A Study on Optimizing Supply Chain Resilience: Emergency Parts Ordering Analysis

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Abstract: This research addresses the issue of undeclared rejections leading to emergency parts ordering in the automotive supply chain, a critical factor disrupting production efficiency. Undeclared rejections, and defects found during production rather than initial inspections, contribute significantly to unexpected shortages. Using the Holt-Winters model, the study analyzes 15 months of data to predict rejection trends and identify the root causes of these disruptions. Statistical tools, including ANOVA and autocorrelation analysis, reveal management and handling issues as key contributors. The findings highlight the need for improved practices to enhance supply chain resilience, reduce emergency orders, and maintain operational stability.

Keywords*: Supply Chain Resilience, Undeclared Rejections, Emergency Parts Ordering, Holt-Winters Model, Root Cause Analysis.*

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I. INTRODUCTION

In today's fast-paced automotive industry, effective supply chain management is essential for ensuring production efficiency and customer satisfaction. Disruptions, such as delays and quality issues, can significantly impact operations, highlighting the need for supply chain resilience. This resilience refers to a system's ability to withstand and recover from unexpected disruptions, with emergency parts ordering being a critical concern.

Emergency parts ordering occurs when unforeseen shortages or defects, particularly undeclared rejections found after initial inspections, necessitate rapid procurement of materials. The manufacturing process involves several key stages, including stamping, welding, painting, assembly, and quality inspection. Any defects not caught early can disrupt production and lead to costly emergency orders due to expedited shipping and increased operational expenses.

This research focuses on understanding the impact of undeclared rejections on supply chain resilience, employing predictive models like the Holt-Winters method to analyze data collected over 15 months. The study aims to identify the root causes of emergency orders and provide insights for reducing their frequency while enhancing overall supply chain processes. By addressing the financial and operational implications of emergency parts ordering, the research seeks to establish strategies for optimizing costs and improving efficiency, ultimately contributing to a more resilient supply chain.

II. LITERATURE REVIEW

Ramakrishnan, Ramasamy, Dev Anand, & Santhi (2024) emphasised Supply Chain Management efficiency improvement in the Automobile industry using Lean Six Sigma and Artificial Neural Network. This study improves automotive supply chain efficiency by enhancing demand forecasting and product quality through Lean Six Sigma and reducing response times via Just-In-Time principles. The findings indicate that an Artificial Neural Network with optimization significantly boosts forecasting accuracy, reduces waste, and enhances customer satisfaction.

Narassima, Gedam, Gunasekaran, Anbuudayasankar, & Dwarakanath (2024) reported a novel Coexistent Resilience Index to Evaluate the Supply Chain Resilience of Industries Using Fuzzy Logic. This study introduces a Coexistent Resilience Index (CRI) to assess supply chain resilience in 37 organizations across 22 industries. It identifies 33 key resilience attributes,

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highlighting the significance of mutual learning and collaboration in enhancing overall supply chain resilience.

Keith, & Eunice (2023) reported an optimizing Inventory management through advanced forecasting techniques. This study examines the role of advanced forecasting methods in enhancing inventory management within global supply chains. It investigates their impact on performance, emphasizing improvements through real-time data and machine learning. The findings highlight significant benefits in demand prediction accuracy and cost reduction, providing actionable insights and policy recommendations for practitioners in the field.

Huang Kai, Wang, Jian Zhang, & Jinxin (2023) narrated automotive Supply Chain Disruption Risk Management: A Visualization Analysis Based on Bibliometric. This bibliometric analysis of 866 articles (2000-2022) identifies key trends, influential authors, and organizations in automotive supply chain disruption risk management. The study highlights the need for improved risk mitigation strategies and offers insights for future research in the field.

Gupta, Vijaygarg, & Sarkar (2022) studied a Bi-Objective integrated transportation and inventory management under a Supply Chain network considering multiple distribution networks. This research presents a model to minimize transportation and inventory costs in supply chains by optimizing order allocation from multiple sources. Employing a value function approach, it addresses multi-objective logistics challenges and offers insights into decision-making processes for improved supply chain efficiency.

Han, Yang, & Zhao (2021) examined joint optimization of inspection, maintenance, and spare ordering policy considering defective product loss. This study develops a cost-minimizing model for inspection, maintenance, and spare parts ordering in manufacturing systems facing defective product losses. It identifies optimal intervals for inspections and maintenance through simulation, demonstrating improved cost efficiency compared to existing approaches, thus offering insights for enhancing manufacturing efficiency.

Nallusamy (2021) analysed the performance measurement on inventory management and logistics through various forecasting techniques. This study evaluates inventory management and logistics in manufacturing, utilizing forecasting techniques to improve practices. Key findings emphasize the need for optimized inventory policies and address challenges related to vehicle capacity utilization (VCU), highlighting their critical role in enhancing manufacturing efficiency and competitiveness.

Tavukçu, & Sennaroğlu (2021) applied robust forecasting methods to reduce the cost of spare parts inventory in a Company. This research evaluates advanced forecasting methods, such as Holt-Winters and ARIMA, to enhance demand forecasting and lower inventory costs in a construction equipment company. The Holt-Winters method resulted in a 35% cost reduction, while ARIMA (1,0,0) achieved a 21% reduction, demonstrating the effectiveness of sophisticated forecasting techniques in minimizing inventory expenses and improving spare parts availability.

Jain, & Arora (2021) examined and analysed time series forecasting techniques for Indian Automotive Industry. This research evaluates nine forecasting models for vehicle demand in India, finding the Holt-Winters Linear Trend method to be the most accurate, with a MAPE of 8%. Other models like Exponential Smoothing and ARMA were less effective. The study highlights that precise forecasting can improve production planning and minimize overproduction costs.

Dhingra, Kumar, & Singh (2019) studied cost reduction and quality improvement through Lean Kaizen concept using Value Stream Map in Indian manufacturing firms. This study demonstrates how Lean-Kaizen principles and the Value Stream Map (VSM) can reduce costs and enhance quality in Indian SMEs in the gear sector. The implementation led to a notable reduction in quality rejection costs (approximately 1250 INR per day), highlighting the effectiveness of continuous improvement practices for operational excellence and competitiveness.

Vijayakumar, & Vennila (2016) attempted a comparative analysis of forecasting reservoir inflow using ARMA Model & Holt Winters Exponential smoothing technique. This study evaluates the effectiveness of the ARMA model versus the Holt-Winters Exponential Smoothing technique for forecasting inflow in the Krishnagiri Reservoir, Tamil Nadu. Findings indicate that the ARMA (2, 4) model fails to capture seasonal trends, while the additive seasonal Holt-Winters model offers superior accuracy, with an R^2 of 0.9659 and a mean error of 19.3%.

III. DATA AND METHODOLOGY

This research utilizes an analytical cross-sectional design to investigate emergency parts ordering and the root causes of undeclared rejections. Data is collected from primary sources through direct investigations and from secondary sources, including internal records on emergency orders and rejections. Key variables include emergency order quantity, declared rejections from inspections, and undeclared rejections from internal operations. Statistical tools employed include descriptive statistics for normality testing, one-way ANOVA for inferential analysis, correlogram for autocorrelation detection, the Augmented Dickey-Fuller test for unit root analysis, and the Holt-Winters Exponential Smoothing model for forecasting. The Holt-Winters method incorporates level, trend, and seasonality components to predict emergency parts ordering patterns.

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A. *Testable Hypotheses*

➢ *Hypothesis for Normality Test (Shapiro-Wilk Test)*

- Null Hypothesis (Ho): The data points for undeclared rejections are normally distributed for the given parts.
- Alternative Hypothesis (H1): The data points for undeclared rejections are not normally distributed for the given parts.

➢ *Hypothesis for Declared Rejections (Shapiro-Wilk Test)*

- Null Hypothesis (Ho): The data points for declared rejections are normally distributed for the given parts.
- Alternative Hypothesis (H1): The data points for declared rejections are not normally distributed for the given parts.

➢ *Hypothesis for One-Way ANOVA*

- Null Hypothesis (Ho): There is no significant difference between the mean scores of undeclared rejections and the mean scores of declared rejections for the given parts.
- Alternative Hypothesis (H1): There is a significant difference between the mean scores of undeclared rejections and the mean scores of declared rejections for the given parts.

➢ *Hypothesis for Correlogram*

- Null Hypothesis (Ho): There is no significant autocorrelation up to 10 lags for the given parts.
- Alternative Hypothesis (H1): There is significant autocorrelation up to 10 lags for the given parts.

➢ *Hypothesis for Unit Root Test (Augmented Dickey-Fuller Test)*

- Null Hypothesis (Ho): The received parts have a unit root, indicating non-stationarity.
- Alternative Hypothesis (H1): The received parts do not have a unit root, indicating stationarity.

B. *Limitations*

- Data confidentiality constraints
- Time limitations
- Data confined to a 15-month period

IV. DATA ANALYSIS AND INTERPRETATION

➢ *Analysis 1: Root Cause Analysis*

Table 1 Root Cause Analysis

KANBAN ID	LOCATION OF FITMENT	ROOT CAUSE
CK75	Bumper shop	Undeclared/ Late Rejection
CU07	Paint shop	Undeclared/ Late Rejection
IT69	Paint shop	Undeclared/ Late Rejection
IT43	Assembly	Handling issue
FT76	Assembly	Undeclared/ Late Rejection
1404	Weld	Undeclared/ Late Rejection
CD61	Assembly	Undeclared/ Late Rejection
CM66	Assembly	Undeclared/ Late Rejection
IG69	Assembly	Handling issue
IG58	Assembly	Handling issue

- Interpretation: The data reveals issues with components in various fitment locations, mainly classified as "Undeclared/ Late Rejection" and "Handling issue."

➢ *Analysis 2: Normality Test Summary*

Table 2 Normality Test Summary

PARTICULARS	UDR	DR
Number of parts whose H_o is rejected	9	4
Number of parts whose H_o is not rejected	1	2

- Interpretation: The UDR dataset shows deviations from normality in 9 parts, with only 1 part following a normal distribution. In contrast, the DR dataset displays non-normal patterns in 4 parts, while 2 parts align with normal distribution.

➢ *Analysis 3: Inferential Analysis*

Table 3 Inferential Analysis

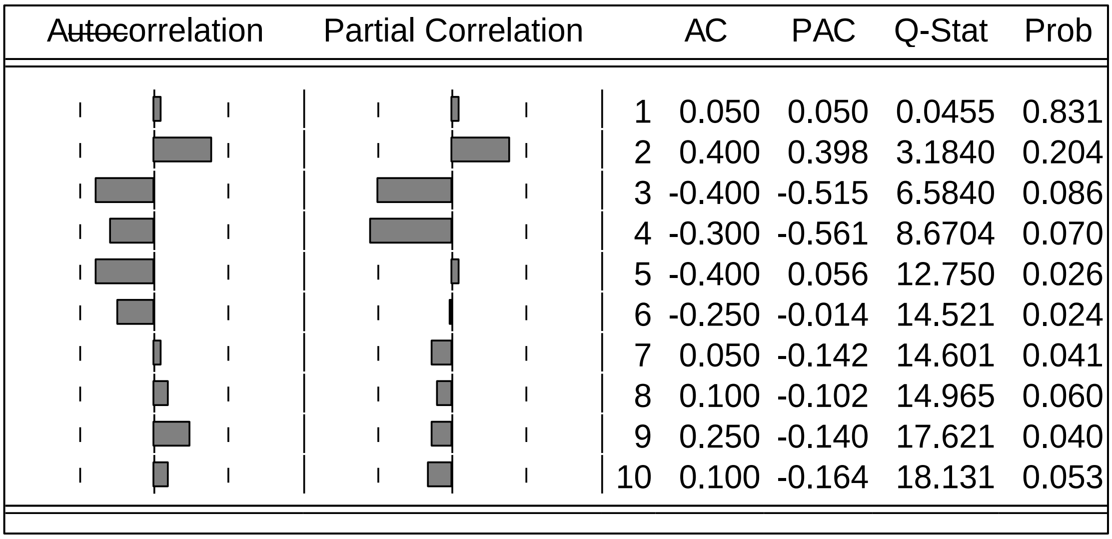
Kanban ID	df	F_c	p-value	Decision
CK75	1,28	8.4***	0.007	Reject
CU07	1,28	15.48***	< .001	Reject
IT69	1,28	10.5***	0.003	Reject
IT43	1,28	9.07***	0.005	Reject
FT76	1,28	20.01***	< .001	Reject
I404	1,28	2.88	0.101	Do not reject
CD61	1,28	2.06	0.162	Do not reject
CM66	1,28	1.02	0.321	Do not reject
IG69	1,28	2.5	0.125	Do not reject
IG58	1,28	2.23	0.147	Do not reject

Source: Researcher's own calculation,
*α: 0.01***, 0.05**, 0.1**

- Interpretation: The parts CK75, CU07, IT69, IT43, and FT76 show significant deviations with p-values below 0.05, leading to rejection of the null hypothesis. Conversely, parts I404, CD61, CM66, IG69, and IG58 do not show significant deviations, as their p-values are above 0.05, so the null hypothesis is not rejected.

➢ *Analysis 4: Autocorrelation For Kanban Id It69*

Table 4 Autocorrelation for Kanban Id It69



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.050	0.050	0.0455	0.831
		2	0.400	0.398	3.1840	0.204
		3	-0.400	-0.515	6.5840	0.086
		4	-0.300	-0.561	8.6704	0.070
		5	-0.400	0.056	12.750	0.026
		6	-0.250	-0.014	14.521	0.024
		7	0.050	-0.142	14.601	0.041
		8	0.100	-0.102	14.965	0.060
		9	0.250	-0.140	17.621	0.040
		10	0.100	-0.164	18.131	0.053

- Interpretation: The autocorrelation and partial autocorrelation plot show a significant pattern at Lag 5 (p = 0.026), indicating a repeating cycle every five intervals. Other lags, including Lag 2 (p = 0.204) and Lag 9 (p = 0.040), exhibit less consistent patterns, with Lag 9 approaching significance.

➢ *Analysis 5: Augmented Dickey-Fuller Test*
To analyze the stationarity and non-stationarity using unit root.

Table 5 Augmented Dickey-Fuller Test

Kanban ID	t- Statistic	P value	Decision
CD61	-2.4272	0.3482	Do not reject
CK75	-1.604	0.7339	Do not reject
CU07	0.5125	0.9959	Do not reject
CM66	-1.8952	0.5754	Do not reject
I404	-9.1687***	0.0003	Reject
IT69	-3.8764*	0.0543	Reject

IG69	2.1266	0.9999	Do not reject
IT43	-1.8224	0.6208	Do not reject
FT76	-1.8074	0.6217	Do not reject
IG58	-6.5647***	0.0007	Reject

Source: Researcher's own calculation
*α: 0.01***, 0.05**, 0.1**

- Interpretation: The unit root analysis shows that three Kanban IDs (I404, IT69, IG58) reject the null hypothesis of non-stationarity, indicating these series are stationary. For the remaining Kanban IDs, the null hypothesis is not rejected, implying non-stationarity in the data.

➢ *Analysis 6: Holt Winter Exponential Smoothing (Additive Model)*
Exponential smoothing of data related to undeclared rejections

Table 6 Holt Winter Exponential Smoothing (Additive Model)

Kanban ID	Level Value (α)	Trend Component (β)	Seasonality Component (γ)
CD61	0.560	1.000	0.120
CK75	0.000	0.000	0.100
CM66	0.000	0.000	0.100
CU07	0.890	0.120	0.100
FT76	0.000	0.000	0.100
I404	0.080	0.010	0.100
IG58	0.370	0.000	0.100
IG69	0.100	0.100	0.100
IT43	0.000	0.000	0.100
IT69	0.560	1.000	0.100

Source: Researcher's own calculation
*α: 0.01***, 0.05**, 0.1**

- Interpretation: The Holt-Winters Exponential Smoothing results show CD61, CU07, and IT69 have high level values (α), indicating fast response to new data. CD61 and IT69 also exhibit strong trends, while other parts show minimal or no trends and stable seasonality effects.

V. CONCLUSION

Managing emergency parts ordering requires addressing underlying challenges like undeclared rejections and operational inefficiencies. Statistical analyses revealed significant deviations from normal distribution in rejection patterns, highlighting the need for improved forecasting techniques. By implementing predictive models such as the Holt-Winters methodology, organizations can better anticipate future trends and mitigate disruptions. Addressing root causes like mismanagement, mishandling, and production inconsistencies through proactive strategies will enhance supply chain resilience, streamline production schedules, and ultimately lead to improved operational performance and customer satisfaction.

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