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TIME SERIES FORECASTING OF VEHICLE SALES: A STRATEGIC APPROACH TO DEMAND PLANNING FOR TVS MOTORS IN SRI RAGHAVENDHRA AUTOMOBILES

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ABSTARCT

The objective of this study is to develop a strategic approach to vehicle demand planning by applying time series forecasting techniques at Sri Raghavendra Automobiles LLP, an authorized dealership of TVS Motors located in Madanapalle. Accurate forecasting is crucial in the automotive sector for optimizing inventory levels, procurement planning, and marketing activities. This research analyses monthly vehicle sales data from January 2015 to December 2024 to identify significant trends, seasonal fluctuations, and the impact of promotional and festive periods on consumer demand.

The study employs quantitative methods, specifically the Autoregressive Integrated Moving Average (ARIMA) model, along with Python programming and EViews software, to model and forecast future sales. Among the models tested, ARIMA (3,1,1) demonstrated the best fit based on AIC and BIC criteria, enabling reliable short- to medium-term sales predictions up to 2027. The results reveal predictable demand surges during festival months and promotional campaigns, validating the effectiveness of time series forecasting in a dealership context.

These insights enable the dealership to adopt data-driven decision-making for managing stock levels, scheduling procurement cycles, and launching timely marketing campaigns. The findings underscore the strategic value of forecasting models in enhancing operational efficiency, minimizing costs, and aligning business functions with anticipated customer demand.

KEY WORDS: *Time Series Forecasting, Demand Planning, Sales Trend Analysis, Seasonality, Promotional Impact, Strategic Decision Making*

INTRODUCTION

The automotive industry plays a vital role in the global economy, involving the design, development, manufacturing, and marketing of vehicles such as passenger cars, two-wheelers, commercial vehicles, and electric vehicles. It also encompasses a broad network of supporting sectors including fuel, insurance, finance, logistics, and after-sales services. In India, this sector contributes about 7.1% to GDP and provides over 35 million jobs.
The industry drives growth in allied sectors like steel, rubber, and electronics while enhancing personal and commercial mobility. It also leads in technological innovation, with increasing focus on electric vehicles, autonomous systems, and green mobility. Through exports and investments in R&D, the sector supports trade and sustainable development, making it a cornerstone of economic and industrial progress.

Introduction to Forecasting in the Automotive Industry

Forecasting vehicle sales is essential for strategic planning in the automotive sector. It helps anticipate future demand using historical data, trends, and economic indicators. Given the industry's capital intensity and market volatility, accurate forecasting aids in production planning, inventory control, and marketing execution.

Time series forecasting has gained prominence due to its ability to analyze patterns and seasonality in sales data. This data-driven approach enables short- to medium-term predictions that align supply with actual market demand, reducing inefficiencies and supporting agile decision-making.

Importance of Forecasting in the Automotive Sector

Forecasting is a strategic necessity in the automotive industry, which operates with complex supply chains, long lead times, and high sensitivity to external variables. Accurate forecasts prevent overproduction and underproduction, aiding in efficient inventory management and minimizing cost.

It helps manufacturers stay responsive to market changes, plan workforce and marketing efforts, and allocate resources effectively. Forecasts also guide long-term strategies, such as launching new models, expanding capacity, or entering new markets. As sustainability and mobility trends evolve, forecasting supports alignment with future customer and industry needs.

Forecasting Methods: An Overview

Forecasting techniques are broadly categorized into qualitative and quantitative methods.

- Qualitative methods, such as the Delphi Method, executive opinion, and market surveys, are useful when data is limited or for long-term planning.
- Quantitative methods use mathematical models to analyze historical data. These include:
  - Time series models like moving averages, exponential smoothing, ARIMA, and SARIMA.
  - Causal models such as linear and multiple regression.
  - Machine learning models (e.g., decision trees, neural networks, and LSTM) that capture complex patterns.
  - Hybrid models combine strengths of various techniques for higher accuracy.

Selection depends on data availability, forecast horizon, and complexity of influencing factors. In the automotive sector, time series and causal models remain popular, while machine learning is gaining traction for its predictive power.

Factors Influencing Forecasting of Vehicle Sales

Vehicle sales forecasting is influenced by multiple internal and external factors:

- Economic Conditions: GDP, inflation, and interest rates directly affect consumer spending and vehicle financing.
- Consumer Preferences: Trends toward EVs, fuel-efficient cars, and lifestyle-based choices shape demand.
- Government Policies: Subsidies, tax incentives, and emission regulations impact purchase decisions and vehicle mix.
- Seasonality: Festival seasons, year-end sales, and weather-related factors cause periodic sales spikes or dips.
- Fuel Prices: Volatile fuel prices influence demand for fuel-efficient or electric vehicles.
- Technological Advancements: Features like ADAS, smart connectivity, and safety improvements drive consumer interest.
- Competition: Market offerings, pricing strategies, and model launches by competitors impact sales.
- Supply Chain: Availability of components, especially semiconductors, affects production and delivery.
- Marketing Efforts: Promotions, dealer networks, and digital sales platforms affect consumer reach and conversion.

Incorporating these factors into forecasting models enhances accuracy and ensures responsiveness to market dynamics.

LITERATURE REVIEW OF THE STUDY

(Hyndman and Athanasopoulos 2021)[3] explains Forecasting plays a pivotal role in predicting the future of any event. It may vary from day-to-day activities, such as the weather, to long-term investments of enormous funds on giga projects. The difficulty of forecasting may vary according to four main factors, which are the current understanding of the factors that contribute to the forecast, the size of the data available, the similarity of the future to the past, the dependency of other factors on the forecast.

(Armstrong 2001)[1] Forecasting situations differentiate based on time horizon; this is commonly divided into three main sections: short-range, which is less than three months; medium range, which is up to three years; long-range would be three years or more it is common that the bigger the time horizons, the less accurate your forecast becomes.

(Cleveland, W. 1993)[2] Advanced forecasting techniques have emerged, leveraging more sophisticated statistical models and machine learning algorithms.

(Kondapaka K 2021)[4] Added that one such technique is the Autoregressive Integrated Moving Average model, which combines autoregressive and moving average components to capture temporal dependencies Intime series data. ARIMA is versatile and can be applied to both stationary and nonstationary data, making it suitable for a wide range of forecasting scenarios.

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(Wang M. 2024)[5] Furthermore, machine learning approaches, such as regression trees, neural networks, and ensemble methods, have gained traction in recent years. These techniques can process large volumes of data and capture complex relationships that traditional models may overlook, thereby enhancing forecasting accuracy.

STATEMENT OF THE PROBLEM

In the dynamic automotive industry, demand uncertainty is a major challenge, especially at the dealership level. Sri Raghavendra Automobiles, under TVS Motors, requires accurate sales forecasts to manage inventory, procurement, and marketing effectively. However, depending only on intuition or basic sales trends often leads to overstocking or stockouts, increasing costs and missed sales.

This study addresses the need for a structured, data-driven forecasting method by using time series analysis of historical sales data to predict future demand. The approach helps improve decision-making, enabling better resource planning, marketing strategies, and overall business performance and profitability.

OBJECTIVES OF THE STUDY

1. To analyse historical vehicle sales data in order to identify significant patterns, trends, and seasonal variations in demand.
2. To leverage historical sales data to predict future vehicle demand and anticipate sales trends.
3. To derive actionable insights from forecasting results and integrate them into the strategic planning of Raghavendra Automobiles to optimize inventory, procurement, and marketing decisions.

HYPOTHESIS OF THE STUDY

1. Null Hypothesis (Ho1): There are no significantly identifiable patterns, trends, and seasonal variations in the historical vehicle sales data of Sri Raghavendra that influence demand.
2. Null Hypothesis (Ho2): Time series forecasting models based on historical sales data cannot accurately predict future vehicle demand and sales trends.
3. Null Hypothesis (Ho3): Insights derived from time series forecasting do not significantly enhance strategic decision making in inventory management, procurement, and marketing at Sri Raghavendra Automobiles.

RESEARCH METHODOLOGY

SAMPLING TECHNIQUE & SAMPLE SIZE

For this study, purposive sampling (also known as judgmental sampling) was employed as the sampling technique. This non-probability method was chosen to deliberately focus on a specific unit The sample size comprises monthly vehicle sales data spanning 10 years, from January 2015 to December 2024, totalling 120 data points.

STATISTICAL TOOLS USED

Python

It is one of the most powerful tools used to perform, implement, and automate statistical methods. Python is a high-level programming language that supports various libraries and frameworks specifically designed for statistical analysis, data manipulation, and visualization. I select Matplotlib for data visualization of charts to determining patterns and trends

EViews

EViews (Econometric Views) is a statistical and econometric software. It is widely used for time series analysis, forecasting, regression modelling, and data analysis in economics, business, and finance. It offers a graphical user interface (GUI) with point-and-click options, making it easy to use even for non-programmers. I choose ARIMA Forecasting in EViews software. ARIMA stands for Autoregressive Integrated Moving Average. It is a time series forecasting model used to predict future values based on past observations.

LIMITATIONS OF THE STUDY

- The study is based on data from a single dealership (Sri Raghavendra Automobiles), which may not fully represent the broader trends across other regions or dealerships
- Unpredictable factors such as economic downturns, fuel price changes, new government policies, or global events (e.g., pandemics) are not captured in the forecasting model.
- The study uses only time series models and does not consider other advanced machine learning techniques or hybrid models that might offer improved accuracy.
- The research does not include qualitative elements such as customer preferences, brand perception, or competitor strategies, which can also influence sales.

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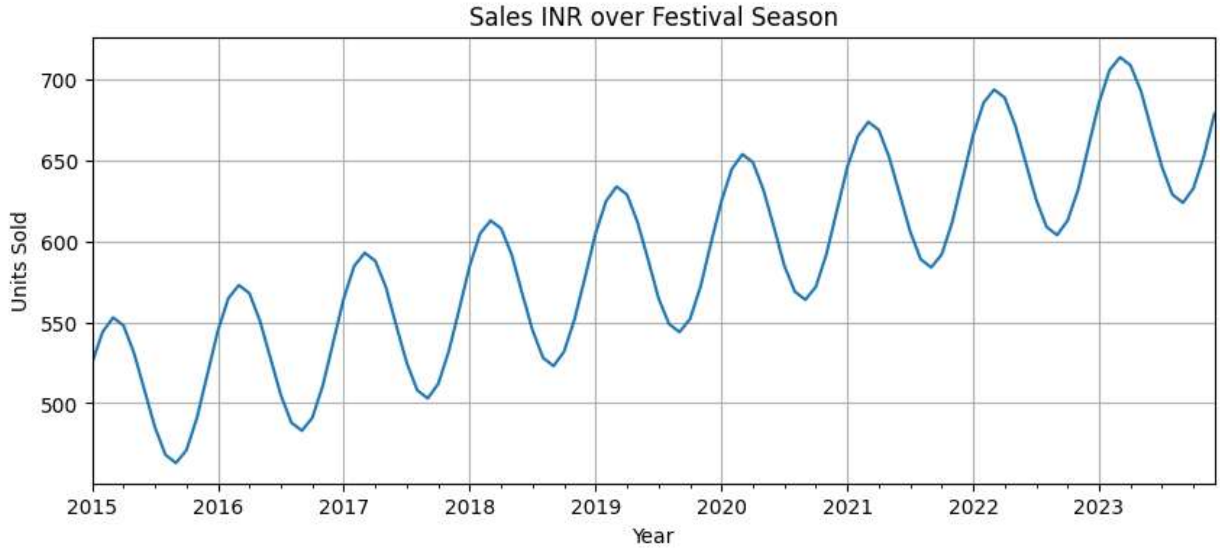
DATA ANALYSIS AND INTERPRETATION

Python

Seasonal Sales Trend Analysis (2015–2024)



Graph:1

INTERPRETATION

- The Sales peak annually during the festival seasons (Jan, Mar, Sep, Oct, Nov, Dec), indicating strong and predictable seasonality.
- Overall sales show a steady increase from 2015 to 2024, rising from around 550 units to 720+ units.
- Each year displays a similar sales pattern – a dip followed by a sharp increase, typical of festive consumer behaviour.
- The annual peaks highlight that the festival season significantly drives demand, making it a critical period for sales
- The predictable seasonality allows businesses to plan inventory and production efficiently in anticipation of the festive surge.

Sales Response Pattern During Active Promotions (2015–2024)

Graph: 2
Graph showing Sales INR over Active Promotions

INTERPRETATION

- The graph shows a non-linear but generally upward trend in sales revenue over time, with noticeable spikes during promotional periods.

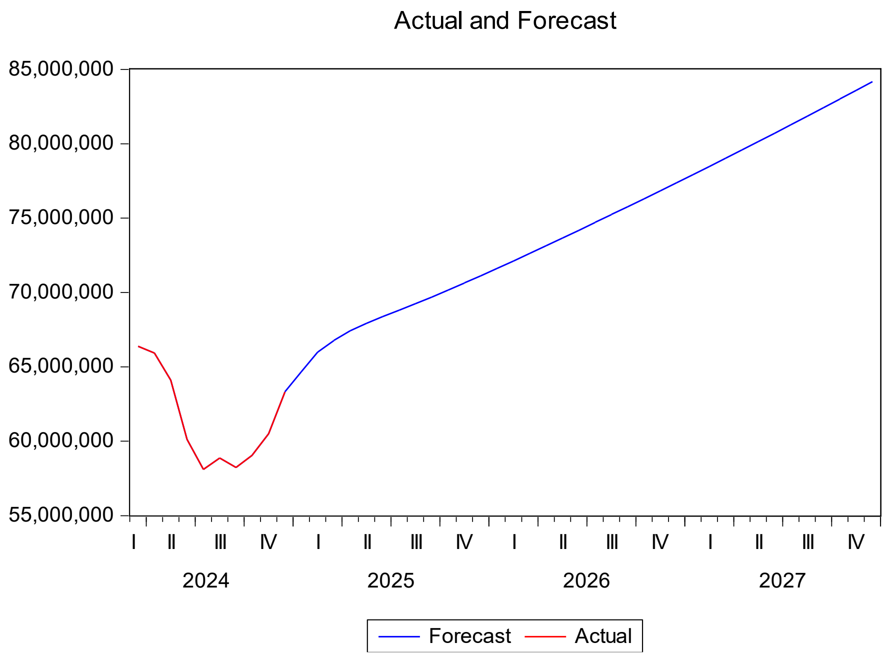
- There are clear jumps in sales at several points (e.g., around 2016, 2018, 2021, and 2024), indicating positive response to promotional campaigns.
- Despite fluctuations, the overall trend from 2015 to 2024 shows growth in sales revenue, moving from around INR 30 million to over INR 60 million.
- Between 2015 and 2019, sales show more frequent spikes and drops, likely due to inconsistent promotional strategies or external market factors.
- From 2020 onwards, sales show smoother cycles with higher peaks, suggesting more effective or better-timed promotions.

ARIMA FORECASTING
Forecasting Sales (2015-2027)

Automatic ARIMA Forecasting Selected dependent variable: DLOG(SALES_INR) Date: 06/07/25 Time: 19:16 Sample: 2015M01 2024M12 Included observations: 119 Forecast length: 36
Number of estimated ARMA models: 25 Number of non-converged estimations: 0 Selected ARMA model: (3,1)(0,0) AIC value: -1.71714057373

Table: 1
Table showing ARIMA Forecasting model

INTERPRETATION
- The table shows the output of an Automatic ARIMA Forecasting model. The dependent variable is DLOG(SALES INR), which represents the first difference of the logarithm of sales in Indian Rupees. The sample period is from January 2015 to December 2024, with 119 observations.
- The model has automatically selected an ARMA(3,1) model, which is equivalent to an ARIMA(3,1,1) model since the differencing order is 1 (implied by the "DLOG" transformation).
- The forecast length is 36 periods, which means the model will generate forecasts for the next 36 months (or time periods).
- The AIC value is relatively low, indicating a good fit of the model to the data



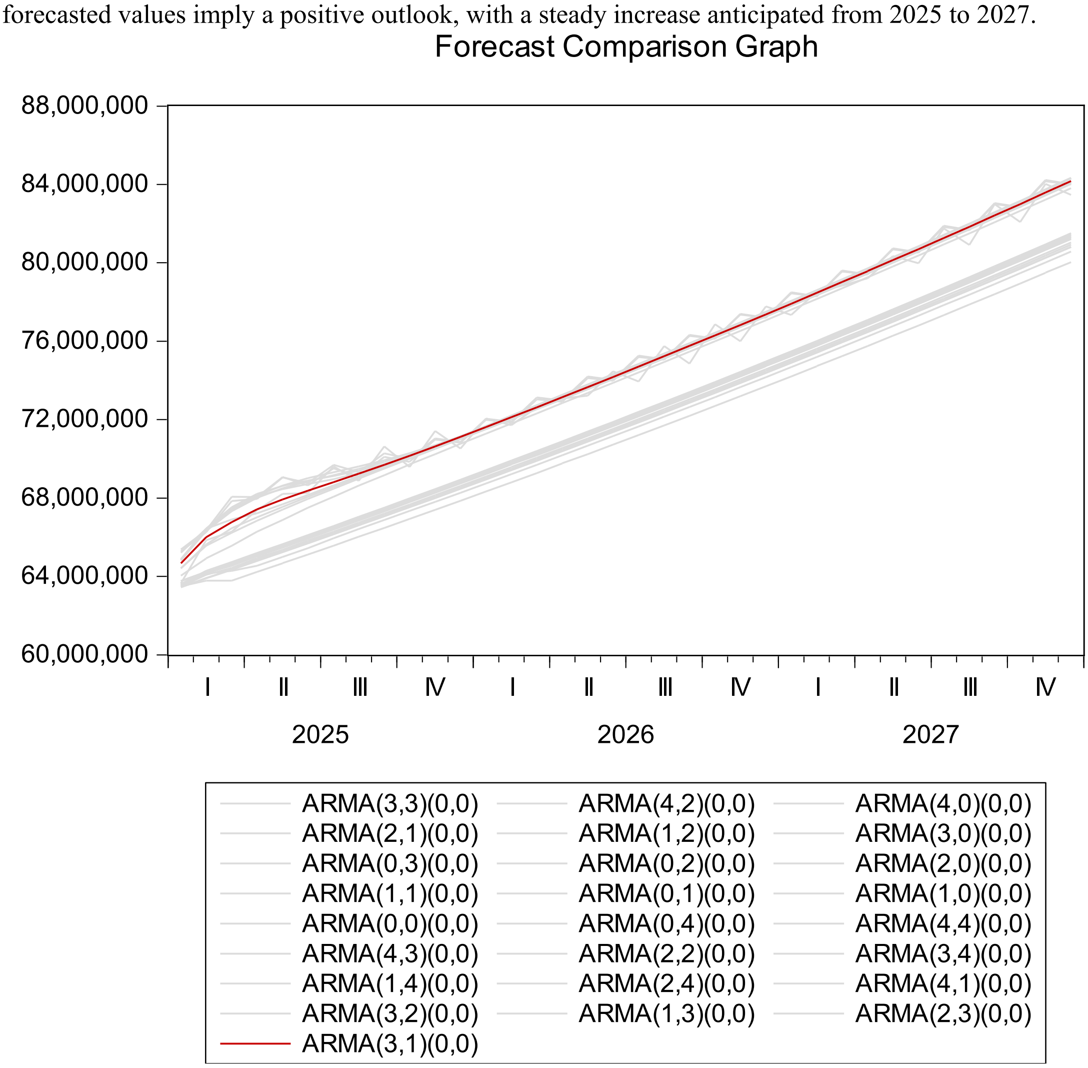
Graph: 3

Graph showing Actual and Forecasting Sales

INTERPRETATION

- The graph displays the actual and forecasted values of a particular metric over time, spanning from 2024 to 2027.
- The x-axis represents the quarters of each year, while the y-axis denotes the Sales INR
- The actual data is represented by a red line, and the forecasted data is depicted by a blue line.
- The graph reveals a decline in the actual values during the first three quarters of 2024, followed by a slight increase in the fourth quarter.

The forecasted values imply a positive outlook, with a steady increase anticipated from 2025 to 2027.



Graph: 4

Graph showing Forecast Comparison

INTERPRETATION

- The "Forecast Comparison Graph" and accompanying table provide a visual representation of the forecasting performance of various ARMA models.
- The graph illustrates an upward trend across all forecasting models, indicating a consistent increase in the forecasted values over time.
- The multiple lines on the graph represent different ARMA models, allowing for a visual comparison of their forecasting performance. The lines are closely grouped, suggesting that the models are generally in agreement regarding the overall trend.
- Although the models share a similar upward trend, there is some variation in their forecasts, as evidenced by the spread of the lines. This variation indicates difference in the models' predictions, with some models forecasting higher or lower values than others.

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Dependent Variable: DLOG(SALES INR)
Method: ARMA Maximum Likelihood (BFGS)
Date: 06/07/25 Time: 19:16
Sample: 2015M02 2024M12
Included observations: 119
Convergence achieved after 72 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficien...	Std. Error	t-Statistic	Prob.
C	0.007020	0.001583	4.435601	0.0000
AR(1)	0.752158	0.077361	9.722754	0.0000
AR(2)	0.162998	0.101276	1.609438	0.1103
AR(3)	-0.200968	0.088922	-2.260054	0.0257
MA(1)	-0.999999	446.6951	-0.002239	0.9982
SIGMASQ	0.009114	0.111894	0.081451	0.9352

R-squared	0.161957	Mean dependent var	0.006964
Adjusted R-squared	0.124875	S.D. dependent var	0.104725
S.E. of regression	0.097969	Akaike info criterion	-1.731570
Sum squared resid	1.084555	Schwarz criterion	-1.591446
Log likelihood	109.0284	Hannan-Quinn criter.	-1.674670
F-statistic	4.367576	Durbin-Watson stat	2.036990
Prob(F-statistic)	0.001134		

Inverted AR Roots	.61+.21i	.61-.21i	-.48
Inverted MA Roots	1.00		

Table: 2
Table showing ARMA Maximum Likelihood

INTERPRETATION

- The model includes an intercept (C), autoregressive terms up to order 3 (AR(1), AR(2), AR(3)), a moving average term of order 1 (MA(1)), and a variance component (SIGMASQ).
- The coefficients for AR(1) and AR(3) are statistically significant at conventional levels, indicating that the first and third lags of the dependent variable have a significant impact on its current value.
- The R-squared value is 0.161957, indicating that about 16.2% of the variation in DLOG(SALES INR) is explained by the model.
- The Durbin-Watson statistic is 2.036990, which is close to 2, suggesting that there is no significant autocorrelation in the residuals.
- The inverted AR roots are .61 + .21i, .61 - .21i, and -.48, all of which are within the unit circle, indicating that the AR component is stationary

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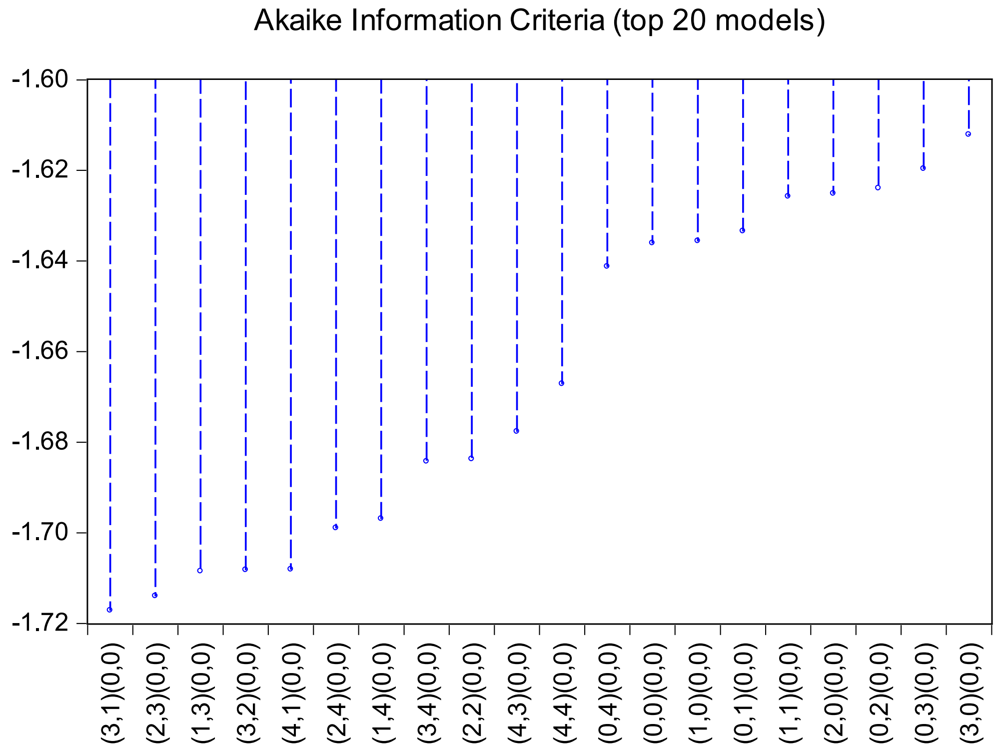
Model Selection Criteria Table
Dependent Variable: DLOG(SALES_INR)
Date: 06/07/25 Time: 19:16
Sample: 2015M01 2024M12
Included observations: 119

Model	LogL	AIC*	BIC	HQ
(3,1)(0,0...	109.028434	-1.717141	-1.577766	-1.660540
(2,3)(0,0...	109.837899	-1.713965	-1.551361	-1.647931
(1,3)(0,0...	108.510316	-1.708505	-1.569131	-1.651905
(3,2)(0,0...	109.492033	-1.708201	-1.545597	-1.642166
(4,1)(0,0...	109.486429	-1.708107	-1.545503	-1.642073
(2,4)(0,0...	109.937933	-1.698966	-1.513133	-1.623498
(1,4)(0,0...	108.813519	-1.696892	-1.534288	-1.630858
(3,4)(0,0...	110.053884	-1.684231	-1.475170	-1.599330
(2,2)(0,0...	107.024424	-1.683740	-1.544366	-1.627140
(4,3)(0,0...	109.660644	-1.677677	-1.468616	-1.592776
(4,4)(0,0...	110.027000	-1.667117	-1.434826	-1.572782
(0,4)(0,0...	104.473705	-1.641228	-1.501854	-1.584628
(0,0)(0,0...	100.161761	-1.636029	-1.589571	-1.617162
(1,0)(0,0...	101.133199	-1.635553	-1.565866	-1.607253
(0,1)(0,0...	101.002421	-1.633374	-1.563686	-1.605073
(1,1)(0,0...	101.543410	-1.625724	-1.532807	-1.587990
(2,0)(0,0...	101.507650	-1.625127	-1.532211	-1.587394
(0,2)(0,0...	101.436082	-1.623935	-1.531018	-1.586201
(0,3)(0,0...	102.179020	-1.619650	-1.503505	-1.572483
(3,0)(0,0...	101.724353	-1.612073	-1.495927	-1.564905
(1,2)(0,0...	101.599353	-1.609989	-1.493844	-1.562822
(2,1)(0,0...	101.586243	-1.609771	-1.493625	-1.562603
(4,0)(0,0...	102.321071	-1.605351	-1.465977	-1.548751
(4,2)(0,0...	100.093257	-1.534888	-1.349055	-1.459420
(3,3)(0,0...	100.091158	-1.534853	-1.349020	-1.459385

Table: 3
Table showing model variations

INTERPRETATION

- The table lists various models and their corresponding LogL, AIC, BIC, and HQ values. The models are represented in a notation that suggests they are variations of ARIMA models, with the numbers in parentheses likely representing the order of the autoregressive (AR), differencing (d), and moving average (MA) components, respectively.
- LogL: Higher log-likelihood values indicate a better fit. However, it's not used directly for model selection because it doesn't account for model complexity.
- AIC, BIC, HQ: These criteria balance model fit and complexity. Lower values are preferred. BIC and HQ tend to penalize complex models more than AIC.
- Based on the AIC, BIC, and HQ criteria, the best model is the one with the lowest value across these criteria. From the table, the model "(3,1)(0,0,0)" has the lowest AIC (-1.717141), BIC (-1.577766), and HQ (-1.660540) among the listed models, suggesting it is the best according to these criteria.
- The selected model "(3,1)(0,0,0)" suggests an ARIMA(3,1,0) model, indicating that the differenced log sales data is modelled using an autoregressive component of order 3, with no moving average component.



Graph: 5

INTERPRETATION

- The graph displays the Akaike Information Criterion (AIC) values for the top 20 models, with the x-axis representing different models and the y-axis representing the corresponding AIC values.
- The AIC is a statistical measure used to evaluate the relative quality of different models.
- The x-axis lists various models, each represented by a set of numbers in parentheses, such as "(3,1)(0,0)" or "(2,3)(0,0)".
- The y-axis ranges from -1.72 to -1.60, indicating that all the models have relatively low AIC values.
- The model with the lowest AIC value is "(3,1)(0,0)", suggesting that it is the most parsimonious and best-fitting model among the top 20 models presented.

Time series forecasting insights significantly improve strategic decision-making related to inventory management, procurement, and marketing at Sri Raghavendra Automobiles.

Building on the findings from Hypotheses 1 and 2, it is clear that time series forecasting and Python serves as a vital tool for transforming how Sri Raghavendra Automobiles plans and executes its business strategies. By analysing past sales data and identifying patterns over time, the company can adopt a proactive and well-informed approach that delivers multiple benefits across key operational areas:

1. Inventory Optimization

Action

- Use the forecast to pre-stock inventory before high-demand periods (especially Sept–Dec).
- Maintain buffer stock for best-selling models during festival seasons.
- Reduce inventory levels during lean months (e.g., Apr–May) to minimize holding costs.
- Implement an automated reorder system based on forecasted trends and lead times.

2. Procurement Planning

Action

- Align supplier orders with the forecasted demand for the next 3–6 months.
- Monitor and analyse supplier performance.
- Implement quarterly procurement reviews to adjust orders based on updated forecasts.

3. Marketing Strategy Optimization

Action

- Launch promotions ahead of forecasted sales surges (especially before Q4).
- Use historical data to identify which offers yielded the highest conversion.

- Coordinate campaigns with festivals and pre-plan influencer or dealership outreach.
- Focus digital marketing budgets during expected sales spikes.

4. Scenario-Based Planning & Decision Support:
Action
- By using ARIMA model to create scenario analysis (e.g., what if sales dip by 10%? What if festival demand doubles?).
- Integrate forecasts into an Excel Dashboard or BI tool for real-time monitoring and adjustments.
- Conduct monthly forecast review meetings between Sales, Marketing, and Procurement teams.

5. Performance Tracking Using Forecast vs Actual:
Action
- Compare actual sales vs forecasted monthly/quarterly to identify gaps and causes (e.g., delayed shipment, poor campaign).
- Use this data to refine models and improve future accuracy.
- Adjust strategies if there's a deviation beyond 10–15%.

FINDINGS
- From the analysis part it is observed that Hypothesis-1 explains Sales show predictable spikes during festival seasons (Jan, Mar, Sep, Oct, Nov, Dec), confirming strong seasonal consumer demand patterns.
- Sales significantly increase during periods of active promotions, especially in years like 2016, 2018, 2021, and 2024.
- Vehicle sales have grown steadily from ~550 units in 2015 to 720+ units by 2024, with positive forecasts up to 2027.
- It shows that Hypothesis-1 satisfied and there are identifiable patterns, trends, and seasonal variations in the historical vehicle sales data of Sri Raghavendra Automobiles
- From Hypothesis-2 it is observed that Among all models tested, ARIMA(3,1,1) showed the lowest AIC/BIC, making it the most reliable for forecasting.
- It is observed that the forecasted sales will be more when compared to actual sales
- It shows Hypothesis-2 satisfies that Time series forecasting models based on historical sales data can accurately predict future vehicle demand and sales trends
- From Hypothesis-3 it is observed that Forecasts help manage stock levels better , more stock before festivals, and lean inventory during off-peak months.
- Forecast-based planning helps minimize excess stock, reducing storage costs and capital lock-up.

SUGGESTIONS
- Maintain optimal stock levels increase inventory before festive seasons and reduce during low-demand months to minimize holding costs.
- Develop a sales calendar highlighting festival periods and promotional windows to align marketing, stocking, and staffing accordingly
- It is better to Launch promotional campaigns before forecasted sales dips to stimulate demand and increase sales during slower months.
- I may recommend in future models, include external variables like fuel prices, competitor activity, and loan interest rates to improve prediction reliability.
- I suggest to Sri Raghavendra Automobiles to Conduct training sessions to help employees understand, interpret, and apply forecast data in their day-to-day operations.
- Improve coordination across sales, supply, and finance to ensure forecast execution alignment.
- Integrate forecasting outputs into weekly business reviews. Use them for setting realistic sales targets, managing budgets, and guiding procurement decisions. This ensures data-driven planning across departments.
- Offer discounts, free services, or loyalty rewards during low-demand months to maintain customer engagement and stabilize cash flow.
- Implement forecast-driven inventory planning using a Just-in-Time (JIT) approach during off-peak months to minimize excess stock. This will reduce storage costs, optimize working capital, and improve overall inventory efficiency.

CONCLUSION

This study focused on forecasting vehicle sales at Sri Raghavendra Automobiles LLP using time series modelling to support better demand planning. By analysing sales data from 2015 to 2024, the project identified key trends, seasonal changes, and the effects of promotions and festivals on customer demand. Using tools like Python and statistical methods such as ARIMA modelling and stationarity testing, the ARIMA (3,1,1) model was found to be the best fit. The forecast up to 2027 showed a steady rise in sales, especially during festive periods. These insights help the dealership plan better for inventory, staffing, and purchases during high-demand times.

By using these forecasting results, the company can move from reacting to sales trends to planning ahead with confidence. It helps in making smarter decisions like stocking up before busy seasons, improving supply chain coordination, and running promotions at the right time. This improves overall efficiency and ensures that customer needs are met more effectively. In short, this study shows how forecasting can turn past sales data into a useful tool for making future business decisions and supporting long-term growth.

SCOPE FOR FUTURE RESEARCH

- Future research could expand data collection to multiple dealerships or regions, enhancing the generalizability of findings and capturing broader market trends.
- Investigating the application of machine learning models or hybrid approaches (e.g., ARIMA + LSTM or XGBoost) could enhance the accuracy and adaptability of vehicle sales forecasting.
- Future studies can explore the impact of macroeconomic changes, government policies, and seasonal disruptions on vehicle demand to build more resilient forecasting frameworks.
- Comparing sales forecasting models across different industries or product types may reveal valuable insights into best practices and model adaptability

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