Risk Quantification and management in Retail Warehouse Logistics through Evidence from Transport System Data

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In partial fulfillment of the Requirements for the Degree of

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in

Industrial Engineering and Management

by

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I, **R. Dushyanth,** hereby certify that the work which is being presented in The thesis entitled **"Risk Quantification and management in Retail Warehouse Logistics through Evidence from Transport System Data"** in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Mechanical Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from 2022 to 2024 under supervision of **Dr. K. Srinivas**, Assistant Professor, Department of Mechanical Engineering, Delhi Technological University, Delhi.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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Certified that **R. Dushyanth (**23/IEM/04) has carried out the research work presented in this thesis entitled **"Risk Quantification and management in Retail Warehouse Logistics through Evidence from Transport System Data"** for the award of **Master of Technology** from Department of Mechanical Engineering, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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Risk Quantification and Management in Retail Warehouse Logistics through Evidence from Transport System Data

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Abstract

In today's crowded and speedy retail environment, a dependable way of moving goods is essential to satisfy customers and run the business well. Many uncertainties like delays from traffic jams, broken-down vehicles, bad weather and workers' mistakes can interrupt and slow down the movement of transportation networks. If a warehouse sends items to various stores, small problems may negatively affect the entire supply chain and harm the business..

The thesis shows how to spot, measure, cut down and oversee risks in the Transport Management System (TMS) of a retail warehouse. Thanks to real transportation data from a retail company, the study finds that the performance of deliveries is largely determined by features like the chosen delivery vehicle, how much experience the driver has, the shipment value, traffic situations, the sensitivity of cargo and any problems during delivery. Since these factors are uncertain, a Monte Carlo simulation model was built by using Microsoft Excel. It examines various scenarios to find out every potential risk and its likelihood. With the study, it is easier to understand what leads to major delays and reveals how often such issues as late deliveries, breakdowns or financial losses will happen—which are all helpful for improving the reliability of our transportation systems.

As a result of the simulation, using tools for fleet assignment, scheduling and route planning are encouraged to guard against unforeseen risks. The conclusions of this study provide a cheap tool for practitioners built in Excel which contributes both academically and in practice to the area of logistics risk management. In summary, using simulation along with specially designed risk management principles in retail logistics, the findings of this thesis can easily be implemented in real life. The study gives decision-makers suggestions for making the retail supply chain more reliable, certain and able to withstand tough situations.

Keywords- logistics risk management, Monte carlo simulation

S. No.	Table of Contents	Page No.
1	Introduction	
	• 1.1 Background	3
	• 1.2 Problem Statement	3
	• 1.3 Research Objectives	4
	• 1.4 Scope of the Study	4
	• 1.5 Significance of the Study	4
	• 1.6 Research Gap	6
2	Literature Review	7
3	Data Collection	
	• 3.1 Data Source	20
	• 3.2 Description of Key Data-fields	20
	• 3.3 Data Preparation and Transformation	21
4	Methodology	
	• 4.1 Monte Carlo Simulation for Risk management	23
	• 4.2 Outline	24
	• 4.3 Data Preparation	24
	• 4.4 Travel Time Prediction Modelling	25
	• 4.5 Monte Carlo Simulation for Risk Modelling	25
5	Results and Analysis	
	• 5.1 Description of the Random Number Usage	29
	• 5.2 Description: How Hours Are Generated in the Monte Carlo Simulation Table	30
	• 5.3 Description of the SORT Function Usage in Monte Carlo Simulation	30
	• 5.4 Description of Probable Delivery Days	31
	• 5.5 Description: Rationale and Use of Random Values in 10,000 Monte Carlo Simulations	31
	• 5.6 Tail Risk Analysis Using Value at Risk (VaR) and Conditional Value at Risk (CVaR)	32
	• 5.7 VaR Calculation	33
	• 5.8 CVaR Calculation	33
	• 5.9 Histogram Generation and Interpretation in Monte Carlo Simulation	35
	• 5.10 Interpretation of Scatter Plot: Distance vs Days	36
6	Risk Mitigation Strategies	51
7	Risk Management Strategies	52
8	Conclusion and Future scope	53
9	References	56
10	List of figures	59
11	List of Tables	60

1. Introduction

1.1 Background

Omnichannel shipping options, high levels of competition and demanded by consumers are speeding up the global retail sector's changes. How responsive and efficient supply chains are largely depends on transportation these days. Most of the time, retail warehouses act as the center for stocking and transporting products to various stores. How effectively the Transport Management System (TMS) handles scheduling, routing, dispatching and delivery matters a lot for the company's operation.

There are many threats and possibilities of change that can cause difficulties in transport and delay the shipment of goods. The biggest challenges include slow traffic, some bad things happening with the weather, problems with vehicles and equipment, a rise in fuel expenses, a shortage of drivers and delays in activities like loading and unloading. As a result, consumers may not receive their products by the planned time, shops might be short on supplies and companies end up spending more money in retail, as having a quick service is very significant there.

While businesses usually focus on warehousing and inventory, transport continues to be at risk from outside and unpredictable effects. Having a good risk management strategy is important to keep the supply chain working smoothly at all times.

New studies in supply chain and logistics point out that using intelligent solutions, predictive models and simulations can help deal with such problems. Many researchers prefer to use Monte Carlo simulation. The system simulates various scenarios and outcomes by analyzing data and values that may cause unpredictability. Thanks to these assessments, it is easier for decision-makers to calculate the chances of a risk and the possible consequences.

1.2 Problem Statement

Even though TMS are being widely used in retail to oversee transportation, few companies manage to link these systems with risk analysis techniques. In most cases, companies depend on basic assessments or fixed schemes that fail to include the unexpected issues in transport. For major operations, one small issue or failure in delivery can have a huge effect and disrupt other parts of the supply chain.

Although studying and using Monte Carlo simulation in academia as well as in some industries is popular, its adoption in retail logistics—specifically in less-resourced or smaller firms—is still rare because practitioners often find it too complicated and there are no simple methods to use it.

Thus, it is clear that a planned yet helpful approach is needed for enterprises to use transport data to simulate, measure and lower the risks involved in their operations. Specifically, Monte Carlo simulation and Microsoft Excel are chosen here to develop a risk management framework so that logistics specialists can benefit from this approach.

1.3 Research Objectives

This study's main goal is to create a framework for addressing transport-related risks in a retail warehouse setting using simulation. The study specifically aims to:

- Use actual TMS data to identify the key risk variables related to transport operations. Based on their characteristics and effects, group these risk variables into operational, environmental, human, and financial categories.
- To evaluate the overall risk exposure, create an Excel Monte Carlo simulation model that takes these factors into account.
- Calculate the likelihood of major risk events including cargo loss, delivery delays, and higher fuel expenses.
- Using the information gleaned from the simulation model, suggest focused risk mitigation techniques.

1.4 Scope of the Study

The investigation was set up using data recorded at the warehouse that ships merchandise to multiple stores. In the dataset, there is information on the time it takes to dispatch the cargo, the actual arrival time, how often the vehicles break down, road conditions, weather conditions, the monetary value of what is carried, how fuel is used and the driver's level of experience. The program used for the simulation is Microsoft Excel and it creates a gamelike experience that imitates what could happen in transportation using random numbers and probabilities.

Since the deliveries are made only within a regionally limited area, analyzing logistics operations is not complicated. Only the process of moving goods is assessed in this study, while the risks of having inventory and buying materials are ignored. Furthermore, because the framework is flexible, it can still be used in different retail logistics situations even if the conclusions focus on just one business.

1.5 Significance of the Study

It develops the areas of risk management and logistics in schools and in the workplace. As far as logistics managers and planners are concerned, Simulation Models allow them to simulate situations without spending time or money on various software and programming. On a scholarly level, the experts' work connects quantitative risk modelling and TMS data analytics, an issue that has attracted little notice, especially in the retail sector.

Besides, Monte Carlo simulation helps improve the risk management process in logistics by making choices more detailed and progressive. Identifying the chances and impact of major incidents helps managers improve management of resources, plan response actions and improve logistic systems. This study is set to contribute information and guidance to forthcoming studies and practices in this field.

1.6 Research Gap

So far, simulating delivery uncertainty and transit time variability using Monte Carlo simulation within Transportation Management Systems (TMS) has had very little attention. Most research done previously on logistics risks relied on fixed or linear approaches in modeling. On the other hand such models don’t always represent the unexpected events in real transport, letting major delays in deliveries go unnoticed. By using Monte Carlo simulation, this study simulates many possible delivery situations. Thanks to this method, we are able to use VaR and CVaR to approximate risks more precisgelytely. Unlike traditional approaches, this approach offers a better and realistic process for handling delivery risks and makes logistics operations more prepared for surprises.

2. Literature Review

1. Mogale et al. (2023) They performed simulation trials to observe the performance of UK's online food retail supply chains during COVID-19. They created several examples to understand how things like shifts in supply and demand, hazards through the supply chain and even stoppages of work affect the system. Even though both lessening the amount of items available and reducing slots for delivery yielded positive results, managing supply chain operations was more successful with fewer choices than with fewer delivery times. It was also found that increasing the capacity in distribution centers and using extra suppliers in case of emergencies made the system stronger. In general, the study helped give advice to decision-makers on how to improve their online grocery supply chains to handle any number of disruptions. It provided useful insights to scientists and people working in industry.

2. Xu et al. (2019) The authors investigated risks in e-commerce logistics mainly by looking at problems that arise in warehousing and shipping. Researchers applied the statistical technique GMM to previous transaction records to pinpoint issues that occur in each phase of logistics. When they divided the entire process into hours, they found out which sections are more likely to have challenges. During the transportation step, it was clear from the patterns that things were not doing right which meant there could be risks. Xu and his team chose actual e-commerce data for their case study and introduced useful tips to make improved choices when dealing with risk. By using their approach, companies can supervise logistics risks efficiently which is especially significant in big and active online shopping systems.

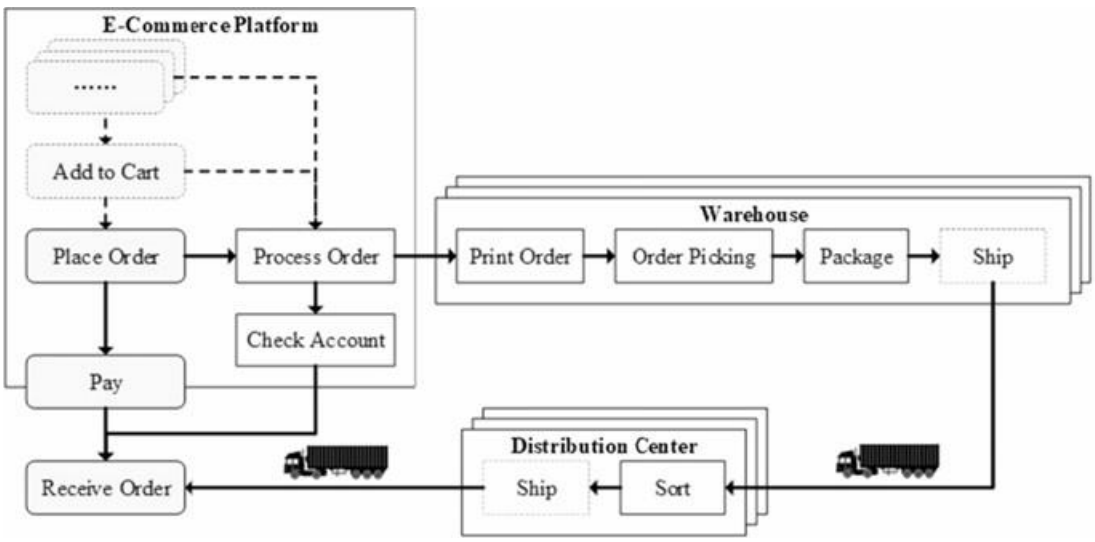


Fig. 2.1 General Working Process of E-commerce Platform

3. Schroeder and Ludeman et al. (2021) Many research papers were reviewed by the authors to understand the contribution of machine learning in risk management along the supply chain. The study examined the use of ML to detect dangers early and respond promptly in production, transportation and relations with suppliers. They classified the use of ML into two groups: proactive methods meant to avoid risks and reactive methods aimed at handling risks after they have appeared. They observed that combining fresh data such as images from satellites and opinions posted on the internet, with ERP data has become an important trend. At the same time, they observed that there are not enough trained individuals in ML and it is hard to mix data from different sources. To conclude, they shared four suggestions for studying how ML could help manage supply chains with numerous levels and complexity. Overall, the study provides a good starting point for anyone in research or industry who plans to use machine learning to automate and enhance risk management in the supply chain.

4. Aljohani et al. (2023) This study presented a neat method that helps supply chains be more flexible and cope with sudden issues The company does not only react to surprises; it uses advanced tools to predict and address problems as they first appear. Anomaly detection, time series forecasting and language processing assist in spotting problems before they cause big issues. Several companies in different sectors showed that including these prediction tools in their supply chain monitoring helped them solve challenges smoothly and act more promptly. It was also discovered that these processes work well only when regular updates are made as situations change. In general, this way of thinking allows companies to be ready for problems instead of just reacting which helps them remain competitive and run their business without disruption during crisis.

5. Lochan et al. (2021) Researchers depended on the AnyLogistix model to discover ways to address risks in food retail supply chains, especially with uncertain situations. They analyzed the effects that problems such as production cuts from suppliers and hiccups at distribution and storage facilities have on a company's operating costs, finances and clients' satisfaction. According to their study, a dairy supplier having to close for even a week might suffer losses of more than 180 million US dollars. In their results, they pointed out that major issues should be dealt with by stronger collaboration and greater investment, whereas smaller delays are simpler to manage. Because empty shelves influence customer demand in retail a lot, the researchers suggested that companies use simulation models to make their systems more sturdy.

6. Wang et al. (2016) The authors explained in detail how Big Data Analytics (BDA) can be used to boost logistics and supply chain management (LSCM). They explained that there is a Supply Chain Analytics (SCA) model demonstrating how organizations can move from basic operations to advanced, solid analytics. Studying other research on logistics strategies and operations, they pointed out how analytics is valuable in making good decisions. They divided analytics into three categories.

- **Descriptive analytics** (what happened),
- **Predictive analytics** (what might happen), and
- **Prescriptive analytics** (what should be done).

Big data in advanced supply chain analysis encourages businesses to unite various departments and cooperate more smoothly. Firms can choose the smarter approach of connecting different areas of their supply chain and using data. By reading this work, businesses that handle logistics

Tasks regularly can use analytics to improve and link their operations.

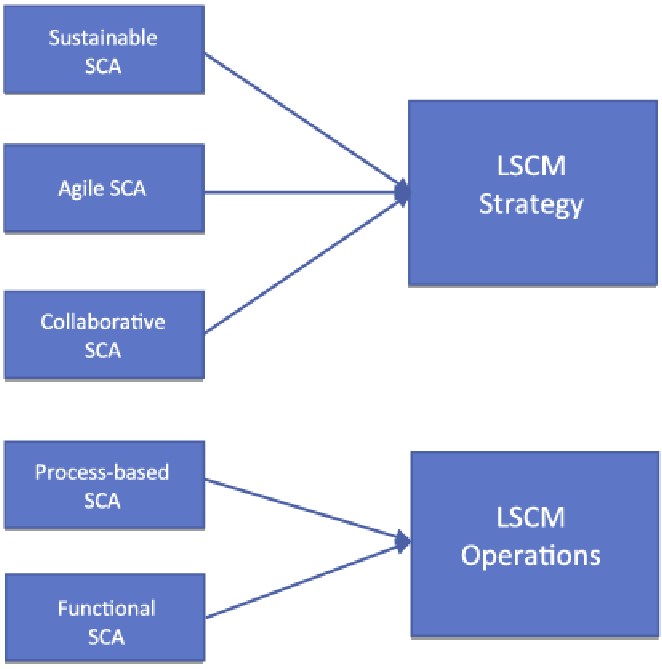


Fig. 2.2 Supply Chain Analytics

7. Choi et al. (2016) This editorial points out that controlling risks is becoming more challenging in logistics, especially now that the business world is so unpredictable. It mentions various risks such as usual workplace problems, emergencies and incidents brought on by things like natural disasters or accidents on the road. They suggest using different layers to address risk management. Handling risks requires managers to handle short-term problems and plan ahead for the future. These experts also remark that adopting third-party services or partnering with other firms introduces fresh risks for companies. Due to these changes, companies have to reconsider their strategies for service quality and dividing responsibility in contracts. All in all, the report suggests companies create strong links between their risk management efforts and ensure different departments join in to respond to new challenges.

8. Munir et al. (2020) This research discusses how SCI, SCRM and performance in warehouses connect to each other in actual situations. Survey information was collected from 931 manufacturing companies and researchers examined the data using structural equation modeling. It was discovered that organizations manage risks much better when they connect their internal workflows, deal with suppliers and communicate with customers. It was also discovered that just having integration is not as effective as it could be. In order for integration to result in better performance, proper risk management should not be overlooked. The findings suggested that information must be shared and everyone needs to work as a team. They support strong services and help businesses successfully deal with sudden obstacles. All in all, the study helps managers understand that for a business to perform well, global supply should be well linked and risks managed efficiently in all parts of the chain.

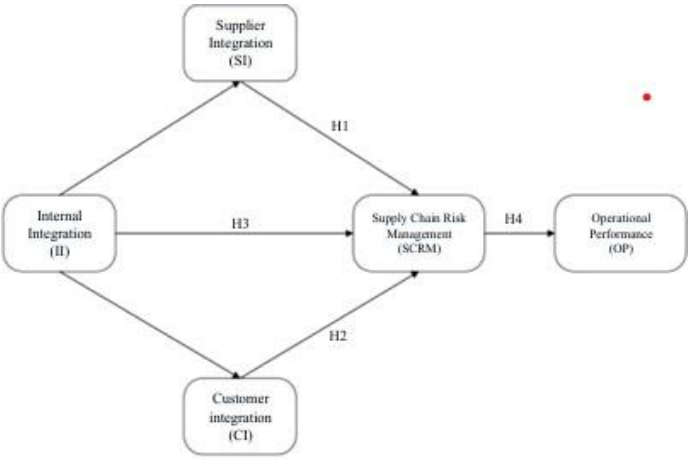


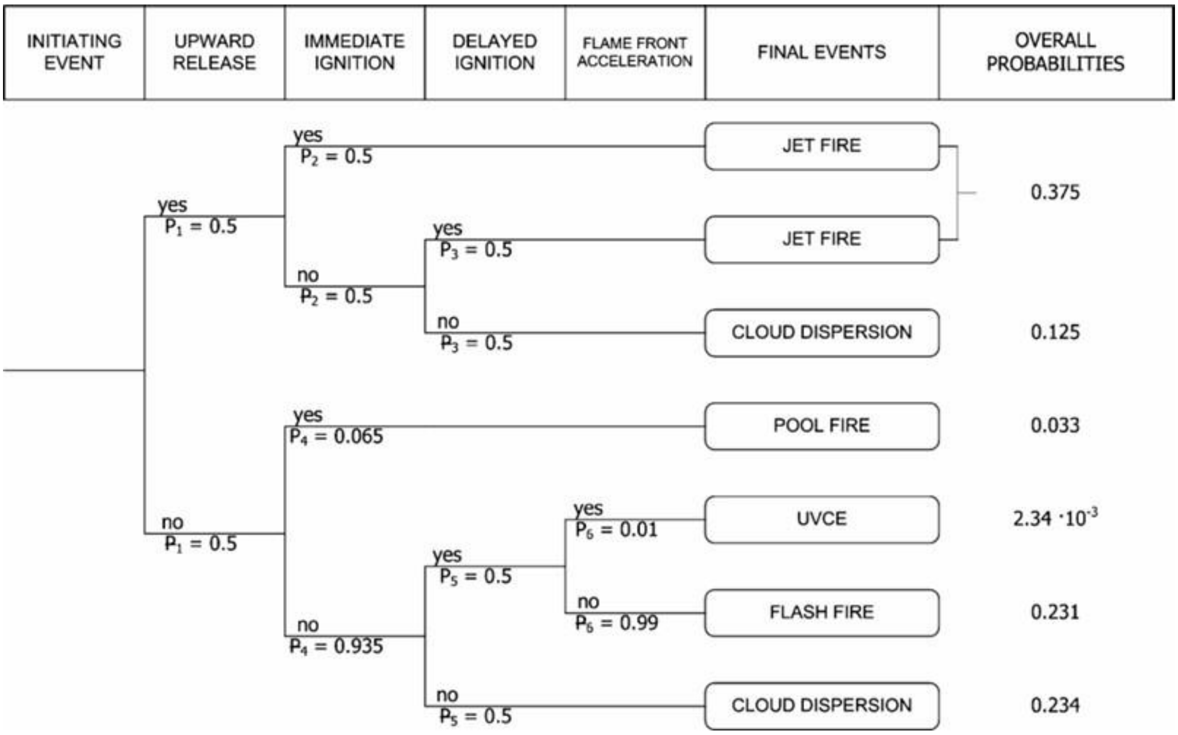
Fig 2.3 Research Model

H_5: II → SI → SCRM	H_7: II → SCRM → OP
H_6: II → CI → SCRM	H_8: SI → SCRM → OP
H_9: CI → SCRM→OP	

9. Ivanov et al. (2021) After COVID-19 outbreaks, experts outlined a different approach for looking at risks in the logistics industry. From the previous studies, they could see that using downside variance, VaR and CVaR is not common in logistics planning. Authors noted that in such cases, logistics systems should be both versatile and reliable. Calls were made to examine in the field how lockdowns of regions, closed borders and world health crises impact supply chains. Ivanov and his team offered a suggestion in the report to develop models that use various methods and can aid decision-makers who have to act swiftly in an emergency.

10. Zhang et al. (2025) Zhang analyzed the benefits of utilizing big data for improving the strength of supply chain risk management. He pointed out that by using technologies such as deep learning, cloud-based analytics and IoT, it's possible to recognize both modest risks including capacity issues and major risks such as cyberattacks and worldwide disturbances to economies. The report also identified more serious challenges such as a breakdown in teamwork, divided data systems and the lack of skilled people. He recommended three ways to deal with these issues: boosting teamwork, improving online safety and training employees in modern technologies. Not only does it help us identify risks, but big data is discussed as the basis for constructing modern and flexible supply chains. All in all, the study supports that digitalization is at the heart of good risk management now.

11. Ronza et al. (2006) The author presents a comprehensive approach for conducting QRA on the movement of hydrocarbons at marine terminals which hasn't received much attention in past risk studies. Within the framework, one must spot possible accident scenarios, estimate their frequencies and model the consequences they could have. The regulations include analyzing risks associated with tanker by going to and from ports, as well as related tasks of loading and unloading. Important aspects included in the approach are how large a spill could be, the possibility of ships colliding in the area and how people living near the area would be affected. The model was used to analyze the Port of Barcelona to check its effectiveness. It successfully shows the management of scenarios such as dying, being injured or being evacuated. With a lot of ships moving in a busy port, this complete QRA model allows port managers to handle and control petroleum product-related dangers well.



12. Zhen et al. (2016) In this study, four methods of dealing with transport disruptions were examined: using backups, buying BI insurance, opting for a basic risk plan and pairing strategies (such as both BI insurance and backup transport). The scientists came up with a model that explores the ways these approaches might either cooperate or stand in place of one another. Disruption of services may also lead to uncertain recovery costs which is a factor to consider. While the most financially secure approach (using BI insurance as well as backup transport options) was suggested, this method might actually cause a recovery to take longer. The study adds that the right strategy for managing risks varies according to both the layout of the insurance industry and the unique business environment of each company. To sum up, the research reveals that backup transport and insurance can intertwine during emergencies which helps us learn how companies can manage transportation risks.

13. Li et al. (2023) The researcher developed a new way of assessing risks involving HazMat that takes into account urban ‘stay points’ like rest areas, gas stations and toll booths. Such places are often not considered in common transport risk studies, even though they may cause major safety problems.

The framework examines four important elements of risk.

1. The simple fact that our environment can be easily disturbed,

2. What makes evacuating a complicated process.

3. Having solutions for rescue services.

4. Possible direct harm caused by a disaster.

To assess these factors, the experts in the study use entropy-weighted TOPSIS and then use GIS mapping and SAFETI models. A study from Chengdu, China, proves how this strategy functions in reality. Since the report focuses on hazards at stops and pauses as well, it provides useful information for improving emergency measures in urban HazMat transport.

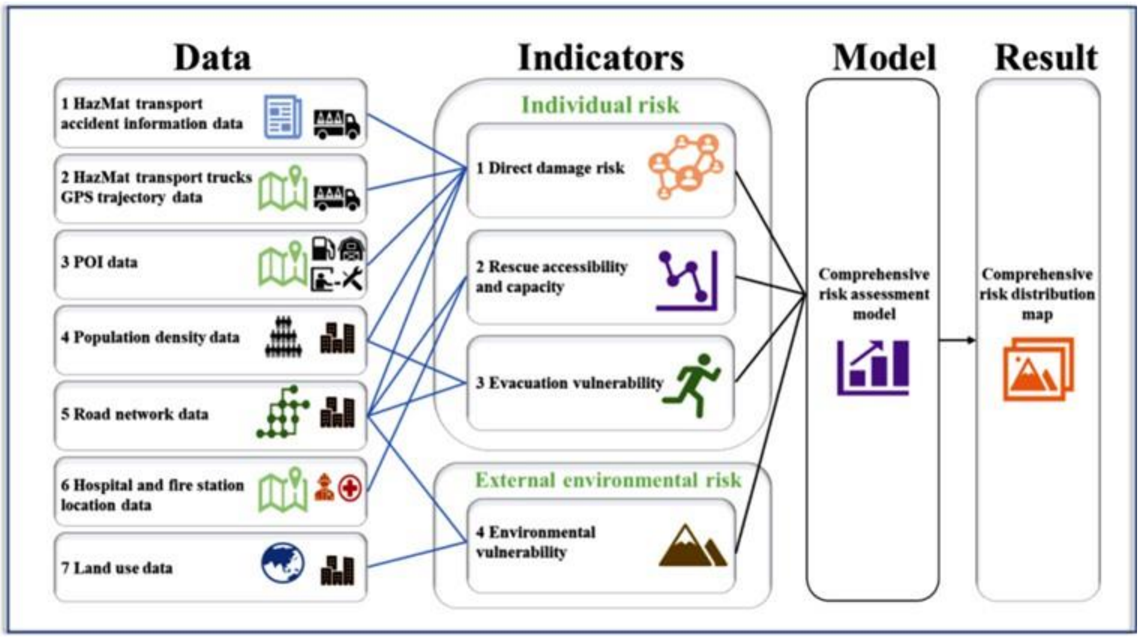


Fig. 2.5 Risk Assessment Framework of HazMat Vehicles

14. Liang et al. (2022) A Bayesian Network (BN) was made to assess and forecast the likelihood of cargo theft in freight chains. The model uses information from more than 9,300 theft cases that happened in the UK from 2009 to 2021. It takes into account important elements that increase the risk of theft, for example, what is being transported, the location, how theft was carried out and exactly where the theft took place.

The BN model highlights how these factors relate which lets it forecast different chances of theft under given conditions. Thanks to this approach, you can understand potential threats and reduce the risk of theft while utilizing safe routes and setting up better security methods.

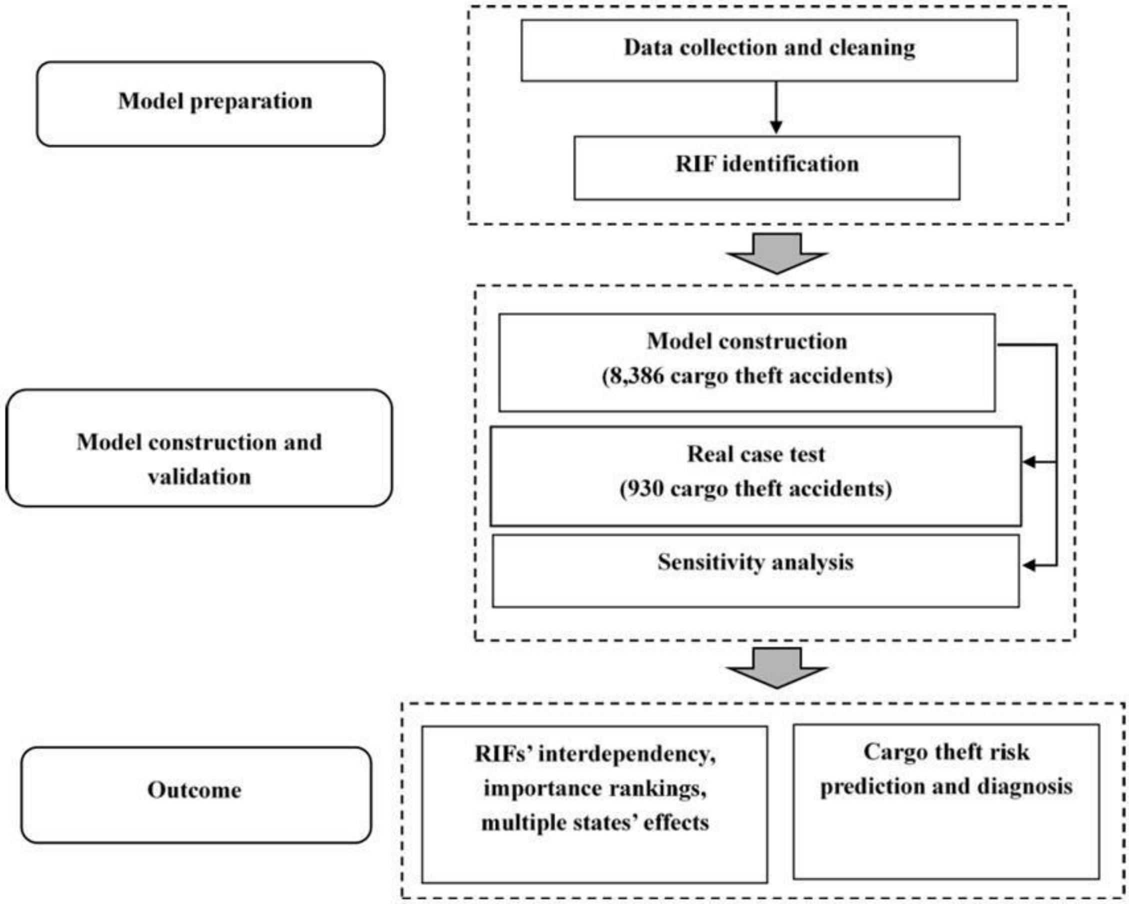


Fig. 2.6 Flowchart of Data Analysis

15. Nguyen et al. (2021) The paper describes a simple model for looking at operational risks in containers by employing Bayesian networks with evidential reasoning. The model was constructed to deal with two types of uncertainties: the first comes from incomplete or faulty data, while the second comes from uncertain future situations. Assessing the threat and the amount of uncertainty is done with two indicators: the Risk Magnitude Index and the Uncertainty Index. The case study gives us the information that there are 3 important risks in the industry: prices of fuel can change, there may be incorrect data about the cargo and maritime piracy exists. Seeing all the uncertainty in maritime operations, this analysis helps guide better decisions related to global container transport.

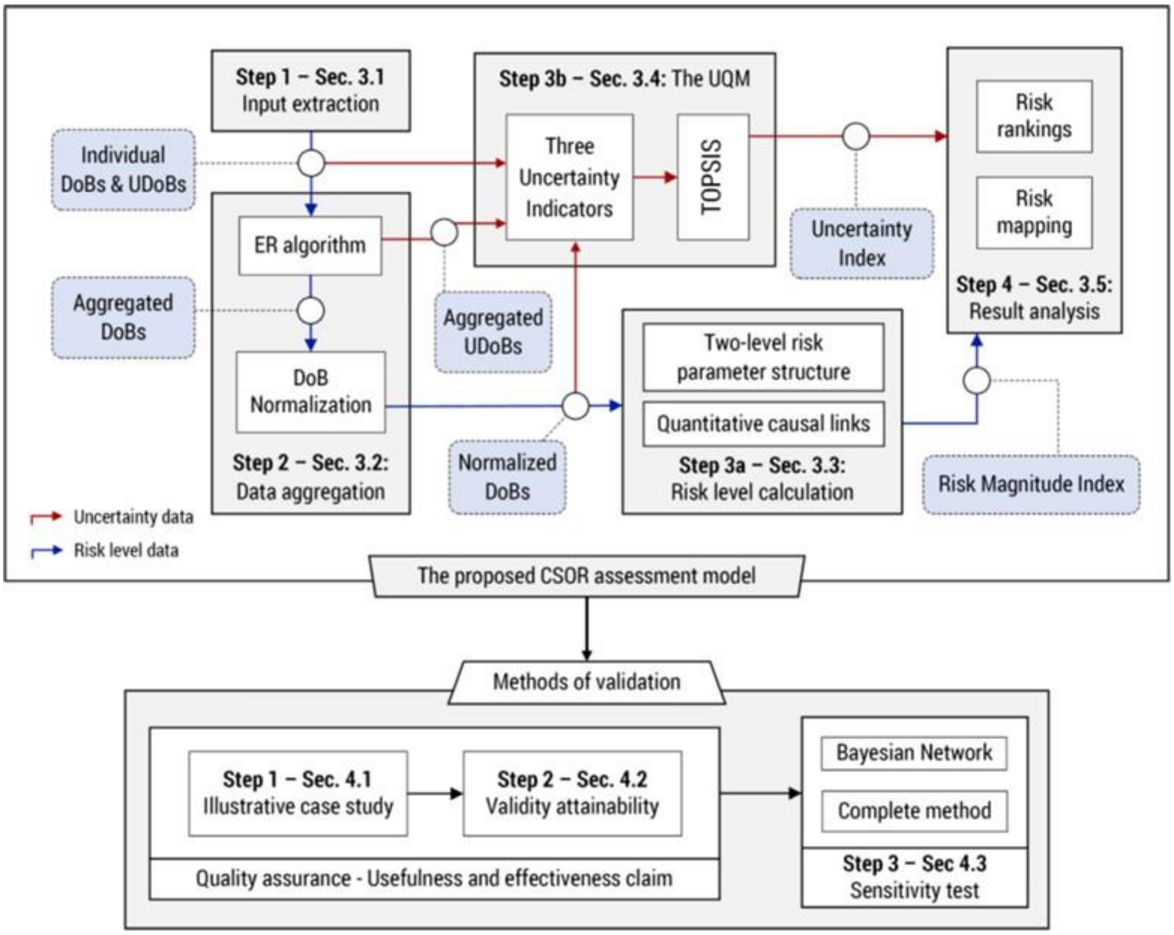


Fig. 2.7 Quantitative Risk Assessment model validation

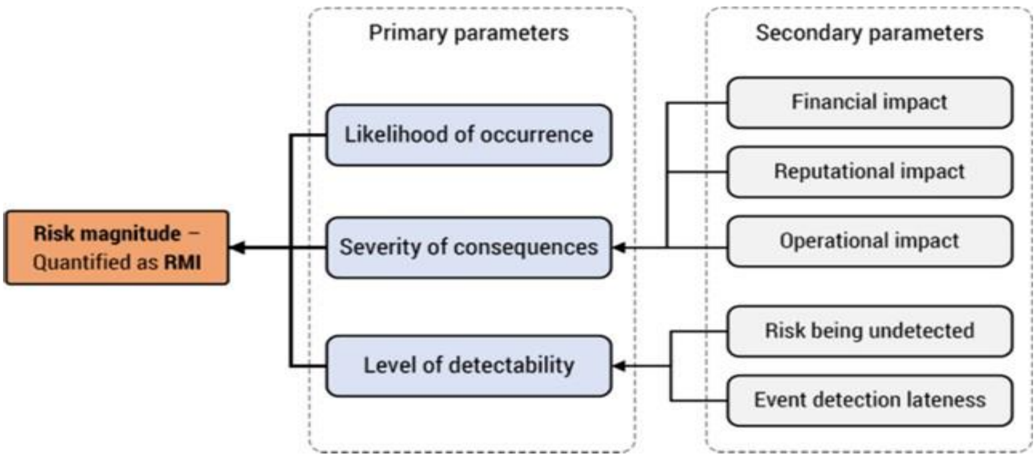


Fig. 2.8 The Risk Parameter Structure

16. Barmuta et al. (2022) Check how well logistics manage risks in situations where the economic situation changes rapidly and unpredictably. A mathematical model is applied to measure and organize hazards, after which they come up with a system for classifying risks using our own strengths and weaknesses, as well as those of our surroundings. The effectiveness of the model in spotting hazards such as delays, problems with documentation and errors in routes was assessed along the logistics process of a trade business. The study reveals that logistic services can improve their performance and resilience in stormy markets by relying on well-established risk registers and numbers.

Risk category	**Brief description of the category**	**Examples of risks**
Organizational risks	Risks caused by the mistakes of managers or employees of the organization; risks associated with organizational culture, available resources, and other factors of the internal environment	• choosing wrong distribution channels for products, • inefficient communication between systems of production, distribution, and delivery of products, • surplus stocks /shortage of stocks in the warehouse, • low elasticity of production, distribution, and delivery systems, • the failure to meet the terms of production and distribution of products, • underestimation of costs associated with the implementation of logistics operations.
Information risks	Risks related to the management of the information subsystem of the company's logistics processes, as well as with the use of information technologies	• -leakage of company confidential information, • information security issues (regarding client data security), • wrong choice of methods for receiving, storing,

		and transmitting data, • incorrectly designed (inefficient) process of information exchange during the implementation of logistics operations, • the risk of a bullwhip effect,-software malfunctions/failures
Risks associated with suppliers and partners	Risks arising in the process or as a result of interaction with suppliers and partners; risks related to the characteristics of suppliers and partners	• inconvenient localization of suppliers, • unfavourable terms of contracts with suppliers (prices, payment methods, transport conditions, etc.), • outsourcing risks (financial risks, possible information leak, loss of control over logistics processes, poor quality of the contractor services, etc.), • the risk of opportunistic behavior of partners, • low elasticity of partners in the field of response to changes, • inefficient communication with partners and suppliers, • violation of the terms of contracts by partners/suppliers, • getting the materials/goods from suppliers that do not meet the requirements of

		quality, quantity, price, place and/or time of delivery.
Customer-related risks	Risks arising in the process or as a result of interaction with consumers; risks related to the characteristics of consumers	• losing clients, • non-compliance of the company's delivery proposals with the expectations of consumers, • lack of flexibility in responding to changing consumer expectations, • lack of feedback / negative customer reviews, • poor communication with consumers, including the processes of informing them about all changes in the status of delivery of orders, • decrease in the number of orders, • risk of customer insolvency.
Transport risks	Risks arising during the transportation of goods by various modes of transport	• the failure to meet the terms of order fulfilment, • the failure to comply with the requirements for the carriage of goods, • damage/destruction of goods, • changes in the cost of transporting products, • environmental risks caused by violation of the rules for the transportation and storage of goods, • accidents.

Force majeure	Risks caused by force majeure circumstances	• damage caused by epidemics, • damage caused by natural disasters, • damage caused by fires, • complications caused by port closures, • complications caused by the changes in legal regulations.

Table2.1 Possible risk causes

17. Mani et al. (2017) See what role BDA could play in minimizing the risks linked to social sustainability in manufacturing supply chains. They explain that BDA plays a role in stopping mischief, accidents at the work site, fuel wastage and wrongdoing through studies and review boards. They showed that being transparent with data enables companies to respond quickly, joining sustainability and SCRM. The study adds value to research by showing how operational risk and corporate social responsibility (CSR) interact and describes how BDA can impact ethical and sustainable decisions in the supply chain.

18. Fahimnia et al. (2015) conduct a thorough study of SCRM models with the help of network analysis and the analysis of scientific articles. The growth of three basic modelling methods—stochastic modelling, simulation and optimization—is studied in contexts such as agility, flexibility and resilience. The study highlights that working on risks together is growing in popularity, since it is clearer that risk-related problems exist. The final point of the article is to stress that big data systems and effective quantitative tools should be used together to increase supply chain resilience. The study serves as the foundation for coming SCRM modeling projects.

Relationship between the generative research areas and primary risk modeling research areas.

Generative research area	The most related risk modeling research areas
1. Fuzzy modeling	2. Downstream supply chain risks 4. Uncertainty in tactical/operational supply chain planning
2. Information sharing	1. Upstream supply chain risks 3. Uncertainty in supply chain network design 8. Uncertainty in purchasing and retail sourcing
3. Risk theories	1. Upstream supply chain risks 2. Downstream supply chain risks 3. Uncertainty in supply chain network design 6. Uncertainty in inventory management and process control
4. Pricing and contracting	3. Uncertainty in supply chain network design 5. Supply and demand forecasting analysis 8. Uncertainty in purchasing and retail sourcing
5. Performance measurement	1. Upstream supply chain risks
6. Supplier/vendor selection	1. Upstream supply chain risks
7. Network design and facility location	2. Downstream supply chain risks 3. Uncertainty in supply chain network design 6. Uncertainty in inventory management and process control 7. Sustainability risks

Fig. 2.9 Risk relative modelling

19. Liu and Ding (2023) employ data analysis to evaluate and boost the sustainable growth of logistics industries across regions. A system based on economy, society, environment and innovation is built using entropy weight and min-max normalization. To review bottlenecks and synergy between subsystems, a degree-of-obstacle model and two coupling models are used. Data from Anhui Province was studied through logistics and this revealed that poor innovation and environmental stress were the leading problems the strategy needed to address. If policymakers want to ensure consistency in expanding logistics while keeping their region sustainable, this study supplies a pipeline model that can be reused.

20. Pokrovskaya et al. (2019) The study focuses on the dangers businesses encounter while trying to improve their delivery planning and routes. Some problems that are commonly mentioned include breakdowns, missed delivery time frames and using excess fuel. It investigates how looking at different events and using equations can aid in lowering risks. They also focus on needing risk analysis within transport optimization, so companies can adjust to differently moving and avoiding traffic jams. The things discussed in the study allow businesses to manage and handle transportation planning in a faster and more efficient manner.

3. Data Collection and Description

Actual records of the transportation process at the V-Mart warehouse in Palwal, Haryana were used in this study. They are overseen by the Fretron Transport Management System (TMS), a real-time tool that reports every part of the outbound process. With the data, I can see exactly how vehicles are arranged, how goods are carried which routes are followed and what happens in delivery. Here, you will find out the origin of the data, its organization and what it can do for us. Afterward, the same data is applied to look for transport-related risks, carry out simulation studies and create approaches to reduce them in the next chapters.

3.1 Data Source

All the information used in this study is sourced from the "In-transit & Delivery Status" part of the Fretron TMS module. Details of more than 800 shipments from April 2025 are given in this report. A separate entry shows every delivery, beginning from the warehouse up to the final drop-off point. They hold both details that may change, for example, when a delivery is scheduled and if there are any delays and fixed dates like what vehicle was used and what was carried.

3.2 Description of Key Data-fields

- **Warehouse Out Date**: This is the date when the item leaves the warehouse. It helps track how long it takes to reach the destination.

- **Warehouse Out Time**: This tells the exact time the vehicle started its journey from the warehouse, useful for checking how well the dispatch is managed.

- **Transporter Name**: The name of the delivery company or in-house transport team. This helps compare how different transporters perform.

- **TMS Shipment ID**: A unique ID given to each shipment in the Transport Management System. It's used for tracking and managing shipments.

- **Vehicle Number**: The registration number of the vehicle used for delivery. It's useful for keeping track of vehicles and studying routes.

- **Vehicle Type**: The size or kind of vehicle used (like 24FT trucks). This matters because different vehicles suit different types of deliveries and routes.

- **Driver Name & Contact Number**: The driver's name and phone number, which help with communication during delivery and quick resolution of any issues.

- **Store Address**: The final delivery location. This is needed to plan routes and measure delivery performance across different areas.

- **Distance (KM)**: The number of kilometers between the warehouse and the delivery point. It helps calculate fuel usage, delivery cost, and efficiency.

- **Delivery Date & Time**: When the delivery actually happened. This shows the total time taken and whether it met the promised delivery time.

- **Delay (in days/hours)**: Shows how late the delivery was compared to the planned time. It's important for spotting and fixing delivery problems.

- **Delivery Status**: Tells whether the delivery was on time, late, or missed. This helps track overall performance and manage issues.

- **Delivery TAT (Turnaround Time)**: The total time taken from dispatch to delivery. It's a key performance metric in logistics to measure efficiency.

3.3 Data Preparation and Transformation

Microsoft Excel was used to clean and organize the dataset after it was exported from Fretron.

Among the steps were:

Timestamp Normalization: Dates and times were transformed into understandable datetime formats from numeric serial formats.

Consolidation of Categories: To model cargo-based risk exposure, product types and values were categorized into broad groups.

Derived Variables: Individual product value data were used to calculate metrics like total cargo value and cargo type percentages.

Error Filtering: Rows with inconsistent Vehicle Type information or missing Shipment IDs were not included.

Estimated consequences of risk were predicted using warehouse out time and group screws, as in some cases the exact information such as delivery time or delay tags, was missing.

As a result, we can now use simulations to explore several risks, both financial, environmental, human and operational. The system in the following chapters is centered on fields that straighten the study of transport activities, the calculation of financial effects and evaluation of delays.

To ensure the accuracy of the data, 50 shipments were both searched in the organization's internal logs and verified on Fretron reports. It turned out that certain operational events like determining cargo type, assigning new shifts and talking about what to expect were accurately kept in writing.

The interquartile range (IQR) was used to detect any outliers in the cargo's value and quantity. Should an inconsistency be noticed, the entry was saved, but if it was normal, it was checked again and not thrown away at random.

The dataset only contains information about outbound shipments from the Palwal warehouse during one month. Routes, list of products and inward movements are not included in tracing shipments. Because such variables are hard to collect, most models either freeze them at certain levels or use other ways to represent them.

Fretron TMS data gives a reliable and useful basis for risk analysis in the retail logistics industry in India. Important shipment details, key features of the cargo and various vehicle deployment aspects are captured to allow a comprehensive simulation of risk with the data. Chapters ahead will show how the Monte Carlo simulation and risk management architecture rely on these records as collected data.

4. Methodology

4.1 Monte Carlo Simulation for Risk management

Monte Carlo simulation is a way to predict how uncertain processes might end up by using probability distributions and random numbers. Since it makes it easier to model complex systems where variables such as travel time, vehicle breakdowns, traffic conditions and delays in loading can all cause potential issues together, Monte Carlo simulation is very useful in logistics and transportation risk management.

Doing this, Monte Carlo simulation can create a wide range of scenarios while deterministic models can only give a single result. Every repeated simulation produces a result that looks realistic. This model allows one to see the probability of both common and severe outcomes because it shows many possible instances of the process.Monte Carlo simulation is utilized in this study to model risks associated with transportation, including:

- Delays in delivery
- Dependability of the route
- Probability of malfunction or disturbance
- Effects of operational exceptions (such as route blocks and loading delays)

Using historical data to simulate changes in journey time, the model calculates:

- The likelihood that deliveries will be delayed
- The anticipated range of transit times (and their variations)
- Risk profiles that are specific to a route or transporter

The quantitative risk assessment approach is possible using this method, so risk events can be measured and studied using statistics. Additionally, the model includes qualitative factors affecting delivery performance by including things like “manual hold” and “rain delay” in its rules. Since the simulation offers many risk outcomes, decision-makers can find useful information such as:

- using percentiles like the P90 level of travel time
- The chances of providing higher levels of service than what is promised in SLAs
- Things like routes, the type of vehicle used or the days for delivery are sorted according to their risk.

Therefore, managing risk through Monte Carlo simulation is the main foundation of the approach. Thanks to this, resources can be planned, proactive choices can be made and solutions are based on data instead of guesswork. Managers are able to make good decisions during uncertainty since analytics transforms data into useful information.

4.2 Outline

We will find a detailed account of how the authors estimate travel times, model risk involved in shipments and analyze logistics performance at V-Mart's Palwal warehouse by using data from the Fretron TMS. All parts of the framework are in Microsoft Excel and they use data from previous shipments. The approach presents a simple, data-driven way for managing risks and quantifying them in retail warehouse transportation through the use of statistics, modeling, error monitoring and graphs.

Monte Carlo simulation is the main way to handle uncertainty and determine risks. Many things that cannot be controlled, including traffic, weather problems, the reliability of cars and trucks and operational problems, impact the outcomes of transport logistics. Such a technique enables handling changes in figures because it produces many believable delivery scenarios from previous results.The approach is divided into five main stages:

1. Cleaning and preparing data
2. Predictive modelling for travel time
3. Monte Carlo modelling for risk and delay prediction
4. Including operational remarks to improve accuracy
5. Results visualization and performance dependability

4.3 Data Preparation

Data Source

The Fretron TMS's "In-transit & Delivery Status" report, which included every outgoing dispatch from the Palwal warehouse for a given month, served as the dataset's source. Shipment identifiers, dispatch and arrival times, vehicle information, delivery locations, and comments or exceptions noted throughout transportation are important logistics variables.

Data Cleaning

The dataset was cleaned to eliminate missing records, fix timestamp formats, and standardize vehicle and route labels in order to guarantee correctness and consistency. For qualitative investigation and eventual incorporation into the risk model, comments and exception records were kept.

Variable Derivation

A number of derived fields were produced from the cleaned data:

- The difference between the dispatch and delivery timestamps was used to compute the travel time.
- Each origin and its matching delivery location were combined to create route identifiers.
- In order to reflect warehouse efficiency, loading time was calculated where start and finish timestamps were available.

4.4 Travel Time Prediction Modelling

To determine anticipated delivery times for upcoming shipments, historical travel time trends were examined. This was accomplished by calculating the average travel times of previous deliveries and classifying them by route, vehicle type, and day of the week.

To increase the precision of predictions:

- Typical speed variations were reflected in the adjustments made according to the kind of vehicle.
- Consistent traffic differences were taken into consideration by taking into account the day of the week.
- Different trends were identified for in-house and third-party transporters.

This model serves as the standard by which simulated delays are assessed and measured.

4.5 Monte Carlo Simulation for Risk Modelling

Role of Monte Carlo Simulation

By modelling thousands of delivery scenarios using randomized inputs derived from historical patterns, Monte Carlo simulation is used to assess uncertainty in logistics operations. It makes it possible to estimate delay probabilities, disruption intensity, and the operational impact of risky routes or vehicle types in a probabilistic manner.

Based on past averages and standard deviations, hypothetical scenarios for delivery timeframes are created for this study. To simulate common deviations brought on by traffic, operational delays, and unanticipated circumstances, randomized variants are used.

Simulation Implementation

A static simulation model was constructed in Excel, where each row represents every individual simulated shipment. To represent the entire range of potential outcomes, inputs for travel time, delays, and interruption events are changed throughout thousands of iterations.

The results of the simulation include:

- Simulated travel time distribution
- percentage of simulated trips that have delays higher than a predetermined level
- Finding shipment types or routes with a persistently high risk

Probability-based performance metrics, including the likelihood of on-time delivery and the anticipated delay duration, are derived from the simulation's outcomes.

Integration of Remarks and Operational Exceptions

Qualitative comments and exception notes were methodically tagged and examined in order to increase accuracy. When necessary, these comments were converted into binary indicators and applied to modify simulation inputs.

To account for these operational realities, extra delay factors were added to the simulation, for instance, if a specific route or transporter was regularly linked to exception flags. This guarantees that the model is context-sensitive in addition to being data-driven.

Visualisation and Performance

In order to facilitate comprehension and decision-making, the model integrates visual aids for results presentation:

Scatterplot of Data

To show the correlation between delivery routes and actual trip times, a scatterplot was created. Finding high-variability routes and spotting odd trends or outliers are made easier with the aid of this visual trendline.

Distribution Plots for Simulations

The distribution of simulated delays and anticipated travel times was displayed using histograms and percentile charts. These graphs aid in forecasting delivery performance in the face of uncertainty and visualizing risk concentration.

Dashboard for Reliability

A dashboard summary monitors:

- Predictive accuracy versus actual delivery results
- Exchange of complete and clear data records utilized in simulation
- Actual versus simulated delay performance for important routes and vehicle categories

This dashboard facilitates continuing validation of the risk management tool and provides constant visibility into model reliability.

This approach combines exception handling, simulation modelling, and historical analysis into a single framework for managing transportation risk. By adding statistical depth to operational planning, the Monte Carlo simulation component enables logistics managers to comprehend the entire spectrum of possible events and their probabilities in addition to forecasting typical journey durations.

Because the entire procedure is embedded in Excel, the solution is easily updated, accessible, and flexible enough to accommodate changes in operations. The simulation findings, risk trend interpretation, and mitigation strategy recommendations will be presented in the upcoming chapter.

5. Results and Analysis

Monte Carlo simulation Random Value	2.9728	Hours	Days	Probably of delivery days
1	2.445	-4.42	-0.18	2.85
2	0.787	-4.09	-0.17	2.86
3	3.037	-3.88	-0.16	2.87
4	1.670	-3.50	-0.15	2.89
5	3.436	-3.47	-0.14	2.89
6	4.371	-3.36	-0.14	2.90
7	0.867	-3.12	-0.13	2.91
8	4.803	-3.10	-0.13	2.91
9	2.534	-3.09	-0.13	2.91
10	0.075	-3.06	-0.13	2.91
11	0.225	-3.06	-0.13	2.91
12	4.333	-3.05	-0.13	2.91
13	2.882	-2.97	-0.12	2.91
14	-0.358	-2.95	-0.12	2.91
15	4.597	-2.83	-0.12	2.92
16	4.428	-2.80	-0.12	2.92
17	4.920	-2.79	-0.12	2.92
18	4.345	-2.78	-0.12	2.92
19	1.504	-2.76	-0.12	2.92
20	0.738	-2.75	-0.11	2.92
21	2.478	-2.73	-0.11	2.92
22	4.714	-2.72	-0.11	2.92
23	3.587	-2.67	-0.11	2.92
24	4.289	-2.66	-0.11	2.92
25	6.771	-2.60	-0.11	2.93
26	2.639	-2.48	-0.10	2.93
27	5.587	-2.47	-0.10	2.93
28	2.379	-2.44	-0.10	2.93
29	-1.518	-2.36	-0.10	2.94
30	2.474	-2.36	-0.10	2.94
31	2.702	-2.35	-0.10	2.94
32	5.802	-2.34	-0.10	2.94
33	0.209	-2.33	-0.10	2.94
34	4.165	-2.30	-0.10	2.94
35	1.905	-2.28	-0.09	2.94
36	-1.260	-2.25	-0.09	2.94
37	3.774	-2.25	-0.09	2.94
38	6.027	-2.24	-0.09	2.94
39	1.159	-2.23	-0.09	2.94

Table 5.1 Monte Carlo Simulation

5.1 Description of the Random Number Usage:

In the above table:

- "Tail Risk" uses probability quantiles, like 0.01, 0.05, and 0.10, to indirectly represent random values.
- The simulation's worst-case possibilities, or the 1%, 5%, and 10% tails of the result distribution, are represented by these quantiles.
- Value-at-Risk (VaR) and Conditional Value-at-Risk (CvaR) are computed for every quantile:
- Value at Risk, or VaR, is the percentage of the transportation delay threshold that is not surpassed, such as 95% or 99%.
- Given that the delay is in the worst-case tail (beyond the VaR threshold), CvaR (Conditional VaR) is the predicted value of the delay.

These are produced by assuming a certain distribution (presumably normal, given mean = 3.03 days and standard deviation = 2.00 days) in random simulations of transportation days.

In a Monte Carlo simulation:

- A probabilistic distribution would have been used to create thousands of random samples of transit days.
- The simulation's tail-based results are extracted using the quantiles (0.01, 0.05, 0.10) as random number thresholds.

The Monte Carlo simulation table uses random numbers as its main input to predict possible outcomes connected to probabilistic factors of transportation risk analysis. From time to time, samples are drawn from a probability distribution with a mean of 3.03 days and a standard deviation of about 2.00 days and this helps the simulation estimate how long it will take for the goods to arrive.

Generally, random numbers are arranged from 0 to 1 and changed into numbers from a normal distribution which represent travel times. As a result of this simulation, the model can present the range of unpredictable and diverse delivery times in the system. VaR and CvaR are measured with tail quantiles like 0.01, 0.05 and 0.10. For serious situations, these metrics are used to judge how much the delay might be.

- With 99%, 95%, and 90% certainty, VaR denotes the delay threshold that is not anticipated to be surpassed.
- Assuming that the VaR-defined threshold is crossed, CvaR gives the average delay.

The model aids in determining key delay thresholds and worst-case situations by using random numbers and simulating hundreds of potential outcomes. Within the logistical framework, this facilitates well-informed decision-making and thorough risk mitigation planning.

5.2 Description: How Hours Are Generated in the Monte Carlo Simulation Table

The "Hours Estimation" numbers in the Monte Carlo simulation table are obtained by converting the simulated transit time from days to hours. A direct unit conversion is used for this:

$$\text{Hours Estimation} = \text{Days Estimation} \times 24$$

After the simulation uses random sampling techniques to obtain a distribution of potential transportation durations in days, this conversion is implemented. For greater granularity and more useful insights in logistics planning, the simulations' likely day predictions for a specific trip distance are scaled to hours.

5.3 Description of the SORT Function Usage in Monte Carlo Simulation

The SORT function is essential to the Monte Carlo simulation model used to analyze transportation data because it arranges the randomly generated results in a way that makes precise risk assessment and time analysis possible. Through random number-based simulations, a large number of transportation time samples (in days) are generated. These numbers are then arranged in ascending order using the SORT function.

This method of sorting is necessary for:

- determining quantiles, such as the first, fifth, and tenth percentiles, that are utilized in the computation of Conditional Value at Risk (CvaR) and Value at Risk (VaR).
- defining the tail risks in transportation delays by mapping ranks to particular probability levels.

Following the sorting of the simulated transportation days, a linear transformation is used to determine the associated hours estimation:

$$\text{Hours Estimation} = \text{Sorted Days Value} \times 24$$

This keeps the underlying risk structure and outcome ranking intact while enabling the model to produce time estimates in both days and hours. By arranging simulation data in a way that makes it appropriate for percentile-based risk interpretation and operational decision-making, the SORT function plays a crucial role in gleaning valuable insights from the data.

5.4 Description of Probable Delivery Days

The range of anticipated delivery times calculated using stochastic modeling is referred to as “Probable Delivery Days” in the Monte Carlo simulation-based transportation risk analysis. These figures are not set in stone; rather, they are statistically deduced from past transportation data, taking into account fluctuation and uncertainty through random sampling methods.

By sampling from a distribution determined by the observed average transportation days and standard deviation, the simulation produces millions of delivery time scenarios. A possible delivery time under a variety of real-world circumstances, such as traffic jams, inclement weather, or operational delays, is represented by each sampled figure.

The most likely range of delivery durations is then ascertained by analyzing the results from these simulations:

- The average delivery time under typical circumstances is represented by central trends like the mean.
- The delivery time that won’t be surpassed with a given degree of confidence can be found using percentile-based metrics. The 95th percentile, for example, would show that 95% of shipments should arrive in a specific number of days.
- The selection of likely delivery days is further supported by sorted simulation results, which are then tabulated with matching hours for a more detailed evaluation.

Supply chain managers may optimize route planning, set reasonable expectations, and create mitigation plans for high-risk deliveries with the use of these likely delivery days. The approach provides a strong framework for transportation planning in the face of uncertainty by taking into consideration both common and extreme scenarios.

5.5 Description: Rationale and Use of Random Values in 10,000 Monte Carlo Simulations

To model the uncertainty in transportation time forecasts, 10,000 iterations are performed in the Monte Carlo simulation sheet. These randomly produced inputs, which go beyond the typical [0, 1] uniform distribution and range up to roughly 5, are contained in the column titled "Random Value". A normal (Gaussian) distribution, which is frequently used to mimic natural changes like delivery delays, is most likely the source of these values.

- Statistical Confidence: More accurate calculation of delivery probability, especially in the distribution's tails, is ensured by a larger sample size.
- trustworthy Quantiles: Only with adequate sample granularity can percentile computations (such as those for Value-at-Risk and CVaR) become statistically trustworthy.
- Low Sampling Error: 10,000 simulations enable smoother outcome distributions and less error caused by randomness.

	Tail Risk		
Percent	1%	5%	10%
i	9900	9500	9000
VAR(%)	6.39	6.34	6.31
CVAR(%)	6.42	6.37	6.35

Average Transportation Days
3.04

	Tail Risk		
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	153.45	152.07	151.35
CVAR(%)	154.06	152.89	152.28

St.dev. of Transportation Days
2.00

Average Distance
1292.8

Table 5.2 Quantified Risk at different confidence levels

5.6 Tail Risk Analysis Using Value at Risk (VaR) and Conditional Value at Risk (CVaR)

The Tail Risk Table offers important insight into how delays behave in low-probability, high-impact scenarios by summarizing the extreme (worst-case) results from the Monte Carlo simulation of transportation durations. Three important indicators that are assessed at 1%, 5%, and 10% confidence levels are included:

1. Percentile Index (i)

- The rank positions in the sorted list of 10,000 simulated outcomes are denoted by the percentile index (i) 9900, 9500, and 9000.
- For instance, the 9900th number, which is used to calculate the 1% tail, indicates the point at which 99% of delays are anticipated to be less severe.
- The tail-end values, which reflect the infrequent but significant delivery delays, are extracted from the simulation with the use of these indices.

2. Value at Risk (VaR)

The highest projected loss (delay) within a specified confidence level is indicated by VaR(%). It indicates the delay that, with a given probability, won't be exceeded:

- At the 1% level, the likelihood of delays being less than or equal to 6.39% is 99%.
- Delays are 95% likely to be less than or equal to 6.34% at the 5% level.
- 90% of the time, delays will be less than or equal to 6.31% at the 10% level.

VaR establishes the cutoff point for the worst-case scenarios and is a threshold-based metric.

3. Conditional Value at Risk (CVaR)

Expected Shortfall, or CVaR(%), provides the average delay in the worst-case scenario outside of the VaR threshold:

- It tells us: How terrible may a delay get on average if it happens and is worse than the VaR level?
- CVaR offers a more thorough assessment of tail risk than VaR alone and consistently surpasses or equals VaR.

4. Interpretation and Use

- Supply chain managers can better grasp the extreme risk profile of transportation delays with the use of these tail risk measurements.
- In high-risk situations (such as military logistics or emergency supplies), where even infrequent delays might be crucial, the 1% and 5% levels are particularly helpful.
- In contractual delivery systems, they also operate as standards for insurance thresholds, buffer time planning, and penalty risk estimation.

Extreme transportation delays are **quantified** in probabilistic terms by the Tail Risk table using VaR and CVaR. It is an essential part of risk-sensitive logistics planning in uncertain contexts because it gives decision-makers practical insights to reduce infrequent but severe disruptions.

5.7 VaR Calculation

$$\text{Index } i = (1 - \text{Confidence Level}) \times N$$

For 10,000 simulations:

- At 1% → i = 0.99 × 10,000 = **9900**
- At 5% → i = 0.95 × 10,000 = **9500**
- At 10% → i = 0.90 × 10,000 = **9000**

VaR value = value at the i-th position in the sorted list:

- For 1%: VaR = value at 9900th index = **6.39%**
- For 5%: VaR = value at 9500th index = **6.34%**
- For 10%: VaR = value at 9000th index = **6.31%**

5.8 CvaR Calculation

$$\text{CvaR},\alpha = 1/N(1-\alpha)\sum Xj$$

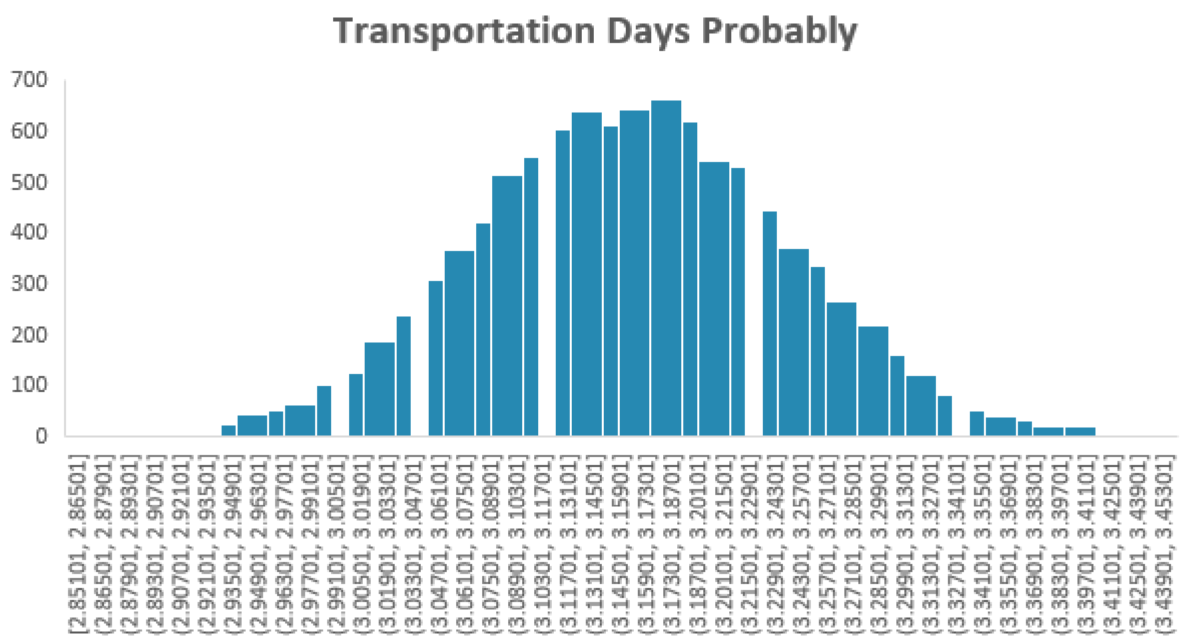
Where:

- Alpha, α is the confidence level (e.g., 0.99 for 1%)
- Xj are the simulated values beyond the VaR index
- NNN is the total number of simulations (10,000)

Example:

- For 1% (i = 9900):
  - CVaR = average of values at positions 9900 to 10,000
  - Result = **6.42%**
- For 5% (i = 9500):
  - CVaR = average of 9500–10,000 → **6.37%**
- For 10% (i = 9000):
  - CVaR = average of 9000–10,000 → **6.35%**

Figure 5.1 Histogram of days interval and frequency



5.9 Histogram Generation and Interpretation in Monte Carlo Simulation

A histogram part of the Monte Carlo simulation shows the frequency distribution of the simulated delivery outcomes both graphically and mathematically. When examining the uncertainty and distribution of transportation days obtained from random simulations, this histogram is an essential tool.

1. Generation of the Histogram

10,000 simulated delivery durations are used to create the histogram; each simulation generates a distinct delivery time based on a random input number. The following steps are involved in the process:

- **Random Input Sampling:** Every simulation employs a unique random value, most often taken from a normal distribution, some of which exceed the range [0, 1].
- **Transformation to Delivery Time:** A deterministic transformation method is used to translate these random inputs into delivery durations (in days and hours).
- **Binning:** Discrete intervals, or bins, are created from the range of simulated delivery days (e.g., 0.5-day intervals).
- **Frequency** counting involves placing each fictitious delivery day in a container and counting how many times each bin occurs.
- **Tabulation:** The histogram's foundation is this frequency count, with each row denoting a distinct delivery duration range and frequency.

2. Parameters in the Histogram

The parameters are shown in the following columns of the histogram table:

- **Random Value:** The input from which the simulation's outcome is produced.
- **Simulated Hours/Days:** The amount of time needed for transportation based on the random input.
- **Delivery Probability:** A mapped probability that shows the likelihood that a delivery will take place during that certain time frame. It can be either cumulative or per-bin.

Each simulation result is assigned to a corresponding interval in the histogram using the Bin Index, which is implied by the serial number.

3. Interpretation of the Histogram

- Peak Frequency (Mode): The most typical delivery time, which is the one that is most likely to occur under typical circumstances.
- Skewness: Longer delays could result from infrequent but severe occurrences if the histogram tilts to the right.
- Tail Behavior: Especially for worst-case planning, the tail's thickness and form aid in determining Conditional VaR (CVaR) and Value at Risk (VaR).
- Cumulative Distribution Insight: The likelihood that a cargo will arrive by a specific day can be estimated by gradually adding up the frequencies.

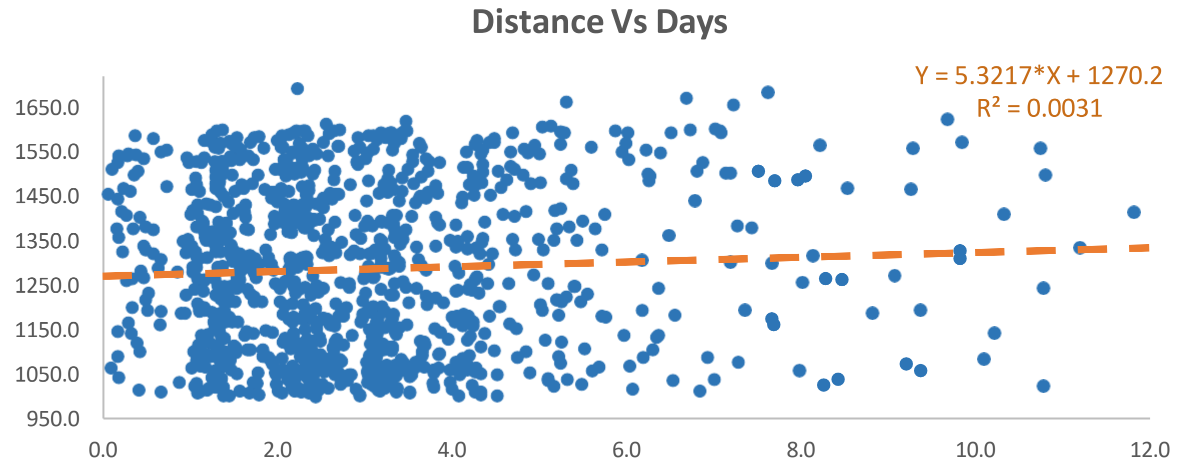


Figure 5.2 Scatter Plot b/w distance and days

5.10 Interpretation of Scatter Plot: Distance vs Days

The relationship between two crucial logistical characteristics is depicted by the scatter plot in the "Scatterplot" sheet:

- X-axis: shows the total delivery time in days, expressed in decimal.
- Y-axis: The store's distance (in kilometers) from the warehouse

A unique transportation event is represented by each point on the scatter plot; each trip had a certain distance and required a matching amount of time (measured in days) to finish. Together with the corresponding regression equation and coefficient of determination (R^2), the plot also features a regression trendline that represents the best-fit linear relationship between these variables.

Regression Output

The line of linear regression is given as:

$$y=5.3217x+1270.2$$

Where:

- y = Warehouse to store distance (in kilometers)
- x = Total number of delivery days
- R^2 = 0.0031 shows how much of the variation in distance may be attributed to delivery time.

Distribution and Pattern

A visual examination of the scatter plot reveals several important features:

- **Data Horizontal Dispersion**
  Approximately 0 to 11 days is the range of the delivery time values (X-axis). The data points, however, are closely grouped between 1 and 7 days, suggesting that the majority of deliveries take place within this period.
- **Spread Vertically**
  All delivery durations show considerable variation in the distances (Y-axis), which typically range from roughly 950 km to more than 1650 km. Even for the same delivery length, there is a great degree of diversity in trip distances, as seen by the lack of any discernible narrowing or tapering of values.
- **Even Distribution of Points**
  The lack of a distinct linear trend is implied by the data's appearance as being widely and randomly dispersed without developing a distinctive upward or downward direction.

Regression Line Interpretation

A linear regression line has been used to quantify the link between delivery days and journey distance, despite the fact that the data is widely dispersed. The formula:

$$y=5.3217x+1270.2$$

suggests a little positive slope, indicating that the distance increases by roughly 5.32 km on average for every unit increase in delivery days. In the context of logistics planning, this rate of growth is insignificant and has no practical impact.

The 0.0031 R^2 value supports this finding. The coefficient of determination, or R2, shows the extent to which the independent variable (days) can account for the variance in the dependent variable (distance). Only 0.31% of the distance variance can be attributed to variations in delivery time, according to an R^2 of 0.0031. Given the incredibly low connection, it appears that delivery time and distance are essentially unrelated in this sample.

Implications for Logistics Analysis

The following are some consequences of this analysis:

- **Delivery Time Not Just Dependent on Distance**
  The intricacy of real-world logistics is highlighted by the weak relationship between delivery time and distance. Regardless of the distance, a number of factors, including traffic, vehicle availability, route optimization, regulatory stoppages, driver shifts, and warehouse handling time, can have a substantial impact on delivery time.

- **Multi-Factor Models Are Needed**
  Multiple factors, such as vehicle type, delivery priority, loading/unloading time, route congestion data, terrain type, and service level agreements (SLAs), should be included in models in order to effectively anticipate delivery time.
- **Using Linear Models for Forecasting with Caution**
  Because of the poor R2, the linear regression model that was created from this scatter plot has little explanatory power. This implies that using distance alone to predict delivery time would not be accurate. Better predicted accuracy could be obtained using alternative techniques like machine learning models or multi-variable regression.

Delivery time and distance have a very weak linear relationship, according to the "Distance vs. Days" scatter plot. Despite its mathematical validity, the regression model's low explanatory power limits its usefulness in real-world situations. In order to create more accurate and dependable predictive models, this study emphasizes how crucial it is to take into account extra operational and contextual factors in transportation studies.

	Tail Risk	14ft vehicle loading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	8.60	7.95	7.60
CVAR(%)	8.94	8.36	8.06

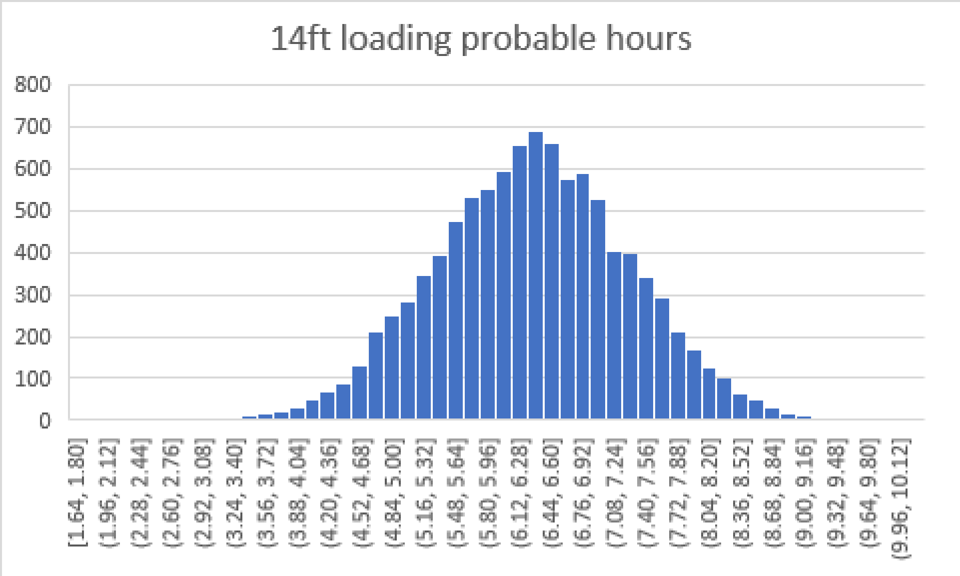
Average loading hours
3.162426901

14ft vehicle loading

Monte carlo simulation

s.no	Random value	hours	probable hours
1	1.23	-1.53	1.64
2	3.39	-0.41	2.75
3	3.38	-0.15	3.01
4	5.49	-0.15	3.02
5	3.35	-0.12	3.04
6	4.08	-0.06	3.10
7	1.90	0.01	3.18
8	4.72	0.01	3.18
9	3.84	0.08	3.24
10	4.15	0.09	3.25
11	2.67	0.09	3.26
12	3.74	0.11	3.27

St.div of loading hours
0.974878182



14ft Vehicle Loading

→ Loading shows moderate average time (3.16 hrs) and high tail risk with VAR up to 8.60%, indicating greater risk during peak times.

	Tail Risk		14ft vehicle unloading(hours)
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	2.66	2.41	2.29
CVAR(%)	2.77	2.56	2.45

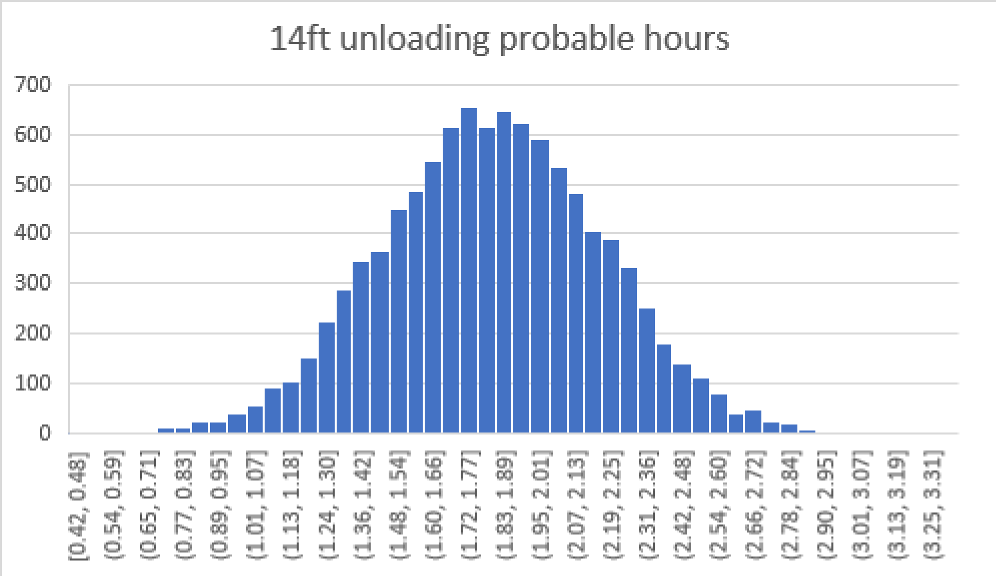
Average unloading hours
0.912865497

St.div of unloading hours
0.359702127

14ft vehicle unloading

Monte carlo simulation

s.no	Random value	hours	probable hours
1	0.79	-0.50	0.42
2	0.90	-0.44	0.47
3	1.22	-0.33	0.58
4	1.02	-0.32	0.59
5	0.44	-0.30	0.61
6	0.40	-0.29	0.62
7	1.01	-0.24	0.67
8	0.83	-0.24	0.68
9	0.85	-0.23	0.68
10	1.32	-0.20	0.71
11	1.35	-0.20	0.71
12	0.92	-0.19	0.72
13	1.40	-0.18	0.73
14	1.06	-0.17	0.74



14ft Vehicle Unloading

→ Unloading is efficient (0.91 hrs avg) with low volatility and minimal tail risk, making it a predictable operation.

	Tail Risk	17ft vehicle loading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	9.00	8.43	8.13
CVAR(%)	9.28	8.78	8.53

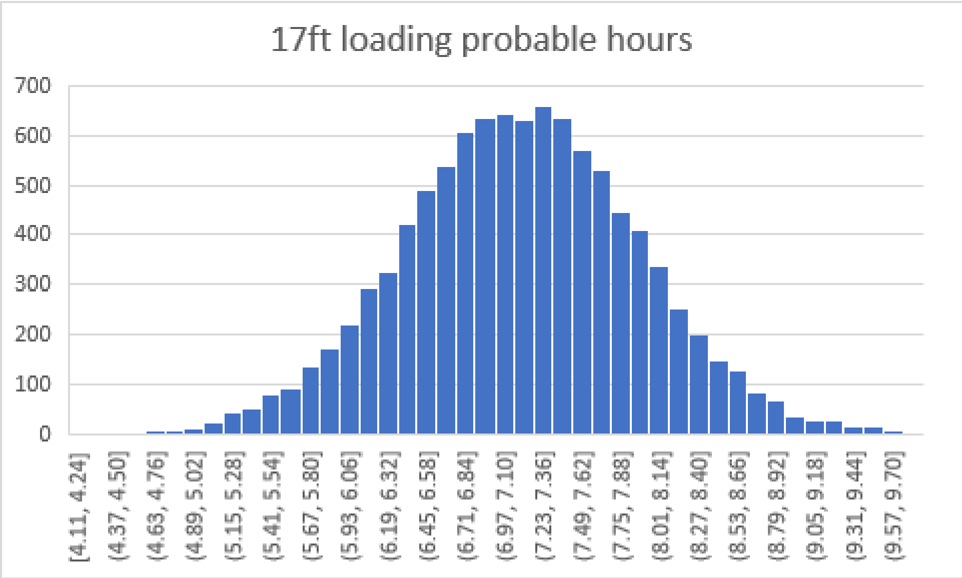
Average loading hours
3.568364929

St.div of loading hours
0.78485374

17ft vehicle loading

Monte carlo simulation

s.no	Random value	hours	probable hours
1	3.06	0.54	4.11
2	4.38	0.94	4.51
3	3.07	1.02	4.58
4	3.13	1.06	4.63
5	3.71	1.13	4.69
6	3.69	1.13	4.70
7	2.96	1.15	4.72
8	2.09	1.19	4.76
9	4.00	1.20	4.77
10	4.13	1.23	4.79
11	4.81	1.23	4.80
12	3.15	1.27	4.83
13	2.63	1.29	4.86



17ft Vehicle Loading

→ Slightly longer average load time (3.57 hrs) than 14ft, with higher VAR (up to 9.00%) indicating increasing inefficiency at extremes.

	Tail Risk	17ft vehicle unloading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	2.86	2.60	2.47
CVAR(%)	2.98	2.76	2.65

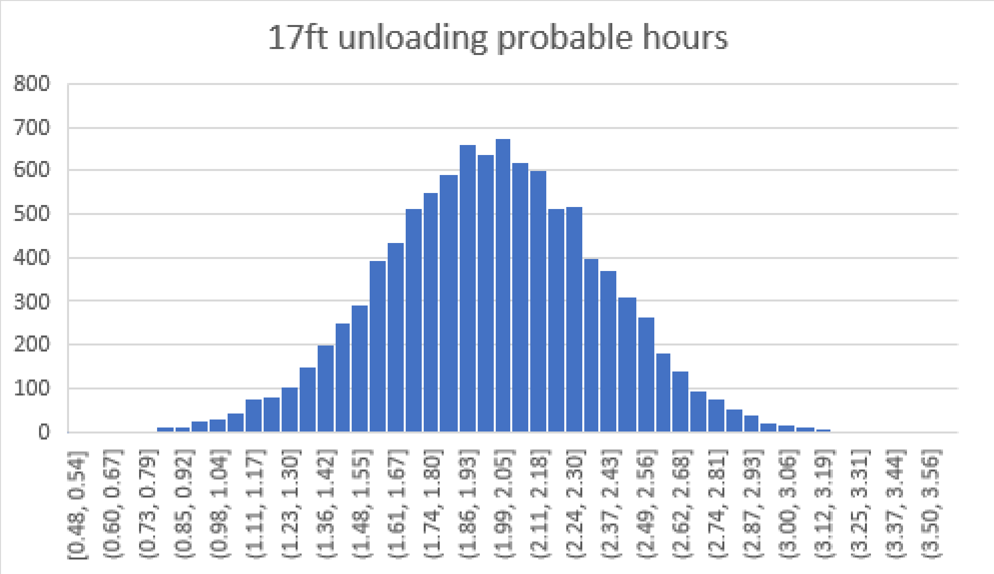
Average unloading hours
0.99178515

St.div of unloading hours
0.385417651

17ft vehicle unloading

Monte carlo simulation

s.no	Random value	hours	probable hours
1	0.78	-0.52	0.48
2	0.51	-0.51	0.48
3	1.79	-0.43	0.56
4	0.68	-0.42	0.57
5	1.17	-0.37	0.62
6	1.38	-0.34	0.65
7	0.91	-0.31	0.68
8	0.63	-0.29	0.70
9	0.65	-0.27	0.72
10	0.89	-0.26	0.73
11	0.19	-0.23	0.76
12	1.80	-0.20	0.79
13	1.04	-0.19	0.80
14	1.26	-0.19	0.81



17ft Vehicle Unloading

→ Average time is 0.99 hrs with mild risk (VAR 2.86%) and low variability, suggesting steady unloading operations.

	Tail Risk	20ft vehicle loading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	9.30	8.85	8.59
CVAR(%)	9.54	9.13	8.92

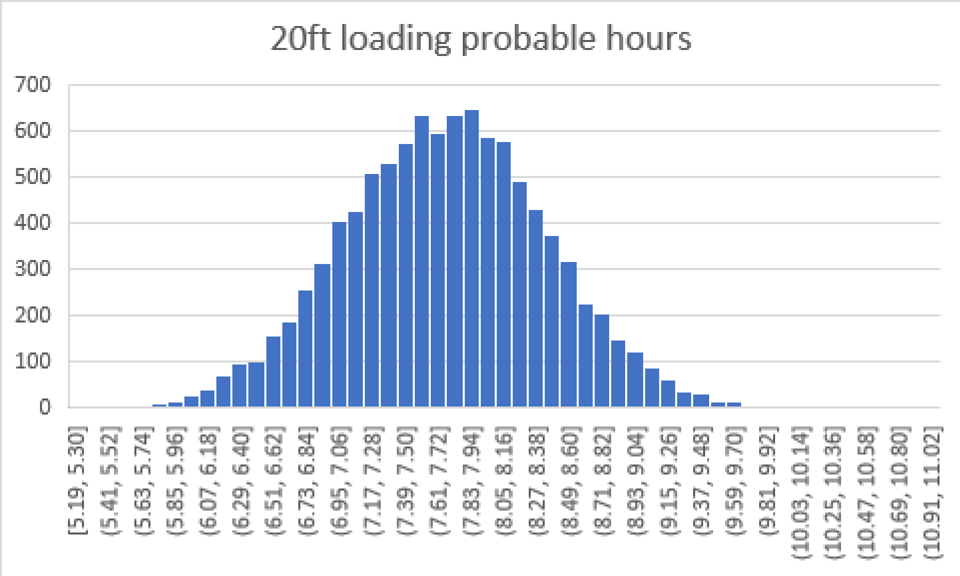
Average loading hours
3.854670674

St.div of loading hours
0.690682479

20ft vehicle loading

Monte carlo simulation

s.no	Random value	hours	probable hours
1	4.73	1.34	5.19
2	2.51	1.37	5.22
3	4.18	1.38	5.24
4	3.64	1.44	5.29
5	4.47	1.52	5.38
6	3.89	1.62	5.48
7	3.59	1.64	5.50
8	4.25	1.71	5.57
9	3.30	1.74	5.60
10	4.85	1.77	5.62
11	3.73	1.79	5.64
12	3.56	1.79	5.64
13	4.50	1.80	5.65
14	2.95	1.83	5.68



20ft Vehicle Loading

→ Loading time rises (3.85 hrs) with increased risk (VAR up to 9.30%), showing scalability challenges for larger vehicles.

	Tail Risk	20ft vehicle unloading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	2.64	2.43	2.32
CVAR(%)	2.75	2.56	2.46

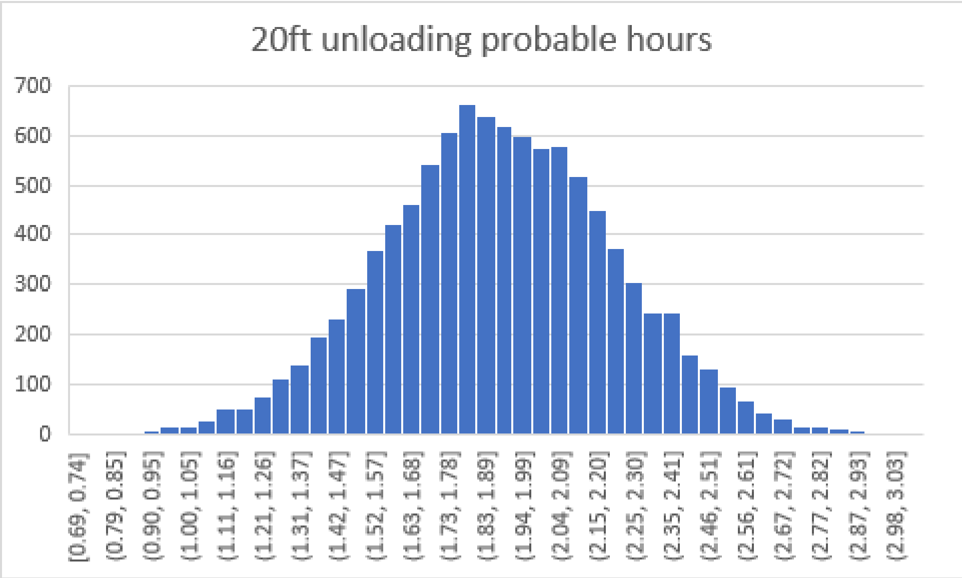
Average unloading hours
0.94914851

St.div of unloading hours
0.3198431

20ft vehicle unloading

Monte carlo simulation

s.no	Random value	hours	probable hours
1	1.25	-0.26	0.69
2	0.55	-0.19	0.76
3	0.79	-0.18	0.77
4	0.63	-0.16	0.79
5	1.53	-0.13	0.81
6	0.62	-0.10	0.85
7	1.09	-0.10	0.85
8	1.00	-0.10	0.85
9	1.42	-0.08	0.87
10	0.56	-0.06	0.89
11	0.29	-0.05	0.90
12	0.97	-0.05	0.90
13	0.94	-0.03	0.92
14	0.88	-0.02	0.93



20ft Vehicle Unloading

→ Unloading is stable (0.95 hrs avg), with low standard deviation and tail risks similar to smaller vehicles.

	Tail Risk	22ft vehicle loading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	9.58	9.13	8.92
CVAR(%)	9.79	9.40	9.21

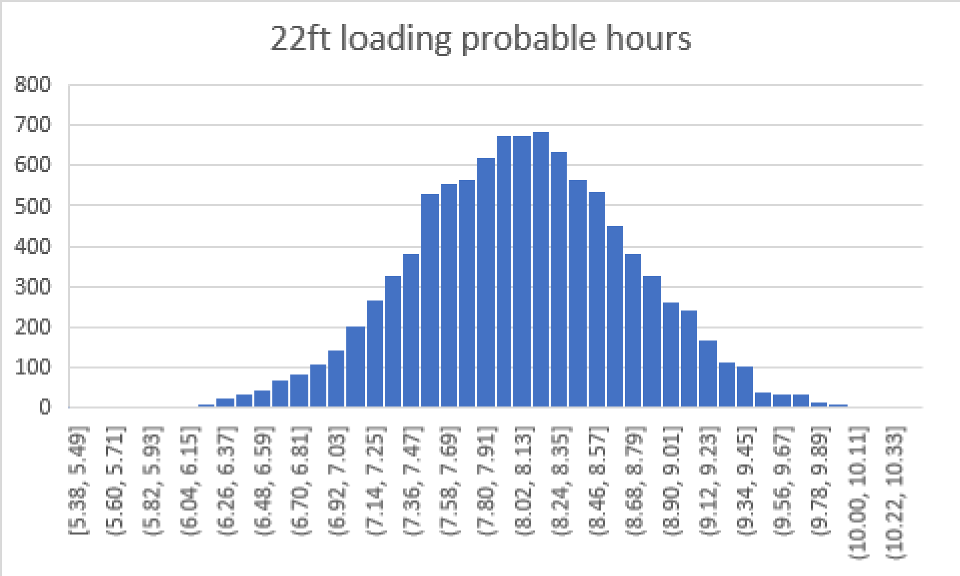
Average loading hours
4.044227642

St.div of loading hours
0.654265934

22ft vehicle loading

Monte carlo simulation

s.no	Random value	hours	probable hours
1	3.28	1.33	5.38
2	3.30	1.33	5.38
3	4.46	1.51	5.55
4	3.52	1.54	5.59
5	3.90	1.65	5.69
6	4.18	1.75	5.79
7	2.65	1.86	5.90
8	4.58	1.89	5.94
9	4.88	1.94	5.98
10	4.78	1.97	6.02
11	5.12	1.98	6.03
12	4.57	2.00	6.04
13	3.45	2.03	6.08
14	3.41	2.06	6.10



22ft Vehicle Loading

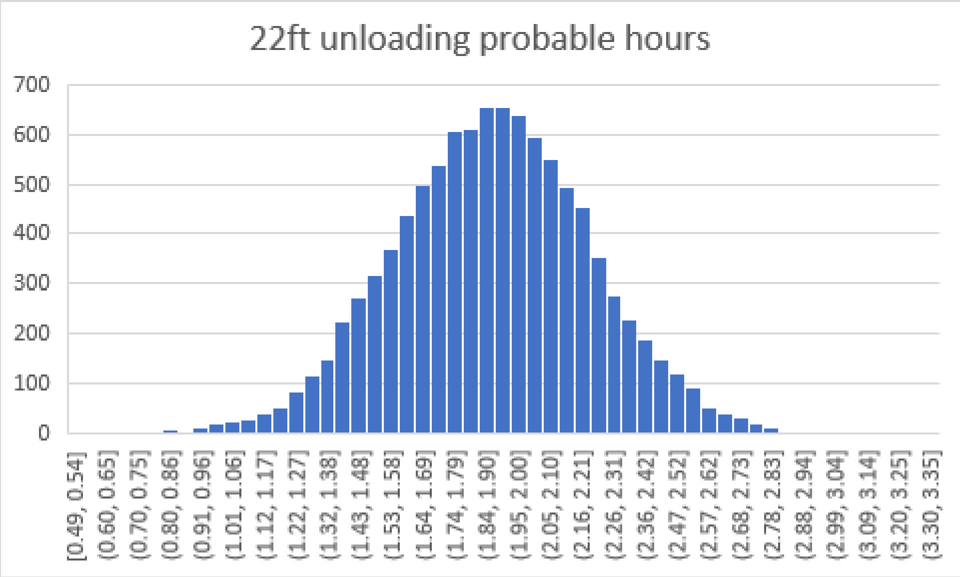
→ Longest average load time so far (4.04 hrs) and highest tail risk (VAR up to 9.58%), signaling capacity-induced delays.

	Tail Risk	22ft vehicle unloading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	2.63	2.42	2.30
CVAR(%)	2.74	2.55	2.45

Average unloading hours
0.941869919

St.div of unloading hours
0.318625924

22ft vehicle unloading Monte carlo simulation			
s.no	Random value	hours	probable hours
1	0.92	-0.45	0.49
2	0.09	-0.39	0.55
3	0.88	-0.14	0.80
4	0.77	-0.13	0.81
5	0.66	-0.09	0.85
6	1.38	-0.09	0.85
7	1.06	-0.09	0.85
8	1.72	-0.07	0.87
9	0.76	-0.06	0.88
10	0.45	-0.03	0.91
11	0.41	-0.03	0.91
12	1.01	-0.03	0.91
13	0.27	-0.02	0.92
14	1.64	-0.01	0.93



22ft Vehicle Unloading

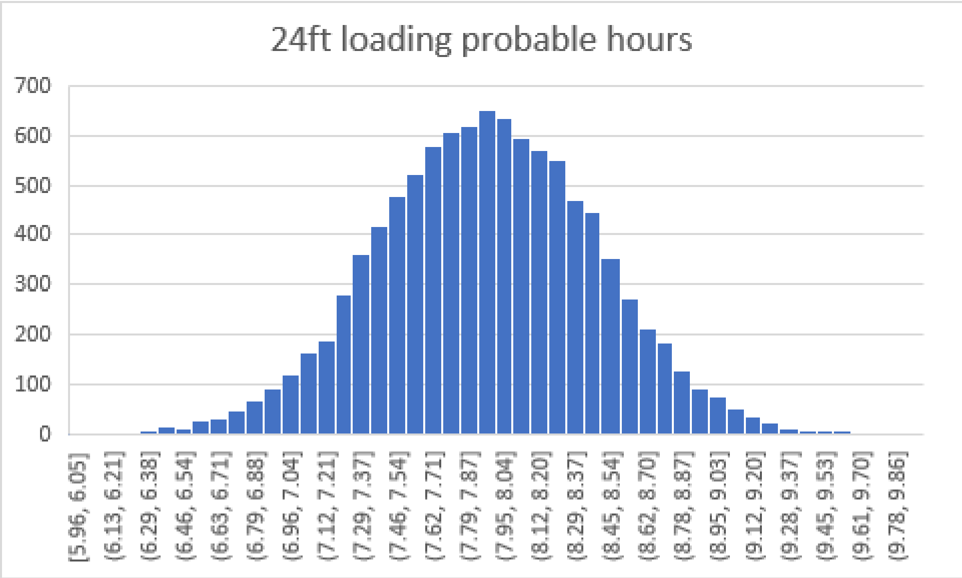
→ Average unloading (0.94 hrs) remains consistent across vehicle sizes with controlled risk levels and low deviation.

	Tail Risk	24ft vehicle loading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	9.09	8.75	8.56
CVAR(%)	9.27	8.96	8.81

Average loading hours
3.960493827

St.div of loading hours
0.503139066

24ft vehicle loading			
Monte carlo simulation			
s.no	Random value	hours	probable hours
1	3.37	2.00	5.96
2	4.21	2.02	5.98
3	3.40	2.11	6.07
4	3.92	2.15	6.11
5	3.22	2.16	6.12
6	4.86	2.16	6.12
7	5.01	2.19	6.15
8	3.85	2.21	6.17
9	3.58	2.23	6.19
10	3.96	2.33	6.29
11	4.03	2.36	6.32
12	4.43	2.36	6.32
13	4.06	2.37	6.33
14	3.74	2.37	6.33



24ft Vehicle Loading

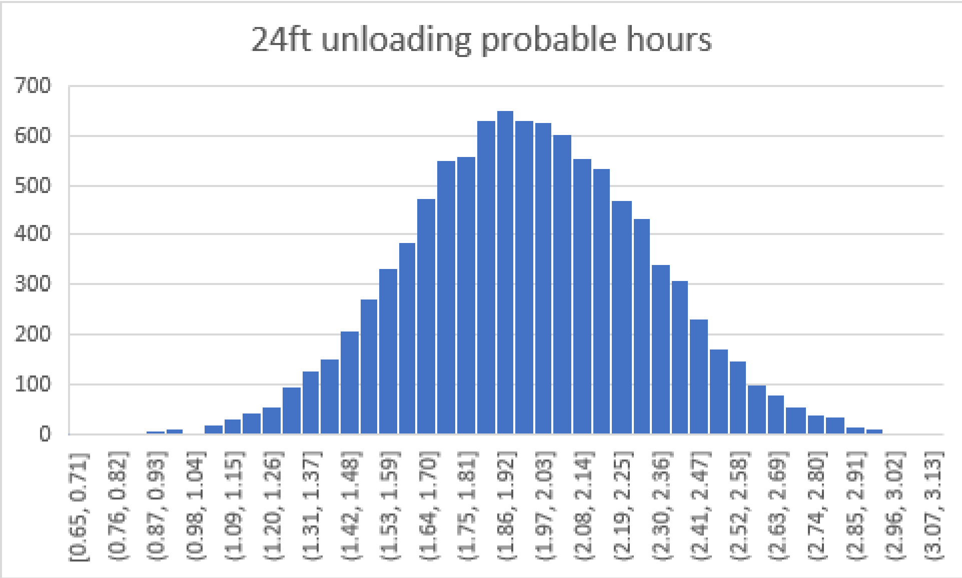
→ Time (3.96 hrs) and risk slightly improve compared to 22ft, indicating minor optimization at this scale.

	Tail Risk	24ft vehicle unloading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	2.76	2.52	2.39
CVAR(%)	2.84	2.66	2.55

Average unloading hours
0.980452675

St.div of unloading hours
0.334256951

24ft vehicle unloading Monte carlo simulation			
s.no	Random value	hours	probable hours
1	0.84	-0.33	0.65
2	0.95	-0.32	0.66
3	0.92	-0.31	0.67
4	1.14	-0.24	0.74
5	0.83	-0.23	0.75
6	1.13	-0.20	0.78
7	0.84	-0.11	0.87
8	1.90	-0.09	0.89
9	0.32	-0.08	0.90
10	1.48	-0.06	0.92
11	0.44	-0.06	0.92
12	1.18	-0.05	0.93
13	0.74	-0.04	0.94
14	0.72	-0.03	0.95



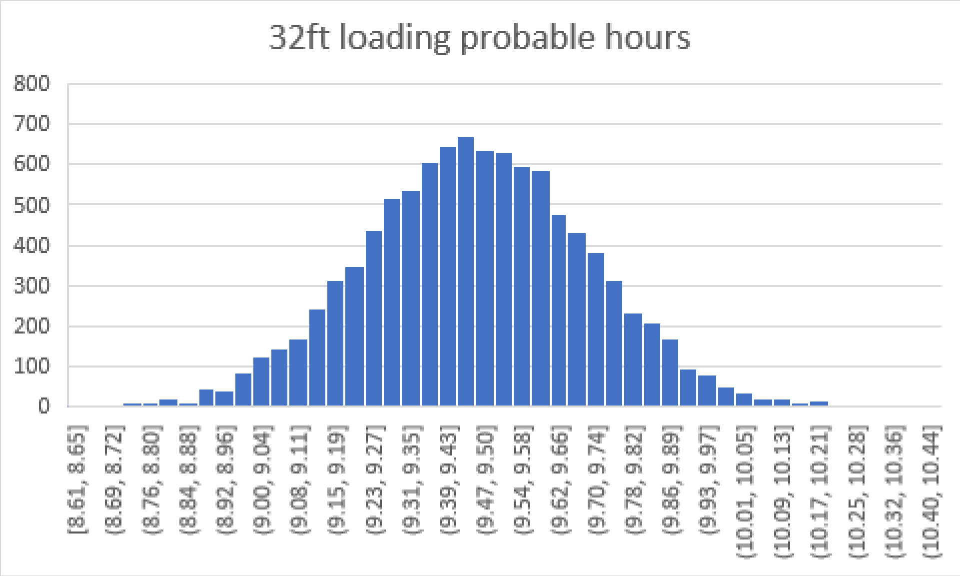
24ft Vehicle Unloading
→ Unloading remains efficient (0.98 hrs), with minor increase in tail risk but within acceptable operational bounds.

	Tail Risk	32ft vehicle loading(hours)	
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	10.02	9.86	9.77
CVAR(%)	10.11	9.95	9.88

Average loading hours
4.732738095

St.div of loading hours
0.234804977

32ft vehicle loading			
Monte carlo simulation			
s.no	**Random value**	**hours**	**probable hours**
1	4.78	3.87	8.61
2	5.14	3.91	8.64
3	4.67	3.91	8.64
4	4.76	3.92	8.65
5	4.51	3.92	8.65
6	5.07	3.92	8.66
7	4.96	3.96	8.69
8	4.96	3.97	8.70
9	4.83	3.99	8.72
10	4.80	4.00	8.73
11	4.67	4.00	8.73
12	4.68	4.00	8.73
13	4.69	4.02	8.75
14	4.51	4.02	8.75



32ft Vehicle Loading
→ Highest loading time (4.73 hrs) but **lowest standard deviation** (0.23), indicating high predictability despite larger size.

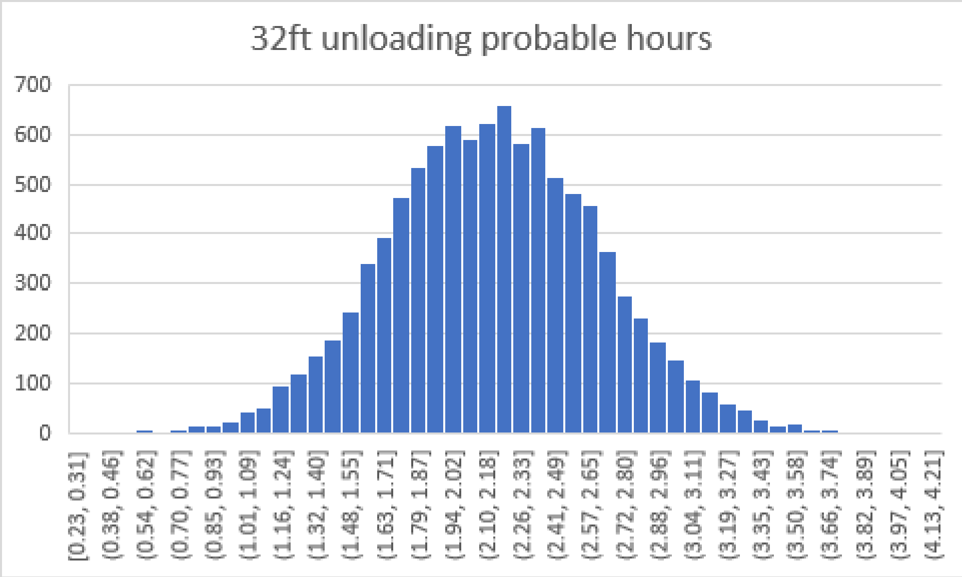
Tail Risk	32ft vehicle unloading(hours)		
Pecent	1%	5%	10%
i	9900	9500	9000
VAR(%)	3.31	2.97	2.78
CVAR(%)	3.49	3.18	3.02

Average unloading hours
1.086309524

St.div of unloading hours
0.484408204

32ft vehicle unloading
Monte carlo simulation

s.no	Random value	hours	probable hours
1	0.92	-0.86	0.23
2	1.49	-0.63	0.45
3	1.06	-0.56	0.52
4	1.03	-0.53	0.56
5	1.26	-0.51	0.58
6	1.49	-0.51	0.58
7	1.23	-0.50	0.58
8	1.09	-0.48	0.61
9	0.14	-0.41	0.67
10	0.60	-0.40	0.69
11	1.11	-0.37	0.72
12	0.92	-0.36	0.72
13	0.58	-0.35	0.74
14	1.85	-0.34	0.74



32ft Vehicle Unloading
→ Although average unloading time is the highest (1.08 hrs), the significantly increased tail risk (VAR 3.31%) and higher deviation indicate growing uncertainty and potential delays at larger vehicle scales.

6. Risk Mitigation Strategies

6.1 Integration of Risk-Based Time Buffers

Mean trip times are frequently used in traditional logistics planning, which ignores variability and tail risks. Organizations can include adaptive buffer periods into planning by using percentile-based risk indicators, namely Value at Risk (VaR) and Conditional Value at Risk (CVaR). For example, buffer insertion procedures should be initiated in proportion to the risk exposure of shipments that surpass the 95th percentile duration.

6.2 Transition to Probabilistic Forecasting Models

Probabilistic models must be used in place of linear regression since linear distance has been shown to be insignificant in predicting trip time ($R^2 = 0.0031$). Monte Carlo simulations provide better insight into normal and abnormal conditions by simulating historical variability across 10,000 scenarios. Forecasts should be assessed using distribution dispersion and confidence intervals in addition to average estimates.

6.3 Route and Vendor Classification Based on Tail Exposure

Tail risk factors that have been historically simulated must be used to implement route risk classification. It is possible to designate routes as high-risk and reallocate more expensive, high-reliability resources to those that regularly above VaR or CVaR thresholds. Reliability indices based on histogram modes, delay frequency, and departure from anticipated durations can also be used to rate vendors.

6.4 Multimodal and Redundant Logistics Design

A redundant and multimodal approach is advised to reduce disruptions caused by regional concentration or single-mode dependency. In order to manage demand spikes or route closures, this entails keeping a flexible mix of air, rail, and road logistics options in addition to standby contractual agreements with other carriers.

6.5 Data Enrichment and Delay Annotation Protocols

Contextual and detailed data are necessary for accurate modelling. To enable machine-readable risk modelling, delays should be identified by structured cause codes (such as weather, customs, or labour strikes). Over time, teaching logistics personnel to accurately and consistently mark occurrences will greatly improve the system's predictive quality.

7. Risk Management Strategies

7.1 Real-Time Risk Monitoring and Alerts

Real-time evaluation of departures from anticipated transit profiles is made possible by integrating real-time data from GPS, weather services, and traffic APIs. Logistics coordinators can take preventative action when risk breaches are identified thanks to threshold-based alert systems that are calibrated using simulation-driven VaR values.

7.2 Scenario-Based SLA Structuring

It is no longer appropriate to compare Service Level Agreements (SLAs) just to past averages. Rather, customers and providers can match expectations with statistically valid service windows through scenario-based SLA design, which is informed by simulation percentiles and CVaR. This lowers financial penalties and customer unhappiness while improving SLA compliance.

7.3 Cross-Functional Risk Coordination Teams

Operations, procurement, compliance, and data science departments should form a special logistics risk committee. This group should test model assumptions, examine simulation findings on a regular basis, and update risk indicators in response to disruption events or new trends.

7.4 Risk-Based Key Performance Indicators (KPIs)

Risk-adjusted KPIs should be incorporated into performance monitoring, such as:

- percentage of deliveries within a 95% confidence interval
- Rate at which delay events surpass VaR thresholds
- Forecasted versus actual durations' rolling standard deviation

These indicators assist distinguish between systemic and random delays and encourage responsibility.

7.5 Rolling Forecast and Adaptive Learning Models

A rolling-window architecture should be used to update the risk model, incorporating the most recent performance data into each prediction cycle. Machine learning methods (such as probabilistic neural networks and gradient boosting) can be incorporated to move from static simulation to dynamic learning systems when more annotated delay data becomes available.

A strong, multi-layered method for reducing and controlling transportation risk in logistics systems is offered by the tactics described here. Logistics networks can develop into robust systems that can handle both predictable variability and emergent disturbances by combining Monte Carlo simulations, extreme value measures, operational feedback loops, and data-driven decision-making. These approaches offer significant value for both academic research and industrial deployment since they are both theoretically sound and practically achievable given the limitations of the enterprise technology infrastructure that is in place today.

8. Conclusions and Future Scope

8.1 Key Observations and Insights

The average transportation duration in the dataset is 3.04 days. The standard deviation is 2.00 days, which reveals a high level of variability even for similar distances. At a 99% confidence level, the Value at Risk (VaR) is calculated at 6.39 days or 153.5 hours. The Conditional Value at Risk (CVaR), which reflects the average of the worst-case scenarios, stands at 6.42 days or 154.1 hours.

The average recorded travel distance is 1,293 kilometres. However, despite the intuitive assumption that distance might be a strong predictor of travel time, the statistical analysis reveals a coefficient of determination (R^2) of just 0.0031. This indicates that less than 0.31% of the variance in transportation time can be explained by distance. A linear regression equation of $y = 5.3217x + 1270.2$ produces an almost flat line, confirming the lack of correlation. This is a crucial finding: distance alone is not a reliable variable for forecasting delivery time.

8.2 Forecast Functionality in Excel

This tool includes a dynamic cell that allows users to input a trip's distance and receive a predicted transportation duration. While the forecast is based on historical patterns, the extremely weak correlation between distance and time highlights the importance of supplementing the forecast with risk-aware metrics, such as percentile ranges, simulation results, and reliability scores.

8.3 Comprehensive Risk Framework

This tool has been designed to support a complete risk management process, consisting of six components:

Risk Identification:

Delays are often caused by factors unrelated to distance, such as customs procedures, weather disruptions, labour strikes, or border policies. Additionally, the underlying data may suffer from inconsistent event tagging or lack of contextual information, making purely quantitative predictions inherently limited.

Risk Quantification:

Using descriptive statistics, the model reveals substantial uncertainty in transportation times. With a mean of just over 3 days and a standard deviation of 2 days, typical durations vary widely. The 99% VaR and CVaR both exceeding 6.4 days emphasize the need to plan for rare but significant delays.

Risk Simulation:

A static Monte Carlo simulation is built into the Excel file. It generates a 10,000 of randomized scenarios that replicate the statistical distribution of the observed durations. The results display a long-tail distribution, confirming that a small percentage of trips take disproportionately longer.

Risk Analysis:

The simulation outcomes help identify the probability of exceeding various time thresholds. For instance, the probability of a delivery taking more than 6 days is non-negligible. The weak relationship between distance and duration underscores the presence of hidden variables not captured in the data, and justifies the need for advanced statistical or simulation based approaches.

Risk Mitigation:

Based on the above, it is recommended to build time buffers into logistics planning, particularly for long-distance or cross-border deliveries. Decisions should rely not only on average forecasts but also on risk boundaries like VaR and CVaR. Improving data quality through standardized tagging of disruptions and delay causes would further enhance the predictive power of this tool.

Risk Management:

This tool allows logistics teams to proactively manage uncertainty by combining historical performance trends with probabilistic forecasts. It can be used to support SLA planning, vendor comparisons, and route selection based on risk-adjusted expectations rather than raw averages.

8.4 Final Considerations and Recommendations

While this tool includes a forecast mechanism based on distance, the statistical analysis clearly shows that distance alone is not a meaningful predictor of travel time. Instead, delivery durations are shaped by operational risks and stochastic variability. As such, decisions based purely on estimated averages may lead to underestimating true delays.

The combination of historical data, probabilistic simulation, and extreme risk measures (VaR and CVaR) provides a more reliable framework for logistics planning. It is strongly recommended to use the prediction cell only in conjunction with simulation insights and scenario-based evaluation.

Finally, to enhance future forecasting power, users should consider enriching the dataset with cause-specific event annotations. Identifying patterns in disruptions would enable the development of more intelligent, dynamic models in future iterations.

8.5 Future Scope

Suggested improvements for the future include enhancing simulation models instead of just using static Monte Carlo which was used in this study. To capture real-world changes, more complex models like agent-based simulation can be designed, so that vehicles, drivers and nodes are all represented as agents with flexible behavior abilities. Another extension, DES, enables DES to model logistics activities such as loading, travel, unloading and queuing, helping in better identifying and handling process flaws and bottlenecks in real time. Long-term effects in the supply chain can also be studied with system dynamics, for example, what effect continuing transport issues could have on my supply or my customers' satisfaction level. Also, hybrid methods using Monte Carlo, DES and agent-based models may make it possible to simulate risks in different operational and environmental scenarios. You can improve simulations even more by integrating them with data collected in real time, ending up with a digital twin that serves predictive and prescriptive analytics needs. Using stochastic programming in such frameworks would help researchers measure risks and determine the best use of resources and control decisions when things are uncertain. Such advancements would greatly boost what risk management tools can do in logistics, giving both a long-term vision and quick responses.

9. References

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10. List of Figures

11. List of Tables