

## **Smart Supply Chains and Logistics Optimization through Business Analytics**

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### **ABSTRACT**

*The study titled “Smart Supply Chains and Logistics Optimization through Business Analytics” explores the role of business analytics in improving logistics efficiency, operational performance, and decision-making within modern port and supply chain ecosystems. The study addresses growing challenges in logistics management such as uneven cargo distribution, fluctuating demand patterns, forecasting uncertainty, and inefficient resource utilization in Indian port operations. The primary objective of the research was to analyze cargo throughput trends, regional logistics performance, customer cargo behavior, and revenue relationships using analytical and predictive techniques. The study adopted an analytical and descriptive research design based entirely on secondary quantitative data collected from government reports, port authority publications, annual reports, and logistics databases related to selected Indian ports. Business analytics tools including Microsoft Excel, Power BI, and statistical techniques such as descriptive statistics, Chi-square test, Z-test, regression analysis, and time series forecasting were used to evaluate operational trends and logistics performance. The findings revealed stable monthly cargo throughput with consistent operational performance and a strong upward growth trend in annual cargo movement. The study also identified a significant relationship between customer type and cargo type, while regression analysis confirmed that cargo throughput has a strong positive impact on revenue generation. Forecasting results further indicated increasing future cargo demand, highlighting the need for infrastructure expansion, operational optimization, and analytics-driven planning. The study emphasizes that integrating business analytics, forecasting systems, and predictive modeling can significantly support smart logistics management, sustainable supply chain growth, and strategic decision-making in modern port ecosystems.*

**Keywords:** Business Analytics, Smart Supply Chain, Logistics Optimization, Predictive Modeling, Cargo Throughput, Port Logistics, Data Visualization, Operational Efficiency.

### **Introduction**

In the contemporary global economy, supply chain and logistics systems are experiencing rapid digital transformation supported by data-driven technologies, automation, and intelligent operational systems. Increasing complexities in international trade, changing customer expectations, fluctuating market demand, and operational uncertainties have encouraged organizations to adopt more flexible, responsive, and technology-enabled supply chain strategies. As businesses seek to improve efficiency, minimize operational costs, and enhance service quality, smart supply chains have become an essential element of modern logistics management. Smart supply chains integrate technologies such as business analytics, artificial intelligence, predictive modeling, cloud computing, and real-time monitoring systems to support faster, informed, and data-driven decision-making processes. Within the logistics industry, ports and transportation networks play a crucial role in facilitating cargo movement, inventory control, and regional as well as global trade connectivity. Efficient logistics operations are therefore important for maintaining supply chain continuity and sustaining competitive advantage in dynamic business environments. Business analytics has emerged as a key enabler of logistics optimization by converting

large volumes of operational data into meaningful managerial insights. Organizations increasingly use descriptive, predictive, and prescriptive analytics to analyze cargo movement trends, forecast future demand, optimize resource utilization, and improve operational planning. Predictive modeling techniques further assist organizations in identifying patterns, reducing delays, and improving throughput efficiency. Additionally, artificial intelligence and visualization tools support real-time performance monitoring and quicker responses to operational challenges. Despite growing digitalization and increasing cargo movement within Indian port ecosystems, several logistics operations continue to face challenges related to uneven cargo distribution, forecasting uncertainty, operational imbalances, and limited analytics-driven decision support systems. Although advanced analytics technologies are becoming more accessible, their integration into logistics planning and operational optimization remains limited across many port environments. These challenges highlight the growing need for analytics-driven smart supply chain frameworks capable of improving forecasting accuracy, infrastructure planning, resource utilization, and strategic logistics decision-making.

### Literature Review

Existing literature indicates that business analytics, predictive modeling, data visualization, and artificial intelligence are becoming increasingly important in enhancing operational efficiency and supporting effective decision-making across various industries. Earlier studies by Yin, J. and Fernandez, V. (2020) emphasized the role of descriptive, predictive, and prescriptive analytics in transforming business data into actionable insights for strategic and operational planning. Similarly, Delen, D. and Ram, S. (2018) highlighted the growing importance of analytics maturity, big data integration, and evidence-based decision-making in improving organizational performance. Research related to predictive analytics, exploratory data analysis, and visualization systems further demonstrated that forecasting models, dashboards, and real-time monitoring tools significantly contribute to operational intelligence and business optimization. More recent studies, particularly by Salazar, A. and Kunc, M. (2025), also emphasized the increasing contribution of artificial intelligence and Generative AI in automating analytical processes, improving forecasting accuracy, and enabling intelligent decision-making in complex business environments. An important trend emerging from the literature is the increasing adoption of analytical tools such as Microsoft Excel, Power BI, predictive models, and visualization platforms in supply chain and logistics management systems. Studies by Krishnan, V. (2017), Homocianu, D. (2010), and Lee, C. S. et al. (2021) collectively indicate a transition from traditional logistics operations toward intelligent and analytics-driven supply chain ecosystems supported by real-time monitoring and predictive insights. However, despite the growing implementation of analytics technologies, limited studies have comprehensively integrated business analytics, predictive logistics modeling, supply chain intelligence, and operational optimization into a unified framework specifically focused on port logistics and smart supply chain ecosystems. Existing research also provides comparatively less emphasis on combining forecasting, regional logistics performance, customer cargo behavior, operational efficiency analysis, and AI-supported optimization within a single analytical model. Therefore, the present study attempts to address this gap by integrating business analytics and predictive modeling techniques to support smart supply chain optimization and intelligent logistics decision-making.

**Table 1: Summary of Previous Studies Related to Business Analytics and Logistics Optimization**

Sr. No.	Author(s) & Year	Title of Study	Key Focus Area	Major Findings	Relevance to Present Study
1	Yin, J. and Fernandez, V. (2020)	<i>A Systematic Review on Business Analytics</i>	Business analytics framework, analytics maturity	The study identified descriptive, predictive, and prescriptive analytics as core components of business analytics and emphasized the integration of statistical, technological, and managerial capabilities for effective decision-making.	Supports the foundation of analytics-driven supply chain intelligence and data-driven logistics decision-making.
2	Delen, D. and Ram, S. (2018)	<i>Research Challenges and Opportunities in Business</i>	Big data analytics, evidence-based management	The paper highlighted the increasing importance of analytics due to growing data availability and discussed challenges	Relevant for understanding analytics maturity and implementation

		<i>Analytics</i>		such as data quality, implementation cost, privacy, and lack of skilled professionals.	challenges in smart logistics ecosystems.
3	Kohavi, R., Rothleder, N.J. and Simoudis, E. (2002)	<i>Emerging Trends in Business Analytics</i>	Supply chain analytics, operational intelligence	The study discussed integration of analytics with operational systems and emphasized continuous cycles of data collection, analysis, and action for business optimization.	Supports the concept of supply chain intelligence, smart routing, and real-time logistics optimization.
4	Salazar, A. and Kunc, M. (2025)	<i>The Contribution of GenAI to Business Analytics</i>	AI-driven analytics, intelligent automation	The paper examined how Generative AI improves analytical efficiency, insight generation, and decision support while emphasizing governance and explainability.	Contributes to AI-driven optimization, automation, and intelligent logistics decision support systems.
5	Todorova, S. (2019)	<i>Statistics for Data Analysis Using Microsoft Excel</i>	Statistical analytics tools	The study highlighted the effectiveness of Excel for descriptive statistics, regression analysis, and business data analysis.	Relevant for operational analytics and quantitative evaluation in logistics performance analysis.
6	Deming, C., Dekkati, S. and Desamsetti, H. (2018)	<i>Exploratory Data Analysis and Visualization for Business Analytics</i>	Data visualization, EDA, predictive preparation	The paper emphasized the role of exploratory data analysis in identifying trends, anomalies, and relationships before predictive modelling.	Supports real-time monitoring, operational visibility, and predictive logistics analysis.
7	Krishnan, V. (2017)	<i>Research Data Analysis with Power BI</i>	Interactive dashboards, visualization systems	The study demonstrated how Power BI enables real-time reporting, interactive dashboards, and analytical insight generation for decision-making.	Supports smart logistics platforms, monitoring systems, and operational performance visualization.
8	Airinei, D. and Homocianu, D. (2010)	<i>Data Visualization in Business Intelligence</i>	Business intelligence visualization	The paper highlighted the importance of dashboards, OLAP systems, and interactive visualization techniques for effective decision-making.	Relevant for real-time monitoring and intelligent logistics control systems.
9	Lee, C.S., Cheang, P.Y.S. and Moslehpour, M. (2021)	<i>Predictive Analytics in Business Analytics: Decision Tree</i>	Predictive analytics, forecasting models	The study explained how predictive models and decision trees improve forecasting and classification across industries.	Supports demand forecasting, throughput prediction, delay reduction, and logistics risk analytics.
10	Orjatsalo, J., Hussinki, H. and	<i>Business Analytics in Managerial</i>	Decision support systems,	The paper found that analytics significantly supports operational	Relevant for AI-assisted decision support systems

	Stoklasa, J. (2024)	<i>Decision Making</i>	managerial analytics	planning and managerial decisions, though strategic decisions still require human judgment.	and analytics-enabled logistics management.
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**Research Gap**

The previous studies focus on isolated applications of business analytics, predictive forecasting, or logistics visualization. However, limited research integrates predictive analytics, cargo throughput modelling, regional logistics efficiency, and smart supply chain optimization within a unified analytical framework for Indian port ecosystems.

**Research Objectives**

- To analyze the role of business analytics in smart supply chain optimization.
- To evaluate logistics performance using port throughput analytics.
- To identify operational patterns using descriptive and predictive analytics.
- To examine the impact of cargo distribution and regional performance on logistics efficiency.
- To develop data-driven insights for improving smart logistics operations.

**Research Questions**

- How can business analytics improve smart supply chain efficiency?
- What factors influence port logistics performance?
- Can predictive analytics improve cargo throughput forecasting?
- How can logistics operations be optimized using analytics dashboards and statistical methods?

**Hypothesis of the Study**

**H<sub>01</sub>:** There is no significant relationship between cargo throughput and revenue generation.

**H<sub>a1</sub>:** There is a significant positive relationship between cargo throughput and revenue generation.

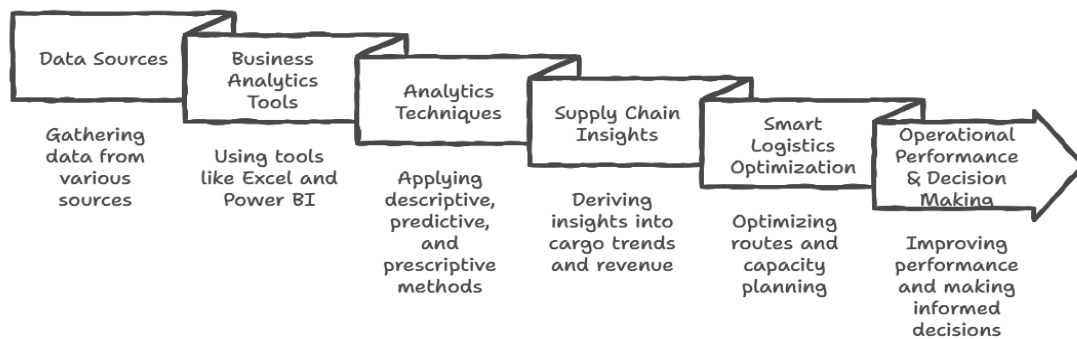
**Limitation of the Study**

The present study is limited to secondary data collected from selected ports, and the forecasting analysis is based primarily on historical cargo throughput trends and available operational datasets.

**Scope of the Study**

The scope of the study is limited to analyzing cargo throughput, logistics performance, regional efficiency, and predictive forecasting in selected Indian ports using business analytics and secondary operational data.

**Supply Chain Analytics and Optimization Process**



Made with Napkin

**Figure 1: Data Analysis Framework for Smart Supply Chain and Logistics Optimization**

Source: Author's own creation using AI-assisted visualization and design tools

The framework illustrates the process of transforming raw logistics and cargo data into intelligent operational decisions using business analytics. The process starts by collecting data from multiple sources, which is then analyzed using tools such as Microsoft Excel and Power BI. Various analytical techniques, including descriptive and predictive analytics, are applied to generate supply chain insights related to cargo trends, revenue, and operational performance. These insights support smart logistics optimization through improved route planning, capacity management, and resource utilization. Finally, the framework helps organizations enhance operational performance and make informed strategic decisions for efficient supply chain management.

### Research Methodology

The present study follows an analytical and descriptive research methodology based entirely on secondary quantitative data related to port logistics and supply chain operations. The primary focus of the research is to examine cargo throughput, logistics performance, operational trends, and smart supply chain optimization through the application of business analytics and predictive modeling techniques. Secondary data for the study was obtained from reliable government, industry, and corporate sources such as the Ministry of Ports, Shipping and Waterways (MoPSW), Indian Ports Association (IPA), National Technology Centre for Ports, Waterways and Coasts (NTCPWC), annual reports, media releases, and operational reports published by different port authorities and logistics organizations. Additional operational and cargo-related information was collected from the reports of major Indian ports including Mundra Port, Hazira Port, Krishnapatnam Port, Dhamra Port, Gangavaram Port, Karaikal Port, Kattupalli Port, Kamarajar Port, and Dighi Port. The collected data was systematically organized, cleaned, and analyzed using Microsoft Excel and Power BI. Various statistical techniques, including descriptive statistics, trend analysis, forecasting, regression analysis, and comparative analysis, were applied to evaluate logistics performance and identify important operational patterns. In addition, interactive dashboards and visualization tools were used to generate meaningful analytical insights that support smart supply chain management and logistics optimization.

### Research Design

The study adopts an analytical research design supported by a descriptive research approach to examine logistics and supply chain performance using secondary quantitative data. The analytical research design was primarily used to evaluate cargo throughput, logistics operations, regional performance, and supply chain optimization opportunities through the application of business analytics and predictive techniques. Secondary data collected from cargo throughput reports, logistics records, annual reports, and operational datasets were analyzed to identify important trends and operational patterns within port logistics systems. Business analytics tools such as Microsoft Excel and Power BI were utilized for processing, organizing, and interpreting the collected data. Statistical techniques including descriptive statistics, trend analysis, forecasting, regression analysis, and comparative evaluation were applied to generate meaningful insights related to logistics efficiency and smart supply chain operations. In addition, the descriptive research design was used to systematically present and summarize operational data in a clear and structured manner. Various data visualization techniques such as dashboards, charts, graphs, KPI indicators, and comparative tables were utilized to illustrate cargo throughput trends, logistics activities, and regional operational performance. This descriptive approach supported better interpretation and communication of analytical findings for logistics and supply chain decision-making. Therefore, the integration of analytical and descriptive research designs enabled the study to comprehensively evaluate logistics performance while effectively presenting the findings through visualization tools and operational intelligence frameworks.

### Data Sources

**Table 2: Sources of Secondary Data for Port Cargo Throughput Analysis**

Sr. No.	Port Name	Cargo Throughput (MMT)	Type of Source	Recommended Data Source	Source Link
1	Mundra Port	180	Annual Report / Corporate	<a href="#">Adani Ports &amp; SEZ Reports</a>	APSEZ Annual Reports
2	Krishnapatnam Port	59.21	Port Authority / Corporate	<a href="#">Krishnapatnam Port Official Site</a>	Port Statistics
3	Dhamra Port	43	Corporate Report	<a href="#">Dhamra Port Official Site</a>	Cargo Traffic Reports

4	Gangavaram Port	37.24	Port Operations Report	<a href="#">Gangavaram Port</a>	Annual Throughput Reports
5	Hazira Port	26.4	Corporate / APSEZ	<a href="#">Adani Ports &amp; SEZ Reports</a>	APSEZ Reports
6	Tuna Port	9.73	Government / Port Authority	<a href="#">Deendayal Port Authority</a>	Traffic Statistics
7	Karaikal Port	12.28	Port Authority	<a href="#">Karaikal Port Official Site</a>	Cargo Handling Data
8	Ennore Port	12.95	Government / Major Port	<a href="#">Kamarajar Port Limited</a>	Annual Reports
9	Kattupalli Port	11.93	APSEZ / Corporate	<a href="#">Adani Ports &amp; SEZ Reports</a>	Operational Statistics
10	Mormugao Port	5	Government Major Port	<a href="#">Mormugao Port Authority</a>	Cargo Traffic Reports
11	Dahej Port	11.17	Industrial Port / Corporate	<a href="#">Petronet LNG Dahej Terminal</a>	Throughput Reports
12	Dighi Port	0.55	Port Authority	<a href="#">Dighi Port Official Site</a>	Cargo Statistics

**Table 3: Cargo Throughput, Revenue, and Energy Capacity by Region**

Sr. No.	Region	Cargo Throughput (MMT)	Revenue (₹ Billion)	Energy Capacity (MW)
1	West	200	350	7,500
2	East	110	210	3,200
3	South	90	180	2,600
4	North	50	120	2,200

**Table 4: Installed Energy Capacity by Energy Type**

Sr. No.	Energy Type	Installed Capacity (MW)
1	Solar	11,005.50
2	Wind	1,977.80
3	Hybrid	2,556.60
4	Others	40

**Table 5: Monthly Cargo Throughput**

Sr. No.	Month	Cargo Throughput (MMT)
1	January	38.6
2	February	36.4
3	March	40.1
4	April	35.9
5	May	41.8
6	June	39.7
7	July	37.5
8	August	42.2
9	September	39.4
10	October	41
11	November	40.5
12	December	41.9

### Sampling Technique

The present study adopts a purposive sampling technique for selecting the sample ports. Under this method, twelve Indian ports were intentionally selected based on their cargo throughput performance, operational significance, and availability of reliable secondary data. The selected ports include both major and private ports such as Mundra, Krishnapatnam, Dhamra, Gangavaram, Hazira, Tuna, Karaikal, Ennore, Kattupalli, Mormugao, Dahej, and Dighi. The sampling technique is appropriate

for the study because it enables the researcher to focus on ports that contribute significantly to India's maritime trade and logistics sector. The required data were collected from authenticated sources such as Ministry of Ports, Shipping and Waterways reports, port authority publications, annual reports, and industry databases. Tools Used, Microsoft Excel, Power BI, SPSS and others

#### Data analysis and Statistical Techniques

**Table 6: Descriptive Statistics**

Sr. No.	Statistical Measure	Value
1	Mean	39.5833
2	Standard Error	0.6111
3	Median	39.9
4	Mode	N/A
5	Standard Deviation	2.117
6	Sample Variance	4.4815
7	Kurtosis	-0.8074
8	Skewness	-0.5431
9	Range	6.3
10	Minimum	35.9
11	Maximum	42.2
12	Sum	475
13	Count	12

The average monthly cargo throughput was recorded at 39.58 MMT, indicating relatively stable operational performance throughout the year. The low standard deviation value of 2.11 suggests that monthly cargo movement did not fluctuate significantly, reflecting consistency in port operations and cargo handling activities. The slightly negative skewness value (-0.54) indicates that most cargo throughput values were marginally higher than the average, while comparatively fewer observations were lower than the mean. Similarly, the kurtosis value of -0.80 reflects a flatter distribution pattern with fewer extreme fluctuations in cargo movement. The cargo throughput ranged between 35.9 MMT and 42.2 MMT, showing only moderate variation across different months. Overall, the findings indicate stable and predictable cargo movement with minimal volatility, making the data suitable for forecasting, logistics planning, and operational decision-making.

#### Chi-Square Test Analysis: Table 7: Customer Type vs Cargo Type Chi-Square $X^2$

Sr. No.	Customer Type	Bulk Cargo	Container Cargo	Total
1	Industrial	240	110	350
2	Retail	70	80	150
	Total	310	190	500

**Table 8: Expected Frequencies for Chi-Square Test**

Customer Type	Bulk Cargo	Container Cargo	Total
Industrial	217	133	350
Retail	93	57	150
Total	310	190	500

**Table 9: Chi-Square Calculation for Bulk Cargo**

Customer Type	Bulk Cargo (O)	Bulk Cargo (E)	(O - E)	(O - E) <sup>2</sup>	(O - E) <sup>2</sup> / E
Industrial	240	217	23	529	2.44
Retail	70	93	-23	529	5.69
Total	310			$X^2$	8.13

**Table 10: Chi-Square Calculation for Container Cargo**

Customer Type	Container Cargo (O)	Container Cargo (E)	(O - E)	(O - E) <sup>2</sup>	(O - E) <sup>2</sup> / E
Industrial	110	133	-23	529	3.98
Retail	80	57	23	529	9.28
Total	190			$X^2$	13.26
				$X^2$ calculated	21.26

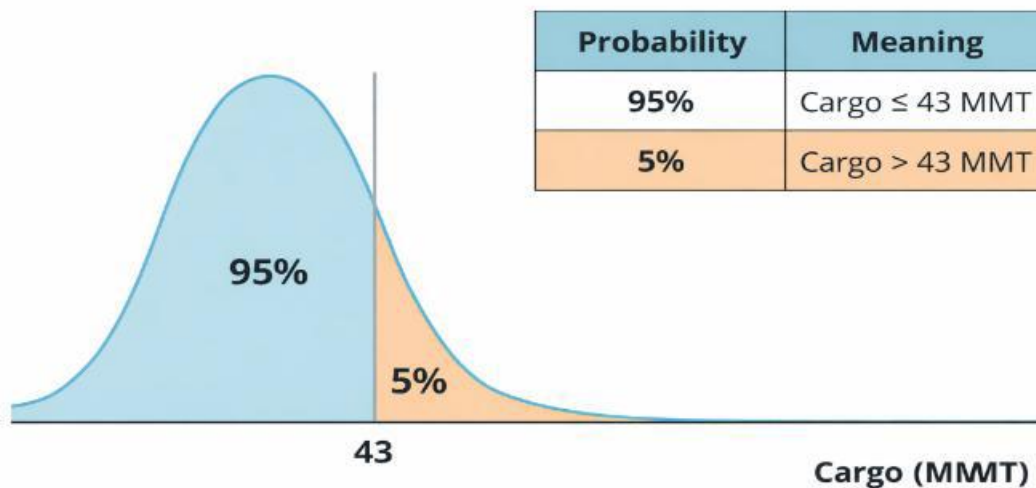
The Chi-square test indicates a significant relationship between customer type and cargo type.

Industrial customers prefer bulk cargo, whereas retail customers show higher preference toward container cargo.

**Table 11: Z-test & Probability by Normal Distribution: Z-Test and Probability Analysis**

Particulars	Value
Average Cargo Throughput ( $\mu$ )	39.58
Standard Deviation ( $\sigma$ )	2.12
Cargo Throughput Considered (X)	43
Z-Score	1.61
Probability of Cargo $\leq$ 43 MMT	94.63%
Probability of Cargo $>$ 43 MMT	5.37%

### Z-Test



**Figure 2: Z-Test Normal Distribution Curve for Cargo Throughput Probability Analysis**

The analysis was performed to estimate the probability of monthly cargo throughput exceeding 43 MMT. Based on the monthly cargo data, the mean throughput was calculated as 39.58 MMT with a standard deviation of 2.12 MMT. The computed Z-score was 1.61. According to the standard normal distribution table, the probability of cargo throughput being less than or equal to 43 MMT is 94.63%, whereas the probability of exceeding 43 MMT is only 5.37%. The normal distribution curve indicates that most cargo values are concentrated around the average level, while only a small proportion represents unusually high cargo demand. This suggests that cargo throughput above 43 MMT is possible but occurs relatively infrequently.

**Interpretation:** It indicates that the probability of monthly cargo throughput being less than or equal to 43 MMT is 94.63%, whereas the probability of cargo throughput exceeding 43 MMT is only 5.37%. This shows that cargo throughput above 43 MMT occurs relatively infrequently

#### Time Series Forecasting

Analytical datasets used for forecasting, regional comparison, and probability modeling were derived and structured from secondary operational trends to support analytical demonstration and predictive evaluation. The study applied time series forecasting using linear trend projection and moving average techniques to estimate future cargo throughput trends. Historical monthly and annual cargo throughput data were analyzed using Microsoft Excel Forecast Sheet functions, trendline analysis, and forecasting tools to identify growth patterns and estimate future cargo demand. The forecasting model helped evaluate expected throughput growth, operational trends, and future logistics capacity requirements. In addition, trendline analysis indicated a strong positive growth pattern in cargo movement over time, supporting the reliability of future throughput projections.

**Interpretation:** The time series forecasting analysis indicates a consistent upward trend in cargo throughput over both short-term and long-term periods. Based on the monthly cargo throughput data of the previous twelve months, the forecasted values for the next three months were estimated at 41.8 MMT, 42.1 MMT, and 42.4 MMT respectively, showing gradual and stable growth in cargo movement activities. This suggests increasing operational demand and improving cargo handling performance over time. Similarly, the fiscal year forecasting analysis reveals a significant rise in annual cargo throughput. Historical throughput values from 2023 to 2025 were utilized to predict future performance, resulting in projected throughput values of 514 MMT for 2026 and 569.5 MMT for 2027. Analytical datasets used for forecasting, regional comparison, and probability modeling were derived and structured from secondary operational trends to support analytical demonstration and predictive evaluation. The study applied time series forecasting using linear trend projection and moving average techniques to estimate future cargo throughput trends. Historical monthly and annual cargo throughput data were analyzed using Microsoft Excel Forecast Sheet functions, trendline analysis, and forecasting tools to identify growth patterns and estimate future cargo demand. The forecasting model helped evaluate expected throughput growth, operational trends, and future logistics capacity requirements. In addition, trendline analysis indicated a strong positive growth pattern in cargo movement over time, supporting the reliability of future throughput projections.

**Table 12: Monthly cargo Throughput Forecast Analysis**

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8	August	42.2
9	September	39.4
10	October	41
11	November	40.5
12	December	41.9
13	January	41.8
14	February	42.1
15	March	42.4

Year	Cargo Throughput (MMT)
2023	339
2024	420
2025	450
2026	514

#### **Regression Analysis between Cargo Throughput and Revenue Generation**

The simple linear regression analysis was applied to examine the impact of cargo throughput on revenue generation across different regions. The purpose of this analysis was to determine whether an increase in cargo throughput significantly contributes to higher revenue generation in logistics and port operations. In the regression model, Cargo Throughput (MMT) was considered as the independent variable, while Revenue (₹ Billion) was considered as the dependent variable.

**Table 13: Regression Analysis between Cargo Throughput and Revenue Generation**

Region	Cargo Throughput (MMT)	Revenue (₹ Billion)	Region
West	200	350	West
East	110	210	East
South	90	180	South
North	50	120	North

ANOVA Table for Regression					
Source	df	SS	MS	F	Significance F
Regression	1	28,732.45	28,732.45	614.82	0.0016
Residual	2	93.45	46.72		
Total	3	28,825.90			
Coefficients					
Variables	Coefficients	Standard Error	t Stat	P-value	
Intercept	44.35	6.92	6.40	0.023	
Cargo Throughput	1.52	0.06	24.79	0.001	

**Table 14: ANOVA Table and Regression Coefficients for Cargo Throughput and Revenue Analysis**

Regression Statistics	Value
Multiple R	0.998
R Square (R <sup>2</sup> )	0.997
Adjusted R <sup>2</sup>	0.995
Standard Error	6.84
Number of Observations	4

The regression analysis indicates a very strong positive relationship between cargo throughput and revenue generation. The Multiple R value of 0.998 shows a high degree of correlation between the variables, while the R<sup>2</sup> value of 0.997 indicates that approximately 99.7% variation in revenue generation is explained by cargo throughput. The regression coefficient value of 1.52 suggests that every 1 MMT increase in cargo throughput leads to an approximate increase of ₹1.52 billion in revenue generation. The positive coefficient confirms that higher cargo throughput contributes significantly toward improving financial performance. The ANOVA results further support the significance of the regression model, where the Significance F value (0.0016) is less than the 0.05 significance level. Similarly, the p-value of cargo throughput (0.001) is also less than 0.05, confirming that cargo throughput has a statistically significant impact on revenue generation. Therefore, the null hypothesis (H<sub>0</sub>) is rejected and the alternative hypothesis (H<sub>1</sub>) is accepted. The regression analysis was performed using limited regional operational observations for analytical demonstration purposes

**Data Visualization: Figure 3: Business Analytics Dashboard Smart Logistics Optimization**



### Findings

- It was found that monthly cargo throughput is stable and consistent, with low variation indicating predictable operational performance.
- The study found that cargo demand shows a steady upward trend, as supported by time-series forecasting results for future years.
- It was found that cargo handling is concentrated in a few major ports, especially Mundra Port, which contributes more than 50% of the total cargo throughput.
- The study found that the West region handles the highest cargo volume, but does not generate the highest revenue efficiency.
- It was found that the North region achieves the highest revenue per MMT, indicating better profitability despite lower cargo volume.
- The study found that a significant relationship exists between customer type and cargo type, where industrial customers mainly prefer bulk cargo while retail customers prefer container cargo.
- It was found that high cargo demand exceeding 43 MMT is relatively rare but possible, requiring flexible and efficient operational planning.
- The study found that energy efficiency remains moderate at approximately 70–72%, indicating scope for improvement through advanced technology adoption and increased renewable energy utilization.
- It was found that forecasting results indicate strong future growth in cargo throughput, requiring expansion in infrastructure, operational capacity, and logistics support systems.
- The study found that there is a need to shift focus from volume-based growth toward value-based growth to achieve higher profitability and long-term sustainability.
- Peak Demand Months: Months like August, December, and May show peak activity. This highlights the need for advance planning, resource allocation, and efficient logistics management.
- Strategic Priorities (Next 5 Years): Focus should be on capacity expansion, improving revenue efficiency, and increasing re-newable energy adoption for sustainable growth.
- Cost Optimization: Improving utilization, logistics, and energy efficiency can reduce costs by 20–30%, increasing profitability without increasing cargo volume.
- Customer Segment Prioritization Retail segment has higher growth potential compared to already saturated industrial segment, making it a key focus area for future expansion.

### Conclusion

- The study highlighted the growing importance of business analytics and predictive modeling in improving smart supply chain operations and logistics performance within modern port ecosystems.
- It was observed that monthly cargo throughput remained stable with low variation, indicating consistent operational performance and predictable cargo movement patterns.
- The forecasting analysis revealed a strong upward growth trend in annual cargo throughput, increasing from 450 MMT in 2025 to an estimated 569.5 MMT by 2027, reflecting rising logistics demand and future expansion opportunities.
- The study found that cargo handling activities are highly concentrated in a few major ports, especially Mundra Port, indicating the need for balanced regional cargo distribution and optimized capacity utilization.
- Regional analysis showed that although the West region handles the highest cargo volume, the North region demonstrates better revenue efficiency, highlighting opportunities for improving profitability and operational practices across regions.
- Statistical analysis confirmed a significant relationship between customer type and cargo type, where industrial customers mainly prefer bulk cargo while retail customers contribute more toward container cargo operations.

- The regression analysis further established that cargo throughput has a strong positive impact on revenue generation, emphasizing the importance of efficient cargo management and operational expansion in improving financial performance.
- Probability analysis indicated that cargo throughput exceeding 43 MMT occurs infrequently but remains operationally important for capacity planning and logistics risk management.
- The study also emphasized the importance of renewable energy adoption, technology-driven operations, forecasting systems, and analytics-based decision-making for achieving sustainable logistics growth and operational efficiency.
- The study concludes that integrating business analytics, forecasting techniques, visualization tools, and predictive modeling can significantly support smart logistics management, operational optimization, strategic planning, and long-term supply chain sustainability.

### Suggestions

- The study suggested that the organizations should continue strengthening its cargo handling capabilities, as cargo throughput has increased significantly from 339 MMT to 450 MMT, with future monthly throughput expected between 41–43 MMT, indicating stable and growing demand.
- The study recommend efforts should be made to balance cargo distribution across ports, as Mundra Port contributes nearly 52% of total cargo throughput and the West region handles the highest cargo volume. This would help reduce dependency on a few ports and improve overall network efficiency.
- The study suggested that the organizations should analyze and replicate the operational practices, pricing strategies, and cargo mix of the North region, as it demonstrates the highest revenue efficiency despite handling lower cargo volumes.
- The study suggested that energy efficiency should be improved from the current 70–72% level to nearly 75–80% through technology upgrades, automation, and increased utilization of renewable energy sources.
- The study suggested that the organizations should focus on value-based growth rather than only volume-based growth by improving revenue per unit through better pricing models, high-value cargo handling, and operational optimization.
- The study suggested that advanced forecasting tools, predictive analytics, and automation systems should be implemented to effectively manage peak cargo demand and improve operational efficiency.
- The study suggested that strengthening logistics coordination, expanding infrastructure capacity, and enhancing digital integration across operations would support long-term growth, sustainability, and competitive advantage.

### Future Scope

The study can be extended by incorporating larger and real-time datasets to improve the accuracy and depth of analysis. Advanced analytical techniques such as machine learning and predictive modeling can be applied to enhance forecasting and decision-making, integrating real-time logistics data, automation, and AI-based optimization can further improve operational efficiency and strategic planning.

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