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RESEARCH

A comparative analysis of machine learning and stochastic methods for hotel occupancy forecasting

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Abstract

In highly competitive hotel markets, accurate demand forecasting plays a critical role in supporting effective revenue and pricing management decisions. This study conducts a comparative analysis between a machine learning approach that is Random Forest optimized with a Genetic Algorithm (RF–GA) and a stochastic method, the Kalman Filter (KF), to forecast hotel occupancy rates. Using monthly operational data from a three-star hotel in Surabaya, Indonesia, covering the period from April 2018 to May 2024, both models were evaluated based on forecasting accuracy measured by Root Mean Square Error (RMSE). The results indicate that the RF–GA model achieved substantially lower forecasting error (RMSE = 0.0320) compared to the Kalman Filter (RMSE = 0.5602), demonstrating that machine learning techniques can more effectively capture nonlinear demand patterns within hospitality data. From a managerial perspective, more accurate occupancy forecasts enable hotel revenue managers to optimize room pricing, anticipate demand fluctuations, and plan resources more efficiently. This research contributes to the revenue management literature by bridging computational intelligence with practical forecasting strategies in the hospitality sector, particularly within emerging market contexts.

Keywords Hotel occupancy · Forecasting · Revenue management · Random forest · Kalman filter

Introduction

The hospitality industry operates in a dynamic environment where fluctuations in demand can significantly influence revenue performance. For hotel managers, particularly those responsible for pricing and capacity allocation, accurate forecasting of occupancy rates has become a critical foundation of revenue management. A small deviation in demand prediction can lead to underpricing during peak periods or overpricing during low-demand seasons, both of

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which diminish profitability. Therefore, the ability to generate reliable forecasts is essential for maximizing room revenue, improving inventory control, and enhancing strategic pricing decisions (Şanlıöz-Özgen and Kozak 2023).

In practice, a variety of forecasting models have been employed to predict hotel occupancy. Traditional stochastic approaches, such as the Kalman Filter (KF) have long been used for their interpretability and recursive updating capability in handling time-series data. However, such models often assume linear relationships and stable noise distributions, which may not reflect the nonlinear dynamics of hotel demand influenced by promotions, market competition, or macroeconomic conditions. As a result, the accuracy of stochastic models may decline in volatile or highly segmented markets.

Recent advances in machine learning (ML) offer new possibilities for capturing complex, nonlinear patterns in hotel occupancy data. Among them, the Random Forest (RF) algorithm has gained attention for its robustness and adaptability in forecasting applications. When optimized through a Genetic Algorithm (GA), the model can automatically select hyperparameters that minimize forecasting errors, thus enhancing predictive accuracy. Previous studies have demonstrated the superiority of ML-based methods in tourism and hospitality forecasting, yet direct comparisons between ML and traditional stochastic approaches remain limited, especially in the context of emerging markets such as Indonesia.

This study aims to address this gap by conducting a comparative analysis of machine learning and stochastic methods for hotel occupancy forecasting. Specifically, it compares the performance of a Genetic Algorithm–optimized Random Forest (RF–GA) with that of the Kalman Filter (KF) using multi-year operational data from a three-star hotel in Surabaya, Indonesia. The analysis focuses on forecasting accuracy, measured by Root Mean Square Error (RMSE), and discusses how improved predictive performance can support better pricing, revenue planning, and resource allocation. By integrating data-driven analytics with managerial implications, this research contributes to the ongoing discourse on how computational intelligence can strengthen revenue management decision-making in the hospitality industry.

Research methods

Revenue management (RM) in the hospitality industry revolves around the strategic alignment of pricing, demand forecasting, and capacity control to maximize revenue per available room (RevPAR). According to Kimes (2003) and Talluri and van Ryzin (2004), forecasting is the cornerstone of RM decisions, influencing rate optimization, overbooking, and market segmentation strategies. Accurate forecasts of occupancy rates enable managers to adjust prices dynamically in response to demand fluctuations, ensuring both profitability and customer satisfaction (Wang et al. 2022).

Inaccurate forecasts can lead to suboptimal pricing decisions. Overestimation of demand may result in excessive prices and lost bookings, whereas underestimation may trigger premature discounting. As hotel markets become more data-rich and volatile, especially in urban destinations such as Surabaya, the ability to generate precise, data-driven forecasts is increasingly crucial. Consequently, forecasting models in RM have evolved from simple time-series smoothing techniques toward more adaptive and intelligent systems.

Traditional forecasting in hospitality has long relied on stochastic models, which treat demand as a random process evolving over time. Among these, the Kalman Filter (KF) is widely recognized for its recursive estimation capability and its suitability for systems with unobserved components (Chen and Schwartz 2008). KF models assume that current observations are a linear combination of past states plus random noise. Their advantage lies in simplicity, transparency, and ease of updating forecasts when new data become available (Weatherford and Kimes 2003).

However, these models typically rely on linearity and Gaussian noise assumptions, which may not capture nonlinear relationships between price, occupancy, seasonality, and external shocks such as macroeconomic changes or online review trends. Several studies (e.g., Cho 2003; Goh and Law 2011) found that while KF performs adequately in stable environments, its predictive accuracy declines when demand patterns become irregular or driven by multiple interacting factors. This limitation has motivated scholars to explore more flexible, data-driven techniques.

Machine learning (ML) offers a data-centric alternative to stochastic modeling by learning patterns directly from historical observations without strict distributional assumptions. Among the numerous ML algorithms, Random Forest (RF) is one of the most effective ensemble methods for regression and forecasting tasks (Sajja et al. 2022). It builds multiple decision trees on random subsets of data and aggregates their outputs, thus reducing overfitting and improving generalization.

The application of RF in tourism and hospitality has been explored in recent years. For instance, Law et al. (2019) demonstrated that tree-based ensembles outperform ARIMA and exponential smoothing in predicting tourist arrivals. Similarly, Anshori et al. (2025a, b) showed that RF models can accurately forecast hotel occupancy rates when optimized using a Genetic Algorithm (GA), which fine-tunes hyperparameters to minimize prediction error.

GA-based optimization enhances model adaptability, particularly when training data exhibit high variability or limited sample sizes.

Compared with stochastic approaches, ML models are nonlinear, data-adaptive, and robust to multicollinearity, making them more suitable for complex datasets where multiple operational and market variables interact. However, they are often criticized for being "black boxes" with limited interpretability, which poses a challenge for managerial adoption in decision-making contexts.

While both stochastic and machine learning methods have proven useful in forecasting applications, direct empirical comparisons between these paradigms remain limited, especially within the hospitality industry of developing countries. Previous comparative studies (e.g., Claveria et al. 2015; Moreira et al. 2021) mainly focused on macro-level tourism demand rather than property-level occupancy forecasting. Furthermore, few studies have examined how methodological differences in forecasting accuracy translate into practical revenue management implications, such as price adjustments, capacity allocation, and profitability optimization.

This study seeks to fill that gap by empirically comparing a machine learning approach (RF–GA) with a stochastic approach (Kalman Filter) using real operational data from a hotel in Surabaya, Indonesia. By linking model performance to managerial decision contexts, this research contributes not only to the methodological advancement of forecasting but also to the strategic integration of data analytics into revenue management practice (Zhou et al. 2018).

This study adopts a quantitative comparative research design aimed at evaluating the forecasting performance of two distinct modelling paradigms: a machine learning method that is Random Forest optimized with a Genetic Algorithm (RF–GA) and a stochastic method, the Kalman Filter (KF) (Smagin 2014). The comparison focuses on forecasting accuracy in predicting hotel occupancy rates, with the objective of identifying which approach provides more reliable results for revenue management decision-making.

The methodology follows three major stages:

1. Data collection and preparation,
2. Model development and parameter optimization, and.
3. Performance evaluation based on statistical error metrics.

The study utilizes monthly operational data from a three-star hotel in Surabaya, Indonesia, covering the period April 2018–May 2024. The dataset consists of 74 observations, representing a continuous time series that includes the following key variables (Table 1):

Before modelling, the data were checked for missing values, typographical inconsistencies (e.g., decimal separators), and outliers. Observations with implausible values (e.g., occupancy below 10%) were validated and corrected using cross-checks from the property management system (PMS). All variables were normalized to ensure comparability and numerical stability during model training.

To identify the most influential predictors for occupancy forecasting, a Pearson correlation analysis was conducted between Occupancy Rate and each explanatory variable. Variables showing significant correlation coefficients ($|r| > 0.5$) were retained as model inputs. This step reduces noise and enhances computational efficiency without compromising forecasting accuracy.

The correlation matrix revealed that Rooms Sold, Average Room Rate, and RevPAR were strongly associated with Occupancy Rate, indicating their relevance to demand forecasting in hotel operations.

Model development

Random forest optimized with genetic algorithm (RF–GA)

The Random Forest (RF) algorithm, introduced by Breiman (2001), constructs multiple regression trees on randomly sampled subsets of data and aggregates their predictions. RF is particularly effective in handling nonlinear and multivariate relationships, which are common in hospitality datasets.

To enhance RF performance, this study integrates a Genetic Algorithm (GA) for hyperparameter optimization. GA operates through selection, crossover, and mutation processes inspired by natural evolution to find the combination of parameters that minimize forecasting error.

Table 1 Dataset

Date	Room sold	Avg room rate	RevPar	Room Rev	Occupation (%)
30/04/2018	1283	370,076	125,610	474,807,004	33.9
30/05/2018	1572	344,352	143,207	541,321,824	4.6
30/06/2018	767	328,872	66,731	252,244,964	20.3
31/07/2018	1823	335,090	156,393	610,869,503	46.7
31/08/2018	1654	346,193	146,596	572,602,618	42.3
30/09/2018	2041	337,250	182,097	688,326,988	54.0
31/10/2018	2449	337,836	211,818	827,360,679	62.7
…	…	…	…	…	…
31/05/2024	3516	355.,88	263,376	1,249,193,708	74.1

The objective function of GA was to minimize the Root Mean Square Error (RMSE) on the validation dataset. The algorithm evolved over 20 generations, with population size = 10, crossover probability = 0.5, and mutation probability = 0.2. The final parameter set producing the lowest RMSE was selected for forecasting.

Kalman filter (KF)

The Kalman Filter is a recursive stochastic estimator suitable for time-series forecasting under uncertainty (Chen and Schwartz 2008; Zhou and Wu 2016). It models the system as a state-space process, where the *latent state variable* represents underlying demand, and the *observation variable* corresponds to actual occupancy.

The model equations can be expressed as:

$$x_t = Ax_{t-1} + w_t, \quad w_t \sim N(0, Q)$$
$$y_t = Cx_t + v_t, \quad v_t \sim N(0, R)$$

where $x_t$is the unobserved demand state, $y_t$is the observed occupancy rate, and Q, Rdenote process and measurement noise variances, respectively. The model parameters were tuned iteratively to minimize RMSE on the validation subset, with process noise set to $Q = 0.01$and measurement noise to $R = 0.1$.

To ensure robustness, the dataset was divided into three training–testing ratios: 70:30, 80:20, and 90:10. Each ratio was used to test the model's generalization capability under different data availability conditions.

Model training and validation were implemented using the Python 3.12 environment with the Scikit-learn and DEAP libraries. RMSE was used as the primary evaluation metric:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\widehat{y_t} - y_t)^2}$$

Lower RMSE values indicate better predictive performance.

Beyond statistical accuracy, the study interprets forecasting results in the context of revenue management decision-making.

A model with lower RMSE offers:

1. More reliable demand anticipation, supporting dynamic pricing strategies.
2. Improved inventory and staffing planning, reducing cost inefficiencies.
3. Better risk management, by minimizing the gap between forecasted and realized occupancy.

This managerial interpretation ensures that the results are not only methodologically rigorous but also practically valuable for hotel practitioners.

Below is a schematic representation of the research process (Fig. 1):

Result and discussion

Both forecasting models that is the Random Forest optimized with a Genetic Algorithm (RF–GA) and the Kalman Filter (KF) were evaluated based on their predictive accuracy for hotel occupancy rate. The evaluation used Root Mean Square Error (RMSE) as the primary metric across three data partition scenarios: 70:30, 80:20, and 90:10 (training: testing ratios) (Figs. 2, 3, 4 and Table 2).

The RF–GA model consistently outperformed the Kalman Filter across all scenarios, achieving its best accuracy at the 80:20 split (RMSE = 0.0320). This result suggests that the hybrid machine learning approach effectively captures nonlinear patterns in occupancy data, while the stochastic model—though stable—shows limited responsiveness to structural shifts in demand.

The comparative plots in Table 3 show that the RF–GA predictions closely follow the actual occupancy trends, including seasonal peaks and troughs. In contrast, KF forecasts exhibit a smoother but lagging pattern, often underestimating sharp fluctuations in demand.

Such lag is typical of state-space models, which rely on recursive updating rather than pattern recognition. The superior performance of RF–GA can be attributed to its ability to learn nonlinear dependencies among predictors such as room rates, revenue, and prior occupancy, enhanced by the parameter search conducted through the Genetic Algorithm.

From a managerial perspective, the increase in RMSE between the RF–GA and KF models has several implications:

1. Pricing agility
   Accurate occupancy forecasts allow revenue managers to anticipate high-demand periods and implement dynamic pricing earlier. For example, a 3% improvement in forecast accuracy can lead to a 1–2% increase in RevPAR when prices are adjusted proactively.
2. Inventory optimization
   Reliable demand prediction supports better room allocation between online travel agents (OTAs) and direct channels, minimizing overbooking and last-minute discounting.
3. Cost efficiency
   Staffing schedules and operational budgets can be aligned with forecasted demand, reducing idle labour

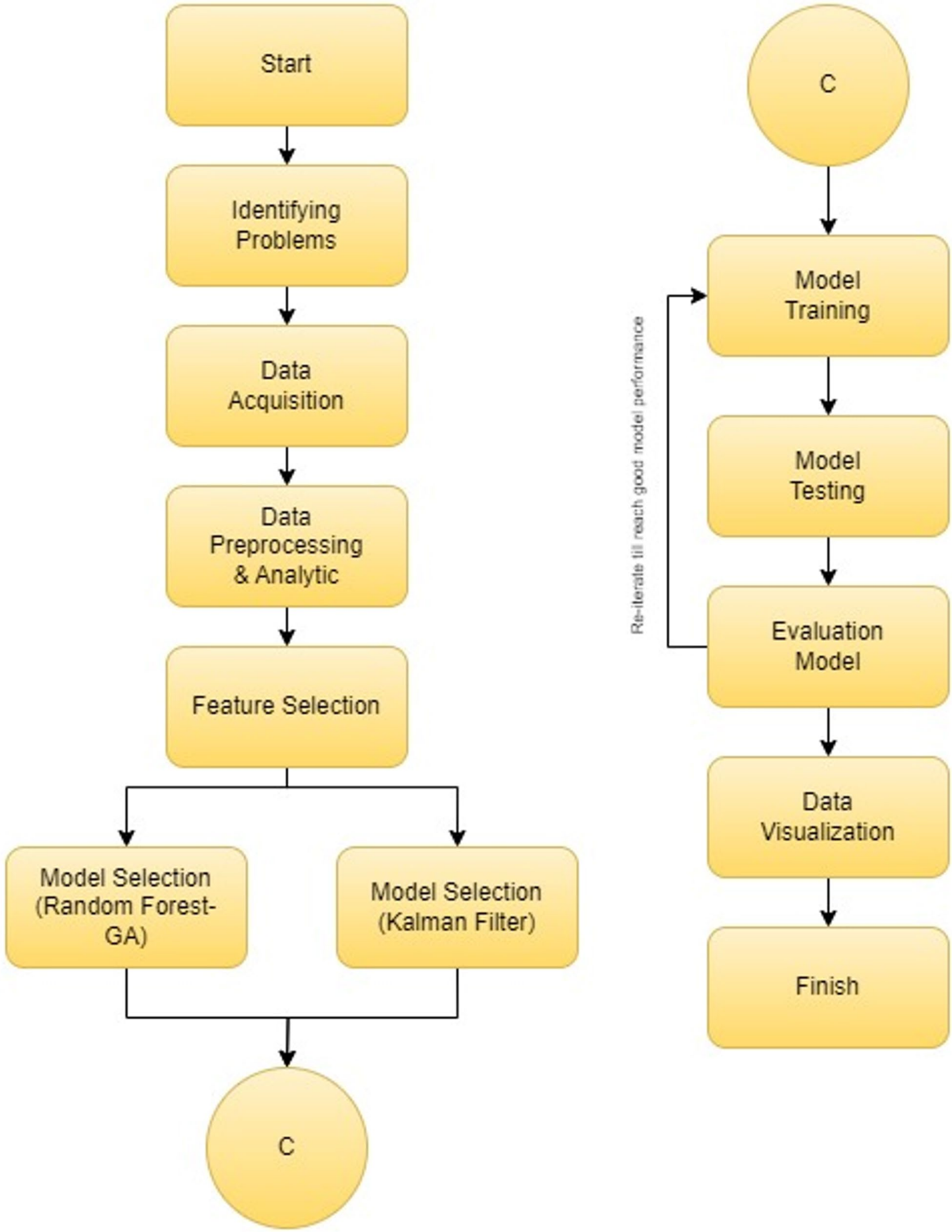

Fig. 1 Research methods

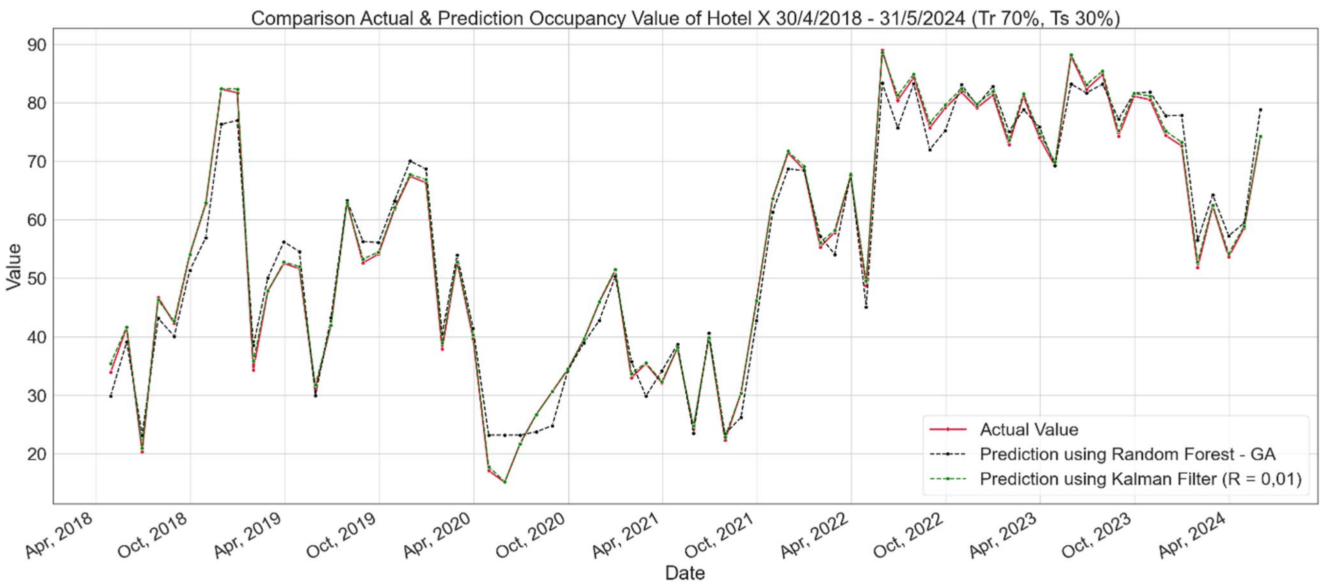

Fig. 2 First plot simulation of random forest–GA and Kalman Filter (70% training data, 30% testing data)

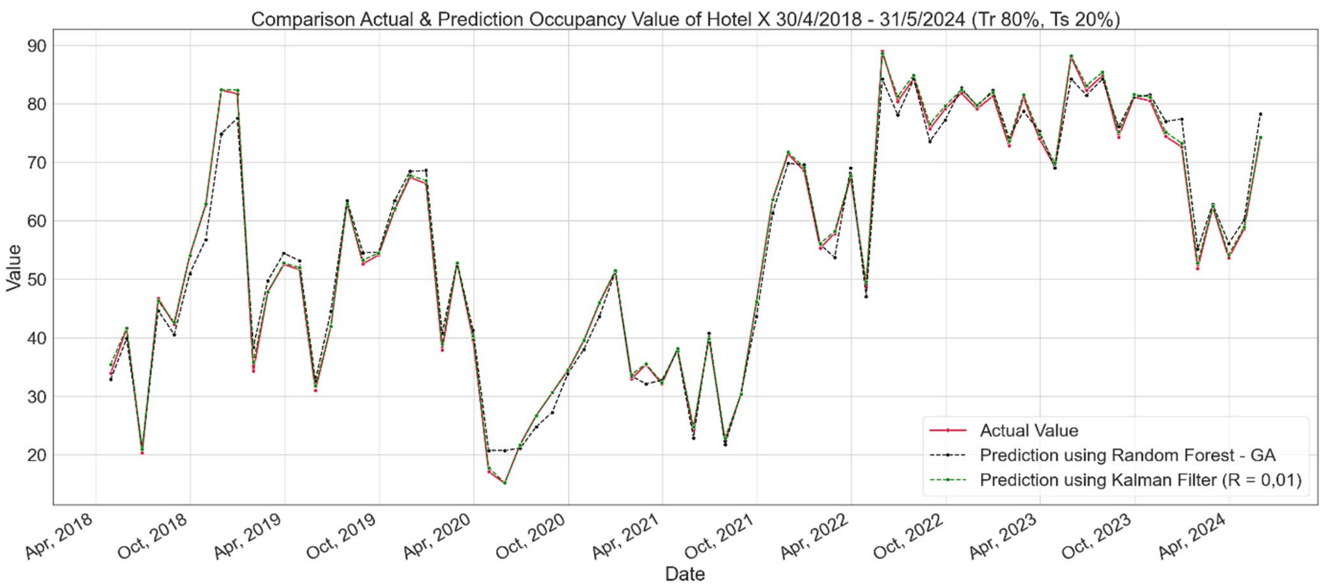

Fig. 3 Second plot simulation of random forest–GA and Kalman Filter (80% training data, 20% testing data)

costs during low seasons and avoiding service degradation during high occupancy.

4. Strategic planning
   Improved accuracy also enhances decision confidence in revenue budgeting, capital allocation, and promotional campaigns—key components of a long-term RM strategy.

These findings reaffirm that forecasting accuracy is not merely a statistical pursuit but a strategic enabler of financial performance in hospitality operations.

The superiority of machine learning models in hospitality forecasting aligns with findings by Law et al. (2019), who reported that ensemble methods outperform classical time-series models for predicting tourist arrivals. Similarly, Claveria et al. (2015) observed that nonlinear models provide better adaptability in volatile tourism environments.

However, this study extends existing literature by focusing on property-level forecasting, demonstrating that even with a relatively small dataset (74 observations), the RF–GA hybrid can significantly outperform stochastic filters. This supports the argument of Anshori et al. (2024) that data-driven intelligence enhances managerial foresight in emerging-market hotels where demand signals are less stable and more price-sensitive.

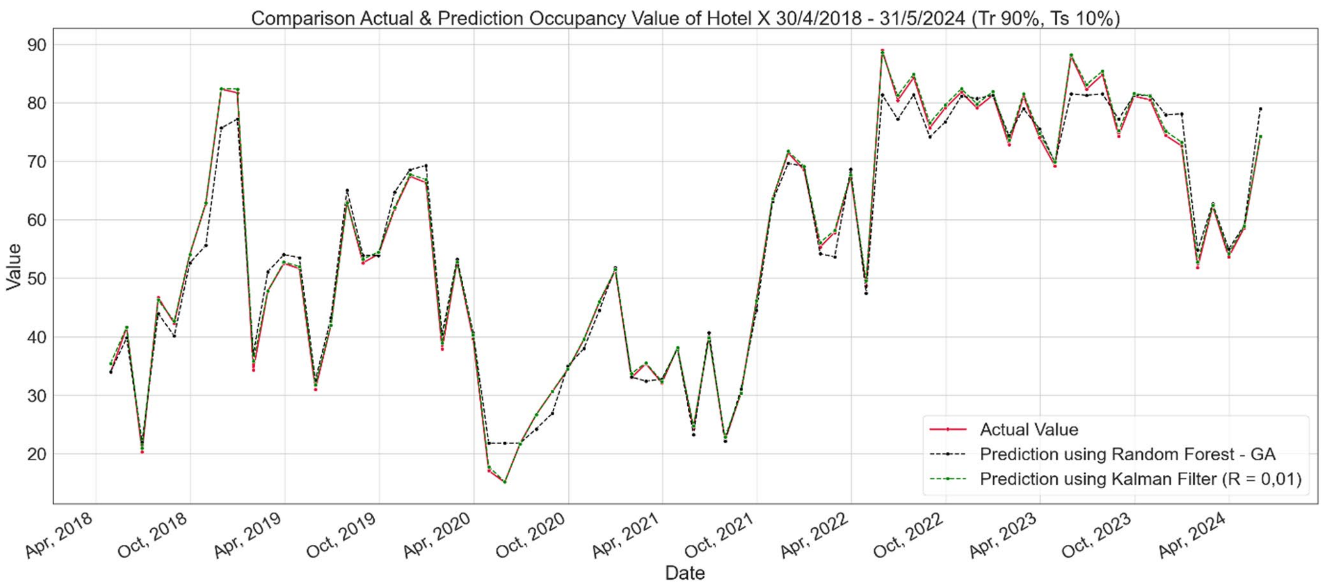

Fig. 4 Third plot simulation of random forest–GA and Kalman Filter (90% training data, 10% testing data)

Table 2 Comparison of RMSE values

Train–test split	RMSE value of random forest–genetic algorithm (RF-GA)	RMSE value of Kalman Filter	Best model
70%: 30%	0.0451	0.6214	RF-GA
80%: 20%	**0.0320**	0.5602	**RF-GA**
90%: 10%	0.0383	0.5809	RF-GA

Table 3 Summary of findings

Aspect	Random forest–genetic algorithm (RF-GA)	Kalman Filter
Model type	Machine Learning (Nonlinear Ensemble)	Stochastic (linear state-space)
RMSE (best)	**0.0320**	0.5602
Responsiveness to demand shifts	High	Moderate
Interpretability	Moderate	High
Managerial usefulness	Excellent for dynamic pricing and forecasting	Suitable for baseline trend estimation

From the lens of revenue management, the results highlight the importance of adopting predictive analytics as a core capability rather than a supplementary tool. Hotels in competitive markets such as Surabaya can integrate the RF–GA model into their daily revenue dashboards to continuously update occupancy predictions and recommend rate adjustments in real time.

A practical implementation workflow may include:

1. Collecting real-time data from the PMS (rooms sold, ADR, RevPAR).
2. Feeding data into an automated RF–GA engine trained on historical performance.
3. Generating short-term forecasts (e.g., next 30–60 days).
4. Linking forecasts to dynamic pricing systems (yield managers or RMS software).

Such integration can transform forecasting from a reactive reporting activity into a predictive decision-support mechanism, directly improving pricing precision and revenue yield.

Despite the strong empirical results, several limitations should be acknowledged:

1. Single-property data: The analysis is based on one hotel, limiting generalizability to other market segments or regions.
2. Monthly granularity: The dataset uses monthly intervals; daily or weekly forecasting could provide finer operational insights.
3. Feature limitation: Only financial and occupancy-related variables were included; incorporating exogenous factors (e.g., events, holidays, online reviews) could enhance model robustness.

4. Model interpretability: Although RF–GA delivers higher accuracy, its “black-box” nature may pose challenges for managerial explanation and adoption.

Addressing these limitations offers potential for future studies exploring hybrid interpretable AI models or ensemble frameworks combining stochastic transparency with machine learning precision.

The machine learning approach (RF–GA) demonstrates superior predictive performance and stronger alignment with the revenue management objectives of modern hotels. Nevertheless, stochastic methods such as the Kalman Filter retain value as transparent baseline models for quick, interpretable demand monitoring.

Conclusion

This study compared the performance of a machine learning model—Random Forest optimized using a Genetic Algorithm (RF–GA)—with a stochastic model, the Kalman Filter (KF), in forecasting hotel occupancy rates. Using monthly operational data from a three-star hotel in Surabaya, Indonesia, covering April 2018 to May 2024, the analysis revealed that the RF–GA model consistently achieved significantly lower forecasting errors (RMSE = 0.0320) compared to the KF model (RMSE = 0.5602) across multiple train–test scenarios.

The findings underscore the superior capability of machine learning methods in capturing complex, nonlinear demand patterns inherent in hospitality data. From a managerial standpoint, improved forecast accuracy enhances the ability of hotel revenue managers to make timely and data-driven decisions regarding room pricing, promotional strategies, inventory control, and staffing. These insights demonstrate that predictive analytics should be viewed not merely as a technical exercise but as a strategic instrument for optimizing revenue performance.

Methodologically, this research contributes to the literature by offering one of the first empirical comparisons between machine learning and stochastic approaches within the context of property-level hotel occupancy forecasting in an emerging market. Conceptually, it bridges the gap between computational intelligence and practical revenue management applications, advancing the discussion on how forecasting technologies can support pricing agility and competitive advantage in dynamic hotel markets.

The results carry three key implications for hotel practitioners:

1. Adoption of data-driven forecasting systems
   Hotels should integrate machine learning–based forecasting engines into their revenue management systems (RMS) to continuously update occupancy predictions and pricing recommendations.
2. Training and analytical capability building
   Revenue managers require upskilling in data analytics to interpret and operationalize machine learning outputs effectively within pricing and budgeting contexts.
3. Strategic decision support
   Accurate forecasts support long-term financial planning, enabling managers to align marketing campaigns, cost control, and investment priorities with projected demand cycles.

By embedding such analytics into daily decision-making, hotel organizations can transition from reactive to proactive revenue management, reducing risk while improving profitability.

Despite its valuable insights, this study acknowledges several limitations that open pathways for further exploration:

1. Single-property scope
   The dataset was limited to one hotel in Surabaya, which restricts generalizability. Future research should extend the model to multi-property or cross-regional datasets.
2. Temporal granularity
   The current analysis used monthly data. Investigating daily or weekly forecasts would better support short-term pricing and yield management.
3. Exogenous variables
   Incorporating external factors—such as public holidays, city events, competitor pricing, and online review sentiment—could improve predictive robustness.
4. Model interpretability
   While RF–GA offers high accuracy, its interpretability remains limited. Future work may combine explainable AI (XAI) techniques or hybrid frameworks blending machine learning precision with stochastic transparency.
5. Integration with decision systems
   Future research could explore embedding predictive models directly into dynamic pricing algorithms or revenue optimization simulators, linking forecasting outputs to direct pricing actions.

By addressing these directions, upcoming studies can deepen understanding of how forecasting intelligence can transform data analytics into actionable revenue strategies, thereby advancing both academic theory and industry practice.

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Author contributions M.Y.A. (Mohamad Yusak Anshori) conceived the study, designed the methodology, supervised the project, and wrote the main manuscript text.T.H. (Teguh Herlambang) curated the dataset, performed data preprocessing, and implemented the Random Forest and Kalman Filter models.D.A.K. (Denpharanto Agung Krisprimandoyo) contributed to the literature review, theoretical framing, and validation of the model results.Z.B.O. (Zuraini Binti Othman) provided methodological support, assisted with statistical analysis, and contributed to the discussion of managerial implications.M.S.A. (Mohd Sanusi Azmi) supported the research design, reviewed analytical procedures, and contributed to manuscript editing.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

References

Anshori, M. Y., T. Herlambang, and M. F. Abu Yaziz. 2025a. Optimizing occupancy of hospitality sector using support vector regression and genetic algorithm. *Journal of Revenue and Pricing Management*. https://doi.org/10.1057/s41272-025-00539-4

Anshori, M. Y., P. Katias, T. Herlambang, N. S. Meutia, Z. B. Othman, and M. S. Azmi. 2025b. Predicting hotel revenue using gradient boosting regression and support vector regression: A comparative analysis. *Journal of Revenue and Pricing Management*. https://doi.org/10.1057/s41272-025-00557-2

Chen, C., and Z. Schwartz. 2008. Forecasting hotel room demand using the Kalman filter algorithm. *Journal of Hospitality & Tourism Research*, 32(3): 325–340. https://doi.org/10.1177/1096348008317391

Devianto, D., E. S. Wahyuni, M. Maiyastri, and M. Yollanda. 2024. The seasonal model of Chili price movement with the effect of long memory and exogenous variables for improving time series model accuracy. *Frontiers in Applied Mathematics and Statistics* 10: 1–11. https://doi.org/10.3389/fams.2024.1408381

Sajja, G. S., H. Pallathadka, K. Phasinam, and M. M. Arcinas. 2022. Machine learning techniques in business forecasting: A performance evaluation. *ECS Transactions* 107(1): 11431–11437. https://doi.org/10.1149/10701.11431ecst

Şanlıöz-Özgen, H. K., and M. Kozak. 2023. Customer experience in five-star hotel businesses: is it an experience for customers? *Consumer Behavior in Tourism and Hospitality* 18(3): 306–320. https://doi.org/10.1108/cbth-11-2022-0197

Smagin, V. I. 2014. State estimation for linear discrete systems with unknown input using compensations. *Russian Physics Journal* 57(5): 682–690. https://doi.org/10.1007/S11182-014-0291-X

Talluri, K. T., and G. J. Van Ryzin. 2004. *The theory and practice of revenue management*. Springer. https://doi.org/10.1007/b100557

Tang, C. M. F., B. King, and N. Kulendran. 2015. Estimating future room occupancy fluctuations to optimize hotel revenues. *Journal of Travel & Tourism Marketing* 32(7): 870–885. https://doi.org/10.1080/10548408.2015.1063827

Wang, X., Y. Kang, F. Petropoulos, and F. Li. 2022. The uncertainty estimation of feature-based forecast combinations. *Journal of the Operational Research Society* 73(5): 979–993. https://doi.org/10.1080/01605682.2021.1880297

Weatherford, L. R., and S. E. Kimes. 2003. A comparison of forecasting methods for hotel revenue management. *International Journal of Forecasting* 19(3): 401–415. https://doi.org/10.1016/S0169-2070(02)00011-0

Zhou, Z., and Y. Wu. 2016. System model bias processing approach for regional coordinated states information involved filtering. *Mathematical Problems in Engineering* 2016: 1–7. https://doi.org/10.1155/2016/4860785

Zhou, Y., G. Qiu, and G. Qiu. 2018. Random forest for label ranking. *Expert Systems with Applications* 112: 99–109. https://doi.org/10.1016/J.ESWA.2018.06.036