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# Improving Inventory for a Large Food Service Supplier

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## I. Introduction

Golden State Foods (GSF) was created in 1947, and ever since they have provided major fast-food chains with condiment sauces the world has come to know and love. In 2022, the company was ranked 101st on Forbes's Largest Private Company List with an annual revenue of $5.1 billion (Murphy 2022). At GSF's Georgia manufacturing plant, they have recently expanded their liquid food production, making condiment inventory their largest asset. The amount of ingredient inventory held heavily impacts their working capital. Working capital determines the amount of interest they must pay, which affects the company's overall profits. So, by reducing the plant's food inventory by modifying their safety stock and order quantities we can increase their profits and help their future expansion efforts. Currently, the company is utilizing anecdotal knowledge to determine its food ordering processes. By analyzing historical data reports, we created an Economic Order Quantity (EOQ) model that accurately determines the optimized order quantity for seasonal and expensive ingredients, reducing excessive supply while preventing stockouts.

### A. Problem Statement

Golden State Food's inventory is one of its biggest expenditures. Our model reduces the amount of excess inventory, limiting the working capital costs. When applied to a set of five high-cost ingredients, our model would reduce GSF's average end-of-week inventory for this specific product by 749.34 pounds (valued at $28,729.70) as compared to the historical ordering process. This could be applied to the rest of GSF's inventory of over 40,000 other ingredients and save significantly more money.

### B. Related Work

The articles by Eruguz et al. (2016), Nobil et al. (2001), and Maddah et al. (2017), and Dural-Secuk et al. (2020) were most fitting as they demonstrated in economic order quantity (EOQ) and reorder points (ROP) to model inventory problems with characteristics like ours.

The article allows for many different applications of the guaranteed service model by relaxing certain assumptions from the original guaranteed service model, providing solutions for different supply chains, and real-world examples. With lead times and safety stocks, we will be able to use a guaranteed service model to optimize inventory settings.

The paper by Maddah et al. introduces a framework for using an economic order quantity (EOQ) model in a situation where demand is nonstationary. This type of model takes in inventory demand, lead time of the inventory items, along with the ordering and holding costs of the item to calculate how much of an item the company should order and how frequent the order points should be.

Within Nobil et al. paper, the authors discuss the importance of a reorder point (ROP) within a manufacturing business because it prevents a company from purchasing too much inventory and increasing its holding cost. An ROP is a point at which a business should reorder a set quantity of goods. It is determined by the company's daily demand, lead time, and safety stock.

### C. Organization

In this paper, Section II showcases the inventory and consumption report data we received from Golden State Foods. We also discuss our methodology for determining which ingredients are the best choice for order optimization, and how we utilize our EOQ/ROP model with those ingredients to display retrospective results with historical data. Section III presents our results where we compare our inventory utilizing our model's ordering process compared to GSF's current ordering process and displays. Throughout Section IV we discuss how much excess stock we could potentially reduce for GSF, recommendations for data gathering, and ordering for the company moving forward. Section V concludes with how the project can be improved and what increasing the scope would potentially look like.

## II. Data, Methodology, and Modeling Approach

We received multiple data sets regarding inventory characteristics for over 40,000 ingredients (lead times, safety stocks, minimum order quantities in terms of days' worth of ingredients) as well as data regarding supplies bought, products sold, and products made by Golden State Foods..

### A. Data

The fundamental dataset we are working with is a coverage export excel sheet that lists each item's characteristics in terms of ordering and manufacturing constraints. For each ingredient, we know the lead time, safety stock, and days of inventory ordered. Each ingredient and product have a unique identification number, allowing us to reference each item between files and observe trends between usage, reorders, and overstock simultaneously.

In addition to the export coverage, we also have many auxiliary datasets. This dataset includes the amount for every ingredient in the plant's quantity in pounds and in dollar value. We have 52 days' worth of data, with the inventory reports taken on nearly every Sunday in 2022. We also determined that measuring weekly inventory would be the most efficient way to observe overstocks or stockouts because GSF re-orders are based on weekly projection data. They average $37 million dollars and 16.5 million and pounds in inventory. These thirty-eight data points allow us to get an accurate representation of inventory trends throughout the entire year. The rest of our datasets include consumption reports for specific ingredients for most of 2022, which we are naming A. We are using this coinciding with the inventory report to gauge how frequently and how much the facility unnecessarily exceeds its safety stock for these ingredients, but also observe and rationalize any trends between consumption, reordering, and overstock.

### B. Methodology

Our client advised us that our biggest opportunity cost lies within over purchased yet still regularly consumed ingredients. These ingredients as well as the most valuable ingredients in terms of price per pound are the most flexible. We first found the price per pound of each ingredient by dividing the value of inventory by the amount held found in the inventory reports. Then, we chose ingredients above $10.00, because GSF said these were the most valuable to gather consumption reports for. We then analyzed inventory and consumption reports to determine how much they use, how much they reorder, and at what point do they reorder for specific ingredients. Our model below shows Ingredient A had the clearest consumption data and with a price of $26.75 per pound, it was more expensive than the most ingredients in GSF's inventory. We then applied our EOQ model and reorder point equation to its inventory over the 2022 period to determine how much money GSF would save on a weekly basis.

### C. Model

Our excel-based model contains data on the consumption of a certain selection of ingredients, the end-of-week inventory for all ingredients over 2022, safety stock and lead time for each ingredient, and our actual EOQ model. Under the tab "EOQ" you can enter a 6-digit ingredient code that will automatically and dynamically update that ingredient's purchase cost, expected demand over a 4-week period (utilizing average weekly demand multiplied by 4), and safety stock. The carrying cost percentage and fixed cost is already known but can be updated by the client if anything of these factors changes. Then, Economic Order Quantity is determined in Equation 1 below:

$$EOQ = \sqrt{(2 * D * F)/(P * H)} \quad (1)$$

where D is expected demand in a specified period, F is the fixed cost of placing an order, P is the purchase cost from the supplier, and H is the carrying cost percentage.

Once the economic order quantity is determined, we calculate a reorder point under the "Model" tab based off when they are projected to dip below safety stock and lead time. Then under Column D, we simulate ~40 weeks of inventory where they are consuming the same amount of the ingredient as in reality but reorder based on our reorder quantity and reorder point. Further, when the ingredient number was initially entered, Column F automatically updates with the actual inventory for that ingredient. There are now columns with actual inventory vs inventory that our EOQ model recommends.

Our model finds an optimal reorder quantity that saves the company money while also being very user-friendly for our client. GSF can easily visualize when to reorder a certain ingredient and how much while the only input needed is an ingredient number. The model also allows them to change or update any assumptions that we made based on new data and information that they obtain post-capstone.

## III. Results and Analysis

With our EOQ model we were able to view what their past year of inventory would have been for ingredient A had they utilized our model compared to what their actual inventory was. The figure below displays GSF's actual weekly inventory values for Ingredient A from February 20th to November 6th, 2022, in comparison with what their inventory values would be using our model's order quantity and reorder point. On average, our EOQ model, if implemented, would reduce GSF's average end-of-week inventory for this specific product by 749.34 pounds (valued at $28,729.70). Assuming that our holding cost is determined by multiplying the dollar value of inventory by the interest rate given to us by GSF (5.09%), we would be saving approximately $1462.34 in holding costs for this specific ingredient.

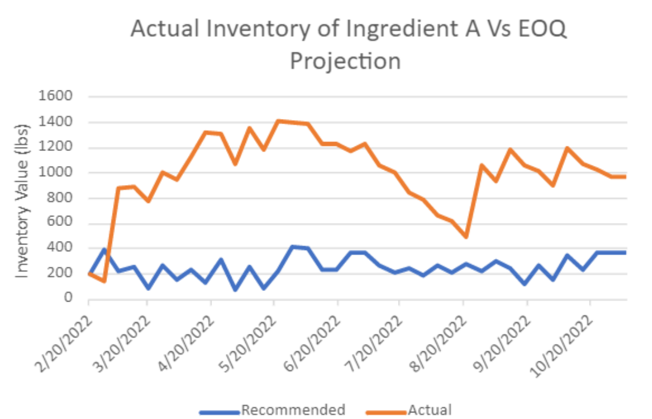


**Figure 1: Actual Inventory of Ingredient A vs EOQ Projection**

A comparison between actual inventory vs model-projected inventory for ingredient B is shown in Figure 2. For ingredient B, our EOQ model would reduce end-of-week inventory by 580.07 pounds on average (an estimated $17,964 in value). Assuming the holding costs as discussed above, GSF would be saving $914.41 in holding costs.

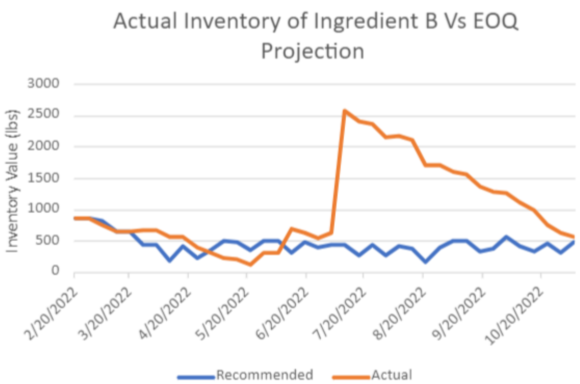


**Figure 2: Actual Inventory of Ingredient B vs. EOQ Projection**

A comparison between actual inventory vs model-projected inventory for ingredient C is displayed in Figure 3. For ingredient C, our EOQ model would reduce end-of-week inventory by 2185.30 pounds on average (an estimated $42,897.44 in value). Assuming the holding costs as discussed above, GSF would be saving $2,157.74 for this item.

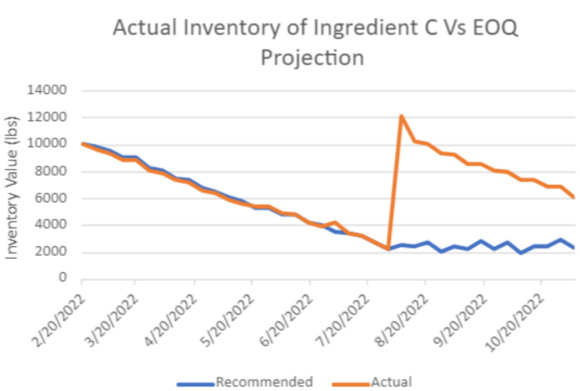


**Figure 3: Actual Inventory of Ingredient C vs. EOQ Projection**

Ingredients A through C demonstrate that for certain high-value, overstocked ingredients our model presents opportunity for large amounts in savings. Our model, when applied to data for certain other ingredients, showcases a less obvious opportunity for inventory reduction. Ingredient D's projected inventory, for example, lines up nearly perfectly with actual inventory values (Figure 4). While we cannot project a specific amount of reduction in inventory for this ingredient, it does showcase that GSF originally greatly overordered for this ingredient. Our projected EOQ for this ingredient was 66.49 pounds, demonstrating that their actual inventory of around 1000 pounds was the result of a significant overorder which would never have occurred if GSF were using our model.

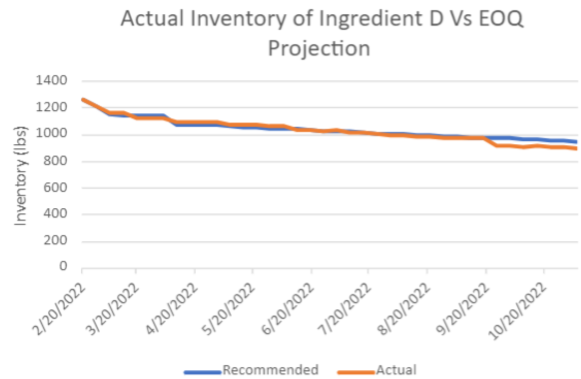


**Figure 4: Actual Inventory of Ingredient D vs. EOQ Projection**

Ingredient E (Figure 5) is an example of an ingredient that presents opportunity for savings through use of our EOQ but is not projected perfectly. According to our projections, our model would reduce inventory for this product by 4665.47 pounds on average (estimated at a value of $90,463.46). Using our assumptions for holding costs, this would reduce holding costs by $4,550 for this ingredient. Our projection, however, does result in negative inventory values and indicates a possible stockout in inventory. This is caused, however, by the fact that we are estimating demand using the weekly average throughout the whole year's data; this does not account for sudden spikes in demand that the client would be aware of and would be able to adjust the EOQ accordingly.

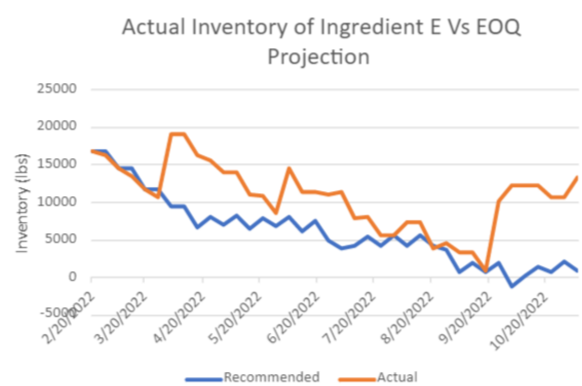


**Figure 5: Actual Inventory of Ingredient E vs EOQ Projection**

## IV. Conclusions and Recommendations

After comparing the differences between historical inventory values and hypothesized values using EOQ, we recommend that Golden State Foods use our model as they would hold significantly less excess inventory. If GSF applies this model to other high-value and frequently used ingredients, they have the potential to save hundreds of thousands more dollars. Certain aspects of our model, specifically demand, would require additional refinements from our client, so there is potential to further improve inventory management. The main risk posed to GSF through the use of this model is that they will consistently be holding less inventory per product, and thus unexpected surges in demand will increase the likelihood of stockout for a certain product. To counter this risk, GSF should apply generous projections of future demand in periods where they suspect that there could be a demand spike. They should also avoid using this model for bulk ingredients which tend to be relatively inflexible to variations in inventory.

## V. Future Research

After implementation of our model for specific ingredients, Golden State Food's should expand this for more ingredients. We found that our model worked best for ingredients over $10.00 and yearly usage is above 2,500 lbs., but with more data mining these constraints can be more specific and include more variable to include varying demand. With over 40,000 ingredients, there are a multitude of other products that can be optimized, and the impact of the savings can be magnified. Also, our model can be a helpful visualization for future ordering decisions. Our scope can increase by utilizing our model for determining new business ventures. For example, if they want to gain more business with a new product, they can see their current usage of ingredients and how an increased demand would impact their inventory. Golden State Foods has plans to expand its manufacturing plant, so utilizing our model will be beneficial in saving more money to contribute to construction costs and for developing better inventory management and ordering processes for future ingredients.

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