

Consulting Project: TechMart Inventory Optimization

Management Science - E-commerce Inventory Management

Client Briefing: TechMart Electronics

Meet Your Client

- Industry: E-commerce / Electronics Retail
- Client Contact: Yola Wang, Chief Operations Officer
- Company Size: 200 employees
- Market: Consumer electronics in Germany

The COO's Inventory Crisis

Yola Wang, COO of TechMart

“We’re drowning in inventory but constantly out of stock on bestsellers. It makes no sense!

Here’s our situation: We sell 30 electronics SKUs online: smartphones, laptops, headphones, smartwatches, tablets. We have two warehouses:

- Fast Warehouse (Hamburg): Right next to our shipping hub. Orders ship in 1-2 hours. But it’s small and has only 8,000 unit capacity.
- Large Warehouse (Poland): Huge storage (50,000+ capacity) but orders take 2-3 days to ship from there.

The problem? We’re making terrible allocation decisions:

- Slow-movers occupy 40% of fast warehouse space
- Shipping delays costing us hundreds of thousands annually in customer refunds
- Customer complaints about “2-day delivery” are up 60%

Black Friday is in 3 weeks. Last year was a disaster... We ran out of top items in the fast warehouse on Day 1, then spent a week scrambling with slow shipping from Poland. Lost a lot of potential revenue.

Here’s the critical constraint: Once Black Friday starts, we CANNOT refill the Hamburg warehouse. All our warehouse staff are 100% busy picking and packing orders and there’s zero time for restocking. Whatever allocation we make beforehand is what we’re stuck with for the entire weeks!

I need you to:

1. Forecast Black Friday demand for each SKU (weeks 47-48)

2. Decide which SKUs (and how many units) to pre-position in the fast warehouse (limited to 8,000 units!)
3. Minimize shipping delay costs
4. Show me the business impact in €€€

I have 3 years of sales history. Can you help us get this right before Black Friday?“

The Business Context

Warehouse System

Fast Warehouse (Hamburg)

- Capacity: 8,000 units total
- Shipping speed: 1-2 hours processing, next-day delivery
- Storage cost: €2.50 per unit (for Black Friday period)
- Perfect for: High-demand, fast-moving items

Large Warehouse (Poland)

- Capacity: 50,000+ units (effectively unlimited for our needs)
- Shipping speed: 2-3 days processing, 2-3 days delivery (4-6 days total!)
- Storage cost: €0.80 per unit (for Black Friday period)
- Perfect for: Slow-movers, bulk storage

The Allocation Problem

Before Black Friday:

You must decide how many units of each SKU to pre-position in the fast warehouse (Hamburg) vs. large warehouse (Poland).

Critical Constraints:

- Total units in fast warehouse $\leq 8,000$
- No refilling during Black Friday! All warehouse staff are busy handling the surge, whatever you allocate is fixed for the entire weekend

During Black Friday:

- Units in Fast Warehouse (Hamburg): Ship quickly (1-2 days), customers happy, no delay penalty
- Units in Large Warehouse (Poland): Ship slowly (4-6 days), customers complain, delay penalty applies

Your Goal: Decide how many units of each SKU go in Hamburg warehouse to minimize total delay penalty costs. Note: While storage costs differ, Yola cares most about customer satisfaction. Minimize the delay penalties first.

Note

Note, we have sufficient total inventory of each SKU. The question is WHERE to store each unit before Black Friday!

💡 Tip

Example Allocation:

```
SKU-001: 450 units in Hamburg, rest in Poland
SKU-002: 380 units in Hamburg, rest in Poland
SKU-003: 0 units in Hamburg, all in Poland
...
SKU-030: 200 units in Hamburg, rest in Poland
Total: ≤ 8,000 units in Hamburg
```

Cost Structure

Delay Penalty (per unit from Poland warehouse):

- 15% of customers cancel order: lost sale (50 % of product price as opportunity costs)
- 85% of customers wait but demand partial refund: €10 compensation

Customer Expectations

- High-demand items: Customers expect 1-2 day delivery (Hamburg warehouse)
- Low-demand items: Customers more tolerant of 4-6 day delivery (Poland warehouse)
- Black Friday: Everyone expects fast delivery! High delay costs for all SKUs.

The Data: 3 Years of Sales History

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime, timedelta

# Set random seed for reproducibility
np.random.seed(2025)

def generate_techmart_sales_history():
    """
    Generate 3 years of sales history for 30 electronics SKUs.
    """

    # Define 30 SKUs across 5 categories with category-specific trends
    # Trend: annual growth/decline rate (e.g., 0.05 = 5% growth per year)
    categories = {
        'Smartphones': {'count': 8, 'trend': -0.15}, # Mature market,
        'Laptops': {'count': 6, 'trend': 0.11},      # Stable with slight
        'Headphones': {'count': 6, 'trend': 0.18},   # Growing premium
        'Smartwatches': {'count': 5, 'trend': 0.22}, # Emerging category,
        'Tablets': {'count': 5, 'trend': -0.15}      # Declining market
    }
```

```

skus = []
sku_id = 1
for category, cat_info in categories.items():
    count = cat_info['count']
    category_trend = cat_info['trend']

    for i in range(count):
        # Each product has unique characteristics
        if category == 'Smartphones':
            base_demand = np.random.uniform(100, 410)
        elif category == 'Laptops':
            base_demand = np.random.uniform(90, 220)
        elif category == 'Headphones':
            base_demand = np.random.uniform(20, 210)
        elif category == 'Smartwatches':
            base_demand = np.random.uniform(20, 140)
        elif category == 'Tablets':
            base_demand = np.random.uniform(80, 170)

        # Seasonal strength: how much seasonality affects this product
        (0.1-0.3)
        seasonal_strength = np.random.uniform(0.1, 0.3)

        # Noise level: product-specific volatility (std: 0.08-0.20)
        noise_std = np.random.uniform(0.03, 0.25)

        # Black Friday boost: product-specific multiplier (1.1-1.5)
        bf_multiplier = np.random.uniform(1.1, 1.5)

        skus.append({
            'sku_id': f'SKU-{sku_id:03d}',
            'category': category,
            'base_demand': base_demand,
            'seasonal_strength': seasonal_strength,
            'noise_std': noise_std,
            'bf_multiplier': bf_multiplier,
            'category_trend': category_trend,
            'price': np.random.uniform(30, 1200)
        })
        sku_id += 1

skus_df = pd.DataFrame(skus)

# Generate weekly sales from 2023-01-01 to 2025-11-15 (almost 3 years)
start_date = datetime(2023, 1, 1)
end_date = datetime(2025, 11, 15)
weeks = pd.date_range(start_date, end_date, freq='W')

sales_data = []

for _, sku in skus_df.iterrows():
    for week_start in weeks:
        week_num = week_start.isocalendar()[1]

```

```

        year = week_start.year
        month = week_start.month

        # Base demand (unique per product)
        demand = sku['base_demand']

        # Component 1: Category-specific trend (small, linear over
time)
        # Calculate years elapsed from start date (2023-01-01)
        years_elapsed = (week_start - start_date).days / 365.25
        trend_multiplier = 1.0 + (sku['category_trend'] *
years_elapsed)
        demand *= trend_multiplier

        # Component 2: Annual cycle (52 weeks) - peak in Nov/Dec (Q4),
trough in summer (Q3)
        annual_seasonality = 1.0 + sku['seasonal_strength'] * np.cos(2
* np.pi * (week_num - 47) / 52)

        # Component 3: Quarterly cycle (13 weeks) - shorter-term
fluctuations
        quarterly_seasonality = 1.0 + (sku['seasonal_strength'] * 0.5)
* np.sin(2 * np.pi * week_num / 13)

        demand *= annual_seasonality * quarterly_seasonality

        # Black Friday boost (product-specific multiplier)
        if week_num in [47, 48]:
            demand *= sku['bf_multiplier']

        # Add normally distributed random noise (product-specific
volatility)
        noise = np.random.normal(1.0, sku['noise_std'])
        demand *= max(0.5, min(1.5, noise)) # Clip to reasonable range

        # Round to integer
        demand = max(0, int(demand))

        sales_data.append({
            'sku_id': sku['sku_id'],
            'week_start': week_start,
            'year': year,
            'week': week_num,
            'month': month,
            'units_sold': demand
        })

    sales_df = pd.DataFrame(sales_data)

    return skus_df, sales_df

# Generate data
skus_df, sales_df = generate_techmart_sales_history()

```

```

print("TECHMART ELECTRONICS - SKU CATALOG")
print("=" * 120)
print(skus_df.to_string(index=False))
print("\n" + "=" * 120)
print(f"Total SKUs: {len(skus_df)}")
print("\nBy category:")
for category in skus_df['category'].unique():
    count = len(skus_df[skus_df['category'] == category])
    print(f" {category}: {count} SKUs")

```

TECHMART ELECTRONICS - SKU CATALOG

sku_id	category	base_demand	seasonal_strength	noise_std
bf_multiplier	category_trend	price		
SKU-001	Smartphones	142.001331	0.277570	0.235173
1.278227	-0.15	484.235589		
SKU-002	Smartphones	179.854895	0.231474	0.138376
1.485695	-0.15	967.151836		
SKU-003	Smartphones	241.113638	0.260212	0.039178
1.407783	-0.15	33.710207		
SKU-004	Smartphones	190.770912	0.222183	0.230866
1.220046	-0.15	320.860405		
SKU-005	Smartphones	306.581553	0.297507	0.133019
1.149315	-0.15	1101.756722		
SKU-006	Smartphones	393.304495	0.155539	0.144324
1.161898	-0.15	47.114003		
SKU-007	Smartphones	200.515394	0.298180	0.142891
1.450598	-0.15	108.853024		
SKU-008	Smartphones	188.087659	0.193780	0.197590
1.469045	-0.15	489.837796		
SKU-009	Laptops	210.781398	0.199922	0.206451
1.458632	0.11	594.091018		
SKU-010	Laptops	200.230887	0.155336	0.104850
1.142030	0.11	642.082831		
SKU-011	Laptops	174.306043	0.279922	0.052851
1.224698	0.11	121.380883		
SKU-012	Laptops	211.923125	0.291817	0.072073
1.481608	0.11	549.536481		
SKU-013	Laptops	124.245171	0.233980	0.112779
1.494186	0.11	810.475763		
SKU-014	Laptops	218.890762	0.294713	0.069920
1.276549	0.11	817.168259		
SKU-015	Headphones	144.177841	0.176608	0.177231
1.387934	0.18	946.536415		
SKU-016	Headphones	80.986683	0.119412	0.213572
1.110089	0.18	309.358839		
SKU-017	Headphones	182.850584	0.110092	0.072704
1.290362	0.18	305.164876		
SKU-018	Headphones	88.229309	0.129033	0.059840
1.139115	0.18	207.471104		
SKU-019	Headphones	47.458748	0.105895	0.190427
1.370478	0.18	548.940060		
SKU-020	Headphones	43.726319	0.135155	0.164134

1.208759	0.18	863.933878		
SKU-021 Smartwatches	63.921751		0.155961	0.223931
1.166687	0.22	147.990342		
SKU-022 Smartwatches	136.894623		0.291290	0.057567
1.152603	0.22	428.359589		
SKU-023 Smartwatches	80.065334		0.269516	0.155000
1.186574	0.22	757.086860		
SKU-024 Smartwatches	66.345697		0.176956	0.071607
1.482957	0.22	174.054069		
SKU-025 Smartwatches	30.384036		0.220347	0.161101
1.150430	0.22	749.579075		
SKU-026 Tablets	109.464296		0.169059	0.104956
1.148955	-0.15	1140.611174		
SKU-027 Tablets	111.850145		0.198087	0.043744
1.295709	-0.15	439.401212		
SKU-028 Tablets	166.496499		0.152798	0.191875
1.299498	-0.15	1114.312833		
SKU-029 Tablets	140.870051		0.114547	0.087424
1.174714	-0.15	783.925103		
SKU-030 Tablets	85.573274		0.168057	0.138067
1.413962	-0.15	71.210130		

=====
Total SKUs: 30

By category:

Smartphones: 8 SKUs
Laptops: 6 SKUs
Headphones: 6 SKUs
Smartwatches: 5 SKUs
Tablets: 5 SKUs

Sales History Overview

```
print("\nSALES HISTORY SUMMARY")
print("=" * 80)
print(f>Date range: {sales_df['week_start'].min().date()} to
{sales_df['week_start'].max().date()})
print(f>Total weeks: {sales_df['week_start'].nunique()})
print(f>Total records: {len(sales_df):,})
print(f>Total units sold (3 years): {sales_df['units_sold'].sum():,})

# Show sample of sales data
print("\nSample sales data (first 20 records):")
print(sales_df.head(20).to_string(index=False))
```

SALES HISTORY SUMMARY

=====
Date range: 2023-01-01 to 2025-11-09
Total weeks: 150
Total records: 4,500

Total units sold (3 years): 674,482

Sample sales data (first 20 records):

sku_id	week_start	year	week	month	units_sold
SKU-001	2023-01-01	2023	52	1	233
SKU-001	2023-01-08	2023	1	1	255
SKU-001	2023-01-15	2023	2	1	158
SKU-001	2023-01-22	2023	3	1	221
SKU-001	2023-01-29	2023	4	1	202
SKU-001	2023-02-05	2023	5	2	150
SKU-001	2023-02-12	2023	6	2	146
SKU-001	2023-02-19	2023	7	2	173
SKU-001	2023-02-26	2023	8	2	78
SKU-001	2023-03-05	2023	9	3	138
SKU-001	2023-03-12	2023	10	3	143
SKU-001	2023-03-19	2023	11	3	93
SKU-001	2023-03-26	2023	12	3	150
SKU-001	2023-04-02	2023	13	4	136
SKU-001	2023-04-09	2023	14	4	148
SKU-001	2023-04-16	2023	15	4	117
SKU-001	2023-04-23	2023	16	4	89
SKU-001	2023-04-30	2023	17	4	104
SKU-001	2023-05-07	2023	18	5	54
SKU-001	2023-05-14	2023	19	5	81

Warehouse Capacity Analysis

```
# Analyze capacity feasibility
warehouses = {
    'Fast Warehouse (Hamburg)': {
        'capacity': 8000, # units
        'description': 'Premium location, fast shipping, limited space'
    },
    'Large Warehouse (Poland)': {
        'capacity': 100000, # 50000 units (effectively unlimited)
        'description': 'Cheap storage, slow shipping, huge space'
    }
}

print("\nWAREHOUSE SPECIFICATIONS")
print("=" * 80)
for warehouse, specs in warehouses.items():
    print(f"\n{warehouse}:")
    for key, value in specs.items():
        if key != 'description':
            print(f"    {key}: {value}")
    print(f"    → {specs['description']}")

print("\n" + "=" * 80)
print("KEY CONSTRAINT: Fast warehouse can only hold 8,000 units total!")
print("\nALLOCATION DECISION:")
print("    - You must forecast Black Friday demand for each SKU")
```



```
print(" - Then decide which SKUs to store in fast warehouse")
print(" - Goal: Minimize total delay costs!")
```

WAREHOUSE SPECIFICATIONS

```
Fast Warehouse (Hamburg):
    capacity: 8000
    → Premium location, fast shipping, limited space
```

```
Large Warehouse (Poland):
    capacity: 100000
    → Cheap storage, slow shipping, huge space
```

```
=====
KEY CONSTRAINT: Fast warehouse can only hold 8,000 units total!
```

ALLOCATION DECISION:

- You must forecast Black Friday demand for each SKU
- Then decide which SKUs to store in fast warehouse
- Goal: Minimize total delay costs!

Minimal Helper Functions

We provide only basic data access and cost calculation functions. You must implement forecasting, optimization, and simulation yourself.

```
def get_sku_sales_history(sku_id, sales_df):
    """
    Get sales history for a specific SKU.

    Args:
        sku_id: SKU identifier (e.g., 'SKU-001')
        sales_df: DataFrame with sales history

    Returns:
        DataFrame with weekly sales for the SKU
    """
    return sales_df[sales_df['sku_id'] ==
sku_id].sort_values('week_start').reset_index(drop=True)
```

```
def plot_sku_sales_trend(sku_id, sales_df, skus_df):
    """Plot sales trend for a specific SKU."""
    sku_history = get_sku_sales_history(sku_id, sales_df)
    sku_info = skus_df[skus_df['sku_id'] == sku_id].iloc[0]

    plt.figure(figsize=(14, 5))
    plt.plot(sku_history['week_start'], sku_history['units_sold'],
linewidth=1.5)
    plt.axhline(y=sku_info['base_demand'], color='red', linestyle='--',
```

```

        label=f'Base Demand: {sku_info["base_demand"]}', alpha=0.7)

# Highlight Black Friday weeks
bf_weeks = sku_history[sku_history['week'].isin([47, 48])]
plt.scatter(bf_weeks['week_start'], bf_weeks['units_sold'],
            color='orange', s=100, zorder=5, label='Black Friday')

plt.xlabel('Date', fontsize=12)
plt.ylabel('Units Sold', fontsize=12)
plt.title(f'{sku_id} Sales History - {sku_info["category"]} (Base:
{sku_info["base_demand"]} units/week)',
          fontsize=14, fontweight='bold')
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

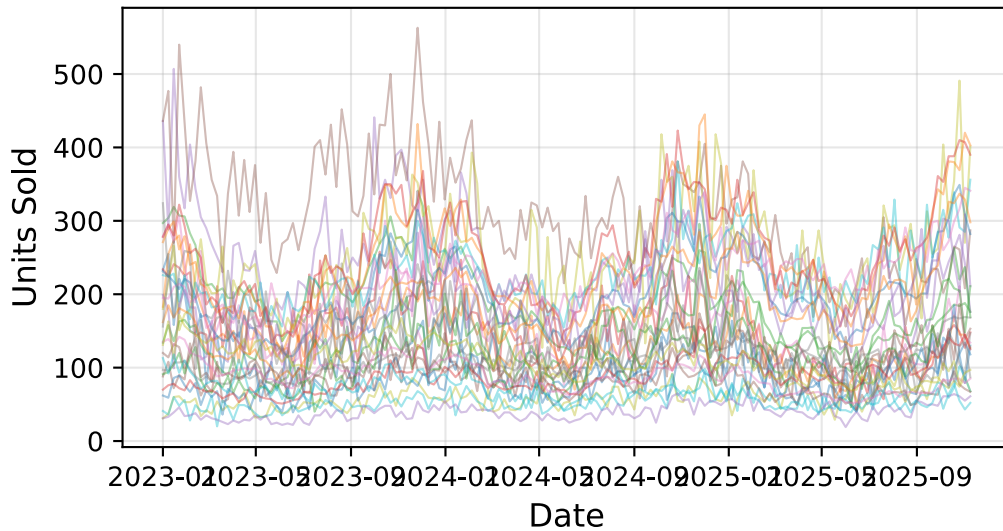
# Plot all SKUs together to visualize the dual seasonality pattern
plt.figure()

for sku_id in skus_df['sku_id']:
    sku_history = get_sku_sales_history(sku_id, sales_df)
    sku_info = skus_df[skus_df['sku_id'] == sku_id].iloc[0]
    plt.plot(sku_history['week_start'], sku_history['units_sold'],
            alpha=0.4, linewidth=0.8)

plt.xlabel('Date', fontsize=12)
plt.ylabel('Units Sold', fontsize=12)
plt.title('All 30 SKUs Sales History (2023-2025)\nDual Seasonality +
Category-Specific Trends',
          fontsize=14, fontweight='bold')
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

```

All 30 SKUs Sales History (2023-2025) Dual Seasonality + Category-Specific Trends



Your Task

You must develop an inventory optimization solution that forecasts Black Friday demand and optimally allocates SKUs to warehouses. Provide:

1. Jupyter Notebook with Complete Solution

Your notebook should include:

- Exploratory Data Analysis:
 - Seasonality patterns (visualize aggregate sales over time)
 - Product lifecycle trends
 - Black Friday spike analysis (2023 vs 2024)
 - SKU categorization (fast-movers vs. slow-movers)
- Demand Forecasting:
 - Forecast Black Friday 2025 demand (weeks 47-48 combined) for all 30 SKUs
 - Report forecast accuracy metrics (MAE, RMSE, or MAPE)
- Inventory Allocation Optimization:
 - Decision: How many units of each SKU to allocate to Hamburg warehouse (total \leq 8,000 units!)
 - Objective: Minimize total delay cost
- Monte Carlo Simulation:
 - Generate 10,000 demand scenarios from your forecast with a variation defined by you
 - For each scenario, calculate total delay cost using your fixed allocation
 - Analyze: Mean cost, standard deviation, 95th percentile (worst-case)

- Insight: How robust is your allocation to forecast errors?
- Results & Business Impact:
 - Total expected delay cost
 - Allocation breakdown: How many units of each SKU in Hamburg vs. Poland
 - Comparison to baseline (e.g., equal allocation across all SKUs, or random)
 - Cost savings in €€€

Note

I won't judge the code quality in this notebook. It's just for me to review your final solution and identify any mistakes if your results seem unrealistic. The final project will be graded primarily based on your presentation and the results you have achieved.

2. Presentation

- Problem understanding: Yola's crisis in your own words
- Your approach: Forecasting method + allocation logic
- Results: Forecasts, allocation decision, Monte Carlo analysis
- Business impact: savings, recommendations, trade-offs, limitations

Note

Please upload both, presentation and jupyter notebook (or `.py` files) for the final project.

3. Key Metrics to Report

- Forecasting: Forecast accuracy and forecasted demand for 2025 Black Friday
- Allocation: Total units allocated to fast warehouse (must be $\leq 8,000$!)
- Expected cost: Total delay Costs based on allocation decision
- Monte Carlo Risk Analysis: Report all important metrics (your choice) and 95th percentile cost
- Business Impact: Cost savings vs. baseline allocation

Constraints and Requirements

! Important

Hard Constraints (Must Satisfy)

1. Capacity: Total forecasted demand allocated to fast warehouse $\leq 8,000$ units

Soft Constraints (Optimize)

1. Minimize delay costs: Fewer units in Poland = lower total cost
2. Robustness: Allocation should perform reasonably under demand uncertainty (Monte Carlo)

Tips for Success

1. No refilling during Black Friday! Your allocation is fixed for the entire weekend.
2. Forecasting is critical: A 10% forecast error can shift which SKUs get priority.
3. Monte Carlo reveals risk: Your allocation might have same expected cost but higher variance.
4. Start simple, iterate: Get a working forecast \rightarrow simple allocation \rightarrow validate \rightarrow Monte Carlo

Common Pitfalls to Avoid

- Overfitting forecast: Don't overfit to historical data. Use simple, robust methods.
- Ignoring capacity: Double-check that total allocated to fast warehouse $\leq 8,000$!
- Poor visualization: Make your allocation decision clear (how many units of each SKU where?)
- No baseline comparison: Always compare to a baseline (e.g., random allocation) to show improvement

Data Access

All data is provided in this notebook:

- `skus_df`: DataFrame with 30 SKUs and their attributes
- `sales_df`: DataFrame with 3 years of weekly sales history
- `warehouses`: Dict with warehouse specifications
- Helper functions: `get_sku_sales_history()`, `plot_sku_sales_trend()`

You must implement forecasting, allocation optimization, and Monte Carlo simulation yourself!

Deadline

- Notebook submission & Presentation: Lecture 12
- Good luck, consultants!

Bibliography