ERROR BEHAVIOR ANALYSIS IN DATA-DRIVEN MODELS FOR ESTIMATING HOTEL DEMAND DYNAMICS

Nurul Riska Novita [1], **Teguh Herlambang** [2*], **Mohammad Romli Arief** [3]

[1] *Undergraduate Department Information and Communication Engineering, Chaoyang University of Technology Jifeng E. Rd., Wufeng District, Taichung City 413310, Taiwan*
[2] *Undergraduate Department of Information Systems, Universitas Nahdlatul Ulama Surabaya Jl. Raya Jemursari 51-57 Surabaya, East Java, Indonesia. 60237*
[3] *Department of Information Systems, Universitas Nahdlatul Ulama Surabaya Jl. Raya Jemursari 51-57 Surabaya, East Java, Indonesia. 60237*
*Corresponding author's e-mail: *teguh@unusa.ac.id*

Article Info

Article History:
Received: 2026-02-09
Revised: 2026-04-15
Accepted: 2026-04-23
Available online: 2026-04-26

Keywords:
Accommodation Demand; Data-Driven Models; Operational Dynamics; Model Evaluation; Estimation Accuracy; Error Analysis

ABSTRACT

Rapid and irregular changes in room demand patterns pose a major challenge for Hotel U in ensuring effective operational planning and revenue strategies. This instability is influenced by the dynamics of last-minute bookings, seasonal variability, and competition on digital platforms. To address these conditions, this study evaluates two data-based modeling approaches, namely Linear Regression and K-Nearest Neighbors (KNN), with the aim of assessing the accuracy of revenue estimates and the consistency of the two models' performance on different proportions of training data. Three data distribution schemes were used 70:30, 80:20, and 90:10 to observe the sensitivity of the models to changes in the amount of historical information. The results show that KNN is more effective on data with high diversity, marked by an RMSE value of 0.057 in the 70:30 scheme. These findings indicate that model selection should be tailored to the analysis objectives: neighbor-based models are superior for short-term changes, while linear models are more appropriate for income movement patterns that follow general trends.

How to cite this article:
Novita, N. R., Herlambang, T., & Arief, M. R. (2026)., "Error Behavior Analysis In Data-Driven Models For Estimating Hotel Demand Dynamics. (n.d.). *Journal of Information System and Data Intelligence*, *1*(1), 1-11. Retrieved April 26, 2026, https://propanoramic.com/index.php/JISDI/article/view/655

Journal homepage: *https://propanoramic.com/index.php/JISDI*
Research Article · Open Access

1. INTRODUCTION

The hospitality industry faces increasingly complex room demand dynamics in line with changes in global travel patterns, the penetration of digital booking platforms, and intensifying competition between hotels [1]. This complexity is influenced by macro factors such as tourist mobility, economic uncertainty, changing consumer preferences, and the development of a digital ecosystem that directs tourist decision-making towards faster, real-time decisions influenced by promotions and online reputation [2]. In this context, a hotel's ability to accurately forecast demand is a strategic element that determines the effectiveness of operational planning, revenue optimization, and long-term business sustainability [3]. Accurate demand forecasting not only serves as the basis for pricing strategy and room inventory management, but is also closely related to resource allocation efficiency, cost control, and reduction of operational waste [4]. This is relevant to the principle of sustainable development in the tourism sector, where dynamic system-based decision making supports the optimization of energy, labor, and material use, while maintaining the financial and operational sustainability of hotels [5]. Therefore, the use of prediction models that are able to represent demand dynamics in a more adaptive manner is becoming an increasingly urgent need [6]. In industrial practice, Linear Regression is still widely used as a basic approach because it is simple, easy to interpret, and has low computational requirements [7]. However, this model works based on the assumption of a linear relationship between variables, so its flexibility is limited when faced with demand patterns that are volatile, heterogeneous, or influenced by unstable contextual factors [8]. To bridge these limitations, alternative prediction methods based on instance-based learning, particularly K-Nearest Neighbors (K-NN), offer a more adaptive approach [9]. Although the K-NN approach has characteristics that are potentially suitable for volatile operational environments, comparative studies evaluating its performance against linear regression methods in the hospitality context are still limited, especially in operational datasets that reflect actual field conditions. This research gap is important to address so that hotels can choose the model that is most relevant to their demand characteristics, while ensuring that operational planning and revenue strategies can run more accurately, efficiently, and sustainably. Therefore, the purpose of this study is to comprehensively evaluate the performance of the K-Nearest Neighbors model compared to Linear Regression in predicting hotel demand based on actual historical operational data, while assessing the extent to which both models are able to capture fluctuating and non-linear demand dynamics. This study also aims to provide empirical understanding of the practical implications of the prediction accuracy of each model on managerial decisions, particularly regarding pricing strategies, room inventory management, and resource planning, thereby supporting more adaptive and sustainable decision-making in the hospitality industry.

2. RESEARCH METHODS

This study aims to compare the performance of Linear Regression and K-Nearest Neighbors (K-NN) in predicting room revenue at Hotel U. The general flow of the study is shown in Figure 1, which illustrates the series of processes from data collection to model evaluation. Each stage is designed to ensure data quality, modeling consistency, and objectivity in performance measurement.

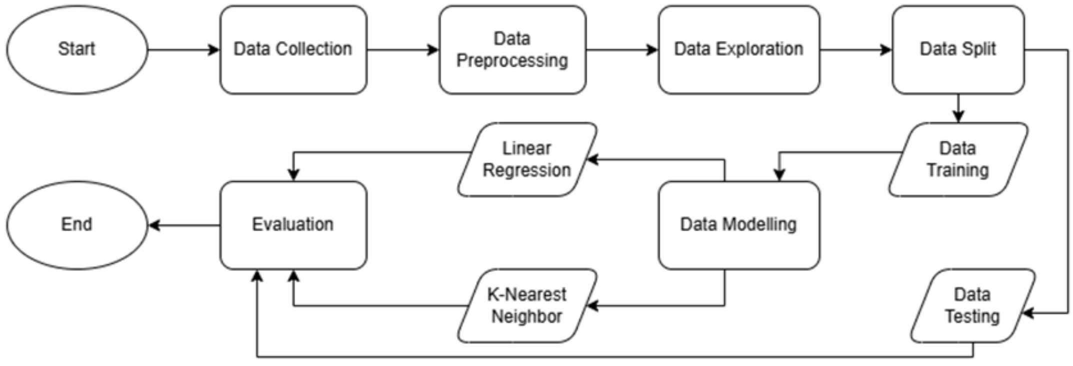

Figure 1. Linear Regression and K-Nearest Neighbors Modeling Workflow

2.1 Data Collection

The data used is hotel operational data that includes room revenue, rooms sold, and other supporting variables. The data was obtained directly from Hotel U in the form of monthly reports. The data range covers several years of operations to reflect realistic demand dynamics and represent market conditions.

2.2 Data Preprocessing

The preprocessing stage was carried out to ensure that the dataset was suitable for use in modeling. Several steps were applied:

1. Data Cleaning, including handling missing values, input errors, or operational anomalies. Inconsistent data was corrected or eliminated through logical and statistical checks.
2. Outlier Detection and Handling, Outliers were detected using a graphical approach (boxplot) and interquartile range (IQR) statistics. Extreme values are reconsidered based on the business context to avoid distortion in the model.
3. Data Transformation and Normalization: Because K-NN is sensitive to scale differences, numerical features are normalized using Min-Max Scaling so that all variables are within the same value range.
4. Data Period Alignment: Data is arranged chronologically and aligned between variables so that all observations have a consistent reference time.Use “Regular List” Style in *Styles* sub-menu.

2.3 Data Exploration

Exploratory analysis is performed to understand data characteristics and identify initial patterns. Descriptive statistics were used to describe the distribution of the main variables, while correlations between variables were analyzed to see the strength of the relationship between rooms sold, revenue, and other operational variables. These initial findings were used as a basis for selecting relevant features in the modeling.

2.4 Data Split (Train-Test Split)

The dataset is divided into two subsets: training data and test data. This separation aims to analyze the model's performance objectively. This study uses three variations of separation ratios, namely:

1. 70:30 → 70% of data for training and 30% for testing.
2. 80:20 → 80% of the data is used for training and 20% for testing.
3. 90:10 → 90% of the data is used for training and 10% for testing.

These three schemes are used to compare the stability and consistency of model performance across different data proportions.

2.5 Modelling

Model Development This study compares two algorithms: Linear Regression (LR) and K-Nearest Neighbors (KNN).

2.5.1 Linear Regression

Linear Regression is used to model the linear relationship between the dependent variable (revenue) and one or more independent variables. The general model of multiple linear regression is expressed as:

$$\hat{y} = \beta_0 + \beta_1 x_{2+\ldots+} \beta_n x_n \quad (1)$$

The estimation parameters β are obtained using the Ordinary Least Squares (OLS) method by minimizing the loss function:

$$J(\beta)=\frac{1}{2M}\sum_{m=1}^{M}(y^{(m)}-\beta^{T}x^{(m)})^{2} \quad (2)$$

The purpose of parameter estimation is to find β\betaβ that makes the loss function at its minimum value

$$Min\ J(\beta_0,\beta_1,\dots\dots,\beta_n) \quad (3)$$

This model works optimally when the relationship between variables is linear and there are no significant structural changes.

2.5.2 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a proximity-based non-parametric algorithm, where predictions are made by comparing a new sample to a number of K closest neighbors in the training data. Unlike Linear Regression, KNN does not build a mathematical model and does not have an equation function. The main steps of KNN are as follows:

1. Calculate the distance between the new data and all training data, usually using Euclidean distance.
2. Sort the distances from closest to farthest.
3. Determine the value of K, which is the number of neighbors to be considered.
4. Establish the prediction result based on information from the K nearest neighbors.

Because KNN works based on the proximity between data, its performance depends on the quality of preprocessing and the selection of the optimal K value.

2.6 Model Evaluation

The performance of both models is evaluated using Root Mean Square Error (RMSE) as the main metric because RMSE gives greater weight to large errors, which is relevant in the context of hotel revenue prediction. RMSE is calculated using the equation:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}[y_i-\hat{y}_i]^2} \quad (4)$$

where M is the number of samples in the test data, y(m) is the actual value, and (y) ̂(m) is the predicted value from the model.

The use of RMSE is important because hotel revenue is volatile and sensitive to large deviations; excessive prediction errors can have a direct impact on pricing strategies, room inventory management, and revenue planning. For this reason, a comparison of the RMSE across the three data splits is used to measure the consistency of performance, model stability, and the level of generalization of each algorithm. In addition, observing changes in RMSE between splits helps identify trends of model overfitting or underfitting, thereby providing a more comprehensive interpretation of the model's effectiveness in projecting hotel revenue.

3. RESULTS AND DISCUSSION

This chapter presents the results of research and analysis conducted using a quantitative approach to Hotel T's room revenue data. The results are presented systematically to provide a comprehensive overview of the data characteristics, research variable dynamics, and their implications for the modeling process. The discussion focuses on three main components, namely room revenue trends, number of rooms sold, and annual average revenue growth. This information forms the basis for model selection and performance evaluation of the Linear Regression and K-Nearest Neighbors (KNN) methods in three data partitioning scenarios.

3.1 Data Analysis

Initial data analysis was conducted to identify patterns, anomalies, and trends emerging from the main variables observed. This stage is important to ensure that the forecasting model is built based on a proper understanding of data behavior.

3.1.1 Monthly Room Revenue Trend

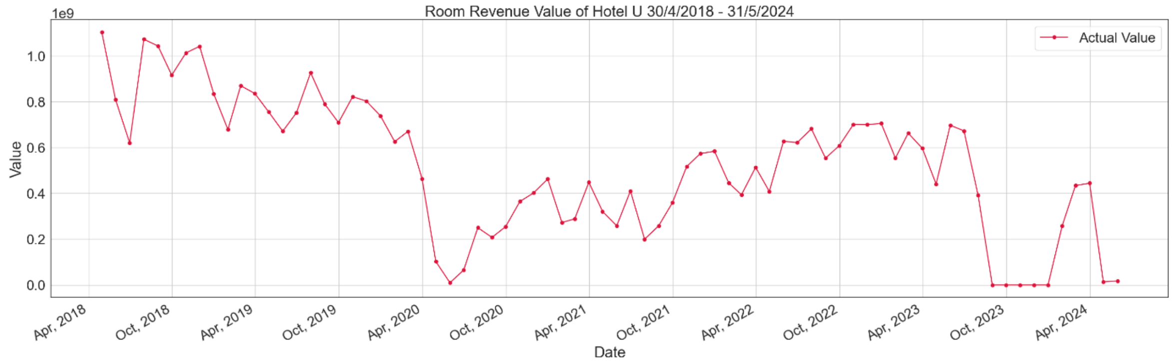

Figure 2. Monthly Room Revenue Trends

Figure 2 shows the dynamics of room revenue from April 2018 to May 2024. In general, revenue in the 2018–2019 period showed a high level of stability, reflecting relatively optimal hotel operating conditions before external disruptions occurred. The year 2020 marked a significant contraction in revenue due to the COVID-19 pandemic, which affected travel demand and hotel occupancy rates. Recovery began to gradually emerge in 2021, with more consistent increases in 2023. The decline in 2024 does not reflect full operational conditions, but is a consequence of data limitations that only cover up to May.

3.1.2 Trends in Number of Rooms Sold

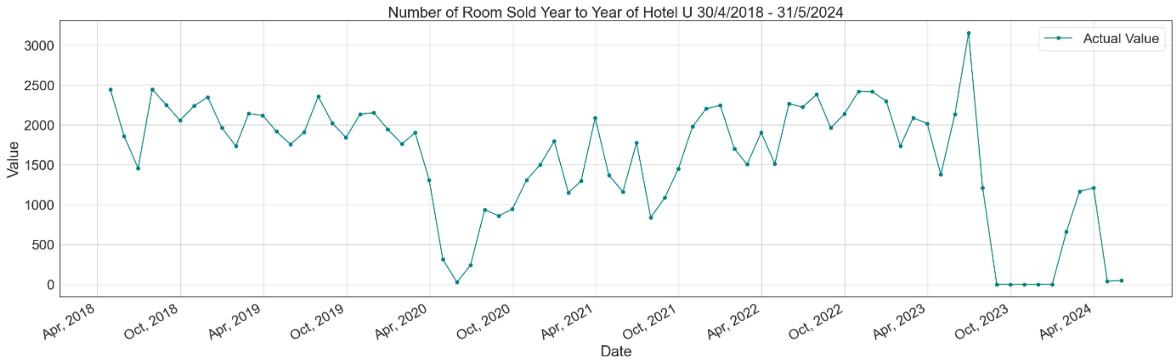

Figure 3. Monthly Trends in Number of Rooms Sold

Figure 3 shows the movement in the number of rooms sold during the observation period. In 2018–2019, room sales volume was stable, ranging from 1,800 to 2,400 rooms per month. The sharp decline in early 2020 to mid-2021 represents the direct impact of mobility restrictions and a decline in tourism activity due to the pandemic. In line with the relaxation of travel regulations and the recovery of the hospitality sector, an increase in the number of rooms sold began to appear in the 2022–2023 period. However, a decline was again seen at the end of 2023 to 2024 due to incomplete data for that period, not because of a change in operational trends.

3.1.3 Development of Average Annual Revenue

Figure 4 shows the development of average room revenue from year to year. The highest revenue was achieved in 2018 and 2019, reflecting stable market conditions before the pandemic. The year 2020 was the lowest point due to a drastic decline in travel activity and room occupancy. After entering 2021, revenue showed a sustained recovery trend until 2023, although it has not yet fully reached pre-pandemic levels. In 2024, there was another decline due to limited data coverage, so it cannot be used as an accurate representation of annual conditions.

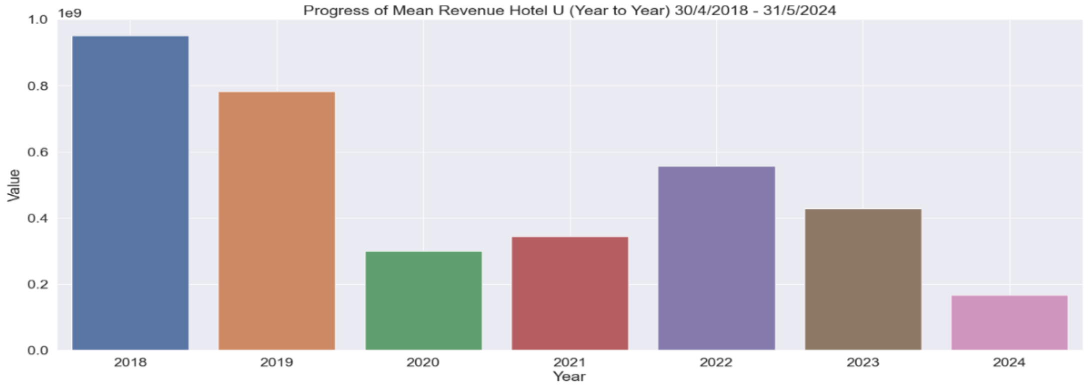

Figure 4. Development of Average Revenue per Year

3.2 Model Performance on the 70% Training – 30% Testing Scheme

3.2.1 Linear Regression

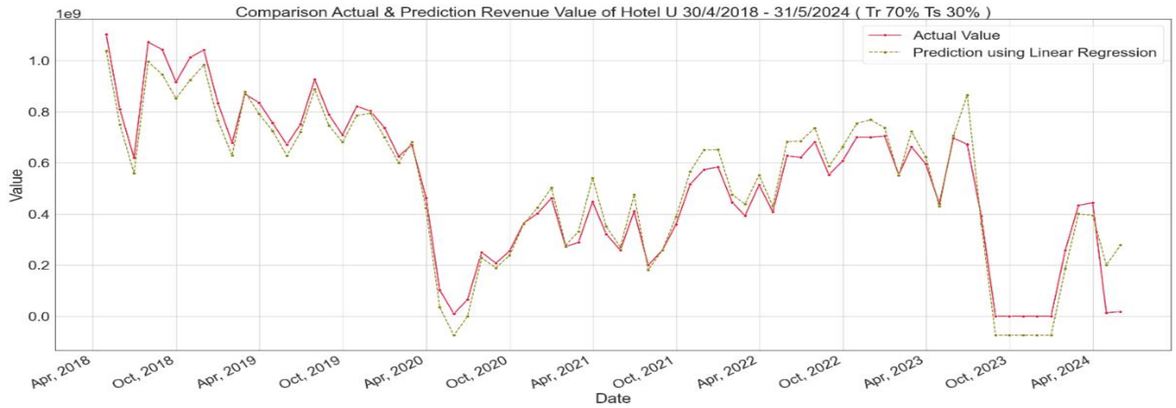

Figure 5. Comparison of Actual and Predicted Revenue Values Using Linear Regression (70:30 Scheme)

The visualization in Figure 5 shows a comparison between actual values and prediction results using the Linear Regression method for the period from April 30, 2018, to March 15, 2024. In general, the prediction pattern follows the main trend of the actual data, especially during periods of drastic decline, such as in early 2020. However, it can be seen that Linear Regression still produces deviations in short-term fluctuations, for example, in several peaks and troughs after 2021. Quantitatively, the model's performance is reflected in an RMSE value of 0.061, which indicates that the Linear Regression prediction error rate is in the moderate category for data patterns with high variability, such as monthly revenue. This value indicates that although the model is able to capture the general trend direction, its accuracy in modeling short-term changes is still limited.

3.2.2 K-Nearest Neighbors (KNN)

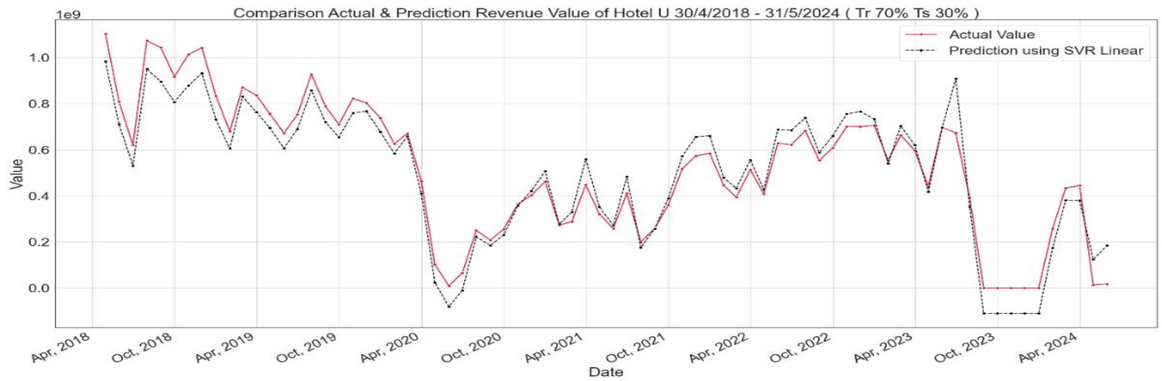

Figure 6. Comparison of Actual and Predicted Revenue Values Using KNN (70:30 Scheme)

Figure 6 shows the prediction results from the K-Nearest Neighbors (KNN) model with the same data distribution scheme (70% training, 30% testing). Visually, the KNN prediction line appears to adhere more closely to the actual data pattern than Linear Regression, especially in sections with sudden changes. This is in line with the characteristics of KNN, which is non-parametric and tends to follow local data patterns. This performance is also reflected in the KNN RMSE value of 0.057, which is lower than Linear Regression (0.061). A smaller RMSE value indicates that KNN provides more accurate predictions on this dataset, particularly in capturing monthly revenue fluctuations. Thus, the KNN model can be considered more suitable for data cases with dynamic variations between periods.

3.3 Model Performance on the 80% Training – 20% Testing Scheme

3.3.1 Linear Regression

Figure 7. Comparison of Actual Values and Revenue Predictions Using Linear Regression (80:20 Scheme)

In Figure 7 shows a comparison between actual values and prediction results using Linear Regression with an 80% training and 20% testing data split. This model is able to follow the general pattern of revenue movement, especially during the sharp decline due to the pandemic and the recovery trend in the following years. However, deviations are still visible at several points with more fluctuating changes, especially after 2022 when revenue variations became more dynamic. The RMSE value of 0.058 indicates that the model's error rate is relatively low and that Linear Regression is quite effective in this data distribution, especially in capturing long-term trends, although its response to sudden changes is not yet fully optimal.

3.3.2 K-Nearest Neighbors (KNN)

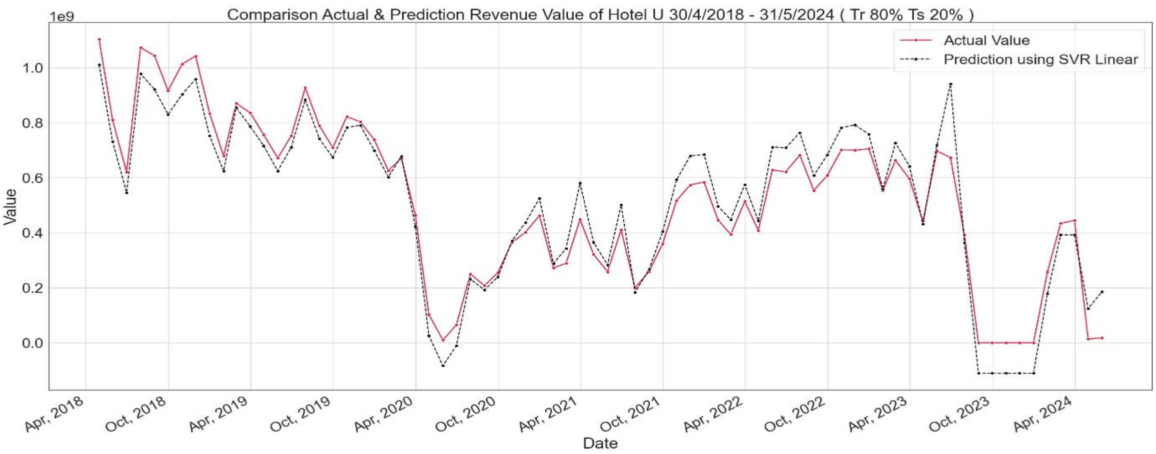

Figure 8. Comparison of Actual Values and Revenue Predictions Using KNN (80:20 Scheme)

In Figure 8, the KNN model produces prediction patterns that are quite close to the actual values, especially in sections with more gradual changes. However, at points of extreme change, such as the pandemic period and the subsequent surge, it can be seen that KNN predictions tend to experience greater deviation. This is in line with the characteristics of KNN, which is highly dependent on the proximity of historical data and therefore less adaptive to patterns that change drastically. The RMSE value of 0.061 indicates that the model's accuracy is slightly lower than that of Linear Regression. Thus, in the 80:20 scheme, Linear Regression is considered more capable of capturing the structure of income patterns consistently than KNN, especially when the data pattern has a dominant long-term trend.

3.4 Model Performance on the 90% Training – 10% Testing Scheme

3.4.1 Linear Regression

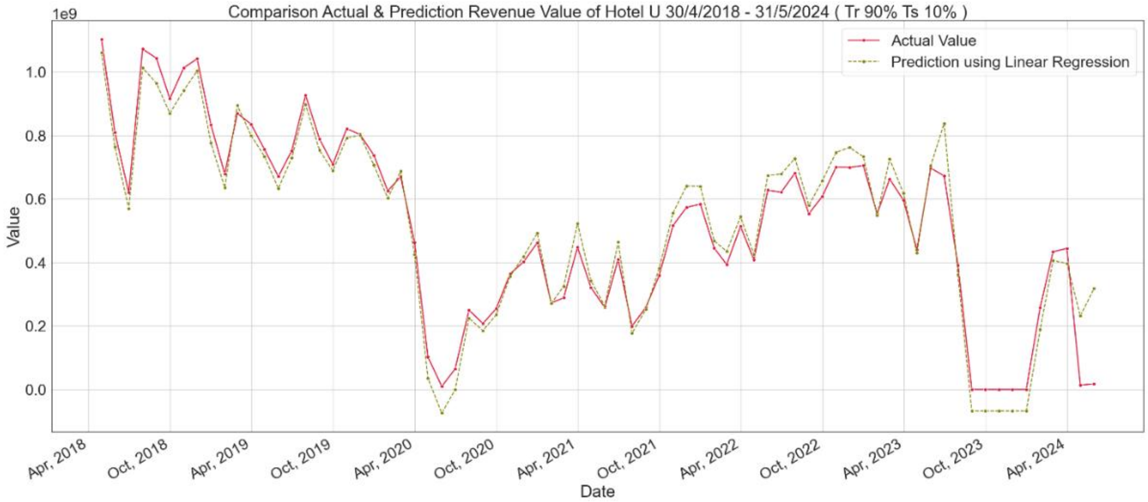

Figure 9. Comparison of Actual and Predicted Revenue Values Using Linear Regression (90:10 Scheme)

In the figure 9 shows that the Linear Regression predictions follow the general pattern of the actual data quite consistently, especially during the sharp decline at the beginning of 2020 and the subsequent recovery phase. Although some local variations still show minor deviations, overall the prediction line appears stable and close to the actual values for most of the testing period. An RMSE value of 0.069 indicates that Linear Regression has a relatively low error rate in the 90:10 scheme, so this method is able to represent long-term patterns well, although its sensitivity to short-term fluctuations is still limited.

3.4.2 K-Nearest Neighbors (KNN)

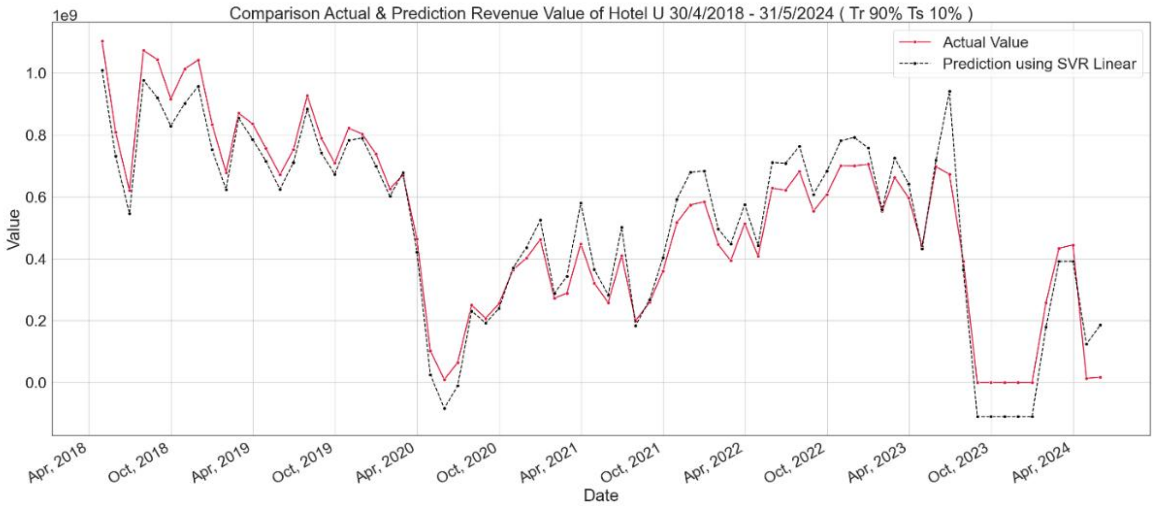

Figure 10. Comparison of Actual and Predicted Revenue Values Using KNN (90:10 Scheme)

In figure 10 shows that predictions using KNN tend to follow local patterns more closely than Linear Regression, especially in sections with sudden changes. However, at some points, the model appears to produce greater deviations compared to other data distribution schemes. This is reflected in the RMSE value of 0.081, which is higher than Linear Regression in the same scheme. Thus, although KNN has adaptive capabilities to local patterns, with a data proportion of 90% training and 10% testing, its performance is less than optimal compared to Linear Regression.

3.5 Discussion

Table 1. Summary of RMSE Values for All Testing Schemes

Scheme	Method	Training (%)	Testing (%)	RMSE
Forecast Simulation I	Linear Regression	70	30	0,061
	KNN			0,057
Forecast Simulation II	Linear Regression	80	20	0,058
	KNN			0,061
Forecast Simulation III	Linear Regression	90	10	0,069
	KNN			0,081

Based on the results shown in Table 1, it can be seen that the performance of the two models shows varying patterns in each data distribution scheme. In the 70:30 scheme, KNN produces a lower RMSE value than Linear Regression, demonstrating its ability to follow local changes in revenue data more effectively. In the 80:20 scheme, the performance of both models changed: Linear Regression actually produced better results with an RMSE of 0.058, slightly lower than KNN at 0.061. This shows that with a larger proportion of training data, the linear model is more stable in learning the general relationship between variables, while KNN tends to be sensitive to small variations in the data.

In the 90:10 scheme, KNN's performance declined significantly compared to the previous two schemes, as seen from the RMSE value which increased to 0.081. This condition is reasonable because KNN is highly dependent on the amount of historical data references to determine proximity values. Meanwhile, Linear Regression shows improved performance in this scheme with an RMSE of 0.069, indicating that the linear equation-based model is still capable of providing stable predictions even though the test data size is smaller. Overall, the test results show that KNN is superior in the initial scheme with more diverse data variations, while Linear Regression works better when the training data portion is larger and the trend pattern is more consistent.

4. CONCLUSION

Based on all the experiments that have been conducted, it can be concluded that the performance of the revenue prediction model is greatly influenced by the method used and the proportion of training and test data. KNN provides the best prediction in the 70:30 scheme with the lowest RMSE of 0.057, demonstrating its ability to capture short-term changes in fluctuating revenue data. However, this model does not maintain the same performance when the data proportion changes, especially in the 90:10 scheme where the error rate increases significantly.

In contrast, Linear Regression showed more stable performance with larger data splits, particularly in the 80:20 and 90:10 schemes. An RMSE value of 0.058 in the 80:20 scheme indicates that the linear model can better learn general relationships when the volume of training data increases. This proves that Linear Regression is more suitable for predicting revenue patterns that follow general trends, while KNN is more effective on datasets with dynamic trends and a broader reference space. Overall, no single model dominates across all schemes. The selection of the best model depends heavily on the analysis objective: KNN for detailed fluctuations, Linear Regression for more stable trend patterns.

Acknowledgment

-

REFERENCES

[1] L. Putri, M. Perhotelan, F. Vokasi, U. Airlangga, S. Indonesia, and B. Suharto, "Analysis of Opportunities and Barriers in the Use of Digital Systems to Optimize Hotel Business Operations," *Jurnal Ilmiah Hospitality Management*, vol. 14, no. 2, pp. 193–212, Jun. 2024, doi: 10.22334/JIHM.V14I2.280.

[2] M. Shintani and K. Umeno, “Average booking curves draw exponential functions,” *Scientific Reports 2023 13:1*, vol. 13, no. 1, pp. 15773-, Sep. 2023, doi: 10.1038/s41598-023-42745-3.

[3] T. Webb, Z. Schwartz, Z. Xiang, and M. Altin, “Hotel revenue management forecasting accuracy: the hidden impact of booking windows,” *Journal of Hospitality and Tourism Insights*, vol. 5, no. 5, pp. 950–965, Dec. 2022, doi: 10.1108/JHTI-05-2021-0124.

[4] J. Hood, “Rapid Communication Operations Management in the Service Industry: Challenges and Innovations,” *Operations Management in the Service Industry: Challenges and Innovations. JRIBM*, vol. 11, no. 4, p. 37, 2024, Accessed: Apr. 13, 2026. [Online]. Available: https://www.interesjournals.org/research-international-business-

[5] S. Yuniar Bahhri, W. Hartati, B. D. Kamariani, E. Asbarini, and I. M. Selong, “Model Pembangunan Pariwisata Berkelanjutan berbasis Collaborative Stakeholder: Perspective System Dynamic,” *Jurnal Ilmu Sosial dan Pendidikan (JISIP)*, vol. 7, no. 1, pp. 2598–9944, 2023, doi: 10.58258/jisip.v7i1.4193/http.

[6] V. Asy’ari, M. Y. Anshori, T. Herlambang, I. W. Farid, D. Fidita Karya, and M. Adinugroho, “Forecasting average room rate using k-nearest neighbor at Hotel S,” *2023 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation, ICAMIMIA 2023 - Proceedings*, pp. 496–500, 2023, doi: 10.1109/ICAMIMIA60881.2023.10427942.

[7] L. N. Pereira and V. Cerqueira, “Forecasting hotel demand for revenue management using machine learning regression methods,” *Current Issues in Tourism*, vol. 25, no. 17, pp. 2733–2750, Sep. 2022, doi: 10.1080/13683500.2021.1999397.

[8] L. Viverit, C. Y. Heo, L. N. Pereira, and G. Tiana, “Application of machine learning to cluster hotel booking curves for hotel demand forecasting,” *Int. J. Hosp. Manag.*, vol. 111, p. 103455, May 2023, doi: 10.1016/J.IJHM.2023.103455.

[9] M. R. Arief *et al.*, “Forecasting revenue rate of hotel v by gradient boost regression and K-nearest neighbors (KNN) methods,” *AIP Conf. Proc.*, vol. 3372, no. 1, Nov. 2025, doi: 10.1063/5.0299502/3371296.

[10] A. Ferisna, T. Herlambang, N. S. Meutia, and E. Sulistiyani, “Time series analysis and forecasting of techmart company’s revenue using autoregressive integrated moving average,” 2025, p. 040014. doi: 10.1063/5.0299504.

[11] M. Y. Anshori, T. Herlambang, and M. F. Abu Yaziz, “Optimizing occupancy of hospitality sector using Support Vector Regression and Genetic Algorithm,” *Journal of Revenue and Pricing Management*, Jun. 2025, doi: 10.1057/s41272-025-00539-4.

[12] A. Suryowinoto, T. Herlambang, A. A. Firdaus, and M. S. Baital, “Trajectory estimation of remote operated vehicle using particle filter for circular motion,” in *AIP Conf. Proc. 3176, 030027*, 2024, p. 010001. doi: 10.1063/12.0026404.

[13] M. Y. Anshori, V. Asy’Ari, T. Herlambang, and I. W. Farid, “Forecasting occupancy rate using neural network at Hotel R,” in *2023 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA)*, IEEE, Nov. 2023, pp. 347–351. doi: 10.1109/ICAMIMIA60881.2023.10427752.

[14] A. Suryowinoto, T. Herlambang, Y. A. Prabowo, and M. S. Baital, “Estimation of ROV trajectory in turning and diving motions using ensemble kalman filter square root method,” 2025, p. 030014. doi: 10.1063/5.0299478.

[15] N. R. Novita, T. Herlambang, F. Yudianto, and D. B. Magfira, “Implementation of Naïve Bayes method for sentiment analysis case study of MBKM,” 2025, p. 040004. doi: 10.1063/5.0299482.

[16] A. Sofia, T. Herlambang, I. Indasah, F. Yudianto, and M. R. Arief, “Forecasting demand for whole blood (WB) and packed red cells (PRC) at PMI Surabaya City using ensemble kalman filter,” 2025, p. 030019. doi: 10.1063/5.0299481.

[17] Y. Yuliana, T. Herlambang, I. Indasah, I. Kurniastuti, and M. R. Arief, “Machine learning-based forecasting of organic contaminants in water quality index (WQI) to improve potable water quality standards with XGBoost modeling,” 2025, p. 040008. doi: 10.1063/5.0299500.

[18] V. Asy’ari, T. Herlambang, M. Y. Anshori, P. Katias, and M. Adinugroho, “Sustainable tourism through SARIMA-based forecasting of international visitors to Bali,” 2025, p. 040012. doi: 10.1063/5.0299503.

[19] T. Herlambang, V. Asy’ari, R. P. Rahayu, A. A. Firdaus, and N. Juniarta, “Comparison Of Naïve Bayes And K-Nearest Neighbor Models For Identifying The Highest Prevalence Of Stunting Cases In East Java,” *Barekeng*, vol. 18, no. 4, pp. 2153–2164, Oct. 2024, doi: 10.30598/barekengvol18iss4pp2153-2164.

[20] I. Kurniastuti, R. Nawawi, T. D. Wulan, F. A. Susanto, and T. Herlambang, “Evaluating user satisfaction in new student registration systems using the DeLone and McLean model,” 2025, p. 030010. doi: 10.1063/5.0299365.

[21] M. Y. Anshori, P. Katias, T. Herlambang, N. S. Meutia, Z. B. Othman, and M. S. Azmi, “Predicting Hotel Revenue Using Gradient Boosting Regression and Support Vector Regression: A Comparative Analysis,” Jun. 19, 2025. doi: 10.21203/rs.3.rs-6910156/v1.

[22] M. Y. Anshori *et al.*, “Implementation of kalman filter method to forecast occupancy rate at hotel X,” 2025, p. 030026. doi: 10.1063/5.0299483.

[23] R. B. Utami, M. Fananni, S. Sumardiyono, and T. Herlambang, "Implementation Of K-Medoids And Fuzzy C Means Algorithms In Clustering Children With Intellectual Disabilities By Quality Of Life," 2025. [Online]. Available: http://e-ndst.kiev.ua

[24] T. Herlambang, H. Nurhadi, M. Adinugroho, and F. Yudianto, "Estimation of middle finger motion using extended Kalman filter," in *AIP Conf. Proc. 3176, 010001*, Nonlinear Dynamics and Systems Theory, 2024, pp. 392–399.

[25] U. Kurniasih and A. T. Suseno, "Analisis Sentimen Terhadap Bantuan Subsidi Upah (BSU) pada Kenaikan Harga Bahan Bakar Minyak (BBM)," *Jurnal Media Informatika Budidarma*, vol. 6, no. 4, p. 2335, 2022, doi: 10.30865/mib.v6i4.4958.