Exploring the dynamic pattern: A Comparative Time Series Analysis of Key Performance Indicators in the Hotel Industries of Doha, Dubai, and London.

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Abstract:

The Middle East and Europe have experienced significant growth in tourism over the last decade, reaching pre-pandemic levels in 2022. Doha, Dubai, and London saw a substantial expansion in their hospitality sectors. With more expected growth, especially in the Middle East due to investments, accurate forecasting is crucial for hoteliers in these competitive markets. The main goal of this study is to comprehensively analyze historical hotel metrics in Doha, Dubai, and London over the past ten years using STR data. This study uses advanced models such as ARIMA, AUTO ARIMA, GARCH, SARIMA, and LSTM to assess and compare their effectiveness in predicting hotel demand and performance indicators, providing insights for the Middle East and European regions. Advanced time series models, including ARIMA, SARIMA, and LSTM, are utilized to assess and compare their efficacy in forecasting hotel demand and KPIs, providing insights for the Middle East and Europe.

Key Words:

Hospitality KIPs, Time series forecasting Models, Machine Learning in Tourism

Background and motivation

Time series forecasting models are essential tools employed across a wide range of fields, including business, finance, tourism, and scientific research. These models automatically generate forecasts for numerous univariate time series, providing invaluable insights into key data features such as trend, cycle, seasonality, and series length(Hyndman & Khandakar, 2008; Petropoulos et al., 2014). These models are also valuable in predicting the scientific data, volatility in financial markets, and tourist quantities, showcasing their versatility across different sectors (Masood et al., 2019; Ramin et al., 2020; Vasilellis & Meade, 1996; Zhang et al., 2016).

In the context of hospitality, time series forecasting models can aid in predicting demand side (tourist arrivals), (Bäurle et al., 2020) and can assist in forecasting the supply side essential for understanding economic trends and planning investments in the hospitality industry (Bandara et al., 2020).

Time series forecasting has been a subject of interest in academia and practice, with the debate between traditional methods and machine learning approaches being a focal point. Traditional methods like ARIMA, Exponential Smoothing, and Error Trend Seasonality forecast (ETS) have long been established as powerful tools for time series prediction (Chintapalli et al., 2020). Although traditional statistical time series models have been widely employed, recent studies have provided compelling evidence that machine learning methods frequently outperform these conventional approaches (Alfeld et al., 2016). The rapid rise of machine learning techniques, particularly deep learning algorithms and neural networks, has revolutionized the field of time series forecasting. These advanced methods capture intricate patterns and nonlinear relationships embedded within complex data, surpassing the limitations of traditional models (Makridakis et al., 2018). The SARIMA model captures linear patterns and seasonality in time series data, while RNN and LSTM models are designed to handle complex, nonlinear relationships and temporal dependencies. Testing these models allows for comparison of their effectiveness in predicting hotel KPIs, particularly under varying conditions like regional differences and industry disruptions.

Objectives

This study aims to identify the most effective forecasting method for predicting hotel KPIs by comparing traditional approaches, such as Auto SARIMA, with advanced machine learning techniques like RNN and LSTM.

Literature Review

Hotel KPIs and Destination Success

During the COVID-19 pandemic, the hotel industry faced challenges, leading to a shift in the relevance of certain KPIs. Many revenues related KPIs (Eg. REVPAR, ADR, Occupancy) designed pre-pandemic to assess hotel performance became unreliable (Magnini et al., 2020). However, the use of good KPIs remains crucial for maintaining competitiveness in top hotel markets (Ballestero et al., 2023). Further it emphasises the importance of performance measures for Destination Management Organizations (DMOs) to enhance decision-making (Morrison et al., 2024). Furthermore, the measurement of tourism success varies across academia, organizations, and governments due to its multi-dimensional nature and diverse stakeholders (Buhalis et al., 2006); Morrison et al., 2024).

Hotel key performance indicators (KPIs) such as Average Daily Rate (ADR), Revenue per Available Room (RevPAR), and Occupancy are crucial metrics for forecasting and assessing the performance of hotels (Schwartz et al., 2021). RevPAR, specifically, is a widely accepted measure of hotel performance that reflects the earning potential of a hotel in offering accommodation (Ognjanović et al., 2023). During the COVID-19 pandemic, the importance of these KPIs has been highlighted, with a focus on revenue management and forecasting to navigate through challenging times (Singh & Corsun, 2023).

Traditional methods (SARIMA)

Traditional methods like Seasonal Autoregressive Integrated Moving Average (SARIMA) play a crucial role in time series forecasting across various domains. SARIMA is particularly effective in capturing seasonal patterns and trends in historical data, making it a valuable tool for forecasting tasks (Kuru & Calis, 2020). The SARIMA method has been successfully applied in diverse fields, in forecasting scenarios related to agriculture, healthcare, and climate variables, showcasing its versatility and applicability (Silalahi, 2020; Wu et al., 2022). While SARIMA models are robust and widely used, they do have limitations. Such as their inability to capture nonlinear information present in some time series data and

SARIMA assumes a linear relationship between successive values of the time series, especially in complex systems (Li et al., 2021).

Machine learning methods (RNN, LSTM)

Recent studies have shown that LSTM, a type of RNN, has been widely used for time series forecasting across various domains, including finance, environmental factors, and energy use (Haq et al., 2021; Sezer et al., 2020). It is evident that machine learning models, particularly LSTM models, outperform traditional methods like ARIMA models in forecasting hotel KPIs, especially during challenging times such as the COVID-19 pandemic (Binesh et al., 2024; Elsaraiti & Merabet, 2021). The authors reported that when the SARIMA was combined with LSTM layers, the model could capture linear and nonlinear data features and resulted in better accuracy in the forecasting trends (He et al., 2021; Wu et al., 2022).

Rationale for Dubai, Qatar, and London City Trends

City trends significantly impact the hospitality industry, influencing various aspects such as tourism, state support, innovation management, and marketing strategies. However, this critical research on city hospitality has been limited (Gesso, 2021).

Dubai has established itself as a significant global destination for hospitality and tourism, with the Dubai tourism strategy aiming to attract millions of visitors annually (AlMutawa et al., 2023). Dubai's rapid growth and investments in construction have bolstered its status as a premier real estate destination, appealing to both investors and tourists (Ajmal et al., 2021). On the other hand, Qatar has been leveraging its strengths in various areas to enhance its global appeal. Qatar's strategic investments in sports, such as hosting international sporting events like the World Cup 2022, play a crucial role in branding the nation as modern, friendly, and legitimate on the global tourism and hospitality stage (Søyland & Moriconi, 2022). At the same time London's prominence in the global market is evident through its continued dominance in cross-border investments, although emerging global cities are also gaining traction (Fadeyi et al., 2022). London's significance in the tourism industry is highlighted by its competitive tourism products and increased global competition for tourist arrivals (Woyo & Slabbert, 2021). Doha and Dubai represent rapidly developing markets, while London, as a major global city, offers insights into a more mature and established market. Comparing these varied destinations helps assess the adaptability and accuracy of forecasting models across different market sizes and economic conditions.

In conclusion, city trends are pivotal in shaping policies and strategies in the hospitality sector. By analysing and forecasting these trends with modern time series, stakeholders can make well-informed decisions to improve service quality and tackle emerging challenges in urban settings. Furthermore, the study of revenue management and RevPAR is essential for sustainable recovery strategies in the hotel industry, especially in the context of crises like the COVID-19 pandemic (Rahman et al., 2021)

Methodology

Data processing

Monthly data for key indicators in the hotel industry, such as Room Occupancy (Room OCC), Average Room Rate (ARD), and Revenue Per Available Room (RevPAR), spanning from January 2013 to November 2023, were collected from the STR database. The COVID-19 period in 2020 and 2022 was excluded from the dataset due to its disruptive nature on time series patterns. Excluding the COVID-19 period improves model performance by focusing on data that better reflects typical operating conditions, enhancing predictive accuracy.

Subsequently, the dataset was divided into 70% for training data and 30% for testing data. This division ensures that models are trained on a significant portion of the data while reserving a separate portion for evaluating model performance and generalization to unseen data.

Data Analysis

Time series models

To develop the forecasting model, both traditional methods such as SARIMA (Seasonal Autoregressive Integrated Moving Average), and advanced machine learning models like RNN (Recurrent Neural Network) and LSTM (Long Short-Term Memory) were employed.

SARIMA

SARIMA (Seasonal Autoregressive Integrated Moving Average) is a powerful time series forecasting technique designed to capture and predict patterns in data with seasonality (Song et al., 2021). It extends the classical ARIMA model by incorporating parameters for seasonal variations (Surendran et al., 2022), making it suitable for datasets with periodic fluctuations over time. SARIMA comprises autoregressive (AR), differencing (I), and moving average (MA) terms, alongside seasonal counterparts denoted by capital letters P, D, and Q, which govern the model's behaviour. By adjusting these parameters, SARIMA effectively models short-term dynamics and seasonal variations in the time series. The 'S' term in SARIMA represents the seasonal period, indicating the frequency at which the seasonal pattern repeats (e.g., 12 for monthly data with yearly seasonality). This model designation encompasses regular and seasonal autoregressive and moving average terms, accounting for correlations with both low and seasonal lags.

The SARIMA model specification is {ARIMA (1,1,1) $(1,1,1)_{12}$}

$$(1-\phi_1 B)(1-\Phi_1 B^{12})(1-B)(1-B^{12})y_t = (1+\theta_1 B)(1+\beta_1 B^{12})e_t$$

Where, $(1-\phi_1 B)$ = non-seasonal AR(1), $(1-\Phi_1 B^{12})$ = seasonal AR(1), $(1-B)$ = non-seasonal difference, $(1-B^{12})$ = seasonal difference, y_t = forecasted value, $(1+\theta_1 B)$ = non-seasonal MA(1), $(1+\beta_1 B^{12})$ = seasonal MA(1), e_t = error term.

Model selection was conducted using an automated approach to identify the optimal SARIMA configuration. The **auto_arima** function from the **pmdarima** library in Python was employed for this purpose. The **auto_arima** function utilizes a stepwise algorithm to iteratively search through the space of possible SARIMA configurations and selects the model with the lowest Akaike Information Criterion (AIC) value.

RNN (Recurrent Neural Network):

Recurrent Neural Networks (RNNs) are a crucial class of neural networks designed for sequential data processing, essential for tasks like sequence modeling and time series forecasting. Unlike traditional feedforward neural networks, RNNs have an internal memory mechanism, enabling them to retain information from previous time steps, thus capturing temporal dependencies within the data. This flexibility allows RNNs to capture intricate patterns and dynamics in sequential data sequences, making them invaluable for tasks where past context influences future predictions. The architecture of an RNN consists of input, hidden, and output layers. The input layer receives data at each time step, while the hidden layer contains recurrent connections allowing information persistence across time steps. However, traditional RNNs face the vanishing gradient problem, limiting their ability to capture long-term dependencies. Despite this challenge, RNNs remain powerful tools for analysing and forecasting sequential data.

LSTM (Long Short-Term Memory):

Long Short-Term Memory (LSTM) networks represent a specialized variant of Recurrent Neural Networks (RNNs) designed to address the vanishing gradient problem and capture long-term dependencies more effectively. Unlike traditional RNNs, which struggle to retain information over long sequences due to the vanishing gradient issue, LSTM networks incorporate gated mechanisms to control the flow of information within the network. These mechanisms, composed of input, forget, and output gates, enable LSTMs to selectively retain or forget information from previous time steps, thus facilitating the learning of long-range dependencies in sequential data. LSTM networks have demonstrated superior performance in various tasks such as natural language processing, time series prediction, and speech recognition, making them a cornerstone in the field of sequence modelling and forecasting.

Model selection and validation

Model selection was conducted utilizing metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). These metrics are essential in evaluating predictive model performance. By comparing MAPE and RMSE values across different models, the most suitable model was identified. This process ensures the selection of a model that provides accurate predictions while considering both the magnitude and direction of prediction errors.

Model selection relied on metrics like Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) to evaluate predictive performance accurately. Comparing MAPE and RMSE values across different models ensured the identification of the most suitable model, considering both the magnitude and direction of prediction errors. Serial autocorrelation in the SARIMA model was assessed using the Durbin Watson (DW) Statistic, where DW around 2 indicates no autocorrelation, less than 2 indicates positive autocorrelation, and more than 2 indicates negative autocorrelation. The Lagrange multiplier (LM) test determined serial autocorrelation in the best-fitting model, with a non-significant result suggesting the absence of autocorrelation. The Jarque-Bera (JB) test detected the normality of residuals, while the ARCH test assessed residual heteroskedasticity. The model selection also considered the lowest Akaike information criterion (AIC), RMSE and MAPE values to identify the best-fitting models. The formulas for calculating JB statistic, MAPE, and AIC are as follows.

$$\text{JB test statistic} = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right]$$

where S = skewness and K = kurtosis.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{O_t - y_t}{O_t}\right|$$

where n = number of time points, O_t = observed value, y_t = forecasted value

$$\text{AIC} = -(\text{log-likelihood}) + 2K$$

where **K** is the number of model parameters.

$$\text{DW} = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}$$

where e_t is the residual figure, and T is the number of observations in the experiment.

Results and Discussion

Figure 1 indicates a pronounced impact of the COVID-19 pandemic on room occupancy rates in Dubai and London compared to Qatar throughout 2020-2021. This disparity highlights the varying degrees of disruption experienced by hospitality sectors in different regions due to the pandemic's effects.

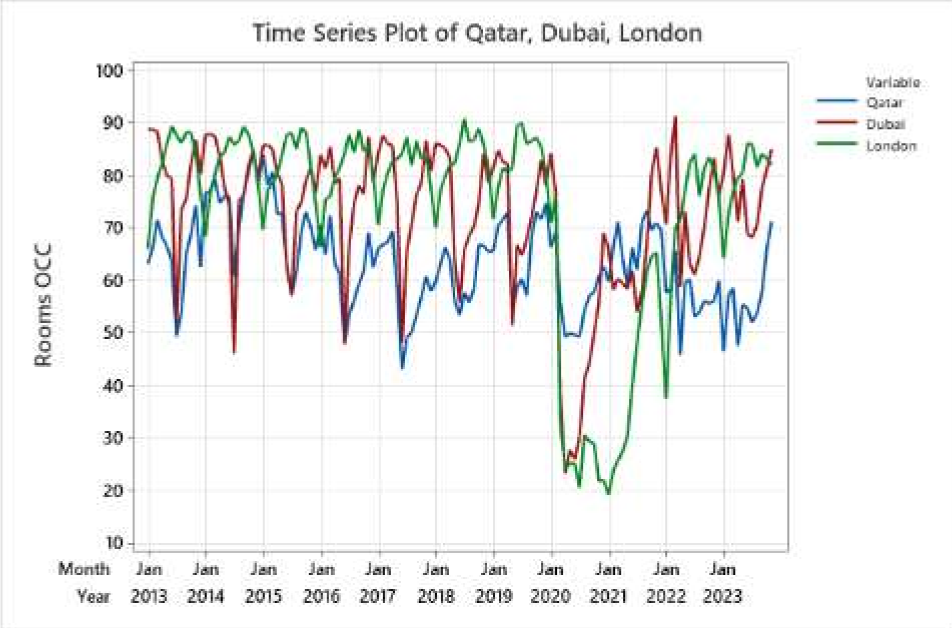

Figure 1: Time series plot of Room occupancy for Qatar, Dubai, and London

The Average Daily Rate (ADR) consistently tends to be higher in London, while Qatar exhibits notably elevated rates in November and December 2022 (Figure 2). This trend underscores the distinct pricing dynamics between the three regions, suggesting potential seasonal and market-specific factors influencing room rates.

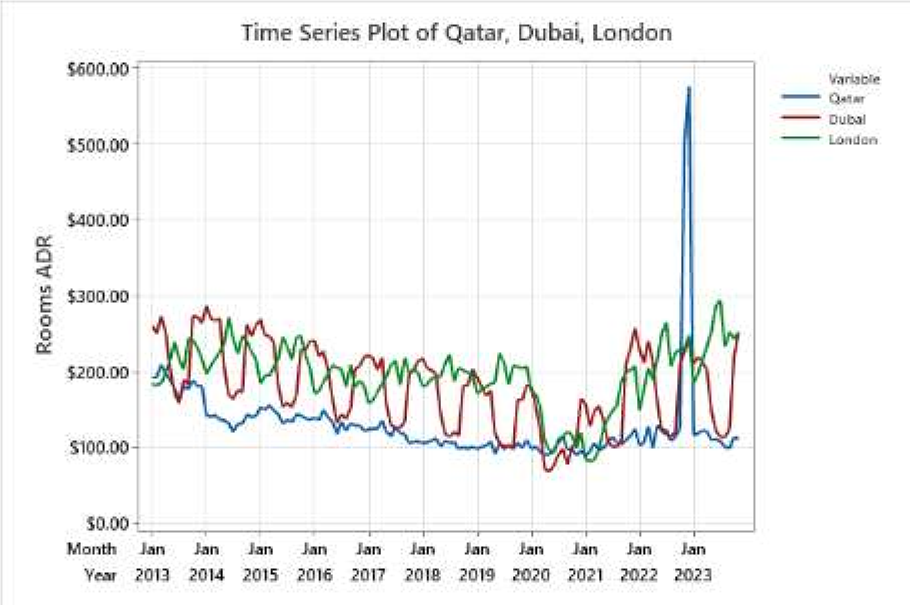

Figure 2: Time series plot of ADR for Qatar, Dubai, and London

The Revenue per Available Room (RevPAR) mirrors the pattern observed in the Average Daily Rate (ADR), with London consistently demonstrating higher figures. Similarly, Qatar exhibits a notable surge in RevPAR during November and December 2022, aligning with the observed trends in ADR.

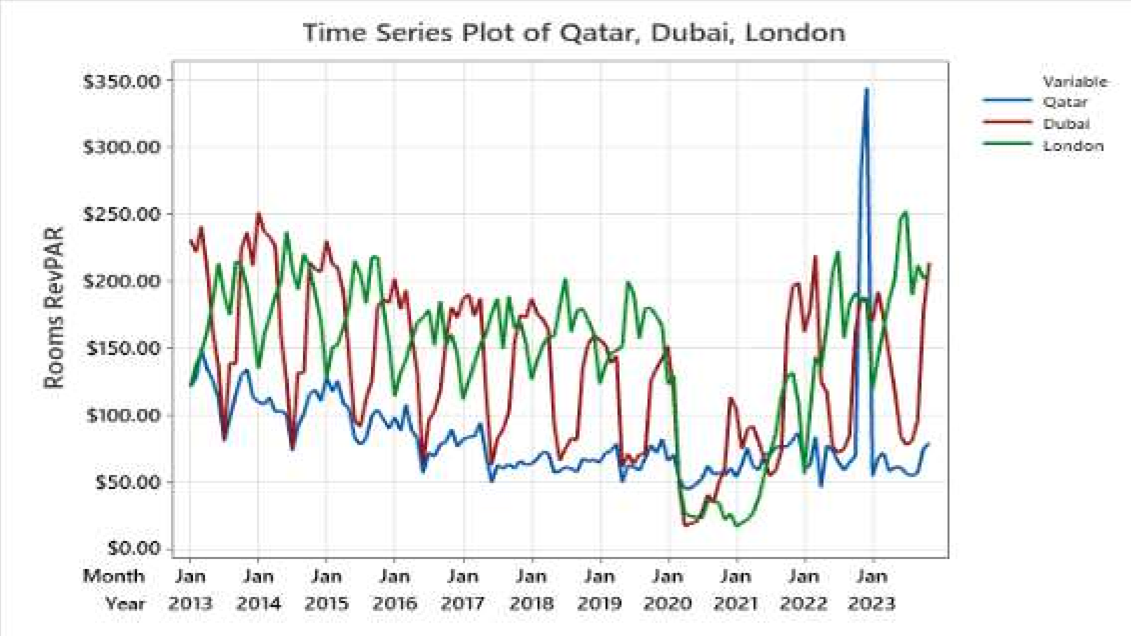

Figure 3: Time series plot of RevPAR for Qatar, Dubai, and London

The subsequent tables and figures provide a comparative analysis of the three time series models across three chosen countries for each indicator, utilizing Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) as evaluation metrics.

Table 1 - Evaluation Metrics based on RMSE and MAPE for Room Occupancy in the UK, Qatar, and Dubai

Rooms Occupancy				
country		SARIMA	RNN	LSTM
UK	RMSE	4.44	**4.32**	4.42
	PAPE	4.42	**4.38**	4.52
Qatar	RMSE	24.56	**6.34**	7.37
	PAPE	15.94	**8.27**	9.58
Dubai	RMSE	8.54	**7.78**	8.28
	PAPE	8.32	**8.42**	9.47

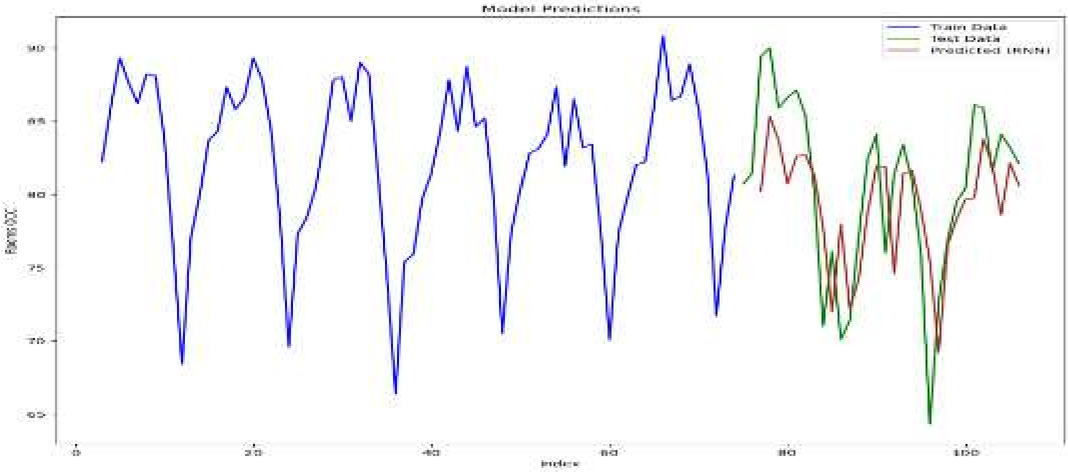

Figure 01a: Best model prediction of Rooms OCC of the UK based on RNN

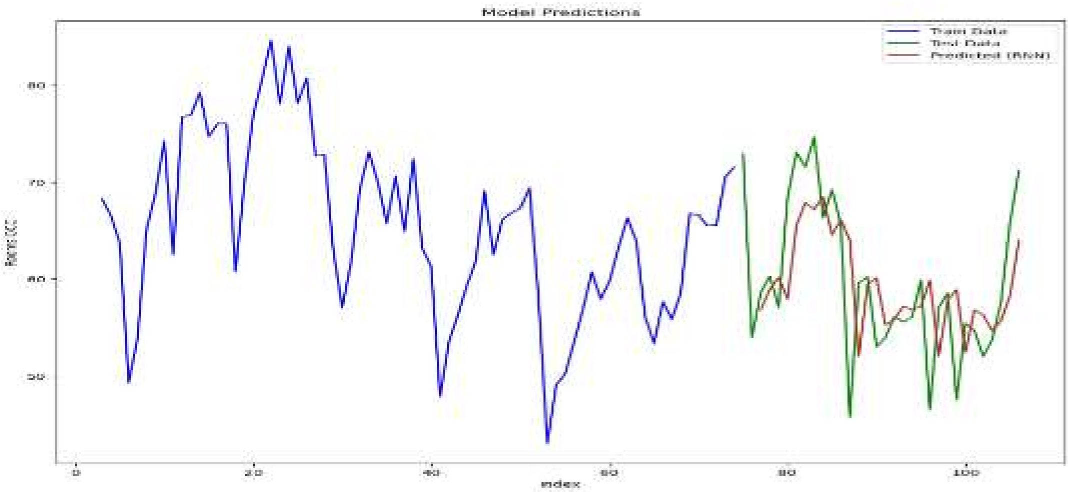

Figure 01b: Best model prediction of Rooms OCC of Qatar based on RNN

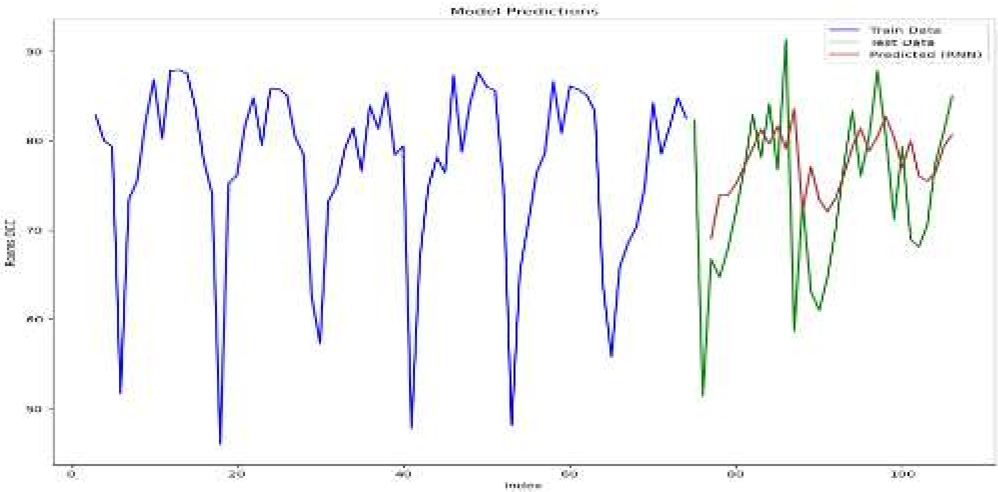

Figure 01c: Best model prediction of Rooms OCC of Dubai based on RNN

Table 2 - Evaluation Metrics based on RMSE and MAPE for Rooms Average Daily Rate (ADR) in the UK, Qatar, and Dubai

Rooms Average Daily Rate (ADR)				
country		SARIMA	RNN	LSTM
UK	RMSE	43.18	**22.9**	18.87
	MAPE	14.21	**6.8**	13.70
Qatar	RMSE	10.35	**8.91**	17.02
	MAPE	10.12	**5.90**	12.13
Dubai	RMSE	30.95	**14.60**	25.65
	MAPE	19.09	**9.20**	11.08

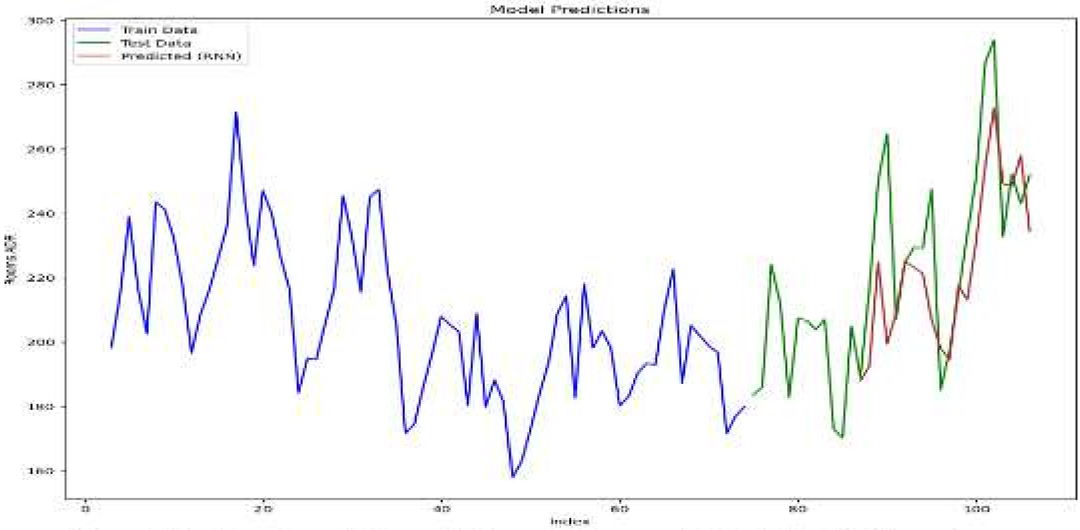

Figure 02a: Best model prediction of Rooms ADR of the UK based on RNN

Figure 02b: Best model prediction of Rooms ADR of Qatar based on RNN

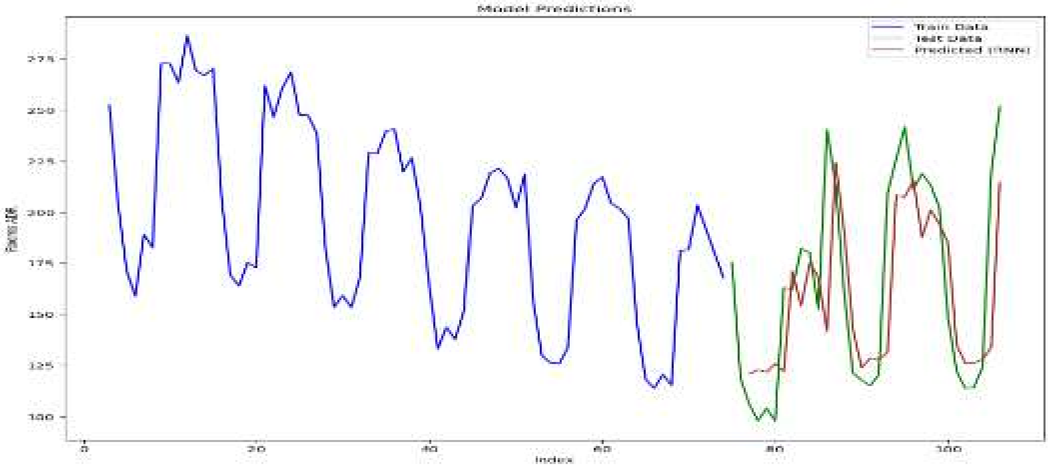

Figure 02c: Best model prediction of Rooms ADR of Dubai based on RNN

Table 3 - Evaluation Metrics based on RMSE and MAPE for Rooms RevPAR in the UK, Qatar, and Dubai

Rooms RevPAR				
country		SARIMA	RNN	LSTM
UK	RMSE	26.33	**19.15**	23.5
	MAPE	10.07	**9.73**	9.2
Qatar	RMSE	8.98	**11.95**	9.40
	MAPE	10.91	**10.33**	12.39
Dubai	RMSE	43.26	**25.86**	26.22
	MAPE	,26.10	**11.03**	17.15

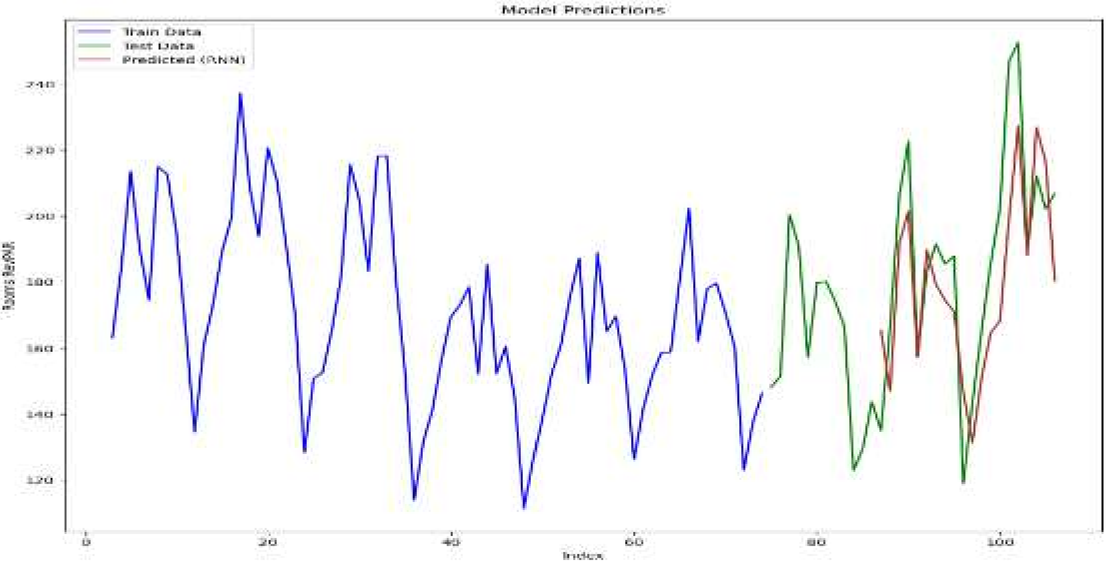

Figure 03a: Best model prediction of Rooms RevPAR of the UK based on RNN

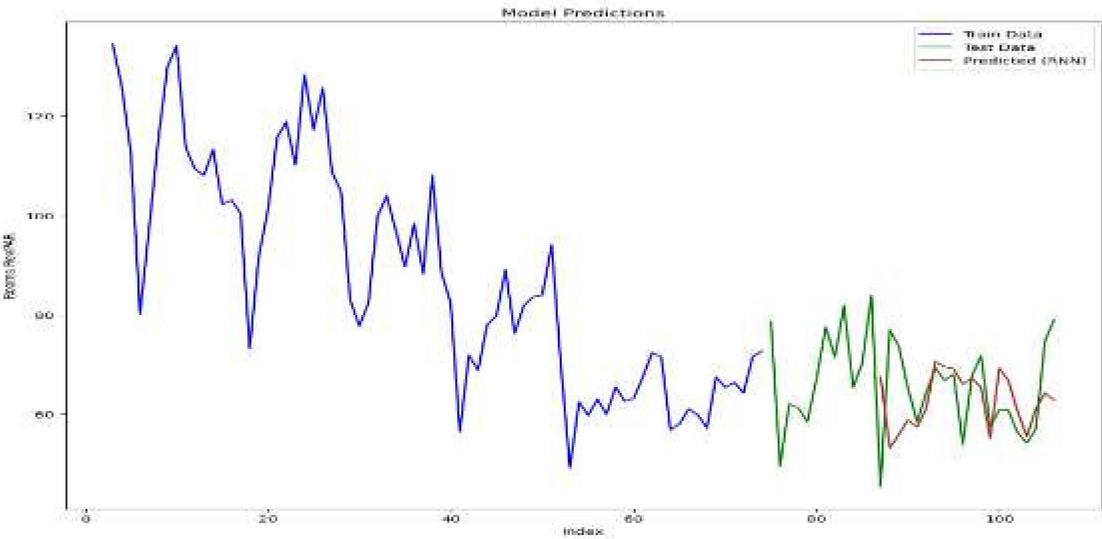

Figure 03b: Best model prediction of Rooms RevPAR of Qatar based on RNN

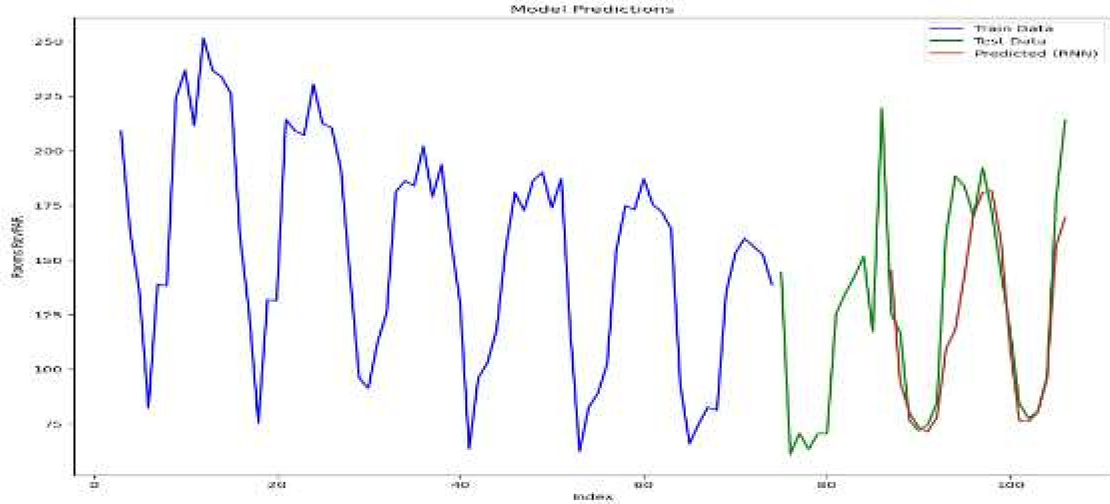

Figure 03c: Best model prediction of Rooms RevPAR of Dubai based on RNN

After comparing SARIMA, a traditional method, with two advanced machine learning techniques, RNN and LSTM, the most effective approach was determined to be RNN based on its superior performance in accuracy measures such as REMS and MAPE. Predictive capability based on Mean Absolute Percentage Error (MAPE) can be categorized into several levels of accuracy. MAPE (Mean Absolute Percentage Error) is a widely recognized precision evaluation indicator in forecasting models across various domains.

Table 04 shows the typical classification scheme based on Makridakis & Hibon, (2000).

Table 4: Predictability of the Modell based on the MAPE

Predictability	MAPE
Excellent Predictive Capability	0 – 5 %
Good Predictive Capability	5 – 10 %
Satisfactory Predictive Capability	10 – 20 %
Fair Predictive Capability	20 – 50 %
Poor Predictive Capability	> 50%

Our predictive models fall into categories of Excellent or Good predictive capability based on Mean Absolute Percentage Error (MAPE) values, indicating high accuracy and reliability for decision-making. The RNN method stood out as the most effective approach, surpassing traditional methods like SARIMA and advanced techniques like LSTM, despite the relatively limited dataset size. This suggests RNN's potential to extract insights and make accurate predictions even from smaller datasets. Factors contributing to RNN's success include its ability to capture temporal dependencies and adapt to varying data patterns, along with its iterative learning process and memory retention capabilities. However, the study's limitations, such as the short time series used, warrant further exploration into RNN's performance with larger datasets and the identification of specific dataset features that contribute to its success, offering avenues for refining forecasting methodologies.

Conclusion

Firstly, the results highlight the significant impact of the COVID-19 pandemic on hotel industry indicators across the analysed regions of Doha, Dubai, and London. By excluding the disruptive pandemic period from the data analysis, the forecasting models were able to better capture the underlying patterns and trends, leading to improved accuracy in predicting future performance. Secondly, the comparative analysis of traditional time series forecasting methods, such as SARIMA, and advanced machine learning techniques, including RNN and LSTM, revealed the superior performance of the Recurrent Neural Network (RNN) model. RNN consistently outperformed the other approaches in terms of RMSE and MAPE, showcasing its remarkable ability to handle the complex, nonlinear relationships, and temporal dependencies inherent in the hotel industry data.

The superior performance of the RNN model, even with a relatively limited dataset, highlights the potential of advanced machine learning techniques to outperform traditional statistical methods in complex forecasting scenarios. This suggests that, under certain conditions, the predictive power of RNN can offset the need for extensive data availability, offering valuable implications for industries with constrained data resources. This is of particular relevance to both newly developing destinations (with minimal historic data) and during times of disruption to the industry during times of short-term shock.

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