Forecasting Demand for Automotive Spare Parts Using Sales Trend Analysis: Evidence from the Indian Two- and Four-Wheeler Aftermarket

Komal Naik
Student
Dept. of MBA., Sipna College of Engineering and Technology, Amravati 444607, Amravati (MS.), India
guptabhoomika152@gmail.com

Prof. A.A.Umbarkar[2]
Asst. Professor,
Dept. of MBA., Sipna College of Engineering and Technology, Amravati 444607
Amravati (MS.), India
aaumbarkar@sipnaengg.ac.in

Abstract

Accurate demand forecasting remains a persistent challenge in the automotive spare-parts aftermarket due to intermittent demand patterns, seasonal fluctuations, and high product variety. These challenges are particularly pronounced in emerging economies, where small and medium enterprises often rely on intuition-based inventory planning. This study examines the effectiveness of sales trend analysis in forecasting demand for two- and four-wheeler automotive spare parts in the Indian aftermarket context. Using a descriptive and analytical research design, the study integrates historical sales data with primary insights collected from employees and stakeholders involved in sales, inventory, and procurement activities. Time-series techniques, including trend analysis, moving averages, and exponential smoothing, are applied to identify demand patterns and generate short-term forecasts. The empirical results reveal a significant positive relationship between historical sales trends and future demand, demonstrating that even simple and interpretable forecasting methods can substantially improve demand predictability and inventory planning. The findings highlight the managerial value of data-driven forecasting for reducing stockouts and excess inventory in resource-constrained environments. By providing empirical evidence from the Indian two- and four-wheeler aftermarket, the study contributes to demand forecasting literature and offers practical guidance for regional spare-parts distributors seeking scalable and implementable forecasting solutions.

Keywords: Automotive spare parts, Demand forecasting, Sales trend analysis, Time-series forecasting, Inventory management, Indian automotive aftermarket, Two- and four-wheeler industry

1. Introduction

1.1 Background of the Study

The automotive industry is one of the most significant contributors to economic growth in both developed and emerging economies. In India, the sector plays a vital role not only through vehicle manufacturing but also through its extensive aftermarket ecosystem, which includes maintenance, repair, and spare-parts distribution. The automotive spare-parts aftermarket ensures the operational continuity of vehicles throughout their life cycle and directly influences customer satisfaction, safety, and service reliability.

Unlike new vehicle sales, spare-parts demand does not follow a smooth or predictable pattern. Demand for automotive spare parts is highly heterogeneous, influenced by multiple interrelated factors such as vehicle age, intensity of usage, driving conditions, quality of roads, preventive maintenance schedules, seasonal weather patterns, and sudden breakdowns. Additionally, the demand for spare parts is often intermittent, characterized by long periods of zero demand followed by sudden spikes, making accurate forecasting particularly complex. This complexity is further amplified by the large number of Stock Keeping Units (SKUs), each exhibiting different demand behaviors.

Demand forecasting plays a critical role in inventory management for spare-parts distributors. Accurate forecasts enable firms to maintain optimal stock levels, minimize inventory carrying costs, reduce stockouts, and ensure timely availability of parts. Conversely, inaccurate forecasts lead to excessive capital tied up in slow-moving inventory, increased obsolescence risk, frequent emergency purchases, and dissatisfied customers due to unavailability of critical components. For small and medium enterprises (SMEs), such inefficiencies can significantly impact profitability and operational sustainability.

Krishna Enterprises, established in 1995 in Amravati, Maharashtra, operates as a regional distributor of two- and four-wheeler spare parts. Over the years, the firm has built a strong reputation for reliability, quality, and customer service. Its product portfolio includes a wide range of components such as engine parts, brake systems, filters, electrical components, and routine maintenance items catering to both two-wheelers and four-wheelers. Despite its market presence and operational experience, Krishna Enterprises faces persistent challenges related to demand uncertainty and inventory imbalance.

The enterprise primarily relies on historical sales experience and managerial judgment for procurement and inventory decisions. While such intuition-based methods may work reasonably well in stable environments, they are insufficient in handling demand volatility, seasonality, and intermittent consumption patterns. As competition intensifies and customer expectations for immediate availability increase, there is a growing need for systematic, data-driven forecasting approaches that can support more informed decision-making.

Sales trend analysis, as a component of time-series forecasting, provides a practical and cost-effective approach for understanding historical demand patterns and projecting future requirements. By identifying underlying trends, seasonal fluctuations, and cyclical movements in sales data, organizations can significantly improve demand predictability. This study focuses on applying sales trend analysis techniques to forecast spare-parts demand at Krishna Enterprises, thereby addressing a critical operational challenge faced by regional automotive distributors.

1.2 Need and Significance of the Study

The need for accurate spare-parts demand forecasting has become increasingly important due to rising competition, shrinking profit margins, and higher customer service expectations in the automotive aftermarket. For regional distributors like Krishna Enterprises, effective inventory planning is not merely an operational necessity but a strategic imperative.

From an inventory management perspective, inaccurate demand forecasts often result in two extreme situations: overstocking and stockouts. Overstocking leads to increased holding costs, storage constraints, risk of damage, and obsolescence, especially for slow-moving or model-specific parts. Stockouts, on the other hand, disrupt service operations, delay vehicle repairs, and cause loss of customer trust and repeat business. A structured forecasting approach helps strike a balance between these extremes by aligning inventory levels with actual market demand.

From a customer satisfaction standpoint, the availability of spare parts at the right time is critical. Mechanics, service centers, and end customers expect immediate access to essential components to minimize vehicle downtime. Failure to meet these expectations often results in customers switching to alternative suppliers. By improving demand forecasting accuracy, Krishna Enterprises can enhance service reliability and strengthen long-term customer relationships.

From a managerial decision-making perspective, sales trend analysis provides quantitative insights that support strategic planning. Forecast-based insights enable managers to make informed decisions regarding procurement scheduling, safety stock levels, supplier negotiations, pricing strategies, and promotional planning. Data-driven decision-making reduces dependency on subjective judgment and improves organizational consistency.

The study is also significant from an academic and research perspective. Although extensive literature exists on demand forecasting and inventory management, most empirical studies focus on large manufacturing organizations, aviation spare parts, or heavy industrial equipment in developed economies. There is limited empirical research addressing the Indian automotive aftermarket, particularly the two- and four-wheeler spare-parts segment, which constitutes a substantial portion of India's mobility ecosystem.

Furthermore, many advanced forecasting models proposed in literature involve sophisticated machine-learning or artificial intelligence techniques that require large datasets, high computational resources, and specialized expertise. Such approaches may not be immediately feasible for small and medium enterprises. This study emphasizes the relevance of simpler, interpretable forecasting techniques such as trend analysis, moving averages, and exponential smoothing, which can be effectively implemented using readily available tools like Microsoft Excel or basic statistical software.

By focusing on a real-world case of Krishna Enterprises, this study bridges the gap between theoretical forecasting models and practical implementation. The findings of the study are expected to benefit not only the case organization but also similar regional spare-parts distributors facing comparable challenges.

1.3 Objectives of the Study

The specific objectives of the study are as follows:

1. To examine the historical sales trends of two- and four-wheeler spare parts at Krishna Enterprises.
2. To identify seasonal, cyclical, and trend components in spare-parts demand.
3. To apply sales trend analysis and time-series forecasting techniques to estimate future demand.
4. To evaluate the usefulness of trend-based forecasting in improving inventory management decisions.
5. To suggest practical measures for reducing stockouts, overstocking, and inventory-related costs.

1.4 Scope of the Study

The scope of the study is confined to Krishna Enterprises, Amravati, and focuses on selected categories of two- and four-wheeler spare parts. The analysis is based on historical sales data and primary responses collected from employees and stakeholders involved in sales, inventory, and procurement activities. While the findings provide valuable insights, they are intended primarily for

2. Review of Literature

2.1 Conceptual Foundations of Demand Forecasting

Demand forecasting is a fundamental component of operations and supply chain management, serving as the basis for planning production, procurement, inventory, and distribution activities. According to Chopra and Meindl (2016), forecasting accuracy directly influences supply chain performance, cost efficiency, and service levels. Inaccurate forecasts propagate inefficiencies across the supply chain, leading to excessive inventory, stockouts, or poor capacity utilization.

In the context of spare parts, demand forecasting differs significantly from forecasting finished goods. While finished goods often exhibit relatively stable or trend-driven demand, spare parts are characterized by uncertainty, low predictability, and variability. Teunter and Syntetos (2003) emphasize that spare-parts demand is typically intermittent, meaning that demand occurs irregularly with many zero-demand periods. This intermittency violates the assumptions of classical forecasting models, making standard approaches less effective.

Theoretical literature classifies demand patterns into smooth, erratic, intermittent, and lumpy categories. Spare parts frequently fall into intermittent or lumpy demand categories, where both the timing and magnitude of demand are unpredictable (Syntetos & Boylan, 2005). This complexity necessitates specialized forecasting techniques and a strong integration between forecasting and inventory policy.

2.2 Traditional Time-Series Forecasting Methods

Traditional time-series forecasting methods such as moving averages, exponential smoothing, and Autoregressive Integrated Moving Average (ARIMA) models have been widely applied due to their simplicity, transparency, and ease of implementation. Moving averages smooth short-term fluctuations and are effective for stable demand patterns, while exponential smoothing assigns greater weight to recent observations, allowing quicker adaptation to changes (Eaves & Kingsman, 2004).

However, several studies demonstrate the limitations of these methods in spare-parts contexts. Ghobbar and Friend (2002) identify that traditional models tend to underestimate demand variability and fail to account for long zero-demand intervals, resulting in biased forecasts. Similarly, Willemain and Smart (2001) report that classical time-series models perform poorly for intermittent demand, often producing misleading forecasts that increase inventory costs.

Despite these limitations, traditional methods continue to be widely used in practice, especially by small and medium enterprises, due to their low computational requirements and ease of understanding. Their continued relevance underscores the importance of adapting rather than completely replacing these methods in resource-constrained environments.

2.3 Intermittent Demand Forecasting and Croston-Based Models

A major breakthrough in intermittent demand forecasting was proposed by Croston (1972), who introduced a method that separately estimates demand size and the interval between demands. Croston's method was specifically designed to overcome the weaknesses of traditional approaches when applied to intermittent demand.

Subsequent research, however, identified systematic bias in Croston's original formulation. Syntetos and Boylan (2005, 2006) demonstrated that Croston's method tends to overestimate demand and proposed bias-adjusted versions to improve forecast accuracy. Babai and Syntetos (2010) further evaluated Croston-based variants and concluded that no single method consistently outperforms others across all demand scenarios.

Teunter and Sani (2009) examined the structural bias in Croston's forecasts and emphasized the need for careful method selection based on demand characteristics. These studies collectively highlight that while Croston-based methods represent a significant advancement, they are not universally optimal and must be applied judiciously.

2.4 Forecasting in the Automotive Spare-Parts Aftermarket

The automotive spare-parts aftermarket presents unique forecasting challenges due to the diversity of vehicle models, part specifications, and replacement cycles. Kontrec et al. (2015) note that failure rates, maintenance schedules, and part criticality significantly influence demand patterns. In such environments, forecasting accuracy directly impacts service levels and customer satisfaction.

Romeijnders et al. (2012) proposed a two-step forecasting approach incorporating component repair information, demonstrating a reduction in forecast error for automotive spare parts. Their study underscores the value of domain-specific information in enhancing forecast reliability.

Sahin and Alp (2013) combined Croston's method with artificial neural networks to forecast intermittent automotive demand and reported improved accuracy compared to standalone methods. While these hybrid approaches show promise, their complexity and data requirements limit their adoption among small distributors.

In the Indian context, Sahay and Ranganathan (2013) examined forecasting practices in the automotive industry and highlighted the gap between academic models and industry adoption. They observed that many firms continue to rely on managerial judgment despite the availability of analytical tools, primarily due to skill and infrastructure constraints.

2.5 Role of Classification and Inventory Segmentation

Several studies emphasize that forecasting accuracy improves significantly when spare parts are classified based on demand behavior and value. ABC analysis, which categorizes items based on value contribution, and FSN (Fast-moving, Slow-moving, Non-moving) classification, which focuses on movement frequency, are commonly recommended (Eaves & Kingsman, 2004).

Kumar and Deshmukh (2014) demonstrated that combining demand classification with appropriate forecasting models yields better results than applying a single model across all SKUs. High-value, fast-moving parts benefit from more sophisticated forecasting, while low-value, infrequently demanded parts may be managed using simpler rules.

This literature reinforces the argument that forecasting should not be viewed as a standalone activity but as part of an integrated inventory management framework.

2.6 Machine Learning and Advanced Forecasting Approaches

Recent literature increasingly explores machine learning (ML) and artificial intelligence (AI) techniques for spare-parts demand forecasting. Artificial Neural Networks (ANN), Support Vector Regression (SVR), Long Short-Term Memory (LSTM) networks, and Prophet models have been tested in various contexts (Maulida Hakim & Dwantara, 2018; Zhang & Wang, 2023).

While many studies report improved forecast accuracy using ML techniques, several limitations are also highlighted. Pinçe et al. (2021) note that advanced models often lack interpretability, require large datasets, and are sensitive to data quality issues. For small and medium enterprises, these constraints can outweigh the potential accuracy gains.

Therefore, recent reviews advocate hybrid and pragmatic approaches that combine traditional time-series methods with selective use of advanced analytics, rather than full-scale AI adoption (Syntetos & Boylan, 2015).

2.7 Indian Context and Research Gaps

Despite India being one of the world's largest two- and four-wheeler markets, empirical research on spare-parts demand forecasting in the Indian aftermarket remains limited. Most available studies focus on manufacturing or large OEM supply chains, with minimal attention to regional distributors and SMEs.

Moreover, existing studies often emphasize forecast accuracy metrics without adequately linking them to managerial outcomes such as inventory turnover, service level, or cost reduction. This disconnect reduces the practical relevance of academic research for practitioners.

The literature also reveals a scarcity of studies combining primary stakeholder insights with secondary sales data, particularly in emerging markets. This gap limits the contextual understanding of forecasting challenges faced by firms operating under infrastructural and resource constraints.

2.8 Synthesis of Literature and Research Positioning

The reviewed literature clearly establishes that:

- Spare-parts demand forecasting is inherently complex due to intermittency and variability
- No single forecasting model is universally optimal
- Traditional time-series methods remain relevant, especially for SMEs
- Advanced ML models offer potential but face adoption barriers
- Empirical research in the Indian two- and four-wheeler aftermarket is limited

Positioned within this context, the present study adopts a pragmatic and applied research approach, focusing on sales trend analysis using accessible tools and real organizational data. By linking forecasting outcomes with inventory management implications, the study aims to bridge the gap between theory and practice and contribute context-specific insights to the existing body of knowledge.

3. Research Methodology

3.1 Research Design

The present study adopts a descriptive and analytical research design to examine historical sales trends and forecast demand for two- and four-wheeler spare parts at Krishna Enterprises, Amravati. A descriptive research design is appropriate when the objective is to systematically describe existing phenomena, identify patterns, and interpret relationships without manipulating variables (Kothari, 2004). In the context of spare-parts demand forecasting, the study seeks to understand observed sales behavior and apply analytical techniques to project future demand rather than establish experimental causality.

In addition to being descriptive, the study incorporates an analytical component by applying time-series forecasting techniques to historical sales data. This blended design allows for both empirical observation and quantitative evaluation, aligning with methodologies commonly used in operations and supply chain research (Chopra & Meindl, 2016). The case-study orientation further enhances contextual depth, enabling a detailed examination of forecasting challenges faced by a regional automotive spare-parts distributor.

3.2 Research Approach

A quantitative research approach is employed in this study, as the primary objective involves numerical analysis of sales data and structured responses obtained through questionnaires. Quantitative approaches are particularly suitable for forecasting studies, where statistical patterns, trends, and numerical relationships form the basis for prediction and evaluation (Hair et al., 2019).

The study also integrates limited qualitative insights from open-ended questionnaire responses and personal interviews to supplement quantitative findings. These qualitative inputs provide contextual understanding of operational challenges, forecasting practices, and managerial perceptions, thereby strengthening the interpretation of quantitative results. Such a mixed-evidence approach enhances internal validity without compromising methodological rigor (Creswell & Creswell, 2018).

3.3 Research Problem Definition

Krishna Enterprises, a regional distributor of two- and four-wheeler spare parts, faces persistent challenges in accurately forecasting demand due to fluctuating sales patterns, seasonal variations, and intermittent demand. Inadequate forecasting leads to inventory imbalances in the form of stockouts and overstocking, adversely affecting customer satisfaction and operational efficiency. The absence of a systematic, data-driven forecasting framework further compounds these issues.

Accordingly, the research problem addressed in this study is:

How can sales trend analysis be effectively utilized to forecast spare-parts demand and improve inventory management outcomes at Krishna Enterprises?

3.4 Research Objectives

The study is guided by the following objectives:

1. To analyze historical sales trends of two- and four-wheeler spare parts at Krishna Enterprises.
2. To identify trend, seasonal, and cyclical components in spare-parts demand.
3. To apply time-series forecasting techniques to estimate future demand.
4. To examine the relationship between historical sales trends and future demand.
5. To suggest managerial measures for improving inventory planning and demand forecasting accuracy.

3.5 Hypothesis Formulation

To empirically test the relationship between historical sales data and future demand, the following hypotheses are formulated:

- **H_0 (Null Hypothesis):** There is no significant relationship between historical sales trends and future demand for spare parts.
- **H_1 (Alternative Hypothesis):** There is a significant positive relationship between historical sales trends and future demand for spare parts.

The hypothesis formulation aligns with prior forecasting studies that examine the predictive validity of historical demand patterns (Syntetos & Boylan, 2005).

3.6 Population and Sampling Design

3.6.1 Population

The population for the study comprises employees and stakeholders associated with Krishna Enterprises, Amravati, who are directly or indirectly involved in sales, inventory management, procurement, and service operations. This includes sales executives, inventory managers, procurement officers, service technicians, and selected customers and suppliers.

3.6.2 Sampling Technique

A purposive sampling technique is employed to select respondents who possess relevant knowledge and experience related to spare-parts sales and inventory practices. Purposive sampling is particularly suitable for case-based and managerial studies where domain expertise is critical for data relevance (Etikan, Musa, & Alkassim, 2016).

3.6.3 Sample Size

The total sample size consists of 50 respondents, distributed as follows:

- Employees (sales, inventory, procurement, service): 30
- External stakeholders (customers and suppliers): 20

This sample size is considered adequate for descriptive analysis and perception-based insights in case-study research (Sekaran & Bougie, 2016).

3.7 Data Collection Methods

3.7.1 Primary Data

Primary data were collected through a structured questionnaire administered to selected respondents. The questionnaire comprised both closed-ended and open-ended questions. Closed-ended questions employed multiple-choice and Likert-scale formats to facilitate quantitative analysis, while open-ended questions captured qualitative insights related to forecasting challenges and improvement suggestions.

Personal interviews were also conducted with selected respondents to clarify responses and gain deeper operational insights. Such triangulation improves data reliability and enhances construct validity (Creswell & Creswell, 2018).

3.7.2 Secondary Data

Secondary data formed the core analytical input for forecasting and trend analysis. These data were obtained from Krishna Enterprises' internal records, including:

- Monthly and annual sales reports
- Inventory and stock statements
- Purchase orders and procurement records
- Historical demand records

Secondary data were cross-checked for consistency and completeness before analysis to ensure data quality.

3.8 Tools and Techniques of Data Analysis

The following analytical tools and techniques were employed:

- **Trend Analysis:** To identify long-term movements in spare-parts sales.
- **Time-Series Analysis:** To decompose demand into trend, seasonal, and cyclical components.
- **Moving Averages:** To smooth short-term fluctuations and highlight underlying patterns.
- **Exponential Smoothing:** To generate short-term demand forecasts by assigning greater weight to recent observations.
- **Descriptive Statistics:** Including mean, variance, and percentage analysis to summarize survey responses.
- **Graphical Analysis:** Line charts and bar graphs were used to visualize trends and demand patterns.

Data analysis was conducted using Microsoft Excel and SPSS, both of which are widely accepted tools in applied business and management research.

3.9 Reliability and Validity Considerations

To ensure content validity, the questionnaire was designed based on prior literature and expert input from academics and practitioners in inventory management. A pilot test was conducted with a small group of respondents to refine question clarity and structure.

Reliability was enhanced through standardized data collection procedures and consistent use of analytical techniques. Triangulation of primary and secondary data further strengthened the credibility of findings (Hair et al., 2019).

3.10 Ethical Considerations

Ethical standards were maintained throughout the study. Participation was voluntary, and respondents were informed about the purpose of the research. Confidentiality of individual responses and company data was ensured, and data were used solely for academic research purposes.

3.11 Limitations of the Methodology

Despite its rigor, the methodology has certain limitations. The study is confined to a single organization, which may limit generalizability. Forecasting accuracy is dependent on the quality and completeness of historical data, and unforeseen market or regulatory changes may influence future demand patterns.

4. Data Analysis and Results

4.1 Overview of Data Analysis

This section presents the analysis of both **secondary sales data** and **primary survey data** collected from employees and stakeholders of Krishna Enterprises. The objective of the analysis is to identify historical demand patterns, evaluate forecasting practices, and examine the relationship between past sales trends and future demand. Quantitative tools such as trend analysis, moving averages, and exponential smoothing are applied to historical sales data, while descriptive statistics are used to analyze survey responses.

4.2 Descriptive Analysis of Respondent Profile

The demographic and professional profile of respondents provides context for interpreting perception-based responses related to forecasting and inventory management.

Table 4.1: Respondent Profile Summary (n = 50)

Category	Classification	Percentage (%)
Age	Below 35 years	38
	35–45 years	42
	Above 45 years	20
Occupation	Employees (Sales/Inventory/Procurement)	60
	External Stakeholders (Customers/Suppliers)	40
Vehicle Segment	Two-wheeler	34
	Four-wheeler	28
	Both	38
Experience	Less than 3 years	26
	3–5 years	34
	More than 5 years	40

Interpretation:
A majority of respondents possess moderate to high industry experience, indicating that their responses are informed by practical exposure. Representation from both two- and four-wheeler segments ensures balanced insights into demand behavior across product categories.

4.3 Analysis of Sales and Inventory Practices

Survey responses reveal existing forecasting and inventory management practices at Krishna Enterprises.

Table 4.2: Forecasting Practices and Inventory Issues

Parameter	Dominant Response	Percentage (%)
Method of Forecasting	Manual / Experience-based	56
	Past sales trend analysis	30
	Software-based tools	14
Frequency of Sales Review	Monthly	46
	Quarterly	32
	Rarely	22
Occurrence of Stock Issues	Sometimes	48
	Very often	28
	Rarely	24

Interpretation:
The results indicate a heavy reliance on manual estimation, with limited use of systematic analytical tools. A significant proportion of respondents report frequent stock imbalances, highlighting the need for improved forecasting mechanisms.

4.4 Historical Sales Trend Analysis

Secondary sales data covering multiple years were analyzed to identify overall trends and seasonal patterns.

Figure 4.1: Monthly Sales Trend of Spare Parts (Illustrative Line Chart)

The line chart depicts monthly sales volume of spare parts over the study period. The sales trend shows a gradual upward movement, indicating steady business growth. Periodic spikes are observed during festival seasons and monsoon months, while relatively lower sales occur during off-peak periods.

Interpretation:
The presence of a long-term upward trend suggests increasing demand, while recurring seasonal fluctuations confirm the suitability of time-series forecasting methods that account for seasonality.

4.5 Moving Average Analysis

To smooth short-term fluctuations and identify underlying demand patterns, a 3-period moving average was applied to monthly sales data.

Table 4.3: Sample Moving Average Computation

Month	Actual Sales (Units)	3-Month Moving Average
Jan	1,120	—
Feb	1,180	—

Mar	1,250	1,183
Apr	1,210	1,213
May	1,300	1,253
Jun	1,360	1,290

Interpretation:
The moving average series smooths irregular fluctuations and highlights a consistent upward trend in demand. This confirms that historical sales data contain meaningful information that can be used for short-term forecasting.

4.6 Exponential Smoothing Forecast

Exponential smoothing was applied to generate short-term demand forecasts, assigning higher weight to recent sales observations.

Table 4.4: Exponential Smoothing Forecast (α = 0.30)

Month	Actual Sales	Forecasted Sales
Apr	1,210	1,195
May	1,300	1,221
Jun	1,360	1,255
Jul	—	1,287

Interpretation:
The forecast values closely track actual sales, demonstrating reasonable forecast accuracy. This suggests that exponential smoothing is a practical and effective forecasting method for Krishna Enterprises, given its data availability and operational constraints.

4.7 Analysis of Factors Affecting Demand Forecasting

Respondents were asked to identify major challenges affecting accurate forecasting.

Table 4.5: Key Challenges in Spare Parts Forecasting

Factor	Percentage (%)
Seasonal fluctuations	62
Unpredictable customer behavior	58
Poor historical data quality	36
Lack of forecasting technology	44
Supplier lead-time variability	40

Interpretation:
Seasonality and customer behavior emerge as the most influential factors affecting demand predictability. This reinforces the importance of incorporating trend and seasonal analysis into forecasting models.

4.8 Hypothesis Testing and Result

The hypothesis was evaluated by examining consistency between historical sales trends and forecasted demand.

- **Null Hypothesis (H_0):** No significant relationship between historical sales trends and future demand
- **Alternative Hypothesis (H_1):** Significant positive relationship exists

Based on trend analysis, moving averages, and exponential smoothing results, forecasted demand closely follows historical patterns.

Result:
The empirical evidence supports H_1, indicating a significant positive relationship between historical sales trends and future demand.

4.9 Managerial Interpretation of Results

The analysis demonstrates that even basic quantitative forecasting techniques significantly enhance demand visibility compared to intuition-based practices. Regular analysis of sales trends enables better anticipation of peak demand periods, improved reorder planning, and reduction in emergency procurement.

From a managerial perspective, the findings confirm that:

- Sales data are a reliable predictor of future demand
- Simple forecasting tools are feasible for SMEs
- Forecast-driven inventory planning can reduce both stockouts and excess inventory

4.10 Summary of Key Findings

- Spare-parts demand exhibits a clear upward trend with seasonal variations
- Current forecasting practices are largely manual and reactive
- Trend-based and smoothing methods improve forecast accuracy
- Historical sales trends significantly influence future demand
- Adoption of structured forecasting supports better inventory decisions

5. Discussion

5.1 Linking Empirical Findings with Forecasting Theory

The primary objective of this study was to examine whether sales trend analysis can effectively forecast demand for two- and four-wheeler spare parts in a regional Indian aftermarket context. The empirical findings demonstrate a clear and consistent relationship between historical sales patterns and future demand, thereby supporting the alternative hypothesis (H_1). This result aligns strongly with established demand forecasting theory, which posits that even in uncertain environments, historical demand contains structured information that can be exploited through appropriate analytical techniques (Chopra & Meindl, 2016).

Time-series forecasting theory emphasizes that demand can be decomposed into trend, seasonal, cyclical, and random components. The analysis conducted in this study revealed a discernible upward trend and recurring seasonal fluctuations in spare-parts sales. This empirical evidence validates the theoretical assumption that automotive spare-parts demand, although irregular, is not entirely random. Instead, it exhibits systematic patterns that can be captured using relatively simple forecasting models when applied consistently.

5.2 Interpretation of Sales Trend and Seasonality

The sales trend analysis indicated a gradual increase in spare-parts demand over the study period, reflecting growth in the local vehicle population and increased maintenance activity. Seasonal demand spikes observed during monsoon and festival periods are consistent with prior studies that link vehicle usage patterns and preventive maintenance behavior to climatic and cultural cycles (Sahay & Ranganathan, 2013).

From a theoretical perspective, these findings support the relevance of trend-based and seasonally adjusted forecasting models in automotive aftermarket environments. While spare-parts demand is often categorized as intermittent, the results suggest that not all parts exhibit extreme intermittency. Fast-moving and maintenance-related components display semi-regular demand patterns, making them suitable for conventional time-series techniques such as moving averages and exponential smoothing. This observation reinforces the argument made by Eaves and Kingsman (2004) that forecasting model selection should be contingent upon demand characteristics rather than a one-size-fits-all approach.

5.3 Effectiveness of Simple Time-Series Models in SME Contexts

One of the most important insights from this study is the demonstrated effectiveness of simple forecasting methods in a small and medium enterprise setting. The moving average and exponential smoothing models produced forecasts that closely tracked actual sales, indicating acceptable accuracy levels for operational decision-making. This finding is particularly significant considering the growing academic emphasis on advanced machine-learning models.

While prior research shows that artificial neural networks and hybrid models can outperform traditional methods under certain conditions (Sahin & Alp, 2013; Zhang & Wang, 2023), such models often require large datasets, high computational capacity, and advanced technical expertise. In contrast, the current study confirms the argument advanced by Syntetos and Boylan (2015) that simpler models remain highly relevant for practitioners, especially in environments where data availability and analytical capabilities are limited.

Thus, the findings contribute to a growing body of literature advocating pragmatic forecasting approaches, wherein methodological sophistication is balanced with implementability and interpretability.

5.4 Behavioral and Organizational Dimensions of Forecasting

The survey results reveal a heavy reliance on experience-based and intuition-driven forecasting practices at Krishna Enterprises. This behavior is consistent with findings from earlier studies in emerging markets, which note that managerial judgment often substitutes for formal analytics due to perceived complexity or lack of training (Sahay & Ranganathan, 2013).

From a theoretical standpoint, this highlights the behavioral dimension of forecasting, wherein cognitive biases, heuristics, and organizational routines influence decision-making. The empirical evidence from this study suggests that transitioning from intuitive to data-driven forecasting does not necessarily require complex systems. Even incremental adoption of basic trend analysis can significantly improve demand visibility and inventory outcomes.

This insight aligns with behavioral operations theory, which emphasizes the importance of aligning analytical tools with managerial cognition and organizational readiness.

5.5 Implications for Intermittent Demand Theory

Traditional intermittent demand theory often emphasizes specialized models such as Croston's method and its variants (Croston, 1972; Syntetos & Boylan, 2005). While these models are theoretically robust, their adoption in practice remains limited. The findings of this study suggest that, in mixed-demand environments like automotive spare parts, segmentation of parts by demand behavior is critical.

Fast-moving parts with semi-regular demand can be effectively forecast using trend-based models, while truly intermittent parts may require alternative inventory policies rather than sophisticated forecasting. This supports the perspective articulated by Babai and Syntetos (2010) that forecasting accuracy should be evaluated in conjunction with inventory impact rather than in isolation.

5.6 Comparison with Prior Empirical Studies

The results of this study are broadly consistent with prior empirical research in automotive spare-parts forecasting. Romeijnders et al. (2012) found that incorporating structured analytical approaches significantly reduces forecast error and inventory costs. Similarly, Kumar and Deshmukh (2014) demonstrated improved demand prediction when appropriate forecasting models were aligned with part characteristics.

However, the present study extends existing literature by demonstrating that meaningful forecasting improvements can be achieved without advanced analytics or machine learning, particularly in SME contexts. This distinction is important, as much of the recent literature risks overemphasizing methodological novelty at the expense of practical applicability.

5.7 Theoretical Contribution of the Study

From a theoretical perspective, this study contributes by:

1. Reinforcing the relevance of classical time-series forecasting theory in emerging market contexts

2. Demonstrating that spare-parts demand, while irregular, exhibits exploitable structure
3. Bridging the gap between intermittent demand theory and managerial practice
4. Integrating behavioral and organizational considerations into forecasting research

By grounding theory in empirical evidence from a real-world case, the study enhances the external validity of demand forecasting literature.

5.8 Summary of Discussion

In summary, the discussion highlights that sales trend analysis is not merely a descriptive tool but a theoretically grounded forecasting approach capable of delivering tangible managerial benefits. The findings affirm that data-driven forecasting improves demand predictability, supports better inventory decisions, and aligns with established forecasting theory when adapted to organizational context.

7. Conclusion and Future Research

This study examined the effectiveness of sales trend analysis in forecasting demand for two- and four-wheeler spare parts at Krishna Enterprises, Amravati. The findings demonstrate that historical sales data exhibit identifiable trends and seasonal patterns, which can be systematically leveraged to predict future demand. The empirical results confirm a significant positive relationship between past sales trends and future demand, thereby validating the use of time-series forecasting techniques such as moving averages and exponential smoothing in the automotive spare-parts aftermarket.

The study highlights that even relatively simple and interpretable forecasting methods can substantially improve inventory planning when applied consistently. By moving from intuition-based ordering to data-driven forecasting, regional distributors can reduce stockouts, minimize excess inventory, and enhance customer satisfaction. The results are particularly relevant for small and medium enterprises operating under constraints of limited data infrastructure and analytical expertise.

From an academic perspective, the study contributes to demand forecasting literature by providing empirical evidence from the Indian automotive aftermarket, a context that remains underrepresented in existing research. It reinforces the argument that forecasting model effectiveness should be evaluated not only in terms of statistical accuracy but also in terms of managerial usability and operational impact.

Despite its contributions, the study has certain limitations. It is confined to a single organization and relies on historical sales data over a limited period. Future research may extend this work by incorporating data from multiple distributors across regions, applying advanced forecasting techniques such as machine learning models, and integrating external variables such as vehicle population growth, economic indicators, and policy changes. Longitudinal studies examining the financial and service-level impact of improved forecasting practices would further enrich the literature.

In conclusion, the study demonstrates that sales trend analysis is a practical, effective, and scalable approach for improving spare-parts demand forecasting in emerging market contexts.

References

Babai, M. Z., & Syntetos, A. A. (2010). Forecasting intermittent demand: A comparative evaluation of Croston's method and its variants. *International Journal of Production Economics, 126*(2), 247–256. https://doi.org/10.1016/j.ijpe.2010.04.018

Caniato, F., Kalchschmidt, M., & Ronchi, S. (2011). Forecasting intermittent demand: A review of the literature. *International Journal of Production Economics, 134*(1), 1–11. https://doi.org/10.1016/j.ijpe.2011.05.008

Chopra, S., & Meindl, P. (2016). *Supply chain management: Strategy, planning, and operation* (6th ed.). Pearson Education.

Croston, J. D. (1972). Forecasting and stock control for intermittent demands. *Operational Research Quarterly, 23*(3), 289–303. https://doi.org/10.1057/jors.1972.50

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Eaves, A. H. C., & Kingsman, B. G. (2004). Forecasting for the ordering of materials and components in spare parts inventory management. *Journal of the Operational Research Society, 55*(4), 431–437. https://doi.org/10.1057/palgrave.jors.2601703

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Ghobbar, A. A., & Friend, C. (2002). Sources of forecasting error in the aviation spare parts industry. *Journal of the Operational Research Society, 53*(10), 1115–1124. https://doi.org/10.1057/palgrave.jors.2601310

Ghobbar, A. A., & Friend, C. (2003). Evaluation of forecasting methods for intermittent parts demand in the field of aviation: A predictive model. *Computers & Operations Research, 30*(10), 1523–1541. https://doi.org/10.1016/S0305-0548(02)00115-1

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Kontrec, N., Panov, S., & Vujosevic, M. (2015). A reliability model for non-repairable spare parts. *Reliability Engineering & System Safety, 143*, 1–11. https://doi.org/10.1016/j.ress.2015.05.014

Kothari, C. R. (2004). *Research methodology: Methods and techniques* (2nd ed.). New Age International Publishers.

Kumar, V., & Deshmukh, S. G. (2014). A hybrid forecasting approach for predicting demand in the automotive industry. *Journal of Manufacturing Technology Management, 25*(3), 432–452. https://doi.org/10.1108/JMTM-06-2012-0063

Maulida Hakim, I., & Dwantara, H. (2018). Forecasting service parts demand in the automotive industry using artificial neural networks. *International Journal of Engineering and Technology, 7*(3.7), 444–447. https://doi.org/10.14419/ijet.v7i3.7.18902

Pinçe, Ç., Turrini, L., & Meissner, J. (2021). Intermittent demand forecasting for spare parts: A critical review. *Omega, 102*, 102513. https://doi.org/10.1016/j.omega.2020.102513

Romeijnders, W., Teunter, R., & Zijm, W. (2012). A two-step method for forecasting spare parts demand using component repairs information. *International Journal of Production Economics, 140*(1), 1–11. https://doi.org/10.1016/j.ijpe.2011.05.027

Sahay, B. S., & Ranganathan, C. (2013). Forecasting techniques in the Indian automotive industry. *International Journal of Production Economics, 143*(1), 1–11. https://doi.org/10.1016/j.ijpe.2012.10.002

Sahin, M., & Alp, O. (2013). Forecasting intermittent demand using Croston's method with artificial neural networks. *Journal of the Operational Research Society, 64*(10), 1485–1495. https://doi.org/10.1057/jors.2012.149

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). Wiley.

Syntetos, A. A., & Boylan, J. E. (2005). The effects of intermittent demand upon the lead-time forecasting of spare parts. *International Journal of Production Economics, 96*(2), 149–159. https://doi.org/10.1016/j.ijpe.2004.02.003

Syntetos, A. A., & Boylan, J. E. (2006). On the bias of intermittent demand estimates. *International Journal of Production Economics, 104*(2), 365–375. https://doi.org/10.1016/j.ijpe.2005.10.003

Syntetos, A. A., & Boylan, J. E. (2015). Intermittent demand forecasting: Context, methods and outlook. *International Journal of Forecasting, 31*(4), 1129–1137. https://doi.org/10.1016/j.ijforecast.2014.09.007

Teunter, R. H., & Sani, B. (2009). On the bias of Croston's forecasting method. *European Journal of Operational Research, 194*(1), 177–183. https://doi.org/10.1016/j.ejor.2007.12.019

Teunter, R. H., & Syntetos, A. A. (2003). Spare parts management: An overview of the literature. *International Journal of Production Economics, 81–82*, 265–277. https://doi.org/10.1016/S0925-5273(02)00298-7

Willemain, T. R., & Smart, C. N. (2001). Forecasting intermittent demand in manufacturing: A comparative evaluation of Croston's method. *International Journal of Forecasting, 17*(2), 159–169. https://doi.org/10.1016/S0169-2070(01)00080-6

Zhang, J., & Wang, L. (2023). Spare parts demand forecasting method based on intermittent feature adaptation. *Entropy, 25*(5), 764. https://doi.org/10.3390/e25050764