

Food Supply Chain Report

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1. Executive Summary

This assessment was conducted by a group of graduate students at Virginia Commonwealth University's INFO 645 Prescriptive Analytics course during the Spring 2025 semester. As a part of our semester assignments, we were tasked with developing a realistic optimization and simulation for our client, Interchange Group. Our work was completed over a six week period, starting in mid-March to early May 2025.

Interchange Group, Inc. a third-party logistics company headquartered in Harrisonburg, Virginia, specializes in blast freezing poultry products. After receiving a grant to build a blast freezer, they aim to increase their output of frozen products through optimization of pallet placement strategies based on current freezer status and stock keeping unit-specific freezing times. They also seek to assess their 30-day operational performance

In our approach, we built an optimization model using both Python and AMPL, incorporating real SKU data, pallet arrival schedules, freeze time requirements, and the current freezer state from our client. Our model is able to allocate each incoming pallet to a freezer cell and balance the load across cells with varying remaining freezing times. The objective function of our model is to minimize the maximum time required to freeze all pallets on a newly arrived truck, constrained by both freezer capacity and SKU freezing durations.

The enhanced model produced revealed hidden capacity and improved average pallet output from 50 to 95. Key recommendations for the organization include adopting the simulation-optimization framework for daily use, prioritizing short-freeze SKUs during peak times, developing a smart dashboard for visibility, and expanding simulation capabilities. These tools support dynamic decision making, operational resilience, and long-term performance tracking.

2. Presentation of Optimization Model

2.1 Summary of the Problem

Interchange Group, Inc. is a third party logistics company in Harrisonburg, VA. They provide blast freezing services for poultry. They aim to increase their output using a decision support framework that determines where to place arriving pallets in the freezer and monitors overall performance during a 30-day period. The freezer features 288 cell, which are divided into 12 zones of 24 pallet positions each. These pallets arrive daily on trucks and contain SKU. Different SKUs will require different freezing times, ranging from 22-72 hours. The goal is to manage freezer load efficiency and identify the maximum truck-handling capacity per month.

2.2 Data

See “Reference 1” in the appendix for an abbreviated summary of “freezerdata.xlsx”.

2.3 Objective in Words

Our objective is to minimize the maximum completion time for all pallets currently on a truck, taking into account; freezing time required for each SKU, the remaining processing time for the cells currently in use, the maximum waiting time allowed for unloading the contents of a truck; and the maximum freezer space constraint of 288 cells in use at maximum.

2.4 Decision Variables

Let $x_{p,c} \in \{0,1\}$: Binary variable, 1 if pallet p is assigned to cell c ; otherwise 0

S = set of SKUs

C = set of freezer cells (up to 288)

P = set of pallets on incoming truck

2.5 Algebraic Formulation

Objective: minimize the maximum completion time across all freezer cells:

$$\min, \max_{c \in C} \left(\sum_{p \in P} x_{pc} \cdot process_p \right)$$

Constraints:

Only One Pallet Per Cell: Each cell can only hold at most one pallet at a time;

$$\sum_{c \in C} x_{pc} = 1 \quad \forall p \in P$$

Cell Time Feasibility Constraint

If modeling start time s_p for pallet p , then for any cell c :

$$x_{pc} = 1 \Rightarrow s_p \geq remaining\ time_c$$

2.6 Implementation

See the attached Jupyter file, __ to see the implementation and solution of the model using Python, AMPL, and Google Collab. A copy of this code can also be found in the appendix under “Reference 1”.

2.7 Results

The optimization model was able to successfully identify the schedule for assigning 608 incoming pallets to freezer cells. The model achieved an earliest complete time of 113.5 hours, which would mean all pallets will have completed their SKU-specific freezing times in just a little under five days. See “Reference 2” for the abbreviated optimization schedule.

2.8 Other Notes

Many changes were made from our first iteration of the model, while the initial model functioned, it did not provide us with an optimal solution. Necessary modifications were made to adjust for inbound pallets on trucks as well as taking into account active freezing cells. This changed our original optimal answer from only 150 SKUs frozen over a 30-day period to 608 SKUs being frozen every 5 days.

3. Presentation of Simulation Model

3.1 Overview

This phase expands on our Phase 1 optimization model by incorporating simulation to reflect the real-world uncertainty in blast freezer operations. We aim to evaluate how pallet arrivals, SKU composition, and freeze durations affect overall utilization in a stochastic environment. The simulation model is integrated directly with the AMPL-based optimization framework to assess performance under uncertainty.

3.2 Updated Dataset and Data Preparation

For Phase 2 of the project, we worked with a newly provided dataset containing daily inbound pallet records from April 2024 to March 2025. This dataset offered a more granular and realistic foundation for modeling the operational behavior of the blast freezer. It included key information such as the SKU, a product description, and the number of hours required to freeze each pallet. In parallel, a separate file provided standardized freeze durations per SKU, which served as a critical input for linking pallets to time-based freezing requirements.

During the data preparation process, we encountered several challenges that required multiple revisions to our workflow. First, the original files contained inconsistent and non-standard column names, such as "Item #" and "Hours", which we renamed to "SKU" and "FreezeHours" for clarity and consistency. One major challenge was the absence or unreliability of date fields in certain files. While we initially planned to use real timestamps to drive our simulation, we discovered that some columns labeled as "Date" actually contained text descriptions. To address this, we programmatically assigned each inbound record a random day between 1 and 30, enabling the simulation of a 30-day operational window despite the lack of explicit date labels.

Another significant issue was that several SKUs appearing in the inbound data did not have corresponding freeze time entries in the reference file. This mismatch resulted in errors during mapping, which we resolved by filtering out SKUs without valid freeze times. However, this filtering sometimes drastically reduced the size of usable data. To avoid overwhelming the solver and to reduce runtime while preserving statistical value, we restricted the simulation and optimization to the top 50 most frequently occurring SKUs. This compromise allowed us to simulate meaningful operational loads while keeping the model computationally efficient.

We also faced frequent parsing errors while transforming the data, especially when attempting to convert text-based date entries or access missing columns. We resolved these by applying robust error-handling techniques, validating column existence, and dropping incomplete rows.

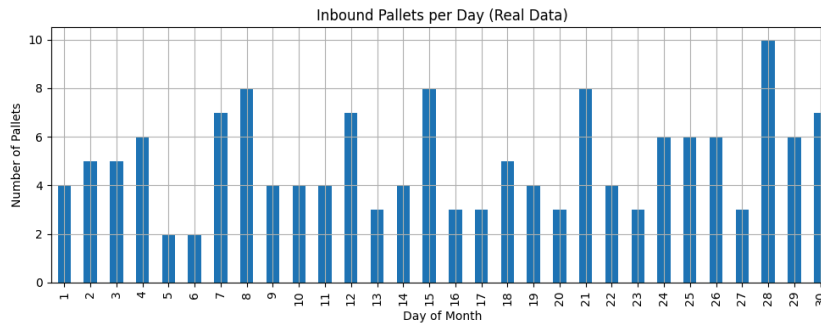
Ultimately, we were able to generate a clean and integrated dataset by mapping SKU-specific freeze durations into a dictionary (`freeze_time_dict`), assigning simulated dates, and constructing a time-based demand dictionary that mapped each (SKU, hour) pair to a corresponding pallet count. This clean dataset was then passed to our optimization model, ensuring alignment between real-world operations and the simulation environment.

3.3 Modeling Optimization-Simulation Integration

To incorporate real-world variability into our blast freezer scheduling, we developed a Monte Carlo simulation model focused on four key stochastic elements: (1) the number of pallets arriving per day, (2) the SKU distribution across pallets, (3) the freeze time associated with each SKU, and (4) the randomized assignment of pallet arrivals across a 30-day planning horizon.

For each of the 50 simulation iterations, we bootstrapped the cleaned inbound dataset with replacement to simulate alternative inbound patterns. Every sampled pallet was randomly assigned a day (from Day 1 to 30), and its freeze duration was determined using the SKU-specific freeze time dictionary. This process generated a unique hourly demand profile, mapping (SKU, hour) pairs to the number of pallets requiring freezing at each time step.

The visualization below provides a snapshot of daily inbound pallet activity from the original dataset. This served as the foundation for generating simulated demand patterns in each run:



This real data distribution helped shape the randomness in daily pallet inflow modeled in the simulation. Each generated demand scenario was passed into the Phase 1 AMPL optimization model, which was adapted to dynamically accept new sets (P for SKUs) and parameters (freeze_time, demand) at each iteration. The AMPL model then computed the optimal freezing schedule over a rolling 720-hour (30-day) horizon, allocating up to 288 freezer cells per hour

while adhering to SKU-specific freezing duration requirements. The simulation aimed to maximize the number of pallets successfully frozen while observing real-world constraints.

To establish a baseline for comparison, we first ran the optimization model using the unaltered real data for the top 50 SKUs. This produced a total of 50 pallets successfully frozen, which serves as a benchmark to evaluate the effectiveness and variability of the simulated demand scenarios.

```
⇒ Solving for 50 SKUs...  
   cbc 2.10.12: optimal solution; objective 50  
   0 simplex iterations  
   Total pallets frozen (real data): 50
```

3.4 Monte Carlo Simulation Results

To assess system performance under uncertainty, we ran a Monte Carlo simulation with 50 iterations. In each iteration, the inbound data was bootstrapped with replacement to create a new 30-day inflow pattern. SKUs were randomly assigned arrival days, and hourly freeze demand was calculated based on SKU-specific freeze durations.

Across all simulations:

- **Average pallets frozen:** 95.12
- **Minimum:** 85 pallets
- **Maximum:** 103 pallets

The histogram referenced in the appendix under “Reference 2” summarizes the distribution of optimal pallet counts across the 50 Monte Carlo simulations. The histogram illustrates the range of system throughput under randomized conditions, highlighting the variability inherent in daily

operations and reinforcing the value of simulation-informed optimization. The sharp contrast between the baseline of 50 frozen pallets (from the real data scenario) and the simulated average (95.12 pallets) underscores how variability in arrivals can either constrain or enable better utilization of freezing capacity.

3.5 Conclusion

By integrating simulation with the AMPL optimization model, we were able to evaluate the blast freezer's capacity under varying daily conditions. The simulation confirmed that Interchange Group's freezer can accommodate higher pallet volumes when arrival patterns align optimally. This approach highlights the value of using historical data and probabilistic modeling to inform operational decisions. Going forward, this framework can help identify peak performance potential and develop robust, flexible scheduling policies that accommodate daily fluctuations in inbound volume and SKU composition.

4. Conclusion and Recommendations

4.1 Conclusion

The Interchange Group, Inc. project broke down the optimization of blast freezer operation into two phases. In phase 1 we created an optimization model in Python and AMPL that optimally assigned incoming pallets to freezer cells in order to minimize the overall time to freeze assigned pallets based on SKU-specific freeze times and existing freezer status. The Phase 1 model was able to be used to obtain a solution within certain assumptions of fixed inputs, but was not flexible to day-to-day variability.

In Phase 2, we improved upon the assumptions of Phase 1 by incorporating a Monte Carlo simulation with the intent of modeling the real-world uncertainty present in the arrival of pallets, SKU mix, and freeze times. After cleaning and formatting a new data file, we created a series of randomly generated demand scenarios (over a 30-day planning horizon) which allowed us to look at. The ability of the simulation to identify blocks to operations associated with freezing pallets and at the same time reveal hidden capacity within the freezer system were essential insights.

Across the fifty simulation runs, the average of frozen pallets in the freezer increased from 50 (the real-data baseline) to 95.12, with a range of 85 to 103. The result is impressive and reinforces the lesson learned on the need to 'accept' variability in business operations and optimize within it. The simulation/optimization platform proved to be a useful platform for facilitating better decision making, improving throughput, and building the resilience of freezer scheduling.

4.2 Recommendations

Based on the new findings, a number of recommendations can be made to improve the operational productivity of the Interchange Group and its decision-making. Firstly, the new optimisation-simulation framework developed as part of this project should be incorporated into the daily scheduling functions. This would enable dynamic placement of pallets depending on the specific freeze times of each SKU and the availability of the freezer. The system would be continually adapting to real-time decisions. During peak inflow periods, pallets with shorter freeze times should be allocated to the freezer first so as to maximize throughput and minimise congestion in the freezer.

To enhance visibility and responsiveness, a smart pallet routing dashboard is recommended to be developed using Python. The dashboard can present real-time cell utilization, freezes, and any constrained areas that are caused by excessive freezing time, or that are clustered on a per-SKU basis. Accuracy of the data is crucial for these types of systems so standardizing the format in which the data is entering, especially SKU codes and dates, and cleaning the data through automation is ideal. Maintaining a verified master file of SKUs and freeze times will help limit disruptions to operations during the optimization.

The simulation can be designed to offer a more comprehensive representation of freezer operations through more than the top 50 SKUs and will do so as long as system resources allow. From a strategic vantage point, using a rolling horizon optimisation strategy - for example, by using a 72-hour forward planning window will be most useful because it allows the process to be updated as pallets arrive. Scenario-based rules should be developed from the outcomes of simulation to assist in decision-making in different loading conditions. As an example, freezer zones can have a predetermined allocation or allocation can be determined based on the range of inflow each day or because 50% of the inflow were long-freeze SKUs.

Also, the simulation outputs, especially the average of 95.12 and the maximum of 103 frozen pallets, can act as performance metrics to facilitate tracking performance over time. In future optimisation models, logistics-related costs, such as energy usage, labour availability, and SKU loss due to spoilage, should also be incorporated to better reflect operational compromises. Automated weekly performance updates should also be leveraged for profitability stabilization as it can support managerial decisions related to resource allocation in staffing and scheduling. Finally, empowering operational teams with the capabilities to interpret simulation and optimisation outputs is vital as it ensures tools are effectively used.

Appendix

Google Colab link for optimization: [🔗 Phase 1 - Optimization Model](#)

Google Colab link for simulation: [🔗 project phase 1+2](#)

Reference 1: Essential Optimization Component - Data

SKU Data

| SKU | Description | Freeze Times (in hours) |
|------|-----------------------------------|-------------------------|
| 1301 | WHOLE WINGS | 51.25 |
| 1306 | PARTY WINGS | 27.75 |
| 1511 | BREAST - B/S - FZ- 40# BULK | 46.00 |
| 1521 | TENDERS -HALAL | 51.25 |
| 1552 | LEG - B/S- 40# Bulk | 51.25 |
| 1710 | BS Trim | 51.25 |
| 1752 | LEG - B/S | 51.25 |
| 5000 | WOG - FZ | 51.25 |
| 5012 | Young Organic Whole Bird - 6 head | 51.25 |
| 5013 | WOG - FZ | 51.25 |

*Not all SKUs/products displayed in data set above, limiting to the first 10 in dataset

Freezer Data

| Bin ID | SKU in Bin | Hours Remaining |
|---------|------------|-----------------|
| L265121 | 5000 | 45.25 |
| L265122 | 5025 | 40.01 |
| L265123 | EMPTY | EMPTY |
| L265124 | 5025 | 40.06 |
| L265125 | 5710 | 35.58 |

| | | |
|---------|-------|----------|
| L265126 | 5528 | 30.36 |
| L266121 | 15017 | COMPLETE |
| L266122 | 5028 | COMPLETE |
| L266123 | 30128 | COMPLETE |
| L266124 | 30128 | COMPLETE |

*Not all Bins/Cells displayed in data set above, limiting to the first 10 in dataset

Inbound Truck Data

| Pallet | SKU |
|---------------|------------|
| 1 | 49278 |
| 2 | 5030 |
| 3 | 5311 |
| 4 | 21431 |
| 5 | 1521 |
| 6 | 21426 |
| 7 | 5040 |
| 8 | 21429 |
| 9 | 42828 |
| 10 | 8003 |

*Not all pallets delivered displayed in data set above, limiting to the first 10 in dataset

Reference 2: Distribution of Optimal Pallet Count

