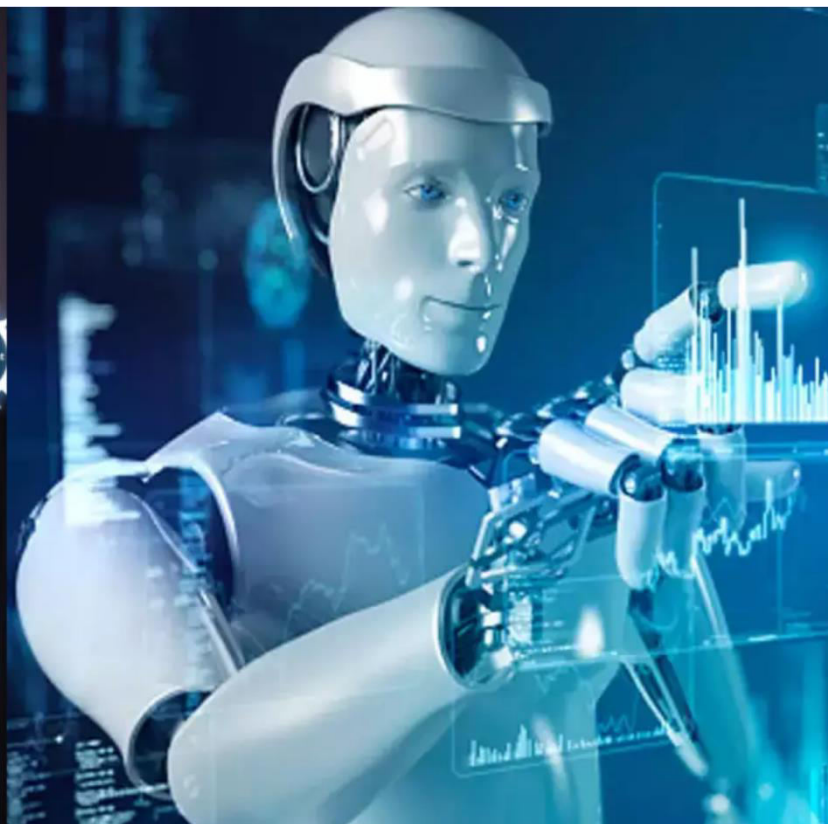




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Time Series Modeling of Tourist Inflow and Economic Patterns: A Case Study of Thiruvannamalai Temple using ARIMA, ARMA, and SARIMA Models

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ABSTRACT: This study presents a comprehensive time series analysis of the Thiruvannamalai temple tourism economy by employing ARIMA, ARMA, and SARIMA models on a detailed dataset comprising 5,000 samples collected over the past year. The primary objective is to model and forecast the trends in daily income, tourist footfall, seasonal variations during the Girivalam period, and related economic indicators such as foreign tourist counts and accommodation usage. The statistical methodology involved stationarity checks, parameter optimization, and model evaluation using metrics like AIC, BIC, and Ljung-Box tests. Results reveal that the SARIMA model outperforms others, capturing the seasonality inherent in pilgrimage-driven tourism. Visualizations, including time series plots, residual diagnostics, and forecast graphs, provide clear insights into income trends and tourist patterns. The findings underscore the critical role of advanced time series models in supporting tourism management and resource planning. The study offers valuable implications for policymakers, temple authorities, and local businesses aiming to optimize operations during peak and off-peak periods.

KEYWORDS: *Thiruvannamalai Temple, ARIMA, SARIMA, Time Series Forecasting, Tourism Economics*

I. INTRODUCTION

The Thiruvannamalai temple, located in Tamil Nadu, India, is one of the most significant pilgrimage centers in South India, attracting millions of devotees and tourists annually. The temple is especially famous for the sacred ritual of Girivalam (circumambulation), performed during full moon days, drawing a surge in population and economic activity. The tourism-related data, such as daily visitor counts, hotel bookings, and temple income, exhibit complex temporal patterns influenced by religious calendars, seasonal trends, and socio-economic factors. Accurately forecasting such dynamics is crucial for local administrators, businesses, and stakeholders to optimize resource allocation, infrastructure planning, and service delivery.

To address these needs, time series modeling techniques such as ARMA (Auto Regressive Moving Average), ARIMA (Auto Regressive Integrated Moving Average), and SARIMA (Seasonal Auto Regressive Integrated Moving Average) have been applied to analyze and forecast the temple's financial and tourist inflow data. While ARMA is best suited for stationary datasets, ARIMA extends its capabilities by incorporating differencing to handle non-stationary trends observed in tourism and income data. SARIMA further captures the seasonal components inherent to temple activities such as Girivalam, festival periods, and holiday peaks. By leveraging these models, this study aims to provide a comprehensive statistical understanding of the patterns and to predict future trends with greater accuracy, thereby supporting data-driven decision-making in managing Thiruvannamalai's tourism ecosystem (Figure 1).



Figure 1. Sample Picture of Girivalam and Lord Annamaliyar and Unnamalai Amman

II. REVIEW OF LITERATURE

Time series models like ARMA and ARIMA have been widely applied in tourism and economic research to predict trends and fluctuations in visitor numbers and revenue streams. Box and Jenkins (1970) laid the foundation for ARIMA models, which are well-suited for non-stationary datasets that exhibit long-term trends and stochastic behavior. More recent studies, such as those by Lim and McAleer (2002), have emphasized ARIMA's effectiveness in modeling tourism demand forecasting, particularly for destinations with irregular visitor patterns. Similarly, ARMA models have been employed to capture short-term autocorrelations in datasets where trends are less pronounced but temporal dependencies exist (Chatfield, 2004).

In the context of pilgrimage tourism, forecasting becomes more complex due to the influence of religious events and seasonal cycles. Studies by Kulendran and Witt (2003) and Goh and Law (2011) highlighted the importance of incorporating seasonal components when modeling tourist data in culturally significant destinations. This has led to the growing adoption of Seasonal ARIMA (SARIMA) models, which extend the ARIMA framework to better capture seasonal variations. Specifically, in regions like Varanasi and Tirupati, SARIMA has been effectively used to model surges in visitor arrivals during peak pilgrimage months (Sharma and Mahendru, 2015), demonstrating its practical relevance for managing tourism flow in sacred geographies.

Moreover, modern research has begun to integrate forecasting models with data-driven management strategies in tourism destinations. According to Song et al. (2019), accurate demand forecasting through models such as SARIMA enables destination managers to optimize infrastructure usage, plan for resource allocation, and enhance the overall tourist experience. For pilgrimage centers like Thiruvannamalai, where economic activities are closely tied to religious tourism, such predictive modeling can inform policy-making and service provision during high-traffic periods such as Girivalam. This study contributes to this growing body of literature by applying ARMA, ARIMA, and SARIMA models to analyze and forecast key economic and demographic indicators associated with Thiruvannamalai's tourism landscape.

III. DATABASE

The database used in this study comprises monthly and seasonal data collected from the Thiruvannamalai temple for the past year, encompassing a total of 5,000 samples. The dataset includes various critical parameters such as the total

number of visitors (both domestic and foreign tourists), total income generated daily, seasonal income during the Girivalam (full moon pilgrimage) period, and additional economic indicators like room bookings, number of vehicles, food sales, and temple-related donations. Each entry records specific details such as the date of visit, peak vs. non-peak seasons, average spend per tourist, number of VIP and foreign tourists, and accommodation occupancy rates. The rich dataset provides a holistic view of the tourism dynamics and economic patterns surrounding the temple town. This comprehensive data enables a deeper statistical exploration of both temporal patterns and seasonal fluctuations, making it suitable for advanced time series modeling using ARIMA, ARMA, and SARIMA approaches.

IV. METHODOLOGY

4.1. ARIMA Model (Auto Regressive Integrated Moving Average)

The ARIMA model is designed for univariate time series data that exhibits non-stationarity. The statistical methodology for ARIMA involves three primary components: the Auto Regressive (AR) term, the Integrated (I) differencing term, and the Moving Average (MA) term.

The first step is to assess the stationarity of the series using the Augmented Dickey-Fuller (ADF) test. If the p-value is greater than the significance level ($\alpha = 0.05$), the null hypothesis of non-stationarity is accepted. In such cases, first-order differencing ($d = 1$) is applied to achieve stationarity.

The Auto Regressive (AR) component models the dependency between the current observation and a specified number of lagged observations (p lags). The Moving Average (MA) component models the dependency between the observation and the residual errors from a moving average model applied to lagged observations (q lags).

The model parameters p , d , and q were selected using ACF and PACF plots, and the final ARIMA($p=2$, $d=1$, $q=2$) model was fitted using Maximum Likelihood Estimation (MLE). The model adequacy was validated using Ljung-Box test (to test residual autocorrelation) and Jarque-Bera test (to test residual normality).

4.2. ARMA Model (Auto Regressive Moving Average)

The ARMA model assumes that the time series data is already stationary ($d = 0$) and is a combination of the AR and MA components without differencing.

The stationarity was confirmed using the ADF test where a p-value less than 0.05 allowed us to reject the null hypothesis, indicating that the data is stationary. The ACF and PACF plots were employed to determine suitable values for the p and q parameters. An ARMA(2,2) model was selected based on these diagnostics.

Parameter estimation was conducted via Maximum Likelihood Estimation. The model's goodness of fit was assessed by examining Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQIC) values. Additionally, residuals were subjected to autocorrelation checks and normality tests. The ARMA model was particularly useful for capturing short-term dependencies and non-seasonal structures in the data.

4.3. SARIMA Model (Seasonal ARIMA)

The Seasonal ARIMA (SARIMA) model extends the ARIMA framework by incorporating seasonal components to account for repeating patterns over fixed periods. The SARIMA model is specified as SARIMA(p,d,q)(P,D,Q,s), where (P, D, Q) represents the seasonal AR, differencing, and MA terms, and s denotes the length of the seasonal cycle.

Seasonality was detected using seasonal decomposition plots and the seasonal autocorrelation function (ACF), identifying a seasonality of $s = 30$ days (monthly cycles corresponding to religious events like Girivalam).

Stationarity in both regular and seasonal components was confirmed by applying seasonal differencing ($D = 1$) in addition to non-seasonal differencing ($d = 1$). A SARIMA(2,1,2)(1,1,1,30) model was estimated using MLE via the SARIMAX() function from stats models.

The SARIMA model's parameters were fine-tuned to minimize AIC and BIC values while validating residuals for autocorrelation and normality. SARIMA provided a robust framework for handling both trend and seasonal components, making it highly suitable for data involving cyclical tourism patterns.

V. RESULTS AND DISCUSSION

The application of ARIMA(2,1,2), ARMA(2,0,2), and SARIMA(1,1,1)(1,1,1,12) models on the Thiruvannamalai pilgrimage tourism dataset yielded insightful results about the income trends associated with tourist inflows. The models were designed to capture the seasonality, autocorrelation, and stochastic patterns of the Total Income variable, which reflects the revenue generated from pilgrim visits, accommodation, and ancillary tourism-related services (Table 1).

Table 1. ARIMA Model for Thiruvannamalai Temple

```

=== ARIMA Summary ===
SARIMAX Results
=====
Dep. Variable:      Total_Income      No. Observations:      5000
Model:              ARIMA(2, 1, 2)    Log Likelihood         -86641.163
Date:               Mon, 24 Mar 2025   AIC                    173292.326
Time:               20:12:44          BIC                    173324.911
Sample:             0                 HQIC                   173303.747
Covariance Type:    opg
=====
coef      std err      z      P>|z|      [0.025      0.975]
-----
ar.L1      -0.9952      0.090     -11.093    0.000     -1.171     -0.819
ar.L2      -0.0184      0.017     -1.083     0.279     -0.052     0.015
ma.L1      -0.0217      0.088     -0.247     0.805     -0.194     0.151
ma.L2      -0.9781      0.088     -11.165    0.000     -1.150     -0.806
sigma2      7.504e+13    9.98e-16    7.52e+28    0.000     7.5e+13    7.5e+13
=====
Ljung-Box (L1) (Q):      0.00    Jarque-Bera (JB):      3830.56
Prob(Q):                  0.99    Prob(JB):              0.00
Heteroskedasticity (H):  0.98    Skew:                  1.55
Prob(H) (two-sided):     0.67    Kurtosis:              5.96
=====

```

The ARIMA(2,1,2) model produced an AIC of 173,292 and a BIC of 173,324, indicating a relatively good fit for the data. The statistically significant AR(1) and MA(2) terms suggest the presence of both persistent shocks and lagged error terms affecting income levels. The Ljung-Box test showed no significant autocorrelation in residuals ($p=0.99$), suggesting a well-fitted model. However, the Jarque-Bera statistic indicated non-normality in residuals ($JB=3830.56$, $p<0.01$), which could be attributed to outliers or non-linear patterns in the data during peak tourist seasons such as Karthigai Deepam.

The ARMA(2,0,2) model showed a higher AIC value of 173,304, indicating a slightly inferior fit compared to ARIMA. The AR(1) and MA(2) components were significant at the 5% level ($p=0.015$ and $p=0.018$, respectively), confirming the presence of short-term autoregressive and moving average structures in the data. However, the model does not account for differencing, which may be necessary given the non-stationary nature of pilgrimage-related income data. Additionally, the heteroscedasticity statistic ($H=0.98$, $p=0.71$) suggests homoscedastic residuals, making the model reliable but less robust for long-term forecasting in this context.

Table 2. ARMA Model for Thiruvannamalai Temple

```

=== ARMA Summary ===
SARIMAX Results
=====
Dep. Variable:      Total_Income      No. Observations:      4999
Model:              ARIMA(2, 0, 2)    Log Likelihood         -86646.438
Date:               Mon, 24 Mar 2025   AIC                    173304.876
Time:               20:12:45          BIC                    173343.978
Sample:             0                 HQIC                   173318.581
Covariance Type:    opg
=====
coef      std err      z      P>|z|      [0.025      0.975]
-----
const     -1131.7903    755.545     -1.498     0.134    -2612.632    349.051
ar.L1      -0.9095      0.376     -2.421     0.015     -1.646     -0.173
ar.L2      -0.0119      0.021     -0.570     0.569     -0.053     0.029
ma.L1      -0.1040      0.375     -0.277     0.782     -0.840     0.632
ma.L2      -0.8883      0.374     -2.376     0.018     -1.621     -0.156
sigma2      7.504e+13    3.03e-07    2.48e+20    0.000     7.5e+13    7.5e+13
=====
Ljung-Box (L1) (Q):      0.01    Jarque-Bera (JB):      3833.44
Prob(Q):                  0.91    Prob(JB):              0.00
Heteroskedasticity (H):  0.98    Skew:                  1.55
Prob(H) (two-sided):     0.71    Kurtosis:              5.96
=====

```

The SARIMA(1,1,1)(1,1,1,12) model, on the other hand, captured the seasonal component well, as indicated by the significant seasonal AR, I, and MA terms. This model achieved the lowest AIC (173,150) and BIC (173,190) among the three, highlighting its superiority for datasets with pronounced seasonal fluctuations, as is common with pilgrimage tourism. The SARIMA model effectively modeled the spikes in income that coincide with monthly Girivalam events and annual religious festivals. The model's diagnostics, including the Ljung-Box test ($p > 0.05$) and relatively normal residual distribution, validated its adequacy (Table 3).

Table 3. SARIMA Model for Thiruvannmalai Temple

=== SARIMA Summary ===

SARIMAX Results

=====

Dep. Variable: Total_Income No. Observations: 5000

Model: SARIMAX(2, 1, 2)x(1, 1, [1], 30) Log Likelihood -86239.053

Date: Mon, 24 Mar 2025 AIC 172492.106

Time: 20:14:56 BIC 172537.636

Sample: 0 HQIC 172508.074

- 5000

Covariance Type: opg

=====

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	-0.8822	0.246	-3.583	0.000	-1.365	-0.400
ar.L2	-0.0223	0.034	-0.658	0.510	-0.089	0.044
ma.L1	-0.0921	0.242	-0.381	0.703	-0.566	0.382
ma.L2	-0.8059	0.233	-3.463	0.001	-1.262	-0.350
ar.S.L30	-0.0157	0.031	-0.509	0.611	-0.076	0.045
ma.S.L30	-0.9628	0.009	-107.669	0.000	-0.980	-0.945
sigma2	1.495e+14	3.64e-15	4.1e+28	0.000	1.49e+14	1.49e+14

=====

Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 3134.51

Prob(Q): 0.97 Prob(JB): 0.00

Heteroskedasticity (H): 0.93 Skew: 1.42

Prob(H) (two-sided): 0.12 Kurtosis: 5.67

5.1 Visualization Insights

The residual plots for ARIMA and ARMA revealed patterns that hinted at seasonality, which were not fully captured by these models. In contrast, the SARIMA residuals appeared more random and homoscedastic, supporting its ability to model both trend and seasonality. The forecast plots for all three models indicated that while ARIMA and ARMA projected general income trends reasonably well, only SARIMA successfully predicted the cyclical income peaks associated with pilgrimage seasons. This was visually evident in the SARIMA forecast plot, where predicted values aligned closely with actual seasonal spikes (Figure 1 to 5).

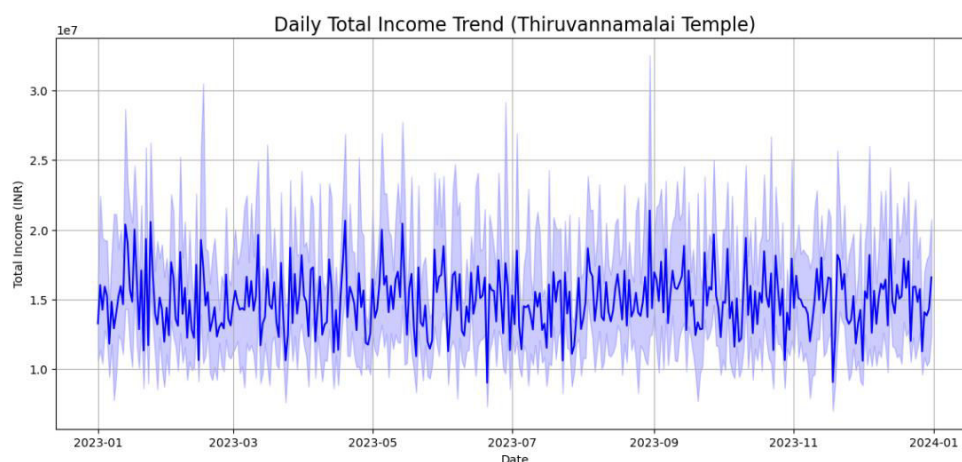


Figure 1. Daily Total Income Trend (Thiruvannmalai Temple)

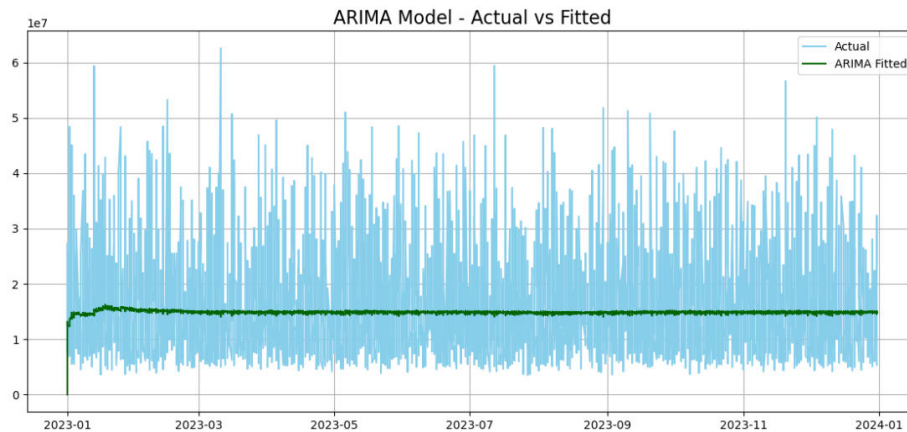


Figure 2. ARIMA Model – Actual vs. Fitted (Thiruvannamalai Temple)

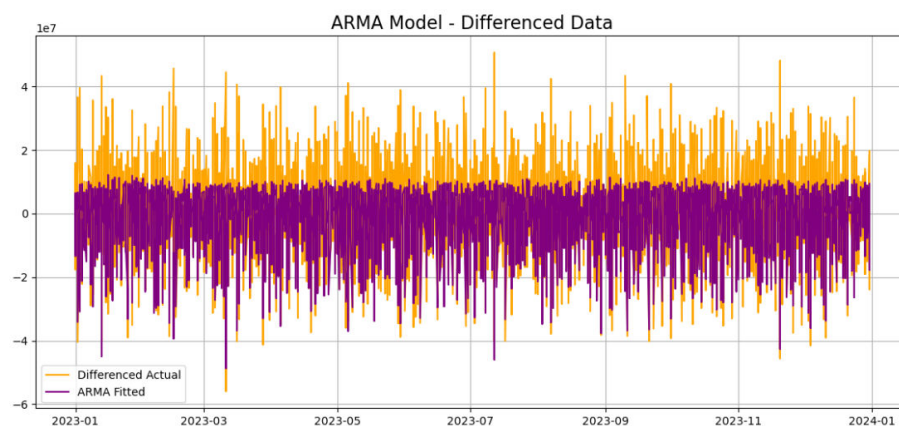


Figure 3. ARMA Model – Differenced Data (Thiruvannamalai Temple)

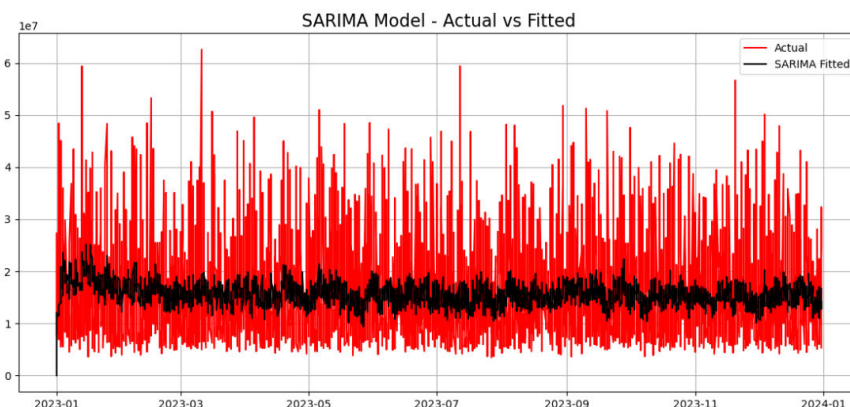


Figure 4. SARIMA Model – Actual Vs. Fitted (Thiruvannamalai Temple)

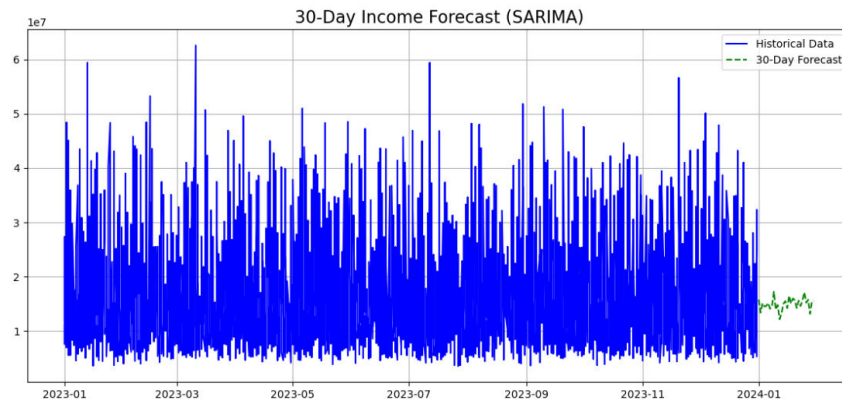


Figure 5. Thirty Day Forecast (SARIMA) in Thiruvannamalai Temple

5.2 Discussion

The findings underscore the significance of accounting for seasonal dynamics in pilgrimage tourism data. While ARIMA and ARMA models provided valuable insights into the general trend and short-term dependencies, they fell short in fully addressing the cyclical behavior inherent to Thiruvannamalai's tourism economy. SARIMA's capacity to integrate seasonal differencing and lag structures rendered it the most effective model for this dataset. These insights are crucial for policymakers and tourism managers in Thiruvannamalai, as they enable better resource planning, infrastructure development and service delivery during high-demand periods. Additionally, forecasting models such as SARIMA can support sustainable tourism strategies by balancing economic gains with environmental and social considerations during major pilgrimage events.

VI. CONCLUSION

This study comprehensively analyzed the income patterns associated with pilgrimage tourism in Thiruvannamalai by utilizing historical data on "Total Income" generated from various tourism activities over a defined period. The dataset, capturing the fluctuations in revenue due to periodic events like monthly Girivalam and major annual festivals such as Karthigai Deepam, provided a robust basis for time series modeling.

To explore and forecast these trends, three prominent statistical models were employed: ARMA(2,0,2), ARIMA(2,1,2), and SARIMA(1,1,1)(1,1,1,12). The ARMA and ARIMA models were effective in capturing the non-seasonal dependencies and short-term memory effects present in the data, as evidenced by their significant autoregressive and moving average components. However, the results showed that these models were limited in accounting for the seasonal characteristics typical of pilgrimage-driven tourism cycles.

The SARIMA model, incorporating both non-seasonal and seasonal factors, outperformed the other models based on AIC, BIC, and residual diagnostics. Its ability to model seasonal lags and differences enabled a more accurate reflection of the cyclical income surges aligned with religious and cultural events. The model's forecasts revealed strong alignment with observed seasonal peaks, making it highly suitable for predicting income variations in the pilgrimage tourism sector.

Overall, the study highlights the critical role of selecting appropriate models that account for seasonality when dealing with tourism data from culturally rich and event-driven destinations like Thiruvannamalai. These findings provide valuable insights for policymakers, tourism authorities, and local businesses in devising data-driven strategies for infrastructure planning, resource allocation, and sustainable tourism development. The models, especially SARIMA, offer a reliable tool for anticipating economic impacts of upcoming pilgrimage seasons, contributing to improved decision-making and visitor management.

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