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HO CHI MINH CITY CAMPUS

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Ho Chi Minh City, April 2025

EXECUTIVE SUMMARY

This report presents an optimization model for supply chain design across five countries: the USA, Germany, Japan, Brazil, and India. The model focuses on selecting factory locations, planning capacities, and minimizing costs. Specifically, it addresses decisions related to facility openings and product movement, aiming to optimize both manufacturing and logistics expenses.

The initial footprint analysis indicates that high-capacity factories in India, Japan, the USA and a low-capacity factory in Brazil are most efficient for meeting demand. However, upon reviewing the result, we identified an unusually high fixed-to-variable cost ratio for the Brazil factory, where the fixed costs significantly impact the average total cost (ATC) of each unit. This raises the question of whether fulfilling certain market demands is cost-effective.

To address this, we examined the trade-off between minimizing costs and fulfilling demand. By allowing some demand to remain unmet and introducing penalty costs in the constraints and objective function, we discovered that regions like Japan justify plant establishment more efficiently. In contrast, Brazil only becomes viable when penalty costs reach 1.2 times the average variable costs of all markets, meaning plant establishment in Brazil is justifiable only when the opportunity cost is at or above this threshold.

To further account for real-world demand fluctuations, we employed Monte Carlo simulation to model various demand scenarios. After evaluating multiple configurations, the initial setup emerged as the most cost-effective and resilient, outperforming the second most frequent configuration (C2), which showed more infeasible scenarios. Consequently, we recommend the initial configuration for its balanced approach to cost management and operational stability.

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LIST OF FIGURES

TABLE OF CONTENTS

I. INTRODUCTION

1.1. Introduction:

In the context of a highly competitive and data-driven business environment, optimizing the supply chain is a critical factor in ensuring operational efficiency and cost-effectiveness since a well-structured supply chain will enable businesses to meet market demand efficiently while minimizing overall costs. One of the fundamental challenges in supply chain management is determining the optimal location and capacity of factories, which directly impacts production efficiency, distribution effectiveness, and financial performance.

From a demand perspective, businesses must rely on sales forecasts for each market to determine an appropriate production level. However, meeting demand is not only about quantity but also involves factors such as delivery time, minimum production requirements, and future scalability. From a supply perspective, companies must decide between high-capacity or low-capacity manufacturing facilities, as this directly impacts fixed costs (which depend on location and scale) and variable costs (primarily influenced by regional labor expenses). Furthermore, logistics strategies also play a crucial role ensuring that orders are processed quickly, inventory is managed effectively, and products are delivered on time and in perfect condition.

Recognizing the importance of this issue for business efficiency, our team has chosen to research the topic "Supply Chain Optimization: Selecting Manufacturing Locations and Scale to Meet Market Demand at Optimal Costs." We aim to apply data analysis methods to identify the most effective solutions for this challenge while gaining a deeper understanding of the factors influencing supply chain decisions. Successfully conducting and applying this research will enable businesses to optimize costs, improve production efficiency, and enhance their competitiveness in the market.

1.2. Background

1.2.1. Fundamentals of Supply Chain Optimization

Supply chain optimization encompasses any activities that a manufacturer takes to improve the efficiency and cost effectiveness of its supply chain – for example, by reducing material waste, getting better insight into regulatory risks, developing backup strategies for unexpected part sourcing issues, and improving product delivery speed and accuracy (Lindquist, 2023). Supply chain optimization involves finding the critical optimal solutions that can generate the most productive and lucrative organizational performance, while including all possible operational constraints and bottlenecks in the process. It also evaluates the various possibilities and includes key considerations such as how much of the product or service to sell and finally choosing the most cost-effective markets to operate in (Anon, 2024).

Supply chain optimization is a critical process that enables businesses to streamline operations, enhance customer satisfaction, and gain a competitive advantage in the global market (Elopre, 2023). Supply chain managers need to identify the best locations for factories, warehouses, and distribution centers and the optimal flows between those locations. The goal is to control costs and increase reliability as well as provide flexibility in case of supply chain disruptions (Lindquist, 2023).

One of the key methodologies employed in supply chain optimization is linear programming, a mathematical approach used to determine the best possible outcome under given constraints. In supply chain decision-making, linear programming helps businesses allocate resources optimally, minimize transportation costs, and balance production capacity across multiple locations. By integrating these techniques, companies can enhance their decision-making processes and develop a more resilient and cost-effective supply chain.

1.2.2 Key Factors Affecting Factory Location Decisions

Location decisions are considered as strategic decisions as they have long term impact on profitability of an organization (Singla, n.d.). Businesses must carefully consider a number of aspects when choosing a factory location in order to guarantee operational effectiveness and profitability. Among these, the capacity constraint and cost structure which includes transportation expenses, variable costs, and fixed costs is crucial to the decision-making process.

Fixed costs are costs that remain constant in total within a relevant range of volume or activity (CEPF®, 2023). One of the most obvious of fixed costs is the cost of rent or property. In high-demand areas, such as city centers or popular retail parks, the cost of renting or buying a property can be significantly higher than in less sought-after locations (Anon, 2024). This can negatively affect the overall profitability of a business, as higher rental or property costs increase fixed expenses, reducing net margins. Moreover, variable costs also play an important role, including labor wages, raw material costs, and energy expenses. In areas with a high cost of living, businesses may need to offer higher wages to attract and retain staff which increases the variable cost per unit, making overall production costs less optimal. Transportation costs are another key consideration. If a business is located far from its suppliers or customers, it may incur high transportation costs. This is particularly relevant for businesses that rely on the import or export of physical goods (Anon, 2024).

Capacity limitations also need to be considered in the decision regarding its use. Every manufacturing facility has production limits, labor limits, and supply chain limits. This makes capacity planning useful to optimize high efficiency of production facilities while eliminating overutilization or underutilization, which may result in high operational costs or supply shortages. Integrating these considerations under one roof as an encompassing assessment, helps in enhancing the efficiency and productivity of the supply chain process. Through the careful analysis of cost structures, market demand patterns, and capacity constraints, manufacturers are able to base strategic decisions on sound data which drives a competitive edge while maintaining long-term viability in an ever-evolving market landscape.

A comprehensive evaluation of these factors is essential for optimizing supply chain performance. By carefully analyzing cost structures, market demand patterns, and capacity constraints, businesses can make well-informed strategic decisions that enhance competitiveness and ensure long-term sustainability in a dynamic market environment.

1.3. Context

1.3.1. Data Understanding

To optimize the supply chain, it is essential to analyze production capacity, market demand, cost structures (fixed and variable), and transportation. The aim is to establish an efficient network that lowers production and logistics costs while simultaneously satisfying demand in different regions. This requires the determination of the right mix of production facilities to decrease costs while, at the same time, addressing market needs. With careful consideration of capacity constraints, cost variations, and patterns of demand, it is possible to develop a strategy that lowers spending while maintaining efficiency and responsiveness in supply chain activities. The data sets include:

- **Production Capacity:** This measure outlines the monthly production capacity for every geographical region, specifying a minimum and maximum limit to enable flexibility in reaction to fluctuations in demand.

Capacity (kUnits/month)	Low	High
USA	500	1500
Germany	500	1500
Japan	500	1500
Brazil	500	1500
India	500	3000

Figure 1. Product Capacity

- **Demand:** Each month's demand for each market with a focus on regions with higher or lower levels of consumption.

(Units/month)	Demand
USA	2,800,000
Germany	90,000
Japan	1,700,000
Brazil	145,000
India	160,000

Figure 2. Demand

- **Fixed Costs:** The information outlined determines the minimum monthly operating expenses involved in the production in different industries, which show significant variability between different markets.

	Low	High
USA	6500	9500
Germany	4980	7270
Japan	6230	9100
Brazil	3230	4730
India	2110	6160

Figure 3. Fixed Costs

- **Freight Costs:** Transport costs between various regions are a key component in determining the most cost-effective shipping routes.

Freight Costs ($/Container)	USA	Germany	Japan	Brazil	India
USA	0	12250	1100	16100	8778
Germany	13335	0	8617	20244	10073
Japan	15400	22750	0	43610	14350
Brazil	16450	22050	28000	0	29750
India	13650	15400	24500	29400	0

Figure 4. Freight Costs

- **Variable Costs:** Per-unit costs, which vary based on production volume and location.

Variable Costs ($/Unit)	USA	Germany	Japan	Brazil	India
USA	12	12	12	12	12
Germany	13	13	13	13	13
Japan	10	10	10	10	10
Brazil	8	8	8	8	8
India	5	5	5	5	5

Figure 5. Variable Costs

The workflow of our analysis is structured as follows: Preparation (including integration of the various tables mentioned), followed by the creation of an optimization model, which defines decision factors and constraints, comes next, followed by in-depth machine learning and scenario modeling to extract useful information. From data collection to decision-making, this flow ensures that each stage of the procedure is handled methodically.

1.3.2. Decision Variables, Constraints, and Objective Function

The primary decision variables in the supply chain optimization model include:

- **Factory Locations:** The geographical location of factories has a significant impact on fixed and variable costs.
- **Production Levels:** Balancing production across various locations to meet regional demand while minimizing overcapacity is essential.
- **Transportation Networks:** Another key feature of the model is the minimization of freight spending realized by choosing the most economical routes.

Our objective function aims to minimize total costs, which include:

Total Cost = Fixed Cost + Variable Cost + Freight Cost

	USA	Germany	Japan	Brazil	India
USA	6	13	20	12	17
Germany	13	6	14	14	13
Japan	20	14	3	21	9
Brazil	12	14	21	8	21
India	22	13	10	23	8

Figure 6. Total Costs

The optimization model needs to minimize these costs while ensuring demand across all markets is fulfilled. Constraints such as factory capacity, demand fulfillment, and the cost structure for each region guide the decision-making process.

1.3.3. Optimization Results and Visualization

1.3.3.1. Customer Demand by Market

The pie chart shows a clear breakdown of the distribution of demand among five different markets. The United State is the largest segment of this demand, representing 57.2% of monthly units sold. Japan is the second-largest market at 34.7% of the total demand, while Brazil (3%), India (3.3%), and Germany (1.8%) each have smaller shares. This information highlights the US as the leading market, which requires the greatest amount of supply resources. Due to the United States' high demand, it is essential to create supply chain strategies that meet its needs. While Japan demand is significantly lower, it still has a significant position as the second-largest market. Germany, Brazil, and India also need to be considered; however, they require relatively smaller quantities of supply.

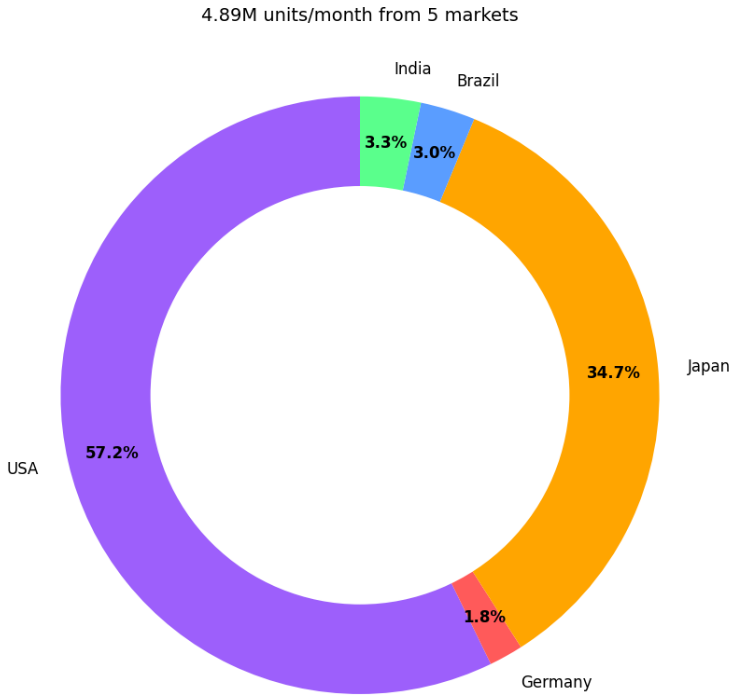

Figure 7. Customer Demand by Market

1.3.3.2. Transportation Cost Matrix and Its Impact

The transportation cost matrix explains the differences in shipping costs between different locations. The Brazil to Japan route is the most expensive shipping cost at $43,610, which is a huge logistical cost. Other routes with high costs are Brazil to India at $29,400 and Japan to Brazil at $28,000, which shows that long-distance shipping, especially intercontinental shipping, tends to be more costly. On the other hand, the cheapest international shipping route is Japan to the USA at $1,100, followed by Japan to Germany at $8,617. To avoid transportation costs, organizations should avoid high-cost routes like Brazil to Japan whenever possible. Instead, supply chain approaches should take advantage of cheaper shipping routes, namely to the USA at $1,100 and Germany at $8,617, to maximize logistics efficiency and minimize overall costs.

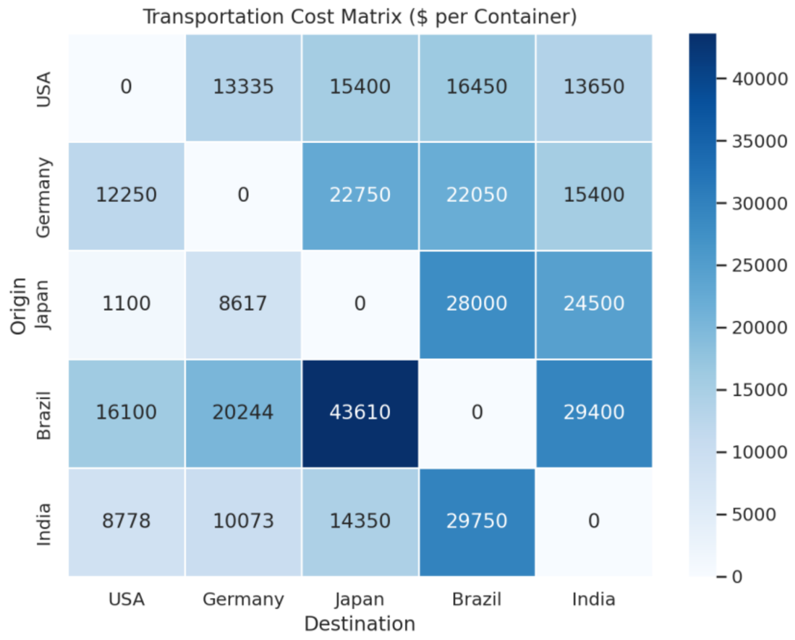

Figure 8. Transportation Cost Matrix and Its Impact

1.3.3.3. Fixed vs. Variable Cost Analysis

The comparison of fixed and variable costs in different manufacturing plants reveals significant differences in the expenditures. The United States ($8,500/month) and Japan ($8,700/month) have the highest fixed cost, while India ($2,500/month) has the lowest, making it a very cost-effective location for manufacturing. For variable costs, Germany has the highest at $13/unit, followed by Japan at $11/unit, adding to the cost of production in these countries. On the contrary, India provides the lowest variable cost of $5/unit, further establishing itself as a cost-effective location for manufacturing. India stands out as the best place for factories given its low fixed cost ($2,500/month) combined with its low variable cost ($5/unit). In contrast, Germany and Japan would not be the best places for large-scale manufacturing operations due to their high variable costs ($13/unit and $11/unit, respectively). Concentrated manufacturing in India is advised for maximum cost-effectiveness, but key activities are maintained at more expensive sites, such as Germany, to ensure profitability.

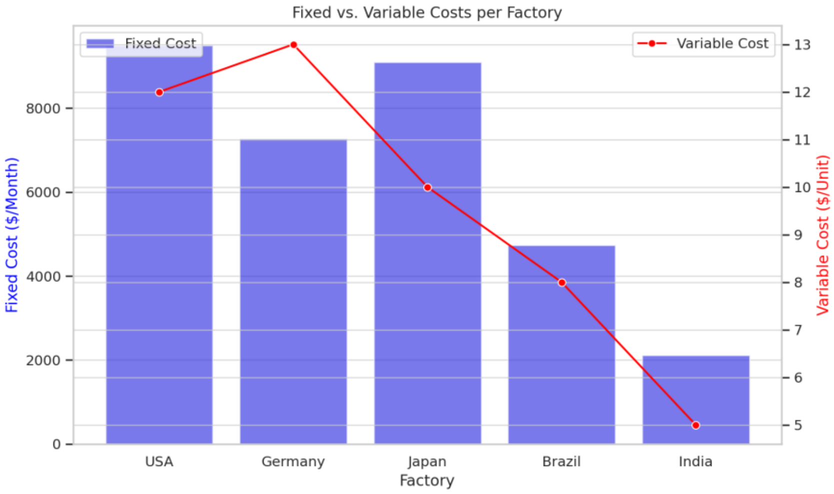

Figure 9. Fixed vs. Variable Cost Analysis

1.3.3.4. Production Capacity per Facility

The bar graph represents the spread of the production capacity among different facilities. There is both a Low and High range of production capacities for each country. The facility in India has the highest production capacity, which goes up to 3000 kUnits per month in ideal cases. The United States, Germany, Japan, and Brazil have similar production capacities, with Low values around 500 kUnits per month and High values around 1500 kUnits per month. India stands out as the most versatile production hub, able to provide the maximum possible output. According to this, India may be a crucial industrial location to satisfy the demands of nations with high levels of consumption, such as Japan. Due to their low production capacities, the other facilities can aid in preserving market equilibrium. Planning for strategic production would make use of India's vast capacity while preserving effective distribution in other markets.

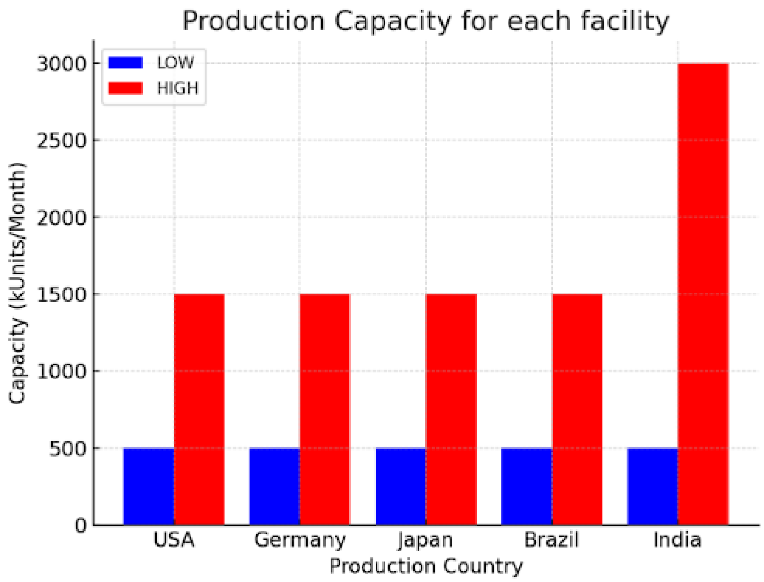

Figure 10. Production Capacity per Facility

1.4. Methodology

1.4.1. Optimization Model Implementation

1.4.1.1. Linear Programming Optimization Model

The Linear Programming Optimization Model (LP) was used in the process of designing an optimization model to minimize overall costs while simultaneously optimizing the efficiency of the supply chain. The model systematically determines the best location for facilities, production, and distribution levels in five countries: the United States, Germany, Japan, Brazil, and India. Central elements of the LP model include an objective function carefully crafted to minimize overall costs, which include fixed facility costs, variable production costs, and transportation costs.

The main decision variables include those relating to plant establishment, carried out as binary indicators showing the opening of a facility with a specific capacity type at a particular site, and decisions relating to production flow that determine the number of units shipped from facilities to market locations. The model operates in a system of constraints aimed at guaranteeing the satisfaction of demand, compliance with capacity limitations, and logical site selection to make sure that every site has only a single type of factory.

The most economically feasible facility layouts and production assignments were successfully determined by using the PuLP optimization solver to the linear program model. The resultant strategy aimed to simultaneously minimize expenses and maximize operational efficiency while designing a globally ideal supply chain.

1.4.1.2. Monte Carlo Simulation

The Monte Carlo Simulation was utilized as a support tool to examine the uncertainties and risk factors inherent in the supply chain. As a departure from the deterministic linear programming model, the Monte Carlo Simulation incorporates variability through the process of conducting multiple iterations that draw from stochastic inputs, thus exploring the impact of variability in cost and unforeseen demand. The simulation methodology examined variable costs, demand uncertainty, and the profitability of building facilities in different economic conditions.

The results obtained from the Monte Carlo Simulation provided useful information about a probability distribution of total cost, explaining the major cost drivers and identifying measures for risk mitigation. While the linear programming model provides an optimum solution under given parameters, the use of Monte Carlo methods facilitates strategic planning by including uncertainties and potential disruptions.

1.4.2. Visualization Tools and Libraries

Effective visualization is crucial for interpreting and communicating data in supply chain optimization. Various tools help represent cost structures, production flows, and logistics networks. Including:

- **PuLP (Optimization Modeling) -** Defines and solves cost-minimization models with constraints.
- **Pandas (Data Handling) -** Structures plant-opening decisions into readable DataFrames.
- **Matplotlib & Seaborn (Data Visualization) -** Creates bar charts, line plots, and cost trends.
- **Plotly (Interactive Visuals) -** Displays dynamic supply chain flows and cost distributions.

These tools enhance decision-making by transforming complex optimization results into clear, insightful visualizations for supply chain management.

1.4.3. Strategic Supply Chain Design and Optimization

1.4.3.1. Initial Footprint

Determining the ideal sites for new factories, their production capacities, and the development of effective production and distribution plans are all part of supply chain planning. This practice is essential for cutting expenses while also economically meeting market demands. To create an ideal supply chain structure, the problem involves a traditional trade-off in the domains of operations and logistics: striking a balance between fixed costs (factory setup and maintenance) and variable costs (production and transportation).

To enable efficient decision-making based on analytical recommendations, the model classifies possible factory locations into two capacity classes: high and low. A binary decision variable is used to determine the rationale for a factory setup at a specific location, while a continuous variable is used to handle the allocation of products from factories to market areas. This systematic approach ensures that every decision is in line with cost-effectiveness and operational efficiency considerations. The overall objective function of the model is to minimize the total monthly cost, including both factory setup costs and transport charges. By balancing the advantages of centralized, high-capacity manufacturing plants with the costs of long-distance transport, the model seeks to determine the most cost-effective supply chain setup.

1.4.3.2. Another Approach

An alternative approach to supply chain optimization involves the incorporation of responsiveness and flexibility into the optimization decision-making process. Traditional models are based on the stability assumption; however, real-world supply chains are subject to uncertainties such as demand variations, changes in transportation costs, and unexpected disruptions. A responsiveness-oriented approach incorporates elements such as stochastic modeling and scenario analysis to mitigate risks and enhance overall responsiveness.

Future techniques will also take multi-objective optimization practices into account. The system can emphasize other important aspects like sustainability, supply chain resilience, and customer happiness rather than only cutting costs. Decision-makers can now anticipate changes in demand, modify production plans in advance, and optimize logistics networks in real-time thanks to the use of advanced analytics and predictive software. This guarantees that even under unpredictable circumstances, the supply chain will continue to be flexible and responsive.

1.4.3.3. Simulation-Based Analysis

The effectiveness of supply chain models largely depends on the use of simulation methods. Through the use of simulations, decision-makers can test different scenarios and analyze the outcomes of different strategic implementations before their actual implementation. This methodological process includes the use of optimization algorithms to determine optimal factory locations, production levels, and logistics routes, while at the same time ensuring cost-effectiveness and responsiveness to demand.

The simulation offers a realistic depiction of the supply chain's operating dynamics under various scenarios by including real-world restrictions, such as production capacity, storage capacity, and transportation limitations. Furthermore, charts and statistical data are used to graphically present the outcomes, making it possible to identify inefficiencies, possible risks, and development prospects. Sensitivity analysis may also be used to evaluate the effects of shifts in market demand, supplier reliability, or regulatory frameworks on supply chain performance.

In summary, the knowledge derived from simulations allows organizations to make informed decisions, manage operational risks, and develop a sound and financially sustainable supply chain strategy. Through the use of advanced simulation tools, companies can determine that their supply chains are properly organized and equipped to address future challenges.

II. Initial footprint

2.1. Introduction

The main objectives of formulating a model would be to optimize the supply chain structure by determining the locations for new factories, defining their capacities, production and shipping outputs for each facility towards market demand in five countries. This issue raises a classic operation and logistics trade-off: minimizing overall costs of production and transportation while satisfying all customer demands. By including factory-opening decisions with product flow planning, the model aims to function as a strategic long-term supply chain design.

2.2. Problem Formulation and Decision Variables

The model sets the stage with the definition of two sets: a set of **locations (loc)** representing five countries, the USA, Germany, Japan, Brazil, and India, and a set of **capacity types (size)** available at each location: Low and High. This structure concurs with standard formats in facility location literature (Daskin 2013), where binary facility opening decisions are systematically paired with continuous flow or production decisions in a Cartesian product of the decision sets.

From these sets, the model defines two important types of decision variables. The first is the **plant opening decision**, y[i, s], which is binary in nature. This variable denotes whether a plant of size s (Low or High) opens at location i and allows the model to identify an optimal facility configuration weighing the trade-offs of fixed costs, availability of capacity, and site-location alternatives. The second is the production flow decision, denoted by the continuous variable x[i, j], which indicates the number of units flowing from location i to market j. These flows represent the operational side of the supply chain, which determines how goods are flowing through the distribution networks to serve local market demands in an efficient manner.

```python
from pulp import LpStatus, value
# Define Decision Variables
loc = ['USA', 'Germany', 'Japan', 'Brazil', 'India']
size = ['Low', 'High']
plant_name = [(i,s) for s in size for i in loc]
prod_name = [(i,j) for i in loc for j in loc]
x = LpVariable.dicts("production_", prod_name,
                     lowBound=0, upBound=None, cat='continuous')
y = LpVariable.dicts("plant_",
                     plant_name, cat='Binary')
```

2.3. Objective Function: Cost Minimization

The next step in this procedure is to draw an **objective function of the model** consisting of cost-minimization strategies. This function involves total monthly costs, which encompasses previously discussed fixed costs, that are incurred upon opening a factory of a specified capacity in a given country, and variable costs pertaining to both manufacturing expenses and freight charges from transporting between countries. Mathematically, the function sums fixed costs for all potential openings of facilities and adds relevant variable costs for all routes of shipment. Recognizing both cost types allows the model to balance the merits of a centralized, high-capacity manufacturing site against the logistics costs to serve far-away markets.

```python
# Define Objective Function
model = LpProblem("Capacitated Plant Location Model", LpMinimize)
model += (lpSum([fixed_costs.loc[i,s] * y[(i,s)] * 1000 for s in size for i in loc])
          + lpSum([var_cost.loc[i,j] * x[(i,j)]   for i in loc for j in loc]))
```

2.4. Constraints

To ensure a good solution is feasible and realistic, various constraints have been implemented by the model. The first constraint is that of demand satisfaction. For every country acting as a market, the model calls for the total quantities shipped to that country to match annual demand. Capacity is the second constraint here, stating that any factory in a given location shall not have total production output in excess of the total capacity of factories, given that only one factory is opened at each location. This reflects real-world strategic investment behavior whereby companies usually commit only to one scale of operation per site to minimize redundancy and avoid inefficiency and maintain fairly consistent levels of operational complexity.

```
# Add Constraints
for j in loc:
    model += lpSum([x[(i, j)] for i in loc]) == demand.loc[j,'Demand']
for i in loc:
    model += lpSum([x[(i, j)] for j in loc]) <= lpSum([capacity.loc[i,s]*y[(i,s)] * 1000
                                                for s in size])
```

2.5. Model Solution and Interpretation

Having constructed the optimization model with its objectives and constraints, it proceeds to the solution step using the **command model.solve()**. This command triggers the internal solver of the PuLP framework for searching an optimal configuration that minimizes the total monthly cost for the supply chain network. Next, the solution status of the model is printed with **LpStatus[model.status]**, which serves to validate whether the solver has found a feasible and optimal solution. Then the total cost submitted for the factory opening and shipping allocations is printed through the objective function value using **value(model.objective)**:

```
# Solve Model
model.solve()
print("Status: {}".format(LpStatus[model.status]))
print("Total Costs: {:,} ($/Month)".format(int(value(model.objective))))

Status: Optimal
Total Costs: 92,981,000 ($/Month)
```

At this stage, the output primarily indicates a check on the feasibility of the model in regard to the optimal status and the magnitude of costing at a total of **92,981,000 ($/Month)**. Specifically, this ensures the model executes correctly and that the solver has arrived at a valid optimal solution.

2.6. Factory Opening Decisions

In order to get feasible insights from the model, the next step consists of an analysis of factories that have been chosen to be opened by the model. This entails assessing the binary decision variables y[i, s] and determining whether or not a factory of capacity types (Low- or High-capacity) is established at location i. Subsequently, the code translates these binaries to a readable DataFrame (df_bool), i.e., each row denotes a certain combination of location and capacity type. For the column 'Plant Opening', a value 1.0 means that a factory has been opened, and 0.0 otherwise:

```
[30] # Results Plant (Boolean)
     df_bool = pd.DataFrame(data = [y[plant_name[i]].varValue for i in range(len(plant_name))], index = [i + '-' + s for s in size for i in loc],
                            columns = ['Plant Opening'])
     df_bool
```

	Plant Opening
USA-Low	0.0
Germany-Low	0.0
Japan-Low	0.0
Brazil-Low	1.0
India-Low	0.0
USA-High	1.0
Germany-High	0.0
Japan-High	1.0
Brazil-High	0.0
India-High	1.0

To further demonstrate the results, the initial solution was visualized via a bar chart:

```
# Plant Opening
capacity_plot = capacity.copy()

ax = df_bool.astype(int).plot.bar(figsize=(8, 5), edgecolor='black', color = 'tab:green', y='Plant Opening', legend= False)
plt.xlabel('Plant')
plt.ylabel('Open/Close (Boolean)')
plt.title('Initial Solution')
plt.show()
```

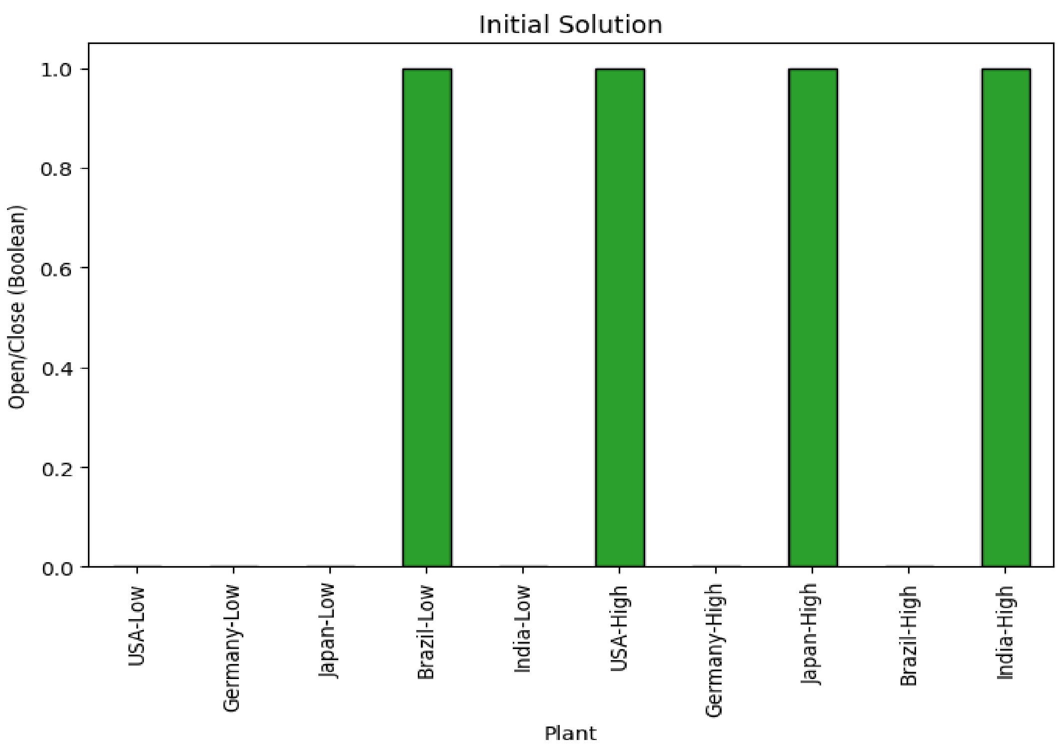

Figure 11. Plant opening decisions chart

From the results, it is observed that the model suggests opening four factories: one high-capacity factory each in the USA, Japan, and India, and one low-capacity factory in Brazil. Also, no facilities are selected in Germany in any configuration, be it low- or high-capacity.

This specific configuration demonstrates how a trade-off balance between demand fulfillment and cost minimization is made by the model. High-capacity factories have been assigned in higher demand locations, like the USA, Japan, and India, to satisfy the large demand effectively. Though incurring higher fixed costs, these plants are long-run economic due to relatively lower per-unit costs after being spread over large production volumes. Brazil has comparatively lower demand; hence a low-capacity factory has been set there, complying with resource investment on actual needs. The exclusion of Germany also indicates that, considering the current cost and demand differential, setting up a factory there will not create sufficient economic benefit. This could be a result of Germany's differentially higher fixed or variable costs, making it an unfavourable location for production within the set network.

In general, the recommendations of the model show a facility configuration being demand-driven and cost-sensitive to maximize expenditures on the total supply chain.

III. Initial footprint analysis

3.1. Introduction

This section delves into the analysis of the initial footprint for the global production and distribution network, focusing on the strategic decisions made to minimize total costs and meet market demand. It considers all factory locations, their sizes, the production and distribution flows, the cost structure, capacity utilization, and demand satisfaction.

Objective:

The main purpose is to provide a complete comprehension of the initial footprint, rationale, and effect on network performance.

- Evaluating the strategic placement of factories and their capacity levels in relation to demand patterns and cost structures.
- Identifying potential bottlenecks and opportunities for optimization within the network.

3.2. Factory Location and Sizing

The supply chain strategy optimizes production through strategic placement of high-capacity plants in the USA, Japan, and India, with capacities of 1.5 million, 1.5 million, and 3 million units respectively. A 500,000-unit lower-capacity factory is located in Brazil. An analysis of production against demand indicates that only India's production exceeds the market demand, which is indeed an interesting feature of the initial configuration.

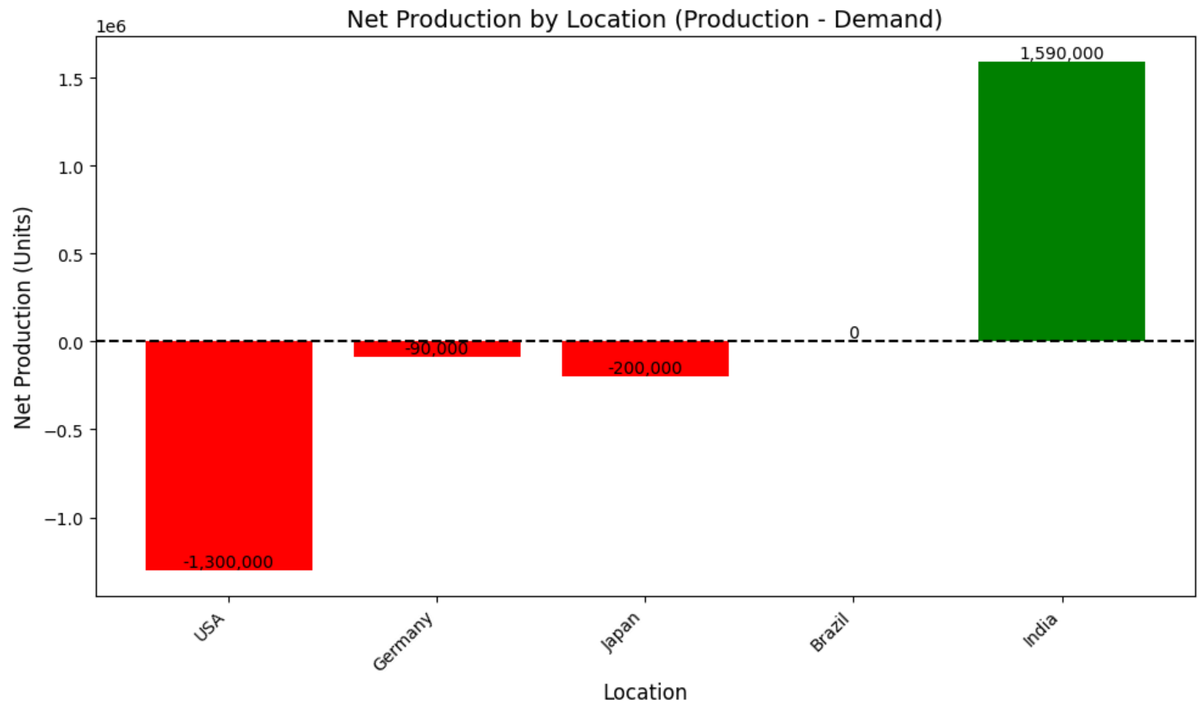

Figure 12. Net Production by Location

Or, in simpler terms, only India produces more than its market demand. This emphasizes that the resulting configuration relies heavily on self-fulfillment of the market and shipment from India. To further confirm this observation, The Sankey diagram (Figure 2) was drawn, providing a visual representation of the production and distribution flows within the initial footprint. It illustrates the movement of goods from factories (left) to markets (right), with the width of the flows representing the volume of units shipped.

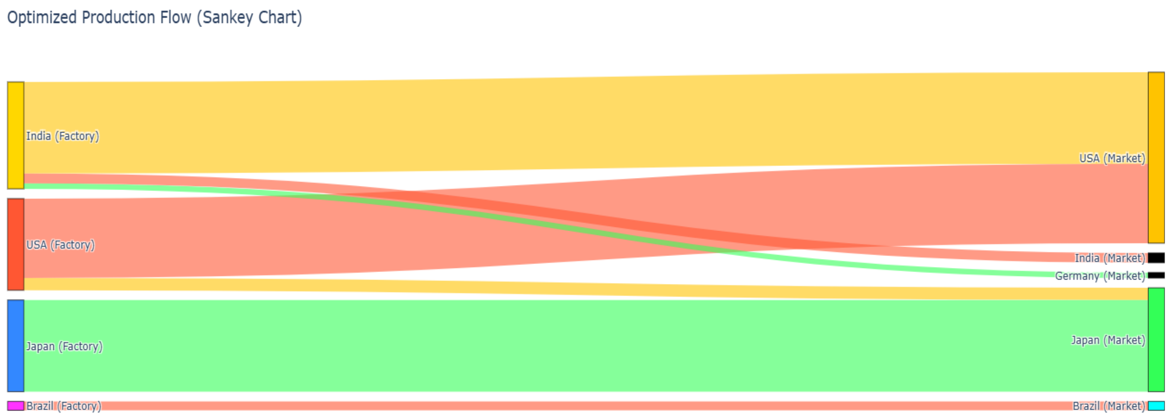

Figure 13. Optimized Product Flow (Sankey Chart)

The Sankey diagram further confirms this strategy by illustrating the flow of goods from the factories (source nodes) to the markets (target nodes). As expected, India acts as a central production hub, supplying Germany's demand of 90,000 units, part of US demand with 1,500,000 units, and its own local demand of 160,000 units. With a low production cost of $5 per unit, this cost advantage makes India an attractive manufacturing hub, allowing the USA and Germany to reduce production expenses while maintaining a stable supply. However, this heavy reliance on a single source also presents a potential bottleneck, making the supply to key markets vulnerable to disruptions in India.

The USA factory, in turn, primarily serves its local demand of 1,300,000 units, with some shipments to Japan. Brazil's factory only fulfills its local demand of 145,000 units while the remaining demand is satisfied through imports from India and the USA. The factory in Brazil serves its domestic requirement of 145,000 units only. The Japanese factory, on the contrary, produces 1,500,000 units against a local requirement of 1,700,000 units, with the remaining 200,000 units being imported from the USA. This highlights a strategy where markets like Japan and Brazil achieve high self-sufficiency, reducing transport costs and dependency risks, though potentially missing opportunities for lower production costs available elsewhere.

3.3. Cost Analysis

The gross costs of the entire configuration amount to $92,981,000, which consists of fixed cost, variable cost, and freight costs. A clarified distribution of the costs per region has been shown below to allow for better insight into each factor contributing to the total costs:

3.3.1. Cost Percentage and Value per Region

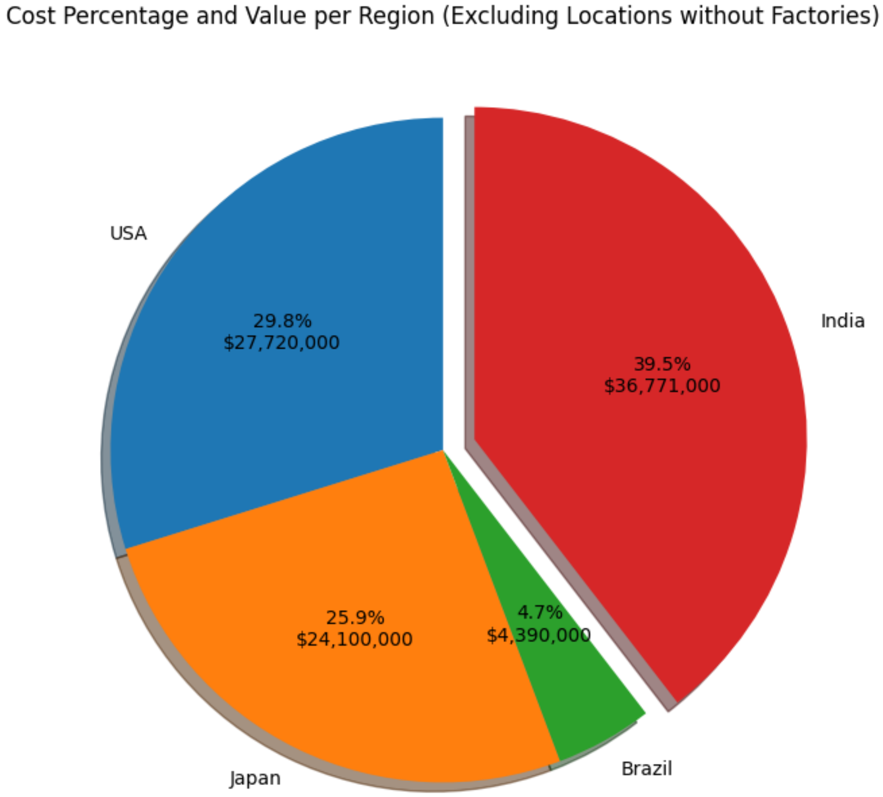

Figure 14. Cost Percentage and Value per Region

India is the largest contributor to total costs, with 39.5% of the total cost at $36.77 million. The high costs are due to the high-capacity plant, which has major fixed, variable and freight costs, since it is considered the main production center.

The USA factory is somewhat smaller in scale compared to India, but it still plays an important role in the supply chain, critical in serving local demand and the Japanese market.

Japan accounts for 25.9% of the total costs, or $24.1 million. Japan’s high fixed costs are linked to its high-capacity plant. Despite a higher production volume, its reliance on local production and import helps to keep its costs relatively lower.

Brazil contributes 4.7% of the total costs, or $4.39 million. Brazil's low production volume results in relatively high fixed costs per unit of production.

3.3.2. Detailed Cost Breakdown by Factory/Region

The stacked bar chart below shows the breakdown of costs in each region by fixed costs, variable costs, and freight costs:

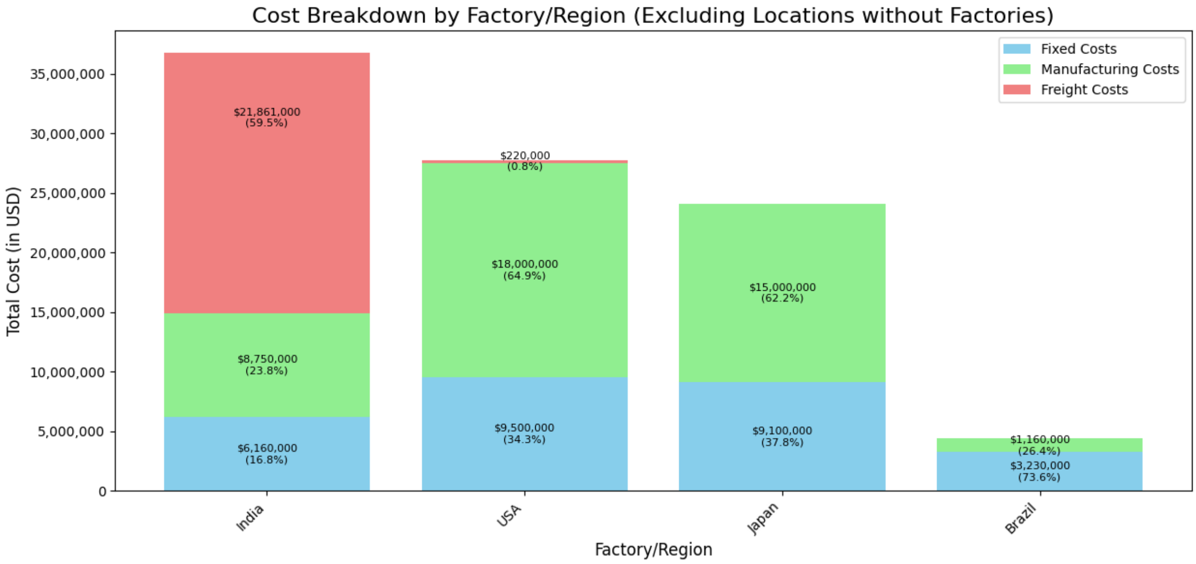

Figure 15. Cost Breakdown by Factory/Region

3.3.2.1. Optimization of Freight Costs: Focus on India-USA and USA-Japan Routes

One of the most important insights from the cost breakdown is that the majority of the company's freight costs results from the movement of goods between India and the USA, with a smaller freight costs incurred from the movements from USA to Japan and India to Germany. Specifically, the freight cost of goods moving from India to the USA is $20,475,000. In contrast, the freight charges incurred for shipments from the USA to Japan only total $200,000, and from India to Germany is $1,386,000. With such differences, we conclude that most of the shipping costs of the company relate to the flow of goods between India and USA, while a lower but worthwhile part is also contributed to the overall freight costs through the flow between the USA - Japan and India - Germany. Considering that, the company, therefore, needs to center attention towards the India-USA shipping route when optimizing supply chain strategies, and the same will also be needed with the lesser USA-Japan route. Optimizing shipping routes, selecting more effective transportation means, and identifying areas to save costs will enable the company to reduce freight costs significantly and improve cost efficiency for the total supply chain.

3.3.2.2. Brazil's Low-Capacity Plant Efficiency

In Brazil, the cost structure shows an interesting dynamic, where fixed costs make up 73.6% of its total costs, while variable costs are at a relatively low level of 26.4%. This significant proportion of fixed costs implies that the low-capacity plant in Brazil suffers from relatively high operational costs with respect to output. Though running at reduced capacity, the plant would still represent considerably high overheads due to fixed costs that include plant maintenance costs, machinery, and personnel. With fixed costs, these costs are incurred whether or not a given volume is produced; therefore, when the factory is running at the lower output, it's becoming less cost-efficient. The cost structure would thus indicate that Brazil's factory is not taking full advantage of economies of scale, leading to higher cost per unit. Conversely, regions with higher utilization (Actual production level in the initial footprint/Plant capacity) rates spread these fixed costs over vast output giving rise to lower cost per unit. The utilization rate of the factory in Brazil further strengthens this conclusion.

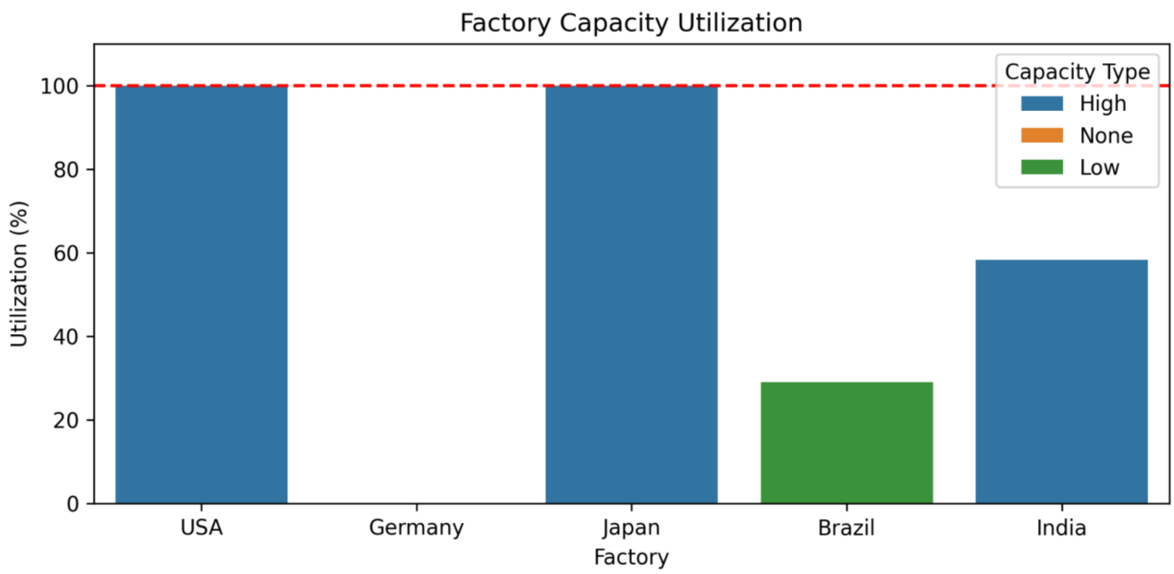

Figure 16. Factory Capacity Utilization

Brazil has a utilization rate of only 29.0%, indicating that they are operating well below its maximum capacity. This low figure appears even less efficient when viewed in the context of the entire network: it contrasts sharply with the full 100% utilization in the high-demand USA and Japan regions, and is significantly lower than even the moderate underutilization (~58.33%) observed at the high-capacity plant in India. This low utilization rate acts negatively upon the existing inefficiencies of fixed cost in that the fixed cost is not spread over sufficient numbers of units. Thus, fixed costs per unit rise in Brazil, making this operation less efficient than higher-capacity countries like the USA, India, and Japan, which have factories operating at full capacity.

Hence, the low utilization and apparent cost inefficiency raise questions about the strategic value of maintaining the Brazil plant at its current operating level. Further analysis should explore several options:

1. Investigating whether achieving higher production volumes in Brazil (potentially by serving other markets if cost-effective, or requiring increased capacity) could sufficiently leverage economies of scale to justify the fixed costs.
2. Evaluating the reallocation of Brazil's production load to other underutilized, potentially lower-cost facilities, such as the high-capacity plant in India, thereby improving overall network efficiency.
3. Considering ceasing operations in Brazil if its demand cannot be met more cost-effectively through other means or doesn't warrant the dedicated fixed costs.

This reflects a limitation of the initial model: while satisfying all demand, it might not yield the most profitable strategy for low-demand regions where fixed costs are substantial. Furthermore, the broader limitations observed in the initial footprint – the reliance on India and capacity constraints in the USA/Japan – suggest a general need to consider supply chain diversification and contingency planning for enhanced long-term resilience.

IV. Route optimization & Risk management

4.1. Analyzing the three primary shipping routes:

The allocation of freight costs emphasizes the need to optimize the India-USA shipping route while increasing efficiencies in the USA-Japan shipping route to yield lower freight costs and enhance the overall cost-efficiency of the supply chain.

4.1.1. Strategies to optimize shipping route from India to the USA

The India-USA shipping route is the most expensive due to large distances (over 13,500 km by sea), shipping costs, and port handling costs. According to FREIGHTOS, the most typical shipping methods from India to the USA are via sea and ocean freight, in which sea freight takes 30-40 days and air freight takes 2-8 business days for typical delivery. Although ocean freight is often accompanied by a longer lead time (due to port congestion, customs delays, slower movement to save fuel, bad weather conditions, etc.), this method of transportation is usually more suitable for carrying bulk goods than air freight.

Based on existing shipping routes from India to the USA, there are two cost-effective and efficient shipping routes:

One is from Mundra Port, India (India's largest private deep-draft port), to Los Angeles Port, USA, with distribution hubs in Southern California. This is an ocean route that covers around 13,000 nautical miles and typically takes around 35 days. When arriving at the Port of Los Angeles, there needs to be a central distribution center 50-100 miles from the port, for example, in the Inland Empire area. The region has ample warehouse space and is a logistics hub center. Products can be shipped across the Western United States through this hub's extensive interstate highway system.

Figure 17. From Mundra Port, India to Los Angeles Port, USA

The second option is Jawaharlal Nehru Port, India (India's busiest container port and has numerous highways to Western and Northern Indian manufacturing centers), to New York Port, USA, with transshipment in the Northeastern USA. This leg is about 12,000 nautical miles and takes about 26 days. Following docking, use a distribution facility in a 50-100-mile radius of the port, i.e., Newark, New Jersey, or some other location in the tristate area. The area is an ideal place from which to ship goods across the Northeastern United States through an extremely dense network of highways and railroads.

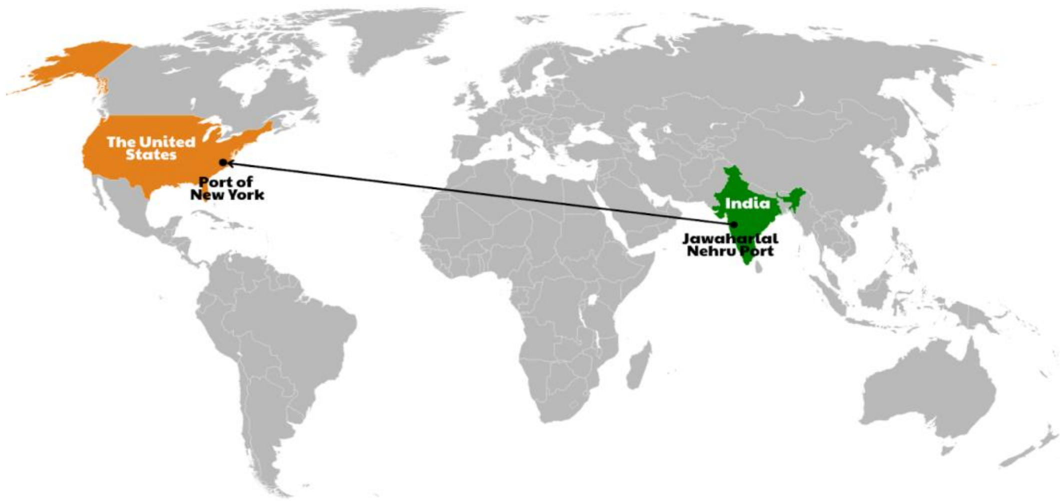

Figure 18. From Jawaharlal Nehru Port, India to New York Port, USA

Through such well-connected ports, the company can reduce transit times, reduce logistics costs, and develop resiliency in its supply chains from various disruptions.

4.1.2. Strategies to optimize shipping route from the USA to Japan

On the other hand, the USA-Japan shipping route is shorter but can also be large-scale, essentially due to shorter distances (~8,000 km) and 14-20-day sea transit times. Ocean shipping can be delayed by weather in the Pacific or suffer from occasional Tokyo Bay port congestion, but it is still cheaper than air shipping for bulk materials.

The most common and cost-effective shipping lane departs from the Port of Los Angeles; vessels traverse the Pacific Ocean directly to the Port of Yokohama. This route covers approximately 5,500 nautical miles, with typical sea transit times ranging from 12 to 14 days, depending on vessel speed and ocean conditions.

The Los Angeles Port is one of the busiest ports in the USA, with many weekly departures to Asian ports, offering scheduling flexibility. Both ports also have modern facilities, shortening loading and unloading times and overall improving efficiency. The directness of this route minimizes the need for transshipments, lessening possible delays and additional handling charges.

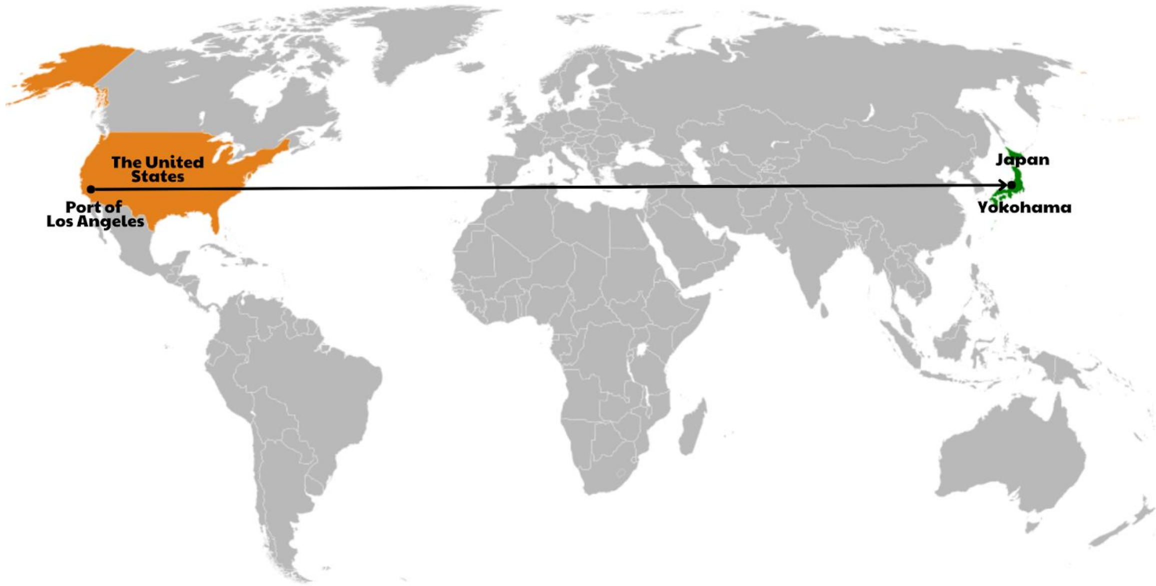

Figure 19. From Los Angeles Port, California to Yokohama Port, Japan

4.1.3. Strategies to optimize shipping route from India to Germany

The India-Germany shipping route, while contributing a smaller portion of total freight costs compared to the India-USA route, remains significant at $1,386,000. The most cost-effective and convenient mode of shipping cargo from India to Germany is via ocean freight, which takes 20-35 days, depending on the ports. This is primarily due to the character of bulk shipment and cost effectiveness of ocean freight.

Figure 20. From Mundra Port, India to Hamburg Port, Germany

One of the most efficient and cost-effective shipping routes is from Mundra Port in India to Hamburg Port in Germany. Mundra, as the largest private unloading port in India, thus having high container handling capacity with lower handling costs. The cargo undertaken will travel via the Suez Canal, eliminating long waiting and transit times for passage through the canal. This takes the overall operational time to 24-30 days from Mundra Port, India, to Hamburg Port, Germany. Meanwhile, Hamburg Port, as Germany's largest seaport, has great rail and road connections to major industrial cities such as Berlin, Frankfurt and Munich, which allows for distribution of the cargo from Germany's largest port to inland Europe.

To increase efficiency while reducing costs, the company may consider establishing warehouses at major ports or even inland hubs with high transportation capabilities. Hamburg is an ideal location seeing as it is Germany's largest port and has railway access to all major industrial cities.

4.2. Risk management

4.2.1. Political impacts on shipping routes

Analysis of freight costs and shipment flows indicates that a large portion of freight costs occurs on shipments in and out of the USA. This means that the use of the United States as a primary logistics hub can pose many transportation-related risks associated with trade policy, especially the current Donald Trump administration. Two of these trade policies have been increasing tariffs and adopting an "America first" position.

In particular, Trump has recently announced the implementation of reciprocal tariffs on trade partners India, China, and the European Union (EU), regardless of their economic status (Archana Rao, 2025). This new policy aims to correct the imbalance where the above mentioned partners impose higher tariffs on US goods than the US imposes on imports from them. While India had trade benefits previously under the Generalized System of Preferences (GSP), they were revoked in 2019 (Kenneth I.J. & Linscott M., 2025), raising the price of its exports to the USA. In addition, with stricter inspections on customs, freight costs for exports shipped from both India and the USA are increased, as there would be additional days required at the US ports (Los Angeles and New York).

Regarding the USA-Japan trade relations, the two countries have had a long-standing, strong trading relationship; however, it is now under increased scrutiny, especially in the automotive and technology sectors. Tariffs or disruptions in the supply chain could affect cost efficiencies between the two countries, which could lead to delays for company's dependent on trade routes or increased costs.

To minimize the political risks from Trump’s policies, the company needs to take various measures. First, leveraging Free Trade Agreements (FTAs) like USMCA to shift some production to Mexico or Canada will support tariff-free exports to the US. Additionally, increasing raw material purchases from U.S. suppliers will lessen exposure to tariffs on imports. Second, the company could redirect approximately 15-20% of all exports bound for the US to other markets, such as the EU or ASEAN, to lower the concentration risk.

4.2.2. The rise of onshoring in manufacturing sectors

To mitigate possible disruptions from US trade policies and reduce supply risks, there has been a global trend to onshore, where companies turn to their domestic manufacturers to insulate their operations and bring production close to points of demand (Manayiti O.M., 2024). Onshoring gives firms the capacity to scale up and down and eliminates the need to hold excessive inventory. If there is any defect in the production process, it is easier to detect and correct when the factory is near, a flight away, instead of halfway across the world (Dalfen S., 2024).

This trend aligns with the high rate of self-manufacturing from the Sankey diagram, where the US factory produces 1,300,000 units and the Japanese factory produces 1,500,000 to meet the local demand. Besides this, the freight charges incurred for shipping between different countries are also very high, with the freight cost from India to the USA being $20,475,000 and from the USA to Tokyo being $200,000 (a lower value, but considered part of the freight charges). This model thus suggests that factories are inclined to produce goods mainly within their country and don't depend on overseas manufacturing.

However, while the USA is both a production and transit point for shipments, this concentration is also risky in terms of capacity constraints, potential tariffs, and geopolitical disruptions. As part of a risk management strategy, the company can look at alternative regional production hubs. For instance, setting up or augmenting production capacity in Mexico to supply the North American market or in Vietnam to supply the Asian market can reduce dependency on long-haul shipments while providing a cost-competitive model.

4.2.3. Current trends in the Logistics and Supply Chain market

The global logistics market is currently facing various challenges, including increased freight rates and congestion at ports. The ripple effect of the Red Sea crisis and the Suez Canal congestion, which accounts for 20-30% of global container shipping volumes, has significantly increased ocean shipping costs and affected various shipping routes around the world (Marsh, 2024). In addition, port congestion can substantially increase costs for shipping companies (Veleda V. & Llop A.D., 2025). According to

Container xChange data, major US ports, including Los Angeles and Long Beach, have an average dwell time of 41 days, whereas the port of New York has the highest dwell time at 61 days on average (Lademan D. & Rubin R., 2022). Companies relying on US ports of entry as lead points can face bottlenecks affecting overall supply chain effectiveness.

Therefore, to increase the resilience of supply chains and reduce costs, the company should take a tactical approach to how products are moved. First, the company should consider alternative shipping routes utilizing transshipment ports (Singapore, Colombo, Rotterdam, for instance). This provides more flexibility and less reliance on direct shipments from India to the USA and back to Japan, which are usually expensive and slow. The transshipment ports consolidate cargo, offer better transit times, and reduce the exposure to delays caused by port congestion or geopolitical issues.

Second, the company could consider multi-modal transportation, such as moving cargo by both freight and rail. For instance, cargo can be shipped by vessel from India to the UAE and then railed to Europe or the US to the extent that it is cost-competitive. This is an optimal use of vessel and rail as it avoids excessive reliance on congested ports, provides cargo transport, avoids market volatility and adapts to demand fluctuations.

V. Another approach - possibility of unmet demand

5.1. Introduction

As demonstrated above, certain markets, such as Brazil need reevaluation of whether it is worth it to provide for this market at all. The initial footprint model fell short as it assumed that all market demand must be fulfilled.

```
for j in loc:
    model += lpSum([x[(i, j)] for i in loc]) == demand.loc[j,'Demand']
```

For experimental purposes, this constraint of fulfilling all demand will be removed. Instead, a penalty will be introduced for each unit of demand neglected to account for the potential opportunity cost of not meeting demand. This will allow us to explore different scenarios where underutilized regions like Brazil may not necessarily need to meet all demand, but will incur penalties based on the level of demand that goes unfulfilled to account for opportunity cost. To test the experiment, we change the specification of objective function in the model to consist of a penalty component for each unmet demand. This approach permits a more comprehensive judgement of the trade-off between minimizing cost and fulfilling demands, and whether forgoing cost-inefficient demand regions may serve as a more profitable strategy. Variations in the level of penalty rates are also introduced to understand how sensitive the model becomes with the cost of unmet demand.

5.2. Modification to the model

To reflect this new approach, we made the following modifications to the model:

a) Penalty Definition:

Instead of forcing the model to meet every market, a penalty is introduced to the model for each unmet unit of demand. The penalty is defined as the percentage of the average variable cost per unit of demand not moderately fulfilled. Via the definition, the model allows for trade-off between satisfying demand and minimizing penalty costs.

```
avg_cost = var_cost.loc[loc, loc].to_numpy().mean()
penalty = penalty_rate * avg_cost
```

b) Unmet Demand Variable:

An unmet demand variable was introduced to track the difference between market demand and production fulfilled. The penalty is applied based on this unmet demand for each region.

```
unmet = LpVariable.dicts("unmet", loc, lowBound=0, cat='Continuous')
```

c) Modification to the Objective Function:

The penalty is then incorporated into the objective function to minimize total cost, which now includes fixed costs (for opening plants), variable costs (for production and freight), and penalty costs (for unmet demand).

```
model += (
    lpSum([fixed_costs.loc[i, s] * y[(i, s)] * 1000 for s in size for i in loc])
    + lpSum([var_cost.loc[i, j] * x[(i, j)] for i in loc for j in loc])
    + penalty * lpSum([unmet[j] for j in loc])
), "Total_Cost"
```

d) Constraints on Demand Fulfillment:

The constraints have now been changed to balance between total production fulfilled and unmet demand through regions. Thus, the total supply coincides with market demand including the unmet portion.

```
for j in loc:
    model += (
        lpSum([x[(i, j)] for i in loc]) + unmet[j] == demand.loc[j, 'Demand']
    ), f"Demand_{j}"
```

5.3. Running Multiple Models with Varying Penalty Rates:

To understand the impact of different penalty rates, the model was run for a series of penalty rates ranging from 0.6, where the penalty started to have effect on the opening of plants, to 2.0 of the average variable cost. For each penalty rate, the model determined whether a plant should open in each region, considering the cost of unmet demand. The rest of the model elements remained the same, with only the penalty for unmet demand being adjusted.

```
penalty_rates = np.arange(0.6, 2.1, 0.1)
```

The model comes down to:

```python
# Definition
loc = ['USA', 'Germany', 'Japan', 'Brazil', 'India']
penalty_rates = np.arange(0.6, 2.1, 0.1)
results_table = pd.DataFrame(index=loc, columns=[f'{rate:.1f}' for rate in penalty_rates])

# Iterate through penalty rates
for penalty_rate in penalty_rates:
    size = ['Low', 'High']
    plant_name = [(i, s) for s in size for i in loc]
    prod_name = [(i, j) for i in loc for j in loc]
    model = LpProblem("Capacitated Plant Location Model", LpMinimize)
    x = LpVariable.dicts("production_", prod_name, lowBound=0, cat='Continuous')
    y = LpVariable.dicts("plant_", plant_name, cat='Binary')

    # NEW: Unmet demand
    unmet = LpVariable.dicts("unmet", loc, lowBound=0, cat='Continuous')

    # NEW: AVC
    avg_cost = var_cost.loc[loc, loc].to_numpy().mean()
    penalty = penalty_rate * avg_cost

    # Objective Function (with incorporation of unmet demand)
    model += (
        lpSum([fixed_costs.loc[i, s] * y[(i, s)] * 1000 for s in size for i in loc])
        + lpSum([var_cost.loc[i, j] * x[(i, j)] for i in loc for j in loc])
        + penalty * lpSum([unmet[j] for j in loc])
    ), "Total_Cost"

    # Constraint
    for j in loc:
        model += (
            lpSum([x[(i, j)] for i in loc]) + unmet[j] == demand.loc[j, 'Demand']
        ), f"Demand_{j}" # New

    for i in loc:
        model += (
            lpSum([x[(i, j)] for j in loc])
            <= lpSum([capacity.loc[i, s] * y[(i, s)] * 1000 for s in size])
        ), f"Capacity_{i}"
    model.solve()
```

The model was solved for each penalty rate to determine whether a plant would open in each country. The results of the model running with different penalty rates show some interesting shifts in plant opening decisions across various regions.

```
Penalty Rate (comparing to Average Variable Cost) 0.6 0.7 0.8 0.9 1.0 1.1 1.2
USA                                                 0   0   1   1   1   1   1
Germany                                             0   0   0   0   0   0   0
Japan                                               0   1   1   1   1   1   1
Brazil                                              0   0   0   0   0   0   0
India                                               0   0   1   1   1   1   1

Penalty Rate (comparing to Average Variable Cost) 1.3 1.4 1.5 1.6 1.7 1.8 1.9
USA                                                 1   1   1   1   1   1   1
Germany                                             0   0   0   0   0   0   0
Japan                                               1   1   1   1   1   1   1
Brazil                                              1   1   1   1   1   1   1
India                                               1   1   1   1   1   1   1

Penalty Rate (comparing to Average Variable Cost) 2.0
USA                                                 1
Germany                                             0
Japan                                               1
Brazil                                              1
India                                               1
```

Initially, at a penalty rate of 0.6, we observe that no plants open in Brazil, USA, or Germany, while Japan opens its factory. This is an interesting and somewhat unexpected result, as one might assume that even at such a low penalty, the model would still prefer to open plants in regions with strong production capabilities. The fact that only Japan opens its factory under this condition suggests that Japan is the most efficient at meeting its demand. This is particularly notable because the other regions, like Brazil, have higher fixed costs, and even a small penalty rate might be deemed insufficient to justify opening a plant, especially when the cost of fulfilling demand might still be higher than the penalty.

As we increase the penalty rate, we begin to see changes in the decisions made by the model. By the time we reach a penalty rate of 1.3, Brazil starts opening its plant. This indicates that as the penalty for unmet demand increases, it becomes more cost-effective for Brazil to meet demand compared to accepting the costs of unmet demand. The model now weighs the opportunity cost of not fulfilling demand more heavily, and this pushes Brazil to open a plant despite its less efficient cost structure.

By 1.4% and above, the model consistently opens plants in all regions, including Brazil, USA, and India, suggesting that at higher penalty rates, fulfilling demand becomes the more attractive option across the board. For Brazil, the penalty cost outweighs the fixed costs associated with operating a low-capacity plant, prompting the decision to open the plant even with its current inefficiencies. This start to aligns with our initial footprint, since higher penalty effectively infers that fulfilling all the demand is always more effective.

These results stress a critical part of real-world supply chain optimization: the actual plant opening decision is subject not only to fixed and variable cost considerations, but also a penalty on unmet demand; thus, it allows the model to trade-off between minimizing costs and fulfilling demand more realistically, leading to a robust decision-making framework.

5.4. Insights and Real-World Implications:

5.4.1. Japan's Effectiveness at Fulfilling Demand:

The results indicate that Japan is the most effective at fulfilling its demand compared to other regions. The key reason for this is Japan's optimized cost structure. Unlike Brazil, which has high fixed costs due to its smaller plant size, Japan operates at a more balanced cost distribution between its fixed and variable costs. As a result, Japan is able to produce the required units at a relatively lower cost, meaning the production cost is actually lower than the penalty for unmet demand, even when the penalty for unmet demand is minimal (as seen with the 0.6% penalty rate).

This finding suggests that Japan is a prime world region to be investigated for market penetration strategies. Since factory operation here is already efficient, we can allow further economies of scale and increased demand to be realized for the company. Additional expense consideration for the market involves investment in additional production capacity, distribution channels, and marketing efforts to leverage Japan's cost-efficient manufacturing setup further.

5.4.2. Brazil's Viability Based on Profitability:

According to the result, the decision to open an industry plant revolves around the profitability of the market. Brazil should not set up a plant at low penalty rates (below 1.2), or the opportunity cost of below 1.2 times the average variable cost - which is around $29.078736 per unit of unmet demand.

```
avg_cost = var_cost.loc[loc, loc].to_numpy().mean()
avg_cost*1.2
```

```
np.float64(29.078736)
```

Thus, for Brazil, careful evaluation should be done for market profitability before any decision is made. On the contrary, if the profit from Brazil does not compensate well for the high fixed costs, avoiding any investment into the Brazilian market and bearing the penalty is a more logical business decision. Thus, information gathering and market analysis plays an important part in investigating whether or not the Brazilian market would be a profitable venture.

VI. Scenario Generation & Sensitivity Analysis

6.1. Multiple Demand Scenarios

The Sankey chart and utilization numbers show that the allocation of factories is leading to an inefficient use of capacity. The USA and Japan factories are running at 100% utilization. This means they will be running at their full output, and may later suffer from wear and tear, production delays or increased maintenance costs. However, the India factory is only utilizing 58.33% of total production capacity, which indicates that almost half of capacity remains available for reassignment. Brazil is more concerning, utilizing only 29% of production capacity and indicating that the factory is being utilized less. Finally, Germany has not yet mobilized or used for backup in case of issues with the supply chains.

This uneven distribution in the production has severe impacts on costs and efficiency. Factories that are swamped with the production of orders can have their process become bottlenecked, leading to delays that increase operating cost and lower quality control. Under-producing factories, meanwhile, incur fixed costs without reducing output and maximizing profit. Without production in Germany, there is a risk where geographical diversification would be advantageous by mitigating the effect generated by an international crisis, trade bans, or even natural catastrophes. Imbalanced supply chain can experience increases in logistics expenses with a high-demanding area having to ship from a clogged-down plant rather than shipping arrangements from a geographically nearer underloaded plant.

Production allocation adjustments are necessary to improve operational efficiencies. Reallocation of manufacturing loads may release capacity-constrained plants' congestion and utilize India's and Brazil's stranded capacity better. Restarting Germany's plant can offer more flexibility during crises. Production planning automation and improved demand forecasting would be more matched with the supply and market demand, reducing operation risks. Finally, the lean supply chain would produce a stronger, lower-cost and more flexible worldwide manufacturing system that can react flexibly to shifts in market conditions.

6.1.1. Function Overview: Purpose of the Optimization Function for Scenario Simulation

In order to test the resilience of the original supply chain setup, we created a general optimization function with the capability of accommodating various input scenarios. The function includes the complete mathematical model with decision variable declarations, minimization of cost, and functional constraints.

By parameterizing key inputs – such as fixed costs, variable costs, demand data, and capacity constraints – we enabled the model to be readily rerun under different demand conditions. This is a prerequisite for conducting large-scale scenario testing and sensitivity analysis.

The software computes fast analysis of multiple "what-if" conditions, such as changes in demand, supply losses, or price. It maintains structural consistency for all the simulations, a key constraint for comparative purposes such as overall cost, plant output, and use.

Finally, this role is the computational foundation to our simulation engine and supports data-driven decision-making in a state of uncertainty.

6.1.2 Modular explanation

The provided optimization model is a capacitated plant location model, which aims to minimize total costs while ensuring that demand is met and production capacity constraints are respected. In global supply chain management, decisions about where to produce goods and how to distribute them significantly impact cost efficiency and operational resilience. The model is structured into distinct components, including sets and indices, decision variables, the objective function, constraints, and output generation. Each component plays a vital role in optimizing the production and distribution process across different locations.

This structured strategy allows companies to plan strategically how the production activity will be distributed among various plants to prevent bottlenecks and unnecessary costs. From fixed costs to shipping considerations, plant capacity, to variable costs, the model is a whole-bodied decision tool. Below is the detailed explanation of each element.

6.1.3. Initialization

In the initialization step, we utilized the initial factory footprint that was previously optimized and discussed in the earlier section. Rather than re-computing it, we directly used this configuration as the baseline reference. The corresponding results were extracted and stored as the first column in the evaluation matrix, serving as the foundation for comparison against all subsequently generated demand scenarios.

6.1.4. Demand Variability Modeling Using Normal Distribution

To simulate realistic demand fluctuations and test the robustness of the supply chain network, we applied a truncated normal distribution to model variability in demand. Specifically, for each market iii, demand D_i was modeled as:

$$D\_i \sim N(\mu\_i, \sigma\_i) \text{ where } \sigma\_i = CV \times \mu\_i$$

Here, μ_i represents the original (mean) demand for market i, and CV is the coefficient of variation, which was set to 0.5 to allow for ±50% variability. The resulting standard deviation σ_i scales proportionally with demand magnitude. To avoid negative or unrealistic values, we truncated the distribution at 0 using:

$$a = (0 - \mu\_i) / \sigma\_i, \; b = \infty$$

This ensured that:

- All simulated demand values remained non-negative.
- The variation in demand still followed a natural, probabilistic structure.
- Implausibly low (extreme) demand values were excluded, enhancing realism.

Using this setup, we generated 50 random demand values for each market with scipy.stats.truncnorm. These values were rounded to integers and stored in a new DataFrame (df_demand), indexed by a “scenario” column from 1 to 50. To maintain the original demand data, we prepended a baseline scenario labeled “INITIAL” to the dataset using pd.concat.

The complete dataset (INITIAL + 50 scenarios) was then saved as an Excel file. To support reproducibility and automated organization, the output folder was created using os.makedirs() if it did not already exist. This final dataset serves as input for downstream scenario-based optimization analysis.

```python
import os
import numpy as np
import pandas as pd
from scipy.stats import truncnorm

N = 50
CV = 0.5

# Khởi tạo khung kịch bản
df_demand = pd.DataFrame({'scenario': np.arange(1, N + 1)})
data = demand.reset_index()  # demand đã chuẩn hóa từ trước

# Tạo truncated demand cho từng thị trường
markets = ['USA', 'Germany', 'Japan', 'Brazil', 'India']
for _, row in data.iterrows():
    market = row['(Units/month)']  # hoặc 'Location' nếu bạn rename lại
    mean = row['Demand']
    sigma = CV * mean

    # Giới hạn từ 0 đến +∞
    a, b = 0, np.inf
    lower = (a - mean) / sigma
    upper = (b - mean) / sigma

    truncated_samples = truncnorm.rvs(lower, upper, loc=mean, scale=sigma, size=N)
    df_demand[market] = np.round(truncated_samples)

# Thêm dòng initial scenario
init_row = {'scenario': 0, **dict(zip(data['(Units/month)'], data['Demand']))}
df_init = pd.DataFrame([init_row])
df_demand = pd.concat([df_init, df_demand], ignore_index=True)

# Export nếu cần
path = '/content/drive/MyDrive/demand_scenarios'
os.makedirs(path, exist_ok=True)
df_demand.to_excel(f'{path}/df_demand_truncnorm_{int(CV*100)}PC.xlsx', index=False)

# Preview
df_demand.head()
```

	scenario	USA	Germany	Japan	Brazil	India
0	0	2800000.0	90000.0	1700000.0	145000.0	160000.0
1	1	1533582.0	145460.0	775877.0	95111.0	149304.0
2	2	2357737.0	35206.0	1576782.0	90784.0	74943.0
3	3	4936827.0	109469.0	850393.0	203817.0	89234.0
4	4	965583.0	189994.0	2686204.0	281464.0	281160.0

To better understand how demand fluctuates across different simulation scenarios, we visualized the generated demand data for each market using individual line plots. For each market (USA, Germany, Japan, Brazil, and India), a subplot was created showing demand values over 50 simulated scenarios. The x-axis represents each scenario number, while the y-axis indicates the number of units demanded.

To provide a meaningful reference, we added a horizontal dashed line at the average demand level of each market. This allows quick visual identification of volatility and skewness in demand patterns across scenarios. For instance, we can easily spot whether a market is more prone to dips below the mean or spikes above it.

This visualization serves as a diagnostic tool, helping us validate the behavior of our scenario generation logic and anticipate potential risks – such as under-utilization of factory capacity or unmet demand in high-variance markets.

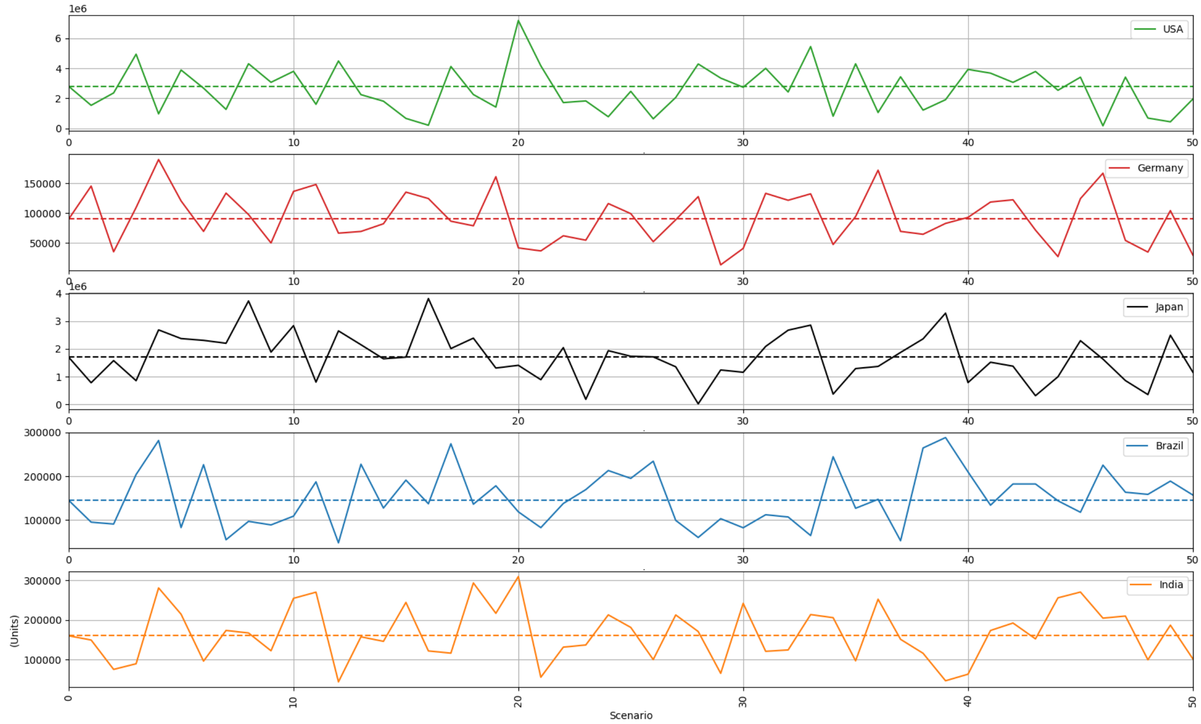

Figure 21. Simulated Demand Scenarios Across Markets

Based on the demand variability chart, several distinct patterns can be observed across the five markets. The USA and Japan consistently exhibit the highest demand magnitudes, with values reaching into the millions. Their demand patterns are relatively stable, fluctuating around the mean, though occasional spikes (such as in scenario 21 for the USA) do occur. This high volume and consistent behavior make them strong candidates for core factory allocation.

In contrast, Germany displays the lowest overall demand levels, averaging around 90,000 units. Some scenarios even show demand dipping close to zero, indicating that this market is highly sensitive to random variations. This volatility and lower demand may explain why the optimization model often chooses not to allocate factory capacity to Germany.

Brazil and India represent mid-level demand markets. Brazil demonstrates more erratic swings, showing high variability across scenarios. India, while still variable, shows a more centered fluctuation around the average. These characteristics suggest that Brazil and India can serve as secondary factory placement options, especially when balancing cost and capacity across scenarios.

6.1.5. Scenario Simulation Process

To evaluate how different demand patterns affect factory location decisions, we implemented a simulation loop that re-runs the optimization model across all 50 demand scenarios generated earlier.

Prepare the Scenario Inputs:

```
# Simulate all scenarios
demand_var = df_demand.drop(['scenario'], axis = 1).T
```

The demand dataset is transposed to allow easy access to each scenario (i) by row index. Each column now represents a country, and each row represents a scenario.

Run Optimization for Each Scenario & Store Key Outputs for Each Run:

```
# Loop
for i in range(1, 50): # 0 is the initial scenario
    # Calculations
    status_out, objective_out, y, x, fix, var = optimization_model(fixed_costs, var_cost, demand_var, i, capacity)
```

We loop over scenarios 1 to 49, skipping the initial (baseline) scenario already solved before.

For each scenario, we pass the demand profile of that scenario into the optimization_model().

This line runs the optimization model and returns:

- status_out: model feasibility status.
- objective_out: total cost of the solution.
- y: factory opening decisions (binary).
- x: shipment flows.
- fix: fixed cost portion.
- var: variable cost portion.

```
    df_bool[i] = [y[plant_name[i]].varValue for i in range(len(plant_name))]
```

Record Factory Openings (Boolean):

For each factory option (e.g. Japan-High, Brazil-Low), we check if it was opened (1) or not (0) in that scenario.

The result is stored in df_bool, a DataFrame where:

- Rows = factory options.
- Columns = scenarios (including the INITIAL baseline column).

Track Other Summary Data & Export Results to Excel:

```
        # Append results
        list_status.append(status_out)
        list_results.append(objective_out)
        df_bool[i] = [y[plant_name[i]].varValue for i in range(len(plant_name))]
        list_fixcost.append(fix)
        list_varcost.append(var)
        total_demand = demand_var[i].sum()
        list_totald.append(total_demand)
        list_scenario.append(i)
# Final Results
# Boolean
df_bool = df_bool.astype(int)
path = '/content/drive/MyDrive/demand_scenarios'
os.makedirs(path, exist_ok=True)
df_demand.to_excel(f'{path}/df_all_scenarios_{int(CV*100)}PC.xlsx', index=False)
# Other Results
df_bool
```

In addition to factory openings, the model saves overall cost, demand served, fixed/variable costs, etc., for later plotting or summary tables.

Result:

	INITIAL	1	2	3	4	5	6	7	8	9	...	40	41	42	43	44	45	46	47	48	49
USA-Low	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Germany-Low	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
Japan-Low	0	0	0	0	1	1	0	1	1	0	...	1	0	0	0	0	0	0	0	0	0
Brazil-Low	1	0	0	1	1	1	1	0	0	0	...	1	1	1	1	1	1	1	1	0	1
India-Low	0	1	0	1	1	0	0	1	1	0	...	0	0	0	0	0	0	1	0	0	1
USA-High	1	1	1	1	1	1	1	1	1	1	...	1	1	1	1	1	1	0	1	1	1
Germany-High	0	0	0	0	0	0	0	0	1	0	...	0	0	0	0	0	0	0	0	0	0
Japan-High	1	1	1	1	1	1	1	1	1	1	...	0	1	1	0	1	1	1	0	0	1
Brazil-High	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
India-High	1	0	1	1	0	1	1	0	1	1	...	1	1	1	1	1	1	0	1	0	0

10 rows × 50 columns

Visualization with the binary grid:

```
# Plot the Grid
plt.figure(figsize = (20,4))
plt.pcolor( df_bool, cmap = 'Blues', edgecolors='k', linewidths=0.5)   #
plt.xticks([i + 0.5 for i in range(df_bool.shape[1])], df_bool.columns, rotation = 90, fontsize=12)
plt.yticks([i + 0.5 for i in range(df_bool.shape[0])], df_bool.index, fontsize=12)
plt.show()
```

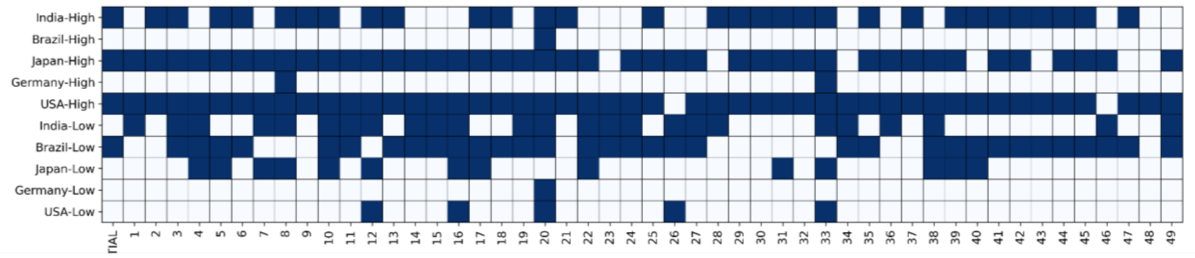

Figure 22. Factory Opening Decisions Across Simulated Scenarios

Combined:

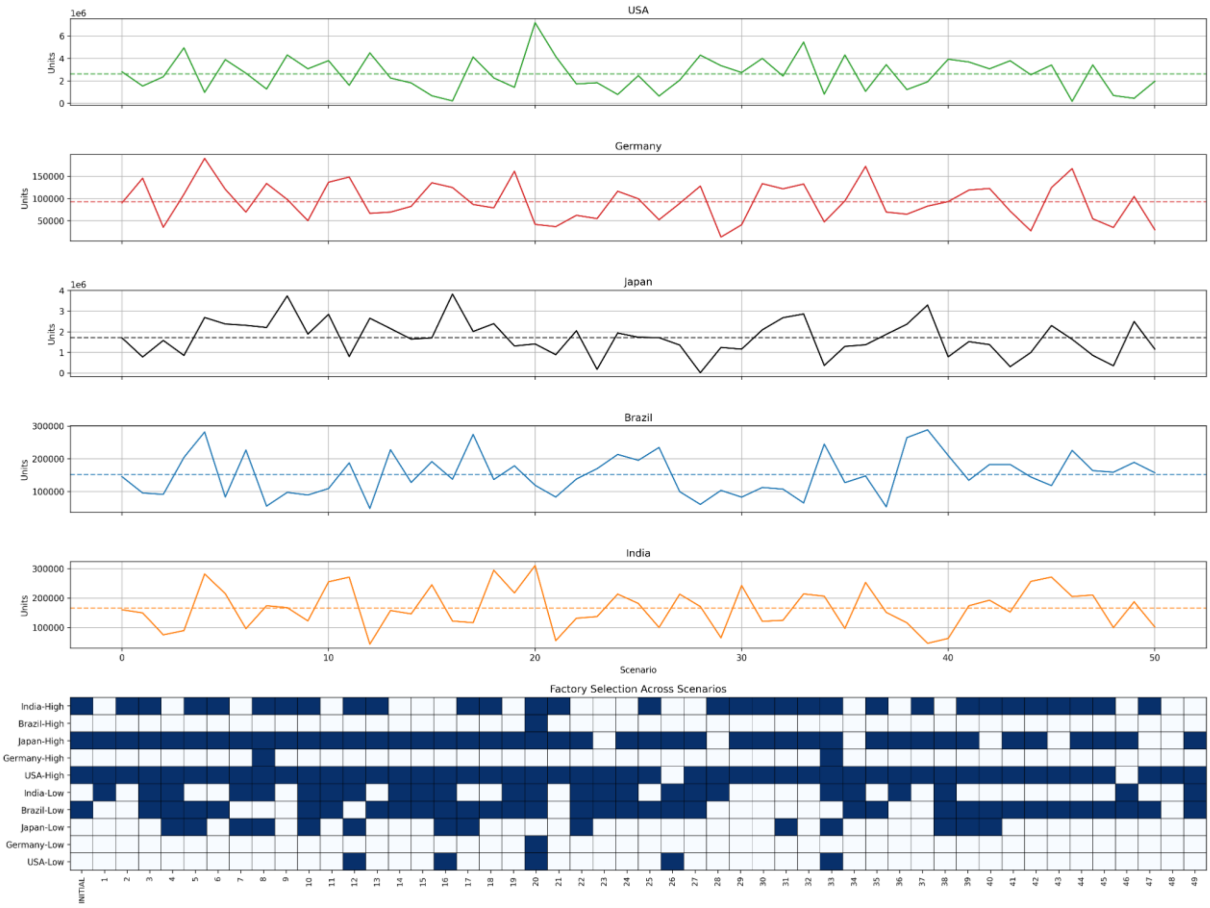

Figure 23. Combined Scenario Analysis: Demand Variability and Factory Deployment Results

```
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec

fig = plt.figure(figsize=(20, 15))
gs = gridspec.GridSpec(6, 1, height_ratios=[1, 1, 1, 1, 1, 2])
colors = ['tab:green', 'tab:red', 'black', 'tab:blue', 'tab:orange']
market_names = markets

for i, market in enumerate(market_names):
    ax = fig.add_subplot(gs[i])
    ax.plot(df_demand['scenario'], df_demand[market], color=colors[i], label=market)
    ax.axhline(df_demand[market].mean(), color=colors[i], linestyle='--', alpha=0.7)
    ax.set_ylabel('Units')
    ax.set_title(market)
    ax.grid(True)
    if i == len(market_names) - 1:
        ax.set_xlabel('Scenario')
    else:
        ax.set_xticklabels([])

ax_grid = fig.add_subplot(gs[5])
ax_grid.pcolor(df_bool, cmap='Blues', edgecolors='k', linewidths=0.5)
ax_grid.set_xticks([i + 0.5 for i in range(df_bool.shape[1])])
ax_grid.set_xticklabels(df_bool.columns, rotation=90, fontsize=9)
ax_grid.set_yticks([i + 0.5 for i in range(df_bool.shape[0])])
ax_grid.set_yticklabels(df_bool.index, fontsize=10)
ax_grid.set_title("Factory Selection Across Scenarios")

plt.tight_layout()
plt.savefig('/content/drive/MyDrive/demand_scenarios/separated_demand_and_selection.png', dpi=300, bbox_inches='tight')
plt.show()
```

6.2. Sensitivity Analysis

Each demand scenario introduces different market conditions, prompting dynamic adjustments in factory utilization and selection.

From the top section of the chart, we observe that demand for markets such as the USA and Japan fluctuates more dramatically compared to others, especially due to their higher average volumes. These swings are captured by the wide vertical spread in their respective line plots, while smaller markets like Germany, Brazil, and India exhibit relatively stable, lower-magnitude variations. The horizontal dashed lines represent the baseline (initial) demand for each market, allowing us to contextualize deviations in each scenario.

The bottom binary heatmap illustrates which factories (e.g., "USA-High", "Brazil-Low") are selected across the scenarios. It is evident that certain factories, like India-High and Japan-High, are consistently activated, indicating their strategic importance and cost-effectiveness in absorbing variable demand. In contrast, factories such as Germany-High or Brazil-Low are used more selectively, only appearing in a subset of scenarios. This reflects their role as contingency options that are only triggered when certain demand combinations or cost trade-offs make them viable.

Notably, there is no single configuration that works across all scenarios, reinforcing the need for flexibility in network design. The model adapts factory footprints based on real-time needs, balancing fixed and variable costs against capacity constraints. This scenario-driven analysis not only demonstrates the robustness of the optimization model, but also helps identify which facilities are critical and which are marginal, aiding in long-term strategic planning and risk mitigation.

6.3. Post-Simulation Analysis: Identifying and Quantifying Unique Plant Configurations

6.3.1. Step 1: Identify Unique Factory Combinations

Using the transposed binary selection matrix (df_bool.T), we dropped duplicate columns to extract the set of unique plant combinations that appeared across all simulated scenarios. Each unique column represents a distinct configuration of active factories, regardless of which scenario it appeared in. This allowed us to reduce the high-dimensional binary matrix into a more interpretable set of configuration patterns.

In total, we identified 21 unique configurations, labeled as C1, C2, ..., C21, in addition to the INITIAL configuration used in the base case.

```python
# Unique combinations
df_unique = df_bool.T.drop_duplicates().T
df_unique.columns = ['INITIAL'] + ['C' + str(i) for i in range(1, len(df_unique.columns))]
# Plot the Grid
plt.figure(figsize = (12,4))
plt.pcolor( df_unique, cmap = 'Blues', edgecolors='k', linewidths=0.5)   #
plt.xticks([i + 0.5 for i in range(df_unique.shape[1])], df_unique.columns, rotation = 90, fontsize=12)
plt.yticks([i + 0.5 for i in range(df_unique.shape[0])], df_unique.index, fontsize=12)
plt.show()
```

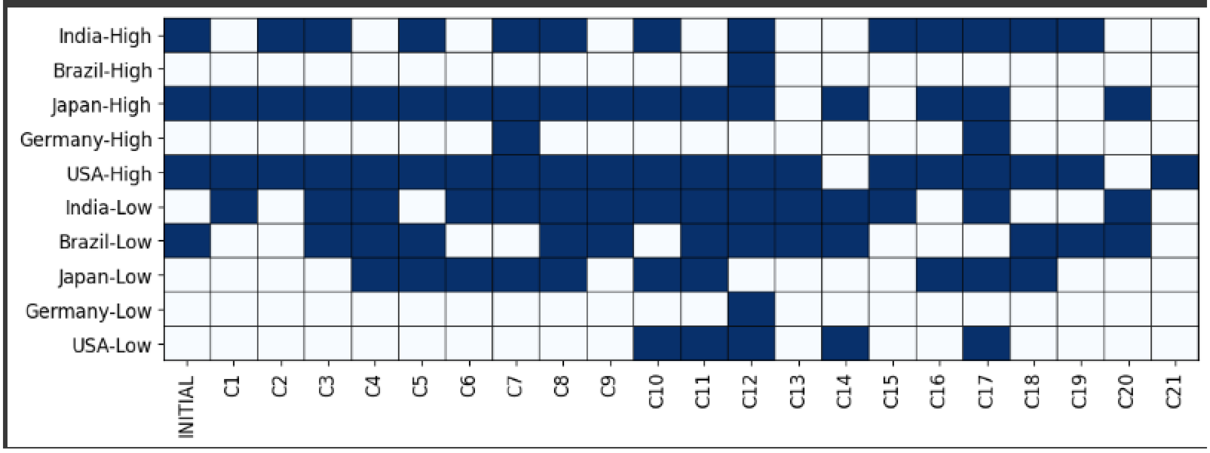

Figure 24. Unique Factory Configuration Patterns Across Scenarios

6.3.2. Step 2: Quantify the Frequency of Each Configuration

We then computed the frequency (i.e., number of scenarios) in which each unique configuration occurred. This was visualized using a donut chart, where each segment represents a configuration, and the size of the segment indicates its relative frequency among the 50 total scenarios.

For example, the INITIAL configuration appeared in 20% of all scenarios, while configurations like C2 and C9 were the next most frequent, each accounting for around 14%.

Other combinations were less prevalent, appearing in just 2–6% of the scenarios. This frequency-based analysis is crucial to identifying robust configurations – those that appear consistently across diverse demand scenarios – and to understand how volatile or stable the supply chain design is in response to demand fluctuations.

To further analyze the solution patterns under different demand conditions, we identified all unique factory selection combinations observed across the 50 scenarios. This yielded 22 distinct configurations, including the original initial solution.

A frequency-based analysis was then performed to evaluate how often each combination was selected. As shown in the doughnut chart, the initial configuration remained the most frequent choice, appearing in 20% of the cases. Combinations C2 and C9 followed with 14% each, suggesting that these may serve as effective alternatives when demand deviates from the base case.

```python
# Number of columns
COL_NAME, COL_NUMBER = [], []
for col1 in df_unique.columns:
    count = 0
    COL_NAME.append(col1)
    for col2 in df_bool.columns:
        if (df_bool[col2]!=df_unique[col1]).sum()==0:
            count += 1
    COL_NUMBER.append(count)
df_comb = pd.DataFrame({'column':COL_NAME, 'count':COL_NUMBER}).set_index('column')

my_circle = plt.Circle( (0,0), 0.8, color='white')
df_comb.plot.pie(figsize=(8, 8), x='column', y='count', legend= False, pctdistance=0.7,
                                      autopct='%1.0f%%', labeldistance=1.05,
                                      wedgeprops = { 'linewidth' : 7, 'edgecolor' : 'white' })
plt.xlabel('Business Vertical')
# plt.title('{:.2f} M€ Budget Applications in 9 Vertical Markets'.format(df_p['TOTAL'].sum()/1e6))
p = plt.gcf()
p.gca().add_artist(my_circle)
plt.axis('off')
plt.show()
```

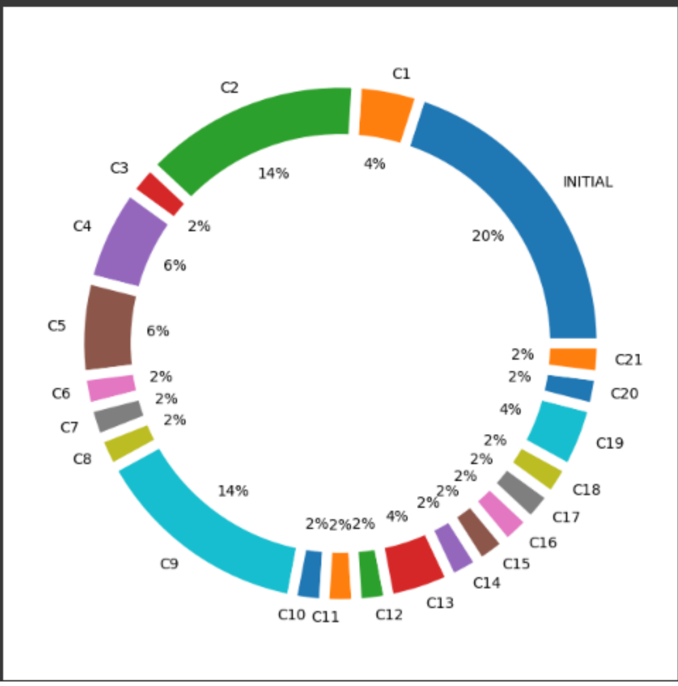

Figure 25. Frequency of Unique Factory Configurations Across Scenarios

Certain factories – such as USA-High and India-High – were robust choices across most configurations, whereas others like Germany-Low were rarely selected. This indicates the strategic importance of some locations in maintaining supply chain efficiency under uncertainty.

To better understand how the optimization model adapts to demand uncertainty, we conducted a comparative analysis between the Initial configuration and two of the most frequent scenario outcomes: C2 and C9. These configurations represent distinct factory selection strategies generated from varying demand conditions.

	INITIAL	C2	C9	C2 >< INITIAL	C9 >< INITIAL	C2 >< C9
India-High	1	1	0	FALSE	TRUE	TRUE
Brazil-High	0	0	0	FALSE	FALSE	FALSE
Japan-High	1	1	1	FALSE	FALSE	FALSE
Germany-High	0	0	0	FALSE	FALSE	FALSE
USA-High	1	1	1	FALSE	FALSE	FALSE
India-Low	0	0	1	FALSE	TRUE	TRUE
Brazil-Low	1	0	1	TRUE	FALSE	TRUE
Japan-Low	0	0	0	FALSE	FALSE	FALSE
Germany-Low	0	0	0	FALSE	FALSE	FALSE
USA-Low	0	0	0	FALSE	FALSE	FALSE

Figure 26. Comparative Analysis of Factory Selection in Key Scenarios

In comparing the three scenarios – INITIAL, C2, and C9 – we observe both consistency and variability in factory selection decisions. Notably, USA-High and Japan-High are selected across all three scenarios, highlighting their strategic importance and consistent cost-effectiveness. In contrast, Japan-Low, Germany-Low, and USA-Low are excluded in all scenarios, suggesting they contribute little value under varying conditions. The C2 scenario introduces Brazil-Low as an additional factory compared to the INITIAL setup, indicating a slight shift in optimization priorities, possibly due to changes in demand or cost structure. The C9 scenario deviates the most, replacing India-High (used in INITIAL and C2) with India-Low, and also including Brazil-Low, reflecting a shift toward more distributed and potentially lower-cost production sources. Interestingly, Brazil-High and Germany-High remain unused in all cases, which may imply high fixed costs or limited utility in fulfilling demand. Overall, the variation in selected factories, particularly in C9, suggests that the optimization model dynamically adapts to different demand profiles, and that facilities like Brazil-Low and India-Low serve as flexible alternatives when conditions shift. Understanding these changes provides valuable insight into capacity planning and cost-minimization strategies under uncertainty.

6.4. Calculating Utilization Efficiency for Selected Scenarios

After generating 50 demand scenarios using the initial optimization model, we selected three representative configurations – INITIAL, C2, and C9 – for in-depth analysis. These configurations were stored in the df_unique matrix, which records the specific factories and capacity levels (Low or High) chosen for each scenario.

To evaluate how effectively the selected factories, utilize their installed capacity, we performed the following process:

6.4.1. Fixing Factory Configuration

For each scenario (INITIAL, C2, C9), we extracted the corresponding factory choices from df_unique. This determined exactly which factories and capacity types were allowed to open.

6.4.2. Re-Optimization Under Constraints

We re-ran the optimization model with the following constraints applied:

- Factory selection (open/close) must follow the configuration from df_unique.
- Total production from each factory must not exceed its installed capacity.
- Demand must still be satisfied for the given scenario.

```
# --- Constraints ---
# Demand satisfaction
for j in loc:
    model += lpSum(x[(i, j)] for i in loc) >= demand_row[j]

# Capacity limit
for i in loc:
    model += lpSum(x[(i, j)] for j in loc) <= lpSum(capacity.loc[i, s] * y[(i, s)] * 1000 for s in size)

# Enforce selection from bool_df (e.g., df_unique)
for i in loc:
  for s in size:
    key = f"{i}-{s}"
    if bool_df.loc[key, scenario_name] == 0:
        model += y[(i, s)] == 0
    else:
        model += y[(i, s)] == 1
```

This modified model ensured that the resulting output was not only cost-effective but also operationally feasible.

6.4.3. Calculating Utilization

Notably, configuration C9 yielded an impossible utilization rate of 341.9% for the Brazil-Low factory. This anomaly indicated a potential issue with the C9 solution as generated in the initial simulations, prompting the validation analysis detailed in Section 6.2.

	Scenario	C2	C9	INITIAL
Factory	Capacity Type			
USA	Low	0.00	0.0	0.00
	High	100.00	100.0	100.00
Germany	Low	0.00	0.0	0.00
	High	0.00	0.0	0.00
Japan	Low	0.00	0.0	0.00
	High	100.00	100.0	100.00
Brazil	Low	0.00	341.9	29.00
	High	0.00	0.0	0.00
India	Low	0.00	100.0	0.00
	High	37.85	0.0	58.33

Figure 27. Factory Capacity Utilization Under Constrained Re-Optimization

6.4.4. Calculating Cost Efficiency for INITIAL and C2 Footprints

Following the utilization analysis (5.4.3) and the subsequent validation that flagged configuration C9 as problematic (detailed in Section 6.2), the next step was to rigorously evaluate the cost performance and feasibility of the two primary candidate footprints, INITIAL and C2, across the full set of 50 demand scenarios.

We employed the modified optimization model (from 5.4.2) that enforces a fixed factory selection. For each of the 50 demand scenarios previously generated (df_demand), this model was executed twice:

1. Once with the factory configuration fixed to match the 'INITIAL' footprint.
2. Once with the factory configuration fixed to match the 'C2' footprint.

For each of these 100 optimization runs (50 scenarios × 2 configurations), we recorded the model's status (Optimal/Infeasible), the total cost, and the breakdown into fixed and variable costs.

```
# Evaluate cost of INITIAL footprint across 50 scenarios
results_initial = []

for i in range(50):
    demand_row = df_demand.iloc[i]
    status, obj, y, x, fix, var = optimization_model(
        fixed_costs, var_cost, demand_row, capacity,
        df_unique, 'INITIAL'
    )

    results_initial.append({
        'Scenario': i,
        'Status': status,
        'Total Cost': obj,
        'Fixed Cost': fix,
        'Variable Cost': var,
    })
df_results_initial = pd.DataFrame(results_initial)
display(df_results_initial)
```

	Scenario	Status	Total Cost	Fixed Cost	Variable Cost
0	0	Optimal	9.298100e+07	2.799000e+07	6.499100e+07
1	1	Optimal	5.884987e+07	2.799000e+07	3.085987e+07
2	2	Optimal	8.032243e+07	2.799000e+07	5.233243e+07
3	3	Optimal	1.269091e+08	2.799000e+07	9.891908e+07
4	4	Optimal	8.198404e+07	2.799000e+07	5.399404e+07
5	5	Infeasible	1.308727e+08	2.854163e+07	1.023311e+08
6	6	Optimal	1.025485e+08	2.799000e+07	7.455852e+07
7	7	Optimal	7.449862e+07	2.799000e+07	4.650862e+07
8	8	Infeasible	1.814274e+08	2.799000e+07	1.534374e+08
9	9	Optimal	1.000942e+08	2.799000e+07	7.210424e+07
10	10	Infeasible	1.430814e+08	2.998616e+07	1.130952e+08

Figure 28. Cost and Feasibility of INITIAL Factory Footprint Across 50 Scenarios

```
# Evaluate cost of C2 footprint across 50 scenarios
results_c2 = []

for i in range(50):
    demand_row = df_demand.iloc[i]
    status, obj, y, x, fix, var = optimization_model(
        fixed_costs, var_cost, demand_row, capacity,
        df_unique, 'C2'
    )

    results_c2.append({
        'Scenario': i,
        'Status': status,
        'Total Cost': obj,
        'Fixed Cost': fix,
        'Variable Cost': var,
    })
df_results_c2 = pd.DataFrame(results_c2)
display(df_results_c2)
```

	Scenario	Status	Total Cost	Fixed Cost	Variable Cost
0	0	Optimal	9.357900e+07	2.476000e+07	6.881900e+07
1	1	Optimal	5.813080e+07	2.476000e+07	3.337080e+07
2	2	Optimal	7.948913e+07	2.476000e+07	5.472913e+07
3	3	Infeasible	1.293762e+08	2.596169e+07	1.034145e+08
4	4	Optimal	8.618469e+07	2.476000e+07	6.142469e+07
5	5	Infeasible	1.292194e+08	2.688830e+07	1.023311e+08
6	6	Optimal	1.052904e+08	2.476000e+07	8.053038e+07
7	7	Optimal	7.272012e+07	2.476000e+07	4.796012e+07
8	8	Infeasible	1.893055e+08	3.912181e+07	1.501837e+08
9	9	Optimal	9.920980e+07	2.476000e+07	7.444980e+07
10	10	Infeasible	1.347873e+08	2.476000e+07	1.100273e+08
11	11	Optimal	6.346411e+07	2.476000e+07	3.870411e+07

Figure 29. Cost and Feasibility of C2 Factory Footprint Across 50 Scenarios

This comprehensive dataset, detailing the performance of the INITIAL and C2 footprints under varying demand conditions, provides the foundation for the comparative analysis and final configuration selection presented in Section 6.

VII. Evaluation and Selection of the Optimal Solution

7.1. Comparative Analysis of Scenarios

To identify the most robust and cost-effective factory configurations, we began by analyzing the frequency of appearance of each scenario across all 50 optimization runs. A donut chart was used to visualize the distribution, revealing three dominant options that occurred most frequently:

- INITIAL – the original optimized configuration from the first scenario
- C2 – a configuration that appeared 14% of the time
- C9 – another frequent candidate, also appearing 14% of the time

These three options were selected for further evaluation.

7.2. Validation via Utilization Efficiency

Before proceeding with final evaluation, we examined the utilization efficiency of each selected footprint to ensure their operational feasibility.

To validate the operational efficiency of each configuration, we calculated the utilization rates for all factories under each of the three selected scenarios.

Initially, the utilization of C9 appeared suspicious – with one factory (Brazil-Low) showing a utilization rate exceeding 340%, clearly violating physical capacity limits.

Upon further investigation, it was discovered that the original optimization model used during scenario generation did not strictly enforce capacity constraints. As a result, the model allowed shipments from factories to exceed their available capacity, causing artificially high efficiency numbers. To correct this, we revised the optimization_model() to tighten the capacity constraints and re-evaluated the same configurations.

After correcting the constraint and re-running the optimization for C9, it became evident that this configuration is infeasible under several demand scenarios. As a result, C9 was eliminated from further consideration.

7.3. Cost Analysis: INITIAL vs. C2

The two remaining footprints – INITIAL and C2 – were evaluated in detail across all 50 demand scenarios, using the corrected optimization model. The following comparison metrics were used:

```python
import pandas as pd
cols_to_analyze = ['Total Cost', 'Fixed Cost', 'Variable Cost']
summary = {
    'Metric': [
        'Avg. Total Cost',
        'Avg. Fixed Cost',
        'Avg. Variable Cost',
        '# Optimal Scenarios',
        '# Infeasible Scenarios',
        'Standard Deviation (Cost)',
        'Max Total Cost (Worst-case)'
    ],
    'INITIAL': [],
    'C2': []
}

def analyze_result(df):
    avg_total = df['Total Cost'].mean()
    avg_fixed = df['Fixed Cost'].mean()
    avg_var = df['Variable Cost'].mean()
    num_optimal = (df['Status'] == 'Optimal').sum()
    num_infeasible = (df['Status'] != 'Optimal').sum()
    std_cost = df['Total Cost'].std()
    max_cost = df['Total Cost'].max()
    return [avg_total, avg_fixed, avg_var, num_optimal, num_infeasible, std_cost, max_cost]


summary['INITIAL'] = analyze_result(df_results_initial)
summary['C2'] = analyze_result(df_results_C2)


df_summary = pd.DataFrame(summary)
display(df_summary)
```

	Metric	INITIAL	C2
0	Avg. Total Cost	9.589407e+07	9.627375e+07
1	Avg. Fixed Cost	2.891512e+07	2.632290e+07
2	Avg. Variable Cost	6.697895e+07	6.995085e+07
3	# Optimal Scenarios	4.300000e+01	4.000000e+01
4	# Infeasible Scenarios	7.000000e+00	1.000000e+01
5	Standard Deviation (Cost)	3.576432e+07	3.538852e+07
6	Max Total Cost (Worst-case)	2.130493e+08	2.130493e+08

Metric	INITIAL	C2
Avg. Total Cost	95.89 million	96.27 million
Avg. Fixed Cost	28.91 million	26.32 million
Avg. Variable Cost	66.98 million	69.95 million
# Optimal Scenarios	43	40

# Infeasible Scenarios	7	10
Std. Deviation (Total Cost)	35.76 million	35.38 million
Max Total Cost (Worse-case)	213.05 million	213.05 million

Figure 30. Cost Comparison: INITIAL vs. C2 Factory Footprints

The comparison between the INITIAL and C2 factory footprints reveals important trade-offs. Although C2 achieved a slightly lower average total cost, this was primarily due to a reduction in fixed costs. However, this cost advantage came at the expense of higher variable (operational) costs. Furthermore, the C2 configuration exhibited a greater number of infeasible scenarios, suggesting that it is less robust when faced with variations in demand. In contrast, the INITIAL footprint demonstrated more stable and reliable performance, with a higher number of optimal outcomes and fewer infeasibilities across the tested scenarios. Both configurations shared a similar worst-case total cost, but the INITIAL setup proved to be more resilient and consistent under uncertainty.

7.4. Final Recommendation

Given the trade-offs, we recommend the INITIAL footprint as the optimal factory configuration. It offers a well-balanced approach between cost and feasibility, demonstrating greater robustness by handling a higher number of scenarios successfully. This configuration also ensures more reliable operations under uncertain demand patterns. While Scenario C2 may still be worth exploring further or considered as a backup strategy, the INITIAL setup currently stands out as the best option, combining cost-efficiency with resilience.

VIII. Final remarks

This study underscores that optimizing a factory network is not merely about cost reduction but a strategic balance between operational efficiency, flexibility, and resilience against market fluctuations. Through an extensive analysis of three key configurations: INITIAL, C2, and C9 – across more than 50 demand scenarios, the findings provide critical insights into long-term sustainability in factory operations.

While C9 initially appeared promising, its severe capacity violations rendered it unfeasible for long-term implementation. This highlights a crucial lesson: cost savings are only valuable if the chosen configuration remains viable under real-world conditions. The evaluation then narrowed down to INITIAL and C2. Although C2 demonstrated lower fixed costs, its higher variable costs significantly reduced its overall efficiency, particularly in fluctuating market conditions. Moreover, C2 lacked stability across multiple scenarios, posing substantial risks to long-term operations. In contrast, while INITIAL may not be the most cost-effective option in the short term, it proved to be the most stable, adaptable, and least prone to operational failures.

The study also emphasizes a fundamental principle: optimization is not solely about identifying the most cost-efficient solution but ensuring the model functions effectively in real-world applications. The discovery of capacity violations in C9 serves as a clear reminder of the necessity for rigorous feasibility assessments. Without adequately accounting for operational constraints, a seemingly optimal model in theory may become impractical in practice, leading to significant disruptions.

In the long-term, businesses can enhance decision-making by leveraging advanced demand forecasting tools to better capture market trends and seasonality. Additionally, constraint management should be refined to ensure that all operational limits are accurately reflected in the optimization model, preventing unrealistic or infeasible outcomes. Further scenario-based risk assessments will also be essential in evaluating how different configurations perform under extreme conditions, enabling businesses to proactively adjust their strategies.

Ultimately, this study provides not only a scientific approach to cost optimization but also highlights the importance of long-term operational sustainability. Factory network decisions should not be driven solely by short-term cost savings but by a commitment to stability and adaptability. A well-designed factory network will not only enhance operational efficiency but also establish a sustainable competitive advantage in an ever-evolving business landscape.

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