Inbound Logistics Optimization

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ABSTRACT

The intrinsic competitive nature of the fast-moving consumer goods (FMCG) industry have made it a priority for companies to maximize profitability by aggressive cost-cutting measures in the context of growing material cost, surging labor expenses and increasing demand for product customization. While exploring optimization opportunities in outbound logistics management, which mainly focuses on delivering goods and services out of a business entity, many market players shifted gears to delve into inbound logistics operations, which center on the management of materials and finished goods into a facility. This project unlocks cost saving opportunities in the inbound logistics system of a consumer goods company by answering two questions: What is the optimal minimum production quantity for finished goods? What is the appropriate minimum order quantity for packaging materials to minimize delivery and storage cost? Multiple machine learning techniques are utilized throughout the research: clustering techniques are used to identify MPQ, and a cost minimization model in Microsoft Excel and Python is developed to compare current cost with simulated cost. It is estimated that 16% cost savings can be obtained by optimizing MPQ and MOQ. Additionally, the models are highly replicable to other manufacturing sites of the CPG company to generate greater operational efficiency.

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Sophia

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Ezra

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1 INTRODUCTION

This section provides a high-level introduction of inbound logistics management and the common industry practices of utilizing logistics service providers (LSP). We put into context the specific issues encountered by the sponsoring company and the motivation to conduct the research. The section concludes with a summary of the two models we developed in order to address the specific challenges in our project.

1.1 Overview of Inbound Logistics Management

The fast-moving consumer goods (FMCG) industry is best known for its high volume, low profitability, convoluted supply chain networks and high stock turnover (Kumar, 2011). Additionally, since many consumer products are commodities, companies utilize value-based pricing as opposed to cost-based pricing to provide buyers with significant tangible value beyond offering cost (Zhang et al, 2018), meaning they set the price at a level the market is willing to pay. These dynamics necessitate a comparatively stringent cost management to maintain competitive profitability in the context of greater need for customization. As logistics has become an integral part in connecting production with consumers, more and more companies are looking for ways to better streamline both interior and exterior flows of goods, information, and capital.

Prior to delving into details of cost saving initiatives in inbound logistics management, it is necessary to distinguish inbound logistics from outbound logistics. As the name indicates, inbound logistics consists of the whole process from the sourcing of raw materials to entry into production facilities. While outbound logistics encompasses the delivery of goods to end customers. **Figure 1** shows the distinction between the scope of these two supply chain management systems.

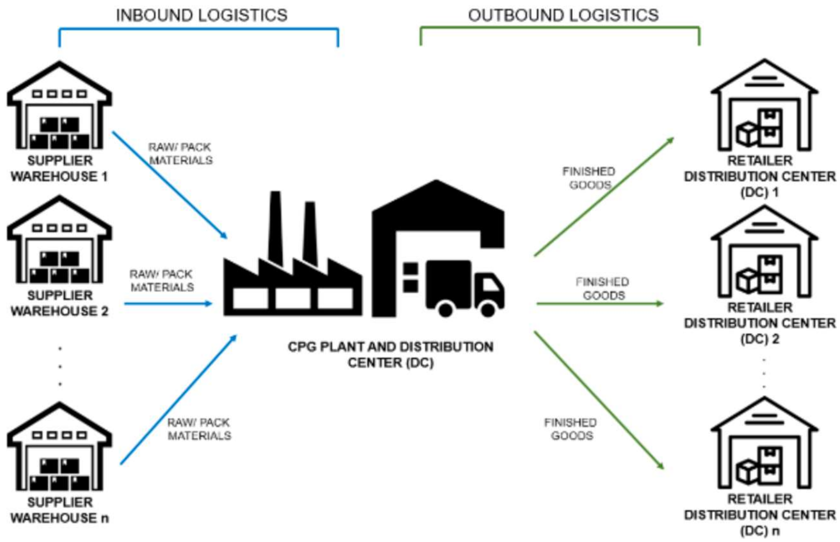


Figure 1: *Generalized Inbound and Outbound Logistics Network.*
Source: Felicio & Sharma, 2018

As inbound logistics involves the planning of materials and resources to meet production demand with a required level of flexibility to hedge against demand volatility, key activities within the inbound logistics management system go beyond the mere scope of material delivery and transportation. Safety stock planning, component ordering cadence and packaging material delivery are among the key performance indices for industry professionals. Due to the complexity of an array of stakeholders in inbound logistics management, a common practice deployed by most FMCG companies is the use of logistics service providers (LSP or 3PL). According to the research conducted by Murphy and Poist, the most common types of services used by companies are detailed in **Table 1.**

Table 1: *The Ten 3PL Services Most Commonly Used.*
Source: Murphy & Poist, 2000.

Most commonly used services	**Percentage of 3PL customers using**
Warehousing	65.7
Freight bill payment	56.7

Freight charge auditing	50.7
Customs clearance	47.8
Pickup and delivery	46.3
Freight consolidation	37.3
Consulting	35.8
EDI Capability	32.8
Internal services	31.3
Order picking and packaging	25.4

However, utilizing outsourced LSP service is not without risks. On one hand, companies are able to allocate resources from cumbersome operational routines to core businesses by outsourcing. On the other hand, the lack of company-specific knowledge on the part of LSPs may lead to a loss of operational efficiency, leaving a multitude of opportunities for further operational integration and improvement. Therefore, it is paramount that companies identify outsourced operational activities that are crucial to overall supply chain performance prior to passing down to third parties.

1.2 The Company and Motivation

The sponsoring company for this research is a FMCG organization with a production location in Europe. The inbound logistics problems we aim to address in our research are driven by both industry and company-specific factors.

First, the highly competitive nature of fast-moving consumer goods industry calls for a high service level and order fill rate for each market player, hence the usual practice of over-driving raw materials. Since home products are mostly homogeneous with readily available substitution in the competitive consumer markets, missing orders not only leads to lost sales but also jeopardizes the long-term relationship with consumers. As a consequence, the plant has historically not emphasized efficiency in material ordering, warehousing, or returns policies, but instead focused on ordering enough to ensure production is completed and dealt with the resulting warehousing and returns afterwards. The plant has a relatively small warehouse for thousands of packaging materials, and therefore relies on third-party vendors for the majority of its warehousing needs. This practice not only adds a substantial fixed cost, but also a large variable cost, which mainly consists of truck maintenance and dispatching cost, palletized transportation cost and remnants storage cost.

Second, the frequent return flows of production materials due to limited material storage space give rise to cumulated production remnants. Products not only flow from the warehouses to the plant, but in the case of returns, can also flow from the plant back to the warehouse, meaning that in certain instances the plant is paying for the same product to be moved three times: the first transportation flow from warehouse to plant for production, the return flow from plant back to the warehouse for remnants and the third flow from warehouse to plant for the second production run. The frequent return flows of materials are dually driven by limited storage space in the production area and an economic production quantity (MPQ) strategy that is solely calculated based on minimum production hours per batch. As a result of this MPQ strategy for finished goods, the actual delivery quantity of packaging materials is in most cases more than the required demand as delivery of packaging materials requires full containers. A typical material flow is illustrated in **Figure 2** demonstrating a three-haul travel for material remnants. Additionally, with customers distributed over a wide range of countries, most of the labels and other packing materials are country-specific, making it difficult for the logistics team to optimize their production schedule by batch production. For instance, one changeover will occur per production line every time new labels are needed. Since the inbound logistics team is the recipient of daily production plan created by the planning team, they cannot project the next time raw materials will be needed, and therefore utilize the 3PL warehouses rather than storing remnants onsite.

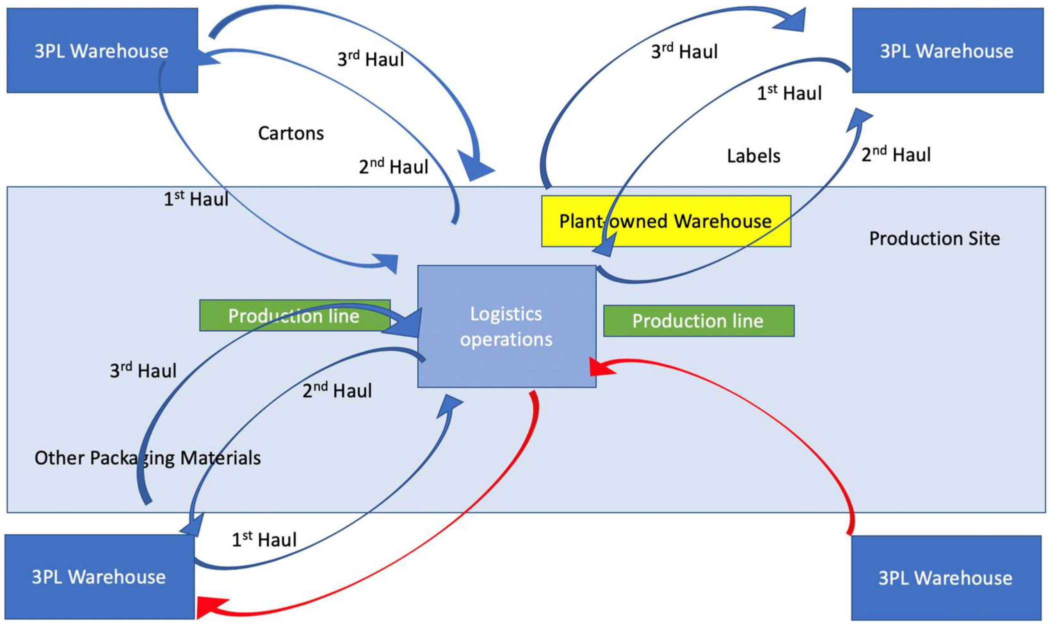


Figure 2: *Typical material flow with remnants between production site and warehouse.*
Notice how packaging materials may have three transportation hauls, each representing costs to the organization.

With rising costs in transportation, material handling, and storage, the inbound logistics team has looked at different ways to optimize their material management process with logistics service providers. A recent analysis by the company estimated that the plant can cut costs by over €1 million by optimizing the lot size of its raw materials. Due to the complexity of the SKU portfolio and packaging materials, it is hypothesized that machine learning might be the right methodology to unlock these opportunities. Furthermore, we believe that upon successful implementation and validation of the model, it is highly replicable and scalable to other management systems of the plant as well as all other production facilities with similar operation structures of the company. It is also worth noting that cost savings and efficiency improvement will also contribute to the development of sustainable logistics thanks to reduced flow of materials.

1.3 Problem Statement

In summary, the company's inbound logistics management system is confronted with two problems:

- Minimum Production Quantity (MPQ) for finished goods: The team is currently following a traditional methodology in calculating MPQ on a nine-month review cycle for hundreds of active SKUs. Calculated MPQ is production driven so as to minimize changeover cost by observing a minimum running rate per product at each production run. The minimum production hours for each product is experimentally identified based on historical orders and independent of the correlated packaging material cost, thus making this methodology prone to unnecessary material remnants. As the focal point is to reduce unnecessary return flows of packaging materials, we have identified MPQ optimization for finished goods as the first step.
- Minimum Order Quantity (MOQ) for packaging materials: With production quantity fixed for each SKU observing MPQ requirements, the Material Requirement System (MRP) is triggered simultaneously to generate material requests on a daily basis, which is then passed down to logistics service providers for planning material delivery. As packaging materials are palletized in delivery and follow a minimum order quantity, the required number of pallets are rounded up whenever there is a decimal in the calculated demand. Specifically, the overdrive in packaging material request is magnified in labels, as labels are packed in reels and two reels fit in one box as the basis unit of delivery. This rounding up approach to drive material is one of the fundamental causes of remnants. That is, the planning team is currently utilizing a round-up policy for all SKUs and only in rare cases does the minimum lot size exactly match the required demand, hence the frequent flows of remnants between production sites and material warehouses. With a stochastic production schedule and a customer base located in a wide range of countries, the plant is currently returning around 30% of the labels which they order for

production, while the industry average is much lower at 8.1% (Terry, 2014). Transportation cost, warehousing cost, together with the overhead cost incurred thereafter may well exceed the economic value of the packaging material itself. However, there is no legacy system in the plant to determine the optimal MOQ for each packaging material to reduce return flows.

Through this project we seek to recommend models to determine the optimal MPQ for finished goods and MOQ for packaging materials to minimize total cost. As finished goods production quantity is a critical input to extrapolate packaging material demand, we will develop the models sequentially. Machine learning techniques were utilized in both models to accommodate the business requirement of on-demand simulations for optimal MPQ and MOQ. This approach distinguished itself from the commonly adopted fixed horizon review practice. The deployment of machine learning will infuse greater flexibility to fit customized optimization requests in view of increasing complexity of the product portfolio. By adjusting review periods and cost parameters on-demand, planners will be able to pivot focus SKUs when needed.

2 LITERATURE REVIEW

This section provides an overview of the research that we utilized to guide our work. The related literature can be segmented into five categories: inbound logistics optimization, machine learning techniques, MPQ optimization, lot size optimization, and reverse logistics management.

2.1 Inbound Logistics Optimization Overview

The crux of inbound logistics management is the system of flows rather than the generation of stocks (Takita & Leite, 2019). A myriad of factors interacts with each other contributing to a significant cost difference to the logistics department and third-party service providers. Factors include the sequence of material flows, the quantity and frequency at each delivery, minimum order quantity, storage locations, as well as the management of return materials and production residuals. The delivery of materials prior to entry into the manufacturing facility is a delicate science that calls for scrupulous planning on both temporal and spatial dimensions.

Traditional inbound logistics optimization efforts are biased towards delivery performance and suppliers' responsiveness to quality disruptions, while the quality and utilization of logistics resources have historically been deprioritized (Kahl, 2006). Quantitative parameters such as On Time Delivery (OTD), Order Fill Rate (OFR) and Inventory Turnover Rate have been continuously tracked via real-time data platforms. However, there have been fewer challenges on the rationale behind a set of parameters that are usually taken by default, such as the rounding methodology in calculating material demand based on container size, the optimal frequency to revise the minimum production quantity (MPQ), as well as the calibration between finished goods MPQ with corresponding material MOQ. Some studies combine MOQ with pack size (Arayapan & Warunyuwong, 2009) using Microsoft Excel's Solver. Arayapan and

Warunyuwong correctly argue that optimizing container loading requires both pack size optimization and a proper MOQ. Meanwhile, Hakim et al (2018) focus on minimizing inbound logistics cost by optimizing the choice of container types and quantity with the use of Mixed Linear Integer Programming (MILP). The inbound logistics cost consists of origin costs, freight costs and destination costs (Hakim et al, 2018). Other studies look into the advantages and disadvantages of various storage locations for materials, and how third-party service providers can alleviate the strain of a lack of storage space for manufacturers (Brahimi & Khan, 2014). *Maulida Hakim et al, 2018* successfully implement Mixed Integer Nonlinear Programming (MINLP) approach to determine the type, number and optimal material load for each container. In their research, the total inbound logistics cost is a function of material cost, transportation cost and administration cost.

2.2 Machine Learning Techniques in Inbound Logistics Management

As companies are serving a more global customer base and with consumer demands changing at a growing speed, manufacturers are increasingly looking for new and creative solutions to satisfy demand rather than relying on knowledge from prior years (Knoll et al, 2016). One of the recent trends in supply chain is turning to machine learning systems that can manipulate vast amounts of data and quickly present optimized outputs. Our sponsor company is looking to be at the forefront of this trend and is eager to develop tools that not only unlock cost saving opportunities but are also adaptable to future changes in product portfolio and demand. Knoll et al explain how machine learning planning systems have several advantages over manual systems, namely that once a machine learning model is trained using a large input data set and supervised learning, it can perform “learned tasks” on new data. This process allows the model to continuously improve over time while also freeing up managers’ time to focus on more value-add areas.

The approach of using machine learning techniques in supply chain has proven to be successful in the healthcare industry, where researchers were able to utilize a machine learning algorithm on healthcare data and achieve a disease detection accuracy rate of 94.8% (Chen et al, 2017). The research used large amounts of input data in order to train the model and then applied real hospital data from China to create predictions of disease. Not only was the model extremely accurate, it also was able to provide the outputs at much faster speed than prior methods. While our research is in a different industry, we aim to create tools for our sponsor company that are similarly effective and can utilize new data to quickly predict future trends. If our tools are adopted, the sponsor company can upload recent production order data to our model and quickly gain insights into ways to manipulate the MOQ and MPQ in order to reduce costs.

2.3 MPQ Optimization for Finished Goods

Previous studies look at the impact of minimum production quantity (MPQ) and the tradeoffs involved in setting the optimal level (Yenipazarli et al, 2016). Most studies we reviewed present the history of minimum production quantity, its benefits to manufacturers, and its strain on buyers driven by improved economies of scale in production and transportation (Bin, 2010). However, Bin also explains:

“Many buyers, on the other hand, are left perplexed as to how to effectively establish their inventory policies.”

These studies are informative to our project. However, as mentioned earlier, only 30% of the plant’s current orders are at MPQ, meaning that 70% of orders are exceeding MPQ given most of its customers are large retailers. The limitation of these studies is that they are only relevant to 30% of the plant’s orders while our research aims to make an impact on a larger proportion of orders.

A typical cost optimization approach to determine MPQ takes into consideration set-up cost, interest and depreciation on stock for each stock keeping unit (SKU). The cost structure model has been widely adopted by various industries since then (Khan et al., 2017). **Figure** 3 shows an increase in the size of the order results in an upside of interest charge and a decrease of set-up cost. A cost optimization model tends to locate the optimal intersection where total cost is minimized.

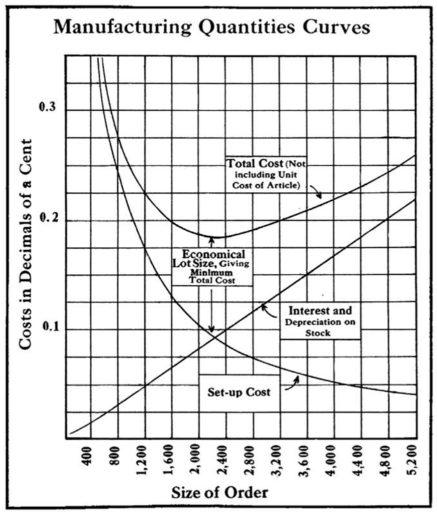


Figure 3: *Relationship of Order size and Cost*
Source: HW. Harris, 1913

2.4 MOQ Optimization for Packaging Material

Most of the studies we reviewed discuss the financial benefits of increasing material lot sizes, including bulk purchase and transportation cost discounts (Taleizadeh, 2018). Other studies looked at the pros and cons of increasing and decreasing lot size of raw materials, with the conclusion that larger lot sizes tend to be more advantageous (Kang et al, 2018). These studies are informative, but do not address the issue of lot sizing in connection with packaging materials. We plan to use the available literature but will not incorporate it into our models since it does not directly address the issue at hand.

2.5 Reverse Logistics and Production Remnants Management

A multitude of studies have been conducted on reverse logistics (Bouzon et al, 2015) and reverse logistics optimization has gained extensive academic attention due to growing concerns on environmental protection, corporate social responsibility and corporate competitiveness (Agrawal et al, 2015). Sarkis et al (2010) discuss the economic, environmental, and social factors that reverse logistics has increasingly introduced into organization's focus. While the focus of our work was mostly driven by economic factors and cost considerations, the sponsor company has voiced a desire to reduce its environmental impact by introducing a compelling win-win situation if returns can be minimized.

2.6 Conclusions

Previous studies assume fixed container lot size upon completion of a review cycle and succeeding shipment will be measured full load or less than full load based on the set value. In practice, however, as in the case of our sponsoring company, the number of labels to carry per roll can be adjusted within certain specifications as long as it does not require change of container design due to ergonomics concerns. Furthermore, the transportation and warehouse cost incurred to deal with production residuals and remnants are barely mentioned, leading to a potential oversight where first-haul logistics cost is minimized while total cost may increase. Finally, cost optimization for finished goods and packaging materials are disconnected and analyzed on separate platforms without visibility of combined benefits. These three areas – an optimal lot size for packaging materials, an economic production quantity for finished goods and the development of a link connecting materials with finished goods are minimally covered by previous researches and are the focus of our project.

3 DATA AND METHODOLOGY

This section provides an overview of the data and the analytical methods used in our research. The two areas we are aiming to improve are MPQ optimization for finished goods, and MOQ optimization for packaging materials. For finished goods we will explain which SKUs were selected, the machine learning techniques, and the results of optimization. For packaging materials, we discussed the different models that we built, and the process flows that were followed to verify model feasibility. Lastly, sensitivity analysis was conducted to ensure that users can make informed decisions when data input changes.

3.1 MPQ Optimization for Finished Goods

The current MPQ is manually identified based on a rule of thumb and is directly linked to the minimum number of hours to schedule a production. We plan to utilize machine learning to measure product similarity and adopt a higher MPQ for SKUs in the cluster to reduce number of production scheduling.

3.1.1 Main Steps in MPQ Optimization

As illustrated in **Figure 4**, four main steps were followed to identify the new MPQ for the selected SKUs. First, candidate SKUs for optimization were identified based on historical production orders. Specifically, the number of current MPQ gating events was calculated with a predefined threshold value to determine whether a product is a potential candidate. Second, (Partition Around Medoids) PAM and K-means clustering were performed for these SKUs and new MPQ values were assigned to SKUs of the same cluster. Based on the clustering results, the expected reduction in the total number of productions was simulated with the updated MPQs. Finally, the estimated benefits were compared and evaluated based on different clustering methodologies. These four steps were executed consecutively and interdependently, which means any change in the output of previous steps would constitute a possible change in the final MPQ.

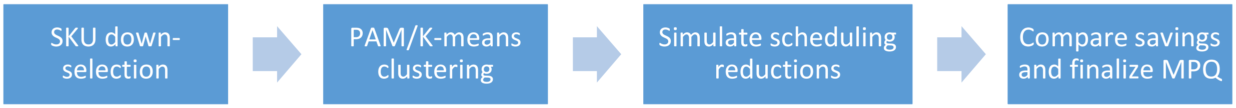


***Figure 4**: Four Step Process Flow in Finished Goods MPQ Optimization*

3.1.2 Identify SKU Candidates for MPQ Optimization

With a wide range of products designed to cater different consumer segments, demand patterns and production volume vary greatly among products, thus high variations among SKUs were observed. Typical characteristics of SKUs which were often scheduled at MPQ quantity are summarized as below:

1) Capacity: Sufficient production capacity
2) Demand: High demand variability with potential risk of obsolescence, mostly seen in C type SKUs
3) Production: Changeover cost relatively low with homogeneity shared with other scheduled SKUs

As the primary target for MPQ optimization is to identify opportunities to increase from its current value to reduce the number of production scheduling without impacting demand fulfillment, we first need to determine the scope of SKUs that are consistently produced exactly at the current MPQ quantity. The attributes listed **Table 2** were selected to identify SKUs that should be in scope for MPQ optimization.

***Table 2:** Selected Attributes to Identify Optimization Candidates for Clustering*

Count	**Attribute**	**Relevance to MPQ Optimization**
1	Number of Production Records	Production frequency
2	Number of Production Records Gated by Current MPQ	Necessity for optimization
3	Percentage of MPQ Gating Events	Necessity for optimization

3.1.3 Clustering

3.1.3.1 Attributes in Clustering

As aligned with the sponsoring company, the selected attributes listed in **Table 3** to determine finished goods clusters mainly consist of two dimensions: package type and production history, which were taken as key indicators of product commonality.

Table 3: *List of Attributes for SKU Clustering*

Variable Category	Variable Name	Data Type	Description
MPQ Observance	MPQ	Numeric	Current MPQ Quantity
Production Quantity	Sum of Production Record	Numeric	Number of times production is scheduled for this SKU
MPQ Observance	MPQ Gating Events	Numeric	Number of times actual production quantity equals current MPQ
Production Quantity	Average Production Quantity	Numeric	Average production quantity per production order
Production Quantity	Average Production Time	Numeric	Actual production time per production order
Packaging	Primary Package Type	Categorical	Box type for each product
Packaging	Case Converter	Categorical	Number of cases per box

3.1.3.2 Clustering Methodologies and Comparison

Given that SKUs in the same cluster were assigned the same MPQ value, it was more plausible to simulate with multiple clustering algorithms than to use a single clustering method in order to maximize possibilities for cost savings. The sponsoring company would also benefit from being provided multiple options as the planning team can apply different MPQ values under different circumstances based on the actual capacity situation and order status. Therefore, PAM clustering and K-means clustering were used to measure product similarity. A comparison of the two clustering methods can be found in **Table 4**.

Table 4:*Comparison of PAM Clustering and K-means Clustering*

Clustering Methodology	Number/Type of Attributes Used	Methodology to Determine Optimal Number of Clusters	Distance Measurement	Center of Cluster
Partition Around Medoids (PAM)	7 (Numeric + Categorical)	Average Silhouette width	Gower distance	Medoids (In the dataset)
K-means without categorical attributes	5 (Numeric, one categorical attribute converted to numeric attribute)	Average Silhouette width	Euclidean distance	Centroids (may not be in the dataset)
K-means with categorical attributes	6 (Numeric)	Average Silhouette width	Euclidean distance	Centroids (may not be in the dataset)

As similarity and distance calculation play a key role in determining the number of clusters as well as the proximity between each pair of SKUs, a general overview of the three distances: The Silhouette width, Gower distance and Euclidean distance are introduced as below.

- The Silhouette width: The Silhouette width calculates the average distance of elements in the same cluster compared to the average distance to elements of the other clusters. A higher value of silhouette coefficient indicates better clustering. The inflection point of Silhouette width indicates the optimal number of clusters.

- Gower distance: The Gower distance measures the partial dissimilarity between elements. For numeric features it compares the distance between two elements to the maximum distance among pairs of all elements in the dataset. For categorical attributes the distance will be a binary value depending on whether two elements belong to the same or different category (Filaire, 2018). A higher value of Gower distance between elements indicates less commonality and similarity.

- Euclidean distance: Different from Gower distance, Euclidean distance is measured in K-means clustering to determine data points in the same cluster. The centroids will not change until the total distance of each data point to its respective centroids reaches the minimum.

3.1.4 MPQ Optimization

Upon completion of each clustering, MPQ for SKUs in the same cluster were assigned two values: the MPQ of the medoid of the cluster and the maximum MPQ of that cluster. An updated production schedule was generated to compare with original production records to calculate cost savings driven by less production set-up and changeover. As changeover loss is difficult to quantify, we shared with the sponsoring company the simulation results using both scenarios.

The guiding rationale to utilize clustering for MPQ optimization is listed as below:

1) Product sequencing in scheduling: Arrange SKUs of the same cluster in production scheduling so that the run rate and throughput for machines are more stable as compared to product scheduling with SKUs with higher variability.
2) Contingency planning and SKU replacement: In case of material shortage, quality issues for certain SKUs, the production plan can be replaced by another SKU of the same cluster so that the impact on overall production scheduling will be minimized.
3) Packaging material demand planning: Due to the high commonality of SKUs in the same cluster, shortage or excess of packaging material in one SKU may trigger preventative actions in other

SKUs of the same cluster. The production planning team is advised to utilize clustering results to improve material management efficiency by product groups.

3.2 Packaging Material MOQ Optimization

MOQ optimization has been performed on every packaging material, and the delivery and transportation of packaging material is triggered by every production order of finished goods. We first converted each production plan into packaging material demand and aggregated the demand per day for each packaging material. A cost minimization function consisting of transportation cost and storage cost was formulated to find the optimal MOQ for each material. As advised by the sponsoring company, we started initial model testing on one label using Microsoft Excel Solver to ensure the trial run result is bought off across the board. Since labels take up a sizeable portion of total material value, we tested the model on more labels prior to replication in Python, a widely used programming language that can efficiently process big data and perform mathematical optimization. Finally, a sensitivity analysis was conducted to quantify how the optimal MOQ value will change in response to changes in cost and demand parameters.

As this would be the initial implementation of Python to find MOQ, the scope of optimization has been scaled to labels only for our project with the potential to be replicated to other material categories.

3.2.1 Packaging Material MOQ Optimization Process Flow

Five steps were followed sequentially for packaging material MOQ Optimization as detailed in **Figure 5**. Microsoft Excel Solver and Python were the two platforms that were utilized for optimization after data collection. A sensitivity analysis concluded this section to provide insights on the model stability.

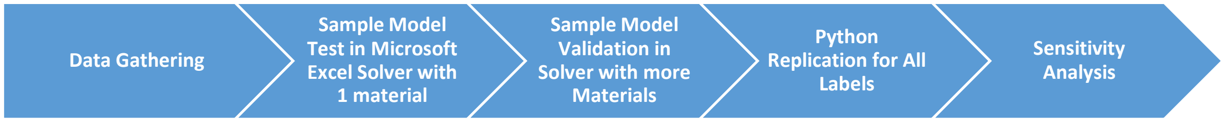


Figure 5: *Five-step Process Flow for Packaging Material MOQ Optimization*

3.2.2 Data Gathering

Finished goods production plan and packaging material Bill of Material (BOM) are the primary data sources extracted from the sponsoring company's Enterprise Resource Planning (ERP) system. As the total cost function needs to be formulated with constraints, secondary data are manually provided from the logistics team. The secondary dataset typically includes packaging material conversion rate such as box to pallet, storage cost, handling cost, warehouse capacity as well maximum packaging material MOQ. A brief workflow of the data gathering process is detailed in **Figure 6**.

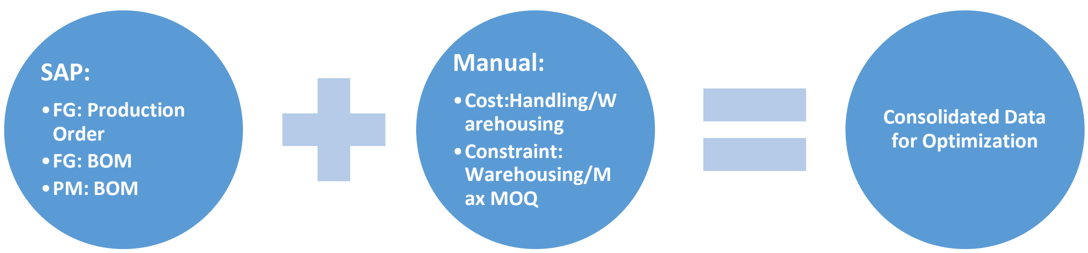


Figure 6: *Workflow of Data Gathering for Packaging Material MOQ Optimization*

3.2.3 Data Types

As optimization will run for each material with a cost minimization function, material demand per day is the required data before optimization. Given that one packaging material is used in multiple products, data conversion from finished goods demand to material demand was completed. Additionally, cost and capacity related parameters were provided manually by the sponsoring company. A summary of main data used for optimization has been detailed in **Table 5**.

Table 5:Data Types and Usage in Packaging Material MOQ Optimization

Data Description	Data Source	Usage
FG Production Order	ERP system	Generate packaging material demand per day based on FG production order and BOM
FG BOM	ERP system	
Material BOM	ERP system	Add material information (price/packaging type) based on packaging material demand
Handling Cost/unit	Manual Input	Calculate total cost in fulfilling production order
Warehousing Cost/unit	Manual Input	
Warehousing Capacity	Manual Input	Constraint in optimization model
Packaging Lot Size Constraint	Manual Input	Constraint in optimization model

3.2.4 Sample Model Test in Microsoft Excel Solver

Microsoft Excel Solver was used to validate the sample model for packaging material optimization given its user-friendly interface and flexibility to allow model testing by changing assumptions. One label was chosen to build the sample model as advised by the sponsoring company prior to more trial runs and Python replication on a larger scale. Data gathering was then implemented to obtain packaging material demand on each day of usage along with its related cost per day. And it is typical that as the same material are used in multiple products. The target of this model is to advise a new MOQ so that the total cost to transport and store the material is minimized. As mentioned previously, the cost includes not only initial delivery cost of the packaging material to fulfill production demand, but also includes the cost to transport production remnants back to warehouse, which is the trigger point and fundamental issue we plan to resolve in this project. The optimal MOQ should be able to reduce the number of return flows based on the material demand. Additionally, assumptions and constraints included in the model were aligned with the sponsoring company.

3.2.4.1 Sample Model Assumptions

Below are the assumptions made in setting up the model and these apply to all other labels once the model is replicated in Python.

1) No material mix per pallet: each pallet can only accommodate one component and there's no material mix in any delivery haul on a pallet level;
2) Cut-off time: Each material is delivered to the production line from the warehouse on day N-1 for production scheduled on day N with a cut-off time at 10pm (Day N production starts from Day N-1 10pm – Day N 9:59pm);
3) Remnant return: Remnants will be returned to the same warehouse where they are initially delivered on day N if there is no material call-off request on day N+1;
4) Material usage: A first-in, first-out (FIFO) approach is assumed for material inbound and outbound operations. Therefore, remnants will be consumed first in case of material call-off from warehouse;
5) Number of returns: Remnants will not be returned to warehouse the second time after initial return to warehouse and will be consumed inline after the third-haul delivery to production. Material scrap cost is out of scope;
6) Warehouse capacity: Warehouse capacity has been translated into the number of pallets as a hard constraint for each packaging material while the sponsoring company planned to use warehouse capacity as a soft constraint. Therefore, the preset limits on warehouse capacity in the model were tentatively relaxed;
7) Optimal MOQ Lower and Upper Bound: As a change in the MOQ for each packaging material may lead to design changes for the material container due to ergonomics concerns, the limit of MOQ upper bound was provided by the sponsoring company manually.

3.2.4.2 Model Formulation

1) Parameter Denotation:

   Ce: Transportation & handling cost per box per day (fixed cost in €/pallet)

   Cw: Storage cost/box/day (fixed cost in €/pallet)

   rv: Decision variable. Labels per base unit (e.g.: reel in box)

   Qb: Number of boxes delivered at first haul, $Qb_t = roundup\left(\frac{Dt}{RV}_1\right) if Fd = 1;$

$$Qb_t = roundup\left(\frac{Dt - Rp}{RVb}\right)\ for\ \ Fd \geq 0$$

   Rb: Number of boxes returned in the second haul delivery. $Rb_t = roundup\left(\frac{Rq}{Rv}/Bu2\right)$

   Ds: Days of storage for a material in the warehouse (calculated from raw data)

2) Decision Variable: rv: Rounding Value per container for one packing material

3) Objective Function: Total cost = 1st haul transportation cost for initial delivery + 2nd haul transportation cost for remnants + 3rd haul transportation cost for remnants + Storage Cost

$$\sum_{t=1}^{i}(\boldsymbol{Ce} * \boldsymbol{Qb_t}) + \sum_{t=1}^{i}(2 * \boldsymbol{Ce} * \boldsymbol{Rb_t}) + \sum_{t=1}^{i}(\boldsymbol{Cw} * \boldsymbol{Ds} * \boldsymbol{Rwp_t})$$

$\forall t = 1, \ldots, 273$

4) Constraints:

   (1) $RVmin \leq rv \leq RVmax$

   (2) RV is an integer

   (3) $Rw_t \geq 0$

   (4) $Rp_t \geq 0$

   (5) $Rwp_t \leq Pm$

5) Other Variables

   (1) t: Day of production, t ∈ i (1,273) (2019/01/01-2019/09/30)

(2) Fd: First day of production (binary, 1 if this production entry is the first of all production records)

(3) Pn: Binary, 1 for production planned on t+1, 0 for no production planned on t+1

(4) Demand: Production demand on day t in pieces

(5) CumDemand: Cum demand to date in pieces

(6) RVb: Labels per box, $RVb = rv * Bu1$

(7) RVmax: Maximum number of labels per base unit (e.g.: reel in box)

(8) RVmin: Minimum number of labels per base unit (e.g.: reel in box)

(9) Bu1: Base unit per box in the first transportation haul for initial delivery

(10) Bu2: Base unit per box in the second/third transportation haul for remnants

(11) Bp: Box per pallet

(12) Qp: Number of pieces delivered at first haul delivery on day t. $Qp = Qb * Bu1 * rv$

(13) Qc: Cum delivery in pieces. $Qc(1) = Qp(1); Qc(t) = Qc(t-1) + Qc(t))\ \ t \geq 2$

(14) Rq: Return quantity in pieces in the second haul. $Rq = (1 - Pn) * (Qp - Dt)$

(15) Rp: Remnants in production line in pieces. $Rp = (Qp - Dt) * Pn$

(16) Rw: Remnants in warehouse in pieces. $Rw = Rq - Rp$

(17) Rwp: Remnants in warehouse in pallets. Rwp = Roundup $(\frac{\frac{Rb}{Bu}}{rv}/Bp)$

(18) Pm: Maximum number of pallets in warehouse for each packaging material

6) Sample model test and trial run in more labels

Upon completion of formulating model constraints and clearing dataset, a nonlinear optimization model was developed using Microsoft Excel Solver. Discussions and review of the optimization result was completed with the sponsoring company. As advised by the planning team, more labels were chosen to test model feasibility prior to replication in Python.

3.2.5 Python Replication on All Labels

Upon successful sample model test in Microsoft Excel solver and in light of the limit of maximum 200 variables in one optimization using Excel, Python programming language was introduced to enable quick iterations for all labels using same optimization model built in Excel. In summary, we followed 4 steps as explained below to complete the MOQ optimization for all labels.

1) Coding in Python using SciPy. As an open source Python-based library, the SciPy optimize function provides solutions for objective minimization or maximization with identified constraints (*Jones, E., Oliphant, T., Peterson, P., & others. (2001)*. Mathematical formulas and constraints were translated into programming language in this step.

2) Python SciPy validation with sample data. As the sample code written in Python will be iterated across all labels, it is critical to validate the optimization result in Python and compare with the result in Excel solver. Data replication will only be initiated upon complete alignment of the two platforms.

3) Python iteration for all labels. In this step, mass data for all labels were loaded into Python. Two outputs were generated: the optimized MOQ and the total cost for each material.

3.2.6 Sensitivity Analysis: Scenario Simulation

In this section, we analyzed the sensitivity of total cost and optimal MOQ to the change of a set of other parameters. As demand patterns varies, one material has been selected to demonstrate model sensitivity. The analysis was performed in two steps in Excel Solver:

1) Total cost sensitivity to the change of MOQ/Unit holding cost/Unit storage cost,

2) Optimal MOQ sensitivity to the change of Unit storage cost/Unit holding cost/Component demand/Upper and lower bound constraint.

4 RESULTS AND ANALYSIS

This section summarizes the results for finished goods MPQ optimization and MOQ optimization for packaging materials with a sensitivity analysis.

4.1 MPQ Optimization for Finished Goods

Following the four steps to optimize MPQ for selected SKUs, insights from SKU selection, clustering, and cost saving estimation are introduced in this section.

Based on the threshold value of selected attributes, 104 SKUs were down selected among three product categories. As clustering analysis was conducted, the six SKUs in the C category were excluded. However, the complete list was shared with the sponsoring company for a separate analysis to optimize MPQ. A complete list of the 104 SKUs with MPQ optimization opportunity is detailed in **Appendix A**.

Table 6: *SKU Down-selection for MPQ Optimization*

FG Category	Production Records	Production Records Gated by MPQ	% of MPQ Gating Events	SKU	SKU with MPQ Gating Events above 9	% of MPQ Gating Events	% of Production Plans for SKU with MPQ Gating Events above 9
A	10150	3187	31.40%	932	98	10.52%	26.82%
B	2013	0	0%	308	0	0%	0%
C	3113	163	5.24%	477	6	1.26%	6.06%

Note: Production records with scheduled quantity at 1100 or less were excluded per request from the sponsoring company.

In summary, the selected 98 SKUs in category A share below commonality:

- Number of MPQ gating events are equal or above 9 times in the nine months from January to September 2019 (at least once/month).
- These SKU are sold regularly and are not seasonal or promotion items.

4.1.1 Finished Goods Clustering

As three clustering methodologies were implemented prior to identify a final MPQ for each of the 98 SKUs, this section briefly summarized the clustering result for each methodology.

4.1.1.1 Partition Around Medoids (PAM)

One input required to cluster SKUs is the optimal number of clusters, which needs to be pre-defined based on the selected parameters to measure SKU proximality. Using the Silhouette width, it can be concluded from **Figure 7** that four clusters would greatly increase the dissimilarity between each cluster groups. As the figure suggests, the clustering accuracy would increase with the number of clusters. However, it is more practical to choose the number of clusters at the inflection point to avoid overfitting.

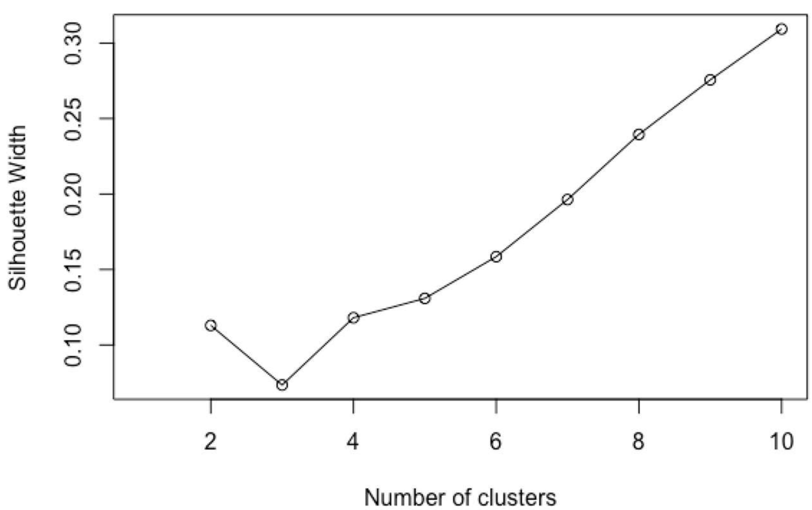


Figure 7:*Silhouette width and number of clusters with numeric and categorical attributes*

With the number of clusters identified at four, a PAM clustering is then conducted in R programming to group SKUs based on the set of production parameters. In conclusion, SKUs in the same cluster are more similar in production patterns and packaging attributes. The clustering result is visualized in **Figure 8** with a complete summary of each cluster in **Appendix B.**

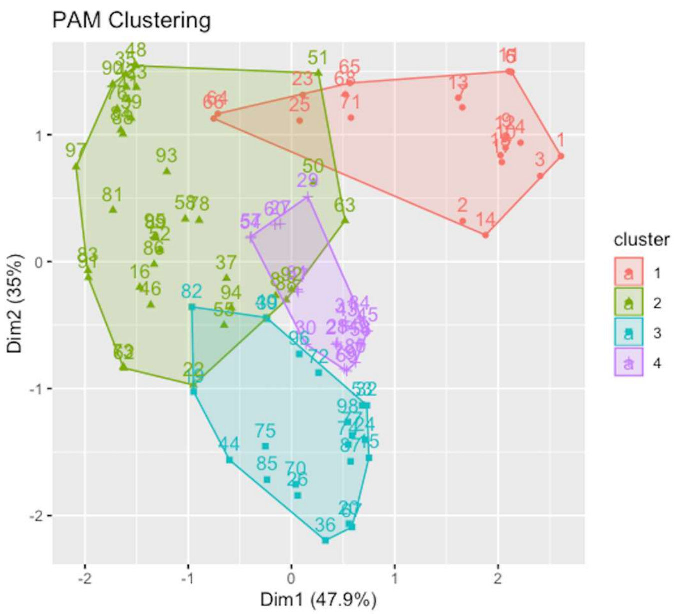


Figure 8: *Clustering Results with 4 Clusters Using PAM*

4.1.1.2 K-means Clustering Without Categorical Attribute Conversion

In order to identify the optimal MPQ for each SKU, K-means clustering was implemented to explore other possible options to measure product similarity. As illustrated previously, we first eliminated two categorical attributes: primary packaging type and case units per container. With the number of clusters identified at 2 as shown in **Figure 9**, the clustering result is visualized in **Figure 10**.

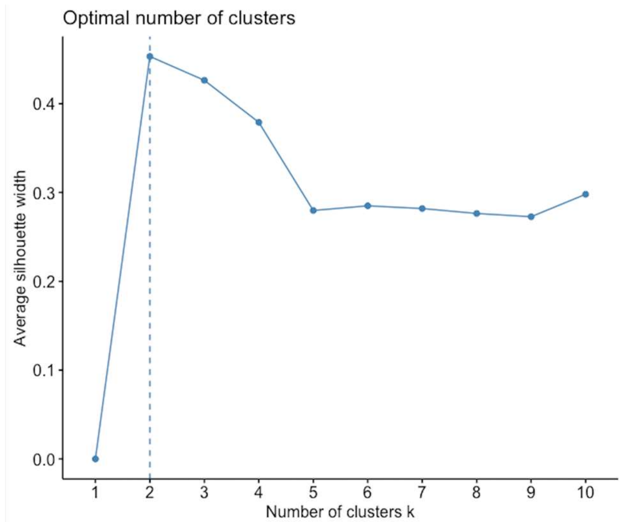


Figure 9: *Silhouette Width and Number of Clusters with Numeric Attributes Only*

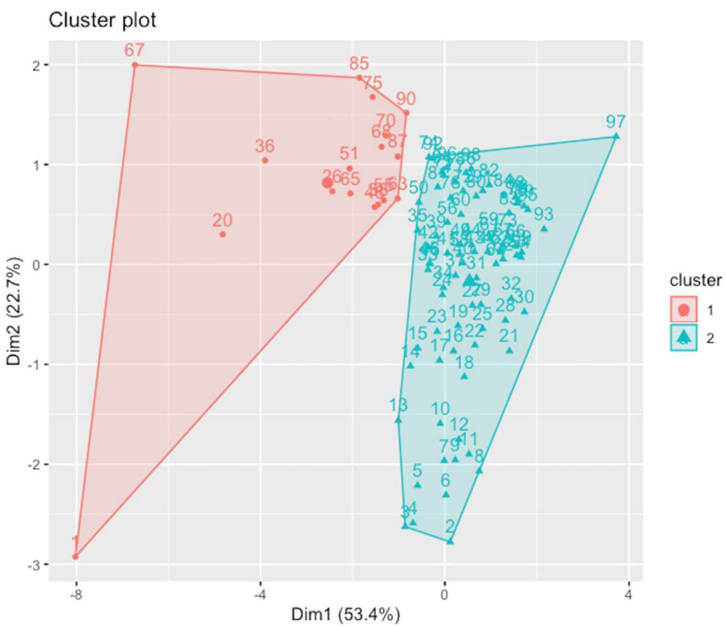


Figure 10: *Clustering results with 2 clusters using K-means*

4.1.1.3 K-means Clustering with Categorical Attributes Conversion

As K-means clustering can only process numeric values, another alternative to deal with categorical data is to convert the categorical values to numeric values on the premise that the number of categories is not widely distributed so as to miscalculate the distance between SKUs. Given the fact that primary package type contains only one value and case units per box is considered a critical parameter to evaluate product similarity, we excluded the primary package attribute and converted the case number attribute in K-means clustering. Similar to the previous K-means clustering with numeric values only, two is suggested as the optimal number of clusters as detailed in **Figure 11** and the clustering result has been displayed in **Figure 12**.

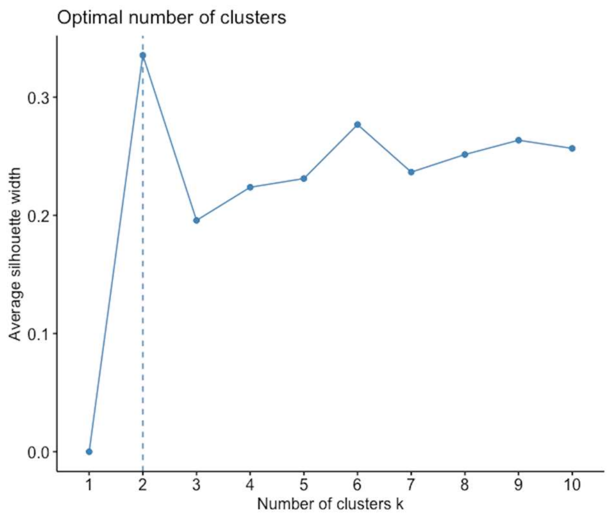


Figure 11: *Silhouette Width and Number of Clusters (categorical attribute converted to numeric values)*

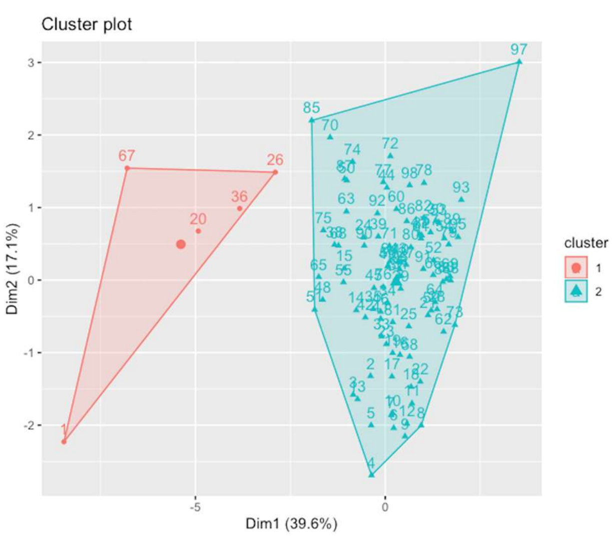


Figure 12: *Clustering Results with 2 Clusters Using K-means*

4.1.1.4 Clustering Result Summary with Max and Medoids MPQ for Finished Goods

Based on the three clustering methods performed, each SKU has been assigned six new MPQs aligned with the max and medoids (central for K-means clustering) values of each cluster. The max value from the three central points and three max points are selected as potential new MPQ for each SKU. Simulations were proceeded to evaluate the number of scheduling reduced with the new value.

Table 7:*Summary of Cluster Size with Medoids/Central Values and Max Values per Cluster*

Methodology	Number of Clusters	Cluster 1 (Size/Medoids /Max)	Cluster 2 (Size/Medoids /Max)	Cluster 3 (Size/Medoids /Max)	Cluster 4 (Size/Medoids /Max)
PAM	4	15/4200/8000	28/4000/5000	28/4000/4500	27/4000/4500
K-means (Numeric)	2	17/4000/8000	81/4000/4500	N/A	N/A
K-means (Numeric +Categorical)	2	5/4000/8000	93/2000/4500	N/A	N/A

The rationale for adopting both the medoid value and max value was to provide more insights to the planning team on the potential gain from using a higher MPQ. In case the new MPQ value equaled current value, we only simulated with the different value. Adopting the max MPQ for all SKUs in the same cluster may lead to FG excess and obsolesce, hence we provided two simulations results to the sponsoring company for review and evaluation.

4.1.2 Estimated Savings with New MPQ

Given the new MPQ and total production quantity required, an updated number of production scheduling was calculated. We then compared the updated scheduling with the original production plans to estimate the cost savings generated from a higher MPQ for each SKU.

The full results for each SKU are summarized in **Appendix B** with estimated reduction in production scheduling for 98 SUD SKUs. A sample simulation result for 1 SKU is shown in **Table 8** below:

Table 8: *Simulation Result of Estimated Reduction in Production Scheduling*

SKUNum	MPQ	Med	Max	ProductionRecordReduction_Med	ProductionRecordReduction_Max	ProductionRecord	NewProductionRecord_Med	NewProductionRecord_Max
[redacted]	4000	4000	4500	0	1	11	11	10

In summary, production scheduling is expected to be reduced by 42 times by using the medoids value and the reduction would add up to 491 with the max value. **Table 9** is a high-level summary of expected production scheduling for all SKUs.

Table 9: *Summary of Estimated Reduction of Production Scheduling with FG MPQ optimization*

MPQ Methodology	**Number of SKUs with New MPQ**	**Reduction of Production Scheduling**
Medoids	36	42
Max	95	491

4.2 Packaging Material MOQ Optimization

In order to ensure that the optimization result for packaging material MOQ is aligned with the expectation of the sponsoring company, seven labels were selected by the sponsoring company after initial model validation using Microsoft Excel Solver. Due to the limited data processing capability of Microsoft Excel Solver, the use of Python programming language facilitates large data processing and optimization. In this section will briefly summarized optimization result in each step.

4.2.1 Sample Model Test Using Microsoft Excel Solver

In order to test model feasibility and to ensure cost components have been correctly formulated, we used one label to run optimization in Microsoft Excel Solver. Material demand for this label on a daily basis was available after data processing. **Figure 13** showed an example of one entry for the selected material. Column BV is the current rounding value for the selected label and column CK is the decision variable – the optimized rounding value. Four cost elements have been highlighted in orange with estimated total savings listed in column BH. The target is to minimize optimized total cost in column DE with previous total cost calculated in column DG.

	A	D	E	N	P	Q	AI	BH	BV	CK	CL	CM	CN	CO	CP	CQ
1	Entry	Component Numb	FG Category	Production Dat	Planned Qty	FG MOQ	FG Planned Qty-Case	LBF-Fianl Usage	Rounding Value Reel	Optimized RV/Reel	Optimized RV/Box	Actual Delivery in Box	Actual Delivery in Pieces	Production Next Day	Quantity Return in PC	Quantity Return in Box
2	1			2019/1/14	546000	4000	**7000**	**42840**	4500	4388	8775	5	43875	0	1035	1

	A	CR	CS	CT	CU	CV	CW	CX	CY	CZ	DA	DB	DC	DD	DE	DG	DH
1	Entry	RM in WH(BOH)	RM in PL(EOH)	Total RM	Cum Demand	Cum Delivery	1st Haul Handling Cost	2nd Haul Handling Cost	3rd Haul Handling Cost	RM in WH in Box	RM in WH in Pallets	Storage Cost/Box/Day	Storage Cost	Total Cost/Day	Grand Total New	Grand Total	Savings
2	1	1035	0	1035	42840	43875	7.1	1.42	1.42	1	1	1	7	16.94	**2036.94**	**2292.42**	**255.48**

***Figure 13**: Sample data of daily demand for one packaging material*

As constraints were critical modeling components and should be aligned with the sponsoring company, a few parameters such as warehousing capacity and packaging limit per container were manually updated in the Excel working sheet. An example of preset constraints is detailed in **Figure 14**.

	A	DH	DI
7	6	Max Pallets/day in WH	1600
9	8	Max Labels/Reel	6000

***Figure 14:** Manually input constraints for model optimization*

Upon completion of data input, parameters were identified in solver with objectives, variables and constraints. The optimization solver then started running with the optimized result available in the working sheet. A snapshot of Excel interface can be found in **Appendix C.** Using the sample model as an example, the updated rounding value for the selected material is 4388 with a previous value of 4500 and an estimated cost savings of 11%, which was worth €255.48.

4.2.2 Sample Model Validation on More Materials Using Microsoft Excel Solver

As the model formulation and constraints would be used for all labels, another 6 materials were selected to further validate the assumptions and key cost parameters. A summary of the optimized result and savings for the seven trial run materials is presented in **Table 10.** It can be concluded from the table that an estimated saving of 34% is expected.

Table 10: *Summary of model trial run on 7 packaging materials with expected cost savings*

Count	Material Number	Previous Rounding Value	Optimized Rouding Value	Delta	Previous Total Cost	Optimized Total Cost	Savings (€)	% of Savings
1	[redacted]	4,500	4,388	(112)	2,292	2,037	255	11.1%
2		4,500	6,000	1,500	145	142	3	2.0%
3		4,500	4,000	(500)	2,437	1,580	857	35.2%
4		2,640	3,422	782	364	295	69	19.0%
5		4,500	3,378	(1,122)	3,979	2,029	1,950	49.0%
6		3,000	3,900	900	114	61	52	46.1%
7		3,000	4,388	1,388	160	123	37	22.9%
Total					**9,492**	**6,268**	**3,224**	**34.0%**

To better visualize the expected cost savings, a comparison chart is detailed in **Figure 15**.

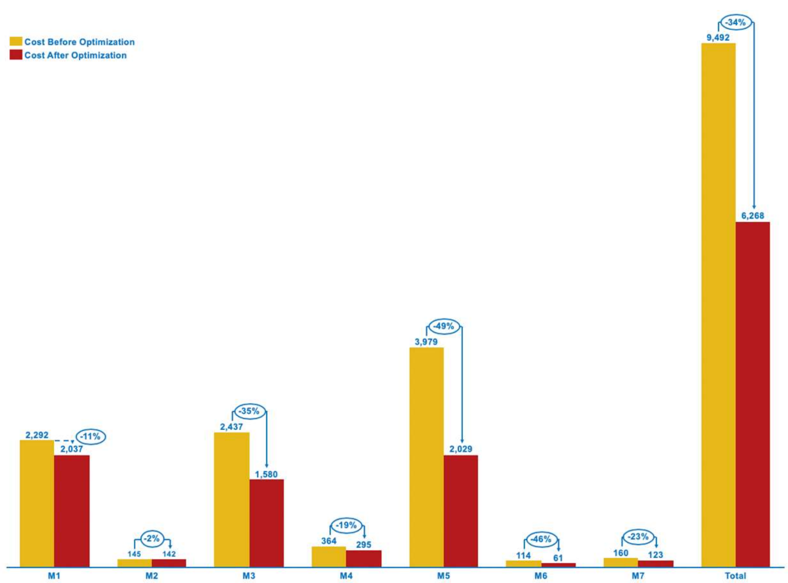


Figure 15: *Total cost comparison for 7 materials after optimization*

4.2.3 Full-scope Optimization Using Python

As illustrated in previous sections, the main benefit of introducing Python in our project is mass data processing and automatic iterations. This section summarized key findings in packaging material MOQ optimization prior to running sensitivity analysis.

4.2.3.1 Single Material Optimization Validation in Python

As Python SciPy enabled automatic replication of optimization, same code would be executed across all labels after the trial run. And we tested validity of the sample code by comparing the results in Excel and in Python to ensure that the sample MPQ was generated in two platforms.

Table 11 is a brief summary of the main components of Python SciPy optimization with its equivalents in Microsoft Excel Solver. The process flow of coding in Python was in essence a mathematical translation from non-programming language to programming language.

Table 11: *Comparison of Optimization in Microsoft Excel Solver and Python*

Components Name	Microsoft Excel Solver	Python
Total Cost	Objective	Objective function
Packaging Material MOQ	Variable	Variable
Limitations	Constraints	Constraints, Bounds
Relations	Excel formulas	Constraints
Platform	Excel Solver Engine	Python SciPy optimization library
Method	GRG Non-linear	minimize(method='SLSQP')

For the selected label, the same optimized value has been generated by both Excel Solver and Python as illustrated in **Figure 16**. The alignment of the optimization results with these two platforms validated the correctness of the sample code and laid the foundation for replication to other materials.

ComponentNum	OptimizedRoundingValueBaseUnit	MaxOptimizedRoundingValueBaseUnit
[redacted]	1961	8000
	1961	8000
	1961	8000
	1961	8000
	1961	8000
	1961	8000

```
In [88]: solution = minimize(objective, var, method ='SLSQP', bounds = bnds, constraints = const)
         sol = solution.x
         print('Rounding value: ', np.ceil(sol[0]),'Total Cost: ',objective(var))
         sol_dict = {'Qb':np.ceil(sol[Qb:Qb+n]),'Qc':np.ceil(sol[Qc:Qc+n]),'Qp':np.ceil(sol[Qp:Qp+n]),'Rb':np.ceil(sol[Rb:Rb+n]
         sol_df = pd.DataFrame(sol_dict)
         sol_df

         Rounding value:  1961.0 Total Cost:  83.56
```

Figure 16: *Comparison of MOQ Optimization Results in Excel Solver and in Python*

4.2.3.2 Optimization Iteration for All Materials in Python

As the logic and formulation for optimizing MOQ applies to all materials, iteration in Python is the recommended solution to complete repeated optimization tasks. It is not only time saving but also reduces errors that could otherwise occur in manual operations.

Per the suggestion of the sponsoring company, MOQ optimization was done per product category with the highest selling product category being prioritized. Upon completion of each iteration, an Excel document was generated with the optimized MOQ value together with the associated total cost. As the sponsoring company is most interested in comparing the original MOQ and the optimized MOQ as well as the estimated cost savings, we created a simple template to facilitate convenient interpretation of the results. **Table 12** showed an example of the optimization result shared with the sponsoring company.

Table 12: *MOQ Optimization Result Shared with Sponsoring Company*

GCAS	PM Type	Category	FP Size	Current RV	New RV	Current Cost	New Cost
[redacted]				3000	3022	385.24	380.98

Based on the optimization result covering three product categories in our research, the estimated cost savings is 16%, over €1 million in savings and 8% of the average value of all materials. In a highly competitive market environment of the CPG industry, a 16% cost saving opportunity is non-trivial. **Table 13** shows a high-level summary of MOQ difference between the original value and the optimized value with its associated cost savings by product category.

Table 13: *MOQ Comparison and Estimated Cost Savings by Product Category*

Product Category	Average Previous MOQ	Average Optimized MOQ	Cost Savings %
A	3674	4555	14%
B	8677	8880	28%
C	4228	2714	24%
Total	5527	5383	16%

4.3 Sensitivity Analysis

As introduced in previous chapters, sensitivity analysis was performed in Excel on the selected material to explore the dynamics of total cost and what might be the underlying parameters driving the change of optimal MOQ for materials.

4.3.1 Total Cost Sensitivity to Change of MOQ

The purpose of the optimization is to identify the optimal MOQ to generate minimized cost. Therefore, it is worthwhile to explore the sensitivity of cost to the change of MOQ. With this insight, the sponsoring company would be able to assess the cost impact in case an optimal MOQ cannot be executed. **Table 14** outlined the cost under different MOQs ranging from 2000 to 8000 on a given packaging material.

Table 14: *Total Cost Simulation with Different MOQ*

Scenario Summary	Current Values:	2000	2500	3000	3500	4000	4500	5000	5500	6000	6500	7000	7500	8000
Changing Cells:														
MOQ	2,371	2,000	2,500	3,000	3,500	4,000	4,500	5,000	5,500	6,000	6,500	7,000	7,500	8,000
Result Cells:														
Cost	91.46	113.82	91.46	91.46	91.46	91.46	105.3	105.3	105.3	105.3	105.3	105.3	105.3	105.3

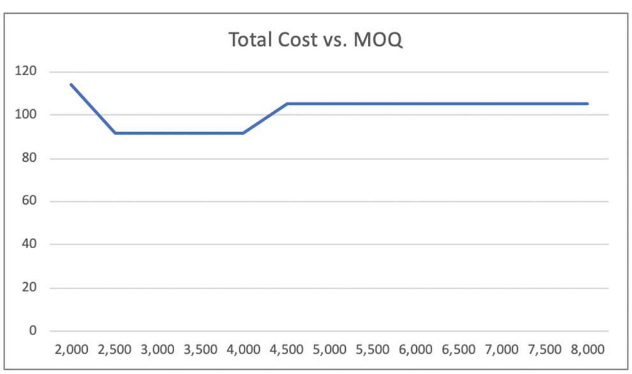
It is self-explanatory from the simulation that there might be multiple optimal MOQs generating the same minimized cost. This can be explained by the fact that the number of containers will not change within a certain range of MOQ values due to the rounding up operation in calculating number of packaging units needed to fulfill a certain demand.

4.3.2 Total Cost Sensitivity to Change of Unit Storage Cost and Unit Holding Cost

Using the same methodology, similar simulation was conducted on the total cost sensitivity to the change of unit storage cost and unit holding cost by keeping other parameters constant. By adjusting unit storage cost and unit holding cost from 1 to 10 on a scale of 1, **Table 15** explains the different sensitivity level of total cost to the change of storage cost and holding cost.

Table 15: *Total Cost Simulation with Different Unit Storage Cost and Unit Holding Cost*

Holding/Storage Cost	1	2	3	4	5	6	7	8	9	10
Total Cost(Change Holding Cost)	86	99	112	125	138	151	164	177	190	203
Total Cost(Change Storage Cost)	91	164	237	310	383	456	529	602	675	748



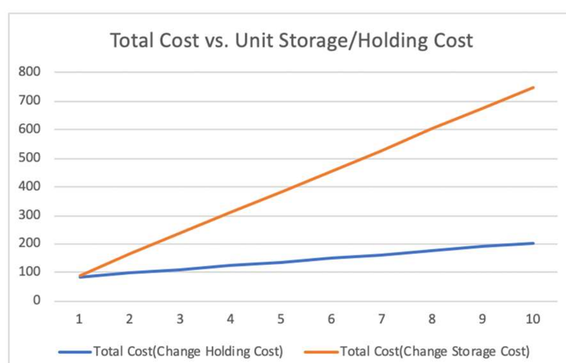


Figure 17: *Total Cost Simulation with Different MOQ, Unit Storage Cost, and Unit Holding Cost*

4.3.3 MOQ Sensitivity to Change in Cost and Demand

For the selected packaging material, we conducted another simulation to understand how MOQ would change under different unit storage cost, holding cost, demand and change of upper/lower bound. These scenarios were simulated separately with only one changing variable while keeping other parameters constant. **Table 16** provides a summary of simulation results under various scenarios.

Table 16: *MOQ Simulation with Different Unit Cost, Demand, Upper and Lower Bound Constraints*

Scenario	Original Value	Simulated Value	MOQ
POR (Plan on Record)	No Change(baseline)	No Change(baseline)	2371
Unit Storage Cost	1	1.42	2371
Unit Holding Cost	1.42	4.26	2371
Component Demand	20701	41402	5203
Upper/Lower Bound	[2000,8000]	[0,20000]	2371

It is apparent from the table that the optimal MOQ is most sensitive to demand patterns. As the number of boxes to be transported between facilities and stored in warehouse is a key factor of the total cost, the optimal MOQ will hold constant within a certain range of cost parameters as long as the number of boxes required does not change. The business team is advised to review demand patterns on a regular basis to explore opportunities for cost saving by adjusting MOQ.

Additionally, as the demand pattern for each material is unique, the above simulation only provided a glimpse of potential methodology to understand the underlying dynamics of the model and how the optimal results may not be optimal given certain changes in various other parameters.

5 DISCUSSION

This chapter provides a high-level summary of some of the limitations of our research, and a roadmap for where the sponsoring company or future researchers can look to gain additional insights on MPQ and MOQ optimization.

5.1 Limitations

For finished goods MPQ optimization, clustering analysis was performed based on the production history of the first nine months of 2019 with packaging size and production order as key attributes to determine SKU commonality. As the primary target for MPQ optimization is to reduce production scheduling frequencies, more parameters can be introduced to explore the possibility of further increasing the MPQ value. These parameters may include shelf life, product life cycle and production set-up cost. The clustering analysis and optimized MPQ for all clusters can serve as a starting point to reduce the number of production runs. While it should be used as a baseline to provide insights on SKU commonality, it is subject to further adjustment and review of the sponsoring company.

For packaging material MOQ optimization, due to the technical requirement of iterations in Python and the need to automate replications for all materials, constraints are set uniformly across all materials. However, the maximum loading for each material container may vary, and the maximum warehouse capacity differs. Therefore, the optimization result may not be the global optimum when the constraints are relaxed. Due to the large scope of packaging materials, it is not feasible to run optimization by each material with customized constraint parameters. Furthermore, the model made many assumptions on the operations of the plant that will likely not occur for 100% of ordering cycles. Our recommendation is for managers to identify a list of critical materials as candidates for separate optimization to further exploit cost saving opportunities. By focusing on high volume and/or high cost items, the company can achieve most of the model's value at a fraction of the time, and also minimize the risk of error from global assumptions. We also recommend that managers who use the model review the assumptions on a quarterly basis in order to verify that any changes in vendors, warehouses, or carriers are updated so the model outputs reflect those changes.

Using standard personal computers, the run-time in Python for materials with more than 60 production records was significantly longer than the rest of materials and could take over 2 hours to complete a single optimization. If managers are going to run optimization on many items, a recommended approach is to separate the optimization for these materials to reduce total run time and increase optimization efficiency.

For the sensitivity analysis, linear relationship was assumed between total cost and various parameters. However, the relationship may not be completely linear, which justifies the use of other non-linear regression methodologies. The assembling of both linear and non-linear regression is more likely to provide an understanding of the leading factors determining the optimal MPQ.

5.2 Alternative Methodology

As cost savings is the main driver behind all optimizations of the sponsoring company, a cost minimization function can also be utilized to identify the optimal MPQ for finished goods with production order history as the reference data. This is a similar approach adopted in identifying the optimal MOQ for packaging materials. Production set up cost, change over cost, production cost, and labor cost are key components of the objective function. The optimal MPQ for finished goods would generate the minimized total production cost for each SKU. If this methodology were to be implemented it would also be necessary to rerun MOQ optimization for packaging materials, as the

MPQ for finished goods is one of the main factors that determine the number of packaging materials ordered. For optimal results, plant managers can run both an MPQ for finished goods and a MOQ optimization for packaging materials on an annual basis, thus ensuring an efficient interaction between both product types and optimization results that are up to date.

For packaging material MOQ optimization, the same warehousing and packaging number constraints are applied for each material in our model. More accurate results can be provided by segmenting materials into smaller groups prior to iterations in Python, enabling a more customized optimization based on the different characteristics for each group of materials. Segmentation would likely improve results as grouping items with commonality in storage and packaging would reflect real-world operations for each group. This approach will need to be adopted by our sponsor company regardless, as the constraints made for our model reflect conditions of one production facility, while the model is intended to be implemented at additional facilities company-wide.

6 CONCLUSION

Our research established a new approach to identify the optimal MOQ for finished goods and MPQ for packaging materials with the cost of production remnants in scope. It is estimated that by simply reviewing production scheduling frequencies and production quantities for finished goods in various packaging sizes, clustering can be a valid approach to identify commonality between SKUs. This dynamic machine learning approach is expected to generate 16% of cost savings by increasing the number of production quantity without increasing the risk of excess and obsolesce.

In regard to packaging material MPQ optimization, Python SciPy optimization is a highly efficient platform for mass data processing and simulation. The number of materials loaded on each material container has a large impact to the number of return flows and this optimal value is highly dependent on the production demand. Our initial optimization in Python anticipates a cost saving opportunity of 16%, which indicates more room for improvement compared to the current practice of manual review. Below actions are recommended for the sponsoring company to improve cost effectiveness in inbound logistics management:

1) Establish a set of key parameters to identify SKU commonality prior to clustering
2) Set up a routine review period for optimization of finished goods and packaging materials
3) Develop a list of critical SKUs and materials for separate runs with customized parameters
4) Form a task force to communicate with suppliers and adjust results based on field practices

Machine learning and programming language are viable approaches for mass data processing and simulation, which releases more resources on the part of planner to analyze and review results. By taking the steps listed, planners can most effectively use machine learning techniques to implement cost savings initiatives.

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APPENDICES

Appendix A. Clustering Result for 91 Category A SKU and 6 Category C SKU for MPQ Optimization

Category A: SKU Candidates for MPQ Optimization

SKUNum	MPQ	CaseConverter	ProductionRecord	MPQGatingEvents	AverageProductionQt	AverageProductionTim	Cluster_PAM	Cluster_K-menas_Non	Cluster_K-means_Con
[redacted]	8000	165U	45	25	8,453	8.81	1	1	1
[redacted]	4000	114U	35	25	4,391	3.03	2	2	2
[redacted]	4000	108U	51	25	5,211	3.30	1	2	2
[redacted]	4200	75U	48	24	5,111	3.00	1	2	2
[redacted]	4200	87U	51	22	4,979	2.89	1	2	2
[redacted]	4200	87U	41	22	4,522	2.67	1	2	2
[redacted]	4200	84U	37	21	4,838	2.80	1	2	2
[redacted]	4200	81U	24	21	4,288	2.55	1	2	2
[redacted]	4200	75U	31	21	4,713	2.79	1	2	2
[redacted]	4200	75U	32	20	4,694	3.47	1	2	2
[redacted]	4200	87U	33	20	4,322	2.49	1	2	2
[redacted]	4200	75U	31	20	4,690	2.73	1	2	2
[redacted]	4200	84U	53	20	5,628	3.21	1	2	2
[redacted]	4000	105U	41	19	5,787	3.67	1	2	2
[redacted]	4000	114U	52	17	5,066	3.46	2	2	2
[redacted]	4200	81U	25	17	4,550	3.68	3	2	2
[redacted]	4200	75U	37	17	4,620	3.50	1	2	2
[redacted]	4200	75U	33	17	4,558	2.73	1	2	2
[redacted]	4000	66U	32	16	4,717	3.32	3	2	2
[redacted]	4000	114U	109	16	8,536	5.53	2	1	1
[redacted]	4000	90U	18	16	3,844	2.70	3	2	2
[redacted]	4200	66U	24	16	4,638	2.84	3	2	2
[redacted]	4200	84U	37	16	5,319	3.10	3	2	2
[redacted]	4000	114U	37	15	5,086	3.46	2	2	2
[redacted]	4200	84U	24	15	4,567	2.65	3	2	2
[redacted]	4000	123U	43	15	7,828	5.50	2	1	1
[redacted]	4000	108U	27	15	4,800	3.02	3	2	2
[redacted]	4000	90U	17	15	4,059	2.83	3	2	2
[redacted]	4200	93U	25	14	4,633	2.68	3	2	2
[redacted]	4000	126U	15	14	3,660	2.56	3	2	2
[redacted]	4000	90U	23	14	4,674	3.27	3	2	2
[redacted]	4000	114U	15	14	3,933	2.89	2	2	2
[redacted]	4200	72U	35	14	5,624	3.51	4	2	2
[redacted]	4200	90U	36	14	5,212	3.14	3	2	2
[redacted]	4000	72U	30	14	5,980	4.27	4	2	2
[redacted]	4000	105U	75	14	8,896	5.62	2	1	1
[redacted]	4000	96U	33	14	5,116	3.19	3	2	2
[redacted]	4000	96U	38	14	6,954	4.66	2	1	2
[redacted]	4000	99U	21	14	4,571	5.20	3	2	2
[redacted]	4000	99U	23	14	5,261	3.35	3	2	2
[redacted]	4400	72U	20	13	5,790	3.22	4	2	2
[redacted]	4400	72U	27	13	6,122	3.34	4	2	2
[redacted]	4000	90U	23	13	4,722	3.39	3	2	2
[redacted]	4000	123U	21	13	4,790	3.58	3	2	2
[redacted]	4200	90U	43	13	5,445	3.19	3	2	2
[redacted]	4200	81U	43	13	5,381	3.22	3	2	2
[redacted]	4000	102U	14	13	3,486	4.41	3	2	2
[redacted]	4400	72U	47	12	6,992	3.76	4	1	2
[redacted]	4200	90U	30	12	5,197	2.94	3	2	2
[redacted]	4000	117U	39	12	5,453	4.28	2	2	2
[redacted]	4500	57U	37	12	8,265	4.21	2	1	2

SKUNum	MPQ	CaseConverter	ProductionRecord	MPQGatingEvents	AverageProductionQt	AverageProductionTim	Cluster_PAM	Cluster_K-menas_Non	Cluster_K-means_Con
[redacted]	4000	96U	22	12	4,323	2.75	4	2	2
	4000	114U	15	12	3,980	2.77	2	2	2
	4000	105U	14	12	4,043	2.60	4	2	2
	4200	81U	48	12	6,687	3.88	2	1	2
	4200	90U	26	12	5,741	3.28	3	2	2
	4000	105U	17	12	4,247	3.01	4	2	2
	4500	45U	22	12	5,518	2.73	3	2	2
	4000	72U	20	12	5,098	2.73	4	2	2
	4000	108U	23	12	4,770	4.01	3	2	2
	4000	102U	21	12	4,650	3.00	3	2	2
	4200	66U	15	12	4,391	2.70	4	2	2
	4000	108U	49	12	6,270	3.89	2	1	2
	4200	84U	21	12	4,467	2.58	4	2	2
	4200	84U	62	12	7,170	4.06	2	1	2
	4200	84U	14	11	4,179	2.47	4	2	2
	5000	114U	84	11	11,137	7.45	2	1	1
	4200	84U	35	11	7,368	4.27	2	1	2
	4200	90U	14	11	4,049	2.34	3	2	2
	4000	123U	34	11	5,938	5.66	2	1	2
	4000	84U	25	11	5,464	4.14	2	2	2
	4000	129U	23	11	5,239	3.61	2	2	2
	4200	66U	13	11	4,418	2.68	4	2	2
	4000	114U	36	10	5,792	3.90	2	2	2
	4000	66U	35	10	6,930	5.42	2	1	2
	4400	72U	27	10	5,656	3.00	4	2	2
	4000	114U	35	10	5,174	3.38	2	2	2
	4000	108U	11	10	4,045	3.06	4	2	2
	4000	90U	13	10	4,154	2.88	3	2	2
	4200	90U	22	10	5,129	2.97	3	2	2
	4500	45U	24	10	6,229	3.10	4	2	2
	4000	99U	19	10	4,963	3.05	4	2	2
	4200	81U	13	10	4,448	2.67	4	2	2
	4000	72U	16	10	4,383	3.09	4	2	2
	4000	120U	32	10	7,206	5.93	2	1	2
	4000	96U	25	10	5,387	3.32	4	2	2
	4000	114U	52	10	6,144	3.97	2	1	2
	4000	72U	11	10	4,182	3.07	4	2	2
	4000	96U	11	10	4,055	2.81	4	2	2
	4000	72U	26	10	6,735	4.68	4	1	2
	4200	81U	16	10	5,194	3.00	4	2	2
	4000	96U	35	10	5,934	3.67	2	2	2
	4000	117U	12	10	3,517	2.33	4	2	2
	4200	81U	28	10	5,916	3.41	2	2	2
	4000	96U	11	10	4,109	2.59	4	2	2
	4200	78U	23	10	5,886	3.51	2	2	2
	2000	141U	22	10	2,516	2.60	4	2	2
	4000	114U	20	10	5,208	3.55	2	2	2

Category C: 6 SKU Candidates for MPQ Optimization

SKUNum	PrimaryPKGType	MPQ	BaseUnitSize	Sum of ProductionPlanVSMPQ	Sum of ProductionRecord	Sum of ProductionDurationHI	Sum of ProductionPlanCases	AverageProductionQuantity	AverageProductionTime
[redacted]	BO	3056	1.1L	11	20	38.36	68,828	3,441	1.92
	BO	3300	1.33L	11	22	113.57	97,012	4,410	5.16
	BO	3056	0.935L	11	25	55.59	103,532	4,141	2.22
	BO	3056	1.1L	10	18	100.13	62,748	3,486	5.56
	BO	3056	0.935L	10	48	218.54	295,120	6,148	4.55
	BO	3056	1.1L	10	30	68.27	124,185	4,140	2.28

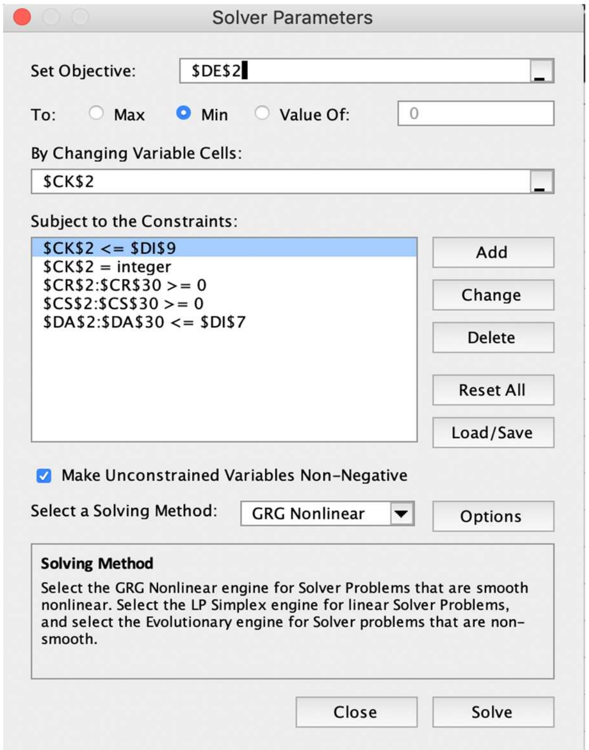
Appendix B. Final MPQ for Each SKU with Estimated Reduction of Production Scheduling

SKUNum	MPQ	Med	Max	ProductionRecordReduction_Med	ProductionRecordReduction_Max	ProductionRecord	NewProductionRecord_Med	NewProductionRecord_Max
	4000	4000	4500	0	1	11	11	10
	4400	4000	8000	1	11	47	46	36
	4400	4000	4500	0	0	27	27	27
	4400	4000	4500	0	0	20	20	20
	4400	4000	4500	0	0	27	27	27
	4200	4000	4500	0	1	25	25	24
	4000	4000	5000	0	2	36	36	34
	4000	4000	5000	1	5	52	51	47
	4000	4000	5000	0	5	35	35	30
	4000	4000	5000	0	3	37	37	34
	4200	4000	4500	0	1	14	14	13
	8000	4200	8000	1	2	45	44	43
	4200	4000	4500	0	1	30	30	29
	4000	4000	4500	1	3	32	31	29
	4000	4000	4500	0	1	23	23	22
	4000	4000	8000	0	8	35	35	27
	4000	4000	4500	0	1	23	23	22
	4000	4000	5000	1	3	15	14	12
	4000	4000	8000	1	10	43	42	33
	4000	4000	4500	0	1	21	21	20
	4000	4000	5000	0	3	39	39	36
	4000	4000	4500	1	2	18	17	16
	4200	4000	4500	0	1	24	24	23
	5000	4000	8000	2	7	84	82	77
	4000	4000	8000	3	20	109	106	89
	4000	4000	5000	0	2	35	35	33
	4500	4000	8000	0	7	37	37	30
	4000	4000	4500	1	2	15	14	13
	4200	4000	4500	0	0	22	22	22
	4200	4000	4500	0	1	26	26	25
	4200	4000	4500	0	1	43	43	42
	4200	4000	8000	1	9	35	34	26
	4000	4000	5000	0	2	23	23	21
	4000	4000	5000	0	3	15	15	12
	4000	4000	8000	1	10	34	33	24
	4000	4200	8000	0	13	41	41	28
	4000	4000	8000	0	14	75	75	61
	4000	4000	4500	0	1	14	14	13
	4500	4000	4500	0	0	22	22	22
	4000	4000	4500	0	1	11	11	10
	4000	4000	4500	0	1	17	17	16
	4200	4000	4500	0	2	36	36	34
	4200	4000	4500	0	1	14	14	13
	4000	4000	5000	0	2	25	25	23
	4200	4000	4500	0	1	24	24	23
	4000	4000	5000	1	3	35	34	32
	4200	4000	4500	0	1	35	35	34
	4000	4000	4500	0	1	21	21	20
	4200	4200	8000	0	14	37	37	23

SKUNum	MPQ	Med	Max	ProductionRecordReduction_Med	ProductionRecordReduction_Max	ProductionRecord	NewProductionRecord_Med	NewProductionRecord_Max
[redacted]	4000	4000	4500	0	1	17	17	16
[redacted]	4000	4000	4500	0	2	23	23	21
[redacted]	4000	4000	4500	1	2	21	20	19
[redacted]	4200	4000	8000	1	14	48	47	34
[redacted]	4200	4000	5000	0	1	28	28	27
[redacted]	4500	4000	4500	0	0	24	24	24
[redacted]	4200	4000	4500	1	1	43	42	42
[redacted]	4000	4000	4500	0	1	30	30	29
[redacted]	4000	4000	8000	1	14	52	51	38
[redacted]	4000	4000	8000	0	7	26	26	19
[redacted]	4000	4000	4500	1	2	16	15	14
[redacted]	4000	4000	4500	1	2	12	11	10
[redacted]	4000	4000	4500	2	3	14	12	11
[redacted]	4000	4200	8000	2	19	51	49	32
[redacted]	4000	4000	8000	0	8	32	32	24
[redacted]	4000	4000	4500	0	1	23	23	22
[redacted]	4200	4200	8000	0	11	24	24	13
[redacted]	4000	4000	4500	0	1	27	27	26
[redacted]	4200	4200	8000	0	12	31	31	19
[redacted]	4000	4000	8000	1	15	49	48	34
[redacted]	4000	4000	4500	0	1	20	20	19
[redacted]	4000	4000	8000	1	10	38	37	28
[redacted]	4200	4000	4500	0	1	37	37	36
[redacted]	4200	4200	8000	0	14	33	33	19
[redacted]	4200	4000	4500	0	1	25	25	24
[redacted]	4200	4000	4500	0	1	15	15	14
[redacted]	4200	4000	4500	0	0	16	16	16
[redacted]	4000	4000	4500	0	1	33	33	32
[redacted]	4000	4000	4500	1	3	22	21	19
[redacted]	4200	4200	8000	1	19	51	50	32
[redacted]	4200	4200	8000	1	15	33	32	18
[redacted]	4200	4200	8000	1	17	41	40	24
[redacted]	4200	4200	8000	0	15	37	37	22
[redacted]	4200	4200	8000	0	13	32	32	19
[redacted]	4000	4000	4500	0	1	13	13	12
[redacted]	4200	4200	8000	0	17	48	48	31
[redacted]	4200	4200	8000	0	12	31	31	19
[redacted]	4000	4000	4500	0	1	19	19	18
[redacted]	4000	4000	4500	0	1	11	11	10
[redacted]	4200	4000	4500	0	0	13	13	13
[redacted]	4000	4000	4500	0	1	25	25	24
[redacted]	4200	4000	8000	0	14	62	62	48
[redacted]	4200	4000	4500	0	1	21	21	20
[redacted]	4200	4200	8000	1	17	53	52	36
[redacted]	4000	4000	4500	0	1	11	11	10
[redacted]	4200	4000	5000	0	1	23	23	22
[redacted]	2000	4000	4500	8	9	22	14	13
[redacted]	4000	4000	5000	1	3	20	19	17
[redacted]	4200	4000	4500	0	0	13	13	13
[redacted]				**42**	**491**			

Appendix C. Microsoft Solver Objective Function and Constraints

Solver parameters user interface using Microsoft Excel Solver:



Optimization completion interface: