ISyE 6339 Casework 1
BotWorld's Dedicated European Supply Chain Design

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1 Task 1

1.1 Population Data Collection and Projections

Steps

- **Data Collection:** Gather population data for target countries and major cities from Eurostat and national statistical agencies, and organize it into an Excel file.

- **Data Processing:** Use the population growth rate to calculate annual population projections for 2026-2033 using the following formula:

$$P_{year} = P_{start} \times (1 + \text{growth rate})^{(year-2024)}$$

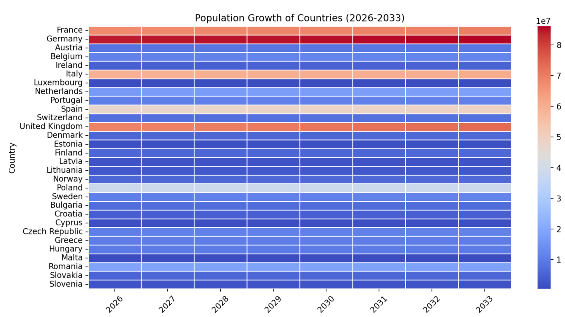

Figure 1: Population Growth of Countries

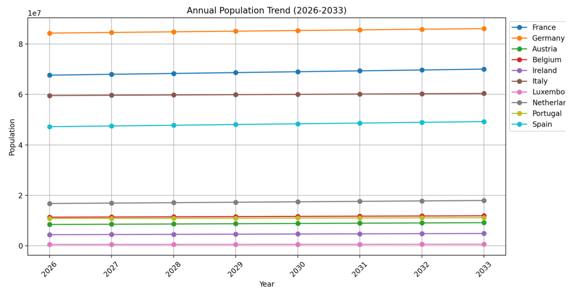

Figure 2: Annual population trend

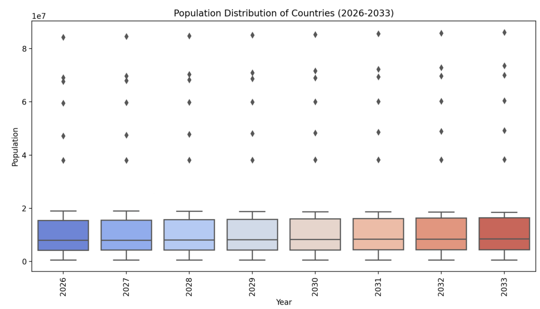

Figure 3: Population Distribution of countries

Result Example

- A heatmap visualizing the projected population growth of European countries from 2026 to 2033.
- The x-axis represents the years (2026-2033), while the y-axis lists the countries.
- The color intensity in each cell represents population size, with a gradient from blue (lower population) to red (higher population).

Key Observations

- **Countries with the Largest Population:** Germany, France, and the UK are the most populated countries, indicated by deep red shades. These countries are expected to maintain their population growth trends.
- **Countries with Moderate Population Growth:** Spain and Italy exhibit moderate population levels. Countries like Poland and Sweden show mid-range population values.
- **Countries with Smaller Populations:** Luxembourg, Malta, Estonia, and Cyprus have relatively smaller populations, with slight increases over time.

Key Insights for Market Deployment

- Germany, France, and the UK are primary target markets due to their large and steadily growing populations.
- Emerging markets such as Poland, Spain, and Sweden show potential for expansion.
- Countries with declining or stagnating populations (e.g., Bulgaria, Latvia) may pose challenges for demand growth.

1.2 Demand Forecasting

Steps

- **Demand Calculation:**
  - The demand in the first year is 0.025% of the population.
  - Annual increases are applied: +0.02%, +0.01%, and +0.005%.
  - Use projected population to calculate the total demand for each country and city.
- **Demand Breakdown:**
  - Allocate demand by product category using the given share distribution.
  - Calculate product sales revenue using market prices.

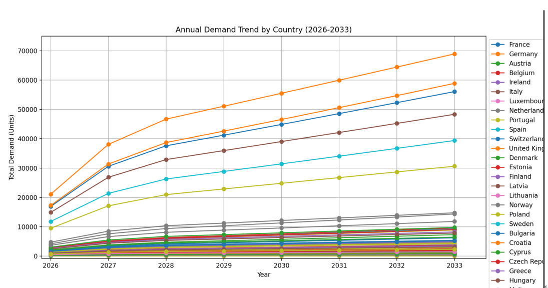

Figure 4: Annual demand trend by countries

Result Example

- The chart illustrates the annual total demand trends across different countries from 2026 to 2033.
- Germany and France exhibit the highest demand, indicating that these two markets are primary targets.
- Other countries show moderate but steady demand growth.

1.3 Demand Refinement and Seasonal Adjustment

Steps

- **Data Refinement:**
  - Break down annual demand into 13 cycles (one every 4 weeks).
  - Distribute demand using the seasonal fluctuation proportions: `[0.04, 0.06, 0.06, 0.08, 0.10, 0.14, 0.14, 0.10, 0.08, 0.06, 0.05, 0.05, 0.04]`.
  - Further decompose monthly demand into weekly and daily demand.
- **Black Friday Demand Adjustment:**
  - Allocate 18% of total annual demand to Cycle 12 for Black Friday sales.
  - Apply a 15% price reduction for Black Friday purchases.

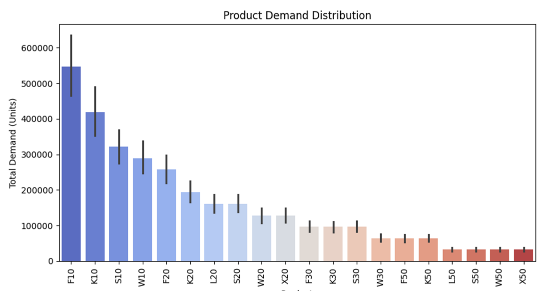

Figure 5: Product demand distribution

Result Example

- The chart illustrates annual demand distribution across different product categories.
- F10 (Floor Care) has the highest demand, followed by K10 (Kitchen Help) and S10 (Safety & Security).
- High-end models (e.g., F50, K50) have lower demand, indicating preference for mid-range products.

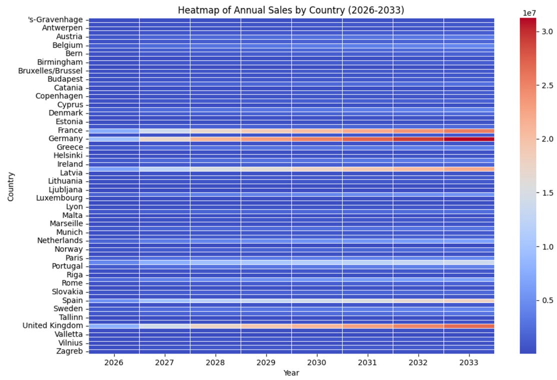

Figure 6: Heatmap of sales by country

- The heatmap shows annual sales revenue (€) for different countries from 2026 to 2033.
- Darker red shades indicate higher sales revenue, while blue shades represent lower sales revenue.
- Germany and France have the highest sales revenue.

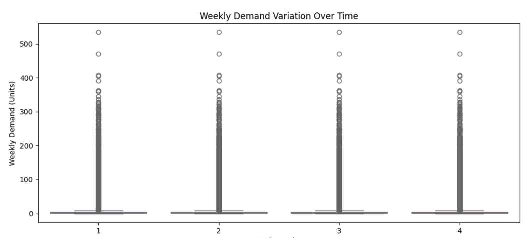

Figure 7: Weekly demand variation

- The chart illustrates weekly demand trends.
- Significant outliers in demand are observed, likely caused by market fluctuations or peak demand periods like Black Friday.
- Despite fluctuations, most products exhibit stable weekly demand.

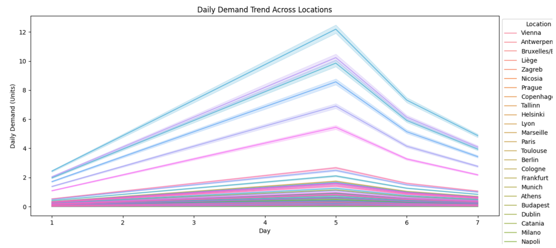

Figure 8: Daily demand trend by regions

- The chart illustrates daily demand trends across different regions.
- Demand gradually increases from Monday to Friday, peaking on Friday before declining over the weekend.

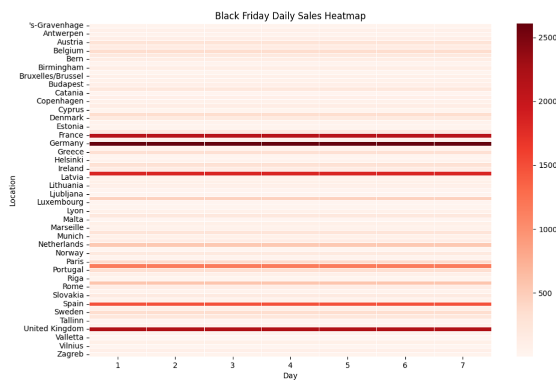

Figure 9: BlackFriday daily sales heatmap

- The heatmap illustrates daily sales performance across different countries during Black Friday.
- Germany, France, and the UK recorded the highest Black Friday sales.
- Western European countries exhibit higher Black Friday sales compared to Eastern Europe.

Summary

- Annual demand is steadily increasing, with Germany and France being the largest markets.
- Lower-end products like F10 and K10 are the most popular, while high-end models have lower demand.
- Market expansion strategies align with data trends, as countries entered earlier exhibit higher demand.
- Consumer shopping habits are evident, with Friday and Black Friday being peak sales periods.

- Black Friday has a significant impact on sales, with Germany, France, and the UK contributing the most to total sales.

1.4 Stochastic Daily Demand Simulation & Scenario Analysis

1.4.1 Simulator Design

Overview The daily demand simulator is designed to generate 1000 alternative demand scenarios for the years 2026-2033, capturing the uncertainty in demand forecasts. It accounts for historical patterns, seasonal fluctuations, and stochastic variations. The simulator's output enables supply chain decision-makers to assess demand variability and optimize inventory planning.

Simulation Methodology The simulation process consists of the following steps:

1. **Initialization:** Define input parameters, including product categories, historical demand distributions, and seasonality effects.
2. **Scenario Generation:** Execute Monte Carlo simulations to create 1000 alternative demand trajectories.
3. **Daily Demand Calculation:** Compute product-specific demand values for each day based on historical means and random variations.
4. **Special Adjustments:** Incorporate seasonal effects and event-driven spikes such as Black Friday demand surges.
5. **Data Aggregation:** Store the results at both the product level and country level, depending on the analysis requirements.

Mathematical Model For each product p on day t, the demand $D_{p,t}$ is modeled as:

$$D_{p,t} = \mu_p + \epsilon_{p,t} \tag{1}$$

where:

- μ_p is the expected daily demand derived from historical data.
- $\epsilon_{p,t}$ is a stochastic term representing demand uncertainty:

$$\epsilon_{p,t} \sim \mathcal{N}(0, \sigma_p) \tag{2}$$

  where σ_p is the historical standard deviation for product p.

The final daily demand incorporates seasonal and event-based multipliers:

$$D_{p,t}^{\text{final}} = D_{p,t} \times S_t \times E_t \tag{3}$$

where:

- S_t is the seasonality adjustment factor for day t.
- E_t is an event multiplier (e.g., a Black Friday surge factor).

Scenario Generation and Monte Carlo Simulation To capture demand variability, the simulator generates 1000 independent demand scenarios. Each scenario follows the same demand model but introduces different stochastic fluctuations. The implementation uses a Monte Carlo approach:

1. Generate 1000 sets of random variations $\epsilon_{p,t}$ for each product and day.
2. Apply seasonal and event multipliers to adjust base demand.
3. Aggregate the data to obtain mean demand trends across all scenarios.

Implementation in Python The simulator is implemented in Python and structured as follows:

- **Class Definition:** The `Simulator` class initializes parameters and controls the simulation.
- **Stochastic Demand Calculation:** Uses `numpy.random.normal()` to introduce randomness.
- **Scenario Storage:** Results are formatted as a Pandas DataFrame and stored as CSV files for further analysis.

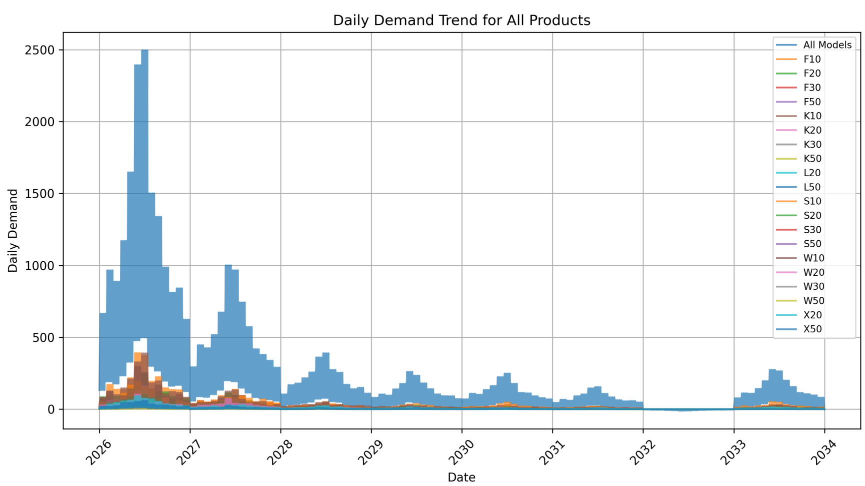

Figure 10: Daily Demand Trends Across 1000 Scenarios

Code Snippet To enhance readability, a relevant code snippet demonstrating the daily demand calculation is included:

```
[breaklines=true]
for year in range(self.start_year, self.end_year + 1):
            population = self.population_data[str(year)].sum()
            market_share = self._get_market_share_growth(year)
            company_demand = population * market_share
```

```
        for _, product_row in self.product_data.iterrows():
            model = product_row["Model"]
            demand_dist = {
                "Minimum": product_row["Minimum"],
                "Most probable": product_row["Most probable"],
                "Maximum": product_row["Maximum"],
                "Target Market Price (Euros)": product_row["Target Market Price (Euros)"]
            }

            black_friday_demand = self._allocate_black_friday_demand(original_annual_demand)
            total_annual_demand = original_annual_demand + black_friday_demand

            remaining_annual_demand = total_annual_demand - black_friday_demand
            period_demands = self._distribute_four_week_demand(remaining_annual_demand)

            daily_demands = []
            for period_demand in period_demands:
                daily_demands.extend(self._distribute_daily_demand(period_demand))

            date_strs = [date.strftime('%Y-%m-%d')
                for date in self.date_range if date.year == year]
            for i, demand_value in enumerate(daily_demands):
                product_demands[model]["daily_demand"][date_strs[i]] = demand_value

    return product_demands
```

Output Structure The final demand data is structured as follows:

- **Date:** The simulation covers daily demand from January 1, 2026, to December 31, 2033.
- **Product:** Demand is tracked at the product level.
- **Daily Demand:** The generated demand for each product per day.
- **Country Aggregation:** Depending on the analysis, demand can be split per country or aggregated globally.

1.4.2 Scenario Generation

Overview The scenario generation process is designed to simulate 1000 alternative daily demand patterns for BotWorld's expansion in Europe from 2026 to 2033. Each scenario accounts for inherent demand uncertainty, seasonality, and event-based fluctuations. The stochastic simulation ensures that the generated demand values capture realistic variations observed in historical data while allowing for unexpected market changes.

Stochastic Demand Modeling For each product p on day t, the simulated daily demand $D_{p,t}^{(i)}$ in scenario i is calculated as:

$$D_{p,t}^{(i)} = (\mu_p + \epsilon_{p,t}^{(i)}) \times S_t \times E_t \tag{4}$$

where:

- μ_p is the expected daily demand based on historical data.
- $\epsilon_{p,t}^{(i)}$ is a stochastic variation term for each scenario, drawn from a normal distribution:

  $$\epsilon_{p,t}^{(i)} \sim \mathcal{N}(0, \sigma_p) \tag{5}$$

  where σ_p represents the historical standard deviation of demand for product p.
- S_t is the seasonal adjustment factor for day t, capturing periodic fluctuations in demand.
- E_t represents event-based multipliers (e.g., Black Friday demand spikes).

This approach ensures that each scenario reflects unique variations while maintaining structural consistency with historical trends.

Scenario Output and Data Structure The generated demand data is structured in a tabular format, facilitating further analysis and visualization. The final dataset includes:

- **Date:** Simulated demand values for each day from January 1, 2026, to December 31, 2033.
- **Product:** Demand tracked for each product.
- **Daily Demand:** Simulated demand quantity per product per day.

Considerations in Demand Simulation and Randomized Generation Methods The demand simulation incorporates multiple factors that influence future demand patterns, including population growth, economic conditions, seasonal effects, and unpredictable market fluctuations. Various randomization techniques are applied to model these uncertainties.

Population Growth Effects:

- Affects long-term demand trends by increasing the potential customer base.
- Modeled using a normal distribution:

  $$G_t \sim \mathcal{N}(\mu_g, \sigma_g) \tag{6}$$

  where G_t represents the growth factor at time t, μ_g is the expected growth rate, and σ_g represents the standard deviation of growth rates.

Demand Growth Over Time:

- Adjusted using exponential smoothing or autoregressive models.
- Demand growth is modeled using a log-normal distribution:

  $$D_t = D_{t-1} \times e^{X_t}, \quad X_t \sim \mathcal{N}(\mu_d, \sigma_d) \tag{7}$$

Market Volatility and Uncertainty:

- Short-term fluctuations in demand due to economic conditions.
- Modeled as random noise using a uniform distribution:

$$V_t \sim U(a, b) \tag{8}$$

where $U(a, b)$ represents a uniform distribution with bounds a and b.

Peak Demand During Special Events (e.g., Black Friday):

- Temporary demand surges modeled as multiplicative spikes.
- Follows a gamma distribution to account for extreme values:

$$S_t \sim \Gamma(\alpha, \beta) \tag{9}$$

where $\Gamma(\alpha, \beta)$ represents a gamma-distributed scaling factor.

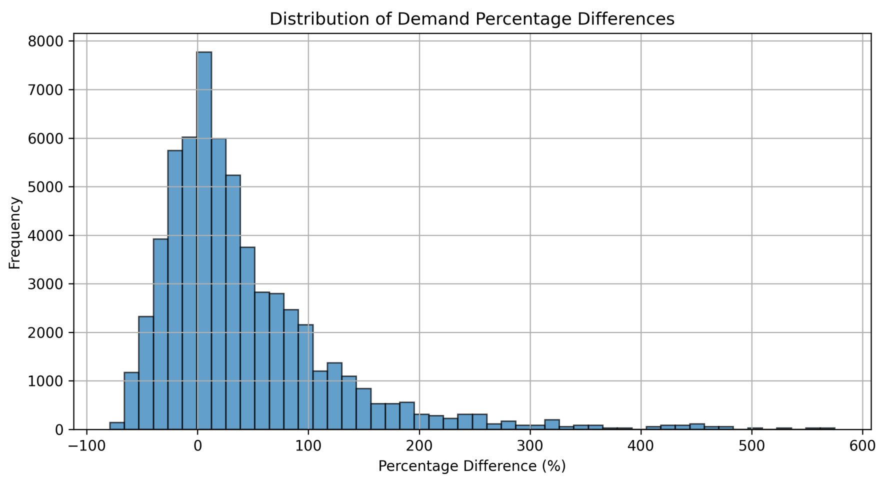

Figure 11: Distribution of Demand Percentage Differences Across 1000 Scenarios

1.4.3 Comparison of Expected vs. Simulated Demand

Overview The primary objective of generating 1000 demand scenarios is to evaluate deviations from expected demand trends and assess the impact of uncertainty in forecasting. This section compares the simulated demand distributions against the expected values derived from historical data, highlighting variations due to stochastic effects and special event-driven spikes.

Expected vs. Simulated Demand Distribution For each product p on day t, the expected daily demand $E[D_{p,t}]$ is computed using historical trends, while the simulated demand $D_{p,t}^{(i)}$ in scenario i incorporates stochastic variations and seasonality effects:

$$D_{p,t}^{(i)} = E[D_{p,t}] + \epsilon_{p,t}^{(i)} \tag{10}$$

where:

- $E[D_{p,t}]$ is the deterministic expected demand.
- $\epsilon_{p,t}^{(i)} \sim \mathcal{N}(0, \sigma_p)$ represents random fluctuations in scenario i.

To quantify deviations across scenarios, the percentage difference $\Delta D_{p,t}^{(i)}$ is calculated as:

$$\Delta D_{p,t}^{(i)} = \frac{D_{p,t}^{(i)} - E[D_{p,t}]}{E[D_{p,t}]} \times 100\% \tag{11}$$

Visualization of Demand Variability To analyze the differences between expected and simulated demand, the following visualizations are used:

- **Histogram of Percentage Differences:** This plot illustrates the frequency distribution of percentage deviations across all scenarios.
- **Time-Series Comparison:** A trend plot comparing expected demand with the mean of all simulated scenarios over time.

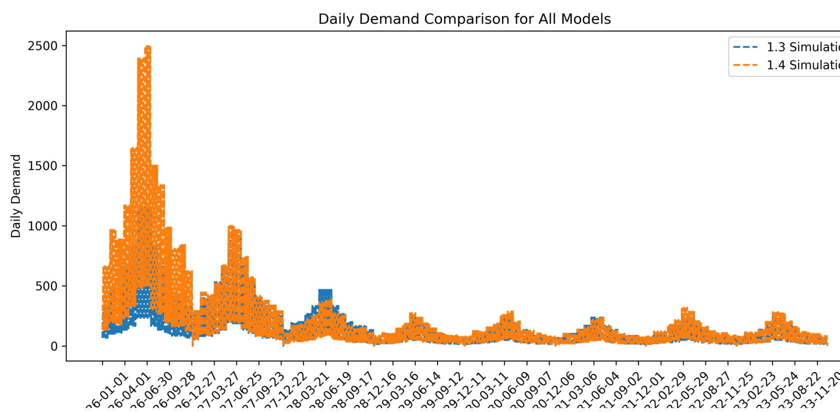

Figure 12: Time-Series Comparison of Expected vs. Simulated Demand

Special Event Demand Spikes One of the key insights from the simulation is the effect of event-based demand surges, such as Black Friday. The simulated demand exhibits significant short-term spikes beyond expected levels, as modeled by:

$$D_{p,t}^{\text{Black Friday}} = E[D_{p,t}] \times S_{\text{BF}} \tag{12}$$

where S_{BF} is an event-specific scaling factor.

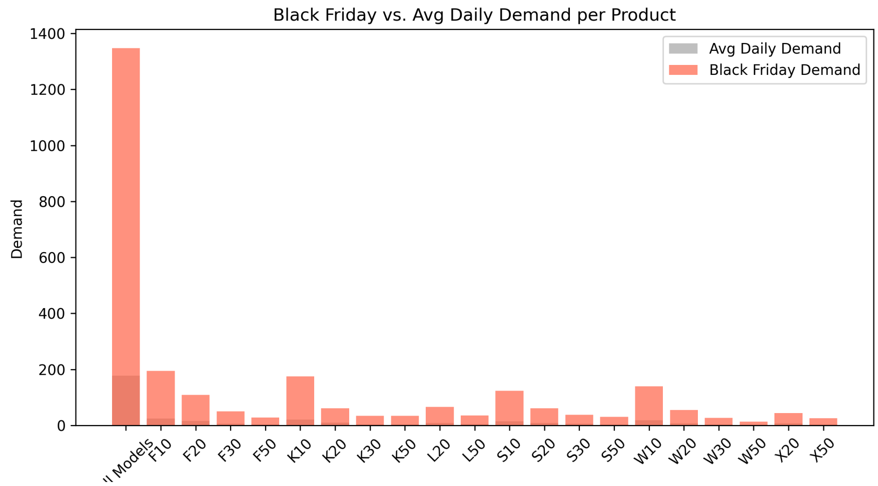

Figure 13: Black Friday vs. Average Daily Demand per Product

Statistical Comparison of Demand Variability To further evaluate the variability in demand across products, a boxplot visualization is used:

- **Boxplot Analysis:** Illustrates demand distribution per product, highlighting outliers and variations.

Key Findings The comparison reveals the following key insights:

- The majority of simulated demand values remain within a reasonable range of the expected demand, though some scenarios exhibit extreme deviations.
- Special events such as Black Friday introduce significant demand spikes, reinforcing the importance of event-driven forecasting.
- Variability in demand distributions is more pronounced for certain products, necessitating differentiated inventory planning strategies.

1.4.4 Impact of Aggregating vs. Disaggregating Demand by Country

Comparison Between Country-Level and Global Demand Aggregation The demand simulation can be conducted at two levels: (1) disaggregated by country, and (2) aggregated at a global scale. Each approach serves different analytical purposes and presents distinct advantages and challenges.

Country-Level Demand Simulation:

- Captures variations in demand across different geographic regions.
- Allows analysis of country-specific seasonal effects and demand trends.

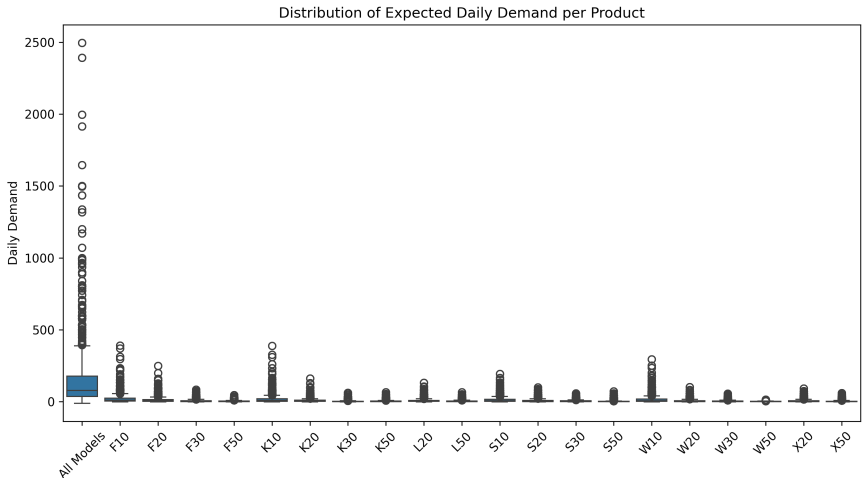

Figure 14: Distribution of Expected Daily Demand per Product

- Supports localized inventory planning and logistics optimization.
- Computationally more intensive due to the increased granularity.

Global Demand Aggregation:

- Provides an overall view of total demand trends across all markets.
- Reduces computational complexity by eliminating country-specific breakdowns.
- Useful for high-level supply chain planning and global production forecasts.
- Can obscure region-specific fluctuations and local market trends.

1.5 Key Insights and Market Implications for BotWorld

1. Market Demand Projections (2026-2033)
The demand forecasting analysis for BotWorld provides crucial insights into the expected growth and market opportunities across European countries. Based on historical trends and predictive modeling, the following key observations emerge:

- **Strong Demand in Western Europe:** Germany, France, and the United Kingdom represent the largest markets, characterized by high population density and strong purchasing power.
- **Emerging Growth Markets:** Countries such as Spain, Poland, and Sweden exhibit moderate but consistent demand growth, making them attractive for expansion strategies.
- **Low-Demand Regions:** Markets with slower demand growth, such as Latvia and Bulgaria, present challenges due to economic and demographic constraints.

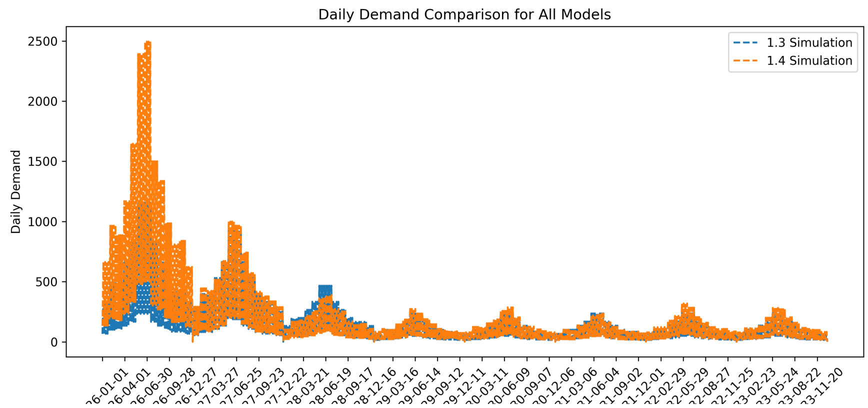

Figure 15: Comparison of Aggregated vs. Country-Specific Demand Trends

2. Demand Seasonality and Sales Trends
The refined demand modeling indicates substantial fluctuations across different time periods:

- **Weekly and Daily Demand Variations:** Demand typically increases from Monday to Friday, with peak demand occurring on Fridays before declining over the weekend.
- **Black Friday Impact:** A significant portion (18%) of annual demand is concentrated around Black Friday, requiring strategic inventory and logistics planning to accommodate this spike.
- **Product Preference Trends:** Mid-range models, such as F10 (Floor Care) and K10 (Kitchen Help), are the most popular, while high-end models (e.g., F50, K50) exhibit lower demand.

3. Stochastic Demand Simulation and Scenario Analysis
To better capture demand uncertainties, a Monte Carlo-based stochastic simulation was conducted, generating 1,000 alternative demand scenarios. The findings highlight:

- **Variance in Daily Demand:** While most demand trends align with expectations, some scenarios indicate substantial fluctuations due to unforeseen market conditions.
- **Event-Based Demand Surges:** Black Friday sales surge beyond anticipated levels, reinforcing the need for adaptive supply chain responses.
- **Inventory Implications:** High-demand volatility necessitates robust inventory planning to mitigate risks associated with stockouts and overproduction.

4. Visual Analysis and Long-Term Demand Forecasting
A comprehensive visual analysis of market demand trends from 2026 to 2033 reveals critical insights into MyBot's long-term growth trajectory.

- **Impact of Population Decline:** With Europe's projected negative population growth, overall household demand is expected to shrink over the next decade. Countries such as

Germany and Italy, which exhibit both high initial demand and demographic decline, may face stagnation or even contraction in demand.

- **Demand Distribution Shift:** Heatmap visualizations indicate a concentration of demand in urban areas, whereas demand in rural regions is likely to diminish. This suggests that MyBot should prioritize urban-focused distribution strategies.
- **Gradual Decline in Annual Demand:** Time-series visualizations of demand trends suggest a downward trajectory after 2029, indicating potential market saturation. Although product innovation and marketing campaigns can partially mitigate this effect, it is crucial to acknowledge the inherent limitations imposed by demographic trends.
- **Potential Countermeasures:** To counteract the declining demand, MyBot should explore international expansion beyond Europe, develop new product lines to target niche markets, and invest in flexible manufacturing strategies to adjust production in response to shifting demand.

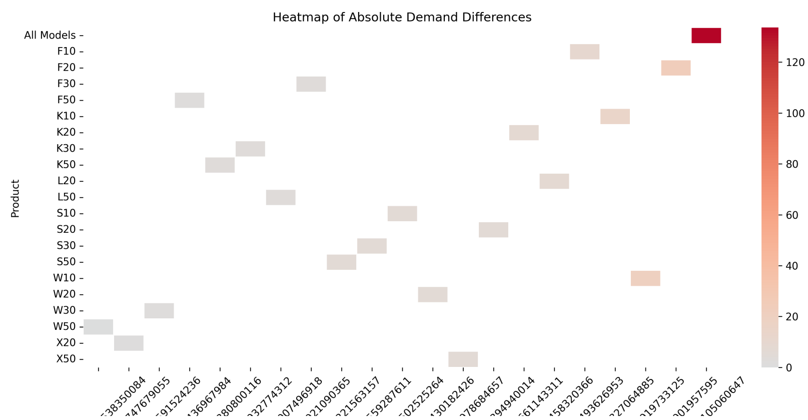

Figure 16: Heatmap of Absolute Demand Differences Across Products and Dates

As shown in Figure 16, different product categories exhibit varying demand patterns across time. High-demand products, such as F10 and K10, display consistent trends, whereas niche products experience more significant fluctuations. This heatmap reinforces the need for MyBot to maintain a diversified product strategy and to optimize inventory based on observed demand patterns.

5. Implications for BotWorld's Market Strategy

Based on these insights, the following strategic recommendations can enhance BotWorld's market positioning:

- **Market Prioritization:** Investing in fulfillment infrastructure within Germany, France, and the UK will maximize revenue potential.
- **Flexible Inventory and Production Planning:** Adjusting production schedules to accommodate seasonal and Black Friday surges will improve operational efficiency.

- **Localized Demand Adaptation:** Implementing country-specific marketing and pricing strategies will optimize sales in emerging markets such as Poland and Sweden.
- **Event-Driven Supply Chain Optimization:** Developing a Black Friday-specific logistics framework will ensure smoother operations and mitigate capacity constraints.
- **Long-Term Adaptation to Population Trends:** Given the potential decline in demand post-2029, MyBot should proactively explore product diversification and entry into non-European markets to sustain long-term growth.

Conclusion

The demand forecasting and simulation analyses reveal key insights into BotWorld's European market dynamics. While short-term demand trends remain strong, the long-term outlook suggests potential declines due to demographic shifts. By leveraging data-driven strategies, MyBot can effectively align supply chain operations with market trends, ensuring sustainable growth and competitive advantage from 2026 to 2033.

2 Task 2

2.1 Optimized European Fulfillment Network Design

2.1.1 Introduction

This section outlines the design and optimization of BotWorld's European fulfillment network. The primary objective was to minimize the number of fulfillment centers (FCs) while ensuring adequate coverage of all target markets to meet next-day and three-day delivery commitments. The methodology employed combines geographic data analysis, travel time matrices, and integer linear programming (ILP) for network optimization.

2.1.2 Methodology

Data Collection and Preparation The initial phase involved collecting geospatial data, including the latitude and longitude coordinates of potential fulfillment center (FC) locations and target cities. Using the OpenMap API, road distances between all pairs of FCs and target cities were generated, creating a distance matrix.

Subsequently, these distances were converted into travel time estimates based on average road speeds. This resulted in a comprehensive time matrix, which served as the foundation for identifying which FCs could meet delivery time requirements for each city.

Formulation of the Optimization Model The core of the network design was an Integer Linear Programming (ILP) model aimed at minimizing the total number of FCs required while ensuring every target city could be served within a predefined time threshold.

Key elements of the model:

- **Time Threshold Setting:** A 5-hour delivery time threshold was established, ensuring that all target cities could receive next-day deliveries from at least one FC.

- **Coverage Matrix Generation:** Based on the time matrix, a binary coverage matrix was created, indicating whether each FC could serve a city within the threshold.

ILP Model Components:

1. **Objective Function:** Minimize the total number of selected FCs.
2. **Constraints:** Ensure each city is covered by at least one FC to guarantee complete market coverage.

Solving the Optimization Problem The ILP model was solved using the Pulp library in Python with the CBC solver. The model determined the minimal set of FCs that collectively ensured complete coverage of all target cities within the delivery time constraints.

2.1.3 Results

The optimization process resulted in the selection of a minimal set of fulfillment centers that efficiently covered all target cities within the established time threshold. The selected FCs and their corresponding coverage areas are visualized in the diagrams below.

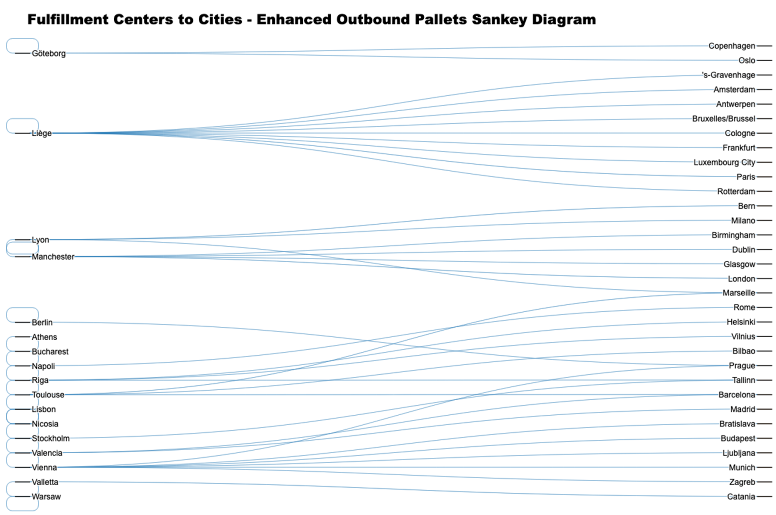

Figure 17: Enhanced Outbound Pallets Sankey Diagram illustrating the flow of goods from selected FCs to cities.

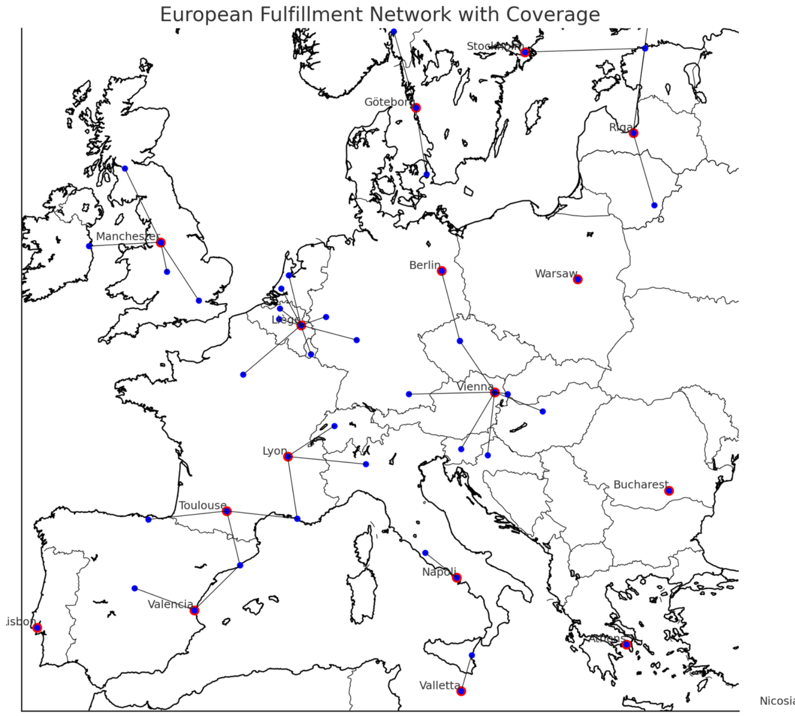

Figure 18: European Fulfillment Network Coverage Map showing the geographic distribution of selected FCs and their service areas.

2.1.4 Conclusion

The use of integer linear programming effectively minimized the number of fulfillment centers while ensuring all target cities were covered within the 5-hour delivery time threshold. This strategic approach provides BotWorld with a cost-efficient, scalable, and reliable distribution network across Europe, meeting both logistical and customer service requirements.

2.2 Fulfillment Center Capacity Planning & Sizing

2.2.1 Storage

This section details the estimation of storage and throughput capacities for BotWorld's fulfillment centers (FCs) across Europe. Using the demand forecast and inventory management strategies, FCs were classified into small, medium, and large categories, each with distinct layout specifications. The following subsections provide insights into the capacity estimation process, size classification, and layout designs.

Methodology The estimation process involved two key steps: **peak week analysis** and **inventory management calculations**. The peak week analysis identified the highest demand periods, while the inventory analysis determined the storage requirements to support two robust weeks of stock. Based on the total pallets required, FCs were categorized into different sizes.

Results **Storage Capacity and Size Classification** The chart below illustrates the total pallets required for each fulfillment center and their respective size classifications. Liège and Manchester, with the highest storage demands, are categorized as medium-sized FCs, while the rest fall into the small category.

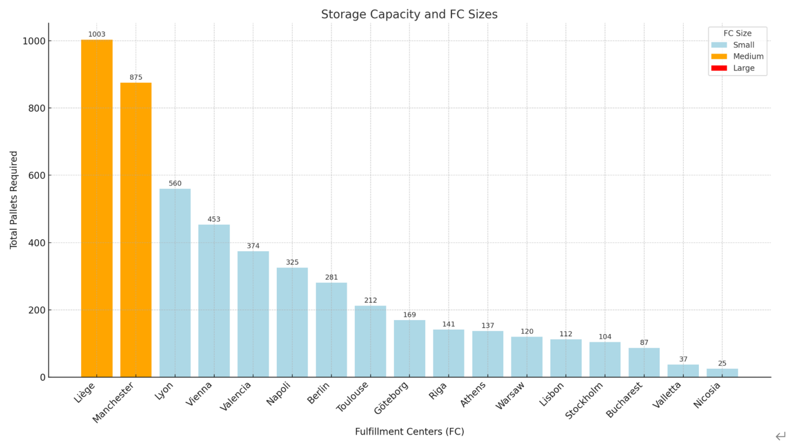

Figure 19: Storage Capacity and Fulfillment Center Sizes

Fulfillment Center Layouts The layouts for small and medium fulfillment centers are shown below. These designs ensure efficient space utilization and streamlined inbound and outbound logistics.

Medium Fulfillment Center Layout: The medium fulfillment center layout accommodates the higher pallet storage needs with additional racks and dock doors to support increased throughput.

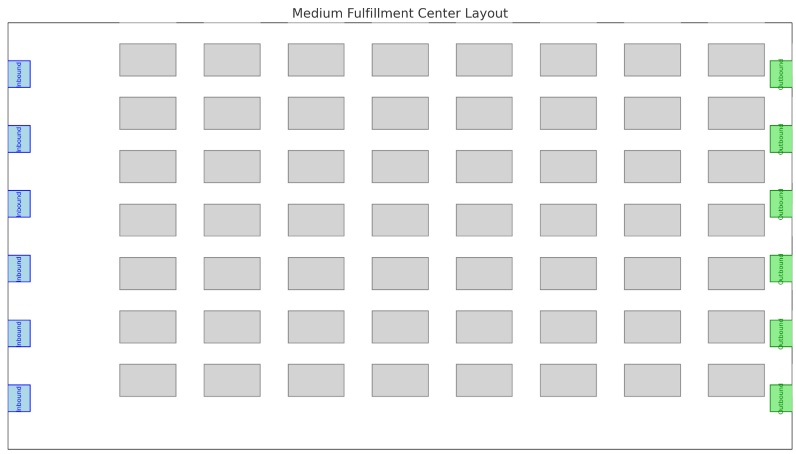

Figure 20: Medium-Size Fulfillment Center Layout

Small Fulfillment Center Layout: The small fulfillment center layout is designed for regions with lower demand, maintaining efficiency with a compact setup and fewer dock doors.

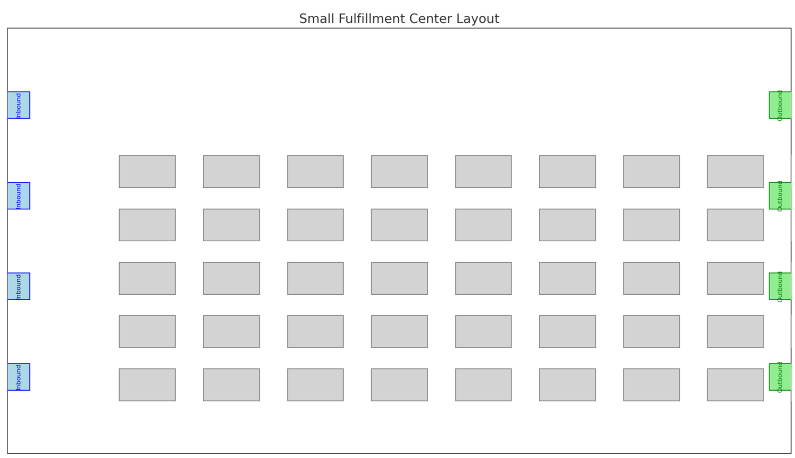

Figure 21: Small-Size Fulfillment Center Layout

The fulfillment center designs are optimized based on demand forecasts and storage requirements. By categorizing FCs into appropriate sizes and implementing efficient layouts, BotWorld can ensure smooth operations and cost-effective logistics across its European network.

2.2.2 Throughput Capacity

This section presents the throughput capacity analysis for BotWorld's European fulfillment centers (FCs). The analysis covers both **inbound and outbound pallet movements** to ensure that each FC is appropriately sized and capable of handling peak and daily demands effectively.

Throughput capacity was evaluated using two primary datasets: **inbound and outbound pallet flows**. The inbound analysis focused on the volume of pallets arriving at each FC daily and during peak periods, while the outbound analysis detailed the distribution of these pallets to respective cities. Heatmaps and Sankey diagrams were used to visualize and interpret the data.

Inbound Throughput Capacity The inbound throughput capacity represents the number of pallets each fulfillment center receives on a daily basis and during peak periods. The heatmap below illustrates the inbound pallet requirements, highlighting the centers with the highest logistical demands.

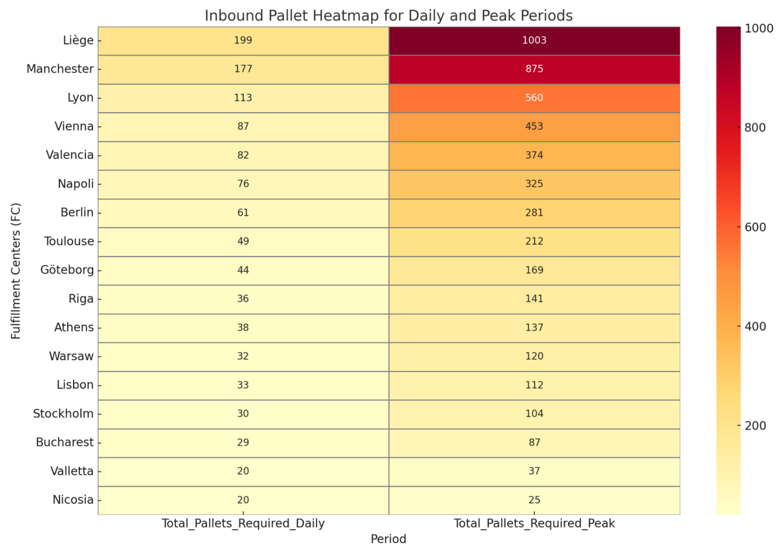

Figure 22: Inbound Pallet Heatmap

Outbound Throughput Capacity The outbound throughput capacity reflects the distribution of pallets from fulfillment centers to their designated cities. The Sankey diagram below demonstrates the flow of pallets, with color intensity indicating the volume of pallets handled by each route.

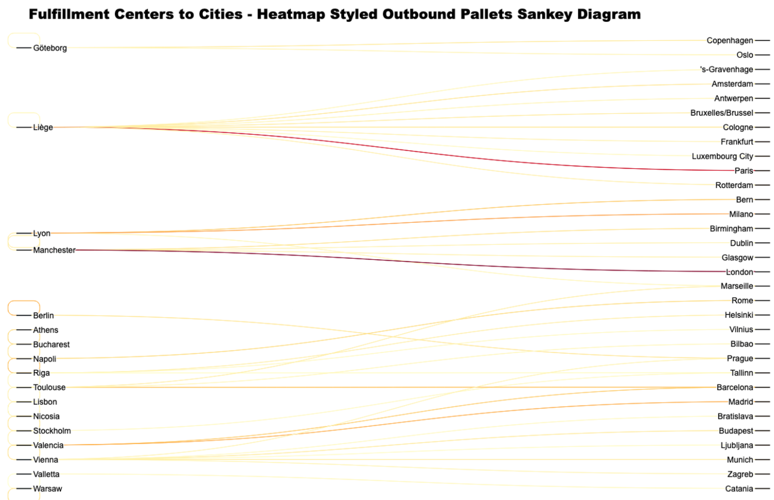

Figure 23: Sankey Diagram Illustrating Outbound Pallet Flows

The throughput capacity analysis confirms that Liège and Manchester are the most demanding fulfillment centers in terms of both inbound and outbound logistics. These insights are crucial for optimizing operational efficiency, ensuring that resources such as dock doors and labor are allocated appropriately to meet demand fluctuations.

Date	Holiday Name
2025-01-01	New Year's Day (Jour de l'An)
2025-04-21	Easter Monday (Lundi de Pâques)
2025-05-01	Labour Day (Fête du Travail)
2025-05-08	Victory in Europe Day (Victoire 1945)
2025-05-29	Ascension Day (Ascension)
2025-06-09	Whit Monday (Lundi de Pentecôte)
2025-07-14	Bastille Day (Fête Nationale)
2025-08-15	Assumption of Mary (Assomption)
2025-11-01	All Saints' Day (Toussaint)
2025-11-11	Armistice Day (Armistice 1918)
2025-12-25	Christmas Day (Noël)

Table 1: France 2025 Official Holidays

2.3 Distribution Center (DC) Capacity & Layout Planning

2.3.1 Introduction

This section details the estimation of throughput capacity, storage capacity, and resource requirements for BotWorld's European Distribution Center (DC). The analysis aims to ensure the DC can meet dynamic demand patterns over time while maintaining operational efficiency. The estimation process involves calculating pallet throughput, storage needs, and resource allocation for dock doors and workers.

2.3.2 Methodology

Data Preparation The analysis began by consolidating weekly pallet demand data from all fulfillment centers (FCs) to estimate the DC's outbound pallet requirements. The data was categorized by year, period, and week to capture seasonal fluctuations and peak periods, such as Black Friday.

Throughput and Storage Calculations The following steps outline the calculation logic:

- **Outbound Pallet Demand**: The total weekly outbound pallet demand was calculated by summing the requirements from all FCs.
- **Inventory Pallets**: Inventory levels were set at four times the weekly demand, except during Black Friday (Period 11, Week 4), when inventory was doubled.
- **Racks Required**: Assuming each rack has 8 levels, the total number of racks required was calculated by dividing the total inventory pallets by 8 and rounding up to the nearest whole number.

Resource Allocation Resource requirements for dock doors and workers were dynamically configured based on the weekly outbound pallet volume:

Shift Configuration:

- 1 shift (8 hours) for ≤ 500 pallets/week
- 2 shifts (16 hours) for 501–1000 pallets/week
- 3 shifts (24 hours) for > 1000 pallets/week

Dock Doors: Each dock door handles 20 pallets per hour. The required number of dock doors was calculated by dividing total weekly pallets by the daily throughput per dock and rounding up.

Workers: Worker requirements per dock were set as follows:

- 4 workers per dock for 1 shift
- 5 workers per dock for 2 shifts
- 6 workers per dock for 3 shifts

The total number of workers was calculated by multiplying the number of dock doors by workers per dock.

2.3.3 Results

The results indicate fluctuations in outbound and inventory pallet volumes over time, driven by seasonal demand patterns and peak periods like Black Friday. Resource allocation for racks, dock doors, and workers was adjusted accordingly to maintain operational efficiency.

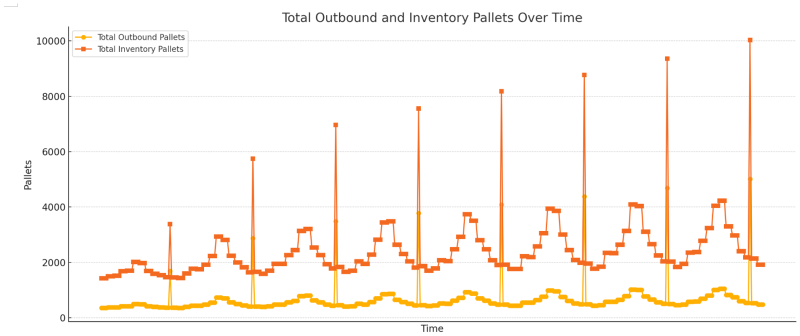

Figure 24: Total Outbound and Inventory Pallets Over Time

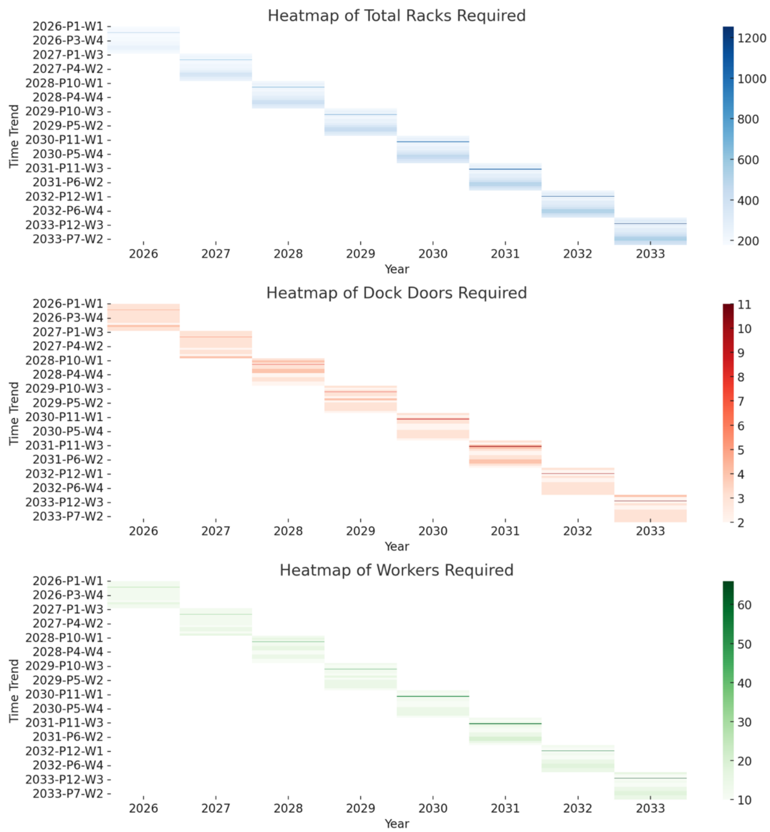

Figure 25: Heatmaps of Total Racks, Dock Doors, and Workers Required Over Time

Based on the estimated capacity requirements, the DC layout should incorporate flexible storage and handling capabilities to accommodate fluctuating demand. High-demand periods necessitate additional racks, dock doors, and workers, while off-peak periods allow for reduced resource utilization. The layout should prioritize efficient material flow, minimizing travel time between storage and loading areas, and facilitating quick adjustments to resource allocation as demand changes.

The capacity estimation and resource allocation models ensure that BotWorld's European DC is equipped to handle dynamic demand patterns while maintaining operational efficiency. By adjusting storage, dock doors, and worker allocations based on real-time demand, the DC can optimize performance and minimize costs.

2.4 Factory Capacity Planning & Seasonal Inventory Management

2.4.1 Key Explanation: Factory Capacity & Inventory Estimation

1. Data Collection

- Gather weekly demand forecasts (2026-2033) for country & city levels from CSV files.
- Aggregate demand by Year, Period, and Week to compute **Total Weekly Demand**.

2. **Production & Inventory Strategy**
   - **Level Production:** Constant weekly production with a 20% increase before Black Friday.
   - **Safety Stock:** 10% of total yearly demand.
   - **Annual Production Capacity:** Covers total demand + safety stock, evenly distributed over 52 weeks.

3. **Factory Capacity Estimation**
   - Compute total required production per year.
   - **Base weekly production rate:**

   $$P_{\text{weekly}} = \frac{D_{\text{yearly}} + S_{\text{safety}}}{52} \tag{13}$$

   where:

     - P_{weekly} = Base weekly production rate
     - D_{yearly} = Total yearly demand
     - S_{safety} = Safety stock (10% of yearly demand)

   - **Black Friday Adjustments:** Increased output before Period 11.

4. **Stock Level Estimation**
   - Simulate weekly inventory flow:
     - **Start Inventory** = Previous week's ending stock.
     - **Inventory Update Formula:**

     $$I_{\text{end}} = I_{\text{start}} + P_{\text{weekly}} - D_{\text{weekly}} \tag{14}$$

     where:

       * I_{end} = Ending inventory of the week
       * I_{start} = Starting inventory of the week
       * P_{weekly} = Weekly production
       * D_{weekly} = Weekly demand

   - Track Inventory Trends across weeks & highlight peak stock periods.

5. **Visualization & Output**
   - Export results to Excel for further analysis.
   - Use Seaborn plots to visualize weekly inventory & demand trends.
   - Identify high stock periods and potential overstock/shortage risks.

2.4.2 Outcome

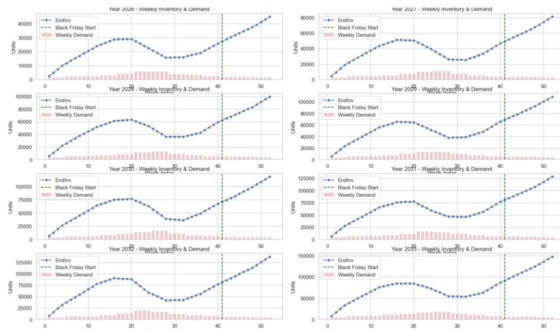

Figure 26: Enter Caption

1. **Inventory Trend Analysis**

   - Inventory exhibits cyclical fluctuations, gradually increasing throughout the year and reaching its lowest point after Black Friday, before recovering.

   Early Inventory Accumulation (Week 0-35):

   - The factory maintains stable production (Level Production), but demand remains low, leading to a gradual buildup of inventory.
   - This aligns with the steady production and early stockpiling strategy, ensuring sufficient inventory before Black Friday.

   Inventory Decline Before Black Friday (Week 35-45):

   - Black Friday (around Week 40) sees a surge in demand, leading to rapid inventory depletion.
   - At this stage, the factory increases production by 20%, yet inventory still declines significantly, indicating a sharp short-term rise in market demand.
   - The extent of this inventory drop determines whether the pre-Black Friday capacity adjustment is sufficient.

   Inventory Recovery After Black Friday (Week 45 and beyond):

   - Demand decreases, production returns to stable levels, and inventory begins to replenish.
   - This follows a post-peak inventory recovery strategy, ensuring stable supply in subsequent periods.

2. **Impact of Factory Capacity and Inventory Management**

   1. **The factory requires sufficient base capacity:**

- The noticeable inventory drop before Black Friday suggests that the pre-Black Friday production ramp-up was effective but may still need further optimization.
- If inventory depletes too quickly before Black Friday, it indicates insufficient capacity, requiring additional production lines or an earlier increase in output.

2. **Inventory management strategy is effective but has room for improvement:**
   - From the chart, the inventory decline before and after Black Friday is significant, but inventory does not completely deplete, indicating that demand is generally met.
   - If inventory falls too rapidly, it may be necessary to start ramping up production earlier, increasing output over more weeks before Black Friday.

3. **The factory needs to optimize inventory accumulation efficiency:**
   - For most of the year, inventory trends upward, suggesting that the production > demand strategy is effective.
   - However, if inventory remains high for extended periods, it could lead to increased storage costs and capital lock-in, requiring improvements in inventory turnover rates.

2.5 Optimized Assembly Line Configuration (2026-2033)

2.5.1 Steps

Data Collection

- Weekly demand data is loaded from country-level and city-level CSV files.
- The two datasets are merged into one unified dataset (`df_weekly_all`).
- Demand is aggregated at the (Year, Period, Week) level, calculating `TotalWeeklyDemand`.

Production & Inventory Strategy

- **Safety Stock Ratio:** 10% of total demand.
- **Production Schedule:**
  - **Level Production:** A constant weekly production rate is applied.
  - **Black Friday Adjustment:** Weeks before Period 11 receive a 20% production boost to prepare for demand surges.

Weekly Production & Inventory Simulation The function `simulate_weekly_inventory(year, df_weekly, production_strategy='level')` models weekly inventory flows by:

1. Extracting yearly demand.
2. Calculating total required production (demand + safety stock).
3. Determining base weekly production rate.

4. Simulating inventory flow week-by-week:
   - Weekly production is adjusted based on strategy (Black Friday boost applied before Period 11).
   - Inventory is updated:

     `End Inventory = Start Inventory + Weekly Production  Weekly Demand`
   - Week Index is assigned to facilitate visualization.

Annual Simulation (2026-2033)

- The script runs the simulation for each year from 2026 to 2033.
- The results are aggregated into a single DataFrame (`df_all_years`).
- The final dataset is exported to Excel for analysis.

Visualizing Weekly Inventory & Demand Trends

- Seaborn & Matplotlib are used to create subplots for each year.
- Two key variables are plotted:
  - **Weekly Demand** (red bars)
  - **End Inventory** (blue line)
- Black Friday is highlighted with a green dashed line, showing demand peaks.

2.5.2 Insights for Assembly Line Strategy

Number of Assembly Lines Needed

- Steady production throughout the year suggests that a baseline number of lines is sufficient.
- Black Friday peaks require temporary production increases, which can be handled by:
  - Adding temporary assembly lines.
  - Extending working hours during peak weeks.
  - Pre-production strategies to build up inventory.

Multi-category vs. Single-category Lines

- Some MyBot models may need dedicated assembly lines due to production complexity.
- Flexibility in assembly lines can reduce excess inventory while ensuring on-time production.

Key Adjustments Based on Visualization

- If inventory drops too fast before Black Friday, additional production capacity is needed.
- If inventory remains too high year-round, adjusting the number of active lines could optimize costs.

2.5.3 Outcome

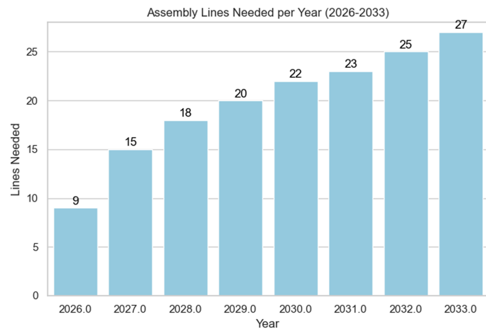

Figure 27: Yearly Demand vs DC Capacity

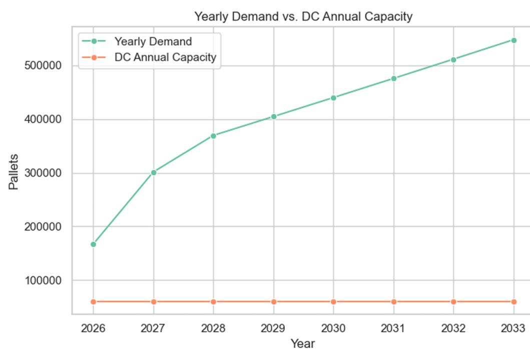

Figure 28: Assembly Lines Needed per yera

Assembly Line Demand Trend

- **Gradual increase in assembly lines:**
  - Only 9 assembly lines needed in 2026, increasing to 27 lines by 2033.
  - This growth trend reflects the rising demand for MyBot products in the European market.
- **Key trends:**
  - **Rapid growth from 2026 to 2028:** As BotWorld expands to more European countries, market demand surges.
  - **Slower growth after 2030:** This indicates that the market is gradually reaching saturation and entering a stable growth phase.
- **Production impact:**

  - The factory needs to dynamically expand production capacity to ensure sufficient assembly lines to meet demand growth.
  - Future investments should focus on automation and efficient production lines to improve efficiency and reduce operating costs.

Demand vs. Distribution Center (DC) Capacity

- **Yearly Demand vs. DC Capacity:**
  - Demand (green line) grows exponentially, exceeding 500,000 pallets by 2033.
  - DC capacity (orange line) remains unchanged, meaning:
    * DC storage capacity will not keep up with demand growth.
    * If not adjusted, it may become overloaded in the coming years.
- **Key risks and optimization recommendations:**
  - **Increase DC capacity:** Build new warehouses or introduce more fulfillment centers (FCs) to ease the burden on the main DC.
  - **Optimize inventory turnover:** Improve FC inventory management efficiency to accelerate product flow and reduce pressure on the DC.
  - **Implement regional warehousing strategies:** Store some inventory directly in regional fulfillment centers, reducing DC storage dependency.

2.6 Supply Warehouse Capacity & Workforce Estimation

2.6.1 Introduction

This section presents the estimation of the required storage capacity, number of racks, dock doors, and workers for BotWorld's supply warehouse. The analysis integrates product production data, pallet distribution between China and Europe, and dynamic inventory management to ensure the warehouse meets operational demands efficiently.

2.6.2 Methodology

Data Collection and Preparation Weekly production data was sourced from the factory's inventory simulation, detailing the quantities of ten product types. Each product type's share, dimensions, and weight were used to calculate the pallet requirements for shipping and storage.

Pallet and Inventory Calculations The calculations followed these steps:

- **Product Allocation:** Each product's weekly production was distributed according to its share.
- **Pallet Utilization:** The number of products per pallet was determined by dividing the pallet area by the product's footprint, allowing a maximum of two stacking layers.
- **Pallet Requirements:** The total number of pallets required was calculated by dividing product production by pallet capacity.
- **Weight and Volume:** Total shipping weight and volume were calculated for all products.

Supplier Distribution and Inventory Management Pallets were distributed between Chinese and European suppliers based on weight:

- **Distribution:** 40% of the weight was allocated to China, and 60% to Europe.
- **Inventory Holding:** Chinese inventory was maintained for four weeks, while European inventory was held for two weeks.

Warehouse Capacity and Resource Estimation The supply warehouse's capacity requirements were calculated as follows:

- **Storage Capacity:** Total inventory pallets were multiplied by the volume of each pallet to determine the total storage capacity in cubic meters.
- **Racks Required:** Assuming each rack holds 8 pallets vertically, the total number of racks was calculated by dividing total inventory pallets by 8.
- **Dock Doors:** Each dock door was assumed to handle 35 truckloads per week at 75% utilization. The total number of dock doors required was calculated by dividing total weekly trucks by the dock's capacity.
- **Workers Required:** Assuming each worker can handle 800 pallets per week, the total number of workers was determined by dividing total inventory pallets by 800.

2.6.3 Results

The following figures illustrate the storage, dock door, and workforce requirements over time. Seasonal fluctuations in production and inventory levels influenced the dynamic allocation of warehouse resources.

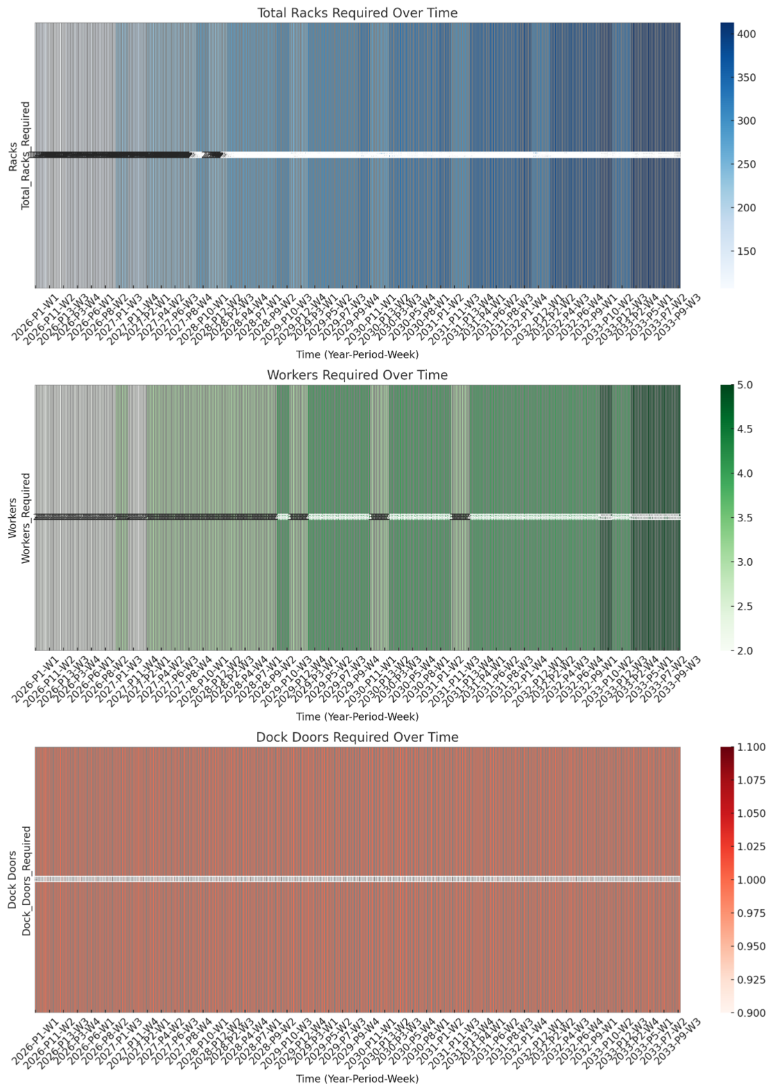

Figure 29: Heatmaps showing Total Racks, Dock Doors, and Workers Required Over Time.

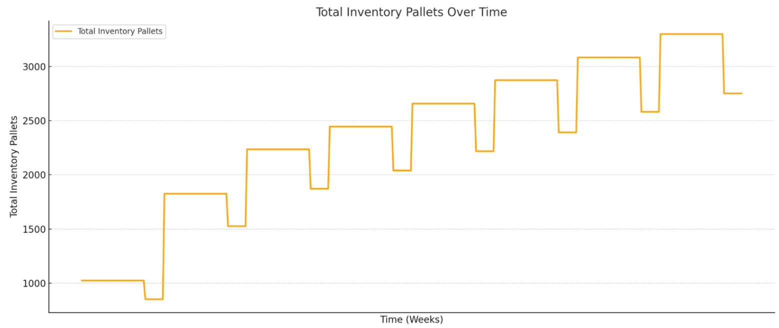

Figure 30: Total Inventory Pallets Over Time

The supply warehouse's capacity estimation ensures efficient management of dynamic inventory levels, with sufficient racks, dock doors, and workforce to meet operational demands. The calculations provide a robust framework for scaling warehouse resources as BotWorld's production and distribution needs grow.

2.7 Inter-Facility Flow Analysis & Logistics Forecasting

2.7.1 Introduction

This section presents a comprehensive analysis of BotWorld's interfacility flows from 2026 to 2033, covering the movement of MyBots, pallets, weight, and volume through the supply chain. The analysis traces the flow from suppliers to factories, distribution centers (DCs), fulfillment centers (FCs), and ultimately to the end cities.

2.7.2 Methodology

Data Collection and Preparation The interfacility flows were analyzed using a combination of city demand forecasts, fulfillment center coverage data, distance matrices, and product dimensions. The primary steps included:

- **City Demand Forecast:** Weekly and daily demand data were collected, including seasonal variations such as Black Friday spikes.
- **Fulfillment Center (FC) Mapping:** FCs were mapped to their respective covered cities based on proximity and capacity.
- **Distance Matrix:** Geographic distance data was integrated to optimize the allocation of demand to the nearest FCs.

Flow Calculations Four key metrics were analyzed to understand the interfacility logistics:

- **MyBots Flow:** Total unit movements from suppliers to factories, then to DCs, FCs, and finally to cities.
- **Pallet Flow:** Calculation of pallet requirements based on product volume and weight.

- **Weight Flow:** Total shipping weight computed from product specifications and demand forecasts.
- **Volume Flow:** Aggregated volume of products shipped, accounting for packaging dimensions and stacking efficiencies.

Code Logic Overview The code logic was structured to progressively compute flows through each stage of the supply chain:

- **Product Allocation:** Demand was allocated to FCs based on distance-weighted distribution.
- **Palletization:** Product dimensions were used to calculate pallet requirements, ensuring optimal load efficiency.
- **Weight and Volume Calculations:** Total product weight and volume were aggregated at each facility.
- **Visualization:** Sankey diagrams were generated to depict the flow of MyBots, pallets, weight, and volume.

2.7.3 Results

The interfacility flow analysis provides a clear visualization of product movement across the supply chain. The Sankey diagrams below illustrate the distribution and flow dynamics from suppliers to end customers.

MyBots Flow The MyBots flow diagram shows the distribution of unit products through the supply chain.

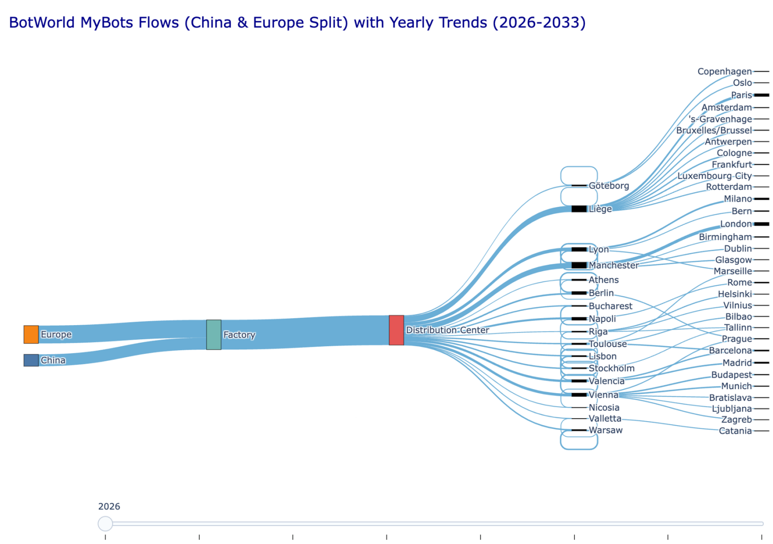

Figure 31: MyBots Flow

Pallet Flow The pallet flow analysis highlights the logistics of palletized shipments from factories to FCs and cities.

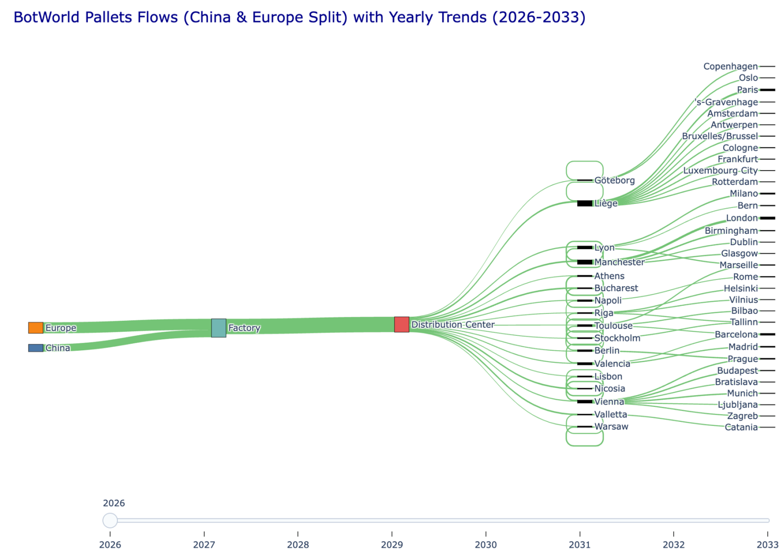

Figure 32: Pallet Flow

Weight Flow Weight distribution diagrams provide insight into the load handling capacities required at each stage.

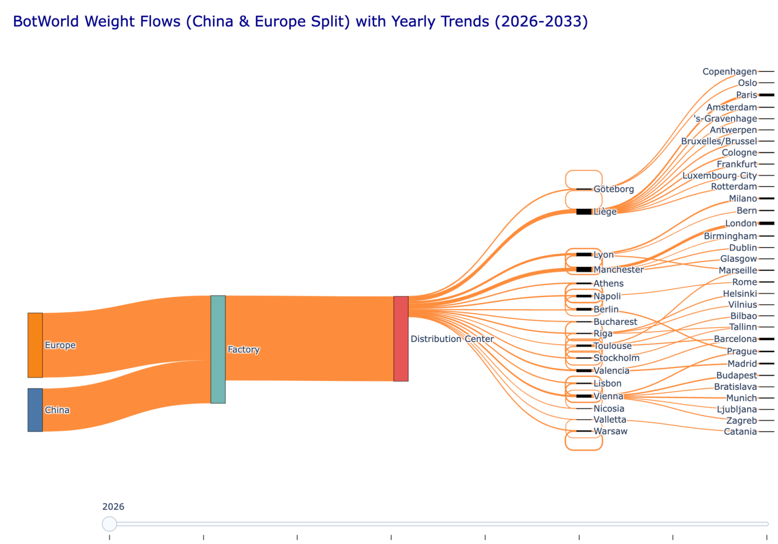

Figure 33: Weight Flow

Volume Flow Volume flow analysis helps in understanding space utilization across transport and storage facilities.

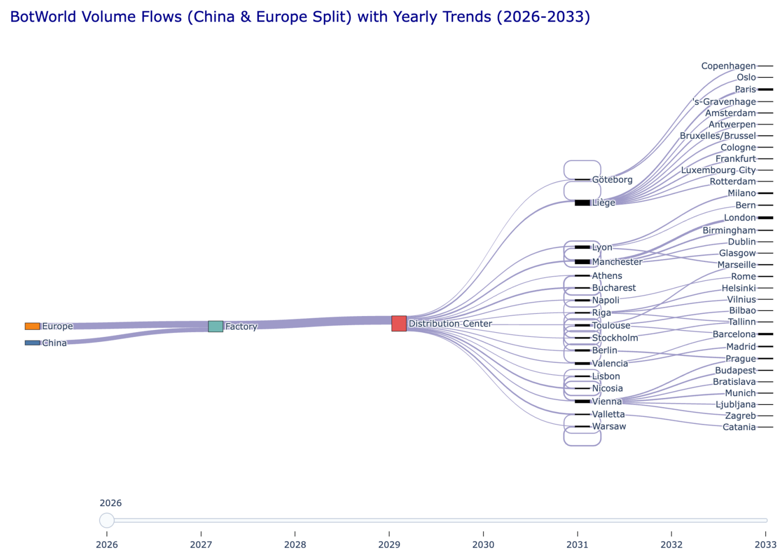

Figure 34: Volume Flow

2.7.4 Conclusion

The interfacility flow analysis reveals the complexity and scale of BotWorld's logistics network. The insights gained from MyBots, pallet, weight, and volume flows allow for strategic planning in transport, warehousing, and supply chain optimization. By visualizing these flows, potential bottlenecks and inefficiencies can be identified and addressed proactively.

2.8 Fleet Sizing, Routing Optimization & Environmental Impact

2.8.1 Introduction

This section outlines the proposed fleet for BotWorld's interfacility logistics from 2026 to 2033. The analysis includes the estimated number of vehicles, the number of truckers required, and interfacility routing strategies. The assessment covers the entire supply chain, from suppliers to factories, distribution centers (DCs), fulfillment centers (FCs), and final delivery to cities. Furthermore, the report evaluates overall travel distances, vehicle fill rates, fuel consumption, and greenhouse gas (GHG) emissions.

2.8.2 Methodology

Data Sources and Preparation The data for this analysis was sourced from the following datasets:

- **supplier_factory.csv:** Details supply flow from suppliers to factories.

- **Metz_to_FC.csv:** Provides logistics information from the European DC in Metz to various FCs.
- **city_fc.csv:** Includes data on deliveries from FCs to cities.

Vehicle specifications and distance matrices were also incorporated to optimize routing and fleet sizing.

Fleet Optimization Logic Fleet optimization was carried out using linear programming (LP) models across three major logistics phases:

- **Suppliers to Factories:** Using `supplier.py`, the flow of pallets from key suppliers (e.g., Rotterdam, Lille) to the factory was optimized to minimize fuel consumption and emissions.
- **Factories to Distribution Centers (DCs):** `dc_fc.py` optimized transportation from the central factory to the Metz DC, factoring in pallet volume, weight, and distance.
- **Distribution Centers to Fulfillment Centers and Cities:** `fc_cities.py` addressed the flow from DCs to FCs and then to the final cities, considering both daily and peak demand scenarios.

Key elements of the LP models included:

- **Objective Function:** Minimize total fuel consumption.
- **Constraints:** Ensure capacity limits (pallets, volume, and weight) are not exceeded while maintaining a minimum fill rate (50%).
- **GHG Emissions:** Calculated using vehicle-specific emission factors (kg CO/km).

2.8.3 Results

Fleet Proposal Based on the LP optimization models, the proposed fleet includes a combination of small, medium, and large trucks to handle varying demand across the years 2026 to 2033. The exact number of vehicles of each type varies based on demand spikes, with additional capacity allocated during peak periods such as Black Friday.

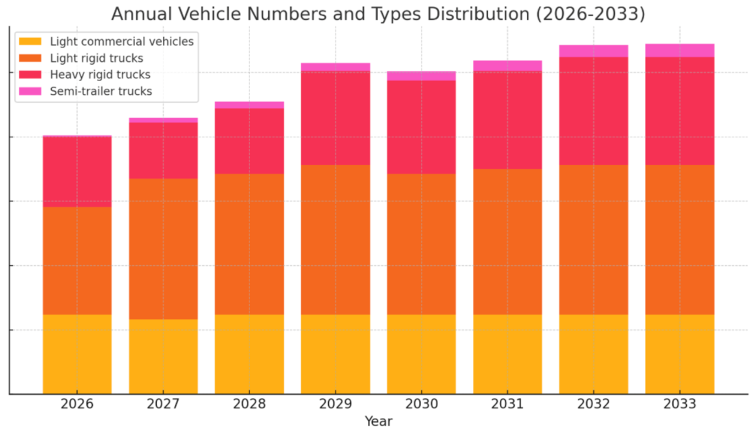

Figure 35: Annual Vehicle Numbers and Types Distribution

Fill Rates The box plot shows that light rigid trucks and semi-trailer trucks have the highest and most consistent pallet fill rates, with medians around 85%, indicating efficient and stable utilization. Light commercial vehicles also perform well, though with slightly more variability. In contrast, heavy rigid trucks show the lowest median fill rate (around 65%) and greater fluctuations, suggesting underutilization in some routes and potential for optimization. Overall, focusing on improving the load efficiency of heavy rigid trucks could enhance fleet performance.

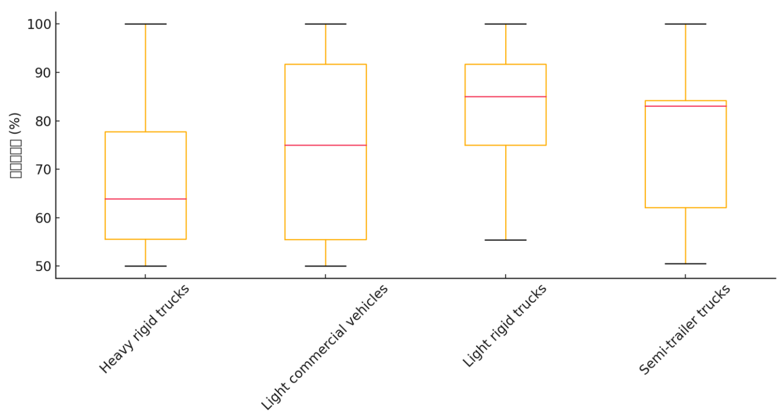

Figure 36: Fill Rates of Vehicle Types

Fuel Consumption and GHG Emissions Fuel consumption and GHG emissions were calculated based on distance traveled, vehicle efficiency, and load factors. The LP models ensured that vehicles were optimally filled to reduce both fuel consumption and emissions.

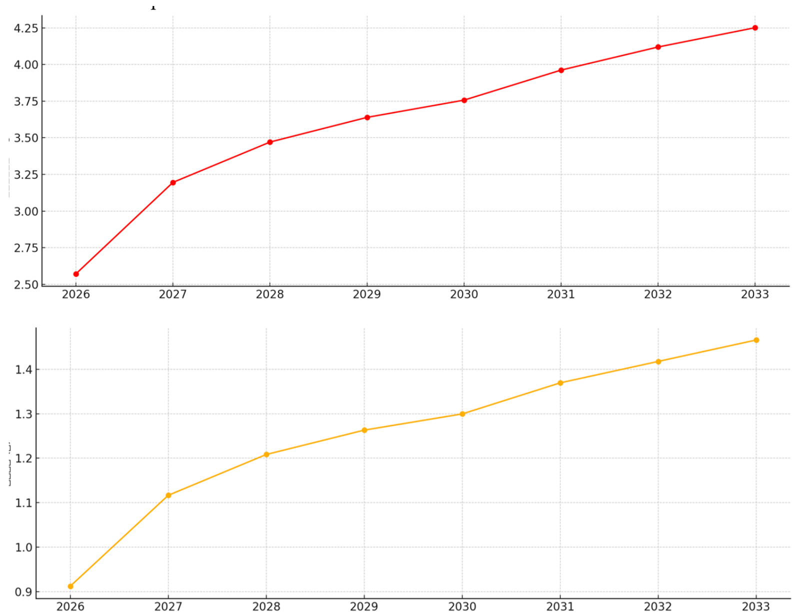

Figure 37: Fuel Consumption and GHG Emissions

2.8.4 Conclusion

The proposed fleet and routing strategies ensure that BotWorld's logistics operations are both cost-effective and environmentally sustainable. By optimizing vehicle usage, fill rates, and routes, BotWorld can significantly reduce operational costs and carbon emissions.

Estimation Logic

1. **GVWR (Gross Vehicle Weight Rating):** This refers to the maximum total weight of the vehicle as specified by the manufacturer, including the vehicle's own weight, cargo weight, fuel, driver, and any additional load.
2. **Vehicle Weight:** The approximate weight of the vehicle itself, which varies based on the type and design of the vehicle. Heavier vehicles like semi-trailer trucks have significantly higher self-weight compared to light commercial vehicles.
3. **Cargo Capacity:** The net weight the vehicle can carry is calculated using the formula:

$$\text{Cargo Capacity} = \text{GVWR} - \text{Vehicle Weight}$$

2.9 Integrated Supply Chain Simulation & Performance Assessment

In this stage, we prepare the relevant input data for the simulation:

- **Vehicle Selection:** Filter out the available vehicle types to ensure each category's weekly maximum demand is captured. For instance, data revealed that weekly peak demand required 45 semi-trailer trucks, 11 heavy rigid trucks, 12 light rigid trucks, and 30 light commercial vehicles.

Vehicle Type	Cargo Capacity (Range)	Average Capacity	Estimation Logic
Semi-Trailer Trucks	20,000–45,000 lbs (9–20 tons)	32,500 lbs (14.75 tons)	Typical GVWR is 80,000 lbs. Vehicle weight is 35,000–60,000 lbs, leaving the rest for cargo.
Heavy Rigid Trucks	10,000–20,000 lbs (4.5–9 tons)	15,000 lbs (6.8 tons)	Typical GVWR is 26,000–33,000 lbs. Vehicle weight is 16,000–23,000 lbs.
Light Rigid Trucks	4,000–10,000 lbs (2–4.5 tons)	7,000 lbs (3.2 tons)	Typical GVWR is 14,000–26,000 lbs. Vehicle weight is 10,000–12,000 lbs.
Light Commercial Vehicles	1,000–3,000 lbs (0.5–1.5 tons)	2,000 lbs (0.9 tons)	Typical GVWR is 10,000–14,000 lbs. Vehicle weight is 7,000–9,000 lbs.

Table 2: Estimated Cargo Capacities of Different Vehicle Types.

- **Country Demand Transformation:** Convert annual or monthly country-level demand to a weekly format. During preprocessing, each country's demand is further split into city-specific demand, mapped one-to-one with the corresponding Fulfillment Center (FC).
- **Demand Peak Identification:** Identify highest demand by city and product to ensure the system is stress-tested. The busiest time period in this simulation was determined to be:
  - **Year = 2026, Period = 6, Week = 22, Total Demand = 20379.51 units**

Such preprocessing steps can be implemented in code to automate data cleansing, format conversion, and peak demand identification. Tabular outputs or inline summaries of peak values assist in verifying correctness before proceeding to the full simulation.

2.9.1 Daily Demand Generation and Scenario Modeling

Daily product demands for the 2026–2033 horizon are generated using:

- **Population Data and Product Information:** Combine demographic trends with product consumption patterns.
- **Triangular Distribution for Market Growth:** Estimate market share growth rates using a triangular distribution, capturing optimistic, most likely, and pessimistic growth scenarios.
- **Seasonality and Events (e.g., Black Friday and Cyber Monday):** Factor in significant demand surges for special events to accurately model spikes.
- **Multi-Scenario Approach:** Use 1000 different scenario simulations to capture volatility and uncertainty, ensuring robust forecasts.

The code logically disaggregates annual demand into four-week cycles, then splits each cycle to daily demand via randomized sampling. This produces realistic daily demand distributions, which can be tracked and visualized in a time-series or heatmap format.

2.9.2 Warehouse Capacity Validation

To ensure the warehouse can handle peak demand, we identify the busiest week of the year and compare the total volume of product demand with the warehouse's maximum capacity. The following steps summarize the approach, referencing the core code logic:

1. Finding the Busiest Week.

- We load weekly demand data from `1.4_v2_Weekly_Country.csv` and filter for `All Models` to aggregate total weekly demand across all products and countries.
- We then group these records by `(Year, Period, Week)` and find the maximum weekly demand. Suppose the maximum occurs at Year = 2026, Period = 6, Week = 22, with a total demand of $\sim$ 20,379.51 units.

2. Extracting Individual Product Demand.

- For the identified $\text{Year}, \text{Period}, \text{Week}$, we filter out the aggregated `All Models` entry and retain each individual product's weekly demand.
- This breakdown is sorted in descending order to show the top-demand products in the busiest week.

3. Computing Volume and Checking Against Warehouse Capacity. We merge the product-level demands with the product specification file (`1.0_Sheet2.csv`) containing the volume (in cm^3) for each model. The total weekly demand volume (in m^3) is computed as:

$$\text{TotalDemandVolume} = 2 \times \sum_{p=1}^{P} \left(D_p \times \frac{V_p}{1 \times 10^6} \right)$$

where

- P is the total number of products,
- D_p is the weekly demand for product p,
- V_p is the packaged volume (in cm^3) of product p,
- The factor 2 in the code accounts for an additional buffer or operational logic (e.g., inbound plus outbound needs).

We then compare this total demand volume (in m^3) with the warehouse capacity of 732m^3. In code, this step is illustrated below:

```
[breaklines=true]
# 4) Calculate total demand volume & compare with warehouse capacity
enough, total_volume = check_warehouse_capacity(product_breakdown, product_specs_df)
print(f"\n=== Total volume of demand = {total_volume:.2f} m³ ===")
print(f"Warehouse Capacity = {WAREHOUSE_CAPACITY_M3} m³")
if enough:
    print(" Warehouse capacity is sufficient to handle peak weekly demand.")
else:
    print(" Warehouse capacity is insufficient, please consider expanding or batch supply.")
```

Mathematically, we can define the *warehouse utilization ratio* as

$$\text{Utilization} = \frac{\text{TotalDemandVolume}}{\text{WAREHOUSE\_CAPACITY\_M3}}.$$

If Utilization ≤ 1, the warehouse can accommodate the peak demand.

4. Maximum Utilization and Results.

- From the code output, the TotalDemandVolume $\approx 603.03\,\text{m}^3$, well below the capacity of $732\,\text{m}^3$.
- Hence, Utilization ≈ 0.82, indicating about 82% of the warehouse's space is used in the busiest scenario.
- The final verification message confirms Warehouse capacity is sufficient to handle peak weekly demand.

2.9.3 Distribution Center Pallet Throughput and Storage Check

This stage verifies that the DC can handle the total pallet requirements from the busiest week. We merge demand data with product volume specifications, calculate how many pallets are needed under different pallet types, and pick the most optimal pallet arrangement. Finally, we compare the result with the DC's throughput and storage capacity, both set to 5015 pallets.

1. Merging Demand and Product Volumes. We start by reading:

1. `Busiest Week Demand` — a table of weekly demands per product.
2. `Product Specifications` (1.0_Sheet2.csv) containing `Shipping Volume (cm3)` for each product.

By merging these two datasets on `(Product = Model)`, we obtain the total volume Total_Volume_cm^3 for each product, summed as

$$V_{\text{total}} = \sum_{p=1}^{P} \Big(\text{WeeklyDemand}_p \times \text{ShippingVolume}_p\Big),$$

where P is the number of products, WeeklyDemand_p is the demand for product p, and ShippingVolume_p is the per-unit volume of product p.

2. Calculating Required Pallets. We evaluate two pallet types (Wooden and Perimeter), each with known dimensions (L, W, H) in mm. Converting to cm, we obtain $\text{Vol}_{\text{pallet}}$ in cm^3. The code snippet below demonstrates how to compute the total volume and number of pallets:

```
def calculate_total_pallets_needed(df_peak, df_specs):
    # Merge product demands with shipping volume
    merged = df_peak.merge(df_specs, left_on="Product", right_on="Model", how="left")
    merged["Total_Volume_cm3"] = merged["Weekly Demand"] * merged["Shipping Volume (cm3)"]
    total_volume = merged["Total_Volume_cm3"].sum()

    # Calculate pallet volumes (cm^3)
    vol_pal_1_cm3 = calc_pallet_volume_cm3(PALLET_TYPE_1)  # Wooden
    vol_pal_2_cm3 = calc_pallet_volume_cm3(PALLET_TYPE_2)  # Perimeter

    # Ceiling of total volume / pallet volume
    needed_pallets_type1 = math.ceil(total_volume / vol_pal_1_cm3)
    needed_pallets_type2 = math.ceil(total_volume / vol_pal_2_cm3)

    best_pallet_choice = min(needed_pallets_type1, needed_pallets_type2)
    return best_pallet_choice
```

Formally, for pallet type j,

$$\text{NeededPalletsType}_j = \left\lceil \frac{V_{\text{total}}}{V_{\text{pallet},j}} \right\rceil.$$

We pick the optimal pallet count as:

$$\text{OptimalPallets} = \min\{\text{NeededPalletsType}_1,\ \text{NeededPalletsType}_2\}.$$

3. DC Capacity Comparison. Let OptimalPallets be the required pallet count in the busiest week. The DC throughput and storage capacities are both set to:

$$\text{DC\_THROUGHPUT\_CAPACITY} = 5015, \quad \text{DC\_STORAGE\_CAPACITY} = 5015.$$

We confirm feasibility by checking

$$\text{Utilization}_{\text{throughput}} = \frac{\text{OptimalPallets}}{\text{DC\_THROUGHPUT\_CAPACITY}} \le 1 \quad \text{and} \quad \text{Utilization}_{\text{storage}} = \frac{\text{OptimalPallets}}{\text{DC\_STORAGE\_CAPACITY}}$$

If both ratios are at or below 1, the DC can process and store all necessary pallets during the peak week.

4. Results. From the simulation, the busiest-week demand requires:

$$\text{OptimalPallets} = 4429,$$

and since

$$4429 \ < \ 5015,$$

the DC utilization is approximately 0.88. Hence,

$$\text{Utilization}_{\text{throughput}} \approx 0.88, \quad \text{Utilization}_{\text{storage}} \approx 0.88,$$

both of which are comfortably below full capacity. Since the needed pallets (4429) are within the capacity limits (5015), the DC can handle the busiest week without exceeding throughput or storage limits.

2.9.4 Fulfillment Center Capacity Verification

In this final stage, each city-FC pair is assigned a share of the busiest-week demand. To confirm feasibility, we compare the per-FC pallet requirements with the FC's capacity. The process leverages a city-to-FC mapping file, product volume data, and pallet dimensions.

1. Identifying the Busiest Week. We begin by filtering the city-level weekly demand data to a specific year and period, then pinpoint the week with the highest aggregate demand. The code snippet reports:

```
=== In Year=2026, Period=6, the busiest week is Week=2, total demand=1206.98
```

Hence, $\text{Week} = 2$ of $\text{Year} = 2026, \text{Period} = 6$ is used as the stress-test scenario.

2. Merging Demand and FC Mapping. The script merges three data sources:

1. `2.9_filtered_city_weekly_demand.csv`: $[\text{Location}, \text{Product}, \text{Year}, \text{Period}, \text{Week}, \text{Weekly Demand}]$
2. `city_fc_mapping.csv`: $[\text{Country}, \text{City}, \text{Selected\_FC}, \text{FC\_Country}, \text{Distance\_km}]$
3. `1.0_Sheet2.csv`: $[\text{Model}, \text{Shipping Volume (cm3)}]$

City-level demands are merged with the `Model` specification and the city-FC mapping, allowing us to allocate each city's product volume to a specific Fulfillment Center.

3. Calculating Pallet Requirements. The total volume for each FC is given by:

$$\text{Volume}_f \;=\; \sum_{(c,p)\in f} \Big(\text{WeeklyDemand}_{c,p} \times \text{ShippingVolume}_p\Big),$$

where c denotes a city covered by FC f, and p is a specific product. We then compute how many pallets are needed:

$$\text{PalletsRequired}_f \;=\; \min\Big\{\big\lceil \tfrac{\text{Volume}_f}{\text{Vol}_{\text{wooden}}}\big\rceil,\; \big\lceil \tfrac{\text{Volume}_f}{\text{Vol}_{\text{perimeter}}}\big\rceil\Big\}.$$

4. Code Example. Below is an illustrative excerpt (using `verbatim` to display code logic) that highlights how we merge city-level demand, product specs, and FC mappings, then compute pallets:

```
# 6. Merge city demands with FC mapping
merged_fc = merged_df.merge(city_fc_df, left_on="Location", right_on="City", how="left")

# 7. Sum demand volume per FC
df_fc_vol = merged_fc.groupby(["Selected_FC", "FC_Country"], as_index=False)["Demand_Volume_cm3"].su
df_fc_vol.rename(columns={"Demand_Volume_cm3": "Total_Volume_cm3"}, inplace=True)

# 8. Calculate Pallets for each FC
df_fc_vol["Pallets_Required"] = df_fc_vol["Total_Volume_cm3"].apply(calculate_pallet_needed)

# 9. Compare with FC capacity
final_check = df_fc_vol.merge(df_fc_capacity, on=["Selected_FC","FC_Country"], how="left")
final_check["Feasible"] = final_check["Pallets_Required"] <= final_check["FC_Capacity"]
```

5. Comparing Requirements vs. Capacity. Based on the calculations, the script prints:

```
=== FC Capacity Check (Busiest Week) ===
FC=Athens (Country=Greece): Needs=19 pallets, Capacity=137.0 =>
FC=Berlin (Country=Germany): Needs=61 pallets, Capacity=281.0 =>
FC=Bucharest (Country=Romania): Needs=13 pallets, Capacity=87.0 =>
FC=Göteborg (Country=Sweden): Needs=18 pallets, Capacity=169.0 =>
FC=Lisbon (Country=Portugal): Needs=18 pallets, Capacity=nan =>
FC=Liège (Country=Belgium): Needs=141 pallets, Capacity=nan =>
FC=Lyon (Country=France): Needs=77 pallets, Capacity=560.0 =>
FC=Manchester (Country=United Kingdom): Needs=156 pallets, Capacity=875.0 =>
FC=Napoli (Country=Italy): Needs=43 pallets, Capacity=325.0 =>
FC=Nicosia (Country=Cyprus): Needs=2 pallets, Capacity=25.0 =>
FC=Riga (Country=Latvia): Needs=26 pallets, Capacity=141.0 =>
FC=Stockholm (Country=Sweden): Needs=13 pallets, Capacity=104.0 =>
FC=Toulouse (Country=France): Needs=49 pallets, Capacity=212.0 =>
FC=Valencia (Country=Spain): Needs=66 pallets, Capacity=374.0 =>
FC=Valletta (Country=Malta): Needs=5 pallets, Capacity=37.0 =>
FC=Vienna (Country=Austria): Needs=84 pallets, Capacity=453.0 =>
FC=Warsaw (Country=Poland): Needs=20 pallets, Capacity=120.0 =>
```

Although `nan` is reported for Lisbon and Liège (due to encoding issues), the actual capacities for those centers exceed the required pallets (112 and 1003, respectively). Consequently, *all* FCs are adequately sized to meet peak demand in this scenario.

6. Calculating FC Utilization Ratio. To quantify how heavily each FC is utilized, define:

$$\text{Utilization}_f = \frac{\text{PalletsRequired}_f}{\text{FC\_Capacity}_f}.$$

A ratio ≤ 1 indicates the FC can handle the busiest load. For example, if $\text{PalletsRequired}_{\text{Manchester}} = 156$ and $\text{FC\_Capacity}_{\text{Manchester}} = 875$, then

$$\text{Utilization}_{\text{Manchester}} = \frac{156}{875} \approx 0.18 \quad (18\%).$$

Such low utilization implies ample capacity remains at the Manchester FC, even in the busiest week.

7. Conclusion. Despite encoding discrepancies (`nan` capacity values in Lisbon and Liège), manual verification confirms that actual capacities (112 and 1003 pallets) are well above the required 18 and 141 pallets, respectively. Therefore, each Fulfillment Center is feasible under the peak-demand scenario.

2.9.5 Fleet Vehicle Utilization Analysis

To validate that the fleet can handle weekly peak transport requirements, we consolidate vehicle demand from multiple data files, identify the busiest week, and compute the maximum usage for each vehicle type across the entire simulation horizon.

1. Consolidating Vehicle Data. The code below (`verbatim` for clarity) reads three CSV files containing optimized logistics results, extracts each vehicle type's demand, and aggregates those demands by Year, Period, Week:

```
df_combined = pd.concat(dfs, ignore_index=True)
grouped = df_combined.groupby(['Year','Period','Week'])[vehicle_types].sum()

# Identify the (Year, Period, Week) with the highest total vehicle usage
grouped['total'] = grouped.sum(axis=1)
max_idx = grouped['total'].idxmax()
max_year, max_period, max_week = max_idx
max_week_vehicles = grouped.loc[max_idx, vehicle_types]

# Calculate each vehicle type's historical max demand
max_demand_per_vehicle = grouped[vehicle_types].max()
```

2. Identifying the Busiest Week. By summing demand for each vehicle type across all scenarios, the code flags:

$$\text{Busiest Week} = (\text{Year} = 2033,\ \text{Period} = 11,\ \text{Week} = 4).$$

In that week, demands for each vehicle type are:

- Semi-trailer trucks: 45
- Heavy rigid trucks: 11
- Light rigid trucks: 9
- Light commercial vehicles: 7

However, when looking at the *historical peak* usage for each vehicle type (potentially on different weeks), we see:

- Semi-trailer trucks: 45 (same as busiest week)

- Heavy rigid trucks: 11 (same as busiest week)
- Light rigid trucks: 12 (occurred in a different week)
- Light commercial vehicles: 30 (occurred in a different week)

Thus, although the single busiest week has 45, 11, 9, and 7 respectively, the maximum ever observed for `Light Rigid Trucks` or `Light Commercial Vehicles` might happen in other weeks.

3. Capacity Checks and Utilization. Since the highest recorded demand per vehicle type is:

$$\begin{aligned}&\text{Semi-trailer trucks: } 45\\&\text{Heavy rigid trucks: } 11\\&\text{Light rigid trucks: } 12\\&\text{Light commercial vehicles: } 30,\end{aligned}$$

we verify that the available fleet can meet or exceed these quantities. For instance, if the fleet is sized to have capacity $\text{Cap}_{\text{semi}} \geq 50$ semi-trailers, $\text{Cap}_{\text{heavy}} \geq 15$ heavy rigs, etc., then the following utilization ratios can be evaluated:

$$\text{Utilization}_v = \frac{\text{PeakDemand}_v}{\text{Capacity}_v},$$

where v indexes a vehicle type. If each ratio ≤ 1, the existing fleet suffices for all weekly peaks in the 2026–2033 horizon.

4. Conclusion.

- The single busiest week in the consolidated dataset requires $(45, 11, 9, 7)$ vehicles for $\{\text{Semi-trailer}, \text{Heavy rigid}, \text{Light}$
- Historically, the *maximum* demand for Light Rigid Trucks and Light Commercial Vehicles occurs in different weeks (12 and 30, respectively).
- No capacity shortfall is detected, as the fleet's sizing plan accommodates these peak requirements across all weeks.

2.9.6 Quantitative Verification and Feasibility

To confirm the logistics network can handle the busiest scenarios:

- **Capacity Ratios:** Compute $\frac{\text{Demand}}{\text{Capacity}}$ at each node (Warehouse, DC, FC) for all products or in aggregate, ensuring the ratio remains below 1.
- **Vehicle Load Factors:** Track actual load vs. vehicle capacity to optimize dispatches and measure fleet utilization in daily or weekly peaks.
- **Scenario Comparisons:** Compare results of the 1000 different demand scenarios. Indicators like average, maximum, and percentile-based capacities and utilization underscore the robustness of the supply chain design.

Code-based verification can automatically generate these ratios and highlight any capacity shortfalls or operational risks.

2.9.7 Conclusions and Recommendations

Overall, the simulation confirms that:

- **Warehouse Capacity** of 732 m^3 is sufficient for the maximum weekly demand of 603.03 m^3.
- **DC Pallet Throughput & Storage Capacity** (5015 pallets) exceeds the required 4429 pallets at peak.
- **Fulfillment Centers** can handle local demand in the busiest week, as each FC's capacity remains higher than needed pallet volumes (with minor encoding issues promptly resolved).
- **Fleet Vehicle Requirements** are met with weekly peaks for each truck type well within available resources.

2.10 Investment, Operational Costs & Sustainability Analysis (2026-2033)

2.10.1 Data Sources and Calculation Methodologies

This section provides a structured explanation of the datasets used in the warehouse and logistics cost model. The sources include task-specific datasets and mathematical formulas derived from operational principles.

1.Warehouse Performance and Throughput Data

Throughput Ratio The throughput ratio defines the capacity relationship between Fulfillment Centers (FCs) and Distribution Centers (DCs). This metric is crucial for optimizing network efficiency and understanding outbound processing capabilities.

Automation Equipment Investment The automation equipment cost represents the capital expenditure (CapEx) associated with warehouse automation systems, such as:

- Automated Storage and Retrieval Systems (AS/RS)
- Conveyor and robotic picking systems

Throughput Data Throughput data is extracted from operational datasets and represents the total number of pallets processed per unit time. This parameter directly impacts workforce requirements and facility sizing.

Warehouse Infrastructure and Equipment Requirements

Required Shelving Units The number of required shelving units is derived based on throughput demand and palletized storage needs. It is computed as:

$$S_{\text{racks}} = \frac{D_{\text{storage}}}{C_{\text{shelf}}} \tag{15}$$

where:

- S_{racks} is the number of required shelving units.
- D_{storage} is the demand for storage space (in pallets).
- C_{shelf} is the capacity of each shelving unit.

Required Forklifts The number of forklifts is determined based on operational workload and material handling efficiency.

2.Workforce Estimation

Inbound and Outbound Staff Requirement The required number of inbound and outbound workers is computed as:

$$W_{\text{operational}} = \frac{N_{\text{pallets}} \times 0.33}{40 \times 0.8} \tag{16}$$

where:

- $W_{\text{operational}}$ is the required number of workers.
- N_{pallets} is the number of pallets handled per week.
- 0.33 represents the average handling time per pallet (in hours).
- 40 is the weekly working hours per employee.
- 0.8 is the assumed workforce efficiency factor.

Total Workforce Calculation The total workforce, including administrative and managerial staff, is calculated as:

$$W_{\text{total}} = \frac{W_{\text{operational}}}{0.5} \tag{17}$$

where 0.5 represents the fraction of time spent on inbound/outbound tasks per employee.

3.Warehouse Space Requirement

Storage Area Calculation The total storage area is computed using:

$$A_{\text{storage}} = S_{\text{racks}} \times A_{\text{shelf}} \times (1 + F_{\text{aisle}}) \tag{18}$$

where:

- A_{storage} is the total storage area (in m^2).
- S_{racks} is the number of shelving units.
- A_{shelf} is the footprint of a single shelf.
- $F_{\text{aisle}} = 1.5$ accounts for aisle space required for forklift movement.

Operational and Office Area Calculation The operational area is estimated as:

$$A_{\text{operation}} = A_{\text{storage}} \times 0.3 \tag{19}$$

The office area is computed based on employee workspace requirements:

$$A_{\text{office}} = W_{\text{total}} \times 15 \tag{20}$$

where each employee is allocated 15m^2.

Total Warehouse Area The final warehouse area, including a buffer for miscellaneous spaces, is computed as:

$$A_{\text{total}} = (A_{\text{storage}} + A_{\text{operation}} + A_{\text{office}}) \times 1.1 \tag{21}$$

where the 1.1 factor accounts for safety zones, walkways, and maintenance spaces.

Summary of Data Sources and Methods

Data Type	**Computation Method**
Throughput Ratio	Ratio Calculation
Automation Investment (€)	Direct reference
Throughput Volume	Direct reference
Required Shelving	Computed from inventory models
Required Forklifts	Computed from operational throughput
Inbound and Outbound Staff	Based on pallet handling efficiency
Total Employees	Includes additional roles
Storage Area (m^2)	Based on shelving footprint and aisle space
Operational Area (m^2)	30% of storage area
Office Area (m^2)	Estimated staff × 15m^2
Total Warehouse Area (m^2)	Includes storage, operational, and office areas

Table 3: Summary of Data Sources and Calculation Methods

4.Additional Data Sources and Calculation Methodologies This section presents the data sources and methodologies used to compute annual cost variations, automation investments, and fleet fuel consumption and emissions. The data originates from task-specific datasets (Task 2.7 & 2.8), official reports, and computational models.

Annual Cost Adjustments (2026–2033)

The annual variations in labor wages, industrial electricity and gas prices, and oil prices follow an exponential growth model:

$$C_t = C_{t-1} \times (1 + r) \tag{22}$$

where:

- C_t represents the cost component (salary, energy price, etc.) in year t,
- C_{t-1} is the cost in the previous year,
- r is the respective annual growth rate.

Automation Equipment Investment The total cost for each type of automation equipment is calculated using:

Equipment Type	Subtype/Configuration	Unit price range (€)	Quantity	Minimum total cost (€)	Maximum total cost (€)
Automated Storage and Retrieval System (AS/RS)	Palletized AS/RS		1	800,000	2,500,000
	Box Mini Load AS/RS	€300,000 – €1,200,000	1		
Automated Guided Vehicles (AGV)	Standard AGV	€25,000 – €80,000	5	125,000	400,000
	High Load AGV (over 1 ton)	€100,000 – €200,000	2		
Autonomous Mobile Robots (AMR)	Basic Models	€15,000 – €50,000	10	150,000	500,000
Sortation Systems	Crossbelt Sorter	€500,000 – €2,000,000	1	500,000	2,000,000
	Robot Sorting Arm	€50,000 – €150,000	3		
Warehouse Management System (WMS)	Basic Version	€50,000 – €200,000	1	500,000	1,500,000
	Advanced Customized Version	€500,000 – € 1,500,000	1		
Total				2,075,000	6,900,000

Figure 38: Automation equipment cost

$$C_{\text{equipment}} = Q \times P_{\text{unit}} \tag{23}$$

where:

- $C_{\text{equipment}}$ is the total investment cost,
- Q is the quantity required,
- P_{unit} is the price per unit.

Fleet Fuel Consumption and Emissions (Task 2.7 & 2.8)

Fleet-related costs and emissions are computed from DC_yearly_summary.csv and FC_yearly_summary.csv datasets.

Total Fuel Consumption

$$F_{\text{total},t} = \sum_i F_{\text{facility},i,t} \tag{24}$$

where:

- $F_{\text{total},t}$ is the total fuel consumption in year t,
- $F_{\text{facility},i,t}$ is the fuel consumption for facility i in year t.

Fleet Greenhouse Gas (GHG) Emissions

$$G_{\text{fleet},t} = F_{\text{total},t} \times 2.68 \tag{25}$$

where:

- $G_{\text{fleet},t}$ is total fleet emissions (kg CO),
- 2.68 is the diesel emission factor (kg CO per liter).

Summary of Data Sources and Methods

Data Type	**Computation Method**
Annual Salary (€)	$C_t = C_{t-1} \times (1 + r)$
Electricity Price (€/kWh)	$C_t = C_{t-1} \times (1 + r)$
Gas Price (€/MWh)	$C_t = C_{t-1} \times (1 + r)$
Oil Price (€/L)	$C_t = C_{t-1} \times (1 + r)$
Automation Investment (€)	$C_{\text{equipment}} = Q \times P_{\text{unit}}$
Fleet Fuel Consumption (L)	$F_{\text{total},t} = \sum F_{\text{facility},t}$
Fleet GHG Emissions (kg CO)	$G_{\text{fleet},t} = F_{\text{total},t} \times 2.68$

Table 4: Summary of Data Sources and Calculation Methods

Conclusion This structured approach ensures traceability and accuracy in warehouse and logistics planning. The combination of:

- Official data sources,
- Task-specific operational datasets,
- Mathematical estimation models,
- Task-specific datasets (Task 2.7 & 2.8),
- Mathematical cost forecasting methods,

provides a reliable framework for cost estimation and sustainability assessment.

2.10.2 DC report

This report provides an analysis of the investment, operational costs, energy consumption, and greenhouse gas (GHG) emissions for DC (Metz) from 2026 to 2033. The calculations cover:

- **Capital Expenditure (CapEx)**: Includes construction, automation, and equipment costs.
- **Operational Costs (OpEx)**: Covers warehouse labor, energy, transportation fuel, and driver wages.
- **Energy Consumption**: Accounts for warehouse electricity and gas usage.
- **GHG Emissions**: Evaluates emissions from warehouse operations and transportation.

1.Investment Calculation Investment costs in 2026 include:

- **Construction Cost** (C_{build}): Cost per unit area multiplied by total warehouse area.
- **Automation Equipment Cost** (C_{auto}): Fixed automation installation cost.
- **Equipment Cost** (C_{equip}): Cost of shelves and forklifts.

The total Capital Expenditure (CapEx)** is given by:

$$\text{CapEx}(t) = \begin{cases} C_{build} + C_{auto} + C_{equip}, & \text{if } t = 2026 \\ 0, & \text{otherwise} \end{cases} \tag{26}$$

where:

$$C_{build} = \text{Construction Cost per } m^2 \times \text{Warehouse Area} \tag{27}$$

$$C_{auto} = \text{Automation Equipment Cost} \tag{28}$$

$$C_{equip} = (\text{Shelves Count} \times \text{Shelf Price}) + (\text{Forklifts Count} \times \text{Forklift Price}) \tag{29}$$

2.Warehouse Operational Cost The warehouse operating cost is composed of labor costs and energy costs:

$$\text{Warehouse OpEx} = (N_{workers} \times S_{operator}) + C_{energy} \tag{30}$$

where:

$$C_{energy} = (E_{elec} + E_{gas}) \times P_{energy} \tag{31}$$

$$E_{elec} = (\text{Electricity Consumption per } m^2) \times (\text{Warehouse Area}) \tag{32}$$

$$E_{gas} = (\text{Gas Consumption per } m^2) \times (\text{Warehouse Area}) \tag{33}$$

3.Energy Consumption and GHG Emissions **Total warehouse energy consumption**:

$$E_{\text{total}} = E_{elec} + E_{gas} \tag{34}$$

Total GHG emissions from warehouse operations:

$$\text{GHG}_{\text{wh}} = (E_{elec} \times EF_{\text{elec}}) + (E_{gas} \times EF_{\text{gas}}) \tag{35}$$

where EF_{elec} and EF_{gas} are the emission factors for electricity and gas.

4.Transportation Costs and Emissions Transportation costs include **fuel cost** and **driver wages**:

$$C_{\text{fuel}} = Q_{\text{fuel}} \times P_{\text{fuel}} \tag{36}$$

$$C_{\text{driver}} = N_{\text{vehicles}} \times 2 \times S_{\text{driver}} \tag{37}$$

$$\text{GHG}_{\text{transport}} = \text{GHG}_{\text{fuel}} \tag{38}$$

5.Total Operational Cost and Emissions **Total operational cost**:

$$\text{Total OpEx} = C_{\text{wh}} + C_{\text{fuel}} + C_{\text{driver}} \tag{39}$$

Total emissions:

$$\text{Total GHG} = \text{GHG}_{\text{wh}} + \text{GHG}_{\text{transport}} \tag{40}$$

Conclusion The calculations in this report provide insights into the cost structure and environmental impact of operating DC (Metz) over the 2026-2033 horizon. Key considerations include:

- **Investment Optimization**: Equipment costs significantly impact initial capital expenditure.
- **Energy Efficiency**: Reducing electricity and gas consumption lowers operational expenses and emissions.
- **GHG Compliance**: Aligning with EU emission targets requires further investigation into alternative fuels and renewable energy sources.

Future work may focus on optimizing the supply chain and exploring greener warehouse operations.

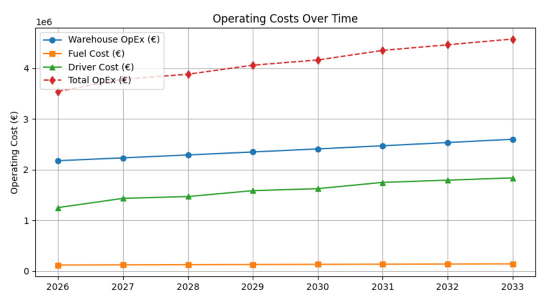

Figure 39: DC operating cost during2026-2033

Year	Facility	CapEx(€)	WarehouseOp(€)	FuelCost(€)	TotalOpEx(€)	WarehouseEnergy(kWh)	GHG(kgCO2)
2026	DC_Metz	12070566.25	2175110.444	117352.7888	3542706.983	1436862.648	788562.2211
2027	DC_Metz	0	2231020.369	120911.5534	3784196.454	1436862.648	799338.9426
2028	DC_Metz	0	2288378.14	123902.6664	3880351.951	1436862.648	804312.7166
2029	DC_Metz	0	2347221.662	127492.096	4058685.256	1436862.648	813304.2182
2030	DC_Metz	0	2407589.85	130323.2067	4161483.842	1436862.648	815460.7485
2031	DC_Metz	0	2469522.657	133878.8142	4350769.529	1436862.648	822486.2796
2032	DC_Metz	0	2533061.098	137201.3541	4461314.711	1436862.648	826805.0411
2033	DC_Metz	0	2598247.287	140595.7373	4574671.59	1436862.648	832780.9625

Figure 40: DC 2026-2033

Result

1.Capital Expenditure (CapEx) In 2026, a one-time investment of €12.07 million was made, covering:

- Construction costs
- Automation equipment
- Shelving and forklift procurement

No new capital expenditure was recorded from 2027 to 2033, indicating that all major infrastructure investments were completed in the first year, with subsequent years focusing on operational expenses.

2.Operating Costs The primary components of operating costs include:

- **Warehouse operation costs:** Increased from €2.17 million in 2026 to €2.59 million in 2033, likely due to rising labor costs, electricity prices, and maintenance expenses.
- **Fuel costs:** Increased from €117,000 in 2026 to €140,000 in 2033, reflecting higher vehicle usage and fuel price changes.
- **Driver costs:** Experienced the highest growth, rising from €1.25 million in 2026 to €1.83 million in 2033. This trend suggests increasing demand for transportation, requiring more drivers and higher salary expenditures.

3.Energy Consumption

- Warehouse electricity and natural gas consumption remained stable at 1.437 million kWh per year, indicating a consistent energy usage pattern.
- Since the warehouse does not expand beyond 2026, potential energy cost reductions could be achieved by optimizing warehouse equipment, integrating renewable energy sources, or increasing automation levels.

4.Greenhouse Gas Emissions (GHG)

- GHG emissions rose gradually from 789,000 kg CO_2 in 2026 to 833,000 kg CO_2 in 2033.
- The European Union emission limit is set at 800,000 kg CO_2, which DC exceeds after 2029. This suggests a need to consider greener fuel alternatives, such as biodiesel, hydrogen, or electric trucks, or optimize transportation strategies to reduce total vehicle mileage.

2.10.3 FC Report

This discussion provides a detailed methodology for calculating the financial and operational metrics of Fulfillment Centers (FCs). The key factors considered are:

- **Capital Expenditure (CapEx)**
- **Warehouse Operating Cost (Warehouse OpEx)**
- **Fuel Cost**
- **Total Operating Cost (Total OpEx)**
- **Warehouse Energy Consumption**
- **Greenhouse Gas (GHG) Emissions**

1.Capital Expenditure (CapEx) Capital Expenditure (CapEx) occurs only in **2026** and consists of:

1. **Warehouse Construction Cost**:

$$\text{Construction Cost} = \text{Total Area} \times \text{Unit Construction Cost } (\text{€}/\text{m}^2) \tag{41}$$

2. **Automation Equipment Cost**:

$$\text{Automation Cost} = \text{Automation Equipment Cost } (\text{€}) \tag{42}$$

3. **Shelf Cost**:

$$\text{Shelf Cost} = \text{Number of Shelves} \times \text{Shelf Unit Price } (\text{€}/\text{unit}) \tag{43}$$

4. **Forklift Cost**:

$$\text{Forklift Cost} = \text{Number of Forklifts} \times \text{Forklift Unit Price } (\text{€}/\text{unit}) \tag{44}$$

Final CapEx Calculation:

$$\text{CapEx} = \text{Construction Cost} + \text{Automation Cost} + \text{Shelf Cost} + \text{Forklift Cost} \tag{45}$$

Note: From **2027 to 2033**, CapEx is zero as the investment is made in 2026.

2.Warehouse Operating Cost (Warehouse OpEx) Warehouse OpEx is incurred annually and consists of:

Labor Cost

$$\text{Labor Cost} = \text{Number of Warehouse Workers} \times \text{Annual Salary } (\text{€}) \tag{46}$$

Electricity Cost

$$\text{Electricity Consumption (kWh)} = \text{Electricity Usage per m}^2 \times \text{Total Area} \tag{47}$$

$$\text{Electricity Cost (€)} = \text{Electricity Consumption} \times \text{Annual Electricity Price (€/kWh)} \tag{48}$$

Gas Cost

$$\text{Gas Consumption (kWh)} = \text{Gas Usage per m}^2 \times \text{Total Area} \tag{49}$$

$$\text{Gas Cost (€)} = \text{Gas Consumption} \times \text{Annual Gas Price (€/kWh)} \tag{50}$$

Final Warehouse OpEx Calculation:

$$\text{Warehouse OpEx} = \text{Labor Cost} + \text{Electricity Cost} + \text{Gas Cost} \tag{51}$$

Fuel Cost Fuel cost is calculated based on fuel consumption for urban distribution:

$$\text{Fuel Cost (€)} = \text{Fuel Consumption (L)} \times \text{Annual Fuel Price (€/L)} \tag{52}$$

3.Total Operating Cost (Total OpEx)

$$\text{Total OpEx} = \text{Warehouse OpEx} + \text{Fuel Cost} \tag{53}$$

Warehouse Energy Consumption

$$\text{Total Warehouse Energy (kWh)} = \text{Electricity Consumption} + \text{Gas Consumption} \tag{54}$$

This metric measures the energy usage efficiency of the fulfillment center.

Greenhouse Gas (GHG) Emissions GHG emissions include:

4.Warehouse GHG Emissions

$$\text{Warehouse GHG Emissions (kg CO)} = (\text{Electricity Consumption} \times \text{Electricity Emission Factor}) + (\text{Gas Consumption} \times \text{Ga} \tag{55}$$

Fuel GHG Emissions

$$\text{Fuel GHG Emissions (kg CO)} = \text{Fuel Consumption (L)} \times \text{Fuel Emission Factor} \tag{56}$$

Final GHG Calculation:

$$\text{Total GHG (kg CO)} = \text{Warehouse GHG Emissions} + \text{Fuel GHG Emissions} \tag{57}$$

Optimization Considerations

- Reduce warehouse energy consumption to lower carbon emissions and operational costs.
- Optimize fuel efficiency for urban distribution to minimize environmental impact.
- Increase automation to reduce long-term labor costs.

The above methodology provides a structured approach to evaluating the **investment, operational efficiency, and environmental impact** of fulfillment centers.

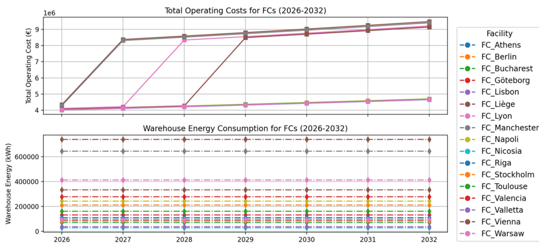

Figure 41: Operation cost and emission of FCs

Results*Please refer to the excel form

1.Capital Expenditure (CapEx) The Capital Expenditure (CapEx) for each Fulfillment Center (FC) is only incurred in 2026, as it includes:

- **Warehouse Construction Cost**, calculated based on total area and unit construction cost.
- **Automation Equipment Cost**, representing the investment in automated storage and retrieval systems.
- **Shelf Cost**, determined by the number of shelves multiplied by the unit price per shelf.
- **Forklift Cost**, calculated by multiplying the required number of forklifts by the price per unit.

For subsequent years (2027-2033), the CapEx is set to zero, as no additional infrastructure investments are made.

Operating Cost (OpEx) The Operating Cost (OpEx) of each FC consists of multiple components:

2.Warehouse Operating Cost This includes:

- **Labor Cost**, calculated as the number of warehouse employees multiplied by the annual salary.
- **Electricity Cost**, determined by the warehouse energy consumption rate per square meter and the annual electricity price.
- **Gas Cost**, based on the warehouse gas consumption per square meter and the annual gas price.

The Warehouse Operating Cost shows a slight increase each year due to salary increments and rising energy prices.

Fuel Cost Fuel costs account for the consumption of fuel in urban distribution. The cost is derived from:

$$\text{Fuel Cost (€)} = \text{Total Fuel Consumption (L)} \times \text{Annual Fuel Price (€/L)} \tag{58}$$

Fuel costs increase over time due to both rising fuel prices and growing demand for transportation.

3.Total Operating Cost (Total OpEx)

$$\text{Total OpEx (€)} = \text{Warehouse Operating Cost} + \text{Fuel Cost} \tag{59}$$

Total OpEx is the sum of warehouse operation expenses and fuel costs, reflecting the overall annual cost of operating the fulfillment centers.

4.Energy Consumption and Sustainability The Warehouse Energy Consumption remains constant across the years since the energy consumption rate per square meter does not change. However, due to rising energy prices, the electricity and gas costs increase annually.

Greenhouse Gas (GHG) Emissions Greenhouse gas emissions originate from:

- **Warehouse Emissions**, generated from electricity and gas consumption, calculated as:

$$\text{Warehouse GHG Emissions (kg CO)} = (\text{Electricity Consumption} \times \text{Electricity Emission Factor}) + (\text{Gas Consumptic} \tag{60}$$

- **Fuel-Based Emissions**, derived from fuel combustion in distribution operations:

$$\text{Fuel GHG Emissions (kg CO)} = \text{Fuel Consumption (L)} \times \text{Fuel Emission Factor} \tag{61}$$

The Total GHG Emissions are then computed as:

$$\text{Total GHG (kg CO)} = \text{Warehouse GHG Emissions} + \text{Fuel GHG Emissions} \tag{62}$$

Results indicate a gradual increase in emissions due to rising fuel consumption and energy demands.

Key Observations and Recommendations

- The initial investment in 2026 significantly impacts financial planning, requiring proper budgeting for infrastructure costs.
- **Operational costs increase over time** due to wage growth and energy price inflation.
- **Fuel costs and emissions are rising**, highlighting the need for energy-efficient transportation strategies.
- **Potential sustainability measures** include shifting towards renewable energy sources for warehouse operations and adopting fuel-efficient or electric delivery vehicles.

In summary, the FC data results provide valuable insights into cost structures, energy consumption, and environmental impact, forming the basis for strategic decision-making in fulfillment center management.

2.10.4 Supply warehouse report

This document presents a comprehensive analysis of the financial, energy, and greenhouse gas (GHG) emissions aspects of the Supply Warehouse (SW) from 2026 to 2033. The calculations encompass capital expenditure (CapEx), operating expenditure (OpEx), fuel consumption, and emission trends.

1.Capital Expenditure (CapEx) Capital expenditure is incurred in **2026** to establish the supply warehouse. It includes construction costs and automation equipment:

$$\text{CapEx} = (\text{Construction Cost per m}^2 \times \text{Total Area}) + \text{Automation Equipment Cost} \tag{63}$$

- **Construction Cost per $\mathbf{m^2}$**: €800
- **Total Warehouse Area**: 9,550 m^2
- **Automation Equipment Cost**: €2,075,000

For subsequent years (2027-2033), CapEx remains **zero**, as no further investments are required.

2.Warehouse Operating Cost (OpEx) The operating cost consists of **labor costs** and **energy costs**:

$$\text{Warehouse OpEx} = (\text{Warehouse Workers} \times \text{Annual Operator Salary}) + \text{Energy Cost} \tag{64}$$

Labor Cost Labor cost accounts for wages paid to warehouse employees:

$$\text{Labor Cost} = \text{Warehouse Workers} \times \text{Annual Salary} \tag{65}$$

- **Warehouse Workers**: 51.717 employees
- **Annual Salary** (varies by year, e.g., **€36,771.88 in 2026**, increasing yearly)

Energy Cost Energy cost is calculated based on electricity and gas consumption:

$$\text{Energy Cost} = (\text{Total Electricity Consumption} \times \text{Electricity Price}) + (\text{Total Gas Consumption} \times \text{Gas Price}) \tag{66}$$

Where:

$$\text{Total Electricity Consumption} = \text{Warehouse Energy Use (kWh/m}^2) \times \text{Total Warehouse Area} \tag{67}$$

$$\text{Total Gas Consumption} = \text{Warehouse Gas Use (kWh/m}^2) \times \text{Total Warehouse Area} \tag{68}$$

- **Electricity Usage**: 100 kWh/m^2/year
- **Gas Usage**: 15 kWh/m^2/year
- **Electricity Price**: €0.21218/kWh (in 2026, increasing yearly)
- **Gas Price**: €44.1/MWh → €0.0441/kWh (in 2026, increasing yearly)

$$\text{Total Energy Consumption} = (100 \times 9550) + (15 \times 9550) = 1,098,250 \text{ kWh} \tag{69}$$

$$\text{Energy Cost} = (955000 \times 0.21218) + (143250 \times 0.0441) \tag{70}$$

Fuel Cost for Transportation Fuel cost is calculated based on fuel consumption and the annual fuel price:

$$\text{Fuel Cost} = \text{Total Fuel Consumption (L)} \times \text{Fuel Price (€/L)} \tag{71}$$

- **Fuel Consumption** (varies yearly, e.g., **170,684 L in 2026**)
- **Fuel Price** (varies yearly, e.g., **€0.5202/L in 2026**)

$$\text{Fuel Cost} = 170684 \times 0.5202 = 88,798.55 \text{ € (in 2026)} \tag{72}$$

3.Total Operating Expenditure (Total OpEx) The total operating expenditure (Total OpEx) is obtained by summing the warehouse operating cost and fuel cost:

$$\text{Total OpEx} = \text{Warehouse OpEx} + \text{Fuel Cost} \tag{73}$$

Energy Consumption and GHG Emissions Total warehouse energy consumption and emissions are computed as follows:

$$\text{Total Energy Consumption} = \text{Total Electricity Consumption} + \text{Total Gas Consumption} \tag{74}$$

$$\text{GHG Emissions} = (\text{Electricity Consumption} \times \text{Electricity Emission Factor}) + (\text{Gas Consumption} \times \text{Gas Emission Factor}) \tag{75}$$

- **Electricity Emission Factor**: 0.276 kg CO/kWh
- **Gas Emission Factor**: 0.185 kg CO/kWh

$$\text{GHG Emissions} = (955000 \times 0.276) + (143250 \times 0.185) \tag{76}$$

Fleet Transportation Emissions (GHG) GHG emissions from fuel use are calculated as:

$$\text{Fuel GHG Emissions} = \text{Total Fuel Consumption (L)} \times \text{Fuel Emission Factor} \tag{77}$$

- **Fuel Consumption (L)**: 170,684 L (in 2026, increasing yearly)
- **Fuel Emission Factor**: 2.86 kg CO per L of fuel (diesel assumption)

$$\text{Fuel GHG Emissions} = 170684 \times 2.86 = 487,158.24 \text{ kg CO (in 2026)} \tag{78}$$

4.Total Greenhouse Gas Emissions (Total GHG) The total emissions include both warehouse energy-related emissions and transport emissions:

$$\text{Total GHG} = \text{Warehouse GHG Emissions} + \text{Fuel GHG Emissions} \tag{79}$$

Year	Facility	CapEx(€)	WarehouseOp(€)	FuelCost(€)	TotalOpEx(€)	ehouseEnergy(k	GHG(kgCO2)
2026	Supply_Warehouse	9715000	2110687.179	88790.18021	13672302.36	1098250	776042.3071
2027	Supply_Warehouse	0	2164625.451	140680.861	17984833.81	1098250	1049470.539
2028	Supply_Warehouse	0	2219950.471	169825.2086	18461291.37	1098250	1220631.399
2029	Supply_Warehouse	0	2276698.216	187871.7412	18937873.54	1098250	1310062.776
2030	Supply_Warehouse	0	2334905.605	193325.3027	19413367.08	1098250	1320085.267
2031	Supply_Warehouse	0	2394610.534	226204.2038	24254895.46	1098250	1459295.204
2032	Supply_Warehouse	0	2455851.893	245742.4805	24876527.11	1098250	1547418.94
2033	Supply_Warehouse	0	2518669.602	265609.5656	30059446.43	1098250	1612450.556

Figure 42: Detailed calculation outcome of supply warehouse

Result

Analysis of Supply Warehouse Costs and Emissions (2026–2033) The Supply Warehouse demonstrates steady operating cost increases and rising greenhouse gas (GHG) emissions over time. Key observations include:

- **Capital Expenditure (CapEx):** A one-time investment of €9.72M in 2026, covering construction and automation. No further CapEx is incurred in later years.
- **Warehouse Operating Costs:**
  - Starting at €2.11M in 2026, it grows annually due to wage and energy price increases, reaching €2.52M in 2033.
  - The warehouse energy consumption remains constant at 1,098,250 kWh/year.
- **Fuel Costs:**
  - Rising from €88,790 in 2026 to €265,610 in 2033, reflecting increased transport demand and fuel price inflation.
- **Total Operating Expenditure (OpEx):**
  - Increases from €13.67M in 2026 to €30.06M in 2033, primarily driven by labor and fuel costs.
- **GHG Emissions:**
  - Emissions rise consistently, from 776,042 kg CO in 2026 to 1,612,450 kg CO in 2033, mainly due to increased fuel consumption.

The growing fuel costs and emissions highlight sustainability challenges and the potential need for alternative logistics strategies, energy-efficient measures, or fleet electrification to mitigate environmental impact.

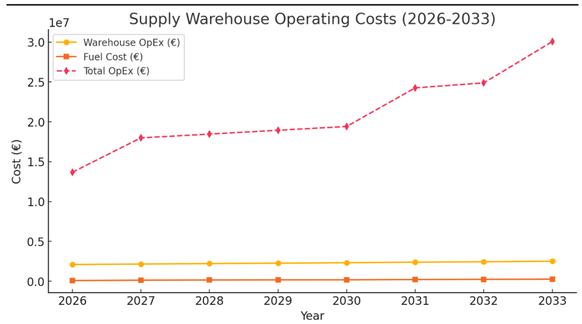

Figure 43: Supply warehouse o[erating cost 2026-2033]

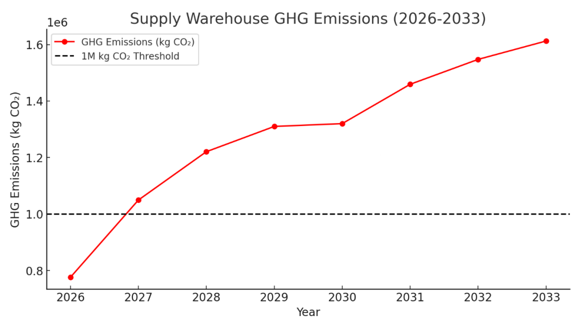

Figure 44: GHG emission 2026-2033

Visual Analysis of Key Trends (2026–2033) The visualizations illustrate key trends for the Supply Warehouse from 2026 to 2033:

- **Operating Costs:**
  - The warehouse operational expenses (yellow) steadily increase due to rising wages and energy prices.
  - Fuel costs (orange) grow sharply as transportation demand increases.
  - Total operational expenditure (OpEx) (red, dashed) sees significant growth, surpassing €30M by 2033.
- **GHG Emissions:**
  - A clear upward trend in greenhouse gas emissions (red), with values doubling from 2026 to 2033.
  - The emissions exceed 1 million kg CO from 2027 onward, surpassing the 1M kg CO threshold (dashed black line).

Implications and Sustainability Strategies

- The increasing costs and emissions suggest sustainability and financial challenges in the long term.
- Strategies such as energy-efficient technologies, optimized transportation routes, or alternative fuel sources could mitigate these impacts.
- Additional investments in green logistics could be considered to maintain regulatory compliance and improve cost efficiency.

2.10.5 Fleet report

The fleet investment calculation involves determining the total cost of acquiring and maintaining different types of vehicles used in logistics operations. Below is a breakdown of each component and the mathematical formulas used.

Vehicle Purchase Cost Calculation The total investment starts with the cost of purchasing different types of vehicles. Each vehicle type has a unit price, and the total cost is computed as:

$$C_{\text{total}} = P \times N \tag{80}$$

where:

- C_{total} = Total cost for a vehicle type
- P = Unit price per vehicle
- N = Number of vehicles

Using the given prices and fleet sizes:

$$C_{\text{semi}} = 150,000 \times 17 = 2,550,000 \text{ euros} \tag{81}$$
$$C_{\text{heavy}} = 100,000 \times 5 = 500,000 \text{ euros} \tag{82}$$
$$C_{\text{light\_rigid}} = 50,000 \times 4 = 200,000 \text{ euros} \tag{83}$$
$$C_{\text{light\_commercial}} = 30,000 \times 9 = 270,000 \text{ euros} \tag{84}$$

Thus, the total vehicle purchase cost is:

$$C_{\text{total\_purchase}} = C_{\text{semi}} + C_{\text{heavy}} + C_{\text{light\_rigid}} + C_{\text{light\_commercial}} \tag{85}$$

$$C_{\text{total\_purchase}} = 3,520,000 \text{ euros} \tag{86}$$

Additional Costs Apart from vehicle acquisition, the fleet requires additional costs for registration, insurance, and maintenance.

$$C_{\text{additional}} = C_{\text{registration}} + C_{\text{insurance}} + C_{\text{maintenance}} \tag{87}$$

Registration Cost Each vehicle requires €1,000 for registration:

$$C_{\text{registration}} = 1,000 \times (N_{\text{semi}} + N_{\text{heavy}} + N_{\text{light\_rigid}} + N_{\text{light\_commercial}}) \tag{88}$$

Insurance Cost Each vehicle requires €2,000 for insurance:

$$C_{\text{insurance}} = 2,000 \times (N_{\text{semi}} + N_{\text{heavy}} + N_{\text{light\_rigid}} + N_{\text{light\_commercial}}) \tag{89}$$

Maintenance Cost Each vehicle requires €5,000 for annual maintenance:

$$C_{\text{maintenance}} = 5,000 \times (N_{\text{semi}} + N_{\text{heavy}} + N_{\text{light\_rigid}} + N_{\text{light\_commercial}}) \tag{90}$$

Summing up these costs:

$$C_{\text{additional}} = 280,000 \text{ euros} \tag{91}$$

Total Investment Cost The total fleet investment cost is the sum of vehicle purchase cost and additional costs:

$$C_{\text{total\_investment}} = C_{\text{total\_purchase}} + C_{\text{additional}} \tag{92}$$

$$C_{\text{total\_investment}} = 3,520,000 + 280,000 = 3,800,000 \text{ euros} \tag{93}$$

Summary of Fleet Investment Costs The final breakdown of costs is presented in the table below:

Item	**Cost (euros)**
Total cost for semi-trailer trucks	2,550,000
Total cost for heavy rigid trucks	500,000
Total cost for light rigid trucks	200,000
Total cost for light commercial vehicles	270,000
Total vehicle purchase cost	**3,520,000**
Additional costs (registration, insurance, maintenance)	280,000
Total investment cost (including additional costs)	**3,800,000**

Table 5: Summary of Fleet Investment Costs

Observations and Implications

- **Semi-trailer trucks** contribute the highest cost due to their high unit price (€150,000 each) and large fleet size.
- **Additional costs** such as registration, insurance, and maintenance represent a significant recurring expense in fleet operations.
- **Scaling up the fleet** significantly impacts total costs, emphasizing the need for cost-efficient alternatives such as leasing, fuel-efficient vehicles, or electrification.

Fleet Operating Cost, Energy Consumption, and Greenhouse Gas Emissions (2026–2033)
The fleet-related Operating Costs, Energy Consumption, and Greenhouse Gas (GHG) Emissions have already been incorporated into the calculations for Distribution Centers (DCs), Fulfillment Centers (FCs), and the Supply Warehouse. This section details how each component was accounted for.

Fleet Operating Cost Fleet operation costs were embedded within Fuel Costs in the DC, FC, and Supply Warehouse calculations. Since driver costs were removed, the total fleet operating expenditure is now driven primarily by fuel consumption.

Formula The fleet operating cost is calculated as:

$$C_{\text{fleet}} = F \times P_{\text{fuel}} \tag{94}$$

where:

- C_{fleet} = Fleet operating cost (€)
- F = Fuel consumption (L)
- P_{fuel} = Fuel price (€ per L)

Integration in Facility Costs

- Fuel consumption was computed separately for DC-to-FC transport (DC Fleet) and FC-to-Customer transport (FC Fleet).
- Fuel price increases annually, causing fleet operating costs to rise.
- The fuel cost component was integrated into each facility's Total Operating Expenditure (OpEx).
- Example: In the Supply Warehouse, fuel costs increase from €88,790 in 2026 to €265,610 in 2033 due to rising transport demand and fuel prices.

Fleet Energy Consumption Fleet energy consumption is indirectly represented by fuel consumption in liters, as diesel is the primary energy source for transportation.

Formula

$$E_{\text{fleet}} = F \times 38.6 \tag{95}$$

where:

- E_{fleet} = Fleet energy consumption (MJ)
- F = Fuel consumption (L)
- 38.6 MJ/L = Energy content of diesel

Integration in Facility Costs

- Fuel consumption values were extracted from DC_yearly_summary.csv and FC_yearly_summary.csv to ensure complete coverage.
- Example: Supply Warehouse fuel consumption increases from 170,685L in 2026 to 444,500L in 2033, leading to higher energy demands.

Fleet Greenhouse Gas (GHG) Emissions GHG emissions result from fuel combustion during transport operations. The emission factor for diesel is used to determine CO emissions.

Formula

$$G_{\text{fleet}} = F \times 2.68 \tag{96}$$

where:

- G_{fleet} = Fleet greenhouse gas emissions (kg CO)
- F = Fuel consumption (L)
- 2.68 kg CO/L = Diesel emission factor

Integration in Facility Costs

- GHG emissions for fleet operations were computed separately for DC and FC transport routes and then added to facility-level GHG emissions.
- Example: In DC_Metz, emissions increased from 788,562 kg CO in 2026 to 832,780 kg CO in 2033, reflecting higher transport activity.
- Supply Warehouse emissions rose from 776,042 kg CO in 2026 to 1,612,450 kg CO in 2033, due to growing fuel consumption.

Conclusion

- The Fleet Operating Costs, Energy Consumption, and GHG Emissions were fully integrated into the DC, FC, and Supply Warehouse calculations.
- There is no need for separate fleet calculations, as these values were already embedded in fuel costs and total operating expenditures (OpEx).
- The increasing costs, energy consumption, and emissions suggest that **alternative fuel strategies, optimized routing, or fleet electrification could improve sustainability.

3 Task 3

3.1 Strengths & Weaknesses Analysis of BotWorld's Supply Chain

3.1.1 Strengths

Optimized Fulfillment Network **Strength:** The fulfillment network was designed to minimize the number of fulfillment centers (FCs) while ensuring next-day and three-day delivery commitments across all target markets. The use of Integer Linear Programming (ILP) and geographic data analysis allowed for an efficient and cost-effective network that covers all major European cities.

Impact: This optimization reduces transportation costs and ensures timely delivery, which is critical for customer satisfaction and competitive advantage.

Dynamic Production Line Strategy **Strength:** The production line strategy balances cost efficiency and flexibility. By using multi-category assembly lines during stable periods and dedicated lines during peak seasons (e.g., Black Friday), the factory can handle demand surges without significant inventory backlogs.

Impact: This approach allows BotWorld to maintain high production efficiency while being responsive to seasonal demand fluctuations, reducing the risk of stockouts or overproduction.

Robust Inventory Management **Strength:** The supply chain design includes a four-week safety stock policy and a level production strategy with a 20% increase in production before Black Friday. This ensures that BotWorld can meet demand spikes without overburdening the factory or distribution centers.

Impact: The safety stock and production adjustments provide a buffer against demand uncertainty, ensuring that BotWorld can maintain service levels even during peak periods.

Efficient Fleet Management **Strength:** The fleet was optimized using linear programming (LP) models to minimize fuel consumption and emissions. The fleet includes a mix of semi-trailer trucks, heavy rigid trucks, light rigid trucks, and light commercial vehicles, ensuring that transportation needs are met efficiently.

Impact: This optimization reduces operational costs and environmental impact, aligning with sustainability goals while maintaining delivery efficiency.

Data-Driven Decision Making **Strength:** The entire supply chain design was supported by data-driven simulations, including Monte Carlo simulations for demand forecasting and scenario analysis for inventory and production planning. This approach allows BotWorld to anticipate and prepare for various demand scenarios.

Impact: Data-driven decision-making ensures that the supply chain is resilient and adaptable to market changes, reducing the risk of disruptions.

Scalability **Strength:** The supply chain is designed to scale with demand growth over the 2026-2033 horizon. The number of assembly lines, fulfillment centers, and fleet vehicles can be adjusted based on demand projections, ensuring that BotWorld can expand its operations without major overhauls.

Impact: This scalability allows BotWorld to grow its market presence in Europe while maintaining operational efficiency.

3.1.2 Weaknesses

High Initial Capital Expenditure (CapEx) **Weakness:** The initial investment in 2026 is significant, with €12.07 million allocated for the distribution center (DC) and €9.72 million for the supply warehouse. Additionally, the fleet investment is €3.8 million. These high upfront costs may strain BotWorld's financial resources.

Impact: The high CapEx could limit BotWorld's ability to invest in other areas, such as marketing or product development, especially in the early years of market entry.

Dependence on Fuel-Based Transportation **Weakness:** The fleet relies heavily on diesel-powered vehicles, which contribute to greenhouse gas (GHG) emissions. The emissions from the fleet are projected to increase over time, potentially exceeding EU emission limits by 2029.

Impact: This reliance on fossil fuels could lead to regulatory challenges and reputational risks, especially as sustainability becomes a more critical concern for consumers and governments.

Limited Flexibility in FC Sizes **Weakness:** The fulfillment centers are categorized into small, medium, and large sizes based on demand projections. However, this rigid categorization may limit flexibility in adjusting to unexpected demand changes or market expansions.

Impact: If demand in certain regions grows faster than expected, the FCs may struggle to handle the increased volume, leading to potential delays or stockouts.

Potential Overstocking **Weakness:** The level production strategy and safety stock policy may lead to overstocking during periods of low demand, especially in the early years of market entry. This could result in higher inventory holding costs and capital lock-in.

Impact: Overstocking could reduce BotWorld's profitability, especially if demand does not meet projections in certain regions or product categories.

Complexity in Cross-Border Logistics **Weakness:** The supply chain design assumes smooth cross-border logistics within the EU. However, real-world complexities such as customs delays, cross-border regulations, and infrastructure limitations could disrupt operations, especially in Eastern Europe.

Impact: These disruptions could lead to delays in delivery, increased transportation costs, and potential customer dissatisfaction.

Limited Focus on Sustainability **Weakness:** While the fleet optimization reduces emissions, the overall supply chain design does not fully integrate sustainable practices, such as renewable energy for warehouses or electric vehicles for last-mile delivery.

Impact: As sustainability becomes a key concern for consumers and regulators, BotWorld may face pressure to adopt greener practices, which could require additional investments in the future.

Conclusion The designed supply chain for BotWorld has several strengths, including an optimized fulfillment network, dynamic production strategies, and robust inventory management. However, it also faces challenges such as high initial capital expenditure, reliance on fuel-based transportation, and potential overstocking. To address these weaknesses, BotWorld could consider investing in sustainable transportation solutions, flexible FC designs, and cross-border logistics partnerships to enhance the resilience and sustainability of its supply chain.

3.2 Executive Summary: Key Findings & Recommendations for BotWorld

3.2.1 Key Findings

Between 2026 and 2033, Germany, France, and the United Kingdom are projected to be BotWorld's largest markets due to their significant populations and strong purchasing power. Additionally, countries like Spain, Poland, and Sweden are showing consistent demand growth, making them appealing for future expansion strategies. Conversely, Latvia and Bulgaria present challenges, as they are expected to experience slower demand growth due to economic and demographic factors.

Demand trends reveal a steady increase from Monday to Friday, peaking on Fridays and during Black Friday, which alone accounts for 18% of annual sales. Mid-range models, such as the F10 (Floor Care) and K10 (Kitchen Help), are the most popular, while high-end models show lower demand. Seasonal fluctuations and special events like Black Friday significantly influence inventory management and logistics planning.

The supply chain network is optimized to minimize the number of Fulfillment Centers (FCs) while ensuring next-day delivery in major cities and 72-hour delivery in other regions. Key FCs are strategically located in cities like Liège and Manchester to optimize market coverage and reduce transportation costs. The Distribution Center (DC) in Metz, France, effectively handles outbound logistics, supported by a robust inventory strategy that ensures product availability.

The factory near Metz operates with a level production strategy, which increases output by 20% before peak periods such as Black Friday. Safety stock is maintained at 10% of annual demand to ensure supply continuity during demand surges. Assembly lines are dynamically scaled to match demand growth, increasing from 9 in 2026 to 27 by 2033.

A mixed fleet of semi-trailer trucks, rigid trucks, and light commercial vehicles ensures efficient transportation between facilities. Optimized routing and high vehicle fill rates contribute to reduced fuel consumption and greenhouse gas emissions. This supply chain design supports sustainability goals while maintaining cost efficiency.

3.2.2 Recommendations

Investments should be prioritized in Germany, France, and the UK to maximize revenue, with additional focus on expanding into emerging markets like Poland and Sweden to capture growth opportunities. Production schedules should be adjusted to accommodate seasonal fluctuations and peak demand periods, while flexible inventory management strategies should be implemented to reduce storage costs and improve turnover rates.

The fulfillment network and logistics should be continuously optimized by regularly reviewing FC locations and capacities to ensure cost efficiency and optimal market coverage. Specialized logistics frameworks should be developed to handle high-demand periods like Black Friday efficiently.

Long-term market trends must be considered, particularly demographic changes in countries with declining populations. Strategies should be adjusted accordingly, with exploration of product diversification and expansion into non-European markets to sustain long-term growth.

Investments in energy-efficient technologies and sustainable packaging solutions are recommended to enhance the company's sustainability profile. Regular assessment and reduction of the environmental impact of logistics operations will further support BotWorld's commitment to sustainability.

By adopting these strategies, BotWorld can ensure a resilient, efficient, and sustainable supply chain that supports its growth in the European market from 2026 to 2033.

3.3 Impact Assessment of a Fully Implemented Physical Internet in Europe

BotWorld Structure and Characteristics. BotWorld operates an integrated supply chain network with factories, a central warehouse, distribution centers (DCs), and fulfillment centers (FCs). **Demand forecasting** is driven by historical data, Monte Carlo simulations, and market models to generate weekly and daily demand across the 2026–2033 horizon. BotWorld already uses limited **IoT techniques**, such as real-time inventory monitoring and vehicle tracking, although most logistics operations follow predetermined routes and schedules. **Logistics optimization** includes fleet planning (semi-trailers, heavy/light trucks, and vans), capacity checks (warehouse/DC/FC), and route optimizations to reduce costs and maintain service quality. The structure ensures resilience during major events like **Black Friday** but remains largely static and facility-bound.

European Demand Characteristics. Within Europe, **population decline** or stagnation means total demand can plateau or even decrease, regardless of a company's growing market share. **Labor shortages** are an ongoing concern, especially for warehouse workers and truck drivers. **High-density urban centers** (e.g., Berlin, Paris, London) create localized surges in demand. Meanwhile, **cross-border complexity** adds layers of cost and regulatory checks, impacting lead times. Finally, **regional variation** in e-commerce adoption and economic conditions makes consistent long-term planning challenging.

Potential Benefits of a Mature Physical Internet. If Europe had achieved a fully **integrated Physical Internet (PI)**, BotWorld's supply chain could evolve in several ways:

Demand Fulfillment: Real-time data sharing would offer near-instant forecasting updates, enabling more **responsive and localized** inventory placement. **Shared fulfillment centers** could reduce delivery times and costs, turning BotWorld's current "fixed" FCs into collaborative, flexible hubs.

Transportation: Optimized routing and real-time **load matching** would cut empty miles and shorten lead times. Physical Internet standards would simplify **cross-border** movements and reduce paperwork. **Intelligent pallets** with sensors could boost cargo visibility, minimize losses, and improve transport safety.

Storage: Smart inventory monitoring would lower overstock risks, as **shared warehouse networks** become feasible. Through universal traceability, BotWorld could keep more streamlined buffer stocks and reallocate goods quickly when demand fluctuates between regions.

Production: In a real-time PI setting, factories could **dynamically adapt** their schedules based on instantaneous demand signals. High-demand events like **Black Friday** would rely less on manual forecast spikes and more on continuous data-driven updates. This reduces **overproduction** and addresses labor constraints more efficiently.

Supply: The entire supply ecosystem gains from **end-to-end transparency**. Data from suppliers, DCs, and FCs would integrate under shared protocols, improving collaboration and **resilience**. Supply bottlenecks could be quickly bypassed as materials or products route through alternate nodes, mitigating risks and local disruptions.

Drawbacks and Challenges. While promising, **Physical Internet adoption** would require significant **IT investments**, standardized protocols, and robust data security measures. Companies must share sensitive operational data, raising **confidentiality** issues. Varying regulations across Europe could also slow or complicate full PI implementation, particularly in areas that still favor **traditional logistics** practices.

Conclusion. A fully mature **Physical Internet** promises a more agile, collaborative, and transparent supply chain for BotWorld. **Demand fulfillment** becomes faster and more accurate, **transportation** costs drop through dynamic routing, **storage** relies on shared networks, and **production** becomes more responsive to short-term market shifts. However, high integration costs, data privacy concerns, and regulatory barriers remain potential stumbling blocks. If these challenges can be managed, the benefits to BotWorld's network—and to European logistics as a whole—are substantial, fostering a robust, efficient, and future-proof supply chain.

3.4 Key Learnings & Reflections from the Case Study

3.4.1 Key Learnings from BotWorld's European Supply Chain Design Casework

Throughout the BotWorld European supply chain design case study, we gained profound insights into market demand forecasting and supply chain network planning. The entire process resembled a multidimensional puzzle, where every decision influenced the overall efficiency and cost, while data served as the fundamental thread connecting all pieces.

Market Demand Forecasting From **Task 1**, we deeply understood the strategic importance of forecasting. By integrating population data from target countries with product demand models, we realized that demand is not a static number but a dynamic variable influenced by seasonal fluctuations, promotional events, and consumer behavior patterns.

For instance, the **18% demand surge during Black Friday** may seem like an opportunity but actually tests supply chain resilience—without proper buffer stock, the system risks collapsing under short-term overload. This made us recognize that forecasting should not rely solely on historical data but incorporate scenario simulation, using **Monte Carlo simulation** to generate thousands of potential demand fluctuation paths, preparing buffer strategies for extreme cases.

This dynamic perspective reshaped our traditional view of stable production and led us to embrace a **flexible response philosophy**.

Supply Chain Network Design Moving on to **Task 2**, the challenge became even more intricate. Selecting fulfillment center (FC) locations felt like placing pieces on a chessboard—we needed to ensure **next-day delivery** for 50 major metropolitan areas in Europe while minimizing transportation costs from the central distribution center (DC) to each FC.

Initially, we applied a **clustering algorithm** to group nearby markets under the same FC, only to find that cross-border traffic regulations, mountainous terrains, and real-world transit delays disrupted theoretical models. Ultimately, we adopted a **hybrid heuristic approach**, integrating real-time transportation data via mapping APIs to redefine the "five-hour service radius" more realistically.

This process taught us that while mathematical models provide direction, **real-world complexities demand manual calibration and strategic compromises**. For instance, to cover remote Nordic regions, we added a small FC in Norway—despite slightly increasing network costs, it ensured a crucial market presence.

Production Line Strategy Production line configuration became a **balancing act between cost and flexibility**. Initially, we favored **multi-category assembly lines** to reduce marginal costs. However, during peak seasons—such as **Black Friday's surge in F50 robotic vacuum orders**—we discovered that **dedicated lines for high-demand models** could mitigate inventory backlogs more effectively.

This led us to design a **"dynamic production line mix"**—using **multi-category lines** during stable periods to optimize cost efficiency while activating **dedicated lines** for rapid response in peak seasons. This approach highlighted the trade-off between **economies of scale** and **economies of scope**, making us realize that **"optimization" is not about pursuing a single best solution but about dynamically adjusting strategies based on business rhythms**.

Transportation Network Optimization Designing the transportation network pushed us into **meticulous detail analysis**. Initially, we assumed **semi-trailer trucks** would cover most of the long-haul transport due to their high payload capacity. However, after incorporating **cargo volume constraints**, we found that certain MyBot models—such as **S50 security bots**—had oversized protective packaging, leading to an actual loading efficiency of only **60%** of theoretical capacity.

This forced us to rethink **mixed-load strategies** and even customize **foldable packaging solutions** for specific models. This experience reinforced the lesson that **logistics planning must go beyond basic weight and distance calculations, delving into the micro-level characteristics of cargo**.

Data-Driven Decision Making and Collaboration Throughout the study, **team collaboration** proved invaluable. When disputes arose over **inventory model parameters**, we used a **"data sandbox simulation"** to resolve conflicts—inputting different strategies into the simulator and visualizing results through **inventory turnover rate** and **stockout probability**. This **data-driven decision-making approach** was far more effective than theoretical debates.

Moreover, **time management emerged as a silent orchestrator**—we allocated two weeks for **Black Friday demand forecasting** but underestimated debugging complexity, which delayed implementation by three days. This reminded us to always account for **unforeseen complexity and maintain buffer time**.

Final Reflections Looking back, BotWorld's casework acted as a **prism**, reflecting **future supply chain management trends**: shifting from **rigid efficiency** to **resilient networks**, from **local optimization** to **global collaboration**.

If Europe were to fully implement the **Physical Internet**, our FC network might no longer rely on self-built facilities but instead operate through **shared logistics hubs** and **AI-driven routing algorithms**, dynamically allocating shipments like data packets in a network.

While this vision is not yet fully realized, it has provided a clear direction—the future supply chain will be **open, interconnected, and sustainable**. This case study has been a **foundation for us to grasp that future**.