Optimizing freight lane lead times: a prescriptive approach for disruption mitigation

by

José Luis López

Bachelor of Economics, Universidad Nacional de Costa Rica, 2016

and

Mingrui Zhang

Master of Engineering Studies (Honours), University of Auckland, 2018

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Signature of Author: _____

Jose Luis Lopez
Department of Supply Chain Management
May 8, 2025

Signature of Author: _____

Mingrui Zhang
Department of Supply Chain Management
May 8, 2025

Certified by: _____

Sreedevi Rajagopalan
Postdoctoral Associate
Capstone Advisor

Certified by: _____

Mauricio Gamez
Postdoctoral Associate
Capstone Co-Advisor

Accepted by: _____

Prof. Yossi Sheffi
Director, Center for Transportation and Logistics
Elisha Gray II Professor of Engineering Systems
Professor, Civil and Environmental Engineering

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José Luis López

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ABSTRACT

To mitigate costly delays in freight transportation, our sponsor, a leading FMCG multinational, sought a systematic solution to reduce shipment lead times during frequent, low-impact disruptions. While their lane managers typically rely on experience-based decisions, the absence of a standardized approach leaves opportunity on the table. We developed a prescriptive optimization model that recommends intervention actions for delayed shipments, balancing lead time recovery with financial and operational constraints.

Our model formulated as a Mixed Integer Program (MIP) suggests which shipments to prioritize and which interventions to apply, given each lane's budget and operational parameters. It mirrors supplier selection frameworks and was validated through simulation using 12 months of historical shipment data from three distinct lanes.

Capstone Advisor: Sreedevi Rajagopalan
Title: Postdoctoral Associate

Capstone Co-Advisor: Mauricio Gamez
Title: Postdoctoral Associate

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To my parents, you will be proud to know that your money has gone a long way in Boston. Specifically just to Trader Joe's. Because cost of living is absolutely criminal.

To my wife, Maggie, thank you for allowing me to come to Boston and focus on my studies. Meanwhile she works a full time job, raises a toddler and keeps our family afloat.

Even though my tuition and accommodation costs are more than a deposit on a house, the best return on investment will be sending my son here in 20 years. At least that's what my wife thinks will happen. Despite MIT having a longstanding policy against legacy admissions. But I am not one to shatter dreams.

Mingrui Zhang

TABLE OF CONTENTS

1 INTRODUCTION 5

1.1 Background 5
1.2 Motivation 5
1.3 Problem Statement and Key Questions 6
1.4 Project Goals and Expected Outcomes 7

2 STATE OF THE PRACTICE 8

2.1 Supply Chain Resilience 8
2.2 Prescriptive Optimization Models 9
2.2.1 Mathematical Programming and Probabilistic Models 9
2.2.2 Mixed Integer Programming in Supplier Selection 9

3 METHODOLOGY 11

3.1 Data Exploration 11
3.2 Problem Definition 12
3.3 Formulating the Model 13
3.4 Defining the Model 15
3.5 Computational Testing 16

4 RESULTS AND DISCUSSION 16

4.1 Data Description 16
4.2 Test Data Description 17
4.3 Parameter Description 17
4.4 Baseline Scenario 18
4.5 Varying Target Lead Time 20
4.6 Varying Budget Per Lane 24
4.7 Varying Target Lead Time and Budget 28
4.7.1 Lane X 28
4.7.2 Lane Y 29
4.7.3 Lane Z 29
4.8 Managerial Insights 30

5 CONCLUSION 31

5.1 Future Work 32

REFERENCES 33

APPENDIX A DISTRIBUTION OF LEAD TIMES 35

APPENDIX B SENSITIVITY ANALYSIS PARAMETERS 37

APPENDIX C - LINEAR REGRESSION TABLES 38

1 Introduction

1.1 Background

As supply chains become more globalized, increasingly complex and dynamic, so too must the frameworks that maintain a network's "capacity to anticipate, respond and recover" (Reyes Levalle & Nof, 2017) from disruptions. By its nature, the fast-moving consumer goods (FMCG) industry is complex in both products and stakeholders (Supply Chain Today, 2021). Moreover, the market itself is "characterized by a wide variety of consumers, potentially volatile demand, and low consumer loyalty" (Jackson et al., 2023). As a result, FMCG supply chains must be dynamic enough to respond to changing customer demands, economically viable enough to compete in a low product margin environment, and strategic enough to remain operational in a disruptive event.

Over the past decade, global supply chains have been subject to supply chain challenges such as "[n]atural disasters, geopolitical conflicts and even unforeseen events like the COVID-19 pandemic" (Gallagher, 2024), Suez Canal obstruction in 2021 (P&G Chemicals, 2021), port congestion (Cox, 2021) and port strikes. Such risks "impose negative implications upon supply chain performance" (Giannakis & Louis, 2011).

In the low-margin consumer goods market, companies cannot afford to have any prolonged disruptions to their supply chain. "[O]rganizations [need] to have necessary strategies to manage these risks and disruptions" (Giannakis & Louis, 2011). The economic impact of supply chain disruptions is obvious. Recent research shows that "supply chain disruptions result in a 3-5% increase in expenses and a 7% decrease in sales" (Sebastian Herz, 2022). Far more striking numbers can be found in the Suez Canal obstruction in March 2021 – where a container ship ran aground and blocked traffic for six days(Tran et al., 2025). Coming at the tail end of the COVID-19 pandemic, this disruption made headlines in part because of the scale of the disruption – an eye watering US$9.6bn in trade per day (Harper, 2021).

1.2 Motivation

Our sponsor company, Company A, is a multinational consumer goods company and can be considered a major player in the FMCG market. Like other FMCG companies, they are susceptible to supply chain disruptions.

Other similar sized players in the same market have already identified supply chain disruptions as a principal business risk. Procter & Gamble identified a need to overcome the challenges posed by its global operation and the resulting complex supply network. The company's 2024 Annual Report even states that "business results depend on [the] ability to manage disruptions in [the] global supply chain"

with a key focus being those that stem from “external factors over which [they] have no control” (Procter & Gamble, 2024). Unilever’s 2024 Annual Report identified the exposure of their supply network to “potentially adverse events such as geopolitical sanctions, physical disruptions… or disruptions at a key supplier” as a principal business risk (Unilever, 2024). It is such a priority for them to remain strategically competitive on this front that they have directed 75% of their forecasted CAPEX budget on growing the supply chain, including €150 million over three years at a major manufacturing and R&D hub in the UK (Unilever, 2024).

Resilient supply networks should be able to “continuously adapt to a dynamic environment” (Reyes Levalle & Nof, 2017). With respect to this, Company A’s supply chain professionals most frequently encounter what can be classified as high-frequency, low-impact events (HFLI) - defined as activities “associated with coordinating demand and supply of multiple supply chain actors” (Roh et al., 2022). Through interviews with several lane managers at Company A, it was clear that in the absence of a systematic and standardized approach, the decision-making behind resolving HFLI disruptions along a trade lane is largely backed by experience. By introducing a systematic approach, backed by an optimization model, the company desires to achieve a more responsive and resilient supply chain with a package that can produce recommendations that are aligned with its four operational objectives: cost reduction, service, cash flow and sustainability.

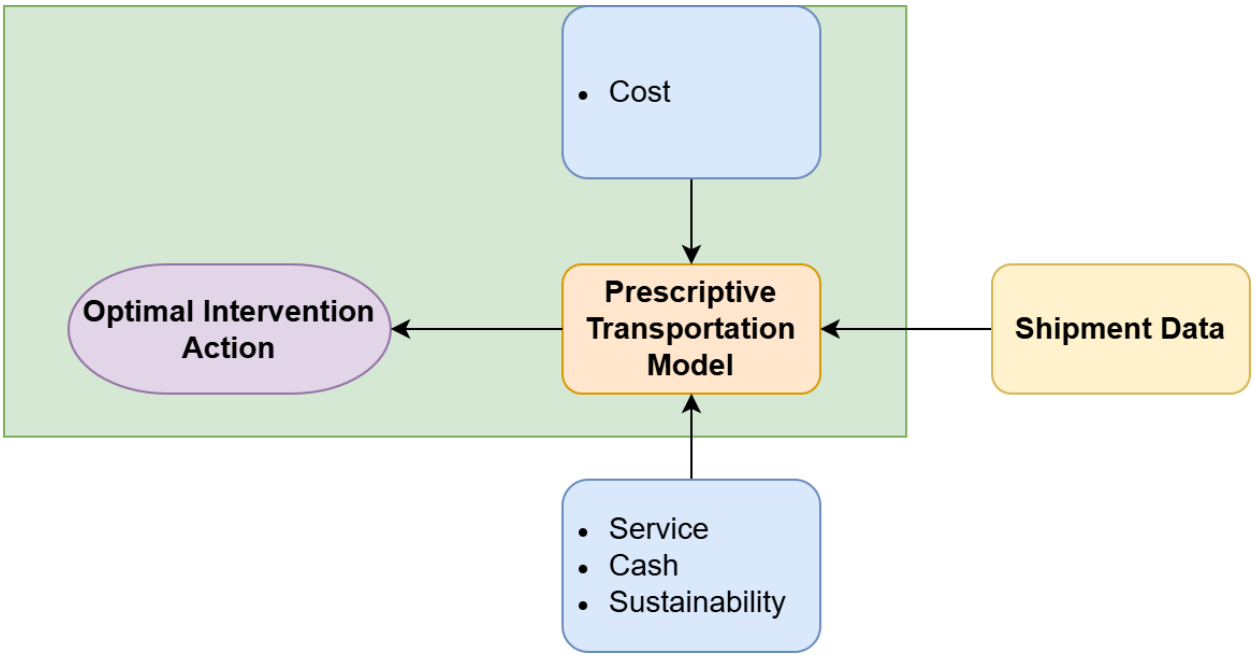
1.3 Problem Statement and Key Questions

One objective driven by the sponsor company’s executive strategy on business operations is to be more dynamically responsive to disruptions to its supply chain. A critical component of its supply chain network are the freight lanes along which its parts are shipped. A disruption to a freight lane ultimately means a customer delivery is in jeopardy. To ensure on-time delivery (OTD), a supply chain agent may opt for an intervention action that brings the delivery time closer to the target delivery date. From the array of intervention actions available to the agent, the selection of one largely comes down to which of the four objectives (cost reduction, service, cash flow and sustainability) the agent deems to be important. With every non-standard decision, scaled across thousands of shipments and hundreds of lanes, becomes a major opportunity to improve outcomes for better operational and financial efficiency.

Company A would like to develop a software package that can optimize lead times while adapting to different types of disruptions. The completed software package would take a delayed shipment and suggest a (series) of intervention actions that would optimally reduce the lead time to its original delivery lead time, factoring in cost reduction, service, cash flow and sustainability. The prescriptive transportation

model sits at the center of their desired end goal. It can be likened to the engine or foundation of the completed software package. Figure 1 shows the process flow for the finished product.

Figure 1: Diagram representation of end product and project scope



In Figure 1, the scope of this project is highlighted in green. We will formulate and build a prescriptive model that focuses on optimizing for lead time variation to prescribe optimal intervention action(s). Accordingly, this project aims to answer the following questions:

1. For each shipment, how can we select the optimal intervention action?
2. For each lane, how can we select which shipment to optimize for?

1.4 Project Goals and Expected Outcomes

By the end of this project, we will deliver an optimization model for shipment lead times when given a target lead time and budget. This optimization model will be validated on sponsor provided data of shipments across three critical lanes over a 52 week period.

Through analysis of the provided shipment data, we will be able to formulate a multiple-input, single-objective optimization model. The analysis of the shipment data allows us to determine the key parameters for this model and the insights from the exploratory data analysis will determine the level of testing required to validate the model.

The model will be a tool that provides insights for Company A's lane managers on the trade-off between target lead time and budget per lane. The lane managers will be able to use it as a simulation tool as part of their fiscal planning.

2 STATE OF THE PRACTICE

As will be evidenced below, the topic of supply chain resilience covers a large area. In this section, we characterize supply chain resilience within the context of our problem. We will also explore prescriptive optimization models used in supplier selection, with a particular focus towards mixed-integer linear programming (MILP) models.

2.1 Supply Chain Resilience

Supply chain resilience can be defined through different lenses, from organizational to ecological and psychological resilience (Ponis & Koronis, 2012). In the case of supply chain resilience, the discourse commonly centres around adaptive capability (Ponomarov & Holcomb, 2009) and a return to a normal or improved state(Novak et al., 2021; Tukamuhabwa et al., 2015). Adaptive capability of a supply chain or organization is its ability to remain "flexible and agile and… change quickly". Breaking down this definition, there are two key steps: respond and recover. A resilient supply chain must be able to dynamically address any disruption and return to its original state or achieve a "more desirable state of supply chain operations" (Ponomarov & Holcomb, 2009).

A popular case study of resilient supply chains is the fire at a Philips semiconductor plant in 2000 (Tabanasi, 2024).Two key customers of Philips semiconductors, Ericsson and Nokia, responded very differently to this disruption. Ericsson chose to do nothing, opting to wait for the plant to return to capacity (Mukherjee, 2008). Nokia, on the other hand, took steps to mitigate the risk by sourcing alternative manufacturers as well as opting to eliminate the risk altogether by redesigning some chips to be manufactured at non-Philips plants (Mukherjee, 2008). At year end Ericsson announced a US$2.34 billion loss in the company's mobile phone division and laid off approximately half of its mobile phone division workforce. In April 2001, Ericsson announced a joint venture with Sony to become Sony Ericsson. Nokia's global market share of handsets and mobile phones increased from 27% to 30% (Sheffi, 2005).

Low-frequency, high-impact disruptions to supply chains, like the Philips example above, present strategic risks to an organization. However, high-frequency, low impact (HFLI) disruptions present small losses that occur at a near daily rate. Such events present operational risk and can be mitigated through tactical approaches (Roh et al., 2022). Characterized as "risks arising from the problems of coordinating supply and demand" (Kleindorfer & Saad, 2005), such disruptions are deemed inherent to a supply chain.

We reduced the effort and time taken to remediate and reoptimize high frequency-low impact disruptions.

The project outcome should look to course correct delayed shipments with appropriate intervention actions, with the aim of restoring the supply chain to normal operation.

2.2 Prescriptive Optimization Models

Prescriptive analytics covers a broad spectrum of optimization models and methodologies, but its primary objective is to provide optimized outcomes of a particular constraint or scenario to assist data-driven decision making (Lepenioti et al., 2020; Niss, 2015). It does so by using optimization models to produce adaptive, constrained, and time-dependent outcomes.

If prescriptive analytics were akin to a toolbelt, then the many models would be its tools. As with any tool, there are some that are a better fit for the application than others. As previously mentioned, we liken the selection of intervention actions to supplier selection in a supply chain. We will explore the use of linear models in supplier selection to draw parallels with this research.

2.2.1 Mathematical Programming and Probabilistic Models

Linear programming is one of the most common tools for solving supply chain problems. It considers a vector of inputs (i.e., disruption, expected lead time, etc.) and optimizes for a singular objective (i.e., lead time). For example, Iraj (2024) used a mathematical programming model to optimize supply chain network design and decision making under uncertainty. This model considers disruptions by creating constraints like limited capacity or higher transportation costs. It also incorporates resilience metrics like redundancy, flexibility and agility into the objective function, and it gives the best solution while considering uncertainty by solving the model under different scenarios with disruptions(Gray & Cullinan-James, 1976; Iraj, 2024; Salvendy, 2001).

In the context of this project, lane selection is similar to supplier selection in that each lane provides a service at a certain cost and quality of delivery.

2.2.2 Mixed Integer Programming in Supplier Selection

We liken the selection of optimal intervention actions and shipments to supplier selection for supply chain design. Just as there are any number of available intervention actions that could be chosen to reduce lead time, there are any number of suppliers that could be chosen for a supply chain to deliver components.

The traditional supplier selection problem aims to optimally select supplier(s) where all suppliers can meet delivery in full, on time and in-spec (DIFOTIS). Ware et al. (2014) modelled a dynamic supplier selection problem using a mixed integer non-linear program. The key differentiator between the traditional and dynamic supplier selection problem is that in the latter, the quantity and quality delivered from each supplier varies over time. Hence, a non-linear model is required to for the variability over time. Sawik (2018) and Hammami et al. (2014) were able to formulate a scenario-based dynamic supplier selection problem using a stochastic mixed integer program. The dynamic aspect in this problem relates to pricing variability due to volume discounts and currency rate fluctuations. However, the model was non-linearised by introducing a second set of binary variables. Where we draw parallels with these works is the need to select from a set of items, where each item delivers the same part to varying degrees. Where the supplier selection problem has suppliers that deliver parts of varying quality and cost, we have intervention actions that deliver lead time reductions at varying magnitudes and cost.

In an earlier work on supplier selection, Sawik (2013) posed two MIP models to describe a “multi-stage supply chain under disruption risks” – one to describe risk-neutral and another to describe risk-averse solutions. The future use of this model is to be able to formulate customer service, sustainability, cost and cash flow as inputs into an optimization model for shipping lead times. A similar multi-objective problem defined by Sawik aims to minimize the total cost which is comprised of ordering cost, holding cost, purchase cost and shortage cost. Faced with a similar problem, Ravindran et al. (2010) proposed “four different … goal programming models to solve the multi-objective optimization problem” (Sawik, 2013). In contrast, Sawik was able to model a similarly complex problem using a series of stochastic MIP models.

The use of multiple optimization models in these works, Ravindran et al. (2010) Sawik (2013) initially led us to consider our problem as a two-phase optimization model. Similar to the approach adopted by Ravindran et al. (2010), the first phase is “determine[ing] the ‘short list’ of qualified suppliers” and the second "determine[ing] the optimal order quantities among the short listed suppliers”. From this, we can envision our problem as an initial phase of short-listing intervention actions assigned to shipments and a follow-up phase of determining which shipment-intervention combination to be included to minimize total costs across a lane. However, unlike these prior works, we simplify the approach by pre-assigning the interventions to shipments and optimize for the best combination of intervention-shipment, thus eliminating the first phase.

3 METHODOLOGY

We model this supplier selection problem as a mixed-integer linear programming model as described in Section 2.2.2. Similar to supplier selection in procurement where cost, quality and delivery need to be balanced to choose the optimal supplier, the selection of intervention actions for each shipment follows a similar logic. Intervention actions should be prioritized when they achieve an optimal balance between lead time reduction and cost.

Section 3.2 will further refine the definition of the problem and describe it in terms of key variables and the relationships between them. The formulation and definition of the model is described in Sections 3.3 and 3.4. These sections will outline the relationships between key variables and how they contribute to the optimization model.

3.1 Data Exploration

Prior to defining and formulating the model, the first step is to clean and process the provided datasets. The provided datasets were extracts from Company A's enterprise requirements planning (ERP) software and contains many descriptive variables for each shipment. The intent of the exploratory data analysis step is to remove any errors or missing values, process the data to understand the key variables and to understand the statistical distribution of the provided dataset.

The data used to develop the model is based on shipment data over the prior 52 weeks for three lanes (X, Y and Z). Between the three lanes, they encompass a range of shipping modes, distance and lead times and cover large geographic areas. Lane X represents a cross border truck crossing. Lane Y represents a sea freight shipment from Europe to the Middle East. Lane Z represents a multi-leg, multi-modal freight shipment from the United Kingdom to Asia.

Within each dataset, each record is a single, unique shipment with requested and actual start dates, requested and actual end dates, planned and actual lead time, and delivery lead times at certain milestones.

For each lane, the dataset was cleaned to remove obvious outliers (i.e., shipments that were more than ten standard deviations from the mean), incomplete records (i.e., no end delivery date for the shipment or any of its legs). Shipments with negative lead times were also not considered. While such shipments can occur, the purpose is to develop a model for disruptions and delayed deliveries. Therefore, expedited shipments will skew the data. For the purposes of computational testing at a later stage, 10 datasets were generated for each lane. Each dataset has the same size as the original dataset. This was done by generating values based on the statistical distribution of total lead time for each lane. A statistical summary of all three lanes is provided in Table 1. The best fit distribution is the statistical distribution that

best models the underlying distribution of the dataset. It was determined using an extension of the SciPy Python library – Fitter (Cokelaer, 2022).

Table 1: Statistical Summary of Lanes

Lane	Average Lead Time, days	Standard Deviation of Lead Time, days	Best Fit Distribution
Lane X	8.98	2.62	Burr
Lane Y	67.64	16.65	Log Logistic
Lane Z	89.17	15.83	Logistic

3.2 Problem Definition

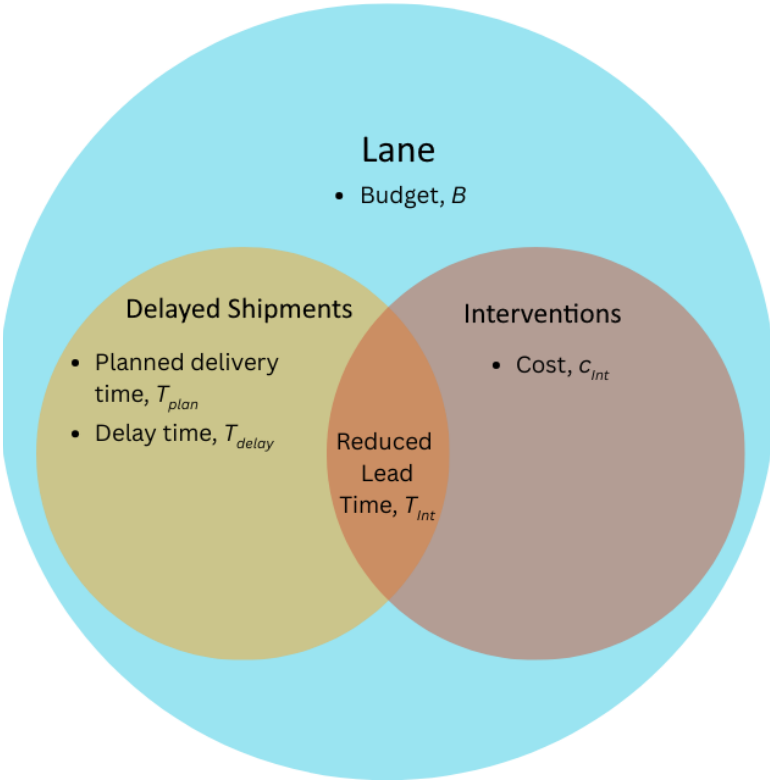
For any delayed shipment, its lead time is composed of three components: the planned delivery time (T_{plan}), the delay time (T_{delay}) and the lead time reduction due to intervention (T_{int}). Intervention is the action of the responsible party to bring the delivery date of the delayed shipment back to, or as close as possible to, the original scheduled delivery date. There is a finite number of plausible actions that can be used to intervene with a delayed shipment. Every such action comes with its own cost (c_{Int}). For example, if a sea-freight shipment missed its vessel due to a fault with its import documentation, it could be re-routed with a new carrier at a surcharge or it could be re-directed to the airport and shipped via air-freight for a much higher fee.

Following the above logic, a freight lane within this dataset consists of multiple delayed shipments. Each lane would have an annual budget (B) to pay for intervening actions. Intervention actions are not necessarily unique to a lane, but not all intervention actions are appropriate for all lanes. For example, in the case of Lane X, while switching to air-freight is possible it would not be considered plausible given that the airport is in a different city than the origin.

As each lane represents a different geographic region with different shipping modes and different intervention strategies, it can be assumed that each lane is independent of another. Therefore, the scope of the model is to optimize for a single lane.

The above relationships are best represented as a Venn diagram as per Figure 2

Figure 2: Relationship between Delayed Shipments, Interventions and Lane



3.3 Formulating the Model

From the definition of the variables outlined in Section 3.1, the total lead time of a delayed shipment $(T_{shipment})$ that has had an intervention action applied can be formulated as:

$$T_{shipment} = T_{plan} + T_{delay} - T_{Int} \quad (1)$$

The provided datasets contain historical shipment details where the completed shipment lead times already includes the delayed component. Therefore equation (1) can be re-arranged as:

$$T_{shipment} = T_{actual} - T_{Int} \quad (2)$$

Where the lead time reduction from the intervention action must be less than or equal to the delay $(T_{Int} \leq T_{delay})$

We will not consider the scenario where an intervention action reduces the lead time by more than T_{delay}. Aside from being an almost impossible scenario, the cost to achieve such a result would be so astronomically high that it would never be considered in practice. Therefore, to prevent the model from selecting this possibility, we constrain it such that it would not be allowed to occur. T_{Int} is wholly

dependent on the intervention action selected. In a vacuum, the intervention action chosen would completely nullify the delay time, i.e., $T_{Int} = T_{delay}$. However, the more a particular intervention action reduces lead time, the more exponentially expensive it becomes. Therefore, not every shipment can receive the perfect intervention action, and when assessing across an entire lane, not all shipments can receive an intervention action. We enforce the intervention constraint that for any shipment i, an intervention action j cannot reduce the delivery lead time $T_{act,i}$ to be less than the original planned delivery lead time $T_{plan,i}$.

Given the problem that has been outlined, it can be concluded that for any shipment i, there are a M finite number of possible and plausible intervention actions that reduces delivery lead time (T_{act}), by $T_{Int,k}$. Then, for all N shipments in a freight lane k, we choose shipments that will receive an intervention action such that the cost of all the intervention actions $c_{Int,k}$ must be less than the budget, B. It can be understood that shipments i and intervention actions j are subsets of the freight lane .

The sets, parameters, and decision variables that define the structure of the optimization model are summarized in Table 2 and Table 3 These tables provide a clear reference for the notations and entries used throughout the mathematical formulation.

Table 2: Sets for optimization model

Notation	Description
Sets	
$\boldsymbol{I}$	Shipment, $i = 1,2, \dots, N$
$\boldsymbol{J}$	Intervention action that produces a lead time reduction, $j = 1,2, \dots, M$
$\boldsymbol{k}$	Freight Lane, $k = 1,2, \dots, K$

Table 3: Parameters and decision variables for optimization model

Notation	Description
Parameters	
$\boldsymbol{c_j}$	Cost of Intervention Action j
$\boldsymbol{X_{ij}}$	Binary variable representing selection of intervention action j for shipment i
$\boldsymbol{B}$	Budget of the lane
$\boldsymbol{T_{act,i}}$	Actual lead time for shipment i
$\boldsymbol{T_{plan,i}}$	Planned lead time for shipment i

3.4 Defining the Model

Following on from the formulations of lead time, we define the objective function as follows:

Objective:

$$Min\ Z = \sum_{i=1}^{N}\sum_{j=1}^{M}\left(T_{act,i} - j\right)\cdot X_{ij} \tag{3}$$

Subject to:

$$\sum_{i=1}^{N}\sum_{j=1}^{M} c_j\, X_{ij} \leq B, \tag{4}$$

$$\sum_{j=1}^{M} X_{ij} = 1\,, \qquad \forall\, i \in I \tag{5}$$

$$T_{act,i} - j \cdot X_{ij} \geq T_{plan,i}, \qquad \forall\, i\ \in I, \forall\, j\ \in J, T_{act,i} \geq T_{plan,i} \tag{6}$$

$$X_{ij}\ \in \{0,1\}, \qquad \forall\, i\ \in I, \forall\, j\ \in J \tag{7}$$

The proposed model includes an objective function which minimizes the final lead time per shipment. The model has been formulated as a mixed integer program (MIP) due to the mix of binary and discrete variables, complex constraints and the fact that this is an optimization problem. The budget constraint (4) ensures that the total costs of all selected shipments and intervention actions do not exceed the freight lane's budget. Constraint (5) ensures that one intervention action per shipment. The intervention constraint (6) is to prevent the model from selecting a solution that would reduce the lead

time to less than the original, planned lead time. Finally, Equation (7) represent binary and non-negativity decision variables.

3.5 Computational Testing

For computation of the model in Equation (3), an array of lead time reductions and appropriate costs were simulated for each lane. The costs of each intervention action were defined as a function of the lead time reduction. This approximates practical cost structure of intervention actions. The model defined in Section 3.4 is implemented using an academic licensed version of the Gurobi library of mathematical optimization solvers. The Gurobi library is a benchmark in complex mathematical optimization solvers and is ideal for handling optimizations involving large datasets with multiple parameters (Jablonský, 2015).

4 RESULTS AND DISCUSSION

4.1 Data Description

This research optimizes for the reduction of lead time variability across three critical lanes for Company A. The raw data provided by Company A details 12 months of shipments from July 2023 to June 2024.

As can be seen in Table 4, Lane X has the greatest number of shipments and the highest on time delivery percentage (OTD%). Given that Lane X only has road freight, it is no surprise that the frequency of shipments in this lane dwarfs the others. The cumulative effect of lead time variation has costly downstream impact on planning and customer deliveries.

Table 4: Summary of raw shipment data

Lane	Total Shipments Between Three Lanes (%)	OTD (%)	Standard Deviation (%)
X	94.2	99.4	29.21
Y	1.5	43.4	24.61
Z	4.3	75.3	17.76

Lane X is a cross-border road freight lane with an average lead time of 9 days. Lane Y is a sea-freight lane with an average lead time of 67 days. Lane Z is a multi-modal freight lane with an average lead time of 89 days.

Conversely, Lane Y has the least number of shipments and less than half of which are on time. It is worth noting that there was significant port congestion along Lane Y that affected lead times for several months.

Lane Y has a mean lead time of 67 days and Lane Z has a mean lead time of 89 days (Table 1). Given the standard deviation for these lanes, lead times can be up to 84 and 105 days respectively. This has significant cost impacts in terms of holding costs of inventory and total pipeline costs.

4.2 Test Data Description

To replicate a longer time frame for model validation, nine additional test datasets were generated based on the mean and statistical distribution of the raw datasets.

Similarly, the possible intervention actions the model could select were also inferred from discussions with Company A lane managers. The costs of each intervention action were modeled such that it increases non-linearly with days of lead time reduced, effectively applying a greater discount the more an intervention action reduces lead time. This incentivizes the model to utilize the intervention actions that reduce more days.

As discussed in Section 3.4, the optimization model minimizes the end-to-end lead time per shipment. It aims to maximize the budget per lane and apportion this to reduce the lead time for as many shipments as possible. The model takes actual and planned (target) lead times, available intervention actions (with estimated cost and lead time improvement per action) as inputs. In the following sections, we will explore the model outcomes from varying lead times and budgets.

4.3 Parameter Description

Of the inputs into the model, the variables we expect to have the highest impact are target lead time and budget per lane. The days of lead time reduced and cost for each intervention action are considered fixed. For the expected application of this model, the cost and impact of interventions would be outside of the control of the lane manager. The target lead time and the budget can be influenced by each lane manager.

For the sensitivity analysis, the maximum budget value was calculated as the average cost per day reduced for all intervention actions per lane and the 85^{th} percentile lead time gives the maximum budget. The expectation is that this figure should be sufficient to resolve 85% of all shipments. During discussions with lane managers, it was noted that there will inevitably be some shipments where the delay cannot be

resolved or is too costly to resolve. Hence 85% was used as the benchmark. The range of budget values was created from the maximum figure in seven equal increments.

The range of lead time values for each lane is generated by setting the system lead time as the median value, with the minimum and maximum values being one standard deviation from the median. The remaining lead time values in the range are equal increments between those three parameters.

A summary of lead time and budget values used in the sensitivity analysis is documented in Table B1 of Appendix B.

. It should be noted that although Lane X is a comparatively simpler freight lane than Lane Y and Z, its budget is approximately ten times that of any other lane due to the sheer number of shipments.

The expected outcome of the sensitivity analysis is that as target lead time increases, there will be fewer delayed shipments and the budget per lane can be distributed across fewer shipments therefore the model will be able to intervene and resolve more delayed shipments.

4.4 Baseline Scenario

For the baseline scenario, the target lead time is based on the system lead time for that lane. The system lead time is the lead time that Company A's ERP system is using for material requirements planning (MRP) and other system driven functions. The budget is fixed at the median value of the budget range previously outlined in Section 4.3.

At the system lead time and based on the distribution of system lead times for each lane, 45.6% of shipments in Lane X, 40.5% of shipments in Lane Y and 55.2% of shipments in Lane Z will not meet system lead time. These represent the opportunities for the model to optimize for lead times. The values of the input variables for each lane are detailed in Table 5.

Table 5: Baseline Scenario Input Values

Lane	Target Lead Time, days	Budget per lane, $	Delayed Shipments, %
Lane X	9	$4,000,000	45.6%
Lane Y	69	$150,000	40.5%
Lane Z	87	$425,000	55.2%

The results in Table 6 show the average figures across all ten datasets. The intervention rate is the number of delayed shipments where an intervention action was taken, where the number of delayed shipments represents the opportunity to take an intervention action.

Table 6: Baseline Scenario Results

Lane	Intervention Rate (%)	Success Rate (%)	Avg Act. Lead Time, days	Avg Lead Time Reduced, days	Avg Cost per Lane($)
Lane X	100	99.92	13	4	3,374,230.11
Lane Y	100	100	81.7	12.7	93,333.79
Lane Z	100	100	100.1	13.1	382,531.28

The Success Rate is the percentage of delayed shipments that have been brought to within target lead time after an intervention action has been applied. The high success rate combined with the average cost per lane being far below the budget suggests the target lead time and/or budget per lane can be improved upon. It is immediately obvious from the actual lead times in the generated test datasets will show that there is at least one shipment within each lane that is at least 4 standard deviations away from the target lead time. Yet the model can apply an intervention action to all shipments. In practice, this would be seen as a very costly decision.

For instance, one shipment in Lane Y has an actual lead time of 138 days which is 4.3 standard deviations from the target lead time (69 days). Yet the model reduced the lead time by 69 days at a cost of $7946.73. In practice, this would not have been a feasible choice. Similarly, several shipments in Lane X have actual lead times between 25 to 29 days (at least 5.5 standard deviations from the target lead time). Yet the model applied the most aggressive (and expensive) intervention action to these shipments and reduced the lead time by 15 days. As even the most aggressive intervention action can only reduce lead time by 15 days, the minimum improved lead time is 10 days. This is still outside of the target of 9 days. Given that the total cost of interventions was approximately $626,000 below the budget, we are positive that if the model had the option to apply more aggressive (and costly) interventions it would do so.

The fact that the model was able to intervene on all shipments suggests that budget value may be too high or the target lead time is not representative of the distribution of lead times within the lane. The parameters can be tuned to produce more optimal outcomes. The baseline scenario demonstrates substantial opportunity for improvement. For the subsequent sensitivity analysis, we explore the effect of varying target lead time and budget.

4.5 Varying Target Lead Time

For this scenario, the target lead time was varied across all three lanes while the budget was fixed as per the baseline scenario. The range of target lead times per lane is shown in Table .

Figure 3, Figure 4 and Figure 5 plots the Intervention Rate against Percentage of Delayed Shipments for Lane X, Lane Y and Lane Z respectively. This confirms the expectations in Section 4.3 where intervention rate should have an inverse relationship with the number of delayed shipments. As target lead time increases, the number of delayed shipments that require intervention will decrease. The same budget can be spread across fewer shipments allowing for more shipments to receive intervention actions.

Figure 3: Intervention Rate against Percentage of Delayed Shipments for Lane X

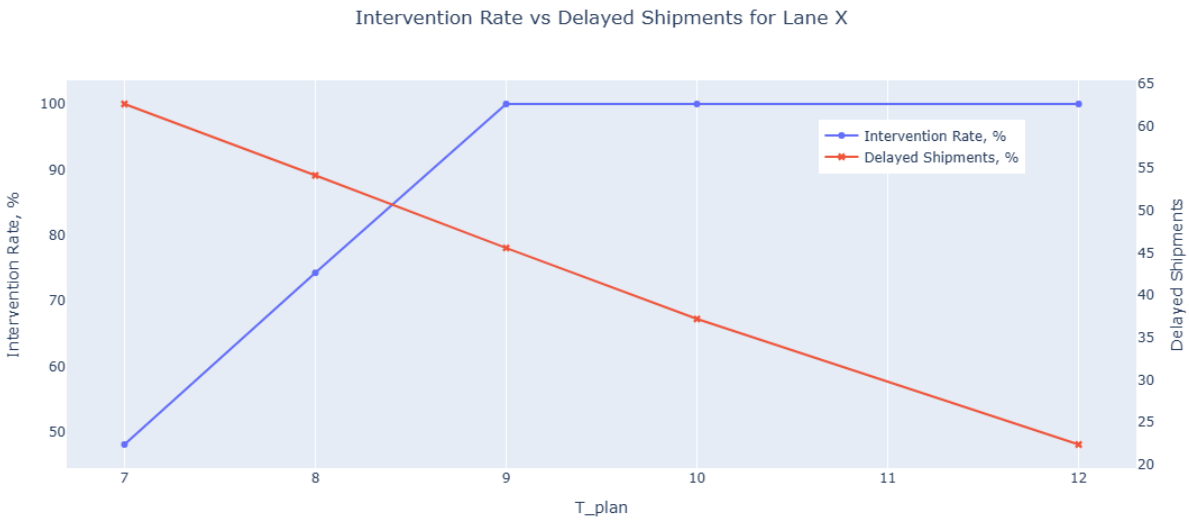


Figure 4: Intervention Rate against Percentage of Delayed Shipments for Lane Y



Figure 5: Intervention Rate against Percentage of Delayed Shipments for Lane Z

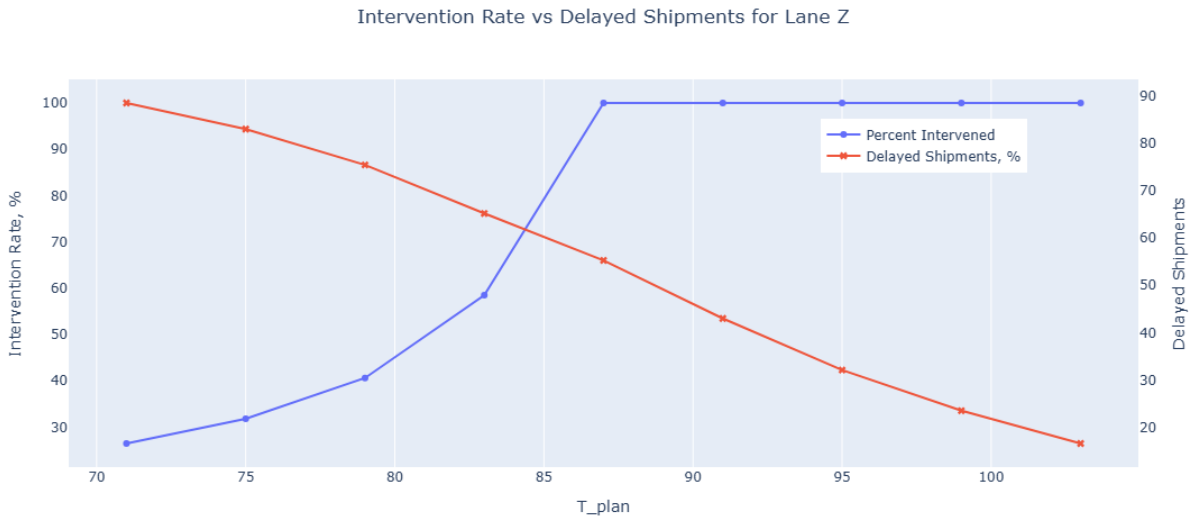


Figure 6, Figure 7 and Figure 8 plots the Success Rate against Percentage of Delayed Shipments for Lane X, Lane Y and Lane Z respectively. Given the budget remains the same as the baseline scenario, then the high success rate at the system lead times and above are expected. System lead times are 9 days for Lane X, 69 days for Lane Y and 87 days for Lane Z. However, it is interesting to note the steep drop-off in both intervention and success rates as soon as the target lead time drops below the system lead time.

Figure 6: Success Rate against Percentage of Delayed Shipments for Lane X



Figure 7: Success Rate against Percentage of Delayed Shipments for Lane Y

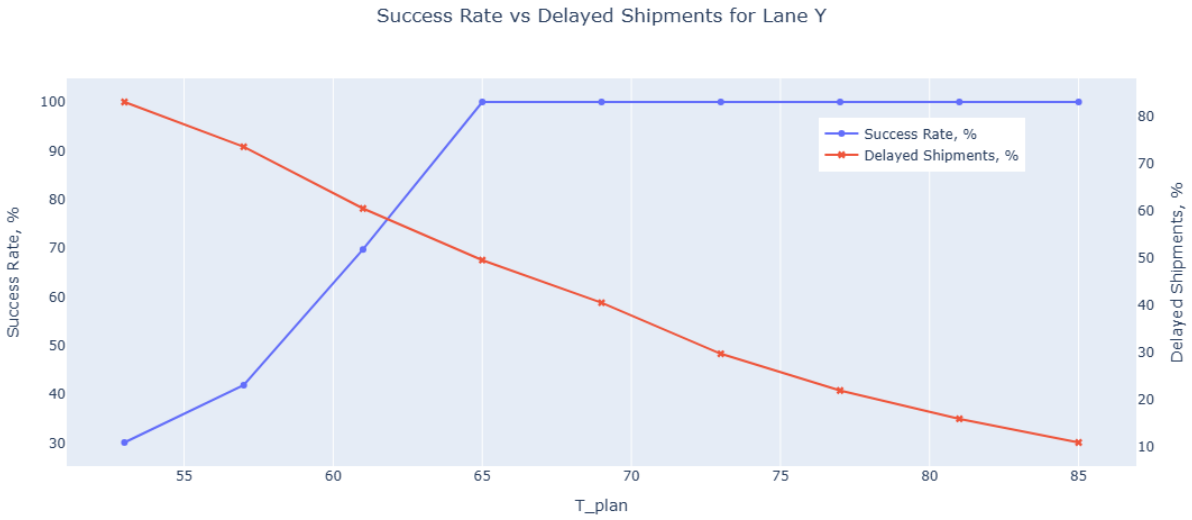


Figure 8: Success Rate against Percentage of Delayed Shipments for Lane Z



For Lane X, the intervention and success rate at target lead time of 9 days is 100% and 99.92% respectively. However, these drop to 74.3% and 74.1% respectively when target lead time decreases to 8 days. Table 7 lists similar instances across other lanes. The records for the system lead time in each lane are banded. Lane Z features the most drastic change, where a 5% decrease in target lead time resulted in a 41.5% and 42.2% decrease in intervention and success rate.

From this, we can conclude that the current system lead time represents a threshold below which improving shipments to a stricter target becomes exponentially expensive.

Table 7: Snapshot of Intervention and Success Rates for different Target Lead Times

Lane	Target Lead Time, days	Intervention Rate (%)	Success Rate (%)
Lane X	9	100	99.92
	8	74.27	74.05
	7	48.08	47.76
Lane Y	69	100	100
	61	74.21	69.75
Lane Z	87	100	100
	83	58.50	57.81

4.6 Varying Budget Per Lane

For this scenario, the budget per lane was varied across all three lanes. The lead time was fixed to the system lead time for each lane. The range of budget values are shown in Table B1 of Appendix B.

The graphs of intervention rate against budget for Lane X, Lane Y and Lane Z are given in Figure 9, Figure 10 and Figure 11 respectively. The graphs of success rate against budget for Lane X, Lane Y and Lane Z are given in Figure 12, Figure 13 and Figure 14. As expected, the profiles for the intervention rate and success rate are aligned – as budget increases, the number of successful interventions also increase.

Unlike the previous scenario, where intervention and success rate have a steep linear relationship with the independent variable (target lead time), those two outcomes have a gentler linear relationship with budget. For example, a 20% drop in budget for Lane Z (from $425,000 to $347,500) causes a near symmetric 29.4% and 30.2% drop in intervention and success rates.

From the outcomes of Section 4.5 and this scenario, it can be concluded that both target lead time and budget have a linear relationship with intervention and success rates. However, target lead time has a greater effect on the outcome.

Figure 9: Intervention Rate against Budget for Lane X

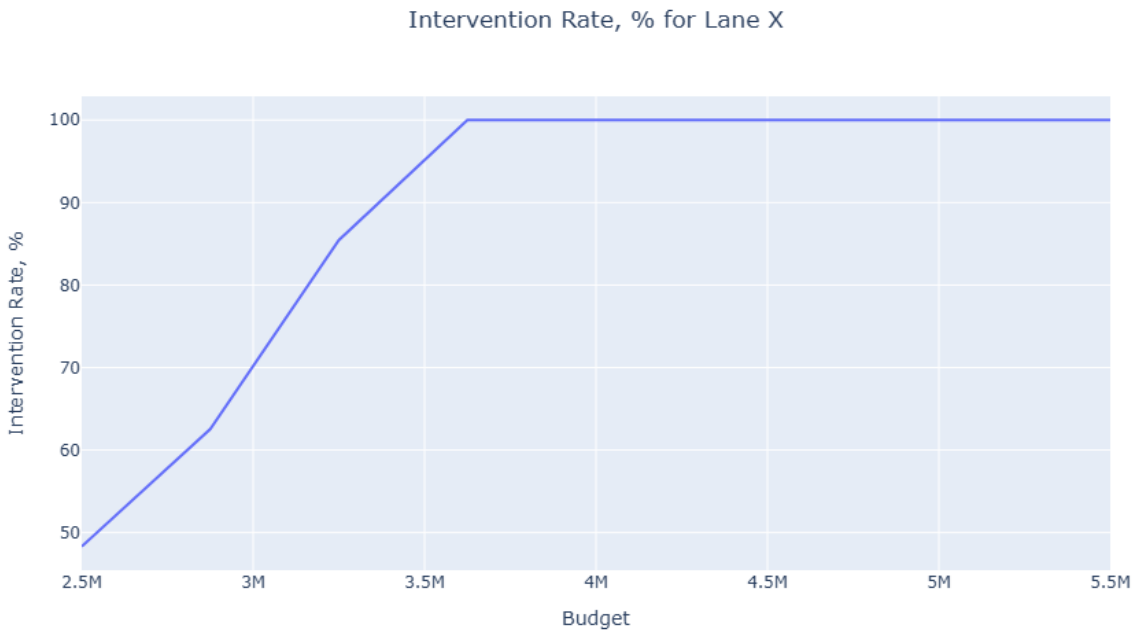


Figure 10: Intervention Rate against Budget for Lane Y

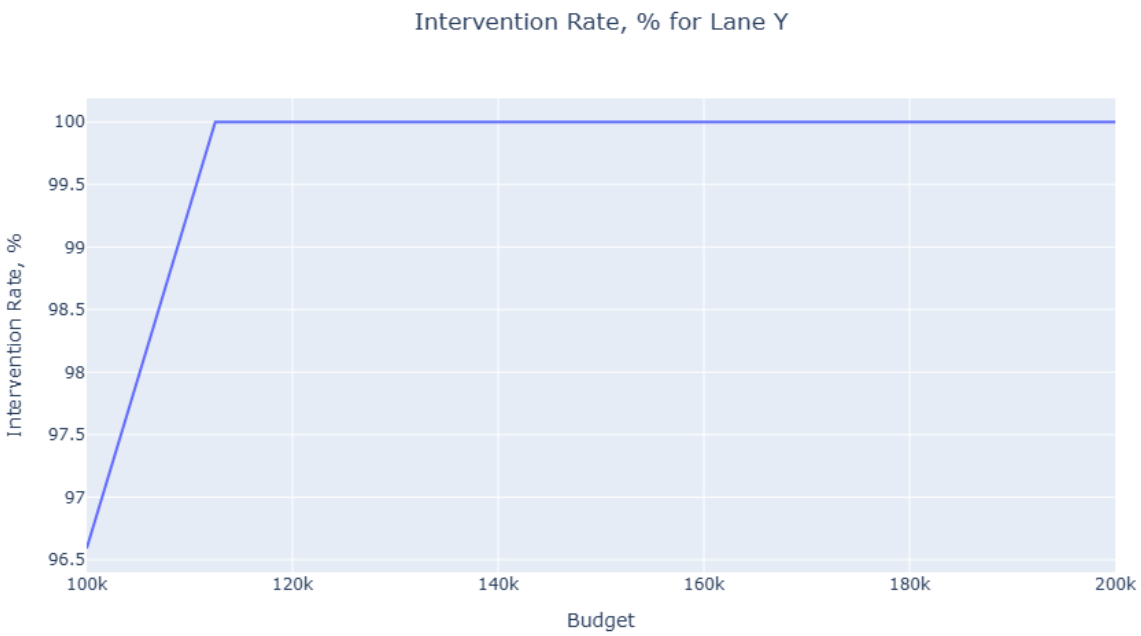


Figure 11: Intervention Rate against Budget for Lane Z

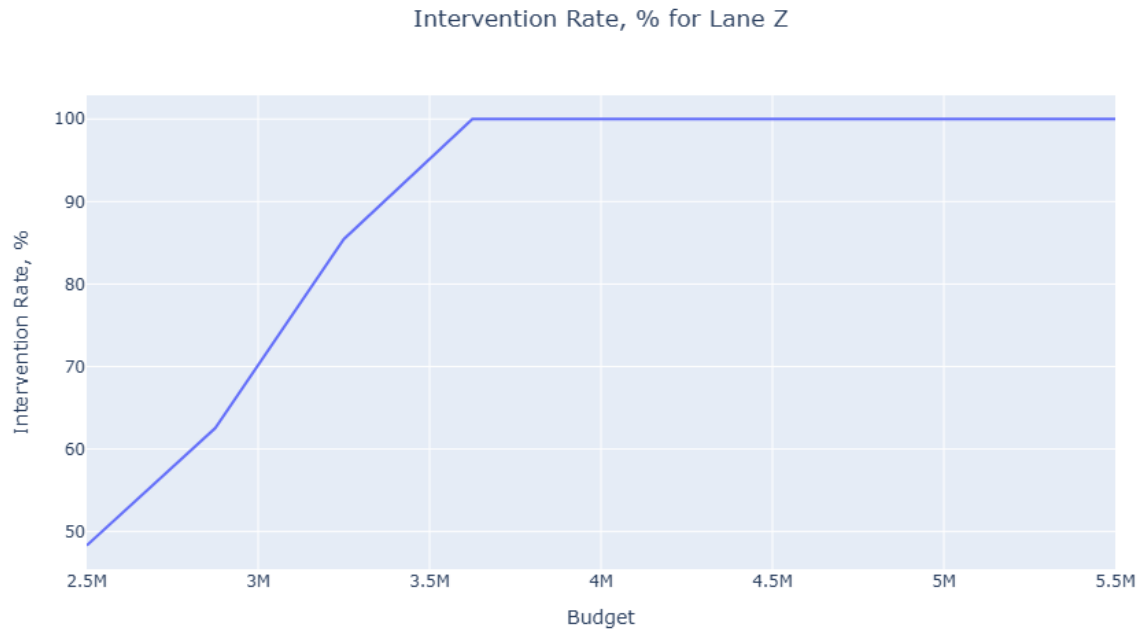


Figure 12: Success Rate against Budget for Lane X

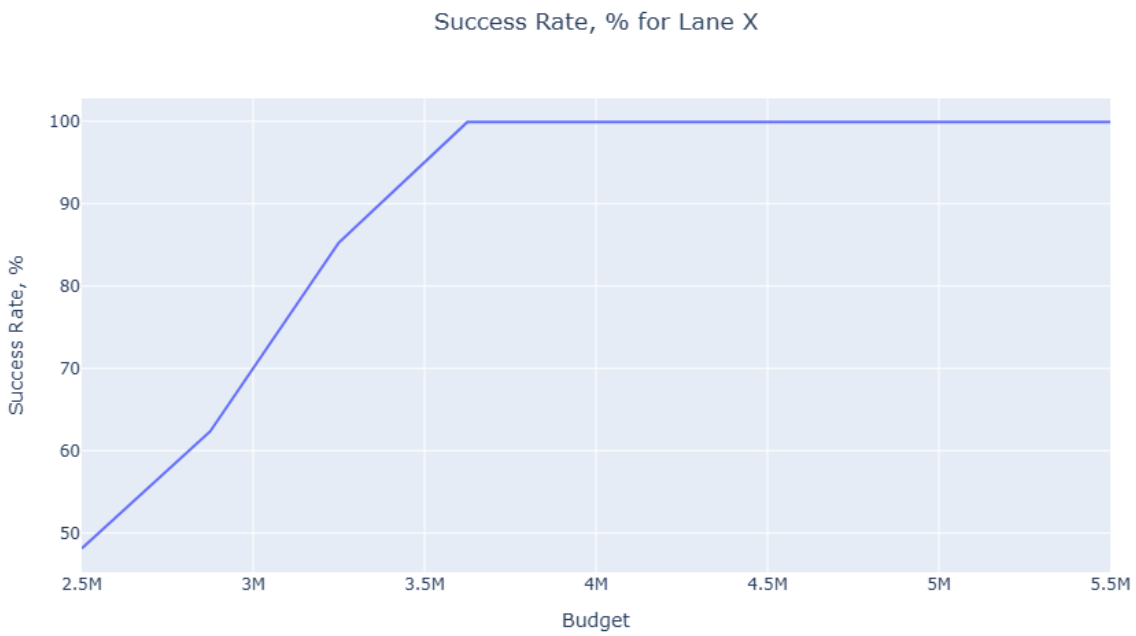
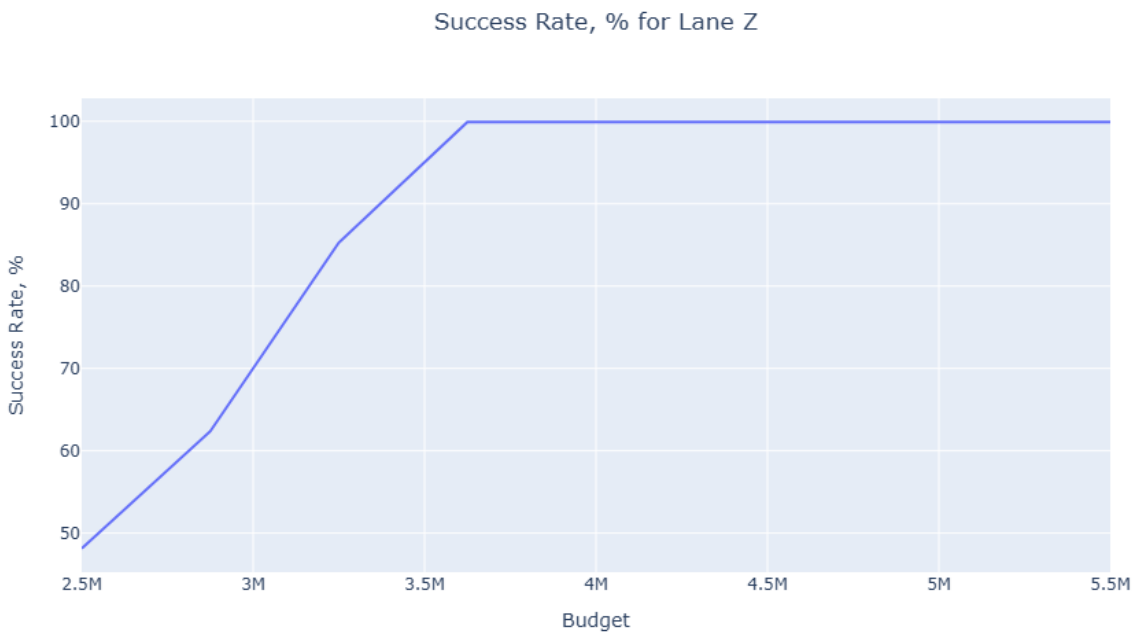


Figure 13: Success Rate against Budget for Lane Y



Figure 14: Success Rate against Budget for Lane Z



4.7 Varying Target Lead Time and Budget

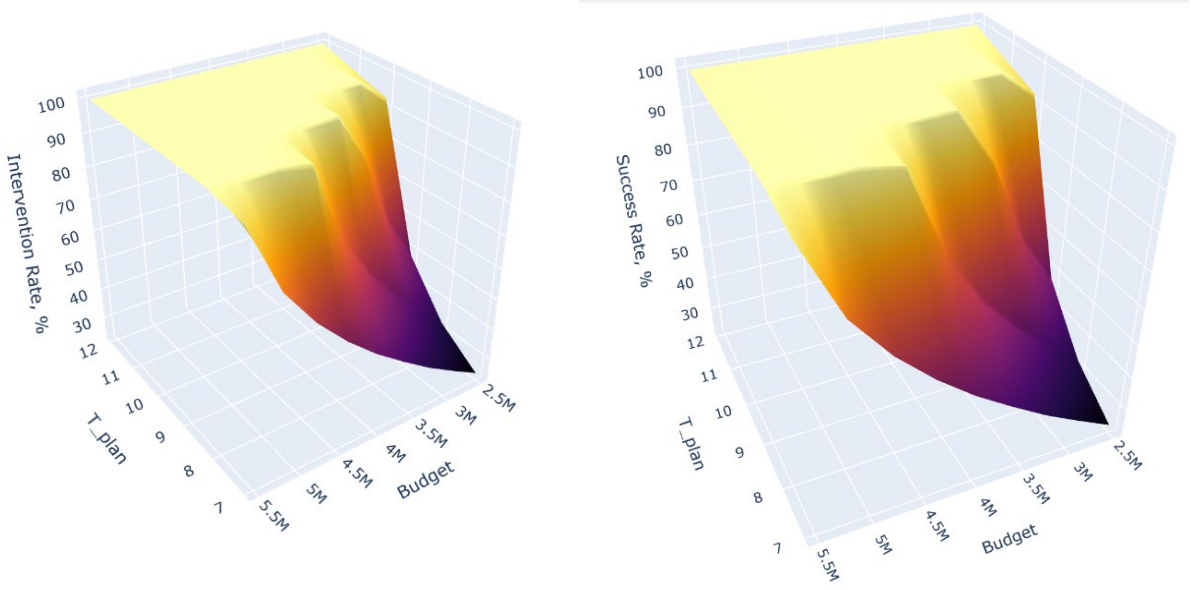
In this scenario, neither the target lead time nor budget are fixed. The model has been run for all possible combinations of lead time and budget for each lane. The general profile of the outcome is expected – as target lead times and budget increases, the intervention and success rates increase. However, as can be seen from Figure 15 (Lane X), Figure 16 (Lane Y) and Figure 17 (Lane Z), the outcomes have a different relationship with the independent variables (target lead time and budget) for each lane.

4.7.1 Lane X

Figure 15 shows the strict relationship between model outcomes and the independent variables. Lane X is extremely sensitive to changes in target lead time. For a target lead time of 10 days, a budget of just $2.5m will achieve 92.6% success rate. Conversely, if the target lead time were set to 8 days, the budget would need to be at least $4.375m to achieve 97.9% success rate. A lower budget would achieve a maximum of 74%.

A linear regression of the results, shown in Appendix C, show that the outcome of the model, the improved lead time, is heavily dependent on the target lead time (coefficient of 0.9998) and less dependent on the budget (coefficient of 0.0012).

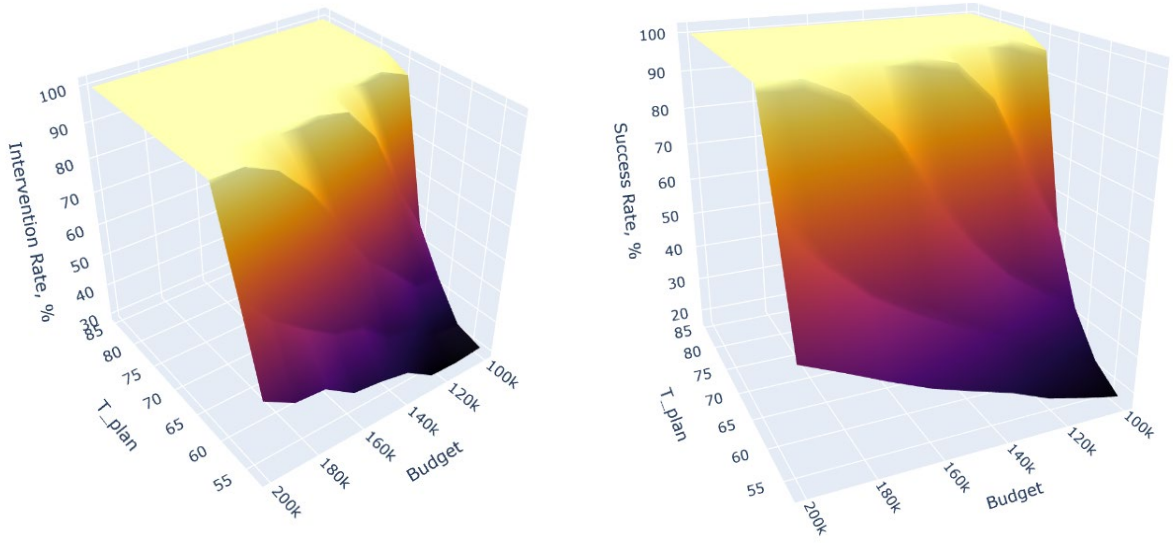
Figure 15: Intervention Rate (%) (left) and Success Rate (%) (right) for Lane X



4.7.2 Lane Y

Unlike Lane X where a decrease in target lead time by 22% renders it unsolvable without adding more than double the minimum budget, it is possible to resolve shipments in Lane Y even if they are 14 days below the "normal" lead time. Similarly, unlike Lane X there is not a clear inflection point in the independent variable where the outcome increases exponentially. This suggests a one-to-one relationship between the independent variables and the model outcomes. This is confirmed in the linear regression results in Figure C2 in Appendix B, where the coefficient of the target lead time (0.9998) is very close to the coefficient of the budget (1.5226)

Figure 16: Intervention Rate (%) and Success Rate (%) for Lane Y

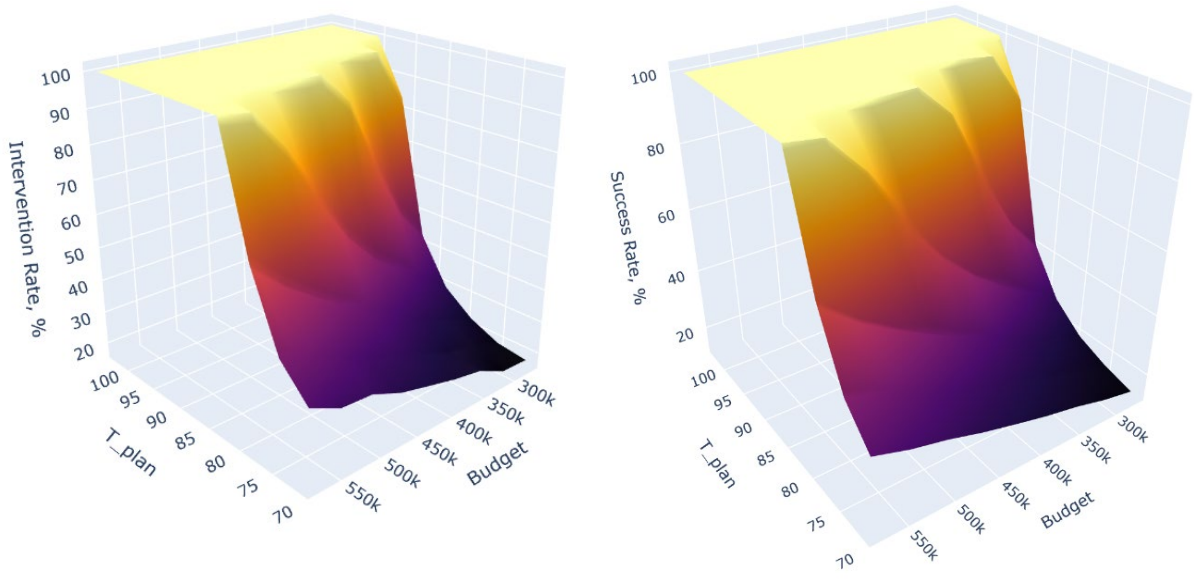


4.7.3 Lane Z

Lane Z has both an inflection point for the model outcome and the model is also able to solve for highly deviated target lead times, albeit with poor results (13.7% success rate at target lead time of 70 days and budget of $300,000). From Figure 17, there is an inflection point at approximately 79 days of lead time and budget of $425,000. The model outcomes – intervention and success rate – drastically increase after these points. The slope of the plots as budget increases is a lot smoother than the slope in the direction of increasing target lead time, suggesting that model outcomes are more impacted by target lead time than the budget.

This is confirmed by the linear regression results in Figure C3 in Appendix C, where the coefficient for target lead time (1.0007) is six times greater than the coefficient for budget (0.1658).

Figure 17: Intervention Rate (%) and Success Rate (%) for Lane Z



4.8 Managerial Insights

Based on the model outcomes, several key decisions emerge that lane managers and executive teams can take to improve how the organization manages disruptions and allocates resources effectively.

First, the model supports the strategic selection of target lead times. Rather than relying on fixed targets or aiming for overly aggressive timelines, leaders can now evaluate the trade-offs between lead time, intervention cost, and available budget. This helps identify a locally optimal point where the organization can solve a meaningful share of disruptions while keeping intervention costs within reasonable bounds. It allows lane specific decision-making grounded in actual outcomes.

Second, the analysis enables more accurate and practical budget planning. For any selected target lead time, the model provides insight into how much budget is required to apply interventions that reduce delays. This helps leaders answer critical operational questions such as: *"How much budget is needed to solve 80% of disruptions in a specific lane?"* or *"Given a fixed budget, how much variation in lead time can we realistically reduce?".* This level of precision allows operations and finance teams to align on achievable goals based on trade-offs.

Third, by identifying the intervention actions most frequently selected by the model, the company can take steps to operationalize them more effectively. This might include working with key third-party partners to secure capacity, streamline approval workflows, or pre-negotiate terms for expedited options.

Knowing in advance which actions will be used the most allows for smoother coordination and fewer delays during execution.

Fourth, this approach offers a repeatable and scalable framework that can be extended across other freight lanes in the network. While this study focused on three representative lanes, the methodology can be applied anywhere historical delay data and intervention options are available. This provides a consistent way to evaluate disruption trade-offs, regardless of geography or mode, and builds institutional knowledge around intervention effectiveness.

Finally, the model can be adapted for use in high-disruption scenarios, such as during major geopolitical events, port shutdowns, or health crises like the COVID-19 pandemic. By stress-testing the model with higher disruption rates or reduced intervention capacity, leadership can simulate how the system would perform under extreme pressure. This creates value not only as a tactical tool for everyday planning, but as a resilience planning asset that supports better decision-making in uncertain environments.

5 CONCLUSION

This research aims to introduce a systematic approach to resolving shipping disruptions through a prescriptive analytics model that optimizes lead time. It takes a holistic approach to optimization and balances the application of intervention actions on a single shipment with the needs of the other delayed shipments. Effectively, it factors in the opportunity cost of applying an action on a single shipment to calculate the reward for the entire lane.

This approach uncovers non-obvious relationships between target lead times and budgets. For example, Lane Y has a 1:1.52 coefficient ratio between target lead time and budget. Such insights will enable more nuanced capital allocation strategies and risk-adjusted decision-making. In theory, the mathematics of the model will hold in any application involving delayed shipments. Therefore, this model can be used by any of Company A's lane managers. However, the insights discussed in this report make assumptions on the impact and cost of the intervention actions.

The use case for this model is primarily to act as a simulation tool that helps lane managers visualize the trade-off between target lead times and budgets.

As discussed in Section 1.3, we liken the model as the engine that drives a complete solution. To further build on this project, the model defined in Section 3.4 can be expanded to cater for customer service, sustainability and cash flow. Ultimately, it will become a multi-input, multi-objective prescriptive

model. In this sense, the formulation will resemble the supplier selection models discussed in Section 2.2.2.

5.1 Future Work

As discussed in Section 1.3, aside from lead time, the company also considers cash, cost and sustainability to be key targets. The model can be modified to factor these additional targets, effectively transforming it into a multi-objective, multi-input optimization model. It would incorporate the same approach as the supplier selection mixed integer programming models discussed in Section 2.2.2. However, computational testing of such large models will require significant processing resources and time. The problem with any optimization models is the inability to run the model in batches. Unlike machine learning algorithms where data can be batched for smaller run size, the optimization model must consider the dataset in its entirety.

Another expansion on this work is to convert the model into a stochastic optimization where lead time variability is modelled as a random variable rather than a deterministic value. This would require expanding the analysis of the lead time distributions to understand the weights placed on contributing factors such as transportation issues and supplier delays.

By pursuing these directions, the company could evolve from tactical disruption management to a proactive, system wide resilience framework that enhances competitive advantage in an increasingly volatile global logistics environment.

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Appendix A Distribution of Lead Times

Figure A1 – Histogram of lead times in Lane X

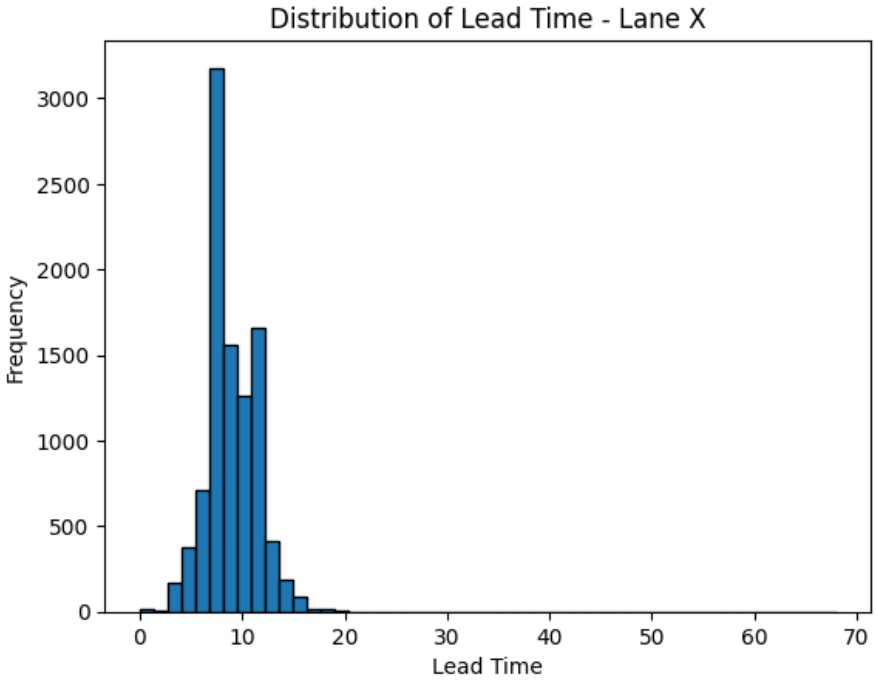


Figure A2 - Histogram of lead times in Lane Y

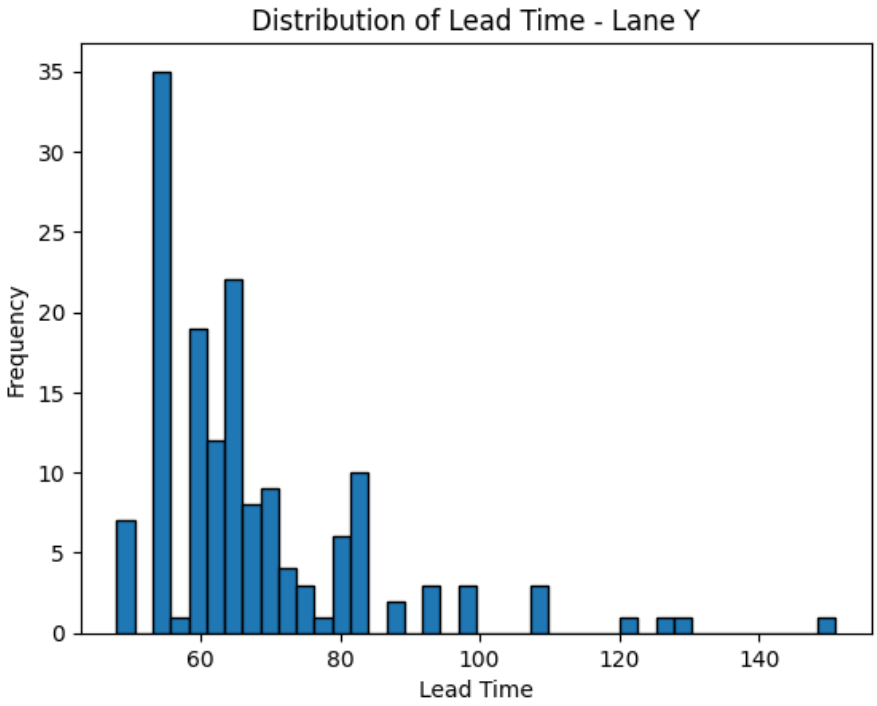
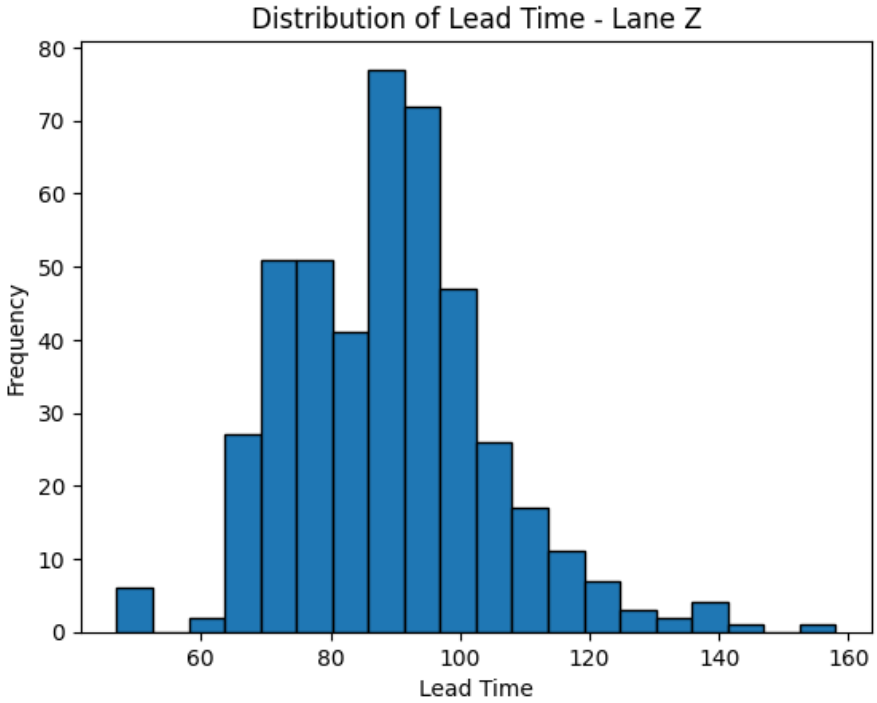


Figure A3 – Histogram of lead times in Lane Z



Appendix B Sensitivity Analysis Parameters

Table B1: List of lead time and budget parameters

Lane	Target Lead Time, days	Budget per Lane, $
Lane X	7, 8, 9, 10, 12	2,500,000; 2,875,000; 3,250,000; 3,625,000 4,000,000; 4,375,000; 4,750,000; 5,125,000 5,500,000
Lane Y	71, 75, 79, 83, 87, 91, 95, 99, 103	100,000; 112,500; 125,000; 137,500; 150,000 162,500; 175,000; 187,500; 200,000
Lane Z	53, 57, 61, 65, 69, 73, 77, 81, 85	270,000; 308,750; 347,500; 386,250; 425,000 463,750; 502,500; 541,250; 580,000

Appendix C Linear Regression Tables

Figure C1: Linear Regression table for Lane X

OLS Regression Results

Dep. Variable:	T_improved	R-squared (uncentered):	1.000
Model:	OLS	Adj. R-squared (uncentered):	1.000
Method:	Least Squares	F-statistic:	6.308e+09
Date:	Sun, 04 May 2025	Prob (F-statistic):	0.00
Time:	20:36:40	Log-Likelihood:	1.3321e+06
No. Observations:	1497652	AIC:	-2.664e+06
Df Residuals:	1497650	BIC:	-2.664e+06
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
T_plan	0.9998	3.04e-05	3.29e+04	0.000	1.000	1.000
Budget	0.0012	6.45e-05	18.360	0.000	0.001	0.001

Omnibus:	4195230.106	Durbin-Watson:	1.964
Prob(Omnibus):	0.000	Jarque-Bera (JB):	187777290186.430
Skew:	36.782	Prob(JB):	0.00
Kurtosis:	1736.129	Cond. No.	8.73

Figure C2: Linear Regression table for Lane Y

OLS Regression Results

Dep. Variable:	T_improved	R-squared (uncentered):	0.999
Model:	OLS	Adj. R-squared (uncentered):	0.999
Method:	Least Squares	F-statistic:	3.526e+07
Date:	Sun, 04 May 2025	Prob (F-statistic):	0.00
Time:	20:47:57	Log-Likelihood:	-70463.
No. Observations:	37943	AIC:	1.409e+05
Df Residuals:	37941	BIC:	1.409e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
T_plan	0.9998	0.000	2101.918	0.000	0.999	1.001
Budget	1.5226	0.201	7.566	0.000	1.128	1.917

Omnibus:	52905.638	Durbin-Watson:	1.688
Prob(Omnibus):	0.000	Jarque-Bera (JB):	11907663.609
Skew:	8.387	Prob(JB):	0.00
Kurtosis:	88.150	Cond. No.	1.68e+03

Figure C3: Linear Regression results for Lane Z

OLS Regression Results

Dep. Variable:	T_improved	R-squared (uncentered):	1.000
Model:	OLS	Adj. R-squared (uncentered):	1.000
Method:	Least Squares	F-statistic:	2.461e+08
Date:	Sun, 04 May 2025	Prob (F-statistic):	0.00
Time:	21:10:17	Log-Likelihood:	-1.9406e+05
No. Observations:	114091	AIC:	3.881e+05
Df Residuals:	114089	BIC:	3.881e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
T_plan	1.0007	0.000	5512.344	0.000	1.000	1.001
Budget	0.1658	0.035	4.767	0.000	0.098	0.234

Omnibus:	198892.924	Durbin-Watson:	1.768
Prob(Omnibus):	0.000	Jarque-Bera (JB):	168758532.914
Skew:	12.597	Prob(JB):	0.00
Kurtosis:	189.722	Cond. No.	770.