rooms has always been greater than that of non-star hotels. However, optimization of room occupancy levels has not yet been achieved. This is indicated by the room occupancy rate which is generally still around 50 percent. The implications of these findings highlight the urgency of increasing hotel room occupancy rather than simply increasing the number of rooms available. With the increase in tourist visits during the school holiday season and year-end moments in Batu City, focusing on increasing hotel room occupancy has become more important than simply increasing room capacity. Although adding hotel rooms can increase total accommodation capacity, it may not provide an optimal solution if the new rooms cannot be adequately filled outside of the holiday season and year-end periods. On the other hand, efforts to increase hotel room occupancy through more effective marketing strategies, partnerships with travel agents, attractive vacation package offers, and improved hotel services or facilities can be a more productive step in maximizing revenue and strengthening the sustainability of the hotel business. By prioritizing efforts to increase hotel room occupancy, Batu City can be more effective in optimizing existing tourism potential and provide greater economic benefits for the local community and tourism industry stakeholders.

The tourism business cycle in Batu City is also depicted in Figure 4. The impact of the slowdown in the tourism industry due to the pandemic can be observed from the decline in room occupancy rates throughout 2020. However, from the 2021 to 2023 period, there are indications of recovery with a gradual increase in room occupancy rates, although it has not yet reached the same level as conditions before the COVID-19 pandemic in 2018.

2. Forecasting of Room Occupancy Rate for Star and Non-Star Hotel

Before starting the modeling process for forecasting, the first step that needs to be taken is to test the stationarity of the data. This process is important to ensure that the data used in the analysis has stationary properties, which is one of the basic assumptions of various forecasting methods. The data stationarity test checks whether the mean and variance of the data remain constant over time or fluctuate randomly. By verifying the stationarity of the data, we can ensure that trends, seasonality, or other patterns have been removed from the data, thereby enabling the use of appropriate and accurate forecasting methods. Additionally, stationarity tests also help in identifying the types of transformations or adjustments that may be required to make the data stationary, if necessary. One method that is often used is unit root testing using the Dickey-Fuller Test (DF Test).

Table 1. Result of Dickey-Fuller Test

Diferensiasi	**p-value**
Star Hotel	
0	0.0365
Non-Star Hotel	
0	0.0004

Source: Processed Data

Based on table 1, it can be seen that the room occupancy rate in star and non-star hotels reaches a stationary condition at the original value without differentiation. After the data is stationary, the order can then be identified in the ARIMA model using a correllogram. Based on the identification results, it was found that the overfit models used for forecasting TPK for star and non-star hotels were ARIMA (1,0,1), ARIMA (2,0,0), and ARIMA (2,0,1).

After obtaining the estimated model, parameter estimation is then carried out to determine the best ARIMA model. The best ARIMA model is if all coefficients (AR or MA) have a significant effect on the value of the observed variables (at the degree of integration) and have the smallest (minimum) Akaike Info Criterion (AIC) and Schwarz Criterion (SC) values. Based on the evaluation results, the best ARIMA model was obtained for TPK for star and non-star hotels, namely ARIMA (1,0,0).

The next stage is checking the residual normality. The results of the Jarque-Bera test carried out on research data showed that the residuals were normally distributed.

After getting the best model results, forecasting is then carried out on the data. Table 2 shows the results of TPK forecasting for Star and Non-Star Hotels in Batu City every month throughout 2024.

Table 2. Forecasting Result using ARIMA Model, January-December 2024

Period	Star Hotel	Non-Star Hotel
January	55.30178	24.62099
February	51.04869	21.47076
March	47.72246	19.76239
April	45.12111	18.83594
May	43.08666	18.33352
June	41.49557	18.06106
July	40.25122	17.9133
August	39.27805	17.83317
September	38.51696	17.78972
October	37.92173	17.76616
November	37.45622	17.75338
December	37.09215	17.74645

Source: Processed Data

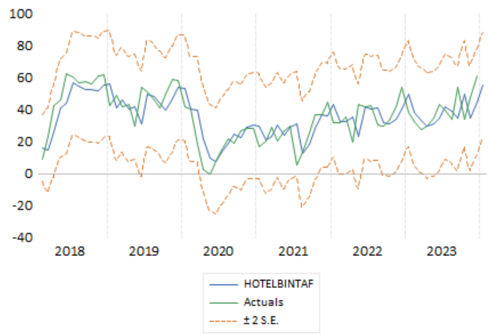
The forecasting results in table 2 can show several indications of phenomena that are predicted to occur throughout 2024. In general, there is a consistent pattern between the forecasting results for star and non-star hotels. Throughout 2024, the room occupancy rate in star hotels will always be higher than in non-star hotels. The research results show that the majority of tourists tend to prefer star hotels compared to non-star hotels. The main reasons behind this preference include higher quality standards, more complete facilities, better service and trust in proven star hotel brands. Apart from that, the guarantee of greater security and comfort is also an important factor in the decision to choose a hotel. These findings provide a better understanding of tourists' preferences in choosing accommodation, which can be a valuable guide for hotel industry stakeholders in improving the quality of services and facilities to meet tourists' expectations.

In terms of achieving room occupancy rates throughout 2024 for both star and non-star hotels, the highest achievement occurred at the beginning of the year and is still limited to an occupancy rate of around 50 percent. Low hotel room occupancy rates have a significant impact on the tourism industry as a whole. Several factors that may influence the low occupancy rate of hotel rooms include seasonal fluctuations, changes in tourist trends, and competition from online platforms providing lodging booking services. The decline in hotel room occupancy rates not only impacts direct hotel revenues, but also secondary revenues generated from related industries such as restaurants, souvenir shops and local transportation. In the long term, a decline in hotel room occupancy rates can damage the image of tourist destinations, reduce investment in tourism infrastructure, and hinder local economic growth. These findings demonstrate the importance of tourism industry stakeholders working together to identify effective strategies to increase hotel room occupancy rates and maintain the sustainability of the tourism industry as a whole.

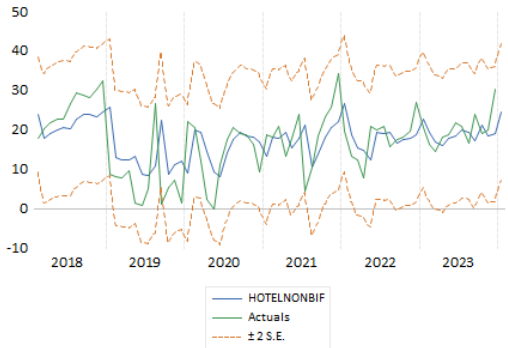
Apart from that, the existence of buffer areas around Batu City, such as Malang City and Malang Regency, which are starting to attract investors to set up tourism infrastructure, especially hotel accommodation, also has an impact on the level of room occupancy in Batu City. Innovation in the hotel industry has a crucial role in increasing hotel room occupancy rates. One of them is the implementation of technology that enables a better user experience, such as intuitive online booking systems, mobile applications that provide room service and local information, as well as the use of artificial intelligence technology to increase the personalization of services. In addition, developing facilities and programs that are attractive to guests, such as spas, restaurants with unique concepts, recreation areas, or local cultural activities, can increase the attractiveness of a hotel. Innovation can also take place in terms of strategic partnerships with well-known brands or influencers, which can increase the visibility and attractiveness of the hotel. By implementing innovative strategies like these, hotels can anticipate changing traveler trends and preferences, increase their differentiation in a competitive market, and in turn, strengthen their room occupancy rates and the long-term sustainability of their business.

Next, based on the research findings in table 2, there is a pattern of gradual decline in the level of hotel room occupancy every month until it reaches its lowest point at the end of 2024. This finding has implications for the need for anticipatory efforts and risk mitigation that could occur in the future period, especially through local government policies. The government's anticipatory efforts in maintaining hotel room occupancy rates in tourism potential areas have a very important role in managing the sustainability of the tourism industry. First, the government needs to collaborate intensively with the hotel industry to improve tourism infrastructure, increase accessibility, and promote tourist destinations through careful marketing campaigns. In addition, local governments can facilitate investment in accommodation development, speed up the licensing process, and provide tax incentives or subsidies to industry stakeholders. In addition, the use of data and statistical analysis to monitor trends in tourist visits and identify opportunities and challenges is also the government's main focus in maintaining hotel room occupancy rates. By taking proactive steps like these, local governments can create a conducive environment for tourism growth, strengthen the competitiveness of tourist destinations, and ultimately, maintain hotel room occupancy rates thereby supporting sustainable local economic growth.

From the forecast results obtained, a comparison is also made between the forecast results and the actual values as shown in Figure 5 below.



(a)



(b)

Figure 5. Graph of Actual vs Forecasting Result (a) Star Hotel (b) Non-Star Hotel

Source: Processed Data

Implications for Government Policy

The gradual decline in forecasted occupancy rates in Batu City's hotels throughout 2024 underscores the importance of preemptive action and strategic interventions from local authorities. As tourism plays a pivotal role in the city's economic vitality, it is imperative for governments to implement initiatives that foster an environment conducive to sustainable growth. In this regard, several key measures can be undertaken:

1. Infrastructure Improvement: Enhancing tourism infrastructure is crucial for accommodating the needs of visitors and ensuring a positive tourism experience. Collaborative efforts between government agencies and industry stakeholders can facilitate investment in accommodation development, transportation networks, and recreational facilities. Streamlining licensing processes and offering incentives to developers can expedite infrastructure projects, while also maintaining quality standards and preserving the natural environment.
2. Marketing and Promotion: Effective marketing campaigns are essential for attracting tourists and promoting Batu City as a desirable destination. Local governments should invest in targeted marketing strategies tailored to seasonal trends and specific demographics. By leveraging data-driven insights, authorities can identify key market segments and design promotional initiatives that resonate with potential visitors. Collaborating with tourism boards, travel agencies, and digital platforms can amplify the reach of marketing efforts, enhancing Batu City's visibility and competitiveness in the tourism market.
3. Data Utilization: Harnessing the power of data analytics is crucial for informed decision-making in tourism management. By analyzing tourist flows, booking patterns, and market trends, local governments can gain valuable insights into visitor preferences and behavior. This data-driven approach enables authorities to anticipate demand fluctuations, identify emerging opportunities, and tailor policies to address specific challenges. Implementing statistical models for trend monitoring and forecasting allows for proactive planning and resource allocation, ensuring optimal utilization of tourism assets and infrastructure.

By proactively addressing these areas, local governments can create an enabling environment for tourism growth and maximize the potential of Batu City as a tourist destination. Investing in infrastructure development, targeted marketing, and data-driven decision-making not only enhances the visitor experience but also contributes to the city's long-term economic sustainability. Ultimately, by prioritizing sustainable tourism practices and fostering collaboration between public and private sectors, Batu City can position itself as a leading destination for leisure and business travelers, driving economic development and prosperity for its residents.

4. Conclusion

From the model obtained, predictions for the next 12 months for Star and Non-Star Hotels will all experience a slow decline. The results of this forecast can be used as a basis for decision making regarding strategies that can be implemented in the tourism sector so as to increase hotel room occupancy rates. The Batu City Government also needs to implement several alternative policies to increase hotel ROR, such as facilitating and encouraging the holding of tourism events as part of efforts to increase tourism attractiveness and economic growth in Batu City.

The forecasted decline in hotel occupancy rates for Batu City in 2024 underscores the urgency for proactive measures by local authorities. Infrastructure enhancements, streamlined licensing processes, and targeted marketing strategies are crucial to sustain tourism growth. Collaboration between public and private sectors, coupled with data-driven decision-making, is essential for optimizing resource allocation and enhancing the visitor experience. By investing in sustainable tourism practices and innovation, Batu City can strengthen its position as a competitive tourist destination, driving economic development and prosperity for its residents. Prioritizing these initiatives will enable Batu City to navigate challenges, capitalize on opportunities, and ensure a vibrant and sustainable tourism industry for the future.

For future research, it is advisable to consider the effects of seasonal tourist surges in more detail. First, researchers can collect tourist arrival data at a more detailed time level, such as monthly or even weekly, to track seasonal fluctuations more accurately. This will help in identifying tourist arrival patterns related to specific seasons, as well as understanding how these seasonal changes affect hotel room occupancy rates. Furthermore, research can consider other factors that may influence seasonal fluctuations, such as local events or festivals, national or international holidays, and changes in weather conditions. An in-depth analysis of the relationship between these factors and seasonal tourist surges can provide better insight into the dynamics of the tourism industry. Additionally, research could involve local tourism industry stakeholders, such as hotel associations, tourism authorities, or tour operators, to gain deeper insights and perspectives on seasonal fluctuations and their impacts. By considering the effects of seasonal tourist surges more comprehensively, future research is expected to provide a deeper understanding of the dynamics of the tourism industry and provide a stronger foundation for the development of sustainable destination management policies and strategies.

References

Bank Indonesia. (2021). *Laporan Tahunan Bank Indonesia 2020 "Bersinergi Membangun Optimisme Pemulihan Ekonomi."* 1–844. https://www.bi.go.id/id/publikasi/laporan/Documents/Laporan-Akuntabilitas-Bank-Indonesia-2020.pdf

BPS Indonesia. (2023). *Tingkat Penghunian Kamar Hotel 2022*.

BPS Indonesia. (2024). *[Seri 2010] Laju Pertumbuhan PDB Seri 2010 (Persen), 2022*. https://www.bps.go.id/id/statistics-table/2/MTA0IzI%253D/-seri-2010--laju-pertumbuhan-pdb-seri-2010.html

BPS Jawa Timur. (2020). Pertumbuhan Ekonomi Jawa Timur Triwulan II-2020. *Berita Resmi Statistik*, *13*, 12. https://jatim.bps.go.id/pressrelease/2020/08/05/1141/ekonomi-jawa-timur-triwulan-ii-2020-terkontraksi-5-90-persen.html

BPS Jawa Timur. (2023). *Statistik Pariwisata Provinsi Jawa Timur 2022*.

BPS Kota Batu. (2023a). *Indikator Perhotelan di Kota Batu, 2020 - 2022*. https://batukota.bps.go.id/statictable/2023/08/28/1494/indikator-perhotelan-di-kota-batu-2020---2022.html

BPS Kota Batu. (2023b). *Jumlah Rumah Makan dan Restoran Menurut Kecamatan di Kota Batu, 2019-2022*. https://batukota.bps.go.id/statictable/2023/08/29/1504/jumlah-rumah-makan-dan-restoran-menurut-kecamatan-di-kota-batu-2019-2022.html

BPS Kota Batu. (2023c). *Pertumbuhan Ekonomi Kota Batu 2022*.

BPS Kota Batu. (2023d). *Tingkat Penghunian Kamar Hotel Kota Batu 2022*. https://batukota.bps.go.id/publication/2023/12/28/506e18a98b7bcf11259ec7dd/tingkat-penghunian-kamar-hotel-kota-batu-2022.html

Fujianti, E. N., & Huda, A. M. (2021). Pembentukan Image Wisata Aman Di Era New Normal (Studi Kasus Alun-Alun Kota Wisata Batu). *Commercium*, *4*(2), 93–104.

Indradewi, I. G. A. A. D., Mulyani, N. P. S., & Parwita, W. G. S. (2022). Forecasting Room Occupancy Rates Based on Hotel Class in Bali Using the ARIMA Method. *CESS (Journal of Computer Engineering, System and Science)*, *7*(2), 325. https://doi.org/10.24114/cess.v7i2.33959

Ismail, I. M., & Sulistijanti, W. (2018). Peramalan Jumlah Tamu Dan Pengunjung Dinner Hotel Mega Bintang Sweet Kabupaten Blora Dengan Pendekatan ARIMA. *Prosiding Seminar Nasional Edusaintek FMIPA UNIMUS*, *1*(1), 64–70.

Ismayanti. (2020). *Dasar-Dasar Pariwisata*.

Kadek, N., Mirayani, S., Arismayanti, N. K., Widyatmaja, I. G. N., Pariwisata, D. I. V, Pariwisata, F., Udayana, U., & Gorris, J. R. (2017). *Studi komparasi persepsi wisatawan terhadap implementasi experiential marketing pada hotel berbintang dan non bintang di kawasan pariwisata candidasa kabupaten karangasem bali*. *1*(2), 249–268.

Pramudita, A. (2020). Prosiding Seminar Edusainstech MEMPERKIRAKAN TINGKAT PENGHUNI HOTEL MENGGUNAKAN ANALISIS ARIMA DENGAN APLIKASI MINITAB. *Prosiding Seminar Edusaunstech*, 249–257.

Pratiwi, S. D. (2019). Peramalan Tingkat Penghunian Tempat Tidur Hotel Bintang Tiga Kota Surakarta Menggunakan Metode Autoregressive Integrated Moving Average (ARIMA). *Indonesian Journal of Applied Statistics*, *2*(1), 53. https://doi.org/10.13057/ijas.v2i1.31428

Silalahi, M. D. (2015). *Peramalan Tingkat Penghunian Kamar Hotel Bintang Menggunakan Metode Arima Dan Fungsi Transfer Forecasting Occupancy Hotel With Star Rating Using Arima and Transfer Function*.

Sirisha, U. M., Belavagi, M. C., & Attigeri, G. (2022). Profit Prediction Using ARIMA, SARIMA and LSTM Models in Time Series Forecasting: A Comparison. *IEEE Access*, *10*(December), 124715–124727. https://doi.org/10.1109/ACCESS.2022.3224938

Soewarno, E., Hudiyani, A., & Fitriana Sugiarti, F. (2021). Pengaruh Kualitas Pelayanan, Fasilitas, Dan Lokasi Terhadap Keputusan Menginap Pada Hotel Abadi Di Pangkalan Bun. *Magenta*, *9*(2), 93–100.

World Bank. (2020, July). *Rebuilding Tourism Competitiveness*. https://doi.org/10.1596/34348

Zulhamidi, & Hardianto, R. (2017). Jurnal PASTI Volume XI No. 3, 231 - 244 PERAMALAN PENJUALAN TEH HIJAU DENGAN METODE ARIMA (STUDI KASUS PADA PT. MK). *Jurnal PASTI*, *XI*(3), 231–244.

Appendix

1. ADF Test Result

Null Hypothesis: HOTELBINTANG has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.034072	0.0365
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: HOTELNONBINTANG has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.566549	0.0004
Test critical values:	1% level	-3.525618	
	5% level	-2.902953	
	10% level	-2.588902	

*MacKinnon (1996) one-sided p-values.

2. Correlogram

Correlogram of HOTELBINTANG

Date: 02/14/24 Time: 01:53
Sample: 2018M01 2023M12
Included observations: 72

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.737	0.737	40.749	0.000
		2	0.540	-0.006	62.956	0.000
		3	0.381	-0.033	74.151	0.000
		4	0.239	-0.063	78.632	0.000
		5	0.180	0.077	81.218	0.000
		6	0.173	0.084	83.639	0.000
		7	0.128	-0.070	84.975	0.000
		8	0.068	-0.071	85.359	0.000
		9	0.044	0.038	85.523	0.000
		10	0.023	0.014	85.569	0.000
		11	0.092	0.177	86.312	0.000
		12	0.200	0.149	89.860	0.000
		13	0.139	-0.256	91.616	0.000
		14	0.108	0.016	92.696	0.000
		15	0.029	-0.085	92.775	0.000

Correlogram of HOTELNONBINTANG

Date: 02/14/24 Time: 01:51
Sample: 2018M01 2023M12
Included observations: 72

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.514	0.514	19.853	0.000
		2	0.281	0.022	25.844	0.000
		3	0.174	0.030	28.187	0.000
		4	0.098	-0.009	28.945	0.000
		5	0.180	0.169	31.525	0.000
		6	0.194	0.051	34.554	0.000
		7	0.159	0.012	36.624	0.000
		8	0.070	-0.070	37.034	0.000
		9	-0.041	-0.094	37.176	0.000
		10	-0.090	-0.063	37.870	0.000
		11	-0.009	0.082	37.878	0.000
		12	-0.047	-0.103	38.075	0.000
		13	-0.058	-0.027	38.378	0.000
		14	-0.009	0.068	38.385	0.000
		15	-0.021	0.024	38.426	0.001

Dependent Variable: HOTELBINTANG
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 02/14/24 Time: 01:55
Sample: 2018M01 2023M12
Included observations: 72
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	35.78563	4.930369	7.258206	0.0000
AR(1)	0.782073	0.090589	8.633165	0.0000
SIGMASQ	100.1613	17.27228	5.798964	0.0000

R-squared	0.585378	Mean dependent var	35.80264
Adjusted R-squared	0.573360	S.D. dependent var	15.65167
S.E. of regression	10.22332	Akaike info criterion	7.541129
Sum squared resid	7211.616	Schwarz criterion	7.635990
Log likelihood	-268.4806	Hannan-Quinn criter.	7.578893
F-statistic	48.70827	Durbin-Watson stat	1.946712
Prob(F-statistic)	0.000000		

Inverted AR Roots	.78

Dependent Variable: HOTELNONBINTANG
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 02/14/24 Time: 01:55
Sample: 2018M01 2023M12
Included observations: 72
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.73823	1.846647	9.605647	0.0000
AR(1)	0.542301	0.094417	5.743662	0.0000
SIGMASQ	48.84854	8.521354	5.732485	0.0000

R-squared	0.283098	Mean dependent var	17.33944
Adjusted R-squared	0.262318	S.D. dependent var	8.312522
S.E. of regression	7.139495	Akaike info criterion	6.814772
Sum squared resid	3517.095	Schwarz criterion	6.909633
Log likelihood	-242.3318	Hannan-Quinn criter.	6.852536
F-statistic	13.62370	Durbin-Watson stat	1.959923
Prob(F-statistic)	0.000010		

Inverted AR Roots	.54

Correlogram of Residuals

Date: 02/14/24 Time: 01:56
Sample: 2018M01 2023M12
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.010	-0.010	0.0068	
		2	0.037	0.037	0.1139	0.736
		3	-0.013	-0.012	0.1269	0.939
		4	-0.069	-0.071	0.5002	0.919
		5	-0.066	-0.067	0.8467	0.932
		6	0.094	0.098	1.5543	0.907
		7	0.069	0.076	1.9393	0.925
		8	-0.041	-0.056	2.0799	0.955
		9	0.007	-0.009	2.0837	0.978
		10	-0.169	-0.158	4.5291	0.873
		11	-0.065	-0.049	4.8996	0.898
		12	0.294	0.320	12.587	0.321
		13	0.008	0.000	12.594	0.399
		14	0.123	0.072	13.991	0.374
		15	0.043	0.021	14.166	0.437

3. Correlogram Residual

Correlogram of Residuals

Date: 02/14/24 Time: 01:58
Sample: 2018M01 2023M12
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.013	-0.013	0.0126	
		2	-0.012	-0.013	0.0244	0.876
		3	0.023	0.022	0.0646	0.968
		4	-0.078	-0.077	0.5368	0.911
		5	0.098	0.098	1.3041	0.861
		6	0.093	0.093	1.9969	0.850
		7	0.091	0.101	2.6745	0.848
		8	0.038	0.034	2.7927	0.903
		9	-0.056	-0.043	3.0580	0.931
		10	-0.132	-0.138	4.5495	0.872
		11	0.078	0.067	5.0798	0.886
		12	-0.027	-0.050	5.1455	0.924
		13	-0.042	-0.068	5.3016	0.947
		14	0.051	0.021	5.5430	0.961
		15	0.064	0.113	5.9211	0.968

4. Normality Test