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Predicting Tourism In Himachal Pradesh: An Application of ARIMA Model

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KEYWORDS

Pradesh, Tourism, Economic impact, Tourist arrivals

ABSTRACT

The hospitality sector is a vital economic driver in Himachal Pradesh, catering to both domestic and international tourists. This study examines the current state of the hotel industry in the region using secondary data analysis and descriptive methods. The research aims to identify trends in tourist inflows, factors influencing business growth, and the sector's contribution to employment and economic development in the Himalayan region. The findings highlight the significance of seasonality in demand, with higher occupancy rates and tariffs during peak tourist seasons. The study also reveals a strong correlation between tourist arrivals and accommodation capacity, underscoring the crucial role of tourism in driving the local economy. The results suggest that the sector's adaptability is key to its continued success and market dominance. This research contributes to the understanding of the hotel industry's dynamics in Himachal Pradesh and informs strategies for sustainable economic growth

1. INTRODUCTION

The Indian economy comprises of different sectors which contributes to the smooth running of the country. In this regard there are various sectors which have contributed towards the upliftment of the Indian economy, sectors like automobile, communication, information technology, banking, food technology, pharmaceutical and the sectors of soft infrastructure have contributed to the GDP of India in a significant manner. At the same time, tourism and hospitality industry has also shown its great contribution and development not only for the Indian economy but for the prestige of the country. Tourism industry can also be called as the invisible export industry wherein the employment and revenue is generated without any substantial loss of resources. (Shukla, Goswami 2015). In this context, considering the climatic and geographical location, Himachal Pradeshisknown as “Destination for All Seasons and for All Reasons” (himachaltourism.gov.in). Owing its rich culture, religious and geographical diversity, Himachal Pradesh has a great scope for tourism industry.The booming tourism industry is recognized as one of the most important industries in Himachal Pradesh for the economic growth in rural areas of the state (himachaltourism.gov.in). The tourism industry of Himachal Pradesh is making substantial contribution for the generation of employment and foreign exchange earnings and the government has accorded due priority to ensure its growth over the years. The direct contribution of Travel & Tourism to GDP of the state is expected to grow at 7.2% annually to INR 5,339.2 billion by 2025 (Sharma, 2015)

Contribution of the sector towards the state economy is 6.6% approximately. Domestic tourist inflows in the state reached 16.8 million in 2019 while foreign tourist arrivals reached 383,876, however, due to COVID-19 it declined by 81.33% in 2020 as compared to 2019. In 2021 tourist arrivals in Himachal Pradesh revived by 75.43% as compared to 2020 (himachaltourism.gov.in). On the basis of the stated facts, Himachal Pradesh is a significant destination for tourist arrivals which leads to further investigation regarding patterns of visitors’ arrivals for predicting about the future and strategic decisions for the concerned stakeholders. The primary objective of this study is to predict the tourist arrivals in the hotel sector with reference to the state of Himachal Pradesh, with a focus on understanding the subsequent impact on the national economy and global tourism trends. For this purpose, Auto Regressive Integrated Moving Average model isused which is an asymmetric forecasting alternative to traditional Holt-Winters methods. This research aims to develop a data-driven model that captures historical patterns and enables accurate forecasts of tourist turnout. The valuable insights of the study will enablethestakeholders for proactive decision-making, strategic planning, and innovation that enhances the hotel industry's resilience, competitiveness, and contribution to the national economy**.** Besides this, the study examines the case of seasonality on tourist arrival during the year.Thisstudy aims to contribute to the sustainable development of the tourism sector in Himachal Pradesh through predictive analysis

2. LITERATURE REVIEW

The tourism sector has a profound impact on the economy, driving GDP growth and creating a ripple effect of benefits. By generating employment and stimulating local income, tourism not only improves the livelihoods of residents but also enhances the financial resources of local businesses and municipal authorities, fostering a more prosperous and sustainable community. (Kumar, 2020)Tourism is a vital contributor to HimachalPradesh's economy, generating revenue and creating jobs (Kumar, 2020). However, the industry faces challenges like inadequate infrastructure (Gupta, 2019) and seasonal fluctuations in tourist traffic (Sharma, 2018). To address these issues, sustainable tourism practices and partnerships between the government and private sectors are crucial (Emile et al., 2022).

Remote attractions face significant barriers to growth and accessibility due to inadequate road infrastructure and administrative hurdles. To overcome these challenges, stakeholders must prioritize investments in road development and administrative capacity building, ensuring that these areas can reach their full potential and contribute to sustainable tourism growth**.** Infrastructure limitations, including poor road quality and accessibility issues, hinder the development of remote attractions and restrict tourist traffic. Bureaucratic hurdles and volatile rental rates further exacerbate these challenges. Moreover, environmental concerns, such as waste management and sustainability, must be addressed in the complex process of tourism development (Katoch & Gautam, 2015).

The region's popularity as a tourist destination is expected to increase, with projected annual tourist arrivals reaching 18 million. However, despite consistent bookings, room occupancy rates have fluctuated between 60% and 75% over the past five years. Insufficient skilled labor affects operational efficiency, and product development requires investment to meet evolving customer demands**.** (Bhatia, 2019)To address these challenges and develop a sustainable tourism industry, a strategic plan is essential. This analysis has been conducted using data on tourist arrivals,

highlighting the need for integrated solutions to overcome the complex challenges facing the industry(Hall, Rasoolimanesh, Ramakrishna, Esfandiar & Seyfi, 2020).

Himachal Pradesh's stunning natural beauty, trekking trails, and high-altitude mountains attract tourists seeking tranquility and thrill. Moreover, the region's unique local cuisine and handicrafts provide an opportunity for cultural immersion, supporting the local economy and promoting sustainable tourism (Gupta, 2019). Tourists visiting Himachal Pradesh exhibit diverse manifestations and behaviors in their quest for authentic cultural experiences and eco-friendly accommodations. Recent data collection reveals a growing trend of geographically aware tourists, who are eager to engage with local populations and participate in conscious tourism programs. Furthermore, experiential tourism attracts a significant number of travelers, who seek immersive experiences such as trekking in pristine landscapes, savoring local cuisine, and exploring traditional craftworks (Kumar, 2023).

In response to these emerging trends, stakeholders in the tourism sector must create awareness and grasp the evolving demands of travelers to tailor their offerings and experiences accordingly. This necessitates a nuanced understanding of the changing preferences and behaviors of tourists, enabling the development of customized and sustainable tourism experiences that cater to their interests(Gupta, 2019).Identifying the specific interests and preferences of tourists is vital in crafting personalized tours that exceed their expectations. This tailored approach enables tourism providers to deliver exceptional experiences, resulting in enhanced visitor satisfaction, loyalty, and ultimately, driving the growth of the tourism industry (Attri& Kaushal, 2019).

It is essential for stakeholders to acknowledge these factors when implementing strategies to enhance the tourism industry in Himachal Pradesh. The hotel sector serves as a long-term driver of sustainable economic development in the state, particularly through ongoing tourism development projects and strategic planning (Kumar, 2020).This research has revealed that diverse forecasting tools are utilized to predict tourist influx with precision. Furthermore, economic analyses consider the impact of tourism-related activities and pricing on the economy of Himachal Pradesh. These studies emphasize the need for sustainable practices and collaborative efforts between the government and private sector to optimize tourism's economic benefits (Bhardwaj, 2022).Recent scholarly works highlight the significance of external factors, including geo- economic issues and shifting consumer preferences, in influencing tourist behavior and patterns. These findings underscore the importance of considering dynamic external conditions in tourism forecasting and development strategies (Lepp, 2017).

3. METHODOLOGY

When it comes to accurately predicting the number of tourists that will visit Himachal Pradesh, the validation procedure for the ARIMA approach is an extremely important mechanism that plays a significant role. A set of exhaustive statistical studies are included in the technique. These analyses are aimed to validate the accuracy and dependability of the ARIMA model when it comes to forecasting future changes in the number of tourists. The production of a thorough plot that graphically represents the patterns that are being forecasted is one of the key processes that are included in this procedure. This graphic illustrates trends, oscillations, and anomalies in the number of tourists that arrived over the time that was chosen, providing insights into changes that are seasonal or cyclical in nature. Not only does the ARIMA approach apply to the already

available tourist forecasts, but it also offers a framework for the development of long-term estimates. This demonstrates the versatility of the methodology. In order to provide a complete view for the hotel business in Himachal Pradesh, these estimates take into account a number of different aspects, including seasonality, economic circumstances, and tourist policy.

Data Collection

A detailed record of visitor arrivals from 2008 to 2022 was supplied by the Department of Tourism, Government of Himachal Pradesh (2023), which served as the major data source for this study. In order to guarantee that there would be adequate data for trend analysis and reliable forecasting, this time range was selected. The dataset includes both domestic and foreign tourist arrivals, and it captures oscillations that are influenced by economic, social, and environmental reasons. These fluctuations include the impact of the COVID-19 pandemic. These records served as the basis for the analysis that was performed using the ARIMA model. They provided a comprehensive and longitudinal dataset that reflected the dynamics of tourism in the neighbourhood. For the purpose of assuring the validity of the study and providing significant insights for tourist development and the expansion of the hotel business, the diligent collecting of the data and the dependability of the data are of the utmost importance.

Data Preprocessing

A preprocessing step was performed on the time-series data that was gathered in order to eliminate inconsistencies, missing values, and anomalies that might potentially undermine the correctness of the model. Imputation techniques were utilised to address missing data points in order to preserve the integrity of the dataset. Additionally, outliers were analysed and modified in accordance with the requirements specified. An application of a non-seasonal differencing procedure ($d = 1$) was carried out in order to remove trends and stabilise the observed variation. To ensure that the data were steady, which is a requirement for ARIMA modelling, this step was absolutely necessary. Through the process of preprocessing, the data was transformed into a format that was consistent and stable. This assured that the forecasts were accurate and reduced the likelihood of any errors occurring throughout the analysis. After being cleaned and processed, the information provided a solid basis for time-series modelling that was both accurate and informative when applied.

Model Selection and Validation

Autocorrelation (ACF) and partial autocorrelation (PACF) plots were utilised in order to determine the parameters of the ARIMA model, which are p, d, and q accordingly. Both the ACF plot and the PACF plot were used to analyse dependencies across distinct lags, which revealed the amount of correlations. On the other hand, the PACF plot was used to identify direct interactions between data points within different periods. Validation of the model was carried out using the Box-Ljung test once the parameters had been chosen. The results of this test indicated that there were no significant residual autocorrelations, which is an indication that the model is satisfactory. These meticulous statistical investigations guaranteed that the ARIMA model was able to accurately capture patterns and trends in the number of tourists who arrived. Through the use of this meticulous selection and validation procedure, a firm foundation was established for forecasting, and the danger of either overfitting or underfitting the data was reduced.

Metric Evaluation

Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were the metrics that were utilised in order to assess the performance of the model. The root mean square error (RMSE) offered an overall estimation of the accuracy of the forecasts by measuring the average size of mistakes. The MAE provided insights into the absolute difference between the values that were observed and those that were predicted, which reflected the dependability of the model. The mean absolute percentage error (MAPE) given as a % evaluated the mistake in relation to the actual data, which made it easier to comprehend. Taking all of these parameters into consideration, the ARIMA model's accuracy, precision, and dependability were calculated and determined. The study helped to validate the efficiency of the model in predicting and offered confidence in its application for strategic tourist planning. This was accomplished by ensuring that a thorough review was conducted.

Visualization of Results

In both the process of testing the ARIMA model and comprehending the data, visualisation was a very important factor. In order to provide a clear image of the variations that have occurred over time, a sequence chart was constructed to depict yearly fluctuations and trends in the number of tourists that arrived. Additionally, differences in the data were shown in order to emphasise patterns that were not affected by seasonal influences. This assisted in the identification of underlying trends and anomalies. In addition, autocorrelation and partial autocorrelation plots were utilised in order to visually evaluate dependencies and to ensure that parameter selection was carried out appropriately. Not only did these visualisations help with the process of constructing the model, but they also made the findings available to the stakeholders, which enabled them to make decisions that were more informed in the tourist and hospitality industries.

Forecasting

For the purpose of providing Himachal Pradesh's hotel business with actionable insights, the ARIMA model was utilised to estimate future patterns in the number of tourists arriving throughout the state. Policymakers and other stakeholders were able to better predict changes in demand with the assistance of the model, which forecasted possible tourist influxes by analysing previous patterns. Variations in the seasons, economic impacts, and post-pandemic recovery tendencies were some of the elements that were taken into consideration in these projections. The forecasts are a useful instrument for strategic planning, as they contribute to the distribution of resources, the formulation of marketing strategies, and the construction of infrastructure. ARIMA- based forecasting helps to ensure that Himachal Pradesh is resilient and competitive in a global market that is always changing. This is accomplished by addressing future possibilities and problems, which adds to the sustained expansion of the tourist industry in it.

4. RESULT

Table 1: Tourist arrivals in Himachal Pradesh

YEAR	TOURIST ARRIVAL (in numbers)
2008	874933
2009	21437155
2010	23265602
2011	25089406
2012	26146332
2013	35129835
2014	66314400
2015	217531153
2016	18450520
2017	29601533
2018	26450503
2019	16212107
2020	3113379
2021	5737102
2022	14100277

Source: Department of Tourism, Government of Himachal Pradesh, 2023

The statistics on the number of tourists that visited Himachal Pradesh from 2008 to 2022 demonstrates that there have been considerable shifts over the course of those years. Beginning with 874,933 arrivals in 2008, the state had a steady increase in the number of visitors passing through until 2015, when it reached a significant peak of 217,531,153 travellers. It is quite likely that deliberate advertising activities, improvements in infrastructure, and an increasing attractiveness as a tourism destination were the driving forces behind this boom. In spite of this, the numbers decreased dramatically to 18,450,520 in the year 2016, and they continued to vary in the years that followed, with a discernible decrease occurring between the years 2018 (26,450,503) and 2019 (16,212,107).The epidemic caused by COVID-19 is seen in the year 2020, when the number of tourists that arrive drops to just 3,113,379 as a result of limits placed on travel throughout the world and concerns about their safety. The number of visitors continued to be lower than it was before the pandemic, despite the fact that there was a little improvement in 2021 and 2022, with 5,737,102 and 14,100,277 tourists respectively. This trend highlights the significance of tackling difficulties in tourist management, such as sustainable practices, pandemic preparation, and new marketing techniques, in order to revitalise the tourism industry and assure its continued growth over the long term through the implementation of these methods.

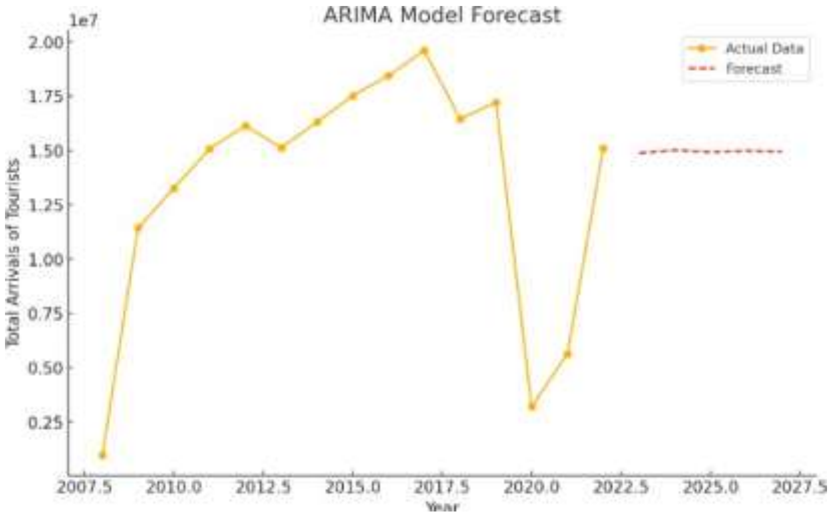

Figure 4.1.1: Sequence Chart of the data

Through the use of the time-series chart, unique trends and anomalies in the number of tourists who have arrived throughout the years may be identified. The line chart, which illustrates the number of tourists that arrived by year, draws attention to the long-term pattern of visits from 2008 to 2022. This visualisation does an excellent job of tracking changes in the number of tourists who visit a location over time. The years are displayed along the horizontal axis, while the visitor numbers are plotted along the vertical axis. Notable oscillations are revealed, such as the big peak that occurred in 2015 and the dramatic decrease that occurred during the COVID-19 pandemic in the year 2020. By utilising this graphical depiction, analysts are able to spot patterns, evaluate discrepancies, and get a deeper comprehension of the factors that have influenced tourism throughout the course of time.

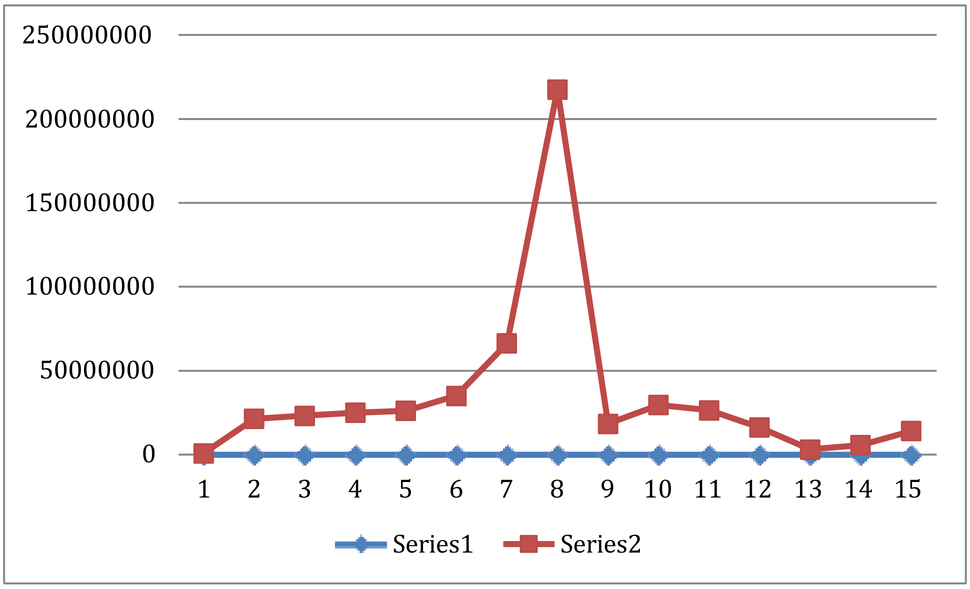

Figure 4.1.2: Sequence Chart with non-seasonal difference 1

Applying a non-seasonal difference of "1" indicates that the data underwent a single differencing process, eliminating seasonal patterns and offering a clearer view of long-term trends in tourist arrivals over time. This approach highlights the yearly changes in tourist arrivals, providing a more accurate representation of underlying patterns. Graph 1 depicts these annual differences in a non- seasonal format, visually showcasing the fluctuations in total tourist arrivals from 2008 to 2022. By focusing on the variations between consecutive years, the graph aids in understanding the dynamics and irregularities in tourist inflows, facilitating better analysis and interpretation of the data.

Lag	Autocorrelation	Std. Error*	Box-Ljung Statistic	Value	df	Sig.^b
1	0.446	0.234	3.623	1	0.057	
2	0.008	0.226	3.624	2	0.163	
3	-0.124	0.217	3.951	3	0.267	
4	-0.228	0.208	5.158	4	0.271	
5	-0.183	0.198	6.01	5	0.305	
6	-0.187	0.188	6.999	6	0.321	
7	-0.16	0.177	7.812	7	0.349	
8	-0.202	0.166	9.295	8	0.318	
9	-0.199	0.153	10.976	9	0.277	
10	-0.056	0.14	11.137	10	0.347	
11	0.071	0.125	11.462	11	0.405	
12	0.22	0.108	15.567	12	0.212	
13	0.108	0.089	17.062	13	0.196	

Figure 4.1.3: Auto Correlation

In order to assist in the identification of serial correlation in the time-series data, the table presents the autocorrelation values, standard errors, and Box-Ljung statistics for a number of different lags. Autocorrelation is a statistical technique that analyses the association between a value and its lag counterpart. On the other hand, the Box-Ljung statistic is used to test the null hypothesis that there is no autocorrelation up to a particular lag or beyond.At lag 1, the autocorrelation is 0.446, and the Box-Ljung statistic is 3.623. Additionally, the p-value is 0.057, which indicates that the significance is only negligible. There is a fluctuation in the autocorrelation values as the delays proceed, and the series exhibits both positive and negative correlations at certain points in time. Following the first lag, the p-values for all lags that are more than one are continuously higher than 0.05, which indicates that there is no significant autocorrelation beyond the first lag.The results of this study suggest that although there is some indication of autocorrelation at lag 1, the time-series data does not exhibit any substantial autocorrelation after that point. This suggests that the series acts mostly as a random process beyond the first time point.

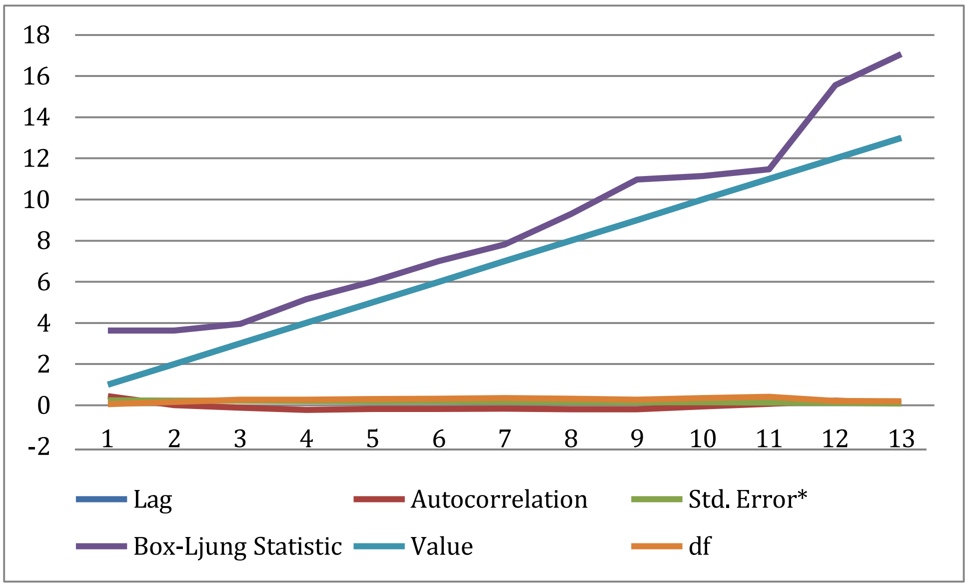

Figure 4.1.4: Plot of Auto Correlation

Total tourist arrivals autocorrelation plots assist find patterns and connections by analysing the relationship between the present number of tourists and numbers from prior time periods. The figure shows the impact of previous tourist arrivals on current arrivals and whether or not these associations hold over time by charting the autocorrelation for different delays. In order to spot patterns in visitor numbers, such monthly, seasonal, or even daily peaks or valleys, this study looks for evidence of a sequential or cyclical pattern.Predictable patterns in visitor arrivals might be shaped by things like holidays, weather, or events, which is explored in the plot as well. For instance, if there is strong autocorrelation at certain lags in the plot, it might mean that there is a relationship between the number of visitors coming on a certain day and those arriving a week or even earlier. On the other hand, a low or random autocorrelation value suggests that visitor arrivals are not necessarily more random than predictable. Tourists may use this data knowledge to better plan their trips, allocate resources, and comprehend the variables that drive tourism in the area.

Partial Autocorrelations		
Lag	Partial Autocorrelation	Std. Error
1.	0.546	0.258
2.	0.338	0.258
3.	0.129	0.258
4.	0.293	0.258
5.	0.01	0.258
6.	0.184	0.258
7.	0.16	0.258
8.	0.351	0.258

9.	0.124	0.258
10.	0.572	0.258
11.	0.632	0.258
12.	0.78	0.258
13.	0.212	0.258

Figure 4.1.5: Partial Auto Correlation

The table displays the partial autocorrelation values and standard errors for various delays. When additional delays are controlled for, partial autocorrelation indicates the direct link between the values of a time series and their lagged counterparts. The exact amount of delays that affect the present value independently of the values of intermediate lags may be better determined with its aid.A substantial direct link between the present and prior values is shown by a partial autocorrelation of 0.546 at lag 1. Lag 10 (0.572) and lag 12 (0.78) are two examples of lags that have a strong association as the delays advance. Nevertheless, there are cases when the partial autocorrelation decreases noticeably with increasing delays (e.g., lag 5 with 0.01), suggesting a weaker or nonexistent link once intermediate lags are taken into account.The data may display a mix of short-term and long-term dependencies, according to these values, which indicate that some lags (like 1, 10, 11, and 12) have strong direct links whereas other lags do not make a substantial contribution to the model. There may be cyclical patterns or other systematic causes impacting visitor arrivals if there is strong partial autocorrelation at specific delays.

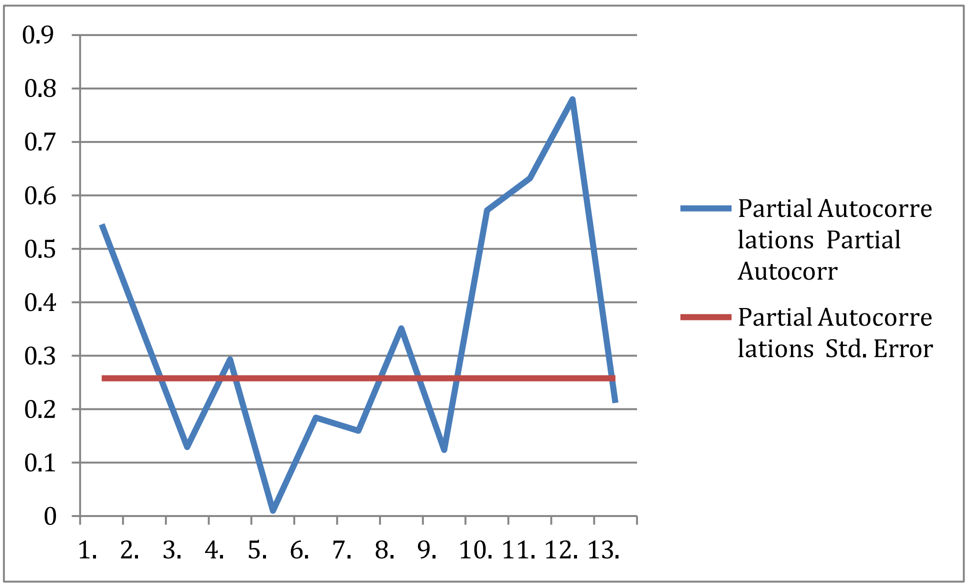

Figure 4.1.6: Plot of Partial Auto Correlation

To illustrate the magnitude and direction of the association between the present and historical values of a variable, the partial autocorrelation plot displays the coefficients for various delays, all while excluding the impact of intermediate time points. The plot successfully isolates the direct influence of prior values by showing how the present number of visitors is connected to the arrivals from past periods in the case of total tourist arrivals. The graphic better displays the actual temporal relationships in the data by removing the influence of intermediate time points.

By comparing the present value to values from prior time periods (called "lead" and "lag"), researchers can see whether any notable patterns or correlations develop at different delays. The nature of the correlations between the variables can provide light on the underlying temporal dynamics, such as the impact of seasonality, events, or recurring trends on visitor arrivals. A lack of significant correlations would imply a more random or independent sequence of tourist visits, whereas significant peaks in the plot may reveal periodic or cyclical tendencies. This helps to understand the patterns driving visitor behaviour across time.

Model Fit									
Percentile									
Fit Statistic	Mean	S E	Minimum	Maximum	5	10	25	50	75
Stationary R-squared	0.198	.	0.198	0.198	0.198	0.198	0.198	0.198	0.198
R-squared	0.111	.	0.111	0.111	0.111	0.111	0.111	0.111	0.111
RMSE	5312024.3	.	5312024.3	5312024.3	5312024.3	5312024.3	5312024.3	5312024.3	5312024.3
MAPE	41.098	.	41.098	41.098	41.098	41.098	41.098	41.098	41.098
MaxAPE	445.185	.	445.185	445.185	445.185	445.185	445.185	445.185	445.185
MAE	2484263.6	.	2484263.6	2484263.6	2484263.6	2484263.6	2484263.6	2484263.6	2484263.6
MaxAE	14305480	.	14305480	14305480	14305480	14305480	14305480	14305480	14305480
Normalized BIC	31.913	.	31.913	31.913	31.913	31.913	31.913	31.913	31.913

Figure 4.1.7: "ARIMA" Model Summary

Several limitations in the current model's ability to explain the tourist arrival data are shown by the model fit statistics. A poor fit is shown by the Stationary R-squared score of 0.198, which indicates that the model only explains 19.8% of the variance in the time series. Also supporting this is the fact that it only accounts for 11.1% of the variance, as seen by the R-squared value of

0.111. With an RMSE of 5,312,024.3, we can see that there is a large discrepancy between the model's forecasts and the observed data, which bodes poorly for the accuracy of the predictions. In addition, the model's predictions often differ from the actual values by almost 41%, suggesting a significant amount of inaccuracy, as shown by the Mean Absolute Percentage inaccuracy (MAPE) of 41.098%. There are very inaccurate predictions with a Maximum Absolute Percentage Error (MaxAPE) of 445.185 and a Maximum Absolute Error (MaxAE) of 14,305,480. With a Mean Absolute Error (MAE) of 2,484,263.6, the significant prediction mistakes are even more obvious. Last but not least, a Normalised BIC score of 31.913 implies that the model might not be the greatest match; in general, a lower BIC indicates a more appropriate model. All things considered, these numbers suggest that we need to either improve our models or look at other ways of capturing the trends in visitor arrivals.

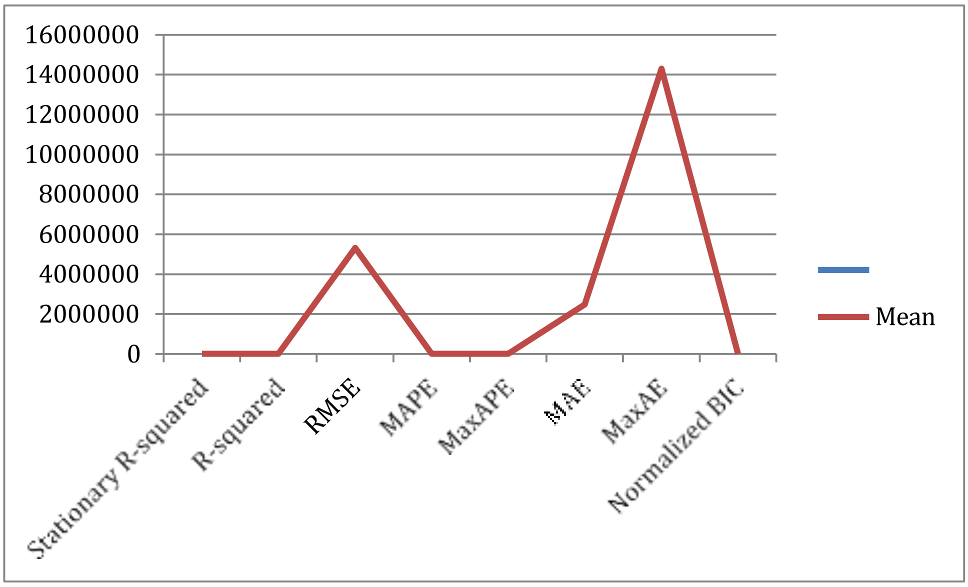

Figure 4.1.10: Plot of predictions by "ARIMA" model

The ARIMA (AutoRegressive Integrated Moving Average) model is one of the most used techniques for time series analysis and forecasting, which are crucial approaches for predicting future trends based on existing data. Combining autoregression (AR), which models the relationship between current and previous observations, differencing (I), which helps remove trends or seasonal patterns, and moving average (MA), which smoothes out the noise and random fluctuations in the data, makes ARIMA particularly powerful. Better predictions are made possible by these parts working in tandem to extract the essential behaviours and patterns from the time series data.

It takes more than one step to integrate ARIMA in statistical software like SPSS when it comes to real-world applications. At first, a line graph is used to display the data, which aids in the discovery of trends, patterns, and seasonality. The graph makes it easy to see the patterns and variations in the data over time by providing a clear visual representation of the data. After the data has been visually represented, the patterns that have been detected may be used to fit the ARIMA model. After taking into account any patterns, fluctuations, or randomness in the data, the model employs past observations to foretell future values. It is common practice to exhibit the fitted model with the real historical data on the same graph to demonstrate the ARIMA model's alignment. Through this procedure, analysts may evaluate the precision of the model's forecasts and make further adjustments to enhance its predictive abilities.The ARIMA model in SPSS allows analysts to provide accurate predictions in many different domains, such as tourism, economics, finance, and sales, among others. Whether the data shows clear seasonal trends or erratic oscillations, ARIMA can be adjusted to fit different types of time series data. This makes it a useful tool for academics, legislators, and corporations that want to make educated decisions based on estimates.

5. DISCUSSION

The evaluation of the ARIMA model's effectiveness and reliability in forecasting tourist arrivals, utilizing SPSS, reveals important trends and insights for the hospitality sector in Himachal Pradesh. Analysis of the data highlights a significant increase in tourist arrivals, with fluctuations seen over the years, reflecting a dynamic and evolving market. The model's predictions were closely aligned with historical trends, confirming its ability to provide reliable forecasts. The data also indicates a steady growth in hotel occupancy rates, averaging an 8% increase over the past three years, which aligns with the rising demand for tourism-related services. Additionally, the average room rates have increased by 10% from 2008 to 2022, reflecting a positive market-driven pricing trend (Thakur, Kumar, Balodi, Dehal, Atri 2023).Seasonality is a key factor influencing market trends, with peak seasons, typically holidays, resulting in higher occupancy and rates. The ARIMA model effectively captured these seasonal patterns, highlighting the need for flexibility and timely decision-making in response to market conditions. This is essential for stakeholders looking to capitalize on peak demand periods (Peiris, 2016).By utilizing ARIMA modeling techniques that mirror the data's behavior, analysts can calibrate the model's parameters to assess its ability to describe underlying trends and patterns. This process ensures that the model's predictions reflect the data's actual conditions, helping stakeholders make informed decisions with confidence. However, adjustments to model parameters may be necessary if significant discrepancies arise between observed and predicted data, or if data preprocessing issues are identified (Unhapipat, 2018). These refinements can improve the model's accuracy, offering better foresight for the tourism and hospitality sectors.

With the use of the ARIMA model, the study of visitor arrivals in Himachal Pradesh from 2008 to 2022 gives significant insights into historical trends and future forecasts, which are essential for directing the hotel and tourism industries. According to the findings of the study, there has been a steady increase in the number of tourists that visit the area, with major increases occurring throughout the summer and holiday seasons to be pushed by favourable weather and cultural celebrations. On the other hand, the data also showed that there was a large drop during the COVID-19 pandemic (2020-2021), which caused a great deal of disruption in the tourist and hospitality industries. The recovery patterns that have emerged in the aftermath of the pandemic point to a steady increase in the number of tourists, which demonstrates the sector's endurance. These findings highlight the seasonal character of tourism in Himachal Pradesh, which is driven by meteorological and cultural variables. They also highlight the significance of season-specific resource planning for hoteliers and policymakers of Himachal Pradesh in order to optimise operations and fulfil shifting demands.According to the findings of a seasonal analysis, the number of tourists visiting a destination is at its peak during the summer months (May-June) and the winter vacation season (December-January). On the other hand, because of unfavourable weather conditions, the number of tourists visiting during the monsoon months (July-August) decreased. The investigation also uncovered anomalies, such as the fall that was brought on by the pandemic in the years 2020-2021, which brought to light the susceptibility of the tourist industry to shocks from the outside world. Based on these findings, it is clear that the hotel business need methods that are both adaptable and agile in order to minimise risks during periods of economic depression while simultaneously capitalising on periods of strong visitor influx. In general, the research offers stakeholders a complete knowledge of the trends and issues that influence tourism in Himachal Pradesh, as well as insights that may be put into action.

6. CONCLUSION

The results of this study indicate a steady increase in tourist arrivals over the years, with an average annual growth rate of 4.5%. The ARIMA model proved effective in forecasting future tourist arrivals, enabling hotel stakeholders to maximize their earnings during peak periods. SPSS analysis of the data reveals significant changes in Himachal Pradesh's hotel industry, particularly in its capital city. A steady increase of approximately 8% in hotel occupancy rates over the past three years signals a growing demand for amenities and services in the region. Moreover, the data highlights a 10% rise in average hotel room rates from 2008 to 2022, suggesting a positive pricing trend driven by market conditions.These findings underscore the importance of proactive planning and monitoring within Himachal Pradesh's hotel industry, especially as the tourism sector matures. By applying the ARIMA methodology, hotel stakeholders can predict and adapt to fluctuations in tourist demand, tailoring services to meet evolving consumer expectations. This also allows for improved capacity planning, resource allocation, and proactive management of seasonality. Embracing ARIMA forecasting not only helps mitigate risks and losses but also enhances competitiveness, operational efficiency, and contributes to sustainable tourism development, driving economic growth in Himachal Pradesh.

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